DICTIONARY LEARNING BASED SYSTEMS FOR MONITORING ACTIVITIES OF DAILY LIVING IN SMART HOMES

Thesis submitted by

Mrs. Pubali De

Doctor of Philosophy (Engineering)

Department of Electrical Engineering,

Faculty Council of Engineering & Technology

Jadavpur University

Kolkata, India

2022

JADAVPUR UNIVERSITY
FACULTY OF ENGINEERING AND TECHNOLOGY

INDEX NO. **63/16/E**

1. **Title of the Thesis:** "DICTIONARY LEARNING BASED SYSTEMS FOR MONITORING ACTIVITIES OF DAILY LIVING IN SMART HOMES"

2. **Name, Designation and Institution of the Supervisor/s:**

(a) Prof. Amitava Chatterjee

Professor, Department of Electrical Engineering

Jadavpur University, Kolkata –700032

(b) Retd. Prof. Anjan Rakshit

Professor, Department of Electrical Engineering

Jadavpur University, Kolkata –700032

3. **List of Publications:**

(a) International Journal Articles (Published)

i. **P. De**, A.Chatterjee, and A.Rakshit, **"Recognition of Human Behavior for Assisted Living Using Dictionary Learning Approach"**, *IEEE Sensor Journal*, vol. 18, no. 6, pp. 2434–2441, Mar. 2018, DOI: 10.1109/JSEN.2017.2787616, (Current IF: 4.325).

ii. **P. De**, A.Chatterjee, and A.Rakshit, **"PIR Sensor based AAL Tool for Human Movement Detection: Modified MCP based Dictionary Learning Approach"**, *IEEE Transaction Instrumentation and*

Measurement, vol. 69, no. 10, pp. 7377-7385, Oct. 2020. DOI: 10.1109/TIM.2020.2981106, (Current IF: 5.332).

iii. **P. De**, A. Chatterjee, and A. Rakshit, **"Regularized K-SVD-Based Dictionary Learning Approaches for PIR Sensor-Based Detection of Human Movement Direction",** *IEEE Sensor Journal*, vol. 21, no. 5, pp. 6459-6467, Mar. 2021. DOI: 10.1109/JSEN.2020.3040228, (Current IF: 4.325).

iv. **P. De**, A. Chatterjee, and A. Rakshit, **"PIR Sensor based Surveillance Tool for Intruder Detection in Secured Environment: A Label Consistency based Modified Sequential Dictionary Learning Approach",** *IEEE Internet of Things Journal* (Early Access), DOI: 10.1109/JIOT.2022.3178160, (Current IF: 10.238).

(b) International Conference Publications

i. **P. De**, A. Chatterjee, and A. Rakshit, **"A hybrid IRLS-KSVD based dictionary learning algorithm for human behavior recognition",** in *Proc. IEEE Appl. Signal Process. Conf. (ASPCON)*, Kolkata, India, Dec. 2018, pp. 234–239. DOI: 10.1109/ASPCON.2018.8748744

ii. **P. De**, A. Chatterjee, and A. Rakshit, **"Human Behavior Recognition: An l_1-l_s KSVD-Based Dictionary Learning and Collaborative Representation Based Classification",** in *Advances in Control, Signal Processing and Energy Systems*, 1st Ed., Vol. 591, Tapan Kumar Basu, Swapan Kumar Goswami, and Nandita Sanyal, Ed. Singapore: Springer, 2020, pp. 97-105. DOI: 10.1007/978-981-32-9346-5_8

4. List of Patents: None

5. List of Presentations in National/International Conferences and Workshops:

a) **P. De**, A. Chatterjee, and A. Rakshit, **"A hybrid IRLS-KSVD based dictionary learning algorithm for human behavior recognition",** in *Proc. IEEE Appl. Signal Process. Conf. (ASPCON)*, Kolkata, India, Dec. 2018, pp. 234–239. (Presented at International Conf. on Applied Signal Processing (ASPCON 2018), Jadavpur University, Kolkata, India, 2018)

b) **P. De**, A. Chatterjee, and A. Rakshit, **"Human Behavior Recognition: An l_1-l_s KSVD-Based Dictionary Learning and Collaborative Representation Based Classification",** in *Advances in Control, Signal Processing and Energy Systems*, 1st Ed., Vol. 591, Tapan Kumar Basu, Swapan Kumar Goswami, and Nandita Sanyal, Ed. Singapore: Springer, 2018, pp. 97-105. (Presented at International Conf. on Advances in Control, Signal Processing and Energy Systems (CSPES-2018), B.P. Poddar Institute of Technology, Kolkata, India, 2018)

JADAVPUR UNIVERSITY
FACULTY OF ENGINEERING AND TECHNOLOGY

STATEMENT OF ORIGINALITY

I, **Mrs. Pubali De**, registered on **16th December, 2016**, do hereby declare that this thesis entitled **"Dictionary Learning Based Systems for Monitoring Activities of Daily Living in Smart Homes"** contains literature survey and original research work done by the undersigned candidate as part of Doctoral studies.

All information in this thesis have been obtained and presented in accordance with existing academic rules and ethical conduct. I declare that, as required by these rules and conduct, I have fully cited and referred all materials and results that are not original to this work.

I also declare that I have checked this thesis paper as per the policy and anti-plagiarism, Jadavpur University, 2019, and the level of similarity as checked by iThenticate software is 4 %.

Signature of the candidate: Pubali De

Date: 27.09.2022

Certified by Supervisors:

(Signature with date & Seal)

1. Amitava Chatterjee 27.9.22

(Prof. Amitava Chatterjee)

Professor
Electrical Engineering Department
JADAVPUR UNIVERSITY
Kolkata - 700 032

2. Anjan Rakshit 27.9.22

(Retd. Prof. Anjan Rakshit)

Retd. *Professor*
Electrical Engineering Department
JADAVPUR UNIVERSITY
Kolkata - 700 032

JADAVPUR UNIVERSITY
FACULTY OF ENGINEERING AND TECHNOLOGY

CERTIFICATE FROM SUPERVISOR/S

This is to certify that the thesis entitled **"Dictionary Learning Based Systems for Monitoring Activities of Daily Living in Smart Homes"** submitted by **Mrs. Pubali De**, who got her name registered on 16th December 2016 for the award of **PhD. (Engg.)** degree of Jadavpur University, is absolutely based upon her own work under the supervision of **Prof. Amitava Chatterjee** and **Retd. Prof. Anjan Rakshit** and that neither her thesis nor any part of her thesis has been submitted for any degree/ diploma or any other academic award anywhere before.

1. Amitava Chatterjee 27.9.22

(Prof. Amitava Chatterjee)

Signature of the supervisor

and date with official seal

Professor
Electrical Engineering Department
JADAVPUR UNIVERSITY
Kolkata - 700 032

2. Anjan Rakshit 27.9.22.

(Retd. Prof. Anjan Rakshit)

Signature of the supervisor

and date with official seal

Retd. *Professor*
Electrical Engineering Department
JADAVPUR UNIVERSITY
Kolkata - 700 032

Dedicated to Almighty God

"Determinism is the thesis that is true at every moment that the way things then are determines a unique future, that only one of the alternative futures that may exist relative to a given moment is a physically possible continuation of the state of things at the moment. Or, if you like, we may say that determinism is the thesis that only one continuation of the state of things at a given moment is consistent with the laws of nature."

~ Peter van Inwagen

* * * * * * * * * *

THE REAVEN

Deep into that darkness peering,

Long I stood there, wondering, fearing,

Doubting, dreaming dreams no mortals

Ever dared to dream before;

But the silence was unbroken,

And the stillness gave no token,

And the only word there spoken

Was the whispered word, "Lenore!"

This I whispered, and an echo

Murmured back the word, "Lenore!"

Merely this, and nothing more.

….. **Edgar Allen Poe**

* * * * * * * * * *

Acknowledgments

"When one door closes, another opens; but we often look so long and so regretfully upon the closed door that we do not see the one which has opened for us."

(Alexander Graham Bell)

It has been a genuinely life-changing experience for me to pursue this PhD., and I could not have done it without the support and direction I received from so many individuals. This thesis represented a journey through a variety of experiences rather than only being a collection of real-world experimental pieces. I have to confess that without certain people and circumstances that I came across along the road, such experiences or indulgences would never have materialized. This is my feeble attempt to recognize their contributions to my mission. I'm hesitant to make a mistake by leaving someone out or underrepresenting them since it's impossible to overestimate the significance of so many people's contributions. Simply put, I was unable to do my thesis work on my alone; I need the support of a large and varied group. The errors, though, are all mine.

My deepest gratitude and respect go out to my supervisor, **Prof. Amitava Chatterjee** and **Retd Prof. Anjan Rakshit,** whose comments and insistence on perfection helped make this dissertation what it is today. My confidence to proceed smoothly with my work has been greatly enhanced by their careful supervision, and also by their personal care and affection. No words can adequately express my gratitude to my supervisors for providing me with constant support and encouragement throughout my PhD tenure. They taught me a lot, and without their assistance, I couldn't have completed my thesis. They have always inspired me to become an independent researcher and assisted me to understand the power of critical reasoning. They provided me with constructive criticism which helped me to develop a broader outlook on my thesis. This endeavor would not have been possible without their moral support in the most difficult and challenging situation during this PhD tenure.

I am also extremely grateful to **Retd. Prof. Pranab Kumar Chattopadhyay, EE department, Jadavpur University**, whose constant encouragement and inspiration to start my PhD work also has a great influence.

Besides my supervisors, I am deeply indebted to the rest of my thesis committee members, **Head of the Electrical Engg. (EE) Dept., Jadavpur University (J.U.), Member of the Doctoral Committee from the EE Dept., J.U., Prof. Debjani Ganguly (External Member), Prof. Madhab Roy, Prof. Sunita Halder** and **Prof. Sugata Munshi**, for allowing me to see and recognize the gaps in my thesis work and make improvements to it as a result of their encouragement, insightful comments, and critical questions.

I spent more than five years learning, discussing, and performing experiments at the J.U. Engineering Department's measurement and Instrumentation (M & I) Section, which offered a secure, tranquil, and lively atmosphere. I want to express my profound appreciation to my lab mates from the M & I Section for the interesting conversations and arguments, for the extended hours we spent working together on experimental work, and for all the enjoyment we have had. Working with individuals like **Mr. Saptarshi Chatterjee, Mrs. Sayanti Chaudhuri** and **Mr. Pritam Paral**—who in the short run become close friends—was a real delight.

I am really thankful to them for their good company and motivation that helped me in all possible ways to get back from any difficult situations.

Without the help of dissertation students from the M & I Section, my experimental work could not have been completed. I am highly grateful to **Mr. Soumyendu Sekhar Ghosh**, **Mr. Saibal Ghosh, Ms. Medha Nag, Mrs. Sayanti Choudhury** and **Mr. Saptarshi Chatterjee**, who volunteered to be a part of this work, and performed excellently and made a significant contribution to this piece of research.

I am also grateful to **Mr. Biswarup Ganguly** and **Mr. Shouvik Choudhury**, whose friendly cooperation and generous help enabled me to present my thesis in a more systematic and comprehensive manner. I would like to appreciate their initiative and sincere efforts to equip me with all the necessary information and documents required for thesis submission. They also helped me in each stage of my thesis writing with their experience.

I want to express my sincere gratitude to the other respectable professors in the M & I Section, **Prof. Debangshu Dey, Prof. Mita Dutta, Prof. Biswajit Bhattacharya** and **Prof. Gautam Sarkar**, for their support and insightful comments that improved the overall strategy I used for my research and enhanced the quality of my research work.

I would also like to acknowledge all the technical assistants and non-faculty members associated with the M & I Section, **Mr. Debabrata Mondal, Mr. Santanu Biswas, Mr. Subhajit Paul** and **Mr. Biswanath Adhikari,** whose endless support helped me to install my experimental setup initially and helped me to adjust to the new environment of the M & I Section during initial days of my PhD work. In order to conduct tests, they frequently offered minimal needs. They also consistently showed their readiness to work with me and assist me as needed during the course of my study.

I also would like to mention that, apart from Jadavpur University, my current organization **Techno International Batanagar** also provided indispensable financial support for the over-length page charges encountered by the international journal articles published in connection with this thesis work and also, provided a research-friendly environment

It is inexplicable to me to explain in words the sacrifices and efforts of my family towards me during these five years of journey. Despite that, I would like to thank my parents, **Mr. Ananta De** and **Mrs. Purnima De** for their constant support, timely encouragement, endless patience, and unconditional trust in me which is the basic foundation of my energy. Their love revives me when I feel tired. It is also my honor to say a heartfelt thank you to my husband, **Mr. Arpan Kumar Manna**, who has been by my side throughout this PhD., living every single moment of it with me, and without whom I would never have been able to embark upon this journey at all. It was his encouragement and assistance that helped me avoid several mistakes. Throughout my PhD tenure, he also provided strong support to the family. I would like to express my gratitude to my parents-in-law **Mr. Lakshmi Narayan Manna** and **Mrs. Gauri Manna** for their unfailing emotional support. I would definitely not be where I am now if it were not for their efforts, encouragement, and blessings.

Last but not least, I would like to express my gratitude to this marvelous institution, which has been like my second home over the past decade. This journey has brought me into contact with many of the individuals mentioned above, who have had significant impacts on my life. Hence, I desire to convey my sincere thanks to **Jadavpur University (J.U.)** for welcoming and supporting me.

Finally, I would like to ask God to give me the courage and strength to overcome all the difficult situations in the future as he has given me so far.

Mrs. Pubali De

PhD Fellow,

Department of Electrical Engineering,

Jadavpur University

ABSTRACT

In recent years, incredible development in medical science has resulted in an increase in average life expectancy (except for the Covid19 pandemic period) and there is a demographic change in the ratio of the number of elderly people to those of working people in society. Due to this propensity, new challenges have been introduced from a social and economic standpoint in society, in providing a self-sufficient living for older age people. **AAL** technology provides a platform of solutions to such problems as monitoring human activities, fall detection, human movement detection, and many other problems related to assisted living. Development of sensor(s) based, signal processing aided, low-cost ambient assisted living tools (**AAL**), essentially for assisting elderly people, home automation, and remote monitoring purposes, has become an important research domain. Hence, designing a sensor-based device that can offer many state-of-the-art functionalities in the **AAL** environment has become a critical challenge. There are many different kinds of sensors for such applications, those are **PIR** sensors, Vibration sensors, wearable accelerometer sensors, etc. The present research work aims to develop a low-cost, sophisticated hardware-software system that can solve several challenges associated with the **AAL** environment.

The first part of this research work is concerned with developing a framework for activity recognition of motion primitives based on a sparse representation of signals which utilizes a sparse combination of atoms from an over-complete dictionary. This research work intends to investigate the suitability of applying dictionary learning algorithms like **K-SVD**, which is usually used to construct an over-complete dictionary, for the effective progress of the **ADL** monitoring system. This work proposes to formulate the classification approach by using **SRC** classifiers, based on the dictionaries learned using the **K-SVD** algorithm. The proposed approach is validated on the publicly available dataset of wrist-worn accelerometer sensors for activity recognition in the context of activities of daily living (**ADL**). Moreover, the experimental study

demonstrated how a sparse representation-based approach can be advantageously applied to one of the most challenging problems in **AAL**, namely, human behavior recognition. Here, it has also been established that the sparse representation-based approach can be efficiently applied for both bi-class and multi-class behavior classification/segregation purposes. Additionally, this research work has shown how a suitable choice of initial dictionary size may have a significant impact on the identification accuracy of the algorithm. In this research work, a new concept of hybrid dictionary learning has also been introduced. Different kinds of greedy and relaxation algorithms are used as candidates both in the dictionary learning stage and in the classification stage for finding out the best solution for sparse representation. Performance analysis demonstrates that the proposed hybrid approach i.e., a hybrid iterative-reweighed-least-squares based **K-SVD** (**IRLS-K-SVD**) dictionary learning algorithm yields satisfactory results among all the other candidate algorithms of the greedy family and relaxation family to find out the best sparse representation of a signal. As part of this research study, the performance study of human behavior recognition problems is presented using $l_1 - l_s$ based **K-SVD** dictionary learning algorithm i.e., $l_1 - l_s$ has been utilized as a viable candidate for solving the stage of sparse representation in conventional **K-SVD** and the effectiveness of a collaborative representation-based classifier (**CRC**) has also been investigated for classification.

The second stage of this research work deals with one of the most important research problems i.e., human movement detection within the smart home environment. The work is involved in developing a sophisticated, low-cost, integrated hardware-software combined intelligent system for human movement detection problems. The solution employs a four **PIR** sensor-based hardware system coupled with a novel dictionary learning algorithm. In this context, the work first successfully implements the recently proposed multiple-cluster pursuit (**MCP**) algorithm-based dictionary learning algorithm for this human movement detection problem and then proposes a new variant of the **MCP** algorithm, called the modified **MCP (MMCP)** algorithm, for this purpose. Extensive real-life performance evaluations have been performed to demonstrate the suitability of **MCP** and the modified **MCP** algorithms for the problem under consideration. However, still, there is a scope for improvement in performance accuracy as it is a real-time system. Keeping this fact in mind, the research work then shows how a novel solution using regularization concept based **K-SVD** dictionary learning (**DL**) can be proposed for passive infrared (**PIR**) sensor-based ambient assisted living (**AAL**) technologies. In this thesis work, the **AAL** system focuses on detecting any human movement in specific directions in an unmanned environment. The regularization concept punishes solutions with large values of sparse representation coefficients and this work has successfully implemented regularized **K-SVD** (**RK-SVD**) and regularized approximated **K-SVD** (**RAK-SVD**) algorithms for low-cost hardware-software based intelligent **AAL** system, indigenously developed in the laboratory. This work also proposes modified versions of both algorithms (named **MRK-SVD** and **MRAK-SVD** algorithms) where novel methods of adapting the regularization parameter have been introduced. Extensive experimentations established that these approaches could significantly improve upon performances of **DL** based state-of-the-art approaches known, e.g., using multiple cluster pursuit (**MCP**) approaches, with **MRAK-SVD** algorithm emerging as the best alternative.

In the final phase of the thesis, the research work is involved to develop an intelligent surveillance tool for intruder detection problems. Identifying intruder (s) among the people who have access to a secured environment is crucial to achieving a flawless surveillance system in residential and office environments within the **AAL** environment. This present work shows how a novel dictionary learning (**DL**) algorithm-based approach can be combined with this indigenously developed hardware modules to design an intruder detection system. A novel **DL** approach is proposed combining the concepts of label consistency with a modified consistent adaptive sequential dictionary learning approach, named here as label consistency based modified consistent adaptive sequential dictionary learning (**LC-MCAS-DL**) algorithm. The conventional objective function in **DL** has been reformulated here by introducing the label consistency (**LC**) constraints along with reconstruction and classification errors. Then, the solution to this objective function is obtained by using a modified version of the consistent adaptive sequential **DL** algorithm (**MCAS-DL**). Extensive experiments have been performed to establish the suitability of this proposed approach for the problem under consideration.

The result obtained in different stages of this research work ensures that the idea of introducing a dictionary learning-based approach has become effective for monitoring **ADL** activities and it may also confirm that this dictionary learning-based low-cost sensor-based indigenously developed system can offer different facilities in the smart home environment.

Table of Contents

List of Algorithms

List of Figures

List of Tables

List of Abbreviations

A	
AI	**A**rtificial **I**ntelligence
AAL	**A**mbient **A**ssisted **L**iving
ADL	**A**ctivities of **D**aily **L**iving
ANN	**A**rtificial **N**eural **N**etworks
B	
BCR	**B**lock **C**oordinate **R**elaxation
BP	**B**atch **P**ursuit
C	
CASAS	**C**enter for **A**dvanced **S**tudies in **A**daptive **S**ystems
CRFs	**C**onditional **R**andom **F**ields
CNN	**C**onvolutional **N**eural **N**etworks
CAS-DL	**C**onsistent **A**daptive **S**equential **D**ictionary **L**earning
CS	**C**limbing **S**tairs
CR	**C**ollaborative **R**epresentation
CRC	**C**ollaborative **R**epresentation based **C**lassifier
D	
DL	**D**ictionary **L**earning
DT	**D**ecision **T**rees

DW	**D**rinking **W**ater

E

EER	**E**qual **E**rror **R**ate

F

FUSS	**F**ocal **U**ndetermined **S**ystem **S**olver
FPR	**F**alse **P**ositive **R**ate
FRR	**F**alse **R**ejection **R**ate

G

GPCA	**G**eneralized **PCA**
GUB	**G**etting **U**p from the **B**ed
GUI	**G**raphical **U**ser **I**nterface

H

HMMs	**H**idden **M**arkov **M**odel**s**

I

IoT	**I**nternet **O**f **T**hings
IRLS	**I**terative **R**eweighted **L**east **S**quares
IR	**I**nfrared **S**ensors
IRLS-K-SVD	**IRLS** based **K-SVD** algorithm
IDL	**I**ncremental **D**ictionary **L**earning

K

KNN	**K**-**N**earest **N**eighbors

L

LSTMs	**L**ong **S**hort-**T**erm **M**emory **N**etworks
LC-MCAS-DL	**L**abel **C**onsistency based **M**odified **C**onsistent **A**daptive **S**equential **D**ictionary **L**earning
LC	**L**abel **C**onsistency
LC-K-SVD	**L**abel **C**onsistent **K-SVD**
l_1-l_s	l_1 regularised **L**east **S**quares
LAOLS	**L**ook-**A**head **O**rthogonal **L**east **S**quares

M

ML	**M**achine **L**earning
MLPs	**M**ulti-**L**ayer **P**erceptrons
MOD	**M**ethod of **O**ptimal **D**irection
MRI	**M**agnetic **R**esonance **I**maging
MCP	**M**ultiple **C**luster **P**ursuit
MMCP	**M**odified **M**ultiple **C**luster **P**ursuit
MCAS-DL	**M**odified **C**onsistent **A**daptive **S**equential **D**ictionary **L**earning
MRK-SVD	**M**odified **R**egularised **K-SVD**
MRAK-SVD	**M**odified **R**egularised **A**pproximated **K-SVD**
MP	**M**atching **P**ursuit

N

NBs	**N**ave-**B**ayes

O

OMP	**O**rthogonal **M**atching **P**ursuit
OLS	**O**rthogonal **L**east **S**quares
OC-SVM	**O**ne **C**lass **S**upport **V**ector **M**achine

P

PIR	**P**assive **I**nfrared
PWG	**P**ouring **W**ater from **G**lasses
POLS	**P**rojection based **O**rthogonal **L**east **S**quares
POMP	**P**rojection based **O**rthogonal **M**atching **P**ursuit

R

RFID	**R**adio **F**requency **I**dentification
RF	**R**andom **F**orests
RK-SVD	**R**egularised **K-SVD**
RAK-SVD	**R**egularised **A**pproximated **K-SVD**
RMSE	**R**oot **M**ean **S**quare **E**rror

S

SVM	**S**upport **V**ector **M**achines
SR	**S**parse **R**epresentation
SRC	**S**parse **R**epresentation-based **C**lassification
SVD	**S**ingular **V**alue **D**ecomposition
SDC	**S**itting **D**own on a **C**hair
SUC	**S**tanding **U**p from a **C**hair
SVDD	**S**upport **V**ector **D**ata **D**escription

T

TP	**T**rue **P**ositive **R**ate
TN	**T**rue **N**egative **R**ate
TNIPM	**T**runcated **N**ewton **I**nterior **P**oint **M**ethod

V

VQ	**V**ector **Q**uantization

W

WK	**W**al**k**ing
WMP	**W**eak **M**atching **P**ursuit

CHAPTER 1

Introduction

Over the past decade, *Smart Home Technology* has evolved from an academic research interest to a commercial industry. Initially, *Smart Home Technology* was used mainly for security and surveillance purposes, the entertainment field, etc. With the recent growth in different technologies including the *Internet of Things (***IoT***)*, *Artificial Intelligence (***AI***)*, and *computing methods*, researchers intend to concentrate more on research and development to address with the most crucial challenges such as assisting aging people, home automation, fall detection, remote monitoring, surveillance in residential or office environment and so on. The fundamental principle behind developing technology or ideas like *Ambient Assisted Living (***AAL***)* very often depends on an "*activity*" performed by a user. **AAL** is the term used to describe technologies that can enable assisted living using ambient intelligence [1]. One of the important problems within the genre of developing **AAL** technologies is monitoring *Activities of Daily Living (***ADL***)* i.e., developing technologies than can assist people in different activities that they perform in their day-to-day life. As manual identification of **ADL** problems is almost impossible in real life, this necessitates the development of sensor-based systems for the automatic acquisition and classification of **ADL** data [2]. Thus, in this context, it is pertinent to develop ambient intelligence-based **AAL** tools, especially for smart homes that can help elderly people to live self- sufficiently in their place and also in other indoor environments, e.g., in office places or in industries, where it is needed to implement safe zone or zones with restricted access. Worldwide, with passage of time, more and more research efforts are being directed at solving these problems. The present study makes a contribution to this emerging field of **AAL** *technology* by developing sensor-based *Ambient Assisted Living System Solutions* utilizing *Dictionary Learning* **(DL)-**based approaches, a state-of-the-art genre from the domain of signal processing. Within the purview of this thesis, several **DL** based state-of-the-art signal processing algorithms have been developed that can be suitably employed in conjunction with different sensor based real systems and these systems can be implemented in real life to solve a variety of **ADL** and **AAL** problems. The system solutions developed can be suitably used for activity recognition or behaviour recognition problems in smart homes, for enabling independent and safe living of elderly people in smart homes and also for intruder detection problems in smart homes or offices having restricted access areas.

This introductory Chapter of the thesis presents a brief overview of the sensor-based activity monitoring module and different kinds of **AAL** problems within the *smart home environment*. This is followed by a comprehensive review of the relevant literature, based on which different relevant research ideas can been identified. This has led to the motivation of this present research work, and following this, the objectives and the contributions of this research work are described. Finally, the outline of the rest of the thesis has been described.

1.1. Monitoring Activities of daily living in Smart Home: An Overview

Monitoring of *Activities of Daily Living* (**ADL**) is one of the key aspects of **AAL**. This becomes an interesting research idea in the modern world where continuous monitoring of various **ADL** events and their automatic classification is a big challenge. Four different categories of monitoring activities have recently received significant attention in the **AAL** context, such as *Human Behavior Monitoring*, *Human Activity Recognition*, *Identification of Human Movement Direction*, and *Intruder Detection Problem* [1], [2]. Recent accomplishments in the **AAL** domain have successfully shown how monitoring devices can be developed by using different sensor technologies for recognizing different **AAL** activities [2]. In connection with the human behavior recognition problem, in [1], Debes *et al.* dealt with the automatic classification of different **ADL** problems which has become a crucial challenge in the **AAL** environment to assist elderly people living in their community and to help them if the need arises.

Similarly, in the context of activity recognition, several contemporary research works have concentrated in developing sensor-based **AAL** devices that can find solutions for various monitoring problems in specific **AAL** environments. In [3], the fall detection problem has been identified as one of the most challenging **ADL** activities for assisted living purposes. In this regard, Yazar *et al.* developed a smartphone-based **AAL** detection tool for recognizing different kinds of falls using an advanced classification paradigm. In the work reported in [4], Andò *et al.* introduced *RESIMA*, a new, multi-sensor-based assistive system that can assist people suffering from disabilities when they undertake mobility tasks in an indoor environment. Recent growth in the application of the *Internet of Things (***IoT***)* along with sensor technology has also resulted in several developments of smart surveillance systems in a

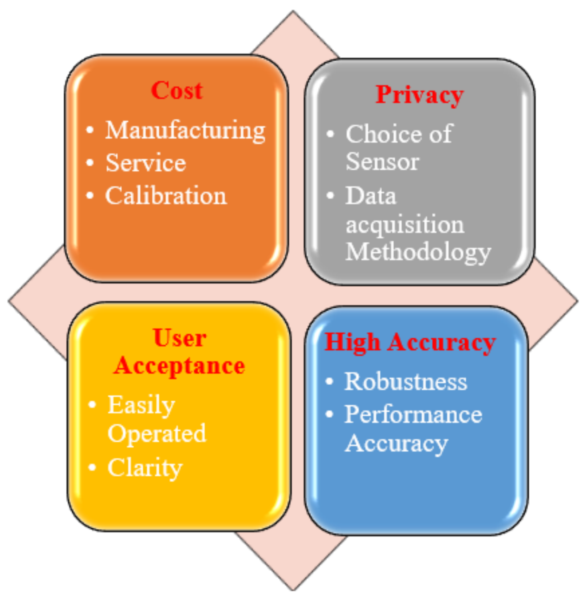


Fig. 1. 1. Some basic requirements in an AAL system

restricted environment which has become another prominent genre of **ADL** problems within the **AAL** domain. In [5], another interesting problem of monitoring activity has been addressed and, in this context, Hao et al. developed a wireless sensor -based module that can find solution for human tracking problems by detecting the angular displacement of thermal targets.

The monitoring of **ADL** raises a number of technical and nontechnical concerns that must be addressed in developing **AAL** devices for assisting living [1], [2]. The technical aspect of any assisted living tool will require the wise selection of the sensors and intelligent configuration of the sensor module and a reasonable choice of the signal processing aided machine learning algorithms, which are crucial for the automatic classification of **ADL** activities. In this regard, there are several challenges in developing an intelligent sensor-based **AAL** tool. Fig. 1.1 depicts some of the crucial challenges of real-life **ADL** monitoring systems.

Next, an overview of the sensor technologies and machine learning-based algorithms used in **AAL** environments are presented.

1.1.1. Importance of Sensor Technology in Assisted Living

The performance of any **AAL** device depends upon the data acquired using different kinds of sensors in the **AL** environment. Hence sensors form a key component in any such experimental set up. As reported in past research efforts, different types of sensors have been used in various experiments for **ADL** classification which led to different configurations and performances of the overall system. The effectiveness of sensors varies significantly based on the type of activity to be recognized. Two different categories of sensors are commonly used for this purpose, e.g., wearable sensors and non-wearable sensors. The current developments in sensor technology and ever-reducing sensor costs have encouraged researchers to place various sensors in various combinations to solve different **ADL** problems, including static setups as well as wearable sensors. Typically, wearable sensors like three-axis accelerometers, gyroscopes, magnetometers, etc., are attached to a person's skin or their clothes, for measuring some basic functions of an individual in daily living, e.g., position, heart rate, body temperature, blood pressure, motion characteristics, etc. Static sensors i.e., contact-free sensors are commonly installed in a fixed location(s) of a house or a room for detecting the presence of an individual or some movement. Contact-free sensors are mostly used to detect the functional status of any object, room temperature, etc. Wearable sensors offer higher positional accuracy and also can specify different basic health functions along with the motions of an individual within the **AAL** environment. A wearable sensor requires direct interaction from the user as well as the user should be aware of the charging of the device regularly. In contrast to this, contact-free sensors do not demand any kind of interaction from the user in a real-life environment. To cite an example, in [6], Bruno *et al.* dealt with human behavior recognition problems based on a wrist-mounted tri-axial accelerometer sensor. Using this wearable sensor, different types of motion primitives of an individual have been acquired, and each motion primitive has been referred to any one of the **ADL** problems. On the other hand, another class of sensory arrangement was considered by Wang *et al.* in [7]. They solved their daily activity and daily routine recognition problem at hand based on a hybrid sensory system where contact-free *Passive Infrared* (**PIR**) sensors were used to identify the location of an inhabitant in a room and wearable accelerometer sensors were used to observe different kinds of motion primitives of user's daily routine.

1.1.1.1 Wearable Sensor based Approaches

Accelerometer sensors have been utilized commonly for human behavior recognition [6], action recognition, human posture recognition, and fall detection [7] [8] among all generally accessible wearable sensors. In order to identify daily activities more precisely, accelerometer sensors are frequently employed in conjunction with contact-free ambient sensors [9]. Magnetic wristbands, multifunctional watches, magnetic sensors, and other hand-worn sensors are also being examined for several activity identification applications. A body-worn sensor device that incorporates accelerometer sensors, gyroscopes, and magnetometers, has been used in [10] to monitor the continuous movement of neurological patients and provide assistance in living independently by identifying their movement patterns. In [11], Choudhury *et al.* proposed a physique-based human activity recognition problem where raw sensor data have been acquired by using an accelerometer and gyroscope sensor module of the smartphone. It should also be noted that watches are often equipped with accelerometers to recognize arm and hand gestures [12].

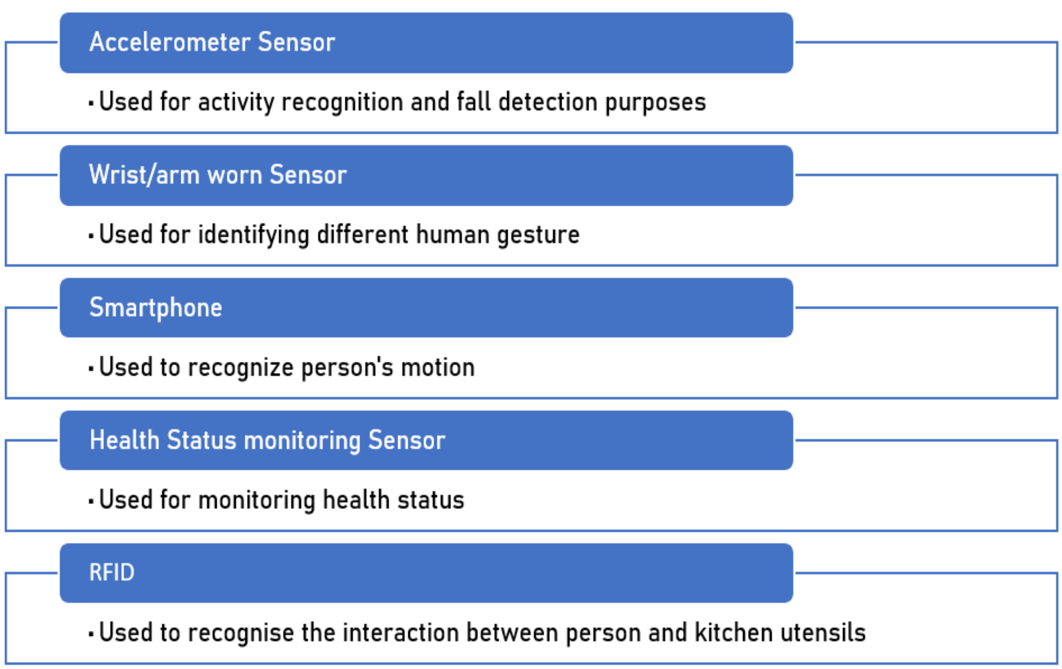


Fig. 1. 2. Different types of wearable sensors used for classifying ADL

In the context of wearable sensor-based approaches for **ADL** recognition, **RFID** tags are widely used to detect **ADL** activities. In [13], Paolini *et al.* presented how a 2.45 GHz *Radio Frequency Identification (***RFID***)* reader was used to perform 3D tracking of various tagged items in an electromagnetic environment, regardless of stationary or moving

conditions. Moreover, a broad range of sensors can be designed to detect vital parameters including blood pressure, pulse rate, body temperature, humidity, and glucose level. In [14], Triantafyllidis *et al.* introduced how such vital health statistics can be monitored and **ADL** classification tasks can be performed and also presented the design of a pervasive health system that enables self-management of patients during their daily activities.

All wearable sensors have the ability to collect detailed information about people's everyday activities and fingerprints, which poses serious privacy concerns. It is evident that sensors which provide detailed information about a person are not always respecting that person's privacy. Video cameras, for example, are not authorized in most rooms as they expose almost all human behaviour in their field of view. Magnet switches, on the other hand, may be installed in any room without significantly intruding on privacy, but they do not supply any thorough information on a person's activities. Multiple low-informative sensors (e.g., magnetic switches) can be deployed to enrich this information, allowing the user to get a deeper and complete understanding of their activity. Different types of wearable sensor based applications have been summarized in Fig. 1.2.

1.1.1.2 Non-Wearable Sensor Based Approach

Recently different types of non-wearable sensors have been used for **ADL** classification. A summary of conventionally used nonwearable sensors is presented in Fig. 1.3. Recent research reveals that infrared sensors are commonly used as non-wearable sensors for identifying a broad range of **ADL** activities. *Passive infrared* (**PIR**) sensor is one of the most commonly used non-wearable sensors due

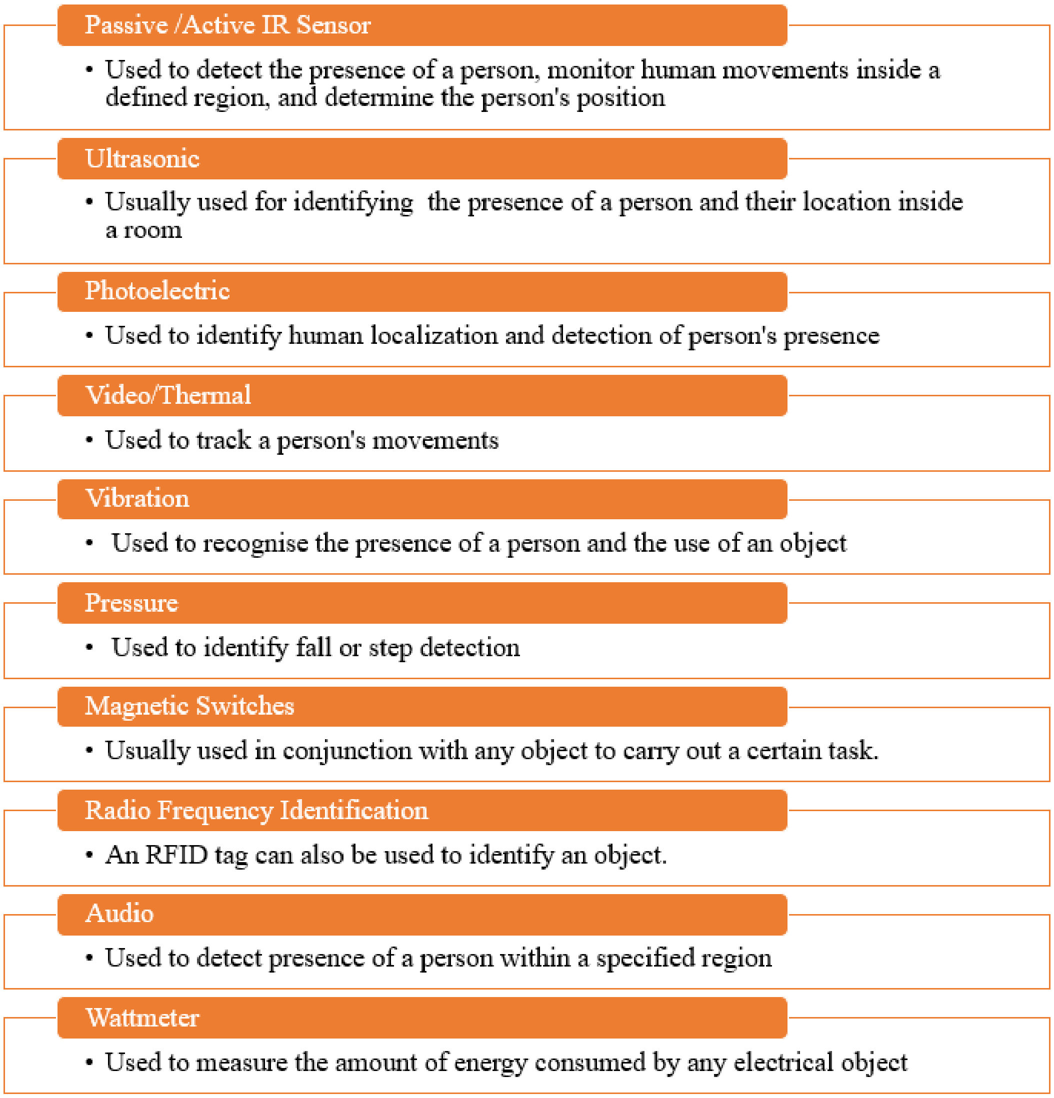


Fig. 1. 3. Different types of non-wearable sensors used for classifying different ADLs

to its low cost, which can be used for developing **AAL** systems in a wide range for **ADL** monitoring. Different configurations of **PIR** sensors have been employed for finding the solution to any **ADL** problem as per the function requirement. In [3], **PIR** sensors were paired with a vibration sensor to build an **AAL** tool that detected a human fall within a room by detecting an inhabitant's movement.

In [15], Fleury *et al.* presented a health smart home that included infrared sensors for location identification, door contact sensors, temperature and hygrometry sensors in the bathroom (to control the use of some facilities), microphone (for sound classification and speech recognition). This system also included some wearable sensors like kinematic sensor that can provide information on postural transition and the authors could establish how this health smart home comprising varieties of wearable and non-wearable sensors can be used to recognize activities of any subject during daily living. In [16], Xiong *et al.* presented a **PIR** sensor based identification module that was developed based on multiple passive infrared sensors, which can be used for human identification by collecting thermal infrared features from multiple parts of a human target. In [17], another genre of **ADL** problems has been addressed where an intruder localization and tracking module was developed to estimate the range of intruders and to track their trajectory by utilizing the strength of heat flux of signals by **PIR** sensors. The work in [18] introduced a **PIR** sensor based typical security system to identify any movement in the monitoring field and also the intensity of movement that is another very important **ADL** problem. In [19], Gopinathan *et al.* introduced a motion tracking system based on **PIR** sensors and that motion tracking system was developed using coded apertures as location structures with the capability of identifying source motion in one of the 15 cells in an area covering 1.6 m × 1.6 m using four pyroelectric detectors in each cell. In [20], a low-cost **PIR** sensor-based motion tracking environment was developed to modify the detection range using a fresnel lens. Different configurations of sensor modules have also been discussed and implemented for such types of motion detection and tracking by Shankar *et al.* In [5], Hao *et al.* developed a wireless pyroelectric sensor-based system. The developed prototype was composed of three modules, i.e., sensing and synchronization, error rejection, and data fusion model and it could identify any angular displacement due to the movement of a thermal target. In [21], another distributed pyroelectric sensor-based system was proposed based on body heat radiation which has been used to solve human tracking problems as well as multiple human identification problems. In [22], a wireless network-based feature extraction technique with **PIR** sensors was introduced for human tracking problems. The work in [23] introduced a movement tracking system using **PIR** sensor employing modified lens and machine learning based classifier for identifying human movement in a hallway. In [24], Jin *et al.* proposed a target detection and classification system based on data collected from **PIR** sensors and seismic sensors.

In some research [25], the functionality of a wireless acoustic sensor network has been successfully established that can extract information from both audio and ultrasound frequency range. Ultrasound sensors are usually combined with other sensors for monitoring **ADL** activities. Photoelectric sensors are devices that detect light and send out a signal whenever the light intensity reaches a certain level. It is not widely used; however, some projects have used it as a presence detection sensor [26], [27].

To identify human movements and/or general activities, a camera is placed in a precise location within a home in video-based systems. In natural conditions, noise and nonconstant lighting prevent this type of sensor from performing as well as it does in laboratory conditions. Furthermore, a video camera-based technique is regarded as substantially violating privacy. A low-resolution thermal sensor has recently been recommended as an alternative to a conventional video camera to solve security concerns [28], [29].

In certain study [30], vibration sensors are generally employed to detect a person falling. Vibration sensors may be employed for other purposes besides fall detection, such as sensing contact with other objects, indoor plumbing, and monitoring flow of water [31], [32], or [33]. Similarly, pressure sensors are used in certain works to detect the presence of an individual, footsteps, and falls. These sensors are often installed using smart tiles and floor mats [34]. Sometimes pressure sensors can also be installed in furniture for obtaining information of usage during activities.

Doors and cabinets are frequently monitored using magnetic switches to determine if they have been opened or closed. These sensors may also record when people enter a certain room and open cabinets, refrigerators, or garbage cans. Details of the application of magnetic switches can be found in [9], [35].

In-house sound detection and sound type distinction are often accomplished with the aid of audio sensors. By grouping ambient noises into categories like speech, phone ringing, dish clanging, and TV/radio, the installation of microphones in [15], [36] enabled us to identify events like talking, a door closing, a person walking, a phone ringing, an object falling, and TV use.

The detection of **ADLs** typically involves the use of a Wattmeter and other sensors that determine the amount of electrical energy consumed by lights and household appliances. This is now regarded as one of the key indicators of a subject's well-being. Electrical activity was recorded using the amount of electricity used by various appliances and room lights in [37], and it was then appropriately transformed into the likelihood of a specific **ADL.**

1.1.1.3 Pros and cons of wearable and non-wearable sensors and factors for sensor selection

By using wearable rings, bracelets, smartwatches, and mobile phones as sensors, technology has made it possible to monitor a wide range of functional metrics connected to health and activities, even at a minimal cost. There is a possibility that older people will not feel comfortable with these sensors since they need to be worn. Sensing devices that are less obtrusive can be included into intelligent clothing, and they can be combined with antennas to identify individuals. A number of more sophisticated sensors for monitoring vital signs are currently in the experimental stages, and even if they have proven beneficial in experimental tests, they still need miniaturization to be accepted as wearable devices [1]. It has been demonstrated that non-invasive optical or microwave sensors can detect activity and monitor vital signs more reliably. Installation may require infrastructural changes for such kind of sensors and they need to be placed properly in the environment. Smart devices or sensors in furniture can be used to keep track of daily activities and interactions with objects. Furthermore, some of the proposed solutions can be further enhanced and successfully implemented with the addition of **IoT** enabled sensors to already existing furniture, while others require smart objects to replace existing ones. Among the factors affecting sensors are their costs, intrusiveness, users' acceptability, the level of intervention required in the environment, privacy concerns associated with each sensor, and so on. Due to their widespread use and huge potential, these sensors are bound to become ubiquitous in near future. In addition to wearing sensors, non-wearable sensors, even those requiring structural modifications, will also be included into new structures, making homes and furnishings smarter.

With a view to consider all these factors for designing a sensor-based **ADL** system, among the various types of sensors, it has been found in Section 1.1.1.2 and 1.1.1.1 that **PIR** sensors are widely acceptable and in use for developing responsive environments due to their low cost, infrared light recognizing capability and ability to offer privacy secured platforms. The utility of **PIR** sensors has been reported in several research environments e.g., surveillance system [38], smart building [39] etc. The performance of **PIR** sensors relies not only on the direction of individual motion, but also on several other factors like the distance of the body from the sensor, its velocity and the presence of other individuals in the tracking location. The objectives in solving such **PIR** sensor-based human localization problems can be e.g., to identify the location of an elderly person in an otherwise unmonitored environment, whether he/she has entered in a potentially hazardous location, whether there is some intruder in a location inside home which is undesired and so on. Several relevant surveys

[18]-[24] have shown the usefulness of **PIR** sensors because of low cost, high precision, and associated secrecy and hence resulted in useful applications.

1.1.2 Sensor Based ADL Monitoring Setups

As was previously stated, one of the main objectives of **AAL** is to evaluate and aid in the self-maintenance of older individuals who live at home. Many ambient intelligence research concentrates on the automated detection of such behaviours in order to identify any changes in the pattern of **ADL** activities including eating, cooking, and bathing. Using a smart home as an experimental setup or some automated system facilities augmenting a traditional home or indoor environment, human activity data can be collected. An intelligent home can be formally described as an environment where technology has been incorporated to enhance the comfort or security of its residents [40]. Smart homes are generally equipped with a variety of sensors that can monitor the behavior of people living inside or can detect any abnormality in the ambient condition in a continuous manner. This necessitates the development of sensor-based systems for the automatic acquisition and classification of **ADL** data. Thus, it is pertinent to develop ambient intelligence-based **AL** tools, especially for smart homes that can help elderly people to live independently in their homes and more and more research efforts, all over the world, are presently directed to solve these problems. In accordance with the focus of the study, the experimental scenario and, consequently, the requirements for the smart home environment vary. A smart home can be a real house with sensors added to it, or it can be a laboratory where a smart home is being developed and temporary occupants can remain for a short or long time [1] [2]. In addition, some studies investigate patterns of normal behavior, while others use predefined scenarios to evaluate activity recognition algorithms. As a final note, the sensor types that are installed can also depend on the purpose to be served, for example, whether it is to improve energy efficiency or ensure privacy.

In [41], Rashidi *et al.* introduced the *Center for Advanced Studies in Adaptive Systems* (**CASAS**) *Smart Home* to investigate the use of machine-learning techniques for human activity recognition purposes. Lin Wu *et al.* introduced a nonparametric approach for activity recognition based on heterogeneous data in a smart home [42]. Fleury *et al.* proposed a health status smart home that can monitor activities of daily living and be used to detect loss of autonomy as early as possible. This health status home is equipped with different kinds of wearable and non-wearable sensors to acquire different human behavior related signals and **SVM**-based classification was used [15].

Over the last fifteen years or so, the phenomenal growth in ambient **AAL** technologies, has resulted in the development of several advanced sensor-based intelligent systems for the **AAL** environment [1], [43], e.g., *human tracking* [5], [21], [44], *activity recognition* [1], [45], *fault detection* [3], and *assessment of wellness* [1]. In [43], Monekosso *et al.* addressed **AAL** research, and the study states that among many topics under investigation in the **AAL** community, human activity recognition and behavior understanding is one of the most important topics which aim to detect and recognize actions, activities, and any abnormal situations, within the restricted environment.

Using *pyroelectric sensors*, Hao *et al.* [5] developed a wireless set up that can be used as human tracking system consisting of sensing modules (slaves), synchronization modules (masters), and data fusion modules (hosts) and also, presented a wireless distributed *pyroelectric sensor* system for tracking and identifying multiple people based on their body heat radiation [21]. As described in [44], will *et al.* introduced a millimeter-wave radar in the 24-GHz ISM band that can detect, track, and classify human targets. In this work, various algorithms for human detection and tracking were analysed and combined to create a new microcontroller signal processing routine that is compact and low-power.

Taking into account the two types of sensors described in Section 1.1.1 i.e. wearable and nonwearable, experimental approaches can be distinguished into locally installed and ambient approaches. A local approach is often tested for a short period of time in a laboratory setting based on predefined scenarios, with the aim of correctly identifying specific activities. The low cost and low power of these sensors make them ideal for installation. There are several types of sensors under these categories, such as accelerometers [7], [9],[10] which are used on human bodies and on objects, **RFIDs** [12] which are also used on bodies and objects, and door contact sensors. In contrast to this, in ambient approach, wearable sensors allow experiments outside a home to take place, but most are used in indoors, and in laboratories. Low-cost and low-power sensors allow the installation to run uninterrupted for a long period of time. Due to their simplicity, these relatively simple sensors, however, require a wide coverage, which makes their initial setup more complex. In real-life settings, ambient approaches are generally applied in longer-term experiments, either in smart homes (for days or weeks, for instance, [41]) or in apartments (e.g., [46]). In a study at the University of Missouri, ranz *et al*. [46] explored the impact of registered nurse care coordination and technology on the ability of aged older adults. Clinical outcomes have been improved through the combination of technology and care coordination. In [46], the authors summarized the research on TigerPlace, a Missouri-sponsored facility that promotes *Aging in Place*, and the sensor technology that has been developed for the purpose of supporting adults. In the controlled environment of a smart home, accurate and balanced data can be collected and annotated, for instance with cameras, making it suitable for testing activity recognition algorithms. Real-time data, however, gives a better representation of normal behavior, making it more suitable for testing behavior-modelling algorithms. In [47], ambient sensors, such as door contact sensors, motion sensors, and float sensors in the toilet, were used to recognize patterns of activities. The **CASAS** project followed this example to detect broad activities like eating breakfast, sleeping, and wandering [60]. Also, growth in the application of the **IoT** along with sensor technology has resulted in several developments of smart surveillance systems in a restricted environment [48], [49]. Identification of intruders has also become a crucial challenge for a researcher in a restricted environment. The importance of pyroelectric sensors-based intelligent modules in surveillance systems has been established in several recent surveys [50], [51].

1.1.3 Machine Learning based Approaches for ADL Systems

The gathering of data and use of straightforward analytical techniques, including threshold-based or distance-based approaches, are frequently the prerequisites for **AAL** systems. These methods could be enough in some **AAL** environments to send out notifications when risky occurrences take place. In this case, the data acquisition phase only requires a statistical analysis to estimate parameters. Multiple heterogeneous sensors require the analysis of several types of features and the recognition of more advanced functionalities. In order to lower **AAL** costs, feature selection is important for enabling algorithms to operate on devices with constrained resources and developing accurate classification models of **ADL** activities. Numerous studies have investigated feature selection techniques on large amounts of heterogeneous data, evaluating the outcomes of various selections of spatio-temporal characteristics. [52]-[53].

1.1.3.1 Sensory Signal Processing and Machine Learning

Combining techniques for sensory signal processing and machine learning (**ML**) allows for the solution of certain **ADL** categorization issues. Simple heuristics and more sophisticated machine learning-based methods are utilised in **ADL** classification. Among the popular machine learning algorithms explored so far in this context, recent research efforts have been directed to use machine learning algorithms like *Hidden Markov Models* (**HMMs**) in the field of machine health assessment [54], classification of *pedestrian activity* [55], and *behavior recognition* *problem* [56]-[58]. In [58], a comprehensive survey is presented by Turaga *et al.* to address the problems of action and activity recognition based on a variety of **HMM** variants. The performance of different approaches has also been investigated to test their ability to consider varying degrees of complexity. Li *et al.* [57] presented a simple and effective motion descriptor which is developed based on oriented histograms of optical flow field sequences. The *Hidden Markov Model* (**HMM**) is used in the instance of human action recognition following dimension reduction using principal component analysis. In this context, *Conditional Random Fields* (**CRFs**) [61], [62] also have enjoyed some initial success for activity and behavior recognition purposes. In [59], a nonparametric model based infinite hidden conditional random field approach has been proposed for activity recognition problem by Bousmalis *et al.* In [63]-[65] some probability-based classification methods have also experienced initial success for activity recognition problems.

To automatically create prediction models, machine learning approaches may be used for feature selection and data processing. *Support Vector Machines* (**SVM**), *Artificial Neural Networks* (**ANNs**), *K-Nearest Neighbors* (**KNN**), *Decision Trees* (**DT**), *Random Forests* (**RFs**), and *Multi-Layer Perceptrons* (**MLPs**) are *Machine Learning* (**ML**) methods that create models for each class through supervised learning stages and then categorise data in complicated scenarios without linear separation [61].[62]. In the case of **SVM** and **KNN**, a similarity measure is used to compare new instances of data to created examples data set, and new predictions are made based on that comparison. A Bayesian method **NB** apparently applies Bayes' theorem that requires the knowledge of *a priori* and conditional probabilities relevant to the problem at hand. The tree-based methods **DTs** and **RFs** construct a model that resembles a decision-making diagram depending on the actual attributes value in the data. Similarly *Artificial Neural Networks* (**ANNs**) and *Multilayer Perceptrons* (**MLPs**) are influenced by biological neural networks. These include various layers of neurons (nodes), each with a unique activation function that aids in mapping the input instances to the level of the output class.

SVMs [66] have been used to classify a variety of tasks, such as activity identification and **ADL** categorization, as a potential discriminative technique. In [67], Chernbumroong *et al.* proposed an activity recognition method based on **SVM** for detecting the daily activities of an elder person using low-cost wrist-worn wearable sensor. **SVMs** may distinguish between classes even on extremely high dimensional vector data by using the idea of structural risk minimization and kernel technique [23]. In **SVMs**, the decision boundaries are described with few samples (called support vectors) which make them memory efficient and noise resistant. *Support Vector Machines* (**SVM**) and *K-Nearest Neighbour* (**K-NN**) algorithms have also been successfully employed in the field of *human tracking* and *health condition monitoring problems* [69, 70], *hand gesture recognition* [71], etc. In this context, the identification of the position of an inhabitant has become an important research problem and this has been reported in [23]. In [23], Yun *et al.* proposed a novel approach for identifying the direction of human movement by using the concept of classical machine learning algorithm such as **SVM** and instance-based learning. In this framework of **AAL**, the interest of researchers is growing day by day in the field of person localization technology and the goal in solving such problems on person localization technology could be e.g., to provide self-sufficiency in ambient assisted living (**AAL**) environment or in common activities of daily living (**ADL**), to keep an eye over whether anyone has entered in a restricted environment, to detect whether there is an intruder inside a restricted environment [72]-[74], etc. Another work in [75] introduced **IoT** driven object identification module under an urban surveillance system. Such kind of intruder detection problem is also reported in [76] where **SVM** and *K-Nearest Neighbour* (K-NN) algorithms have been utilized for identifying the intruder and predicting his state of motion. *Convolutional Neural Networks* (**CNN**) and *Long Short-Term Memory Networks* (**LSTMs**) are examples of *Deep Learning* (**DL**) techniques that have recently been effectively used in a variety of application scenarios to concurrently solve the feature selection and model creation problems [77]. In [78], Mojarad *et al.* proposed a robust multi-label human recognition system that is composed of two modules, an activity recognition module and a correction module. Here, **CNN**, **NB**, **LSTM**, **SVM**, and **DT** have been used for solving this problem. In [79], in an attempt to recognize a person's most common daily activities at home, by combining wearable technology with deep learning techniques, Bianchi *et al.* suggested a wearable device-based human activity identification system.

The use of unsupervised learning techniques, which have been applied in limited cases to **AAL** systems, is another important class of approach. With no prior training phase or knowledge, they can cluster huge volumes of unlabelled data, group user behavior, and recognise high-level variations [80], [81]. In [81], Gupta *et al.* proposed a behavior recognition system, incorporating an unsupervised learning method with ambient sensors. In [80], a mild cognitive impairment detection system using an unsupervised learning technique has been proposed based on ambient and door sensor.

1.1.3.2 Pros and Cons of different Methodologies and factors for their selection

It is apparent from Section 1.1.3.1 that several possibilities for data processing are recognised in the context of **AAL** according to the complexity of the target. The literature has successfully employed a variety of straightforward behavioural recognition techniques, such as threshold-based and distance-based methods for data analysis. Machine learning approaches also have been applied to data processing in this context, inspired by the success of machine learning techniques in the pattern recognition field. Deep learning applications have also been used successfully in several instances. For more sophisticated machine learning, the main challenge is the volume of data needed for the learning phase. For the building of supervised, unsupervised, and deep models, large datasets are required. In situations involving **AAL**, when systems must be immediately deployed and functioning, this vast amount of data could not always be available. Furthermore, these systems also need significant features to be retrieved. Data is frequently redundant, thus important features must be extracted. During the classification or regression phase of a machine learning algorithm, a initial phase of feature extraction is essential to get the overall success of the entire process. Data might be redundant or variable; feature extraction could be too difficult to accomplish without the guidance of subject-matter experts. Deep learning algorithms have been used to overcome this problem since they automatically extract features from data rather of doing so manually. However, compared to conventional machine learning techniques, they frequently require larger data. It has emerged from research presented in Section 1.1.3.1 that it is impossible to compare various methods explored in various works, under one common framework. The majority of the technologies are used and evaluated in constrained contexts, such as laboratories or specific user cases, while others make use of data that has been collected from publicly accessible datasets [82] - [84]. As a result, the presented findings are based on numerous experimental data, making it almost impossible to determine whether an approach can be supremely better than the other ones for a particular problem at hand. However, the decision amongst the variety of approaches might be influenced by the earlier analysis of the pros and cons. For relatively easy tasks like binary classification and few-class classification tasks that entail fundamental feature engineering but cannot be addressed using simple linear discrimination based methods, in this context, traditional machine learning algorithms (**RF**, **SVM**, **CNN**, **ANN**, and others) are successful for finding solutions.

1.1.4 General-purpose ADL system

Increasingly elderly populations require the use of technology to enhance their quality of life and allow them to remain independent. **AAL** systems have been created recently to assist elderly and handicapped persons live better and to offer carers and medical workers behavioural and emergency information that will help them prevent or quickly intervene in situations. **AAL** systems are now important for communication, safety, and security in light of previous pandemic situations that have driven individuals into isolation or into need of help. Simple daily behaviours can be monitored using these systems, such as activity recognition, detection of the direction of movement, assessing the amount of food and medicine consumed by a person, person localization, assessing the presence of any intruder in the restricted environment, etc., and so on. Whether seniors are in private residences or retirement homes, numerous features of their regular activities may be automatically monitored, which lowers expenses and enhances monitoring abilities. **AAL** systems are developed in accordance with the steps outlined in Figure 1.4.

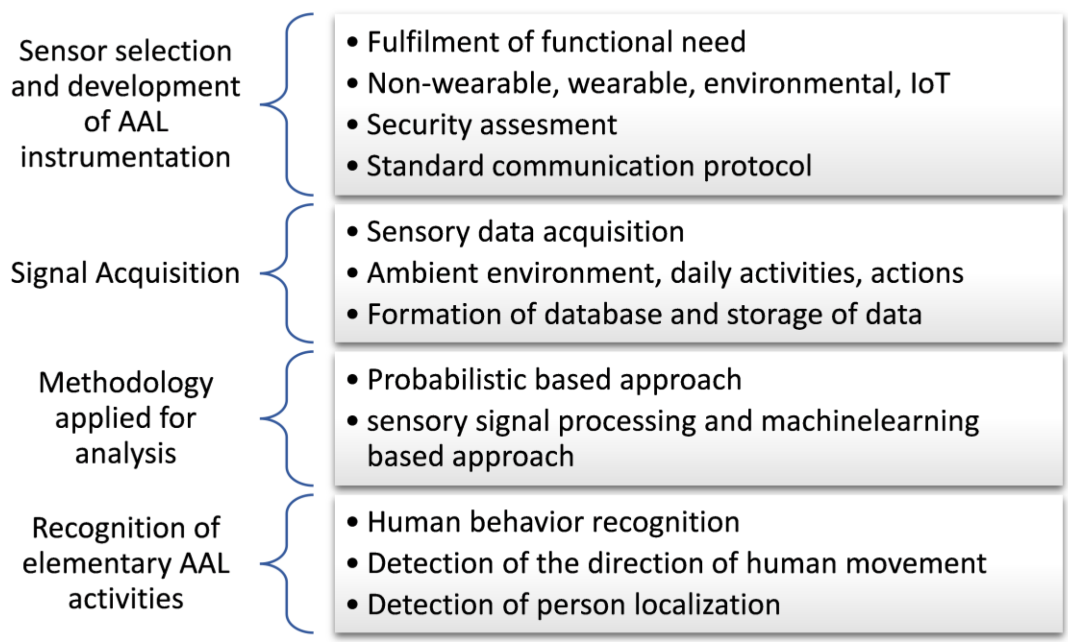


Fig. 1. 4. Outline for designing a general purpose AAL system

These steps require making a number of strong choices that start with the choice of sensors for data acquisition and ending with the functionality that **AAL** systems are intended to offer. The selection of sensors is influenced by both costs and the level of restoring privacy for people which has been already discussed in Section 1.1.1. The mode of data acquisition and the sensors to be used are also constrained by the choice of functions. The approaches for data analysis that, as stated in Section 1.1.3, need learning periods for modelling might also place limitations on the amount of data that can be collected. The development of complete **AAL** systems should thus take into account each of these factors. There are some vital aspects that should be considered for designing a sensor-based **AAL** system.

Those are:

1. Necessity of human-centric approach:

   Researchers should be concerned regarding the admissibility of sensors by people as well as the accuracy of the data collected since the collection of real data can be influenced by conscious human behaviour because people are aware of being watched. In [85], [86], critical challenges of data collection considering privacy concerns of human has been discussed.

2. Requirement of a significant amount of data from the real environment:

   The experimental evaluation of the proposed systems is the second aspect of consideration for designing an AAL system. A lot of studies are conducted in laboratories, using publicly accessible data sets, or by implementing experiments in real-world situations with just a brief time of observation. When it comes to analysing complex behaviors, these tests are rather limited. A real-life scenario should take into account various parameters that are associated with the activities that are performed in the real world.

3. Necessity of assessing the normal behavior of individual:

   Normal behavior cannot be described by any one subject and cannot be generalized. Since it depends on every individual, it must be learned by observing them for a long period of time. In the recent past, technological developments have made it feasible to gather and store vast amounts of data on people's behaviours. In order for future research to be successful, it must concentrate on establishing approaches capable of processing such a massive quantity of data and building distinct models.

4. Requirement of an adaptive **AAL** system and consideration of processing constraint:

   As a person’s behavior can change over time, an **AAL** system should be updated in an adaptive way for making robust. According to the survey, it has been found that sometimes hard real-time data processing is required to send prompt intervention while long observation is required when changes in daily behavior need to detect and researcher should aware of this kind of processing constraint.

5. Requirement of interdisciplinary skill:

   When developing **AAL** systems, it is essential to take into consideration how users interact with assistive technology, considering all factors pertaining to the setup, acceptance, and operation of the system. To design robust and reliable **AAL** systems, interdisciplinary teams should made up of medical professionals, geriatricians, psychologists, and specialists in data processing technologies.

In order for these systems to function effectively, intelligence is still the biggest challenge. To use these acquired data effectively, the scientific community must build intelligence using machine learning, intelligent control, and decision-making techniques while considering the privacy and the needs of residents and the environment.

1.2 Dictionary Learning for Signal Processing

With the incredible success of machine learning aided signal processing in recent years, the *Sparse Representation* (**SR**) of signals and task-driven dictionary learning algorithms are enjoying ever increasing interest among the researchers due to their effective applications in the domains of face recognition, *image classification* [87], [88], *image denoising* [89], *Biometric Person Identification* [94] etc. In [91], Tošic *et al.* provided an extensive overview of dictionary learning methods as well as examples of how they are employed in a variety of contexts, including stereo image approximation and audio-visual coding. The fundamental idea underlying sparse representation is that a signal can be effectively represented using a sparse combination of atoms from an over-complete dictionary [87]. While using a fixed dictionary, comprising several training atoms from several classes, it has shown to provide effective solutions for sparse representation-based classification (**SRC**). However, it has also been shown that, on many occasions, learning or suitably adapting an initial dictionary, from a larger set of data signals, can actually enhance the performances that can be achieved in sparse representation-based solutions. The choice of an effective over-complete dictionary **D** that may culminate into an effective sparse representation can either be given comprising a set of pre-specified functions or by developing a suitable adaptation algorithm that can adapt this dictionary to model a set of training signal exemplars [90]. In [92], the evaluation of these two aspects have been described by Rubinstein et al. and here, a comprehensive survey is presented of the different training options available at the present time, starting with the seminal work of Olshausen *et al*. [93] and following them by the **MOD**, the **K-SVD**, **GPCA**, and others.

1.2.1 Dictionary Learning: An Overview and State of the Art

New developments in sparse representation theory and algorithms have played a significant role in dictionary training, which is a relatively new approach to dictionary design and hence in the genre of signal processing. Recent training approaches place more emphasis on l_0 and l_1 sparsity metrics, which lead to easier formulations and enable effective sparse coding methods. The fundamental benefit of trained dictionaries is their capability to produce state-of-the-art result in a variety of real-world signal processing applications. Some of basic dictionary learning method has been discussed below.

A. **MOD** (*Method of optimal direction*)

Eagan *et al*. introduced the concept of method of optimal directions in [95], [96] that is known as sparsification process. From a given example set $\mathbf{Y} = [\mathbf{y}_1, \mathbf{y}_2, \cdots \mathbf{y}_n]$, the **MOD** aims to determine the best dictionary **D** and sparse matrix **X** for minimizing representation errors that is shown in (1.1).

$$\underset{\mathbf{D},\mathbf{X}}{\arg\min} \|\mathbf{Y} - \mathbf{D}\mathbf{X}\|_F^2 \ \textit{subject to} \ \forall i, \|\mathbf{x}_i\|_0 \le T_0 \tag{1.1}$$

Here, $\mathbf{x}_i$ represents the ith column of **X** and $\|.\|_0$ presents l_0 sparsity measures that counts the number of non-zero entries in the representation. One can only search for a local minimum at most because of its combinatorial nature and nonconvexity. Like previous training methods, the **MOD** alternates between phases of sparse coding and dictionary update. Any conventional approach is used to perform the sparse coding of each signal. The dictionary update is carried out by solving the quadratic problem (1.1) analytically, i.e., $\mathbf{D} = \mathbf{Y}\mathbf{X}^{+}$ (where $\mathbf{X}^{+}$ is pseudo-inverse of $\mathbf{X}$)

Since it often converges within a few numbers of iterations, **MOD** is recognised as an efficient solution in general. As a result of the relatively complex matrix inversion, the method suffers from significant limitations. Consequently, several subsequent studies have attempted to reduce this complexity.

B. *Union of Orthonormal bases*

Lesage et al. [97] suggested training a union-of-orthonormal bases dictionary as a way to create a dictionary with less complexity and that can be trained more efficiently. Additionally, this method is one of the first to train an overcomplete structured dictionary with a restricted frame. The model offers training a dictionary **D** using the $\{\mathbf{D}_i\}$unitary matrices, in which *k* orthogonal bases are concatenated. A *Block Coordinate Relaxation* (**BCR**) method may be used effectively to execute sparse-coding across this dictionary. Due to the relative rigidity of the recommended model, this method's performance, in reality, is inferior to that of more flexible frameworks. The more potent *Generalized PCA* (**GPCA**) model, which is explained next, and this structure are interestingly closely related. Although it differs from the conventional sparse representation paradigm, the **GPCA** also arises from the concept of a union of orthogonal spaces model.

C. *Generalized **PCA***

Another important approach of designing overcomplete dictionaries was introduced in [98], proposed by Vidal *et al*. **GPCA** is an expanded variant of **PCA**, and in this case, a model has been developed as a union of low dimensional subspaces using a collection of examples and the objective of **GPCA** is to determine all the subspaces and fit all the orthogonal bases to them. A signal cannot be represented by a combination of atoms from different subspaces in **GPCA** since each example only makes use of one subspace. It has the benefit of minimizing the overexpressiveness of the dictionary, which is a trait of other over-complete dictionaries, but it can be restrictive for extremely complex natural signals.

However, integrating the **GPCA** perspective with the conventional sparse representation perspective leads to innovative models [98]. For instance, it is simple to envision a generalizations model (1.1) in which many distinct dictionaries are allowed to coexist and each signal is regarded as being sparse across a single dictionary.

D. *The* **K-SVD** *algorithm*

The **K-SVD** technique was proposed by Aharon *et al*. [90] in order to effectively train a general dictionary for sparse signal representation. In a manner similar to **MOD** in (1.1), this algorithm employs block-relaxation to solve the same sparsification problem. The major feature of **K-SVD** includes the dictionary update concept that is done atom by atom, instead of using the dictionary inversion technique. A further acceleration can be achieved by simultaneously updating the current atom and its corresponding sparse coefficients. The *Singular Value Decomposition* (**SVD**) process, which is carried out *K* times as many atoms, is the foundation of the **K-SVD** algorithm. In practice, for representing a signal, **K-SVD** is more effective than **MOD** but both the techniques have some restrictions. In some situations, these two techniques may get stuck at local minima or even at saddle points, if there is presence of significant non-convexity. These techniques work best with signals that are not too large since the training process may yield an unstructured dictionary, which is quite expensive to use. But still, for many dictionary learning problems, **K-SVD** and **MOD** remain as the two most effective algorithms proposed [90], [99].

Here, in this context, Tosic *et al*. The author delineated the possible advantages of employing a dictionary learning approach in image classification and face recognition applications and introduced the discriminative capabilities of sparse representations [87]. Because of the above-mentioned effectiveness, dictionary learning-based sparse representation approaches have drawn increased attention in sensory signal processing and image processing problems.

1.2.2 Dictionary Learning in Sensory Signal Processing Problems

The recent emergence of *Dictionary Learning* (**DL**) and *Sparse Representation* (**SR**) have found several successful applications in the field of sensory signal processing. Many of these problems are essentially pattern classification problems, recognition problems, denoising problems and so on. Some of the important problem domains where **SR** and **DL** have been successfully employed are audio signal processing, machinery fault diagnosis, moving target detection and so on. Kong *et al*. [100] proposed a novel approach for machinery fault diagnosis and in this study, a novel discriminative dictionary learning based sparse classification framework was developed to find the solutions for fault diagnosis problems. In the field of **RF** signal processing [101], Chen *et al*. introduced a novel dictionary learning based feature extraction technique for **RF** signal recognition and here, the proposed approach was evaluated using real wideband **RF** measurement data. Another important problem of audio inpainting by using the concept of dictionary learning has been introduced in [102] by Tauböck *et al*. In this study, the authors have introduced the concept of dictionary learning to learn a dictionary from the reliable part around the gap of any audio signal with the objective to get a signal representation with increased sparsity. Another challenging problem domain which has received attention in recent times is moving target recognition. In this context, Yang *et al.* [103] introduced a three overcomplete dictionary to represent the target and the dictionary learning technique has been proposed to extract the moving status. In [104], He *et al.* introduced a novel dictionary learning approach for the identification of gases and it has been shown how a dictionary learning based approach can improve the performance of gas identification of electronic noses.

1.2.3 Dictionary Learning in Image Processing Problems

The field of image processing, including face recognition, image classification, image denoising, and inpainting, has effectively used dictionary learning for sparse representation as well. In [87], wright *et al*. designed a new framework in which sparse representation based approach has been effectively used for automatic recognition of human faces with varying emotions and illumination. Recently, medical imaging has also become an important research area and dictionary learning based approaches has also been successfully employed in this domain. Successful applications of **DL** have been found in preserving noisy images [106] and in multimodal medical image fusion problems [105]. Sparse dictionary learning was used by Sing et al. in [105] to create a sensor fusion model for multimodal medical imaging. Here, a novel fusion framework is presented for multimodal neurological images, which can capture small details from an input image. In [106], a novel framework based on discriminative dictionary learning has been proposed for fusion and denoising of noisy images and to preserve the fine scale details of an image effectively. In [107], Diamant *et al*. introduced a novel variant for automatic image classification. Here, a new concept of task driven dictionary learning was introduced based on the criterion of mutual information. This algorithm has been successfully implemented for pathological identification and liver lesion classification purposes.

In [89], Elad *et al*. introduced an interesting dictionary learning based approach for finding the solution of image denoising problem where they showed how a Bayesian treatment can be appropriate to generate a simple yet very efficient algorithm. On the other hand, dealing with hyperspectral image requires efficient image denoising to enhance the performance of high-level detection task. In this context, dictionary learning approach has been introduced by Gong *et al*. in [108] and here, along with sparse representation, low-rank tensor representation model has been used to enhance the performance of dictionary learning.

One of the main challenges in multi-view imaging is the definition of a representation that accurately captures the underlying geometry of the visual information. Sparse image representations utilising overcomplete geometric dictionaries have been presented in [91] as a way to effectively estimate these images and make the multi-view geometric structure evident in the representation. Recently, **DL** based methods have also been used effectively for the analysis of *Magnetic Resonance Imaging* (**MRI**) and Functional Magnetic Resonance Imaging (**fMRI**), where various physical reasons result in various observable signals. Sequential dictionary learning using **K-SVD** algorithm has been demonstrated as an effective alternative to traditional data-driven approaches for **fMRI** data analysis, as demonstrated by Seghouane *et al*. [114]. In this study, three variants of **K-SVD** algorithm have been developed for correlated data and evaluated on **fMRI** data set by considering prior information. Video signal classification is another important domain where effectiveness of **DL** has also been investigated in [116]. Here, Romero *et al*. presented an algorithm for detecting forest fires from surveillance video signals. This concept involved learning redundant dictionaries to represent feature vectors extracted from three different regions: smoke, sky, and ground.

1.3 Motivation

It is quite evident from the discussions presented in Sections 1.1.1 and 1.1.2 that the development of sensor-based intelligent **AAL** systems incorporating sophisticated signal processing and image processing techniques with efficient decision making mechanism has become a crucial challenge for solving **ADL** problems such as activity recognition, human movement detection, person localization, human tracking, intruder detection, etc. Some recent researches have shown that effective solutions in this regard can be built using machine learning aided signal processing algorithms. However, there is still huge scope and interest in proposing, investigating and developing more such sophisticated system solutions for a variety of challenging **AAL** problems and, especially, **ADL** problems within that genre, at our hand. On the other hand, dictionary learning based algorithms within the genre of sparse representation and sparse signal processing has demonstrated its usefulness in providing accurate, robust solutions for different categories of signal and image processing problems at large. These two significant findings in the context of contemporary research activities encouraged to investigate the suitability of employing and proposing different dictionary learning based algorithms for solving many challenging **AAL** and especially **ADL** based problems, which constituted the core of this research work. Another motivation of this research work is to develop integrated, low-cost, system solutions for real-life **ADL** and **AAL** problems at smart homes and indoor environments, which will comprise dictionary learning based algorithms in its core.

1.4 Research Objective of the Present Work

As mentioned in Section 1.3, the overall objective of the present thesis work is to develop sensor-based, integrated system solutions for several **ADL** and **AAL** problems using dictionary learning based classification/identification/decision making algorithms that can be suitably applied in smart homes and in other indoor environments.

From the viewpoint of problems to be considered in this thesis, the core objective is to consider three prominent categories of **ADL** problems:

(i) identification of human behavior in an unattended home which will aid local/remote monitoring of all regular activities of daily living inside a home, especially where aged people are leading independent lives.

(ii) Automated detection of human movement in specified directions in home environment which will aid both in local/remote monitoring of regular activities within a home environment and will also aid in signaling any suspicious activity in any specific hour of the day.

(iii) Automated intruder detection in any home, office or other indoor environment where restricted access is only permitted for a few personnel.

From the viewpoint of solution methodologies to be considered in this thesis, the core objective is to develop and implement different **K-SVD** and its variants based dictionary learning algorithms and also to propose some new dictionary learning algorithms, suitable for **ADL** and **AAL** problems under consideration.

From the viewpoint of system solution, another objective of this thesis is to investigate development of an integrated experimental setup that can be used as a prototype for low-cost **ADL** and **AAL** systems.

1.5 Contribution of the Present Work

Based on the research objectives presented in the previous Section, the main contributions of this thesis can be summarized as:

1. At first, this present thesis work has shown how dictionary learning based approach can be effectively applied for finding solution for a human behavior recognition problem in a home environment. Here, **K-SVD** dictionary learning based **SRC** classifier has been proposed to find solution for this problem where the sparse coding stage has been solved using *Orthogonal Matching Pursuit* (**OMP**) algorithm. A publicly available real-life accelerometer data set comprising real data corresponding to different human behaviour has been used to demonstrate the efficacy of the proposed approach. The approach has also shown how the proposed algorithm can be applied for the purpose of classification/segregation of both bi-class and multi-class behavior efficiently.

   The thesis has also thoroughly investigated and shown how several modifications of **K-SVD** based dictionary learning can further improve the quality of solutions, by using different variations of greedy algorithms and relaxation algorithms. For this purpose, **IRLS** and $l_1 - l_s$ based sparse coding stages has been hybridized with **K-SVD** algorithm to develop more efficient **DL** algorithms for human behaviour recognition problems.

2. Next, a sophisticated, low-cost, integrated system is developed in this thesis work which leverages indigenously developed current hardware and software technologies to automate **ADL** monitoring. The solution employs four **PIR** sensor based module coupled with novel dictionary learning approaches. The hardware arrangement has been built with remote monitoring capability, Ethernet Interference Module, and **TCP/IP** interface to the client end.

3. Next, this thesis work has shown how this developed module can be used to solve different **ADL** recognition problems. First, this work addresses the direction of human movement detection problem that is considered as one of the most important **ADL** problems. In this regard, it has been shown how a recently proposed **MCP** based dictionary learning algorithm can be successfully

coupled with the developed hardware module. Secondly, a novel variant of the *Multiple Cluster Pursuit* (**MCP**) algorithm in terms of initialization, multiple atom selection, and termination stage, has been proposed which has been named as *Modified MCP* (**MMCP**) algorithm. The thesis has successfully demonstrated how the performance of **K-SVD** algorithm can be improved upon by employing **MCP** algorithm and then further improved upon by employing **MMCP** algorithm, for the direction of human movement detection problem.

4. The thesis then has proceeded to investigate development of further sophisticated DL based strategies for the same **ADL** problem considered before i.e. detection of human movement direction. In this regard, another dictionary learning-based scheme has been proposed in which the regularization concept based approach has been adopted to punish the solutions with large values of sparse representation coefficient and this thesis work has shown how can a regularized **K-SVD** (**RK-SVD**) algorithm and a regularized approximated **K-SVD** (**RAK-SVD**) algorithm be successfully applied to solve the **ADL** problem in hand, utilizing the indigenously developed integrated setup, mentioned earlier. This thesis has also proposed modified versions of both these algorithms where novel methods of adapting the regularization parameter have been introduced and those algorithms have been successfully implemented for the human movement direction detection problem.

5. At last, this thesis has shown how another novel dictionary learning algorithm can be developed in conjunction with the four **PIR** sensor based hardware setup to develop an intruder detection system for the purpose of smart surveillance in residential and office environments, another interesting problem from the genre of **AAL/ADL** systems. Here, a novel dictionary learning based approach has been proposed that merges the concepts of label consistency with a modified consistent adaptive sequential dictionary learning approach, named as label consistency based *Modified Consistent Adaptive Sequential Dictionary Learning* (**LC-MCAS-DL**) algorithm. In this context, the conventional objective function in **DL** has been reformulated by introducing the

Label Consistency (**LC**) constraints along with reconstruction and classification errors. Then, the solution to this objective function is obtained by using a modified version of the *Consistent Adaptive Sequential DL Algorithm* (**MCAS-DL**).

1.6 Thesis Outline

The contributions mentioned in the previous Section are largely included in the work given in this thesis. The remaining structure of the thesis and the interconnections between the Chapters are explained below.

- Chapter 2 discusses how the problem of continuous monitoring of different human behavioral activities and their automatic classification can be solved by introducing a state-of-the-art signal processing approach based on sparse representation. In this Chapter, first, sparse representation based *Dictionary Learning* (**DL**) approach has been introduced for effective solution of the **ADL** monitoring problem. The learnt dictionary acquired from the **K-SVD** technique is then used to create a classification framework based on the *Sparse Representation Based Classifier* (**SRC**). The **K-SVD** algorithm implemented **OMP** algorithm in its dictionary learning stage. This Chapter validated the effectiveness of the proposed approach on a publicly available accelerometer data set for activity/behavior recognition problems and in this context, both the bi-class and multi-class classification problems have been solved.

- Chapter 3 presents how the modifications introduced in the **K-SVD** algorithm can help achieving better quality solutions for human behavior recognition problem. Here, firstly a modified approach of **K-SVD**, termed as **IRLS-K-SVD**, has been introduced to investigate the impact of **IRLS** algorithm on solving the sparse coding in dictionary learning algorithm and classification algorithm. The **IRLS** technique has a significant computational cost since it addresses the sparse coding stage as a l_1 minimization problem. To overcome this computational burden, in this Chapter another new approach based on $l_1 - l_s$ based regularized method has been introduced for solving the sparse coding stage of dictionary learning and classification. After, successful development of these hybrid approaches, the effectiveness of *Collaborative Representation Based Classification* (**CRC**) approach is also investigated in parallel with **SRC**.

- Chapter 4 addresses a more challenging **ADL** problem of movement detection in a specific direction within **AAL** environment. In this context, this Chapter shows development of a low-cost, integrated, **PIR** sensor-based hardware software combined module for finding the solution to this movement detection problem. Here, for finding this solution, a novel dictionary learning algorithm is coupled with the hardware module. This Chapter firstly implements the multiple cluster pursuit based dictionary learning approach to find the solution of above problem in real life. Then, motivated by the findings, a modified version of **MCP** algorithm has been proposed where the modifications are introduced in three different phases, those are initialization phase, multiple atom selection stage and termination stages. Lastly, a performance comparison is demonstrated to investigate the efficiency of this proposed approach compared to other competing approaches.

- Chapter 5 demonstrates the application of recently proposed regularized versions of **K-SVD DL** algorithm for detecting human movements in a specific direction. The problem has been solved using the same indigenously developed, integrate, low-cost hardware system, developed in the laboratories. These algorithms i.e. **RK-SVD** and **RAK-SVD** have been successfully implemented first and then a modified version of each has been proposed (**MRK-SVD** and **MRAK-SVD**) by varying ζ guided by the evaluation of **RMSE**. Experimental evaluations demonstrated the superiority of the proposed methods and their implementation in real-life scenarios.

- Chapter 6 addresses a different problem of **AAL/ADL** genre i.e., intruder detection problem and also, proposes a novel **DL** algorithm called **LC-MCAS-DL** that can detect intruders in restricted offices and homes environment. The experimental system solution has been developed on the same general-purpose setup developed in the laboratory, mentioned before, which can be used as a multi-purpose **ADL/AAL** system for implementing and testing varied prototypes. Here, **LC-MCAS-DL** has been developed by hybridizing the good aspects of **LC-K-SVD** and **CAS-DL**, and a modification of **CAS-DL** has also been proposed. Several well-established state-of-the-art approaches are compared with the proposed approach using extensive real-life experiments and the supremacy of **LC-MCAS-DL** in solving this problem has been firmly established.

- Chapter 7 finally, summarizes the findings of this thesis. It also highlights prospective opportunities for more future research in this field of study.

CHAPTER 2

Recognition of Human behavior for Assisted Living using Dictionary Learning Approach

2.1 Introduction

It has already been established in Chapter 1 that *Monitoring Activities of Daily Living* (**ADLs**) has become an interesting research idea, where continuous monitoring of various **ADLs** and their automatic classification is a big challenge. In this Chapter, a new approach has been proposed for activity/behavior recognition of motion primitives relying on the sparse representation of signals where signals are represented using a sparse combination of atoms from an over-complete dictionary. An investigation into the suitability of using dictionary learning algorithms like **K-SVD** for the effective monitoring of **ADL** progress has been undertaken in this Chapter. Here, a classification approach is proposed by using **SRC** classifiers, which are based on dictionaries obtained from **K-SVD** algorithms. In this Chapter, the proposed approach has been validated using a publicly available dataset consisting of signals acquired using accelerometer sensors worn on wrists for activity recognition. It is observed from these extensive performance evaluations that the proposed method outperforms several other competing methods.

Researchers have recently been interested in sparse representation algorithms and dictionary learning algorithms which have effective applications in problems like *face recognition*, *image classification* [87], [88], and *image denoising* [89]. The principle behind sparse representation is that it can be effectively represented with a sparse combination of atoms taken from an over-complete dictionary. While using a fixed dictionary, comprising several training atoms from several classes, have shown to provide effective solutions for sparse representation based classification (**SRC**), it has also been shown that, on many occasions, learning or suitably adapting an initial dictionary, from a larger set of data signals, can actually enhance the performances that can be achieved in sparse representation based solutions. The choice of an effective over-complete dictionary **D** that may culminate into an effective sparse representation can either be given comprising a set of pre-specified functions or by developing a suitable adaptation algorithm that can adapt this dictionary to model a set of training signal exemplars [90]. Because of the above-mentioned effectiveness, it has been established that the application of dictionary learning-based sparse representation approaches in face recognition, image classification, video signal classification [110], [111], etc., has increased enormously.

Inspired by the success of dictionary learning based algorithms, mainly used in image processing domain, this Chapter proposes to utilize dictionary learning based **SRC** that can be suitably applied for recognition of several **ADL**. The results achieved with the proposed approach have been demonstrated to outperform other state-of-the-art competing algorithms proposed for this purpose e.g., dynamic time warping and mahalanobis distance.

The rest of this Chapter is presented as follows. The macroscopic view of the activity recognition problem and the signal acquisition procedure from the sensor based instrumentation system are presented in Sections 2.2 and 2.3. The **K-SVD** dictionary learning algorithm used in this Chapter is presented in Section 2.4.1. The classification approach that has been proposed in this Chapter using sparse representation classifier is shown in Section 2.4.2, based on the learned dictionary obtained from **K-SVD** algorithm. The implementation of the proposed approach, performance evaluation and conclusion and discussions are presented in Section 2.5 to 2.6.

2.2 Macroscopic View of Activity Recognition Problem

The recognition of human activities/bahavior from the signals acquired using various types of sensor combination is marked as one of the most vital signal processing problems in the genre of **AAL** systems. Consequently, it has also been observed that various studies on **AAL** technologies emphasize on automatic recognition of human activities that draw parallel to **ADLs** like bathing, cooking, sleeping etc., which provide the capabilities to detect any deviation in their patterns. Two broad categories of sensors, i.e., wearable and non-wearable sensors are usually used for the purpose of solving **ADL** problems.

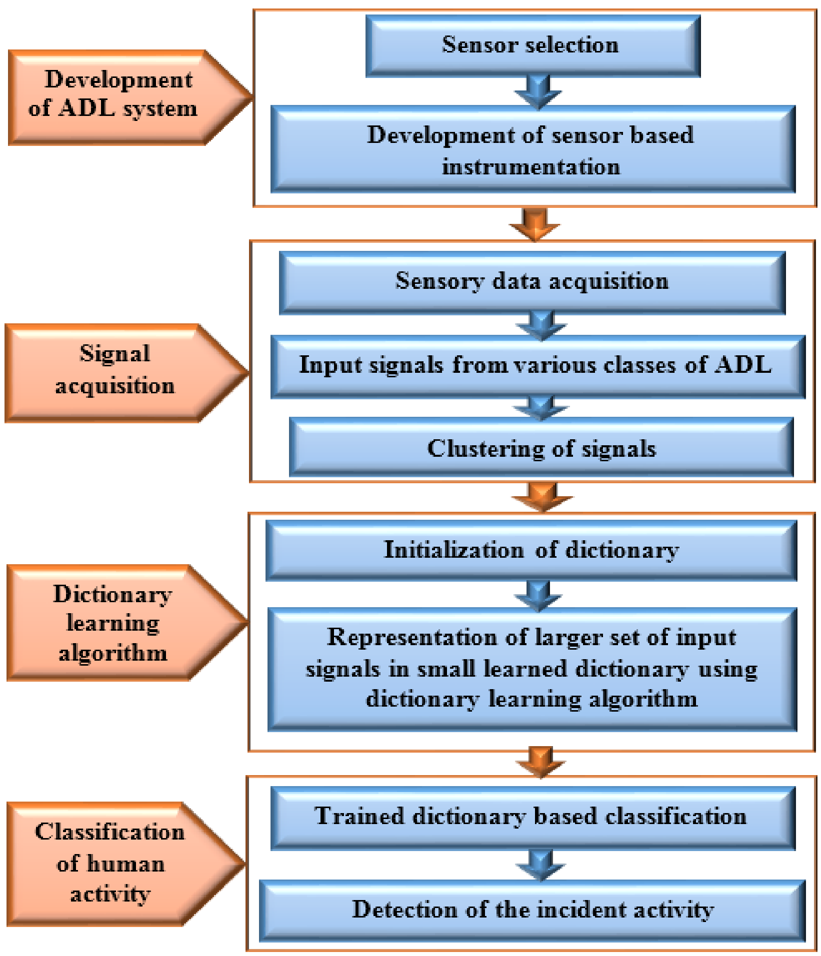


Fig. 2.1 Overall block diagram for activity recognition problem

Wearable sensors, which are attached directly to the body, are commonly used to detect posture changes in humans. It is seen from Chapter 1 that among these all-wearable sensor, accelerometer sensors and wrist-worn smartphones are most often used for detection of **ADLs** like *running*, *walking*, *falling* etc. On the other hand, non-wearable sensors are deployed in a static place in the home or in a community to detect a human's movement and activities. It has also been reported in Chapter 1 that non-wearable sensors like *Infrared Sensors* (**IR**), ultrasonic sensors etc. are most commonly used for **ADL** classification. The complete block diagram of the proposed approach utilizing dictionary learning for activity recognition is shown in Fig. 2.1. The four major steps of this proposed approach have been shown in the block diagram for recognizing the human activities of **ADL** problems. Each step will be discussed in detail in the following Sections.

2.3 Development of ADL System and Signal Acquisition

It is noticed that a successful practical system for monitoring **ADL** activities is one that needs less training and configuration effort as well as it should be attachable with minimum effort in the household. The choice of sensors and their installation that depend upon the type of data to be collected, is being considered two major types of challenges in the **ADL** classification systems. In an **ADL** system, the installation cost of the sensors should be kept as minimum as possible. The privacy should be strictly maintained by the sensors and those sensor also strive to attain enhanced classification. It has already been established that an **ADL** system should ideally give a self-maintainable environment whether utilized for the purpose of helping or monitoring aging community or for intruder detection or for the purpose of fall detection etc., depending on the sensor technology deployed. "Smart Homes" that are equipped with **ADL** technology may include sensor based instrumentation systems fitted in the roof mounting places, wall, and floor-mounting places for non-wearable sensors or wearable sensor based instrumentation systems fitted in the human cloth or a human body. In many situations, the original analog sensor outputs are converted to digital signals by analog to digital converters. Very often, feature vectors are extracted from such digital signals for different **ADLs** for further processing to draw meaningful conclusions. For this problem at hand, a data set has been considered that is freely available [113] and comprises wrist-worn accelerometer signals acquired during the process of different activities or human behaviors.

2.4 K-SVD based Approach for Activity Recognition Problem

In this Section, the **K-SVD** based dictionary learning algorithm will be presented in detail. This algorithm learns a dictionary for the problem based on accelerometer signals acquired for different types of human behaviour. The initial dictionary is constructed with signals collected for each human activity or behaviour corresponding to specific classes and then the dictionary learning stage is invoked. Once the dictionary learning is over, in the testing or implementation stage, any new, unknown signal can be presented to the dictionary and the system should be able to infer to which activity or behaviour or class this signal belongs.

2.4.1 Fundamentals of K-SVD based Dictionary Learning Algorithm

Now, **K-SVD** based dictionary learning approach is explained in detail which is used in conjunction with sparse representation, that can be suitably utilized for classification of human behavior. In sparse representation, each signal is assumed to be composed of a sparse, linear combination of a few atoms from a large, over-complete dictionary. Each input training signal is referred as atom in the training database. In a dictionary learning algorithm, the dictionary is learned in such a fashion, that can achieve best suitable representation of each member within that dictionary, strictly maintaining the sparsity constraints [90]. In the dictionary learning approach, the dictionary is learned from a larger training set, instead of using a predefined basis, such as fourier or wavelet basis [112] using the larger training data set itself [6]. In the latter case, the performance can be potentially improved using the entire set of the input training signals as a complete dictionary, but it may involve large computational burden. The huge computational burden can be overcome by using a dictionary learned from a huge training database and smaller in size than that, suitably maintaining sparsity constraints while maintaining desired performance accuracy.

The **K-SVD** algorithm is known as a prominent alternative, among the other popular dictionary learning algorithms known [90]. **K-SVD** is known to effectively learn over-complete dictionaries from larger sets of input training signals and has been applied suitably for other engineering problems before. The main spirit of sparse representation algorithm can be viewed as a generalization of *vector quantization* (**VQ**) objective, whereas **K-SVD** can be viewed as a generalization of *K-means* algorithm that is utilized to satisfy the **VQ** objective. The following objective function will be minimized by using the **K-SVD** dictionary learning algorithm that is the main objective of this dictionary learning algorithm [90]:

$$\arg\min_{\mathbf{D},\mathbf{X}} \|\mathbf{Y} - \mathbf{D}\mathbf{X}\|_F^2 \ \textit{subject to}\ \forall i, \|\mathbf{x}_i\|_0 \le T_0 \tag{2.1}$$

where T_0 is called the sparsity prior. It is observed from (2.1) that the number of non-zero elements in each $\mathbf{x}_i$ should be less than T_0. A reconstructive dictionary is produced by using basic **K-SVD** where the dictionary is composed of K prototype atoms, each of dimension n. Here, the input signal matrix is presented as $\mathbf{Y}$ which is composed of N input signals, each of dimension n .

$$\mathbf{Y} = [\mathbf{y_1}, \mathbf{y}_2, ..., \mathbf{y}_N] \in \Re^{n\times N} \tag{2.2}$$

and dictionary $\mathbf{D} = [\mathbf{d}_1, \mathbf{d}_2, ..., \mathbf{d}_K] \in \Re^{n\times K}$ (2.3)

The over complete dictionary is obtained for N>>K. Also, it is so chosen that $N >> K$, so that the dictionary, playing the role of a codebook, comprises K code words, that can efficiently represent the original training database.

The sparse coding of input signal **Y** is presented as

$$\mathbf{X} = \left[\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_N\right] \in \Re^{K \times N} \tag{2.4}$$

The **K-SVD** algorithm comprises two fundamental stages [91], implemented in an iterative fashion:

i. sparse coding stage

ii. dictionary update stage

In sparse coding stage, the best possible sparse coefficient matrix **X** is determined by keeping the dictionary **D** static. Here, the objective function in (2.1) can be presented in the modified form, given as [90]:

$$\left\|\mathbf{Y} - \mathbf{D}\mathbf{X}\right\|_F^2 = \sum_{i=1}^{N} \left\|\mathbf{y}_i - \mathbf{D}\mathbf{x}_i\right\|_2^2 \tag{2.5}$$

Although other pursuit algorithms can also be used successfully there, the *Orthogonal Matching Pursuit* (**OMP**) [87] method is a common option for the sparse coding step. In the dictionary update stage, keeping **X** fixed, dictionary **D** is restructured iteratively by updating one atom at a time. These two basic stages are used in an iterative fashion, for minimizing the objective function in **K-SVD** algorithm, given in (2.1). In the dictionary update stage, at any point of time, a specific atom $\mathbf{d}_k$ of the dictionary is focused on and its corresponding coefficients in $\mathbf{X}$ in its kth row, denoted as $\mathbf{x}_T^k$ (it is not the transpose of vector $\mathbf{x}^k$ i.e. the kth column of $\mathbf{X}$). Then the objective function in (2.1) can be given as [90]:

$$\left\|\mathbf{Y} - \mathbf{D}\mathbf{X}\right\|_F^2 = \left\|\mathbf{E}_k - \mathbf{d}_k \mathbf{x}_T^k\right\|_F^2 \tag{2.6}$$

Algorithm 2.1: K-SVD algorithm [90]

Step 1:

- **Initialization of Dictionary**: $\mathbf{D}^0 \in \Re^{n\times K}$ with input signals and the columns of $\mathbf{D}^0$ are normalized using l_2 norm.
- **Input:** $\mathbf{Y} \in \Re^{n\times N}$, T_0, $\mathbf{D}^0 \in \Re^{n\times K}$
- **Output:** $\mathbf{D} \in \Re^{n\times K}, \mathbf{X} \in \Re^{K\times N}$
- **Set** J=1
- **Repeat** until convergence (stopping Criterion)

Step 2:

- **Sparse coding stage:** $i = 1, \dots, N$

$$\min_{\mathbf{x}_i} \left\{ \left\| \mathbf{y}_i - \mathbf{D}\mathbf{x}_i \right\|_2^2 \right\} \text{ subject to } \left\| \mathbf{x}_i \right\|_0 \le T_0$$

Step 3:

- **Dictionary update stage:**

For each Column $k = 1, 2, \dots, K$ in $\mathbf{D}^{J-1}$ Update it by

- Determine indices w_k using (2.7)
- Determine $\mathbf{E}_k = \mathbf{Y} - \sum_{j\neq k} \mathbf{d}_j \mathbf{x}_T^j$
- Restrict $\mathbf{E}_k$ to obtain $\mathbf{E}_k^R$ by selecting only the columns corresponding to w_k
- SVD decomposition is applied as $\mathbf{E}_k^R = \mathbf{U}\Delta\mathbf{V}^T$
- Update $\tilde{\mathbf{d}}_k = \mathbf{U}(:,1)$. And $\mathbf{x}_R^k$ is updated as $\mathbf{x}_R^k = \Delta(1,1) * \mathbf{V}(:,1)$

Set $J=J+1$

where the error involved is depicted as $\mathbf{E}_k$ for all N samples, after removal of the *k*th atom $\mathbf{d}_k$. However, here the purpose will not be solved by using a straightforward *Singular Value Decomposition* (**SVD**) algorithm to determine $\mathbf{d}_k$ and corresponding $\mathbf{x}_T^k$ by approximating $\mathbf{E}_k$, as the solution produced will not satisfy the sparsity constraints in the first place. So, to obtain a solution respecting the sparsity constraints, a set of indices w_k is formed which denotes the positions where the array elements of $\mathbf{x}_T^k$ are nonzero, given as:

$$w_k = \left\{ (i \middle| 1 \le i \le N, \mathbf{x}_T^k(i) \ne 0 \right\} \tag{2.7}$$

where $\mathbf{x}_T^k$ is the *k*th row in **X.**

This array w_k is utilized to form a matrix $\mathbf{\Omega}_k$ which can be utilized to build a restricted array $\mathbf{x}_R^k$ from $\mathbf{x}_T^k$ utilizing the matrix operation $\mathbf{x}_R^k = \mathbf{x}_R^k \mathbf{\Omega}_k$. This row vector $\mathbf{x}_R^k$ is essentially formed from $\mathbf{x}_T^k$ by removing zero entries from $\mathbf{x}_T^k$. It has been ensured that, for subsequent operations, any adaptation carried out for $\mathbf{x}_R^k$ array means the nonzero entries in $\mathbf{x}_T^k$ are essentially adapted and all zero entries in $\mathbf{x}_T^k$ remain unchanged i.e., the sparsity constraints are fully respected. This means that the objective function given in (2.6) can now be transformed to the equivalent form, respecting sparsity constraints, given as:

$$\left\| \mathbf{E}_k \mathbf{\Omega}_k - \mathbf{d}_k \mathbf{x}_T^k \mathbf{\Omega}_k \right\|_F^2 = \left\| \mathbf{E}_k^R - \mathbf{d}_k \mathbf{x}_R^k \right\|_F^2 \tag{2.8}$$

Now, the minimization of (2.8) can be directly obtained using **SVD**, which decomposes the restricted matrix $\mathbf{E}_k^R$ as $\mathbf{E}_k^R = \mathbf{U}\Delta\mathbf{V}^T$. Consequently, the kth column of the dictionary is updated by choosing the first column of **U** i.e., $\mathbf{U}(:,1)$ as the solution $\tilde{\mathbf{d}}_k$. The corresponding coefficient vector $\mathbf{x}_R^k$ is updated as $\mathbf{x}_R^k = \Delta(1,1) * \mathbf{V}(:,1)$ where $\mathbf{V}(:,1)$ is the first column of **V**. This procedure is followed to update each atom of the dictionary (along with its corresponding $\mathbf{x}_T^k$), one at a time, until all atoms are updated. This complete procedure of the **K-SVD** algorithm employed is presented in Algorithm 2.1.

2.4.2 Classification Based on Sparse Representation and Learned Dictionary

The classification of human activities carried out using the philosophy of sparse representation is presented in this Section of this Chapter, utilizing the trained dictionary obtained from **K-SVD** algorithm. For a given test sample $\mathbf{y}$, the coefficient matrix $\hat{\mathbf{x}}_{\text{AL}}$ is computed by using the objective function given in (2.9) [87]:

$$\hat{\mathbf{x}}_{\text{AL}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \text{ subject to} \|\mathbf{Ax}-\mathbf{y}\|_2 \leq \varepsilon \tag{2.9}$$

In this Chapter, the **SRC** problem is solved using matrix **A** as the trained dictionary $\mathbf{D}$ which is achieved from **K-SVD** algorithm. This $\mathbf{A} = [\mathbf{A}_1, \mathbf{A}_2, ..., \mathbf{A}_C] \in \Re^{n \times m}$ is composed of a total of m atoms associated with C classes, each of dimension n and the unknown test sample $\mathbf{y} \in \Re^n$ is identified based upon the trained dictionary. The non-zero entries in the estimated $\hat{\mathbf{x}}_{\text{AL}}$ associated with the columns of the trained dictionary $\mathbf{A}$ from an individual class i help us to assign the test sample $\mathbf{y}$ to that specified class of entity. In this process, a more effective dictionary learning-based **SRC** is used to accommodate a larger set of training databases using a smaller size dictionary and yet strictly maintaining the sparsity constraints, which consequently reduces the computational burden. Now, $\delta_i : \Re^m \rightarrow \Re^m$ (for each individual class i) should be adopted as the specific function that chooses the coefficients linked with the ith class.

Algorithm 2.2: **Sparse Representation based classification** [87]

Step 1: Training samples matrix represented as

$\mathbf{A} = [\mathbf{A}_1, \mathbf{A}_2, \ldots, \mathbf{A}_C] \in \Re^{n \times m}$, for C classes.

Step 2: Normalize the columns of training matrix to have unit l_2 -norm.

Step 3: Solve the l_1-minimization problem to determine coefficient vector $\hat{\mathbf{x}}_{\mathrm{AL}}$:

$$\hat{\mathbf{x}}_{\mathrm{AL}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_1 \text{ subject to } \|\mathbf{A}\mathbf{x} - \mathbf{y}\|_2 \le \varepsilon$$

Step 4: For $i = 1, \ldots, C$

Residuals are computed

$$r_i(\mathbf{y}) = \|\mathbf{y} - \mathbf{A}\delta_i(\hat{\mathbf{x}}_{\mathrm{AL}})\|_2$$

End

Step 5: Output: identity $(\mathbf{y}) = \arg\min_i r_i(\mathbf{y})$

For $\hat{\mathbf{x}} \in \Re^m, \delta_i \in \Re^m$ is defined as a new vector for every class ($i = 1, \ldots, C$) with all zero entries except for the ones associated with class i which are equal to the corresponding ones in the estimated vector $\hat{\mathbf{x}}_{\mathrm{AL}}$ [87]. After obtaining the associated coefficients of the specified object class, the test sample $\mathbf{y}$ for a single class entity can be approximated using $\hat{\mathbf{y}}_{\mathrm{AL}} = \mathbf{A}\delta_i(\hat{\mathbf{x}}_{\mathrm{AL}})$ .Then, the classification of test sample $\mathbf{y}$ can be obtained by determining the minimum among all class specific residuals, calculated using (2.10), between the test sample $\mathbf{y}$ and the approximated test sample $\hat{\mathbf{y}}_{\mathrm{AL}}$ [87].

$$\min_i r_i(\mathbf{y}) = \|\mathbf{y} - \mathbf{A}\delta_i(\hat{\mathbf{x}}_{\mathrm{AL}})\|_2 \text{ for } i = 1, \ldots, C \qquad (2.10)$$

The sparse representation-based classification scheme is presented in Algorithm 2.2. In this proposed approach, the learned dictionary $\mathbf{D}$ is used as the training samples matrix $\mathbf{A}$.

2.5 Experimental Result Analysis

2.5.1 Experimental Framework

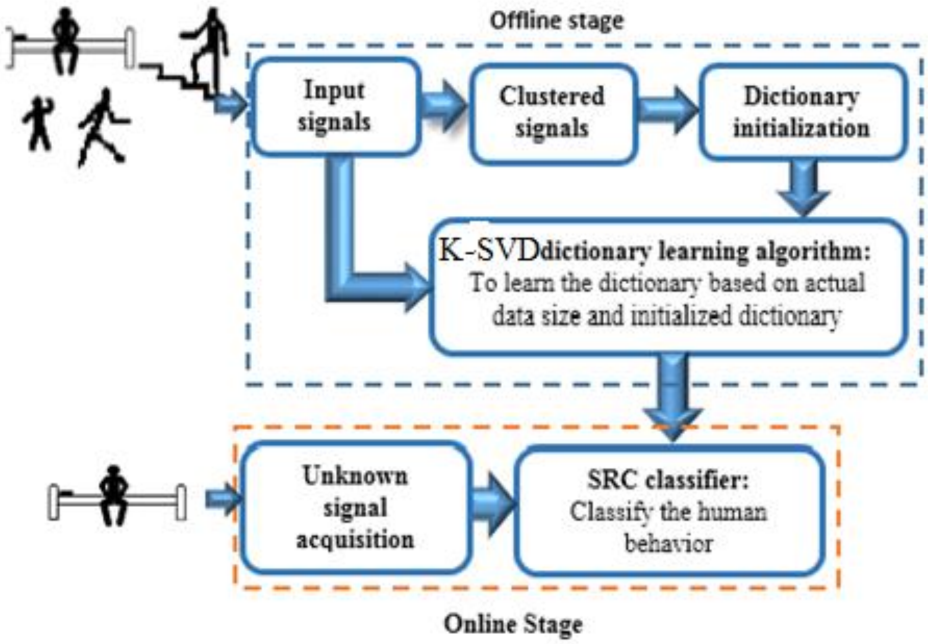


Fig. 2.2 Block diagram for implementation of the proposed approach

As mentioned before, the main purpose of this work is to propose a dictionary learning based **SRC** approach that can be suitably applied for human behaviour activity recognition problems. In this Section, how this proposed approach can be implemented for the activity recognition problem is shown in Fig. 2.2.

In the first step, input training signals are acquired from volunteers or subjects to build the database and the database comprising input training signals of **ADL** problem are clustered to initialize the dictionary. The dictionary initialization can be carried out with different sizes of the dictionary. To be specific, for the freely available benchmark database [113] considered in this Chapter, 5%, 10%, 20%, and 50% clustering have been undertaken to construct the initial dictionary (i.e., for example, for 5% clustering, 5% of actual data belonging to each class have been used to build the initial dictionary and so on). Then this initial dictionary undergoes further adaptation using a dictionary learning algorithm. Hence, this initial dictionary $\mathbf{D}^0 \in \Re^{n \times K}$, which is chosen from original signal database, is the starting point of the **K-SVD** dictionary learning algorithm. In the next step, the learning of the dictionary is carried out using **K-SVD** algorithm, as described in Section 2.4. Once the dictionary is learned, this trained dictionary is used as the dictionary $\mathbf{A}$ (i.e., much smaller in size compared to the input matrix of original training samples of all classes) in Algorithm 2.2 to implement the **SRC** to identify different human behavior. In this Chapter, both bi-class classification and multi-class classification problems have been solved, utilizing the proposed approach, for a benchmark, publicly available **ADL** dataset.

2.5.2 Performance Evaluation

The results obtained using this proposed approach for the benchmark wrist-worn accelerometer sensor database [63], [6], [113], are presented in this Section, which is utilized for the recognition of various types of **ADL** human behavior. These results are also compared with other state-of-the-art, competing algorithms to show the effectiveness of the proposed approach. It has been stated in the dataset description [63],[113], that the sensing bracelet had a sensing range of 3G, used 6 bits/axis for coding information, the sampling frequency was 32 Hz and the sensor was mounted in such a way that the x-axis points towards the hand, y-axis points towards the left and the z-axis points perpendicular to the plane of the hand. In [63], 700 trials of eight motion primitives from 16 volunteers

TABLE 2.1: RECOGNITION ACCURACY OF BI-CLASS CLASSIFICATION FOR DIFFERENT CLUSTER SIZES

Behavior class	TP (%)	TN (%)	Clustering (%)
WK	72.81	82.35	5
	81.46	83.35	10
	85.73	83.31	**20**
	82.60	63.04	50
SUC	63.90	58.11	5
	69.00	56.78	**10**
	64.80	63.78	20
	63.60	57.78	50
DW	89.30	84.53	5
	100.00	80.20	**10**
	86.60	69.72	20
	83.33	70.50	50
SDC	72.00	64.68	5
	75.67	66.68	**10**
	73.10	64.56	20
	74.20	57.00	50
PWG	93.20	78.00	5
	94.10	75.00	**10**
	85.60	79.00	20
	83.40	70.67	50
GUB	62.70	61.33	5
	69.99	62.00	**10**
	65.80	62.44	20
	67.00	65.11	50
CS	74.60	71.22	5
	83.70	73.44	10
	85.00	67.11	**20**
	81.50	63.22	50

(including 11 men and five women) from the database [113] was considered, out of which seven motion primitives are utilized here for the recognition purpose. For each motion primitive, 80% data signal are selected for training purpose and 20% data signal are selected for testing purpose. In this analysis, a training dictionary of K atom has been used by this proposed dictionary learning based classifier.

Here, the classification accuracy is analyzed for initialization of the dictionary using different sizes of clusters, like $K = 5\%, 10\%, 20\%$ and 50% of the size of the input data set is used to determine which is the most suitable cluster size that can achieve superior classification accuracy. Seven classes of **ADL** activities have been considered for analysis of classification accuracy in activity recognition problems which are in conformation with those seven classes utilized in [63]. These seven classes belong to selected motion primitives like *getting up from the bed* (**GUB**), *sitting down on a chair* (**SDC**), *standing up from a chair* (**SUC**), reiterated actions (*climbing stairs* (**CS**) and *walking* (**WK**)) and complex actions (*drinking water* (**DW**) and *pouring water from glasses* (**PWG**)). At first, the problem is solved as a bi-class classification problem where it has been tried to determine whether an unknown behaviour belongs to a specific behaviour or not. For this purpose, the specific behaviour in question constitutes the main event class and a mixture of signals from all other six classes constitutes the other class.

The dictionary learning algorithm can be accordingly utilized for this purpose and the corresponding results obtained are presented in Table 2.1. These results are also presented in Fig. 2.3 in graphical form. It has been observed from these results that with increase in cluster size chosen, recognition error at first starts to decrease and then, after a certain cluster size is attained, the error starts to increase.

In these recognition problems another popular way to assess the performance is to compute the true positive rate or **TP** (i.e., percentage of correct identification of the event activity under investigation) and the true negative rate or **TN** (i.e., percentage of correct identification of those event activities which are not under investigation). It can be seen that the choice of a cluster size beyond an optimum size of the cluster can degrade the accuracy, whereas, the choice of a very small cluster size

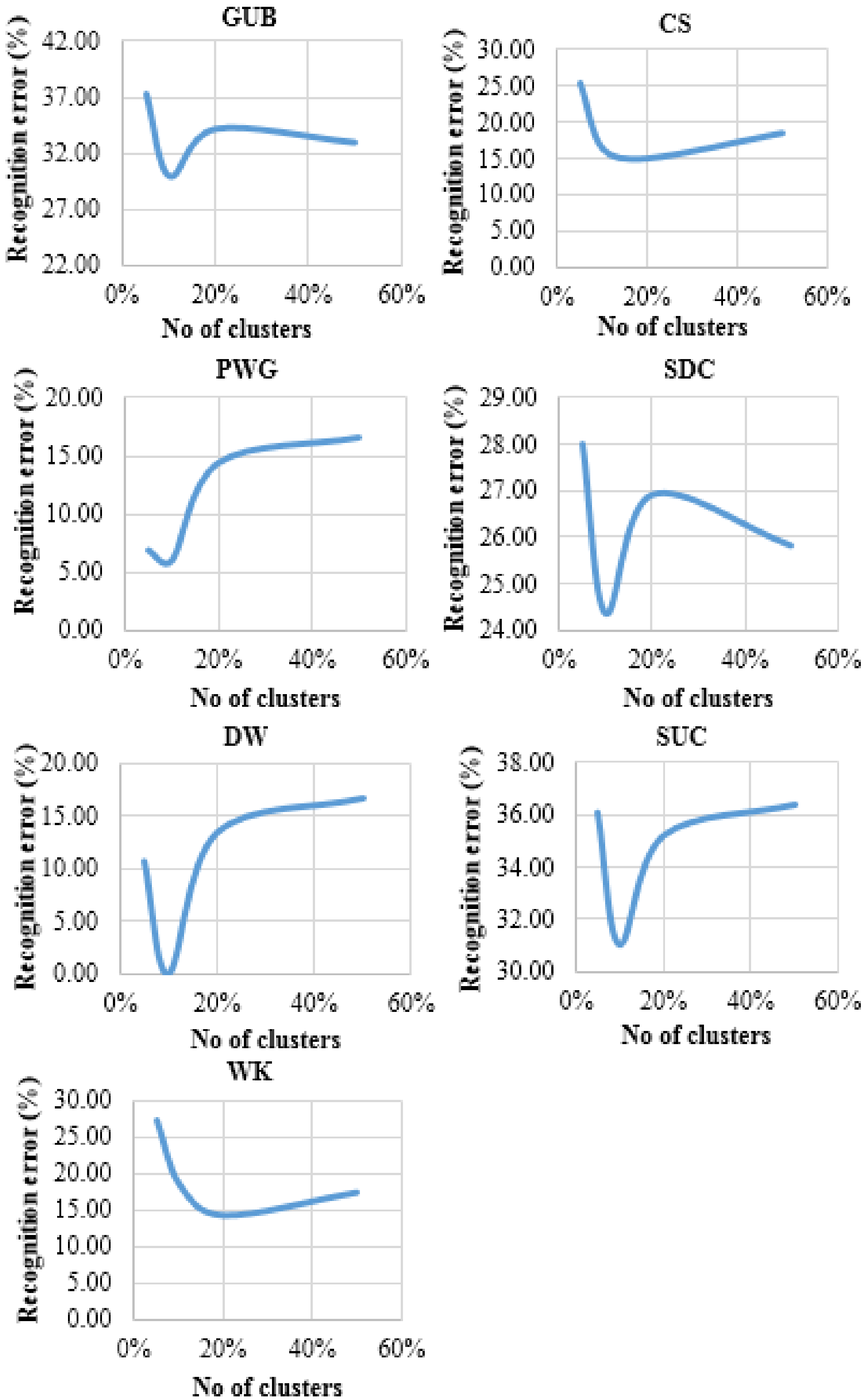


Fig. 2.3 Recognition error vs. number of clusters for bi-class classification of the ADL dataset

is also not desirable. Hence, there is a distinct value for the cluster size for which the best result is obtained with regard to a given activity/behavior recognition problem. Hence, the size of the clusters to obtain the desired accuracy is needed to be chosen very carefully.

The performance comparison of these results with the contemporary, competing work [63] for the recognition accuracies obtained for bi-class classification of human behaviour recognition is presented in Table 2.2. It is seen from the result reported that the proposed method could better identify the true activity under investigation (given by the **TP** values) in case of five out of seven classes under consideration. It has been found that only for the class of 'pouring water', the results reported in [63] are superior. Overall, the superiority of this proposed approach is aptly demonstrated from this reported result. It has already been established that this proposed approach can also identify the class of sitting down on a chair and the class of climbing stairs with satisfactory accuracy although each of these two classes has more challenging composite and reiterated action respectively.

TABLE 2.2: COMPARISON OF RECOGNITION ACCURACY WITH COMPETING WORK

Behavior class	**K-SVD approach**		**Competing work [63]**	
	TP (%)	**TN (%)**	**TP (%)**	**TN (%)**
DW	**100.00**	80.20	**100.00**	83.34
CS	**85.00**	67.10	20.00	93.34
SUC	**69.00**	56.78	60.00	83.34
SDC	**75.67**	66.68	0.00	93.34
WK	**85.73**	83.31	40.00	70.00
PWG	94.01	75.00	**100.00**	80.00
GUB	**69.99**	62.00	60.00	66.67

The overall performance comparison of the results, for bi-class classification, with other state-of-the-art methods based on the recognition accuracies obtained for each class of human behaviour recognition, is presented in Table 2.3. One can see that varied performances have been achieved from these results reported for this challenging problem. It is also observed from the result that among those, this proposed approach was able to achieve the most superior result for three classes, while no other method was able to achieve superior results for more than two classes. Also, it has been found that this proposed method was the most consistent one, as the worst accuracy result, for any class, in this case, was 69%, while for other algorithms it was always less than 65% and even as low as 0% or 8% or 10%. Thus, the appropriateness of this proposed approach is suitably established in the field of human behavior classification.

TABLE 2.3: COMPARISON OF RECOGNITION ACCURACY WITH OTHER STATE-OF-THE-ART APPROACHES

Method	**Behavior class**						
	DW	**CS**	**GUB**	**PWG**	**SDC**	**SUC**	**WK**
KNN	82.15%	75%	64.29%	73.17%	66.67%	62.16%	78.57%
Linear SVM	98.21%	76.83%	**78.50%**	91.14%	76%	64.84%	85.71%
CRC-RLS	97%	71.60%	30%	10%	**76.67%**	**80%**	78.33%
SRC	**100%**	39%	15%	8%	67%	70%	70%
Competing work [63]	**100%**	20%	60%	**100%**	0%	60%	40%
K-SVD approach	**100%**	**85%**	69.99%	94.01%	75.67%	69%	**85.73%**

Next, multi-class classification is performed to solve the human behavior classification problem as a true segregation problem, for the same benchmark **ADL** problem dataset. The recognition accuracy of multi-class classification based on the proposed approach is presented in Table 2.4. Solving the multiclass classification problem is considered as a much more difficult problem and yet the results that could be achieved are reasonably encouraging. The similar trends of error variations with variation in cluster sizes for multi –class classification as was obtained for bi-class classification can be seen and these graphical representations are given in Fig. 2.4.

TABLE 2.4: RECOGNITION ACCURACY OBTAINED FOR MULTI-CLASS CLASSIFICATION

Behavior class	Recognition accuracy (%)
DW	100.00
CS	50.00
SUC	88.67
SDC	54.67
WK	60.67
PWG	62.00
GUB	100.00

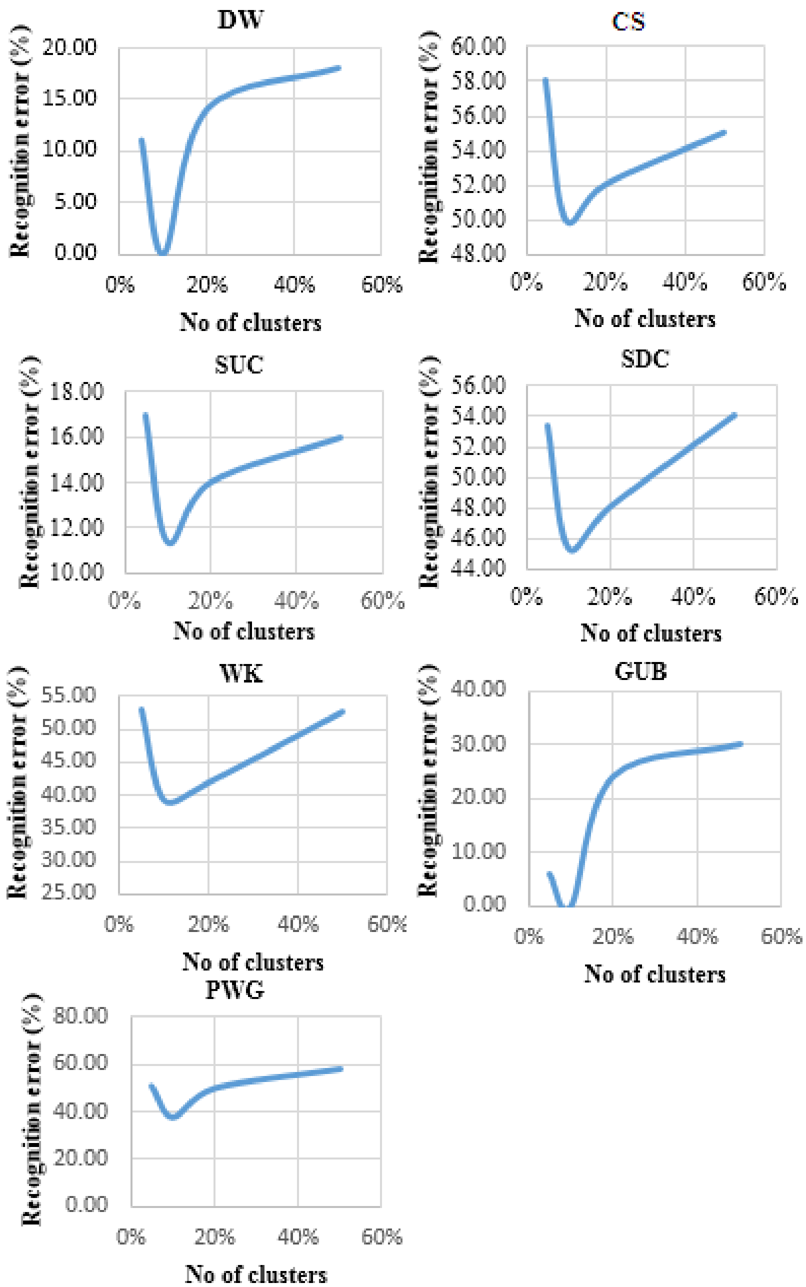


Fig. 2.4. Recognition error vs. number of clusters for multi-class classification of the ADL dataset

2.6 Summary

In this Chapter, the suitability of the dictionary learning algorithm in conjunction with **SRC** has been explored in the field of human behavior recognition. Here, it has also been established that the sparse representation based classification approach can be advantageously utilized for the purpose of human behavior recognition. It has been demonstrated from the results achieved in this Chapter that this proposed approach yields high recognition accuracy with respect to other competing approaches. The proposed approach can be applied for both bi-class and multi-class behavior classification/segregation purposes efficiently. Additionally, this work has shown that a suitable choice of cluster size has a significant impact on the identification accuracy of the algorithm. Hence, it is justified that this proposed approach opens another door of application for dictionary learning-based classification.

CHAPTER 3

Modified K-SVD based approaches for Human Behavior Recognition Problem

3.1 Introduction

As discussed in Chapter 1 and Chapter 2, it has been found that recognition of human behavior is one of the most exciting research trends in recent times and there are lots of techniques associated with machine learning are becoming more and more popular for human behavior recognition in modern days [1] [2]. Here, in this Chapter, a modified **K-SVD** based approach has been discussed and the modification is introduced in the sparse coding stage of conventional **K-SVD** algorithm. It is known that dictionary learning algorithm consists of mainly two stages i.e., sparse modelling or sparse coding stage and dictionary update stage and the most frequently used method in this context is conventional **K-SVD** [89] [90] [92] [99]. **K-SVD**, in its basic form, uses a common greedy algorithm i.e., *Orthogonal Matching Pursuit* (**OMP**) to find a sparse solution [114]. In Chapter 2, the dictionary learning based **SRC** classifier [117] is utilized in a conventional way where **OMP** algorithm is used for the sparse representation of a signal in dictionary learning stage as well as in classification stage for human behavior recognition.

Having been encouraged by the success of conventional **K-SVD** based classification techniques for activity recognition problems, in this Chapter, the feasibility of introducing other sophisticated algorithms in the sparse coding stage are investigated. Firstly, an idea of **IRLS-K-SVD** based dictionary learning algorithm for the same problem has been proposed and then, the benefit of using $l_1 - l_s$ based **K-SVD** approach has also been investigated. For this later problem, the utility of collaborative representation-based classification in human behavior recognition problem, is also investigated.

Firstly, this proposed idea is intended to test the performance of different variations of greedy algorithms and relaxation algorithms as a candidate in the dictionary learning stage as well as in classification stage for finding out the best solution of sparse representation. It will be shown from the resulting analysis that the proposed approach i.e., a hybrid **IRLS-K-SVD** based dictionary learning algorithm yields satisfactory results among all the other candidate algorithms of greedy family and relaxation family [99] to find out the best sparse representation of a signal. The usefulness of this proposed algorithm for activity recognition problems will be established from the obtained result.

Secondly, influenced by the success of applying different greedy and relaxation approaches in sparse coding stage of **K-SVD** [90] and increasing success of l_1 minimization algorithms [115], [116], the effectiveness of l_1 regularised least square method has been investigated to find the solution of sparse coding stage of dictionary learning algorithm. After learning the dictionary **D**, *Collaborative Representation* (**CR**) based classification is also investigated in parallel with **SRC** based classification.

The upcoming part of this Chapter is organized as follows. The concept of the *Iterative-Reweighed-Least-Squares* (**IRLS**) algorithm based on conventional **K-SVD** approach and the **IRLS** based **SRC** classifier for finding the best sparse solution of a signal are discussed in Section 3.2.1. This is followed by the performance analysis and comparisons with many hybrid combinations of **K-SVD** algorithms have also been presented. Then, another modification of

K-SVD algorithm based on $l_1 - l_s$ is introduced and **CR** based classification procedures are presented in Section 3.2.2. The impact of modified **K-SVD** approaches on human behavior recognition problems are presented in a comprehensive manner in Section 3.3.

3.2 Modified K-SVD based Approaches

Now, the modified variants of the conventional **K-SVD** algorithm considered for solving the human behaviour recognition problem at hand will be discussed in detail.

3.2.1 IRLS-K-SVD based Dictionary Learning for Behavior Recognition

Learning a small block size dictionary from the entire training dataset is intended so that it can adapt well to the training database by maintaining the sparsity constraints strictly. The conventional **K-SVD** based dictionary learning [89] [92] approach has been suitably modified in many later variants proposed. According to the basic spirit of dictionary learning algorithm, the objective function [90] that should be minimized is:

$$\underset{\mathbf{D},\mathbf{X}}{\arg\min} \|\mathbf{Y} - \mathbf{D}\mathbf{X}\|_F^2 \ \textit{subject to}\ \forall i, \|\mathbf{x}_i\|_0 \le T_0 \tag{3.1}$$

Here, T_0 is termed as sparsity prior. Input signal matrix is given as:

$$\mathbf{Y} = [\mathbf{y_1}, \mathbf{y}_2, \ldots, \mathbf{y}_N] \in \Re^{n \times N} \tag{3.2}$$

where **Y** comprises *N* number of input signals, each of dimension *n*.

Dictionary **D** is given as: $\mathbf{D} = [\mathbf{d}_1, \mathbf{d}_2, \ldots, \mathbf{d}_K] \in \Re^{n \times K}$ (3.3) where **D** comprises K atoms.

X in (3.4) presents the sparse coefficient matrix and is given as:

$$\mathbf{X} = \left[\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\right] \in \Re^{K \times N} \tag{3.4}$$

According to the dictionary learning algorithm discussed in Chapter 2, the objective function (3.1) should be minimized in two phases, and it should be repeated in an iterative fashion. These two phases are presented as:

i) Sparse coding stage: Here **X** is determined keeping **D** fixed.

ii) Dictionary update stage: Here **D** is determined keeping **X** fixed, determined in step *i*).

These two stages to learn a dictionary have also been followed in the proposed approach. In this proposed approach, the modification is introduced in conventional **K-SVD** [90] [117] based dictionary learning algorithm by using the **IRLS** algorithm in the sparse coding phase. The concepts of the **IRLS** algorithm [99], which is a prominent member from the family of relaxation algorithms, are discussed next in detail.

3.2.1.1 IRLS-K-SVD based Dictionary Learning

A. IRLS based IRLS based Sparse Representation

According to sparse coding stage of dictionary learning algorithm, dictionary **D** is kept constant to solve the optimization problem (3.1). The modified optimization function for sparse coding stage is shown in (3.5):

$$\min_{\mathbf{x}_i} \left\{ \left\| \mathbf{y}_i - \mathbf{D}\mathbf{x}_i \right\|_2^2 \right\} \text{ subject to } \left\| \mathbf{x}_i \right\|_p < T_0 \tag{3.5}$$

where each signal from the training dataset **Y** is presented as $\mathbf{y}_i$ and $\mathbf{x}_i$ is computed for each individual signal by solving (3.5). Generally speaking, both greedy algorithms and relaxation algorithms [99] can be employed to solve the problem (3.5). In Chapter 2, the **K-SVD** problem was solved by using *Orthogonal Matching Pursuit* (**OMP**) algorithm in the sparse coding stage. In this Chapter, **IRLS** based relaxation algorithm is considered to determine sparse solution by smoothing the penalty function $\|\mathbf{x}_i\|_0$. In this algorithm from the relaxation family [99], l_0 norm will be relaxed by replacing it with l_p norm in some range of $p \in (0,1]$. These relaxation algorithms are similar to the *Focal Undetermined System Solver* (**FOCUSS**) [99], which is used to smooth l_0 norm by replacing it with l_p norm over some range of p <1. Ideally, sparse measures would be better in the range of $0 < p < 1$, however, the rise of local minima creates problems in obtaining a sparse solution and the problem becomes non-convex. The above constraint can be converted into a penalty term using Lagrange multipliers to overcome the problem. An iterative method has been used here, called iterative-reweighed-least-squares (**IRLS**) [99] which is imitative to symbolize as l_p i.e., the weighted l_2 norm. According to the **IRLS** algorithm [99], the current state of approximation can be considered as $\mathbf{x}_{j-1}$. Here, pseudo inverse of $\mathbf{x}_{j-1}$ is determined as $\|\mathbf{x}_{j-1}^{+}\mathbf{x}\|_2^2$ instead of taking inverse of $\mathbf{x}_{j-1}$ directly. Pseudo inverse is calculated by making plain inversion of all the non-zero entities of $\mathbf{x}_i$ and putting elsewhere zero. The overall algorithm of **IRLS** for sparse representation [99] is presented in Algorithm 3.1.

Algorithm 3.1: IRLS algorithm for Sparse Coding [99]

Step 1: Determine **x** by approximating the solution of:

$$\min_{\mathbf{x}_i}\left\{\|\mathbf{y}_i-\mathbf{D}\mathbf{x}_i\|_2^2\right\} \text{ subject to } \|\mathbf{x}_i\|_p < T_0$$

Step 2: Initialize $j=0$, set the initialization matrix $\mathbf{x}_0=1$ and the weightage matrix $\mathbf{X}_0=\mathbf{I}$

Step 3: *j* is incremented by 1 to solve the following steps:

- **Solve**: the linear system $\mathbf{x}_j=\left(\mathbf{X}_{j-1}\right)^2\mathbf{D}^T(\mathbf{D}\mathbf{X}_{j-1}^2\mathbf{D}^T)^+\mathbf{y}$ to obtain $\mathbf{x}_j$ either directly or iteratively

- **Weight Update**: The diagonal weight matrix **X** is updated using $\mathbf{x}_j$ **as** $\mathbf{X}_j(i,i)=\left|\mathbf{x}_j(i)\right|^{1-\frac{p}{2}}$

- **Stopping Rule:** apply another iteration until the value of $\|\mathbf{x}_j-\mathbf{x}_{j-1}\|_2$ reaches some predetermined threshold.

Step 4: Output: Desired outcome is $\mathbf{x}_j$.

B. Dictionary Update Stage

The next stage in this learning process is the dictionary update stage where the dictionary **D** is updated for a fixed matrix **X** obtained from **IRLS** based sparse coding stage. The overall **IRLS**-based **K-SVD** algorithm is shown in Algorithm 3.2.

Algorithm 3.2: IRLS based K-SVD algorithm

Step 1:

- **Initialization of Dictionary**: $\mathbf{D}^0 \in \Re^{n \times K}$ with input signals and the columns of $\mathbf{D}^0$ are normalized using l_2 norm.
- **Input:** $\mathbf{Y} \in \Re^{n \times N}$, T_0, $\mathbf{D}^0 \in \Re^{n \times K}$
- **Output:** $\mathbf{D} \in \Re^{n \times K}$, $\mathbf{X} \in \Re^{K \times N}$
- **Set** J=1
- **Repeat** until convergence (stopping Criterion)

Step 2:

- **Sparse coding stage:** $i = 1, \ldots, N$

  Solve **IRLS** to determine $\mathbf{x}_i$ using Algorithm 3.1

Step 3:

- **Dictionary update stage:**

For each Column $k = 1, 2, \ldots, K$ in $\mathbf{D}^{J-1}$ Update it by

- Determine indices w_k using (2.7)
- Determine $\mathbf{E}_k = \mathbf{Y} - \sum_{j \neq k} \mathbf{d}_j \mathbf{x}_T^j$
- Restrict $\mathbf{E}_k$ to obtain $\mathbf{E}_k^R$ by selecting only the columns corresponding to w_k
- SVD decomposition is applied as $\mathbf{E}_k^R = \mathbf{U} \Delta \mathbf{V}^T$
- Update $\tilde{\mathbf{d}}_k = \mathbf{U}(:,1)$. And $\mathbf{x}_R^k$ is updated as $\mathbf{x}_R^k = \Delta(1,1) * \mathbf{V}(:,1)$

- **Set** J=J+1

3.2.1.2 IRLS based Classification for Behavior Recognition

Once the **IRLS–KSVD** dictionary learning algorithm learns a suitable dictionary **D**, then for an unknown signal in testing phase, the classification stage is solved using sparse representation based classifier (**SRC**) to identify a a specific human behavior. Here, **SRC** [88], [99] is implemented for the classification purpose using the **IRLS** algorithm [99] that determines the best representation of a signal using a trained dictionary which was obtained using **IRLS-K-SVD** algorithm. The objective function solved for obtaining the coefficient matrix is given as [117]:

$$\hat{\mathbf{x}}_{\mathrm{AL}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_p \text{ subject to} \|\mathbf{Ax}-\mathbf{y}\|_2 \leq \varepsilon \tag{3.6}$$

Here the trained dictionary **A** represents the output **D** obtained from **IRLS-K-SVD** algorithm (given in Algorithm 3.2) [11]. **A** is given as: $\mathbf{A} = \left[\mathbf{A}_1, \mathbf{A}_2, ..., \mathbf{A}_C\right] \in \Re^{n\times m}$, for C classes.

Algorithm 3.3: IRLS based Sparse Representation based classification

Step 1: Training samples matrix represented as

$\mathbf{A} = [\mathbf{A_1}, \mathbf{A_2}, \dots \dots, \mathbf{A_K}] \in \Re^{nXm}$ $\mathbf{A} = \left[\mathbf{A}_1, \mathbf{A}_2, ..., \mathbf{A}_C\right] \in \Re^{n\times m}$, for C classes.

Step 2: Normalize the columns of training matrix to have unit l_2 -norm.

Step 3: Solve this minimization problem to determine coefficient vector $\hat{\mathbf{x}}_{\mathrm{AL}}$ by using IRLS (given in algorithm 3.1).

$$\hat{\mathbf{x}}_{\mathrm{AL}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_p \text{ subject to} \|\mathbf{Ax}-\mathbf{y}\|_2 \leq \varepsilon$$

Step 4: For $i = 1, ..., C$

Residuals are computed

$$r_i(\mathbf{y}) = \|\mathbf{y} - \mathbf{A}\delta_i(\hat{\mathbf{x}}_{\mathrm{AL}})\|_2 \, r_i(\mathbf{y}) = \|\mathbf{y} - \mathbf{A}\delta_i(\hat{\mathbf{x}}_{\mathbf{1}})\|_2$$

End

Step 5: Output: identity $(\mathbf{y}) = \arg\min_i r_i(\mathbf{y})$

3.2.1.3 Performance Evaluation

Next, the performance analysis of **IRLS-K-SVD** algorithm used for the human behavior recognition problems is presented in detail. For this purpose, the same benchmark database of wrist-worn accelerometer signals that was used in Chapter 1 is considered here [113]. This dataset consists of 700 signals of human activities/behaviors which are acquired from sixteen persons in real-life situations [113]. The dataset comprises signals acquired corresponding to seven different human activities/behaviors which were also considered in Chapter 2. The methodology followed for creating training and testing database from this dataset remains same as was followed in Chapter 2. The seven classes of human behaviour considered remain the same i.e., *sitting down on a chair* (**SDC**), *standing up from a chair* (**SUC**), *get up from the bed* (**GUB**), *climbing stairs* (**CS**), *drinking a glass of water* (**DW**), *pouring water and walking* (**WK**), *Pouring water from a glass* (**PWG**) [113], [117]. The problem has been solved here as a bi-class classification following the same approach of bi-class classification problem that was followed in Chapter 2 i.e., the algorithm tries to identify each human behaviour separately. Hence, in bi-class classification, the main event class is composed of the data from a specific class of behavior and the other class comprises a mixture of the signals from the other six classes in consideration except for the event class [117].

At first, the dictionary learning approach is implemented to learn the dictionary and then it is followed by **SRC** based classification [117]. For the dictionary learning purpose, the sparse coding stage has been solved using a number of greedy algorithms like matching pursuit (**MP**) [99], orthogonal matching pursuit (**OMP**) [99], weak matching pursuit (**WMP**) [99], thresholding algorithm (**THR**) [99] and some variants

TABLE 3. 1: COMPARISON OF RECOGNITION ACCURACY WITH OTHER HYBRID COMBINATIONS OF DICTIONARY LEARNING BASED CLASSIFICATION

LEARNED DICTIONARY	CLASSIFICATION	Recognition Accuracy of Behavior Classes (%)						
		WK	**SUC**	**SDC**	**PWG**	**GUB**	**CS**	**DW**
MP	WMP	95	90	95	95	100	90	90
	THR	70	65	85	80	60	80	80
	IRLS	**100**	**75**	**85**	**100**	**90**	**75**	**90**
	BP	80	85	100	90	100	80	85
	MP	75	70	65	90	90	75	90
	OMP	80	70	95	85	95	75	90
WMP	MP	50	95	65	30	5	30	40
	THR	55	90	50	35	0	45	50
	IRLS	**75**	**95**	**80**	**95**	**10**	**100**	**85**
	BP	25	90	55	40	0	15	50
	OMP	50	95	65	35	0	30	45
	WMP	85	95	90	95	85	95	100
IRLS	MP	80	65	95	90	25	75	85
	THR	70	65	85	85	40	80	80
	WMP	100	100	100	90	95	90	95
	BP	80	85	100	80	30	95	85
	IRLS	**100**	**75**	**100**	**100**	**40**	**100**	**90**
	OMP	90	70	95	90	30	75	85
BP	MP	80	70	95	90	25	70	80
	THR	70	65	85	85	35	80	80
	WMP	95	100	100	100	90	90	100
	IRLS	**100**	**75**	**100**	**90**	**40**	**85**	**95**
	OMP	80	70	95	85	40	75	85
	BP	80	90	100	90	25	95	85
THR	MP	80	70	95	90	30	75	85
	WMP	95	100	100	95	90	100	90
	IRLS	**100**	**75**	**100**	**100**	**45**	**95**	**90**
	BP	80	85	95	90	25	95	85
	OMP	80	70	95	85	30	75	85
	THR	70	60	85	85	35	80	80
OMP	MP	75	75	65	90	95	90	80
	WMP	80	85	80	60	40	95	45
	IRLS	**100**	**80**	**90**	**100**	**50**	**95**	**85**
	BP	75	70	85	85	45	85	80
	OMP	100	85	70	94	75	69	85
	THR	80	75	75	80	45	75	75

of relaxation algorithms like batch pursuit (**BP**) [99] and iterative-reweighed-least-squares (**IRLS**) [99], Similarly, for the classification stage, the sparse coding part in the **SRC** problem has been solved using the same six algorithms mentioned above. The complete comparative performance has been presented in Table 3.1. The corresponding graphical representation of the recognition accuracies for each of the seven-behavior classes is presented in Fig. 3.1. It can be concluded from the results obtained that the best performance is achieved when the dictionary learning is carried out using the **IRLS-K-SVD** algorithm followed by a classification stage employing **SRC** where the

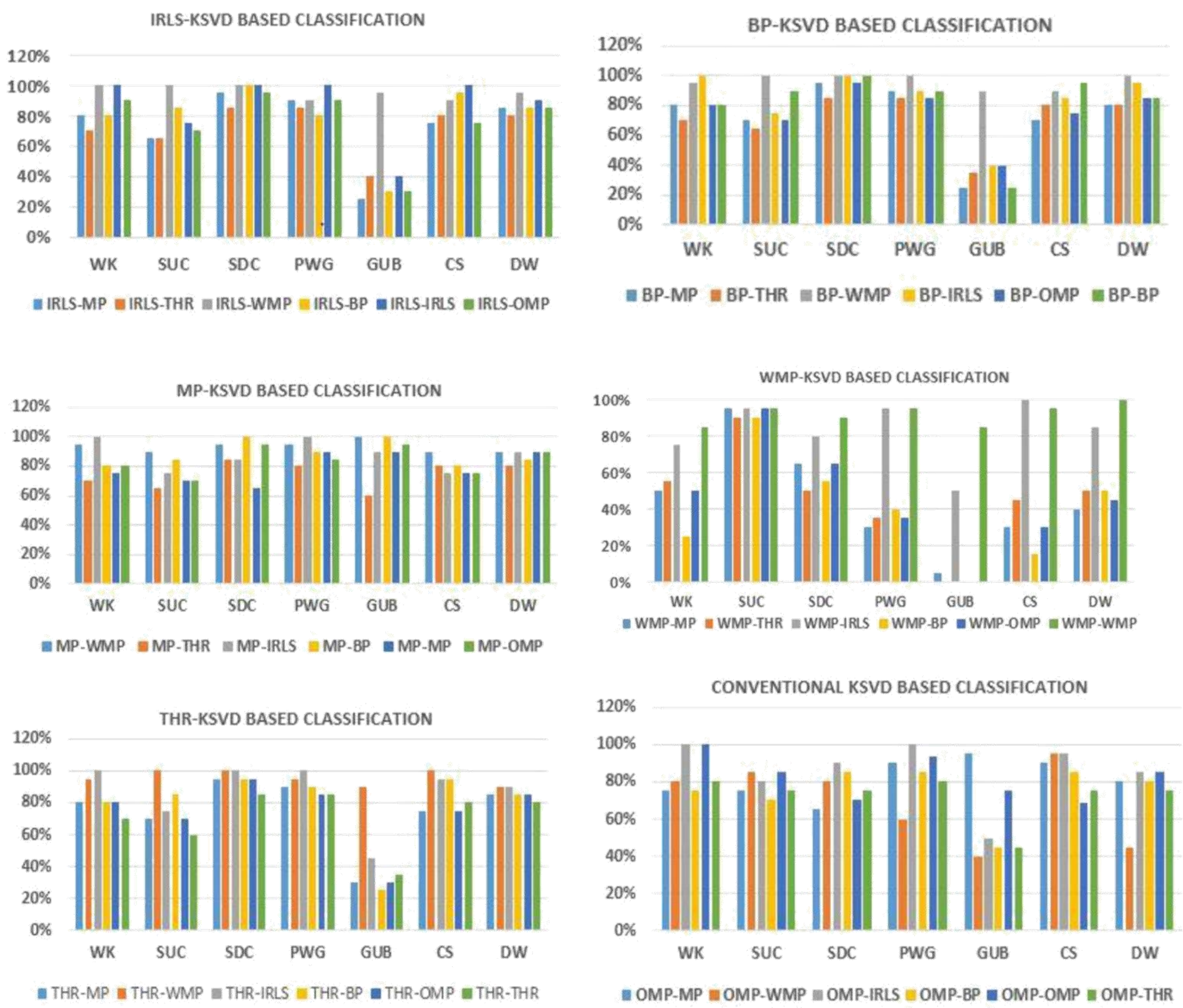


Fig. 3. 1. Comparative study of recognition accuracies obtained with different hybrid combinations of sparse coding stages employed for dictionary learning and for SRC based classification

sparse coding stage in the **SRC** is also solved using **IRLS** algorithm. outperform the conventional **K-SVD** based Hence, this experimentation has conclusively proven that the hybrid **IRLS-K-SVD** based dictionary learning algorithm can dictionary learning algorithm, discussed in Chapter 1 [117], when implemented for human behaviour recognition problem.

3.2.2 $l_1 - l_s$ based K-SVD Dictionary Learning for Behavior Recognition

The next Section will now discuss implementation of another variant of **K-SVD** algorithm called l_1-l_s based **K-SVD** dictionary learning algorithm, which will be employed for the same human behaviour recognition problem.

3.2.2.1 $l_1 - l_s$ based K-SVD Dictionary Learning

Inspired by the initial success of **K-SVD** algorithm in solving human behaviour recognition problem described in Chapter 2 and **IRLS-K-SVD** based dictionary learning approach for the same problem described in the previous Section 3.2.1, in this Section another modification is introduced in **K-SVD** dictionary learning algorithm. Here, $l_1 - l_s$ based **K-SVD** dictionary learning algorithm has been applied where $l_1 - l_s$ algorithm is used in sparse coding stage for finding the sparse solution in place of commonly used greedy algorithms like **OMP** etc. In this $l_1 - l_s$ algorithm [116], [118], a regularization parameter is combined with a standard l_1 minimization problem, which is solved using truncated newton interior point method [118] that provides the essence of fast l_1 minimization [115]. As mentioned before, in the original **K-SVD** algorithm [90] [99], dictionary learning is accomplished by computing the two stages in an iterating fashion i.e., *i*) sparse coding stage and *ii*) dictionary update stage. In this proposed approach, the sparse coding stage is solved as an $l_1 - l_s$ minimization problem, which is followed by the conventional dictionary update stage.

In Section 3.2.1, the performance of modified **K-SVD** based classification approach was investigated for human behavior recognition problem where different algorithms from greedy and relaxation family were introduced for solving the sparse coding stage. Here, in this Section, instead of using l_0 and l_p norm minimization problem in sparse coding stage, l_1 regularized least square ($l_1 - l_s$) problem is introduced in sparse coding stage for finding the sparse solution. The drawback of l_1 minimization problem is resolved by using this modification and the objective function gets converted to a convex one. This optimization problem can be solved using many methods [118]. [119]. Here, interior point based method has been used to solve this minimization problem. Using the Lagrangian method, normal l_1 minimization problem can be rewritten as:

$$\min_{\mathbf{x}} \frac{1}{2}\|\mathbf{y} - \mathbf{A}\mathbf{x}\|_2^2 + \lambda\|\mathbf{x}\|_1 \qquad (3.7)$$

Here the regularization parameter is presented as λ and its value should be chosen as $\lambda > 0$. Now, this above least square problem is combined with l_1 minimization and to reduce the computational burden *Truncated Newton Interior Point Method* (**TNIPM**) is used to solve it to find the best sparse solution and the algorithm is given in [114], [118]. The objective function (3.7) is transformed to a quadratic form with inequality constraints by using **TNIPM**. The objective function (3.7) is modified as:

$$\min_{\mathbf{x}} \frac{1}{2}\|\mathbf{y}-\mathbf{A}\mathbf{x}\|_2^2 + \lambda\sum_{i=1}^{n} u_i \tag{3.8}$$
$$\text{subject to } -u_i \le x_i \le u_i, i = 1, \ldots, n$$

It is already known that after solving the sparse coding stage to obtain the sparse coefficient matrix **X**, the next phase in dictionary learning [90], [99] is to update **D** keeping **X** fixed and to continue these two steps in an iterative manner to obtain a relatively small learned dictionary from a larger training dataset. The overall $l_1 - l_s$ based **K-SVD** algorithm will appear similar to the methodology described in Algorithm 3.2 except that the sparse coding stage will be solved as $l_1 - l_s$ problem by using **TNIPM**.

3.2.2.2 Collaborative Representation (CR) based Classification for Behavior recognition

According to the primary concept behind **SRC** [87] based classification, the unknown test signal **y** is coded based on the fixed matrix data matrix **D** by following the equation $\mathbf{y} = \mathbf{D}\mathbf{x}$ where the sparse vector is $\mathbf{x}$ .This sparse coding vector can be found out by using l_1 or l_0 minimization [87]. It has been observed that l_1 Minimization problem is more advantageous as it can handle over-complete dictionary easily and can provide, theoretically, the sparsest solution. But the chief limitation of this process is that it involves significant computational burden. This problem of computational burden can be somewhat solved by introduction of some fast l_1 minimization algorithms [117], [118].

One possible alternative to **SRC** based classification is to employ collaborative representation based classification (**CRC**) [120]. **CRC** proposed that the regularized least squares method can be used to collaboratively represent the query sample using **D** with a low computational burden. It was argued in proposing **CRC** [120] that perhaps the concept of collaborative representation is more important than the concept of sparsity based representation when a signal is subjected to redundant representation based on atoms in a dictionary. When **CRC** [120] is used in the classification stage in human behaviour recognition problem, the test signal $\mathbf{y}$ is represented based on the learned dictionary obtained from **K-SVD** algorithm by using l_2 regularized least square method. The objective function to be solved in **CRC** is given as:

$$\mathbf{arg\,min}_{\boldsymbol{\rho}} \{ \|\mathbf{y} - \mathbf{D}\boldsymbol{\rho}\|_2^2 + \lambda \|\boldsymbol{\rho}\|_2^2 \} \tag{3.9}$$

(3.9) can be easily and analytically derived as (3.10) for finding the solution of **CR** with regularised least square, given as:

$$\boldsymbol{\rho} = (\mathbf{D}^T\mathbf{D} + \lambda\mathbf{I})^{-1}\mathbf{D}^T\mathbf{y} \tag{3.10}$$

Let $\mathbf{Q} = (\mathbf{D}^T\mathbf{D} + \lambda\mathbf{I})^{-1}\mathbf{D}^T$, this $\mathbf{Q}$ is termed as the projection matrix and $\mathbf{y}$ is coded based on this projection matrix. For a pretrained/fixed dictionary the matrix $\mathbf{Q}$ can be kept computed and stored in offline and once an unknown signal $\mathbf{y}$ comes the coefficient vector $\boldsymbol{\rho}$ can be immediately obtained from (3.10).

3.2.2.3 Performance Evaluation

Next, the performance analysis of l_1 regularized least square [115] [118] based **K-SVD** algorithm used for human behavior recognition problem is presented in detail. For this purpose, the same benchmark database of wrist-worn accelerometer signals that correspond to seven different human activities/behaviors as used in Section 3.2.1.3 and Chapter 2, is considered. Following the same methodology described in Section 3.2.1.3 and Chapter 2, a training and testing database is created using this dataset and the seven categories of human behaviors have been chosen. According to Section 3.2.1.3, the problem has been solved as a bi-class classification problem.

Here, first, $l_1 - l_s$ based **K-SVD** dictionary learning approach is implemented to learn the dictionary which is followed by **SRC** based classification [117]. For the dictionary learning purpose, the sparse coding stage has been solved by using l_1 regularized least square ($l_1 - l_s$) [115] [118] method for finding the sparse solution and also, for classification stage, sparse coding part of **SRC** has been solved by $l_1 - l_s$ method (mentioned as Method 2). Followed by this, after learning the dictionary using $l_1 - l_s$ based **K-SVD**, the **CRC** based classification has been employed in place of **SRC** for this same problem (mentioned as Method 3). The performance of these two above mentioned approaches have been compared with the conventional dictionary learning algorithm (mentioned as Method 1), which is presented in Table 3.2. The corresponding graphical representation of the recognition accuracies for each of the seven-behavior classes is presented in Fig. 3.2. It can be concluded from the results obtained that the best performance is achieved when the dictionary learning is carried out using the $l_1 - l_s$ based **K-SVD** algorithm followed by a classification stage employing **CRC** (i.e. Method 3).

Hence, this experimentation has also shown that Method 3 can outperform other proposed approaches. The graphical representation of comparative analysis of recognition accuracy for three methods is depicted in Fig. 3.2 for each class of behavior and it has been found that the recognition accuracy achieved for each class of human behavior is more than 85% using Method 3 compared to the other two proposed approaches.

TABLE 3. 2 COMPARATIVE ANALYSIS OF TWO VARIANTS OF L1-LS K-SVD DICTIONARY LEARNING-BASED CLASSIFICATION APPROACHES WITH CONVENTIONAL DICTIONARY LEARNING-BASED APPROACH

	Dictionary learning stage	**Classification Stage**	**Recognition Accuracy of Behavior Classes (%)**						
			WK	**SUC**	**SDC**	**PWG**	**GUB**	**CS**	**DW**
Method 1	**OMP** based Sparse coding	**OMP** based **SRC**	**85.73**	69.00	75.67	94.00	69.99	85.00	100.00
Method 2	$\boldsymbol{l_1}$-$\boldsymbol{l_s}$ based Sparse coding	$\boldsymbol{l_1}$-$\boldsymbol{l_s}$ based **SRC**	80.00	30.00	45.00	**95.00**	**100.00**	**100.00**	85.00
Method 3	$\boldsymbol{l_1}$-$\boldsymbol{l_s}$ based Sparse coding	**CRC**	85.00	**95.00**	**100.00**	92.00	90.00	95.00	**100.00**

Finally, the performance comparison of three different approaches, i.e., the conventional **K-SVD** dictionary learning algorithm ((as discussed in Chapter 2), the **IRLS-K-SVD** based approach using **SRC** (as discussed in Section 3.2.1), and l_1-l_s based **K-SVD** approach using **CRC**, is presented in Table 3.3, for the same human behavior recognition problem. Here, from Table 3.3, it can be concluded that **IRLS-K-SVD** based approach (discussed in Section 3.2.1.3) can outperform than conventional dictionary learning based approaches (as discussed in Chapter 2) and in this Section, it has been proven that

$l_1 - l_s$ based **K-SVD** approach can perform better than the **IRLS-K-SVD** based approach for the same human behavior recognition problem.

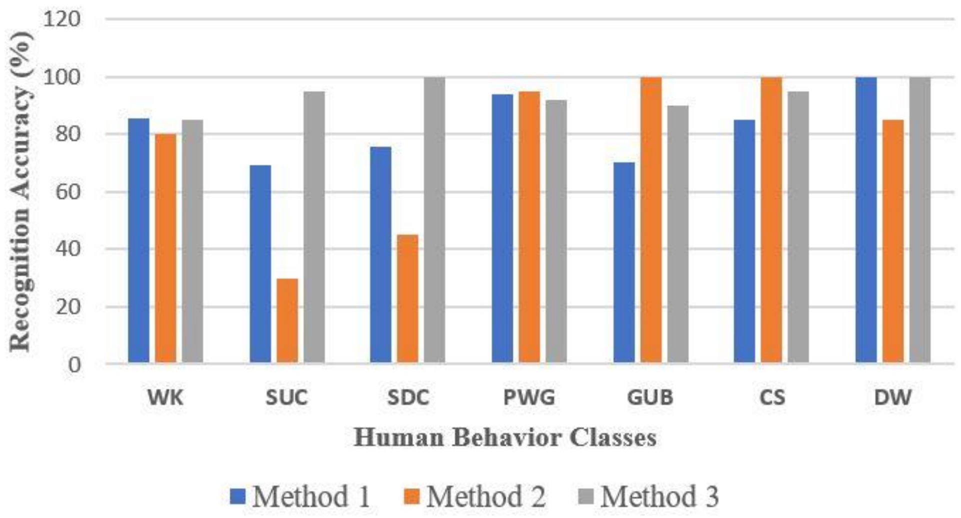


Fig. 3. 2. Performance comparison of two variants of K-SVD dictionary learning-based classification approaches with conventional dictionary learning

TABLE 3. 3 COMPARATIVE ANALYSIS OF RECOGNITION ACCURACIES OBTAINED FOR MODIFIED K-SVD AND CONVENTIONAL K-SVD BASED APPROACHES FOR HUMAN BEHAVIOR RECOGNITION

Dictionary learning stage	**Classification Stage**	**Recognition Accuracy of Behavior Classes (%)**						
		WK	**SUC**	**SDC**	**PWG**	**GUB**	**CS**	**DW**
OMP based Sparse coding	**OMP** based **SRC**	85.73	69.00	75.67	94.00	69.99	85.00	100.00
IRLS based Sparse coding	**IRLS** based **SRC**	**100.00**	75.00	**100.00**	**100.0**0	45.00	**95.00**	90.00
$l_1 - l_s$ based Sparse coding	**CRC**	85.00	**95.00**	**100.00**	92.00	**90.00**	**95.00**	**100.00**

3.3 Summary

In this Chapter, the effectiveness of different modifications of **K-SVD** dictionary learning algorithm has been investigated for human behavior recognition problems and the performance analysis has been compared with the conventional **K-SVD** dictionary learning algorithm as discussed in Chapter 2.

At first, a new hybrid dictionary learning-based classification approach for human behavior recognition has been proposed. Here, it has been established from the performance analysis that the hybrid **IRLS-K-SVD** based approach yields high classification accuracy for bi-class classification of typical seven human behavior, compared to all other possible combinations of the hybrid dictionary learning approaches. So, it can also be observed from the result analysis that instead of using the conventional **K-SVD** based method [117], this proposed hybrid **IRLS-K-SVD** based classification method can be competently applied for behavior recognition problems.

For improving the performance even after, another modified approach of the **K-SVD** dictionary learning based algorithm has also been investigated for the same problem where the dictionary learning stage is carried out by using the $l_1 - l_s$ **K-SVD** algorithm followed by the classification stage employing **CRC**. The conclusion can be drawn from the performance analysis shown in Table 3.3 that $l_1 - l_s$ **K-SVD**-based **CRC** approach outperform the recently proposed **IRLS**-**K-SVD**-based **SRC** approach for human behavior recognition problem.

CHAPTER 4

PIR Sensor-Based AAL Tool for Human Movement Detection: Modified MCP-Based Dictionary Learning Approach

---

4.1 Introduction

In light of the success of dictionary learning algorithms in various fields, researchers have got encouraged to explore potential applications of dictionary learning algorithms in other domains, such as human behavior identification, human tracking, etc. In Chapter 2, the dictionary learning algorithm is first introduced for human behavior recognition purposes utilizing the conventional **K-SVD** algorithm [117] and then, in Chapter 3, several variants of **K-SVD** based dictionary learning algorithms for solving the sparse coding problem were studied in detail for the same human behaviour recognition problem [121], [136]. Inspired by those initial successes, the usefulness of the dictionary learning algorithm is further investigated in solving human movement detection problems. Recent developments in sensor technology along with reduction in sensor costs have enabled the researchers to build sensor-based intelligent *Assisted Living* (**AL**) devices that can offer more safety to an older person to live self-reliant. Encouraged by these recent accomplishments of sensor technology in human tracking field, a new approach has been proposed in this work to identify human movement in eight different directions with a resolution of 45^0 spatial angle. These eight directions are well known directions of **S-N, N-S, SE-NW, NW-SE, SW-NE, NE-SW, E-W** and **W-E**. In this work, a complete system has been developed comprising several indigenously developed hardware and software modules, where four PIR sensors are used for real time data collection. These sensors are aligned in such a fashion that they can cover all eight intended directions for human detection and tracking i.e. towards **N, S, NW, SE, SW, NE, W and E** in the test area. The **PIR** sensor module has been placed on the ceiling of the test room and signals are acquired from several subjects in real time to demonstrate the efficiency of the system for the purpose of human detection. The present work also proposes to use dictionary learning algorithm to solve the human detection problem in different direction as a multi-class classification problem. In this context, it can be seen that developing intelligent systems for human movement detection in specific directions has become a very important problem statement. In this regard, how a sophisticated low-cost integrated system for this purpose can be developed using an indigenously developed hardware-software combination, has been shown in this Chapter. A novel solution is presented based on four **PIR** sensors-based hardware systems coupled with a novel dictionary learning algorithm. Here, the recently proposed *Multiple Cluster Pursuit* (**MCP**) algorithm-based dictionary learning has been implemented successfully for this human detection problem and then proposes a new variant of **MCP** algorithm, called the modified **MCP** algorithm, for this purpose. Extensive real-life performance evaluations have been performed to demonstrate the suitability of **MCP** and the modified **MCP** algorithms for the problem under consideration.

As mentioned before, the fundamental concept of Dictionary learning algorithms is based on sparse representation theory, which has recently achieved excellent results in many fields, such as face recognition, activity recognition [87], biometric person identification, etc [94, 117, 121]. Here, the fundamental concept of this Chapter is motivated by the concept of representing a signal $\mathbf{y}_i$ as a sparse combination of atoms from an overcomplete dictionary **D** and the solution for a set of such signals **Y** can be represented as **Y**= **DX**, where **X** represents the corresponding sparse coding matrix. In dictionary learning algorithms the dictionary is suitably learned to improve both accuracy and the computational burden involved whereas a pre-determined fixed dictionary is used in the traditional sparse representation. A two-stage iterative process is essentially employed for the dictionary learning algorithm using a sparse coding stage and dictionary update stage. Usually greedy algorithms, like **OMP**, are preferred for solving the sparse coding stage [99]. Excellence of **OMP** has been reported in works like [122] where broken rotor bars are detected using vibration signal. However, for significantly correlated data, these traditional variants are not found that effective. For those situations, recently, the *Multiple Cluster Pursuit* (**MCP**) algorithm has been proposed as an effective solution [123]. Motivated by the findings reported in [123], how such **MCP** algorithm-based dictionary learning can be employed for human movement detection problem in real-time, has been demonstrated in this Chapter. A variant of the **MCP** algorithm, called the modified **MCP** algorithm, has also been proposed in this Chapter, where the modifications are proposed in the initialization, multiple atom selection, and termination stages, and this proposed variant is applied to the problem of interest, it has been able to achieve further superior performances compared to the **MCP** algorithm. Several real-time performance comparison studies are performed in the laboratory using different variants of dictionary learning algorithms to justify the usefulness of both **MCP** and this modified **MCP** in solving the real-time human detection problem.

The rest of this Chapter is structured as follows. The motion detection problem at hand is presented in Section 4.2. A detailed description of the experimental setup that has been indigenously developed in the laboratory utilizing **PIR** sensors and the data acquisition procedure employed is described in Section 4.3. The general concept of dictionary learning followed by the **MCP** algorithm and the proposed modified **MCP** algorithm is presented in Section 4.4, applied for intelligent human detection purposes. The classification procedure is described using dictionary learning approaches in Section 4.5. The detailed description of real-time performance evaluation is carried out in Section 4.6. The conclusion is presented in Section 4.7.

4.2 Framework for Motion Identification Problem

Two of the most significant signal processing problems that are studied under the purview of the development of *Ambient Assisted Living* (**AAL**) technologies, is recognition of human behavior and detection of human movement, utilizing various forms of sensor combinations. In recent times, several research efforts have been directed to solve both human behavior and detection of human movement problems, in different forms [1,4]. The problem of detection of human movement which is very important to aid self-sufficient living for senior citizens, is focused on this Chapter. The overall block diagram of the motion identification system developed utilizing non-wearable **PIR** sensors in this work is presented in Fig. 4.1. In stage 1, appropriate **PIR** sensors are selected for this purpose and a hardware set-up/device is designed and fabricated in the laboratory using these **PIR** sensors and other accessories, which are required for signal acquisition purpose. In stage 2, accompanying software is developed in Visual Basic for actual signal acquisition in remote mode using Robodyn Uno processor and LAN interface. Once these signals are acquired, appropriate feature vectors are prepared using prominent **FFT** coefficients and their corresponding frequencies and clustering of signals is carried out. Next, stages 3 and 4 are utilized for actual motion identification using sophisticated machine learning approaches. In stage 3, a new method is proposed based on dictionary learning algorithm, named as **Modified MCP** based approach, which can efficiently learn a small size dictionary from a large size feature matrix that represents the huge sized signal data acquired from the training subjects. In stage 4, the entire system is implemented for actual motion identification in a particular direction utilizing **SRC** based classification.

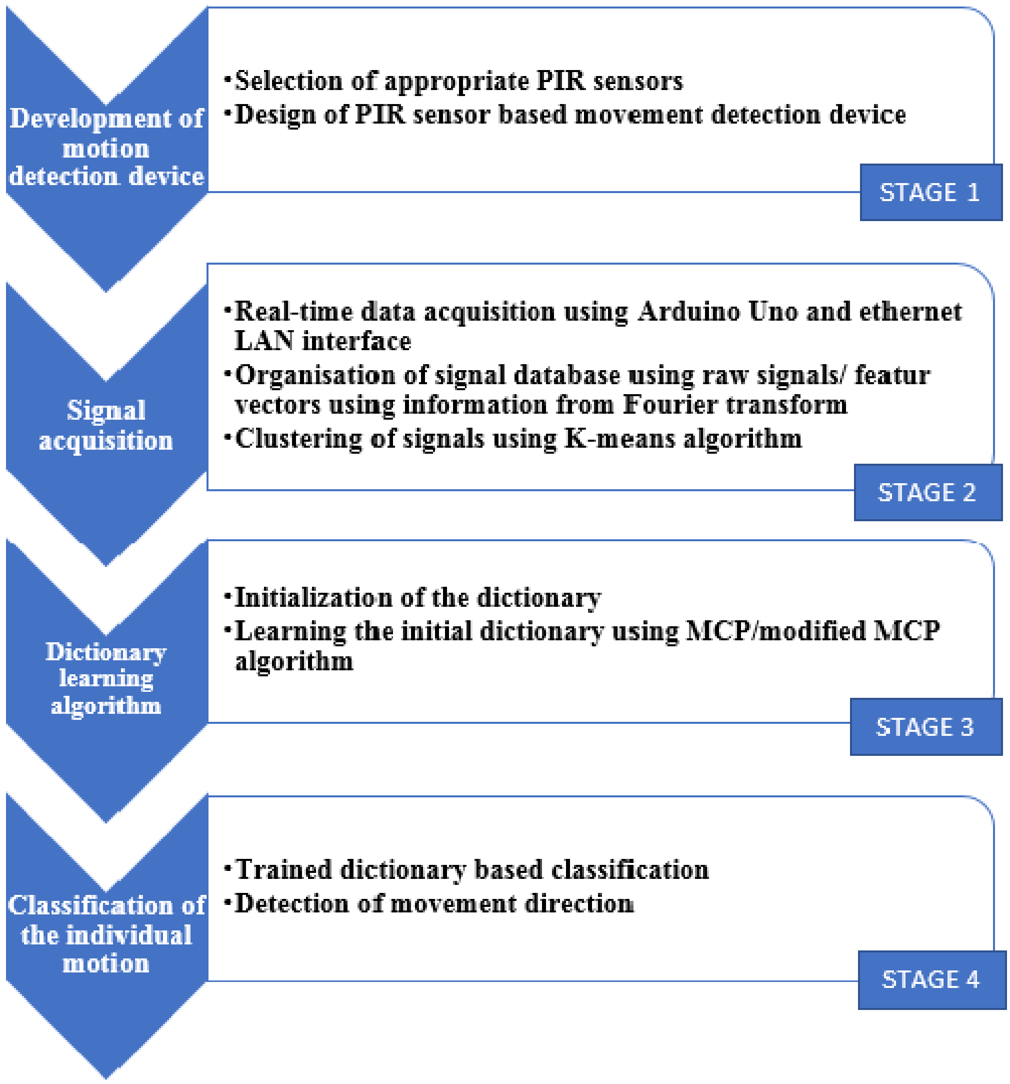


Fig. 4. 1. Overall block diagram for direction of motion detection problem

4.3 Experimental System Developed and Data Acquisition

4.3.1 Brief description of PIR sensor Array

As mentioned before, a pyroelectric infrared (**PIR**) detector is a low-cost instrument that is capable of sensing infrared radiation (**IR**) within its viewing range. They can be used in the dark as they can image infrared light and can differentiate moving objects from stationary ones. **PIR** sensor arrays are widely used in surveillance system, automatic light control system, and for monitoring conditions of elderly patients in hospitals [22] [5]. As the change in IR level can be measured by this **PIR** sensor in a passive manner so this sensor is known as a passive infrared sensor. Variation in temperature can be identified in the surrounding region when an individual movement occurs within its range. The basic working concept of **PIR** sensor with two sensing elements is presented in Fig. 4.2. Two pyroelectric elements of a PIR sensor are associated in the monitoring field in such a way that it can identify the human movement by measuring the difference between the heat generated in the pyroelectric element when an individual enters in the monitoring field. Raw **PIR** sensors, i.e., sensors without Fresnel lenses, are limited to a viewing range of 1 m. This range gets

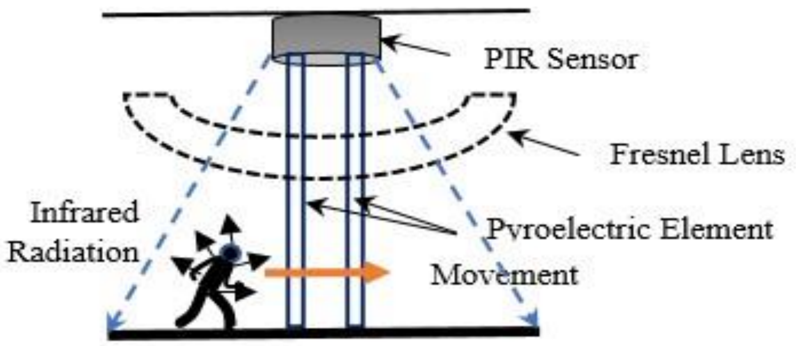


Fig. 4. 2. Movement detection by PIR sensor

increased when a Fresnel lens is used with a **PIR** sensor. In the experiments, **PIR** sensors with a Fresnel lens have been used and the detection range of each sensor, as per the **PIR** manual [124], is limited to 5 m. In order to acquire information from the **PIR** sensor due to human movement, certain parameters must be considered, e.g., the proximity to the sensor, the presence of various objects in the monitoring area, and the velocity of the individual's movements. The difference between the polarities of two sensing elements inside the **PIR** sensor and the difference between the captured signals towards each polarity is depicted in Fig. 4.3.

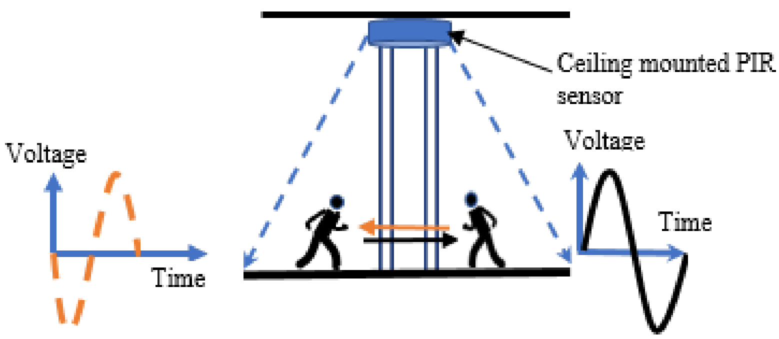


Fig. 4. 3. Output signal when walking towards positive or negative elements

4.3.2 Multi-purpose AAL Experimental Setup with PIR Sensor Array

In this indigenously developed experimental system, four **PIR** sensors are used to detect or identify walking in eight particular directions i.e., toward **N, S, NW, SE, SW, NE, W** and **E**. The direction of detection for each specific **PIR** sensor is depicted in Fig. 4.4. The system is developed using four Panasonic AMN21112 analog sensors [124,125]. This type of sensor is called a standard detection type sensor with an analog output range of 0-5V DC. The maximum detection distance of each sensor is limited to 5 m, horizontal and vertical detection ranges of 1000 and 820 respectively, and 64 detection zones. The specific arrangement of **PIR** sensor array employed in our setup along with the physical layout, the schematic and the viewing range of each **PIR** sensor [124] are depicted in Figs. 4.5 (a)-(d).

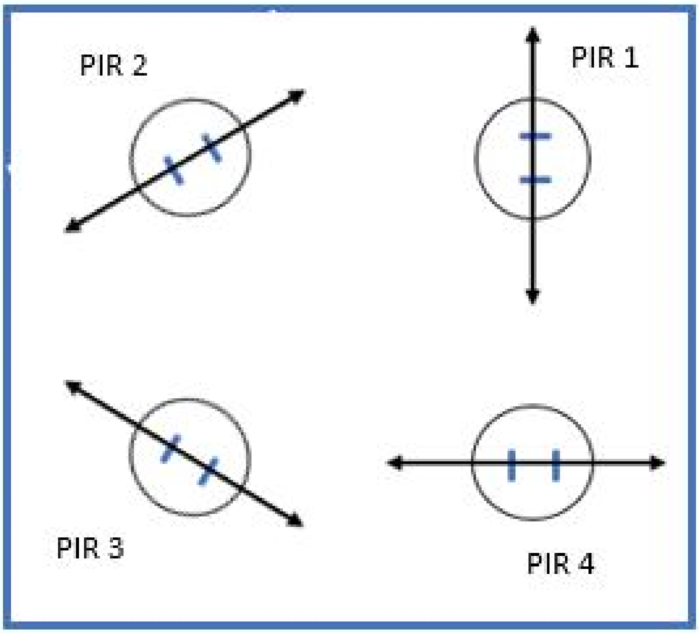
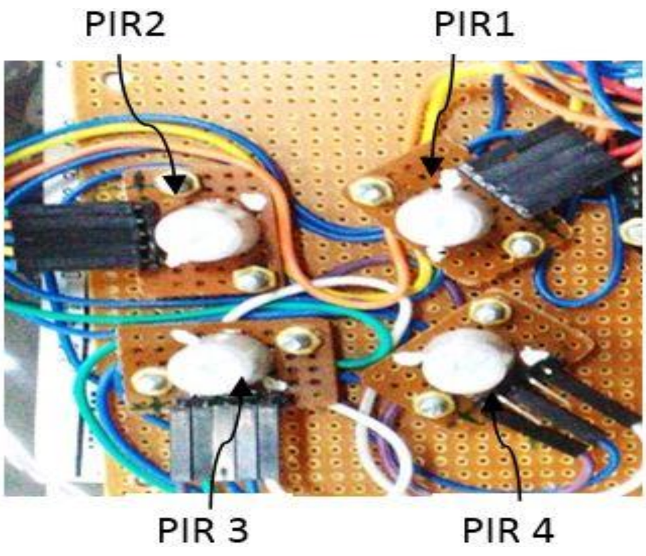
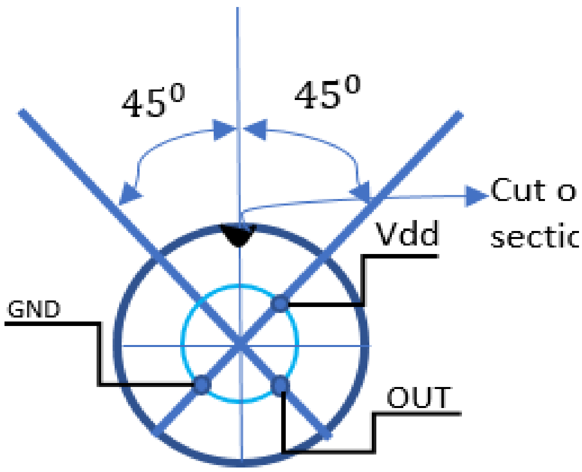


Fig. 4. 4. Detecting direction using each PIR sensor

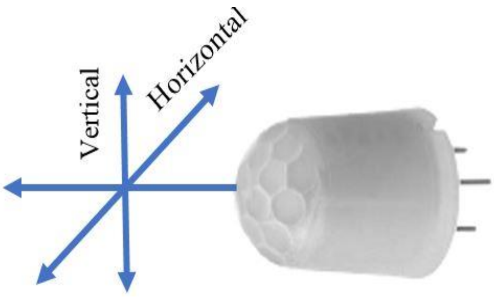
The actual snap of the complete hardware developed is presented in Fig. 4.6(a). Here all four **PIR** sensors are connected to a Robodyn UNO board which is equipped with Micro USB power connection. For each sensor, the Vdd pin is connected to the +5V supply pin of the Robodyn Uno, the GND pin is connected to the GND pin of Robodyn Uno and the OUT pins of sensors 1-4 are connected to the pins A0, A1, A2 and A3 of the Robodyn Uno, respectively. This Robodyn Uno is interfaced with an ENC28J60 Ethernet LAN network module for real time transfer of signal data acquired over Ethernet LAN. The hardware setup is also equipped with a Sony 5V, 2.1A charger with



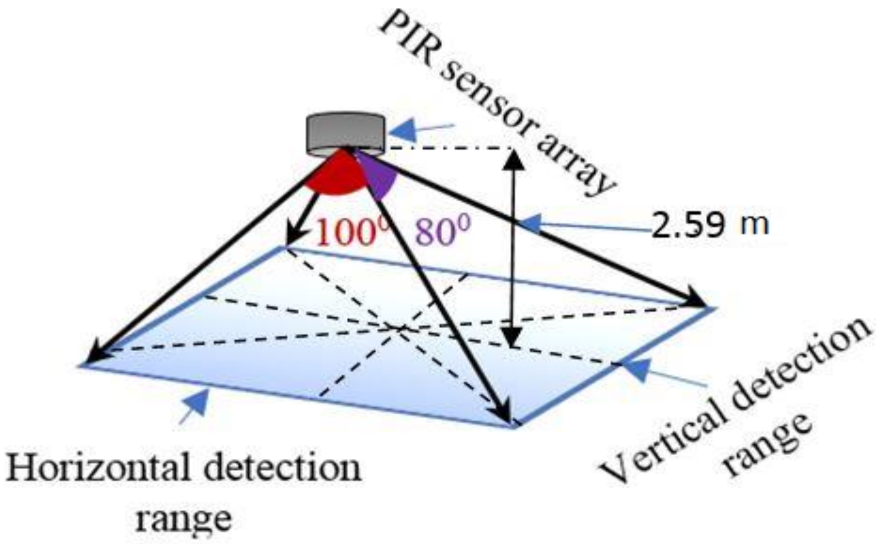
(a)



(b)



(c)

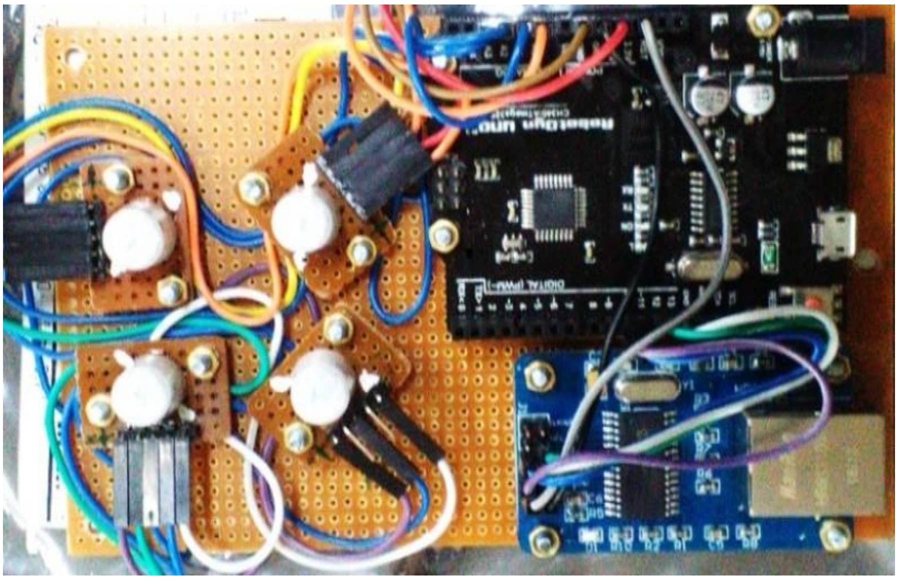


(d)

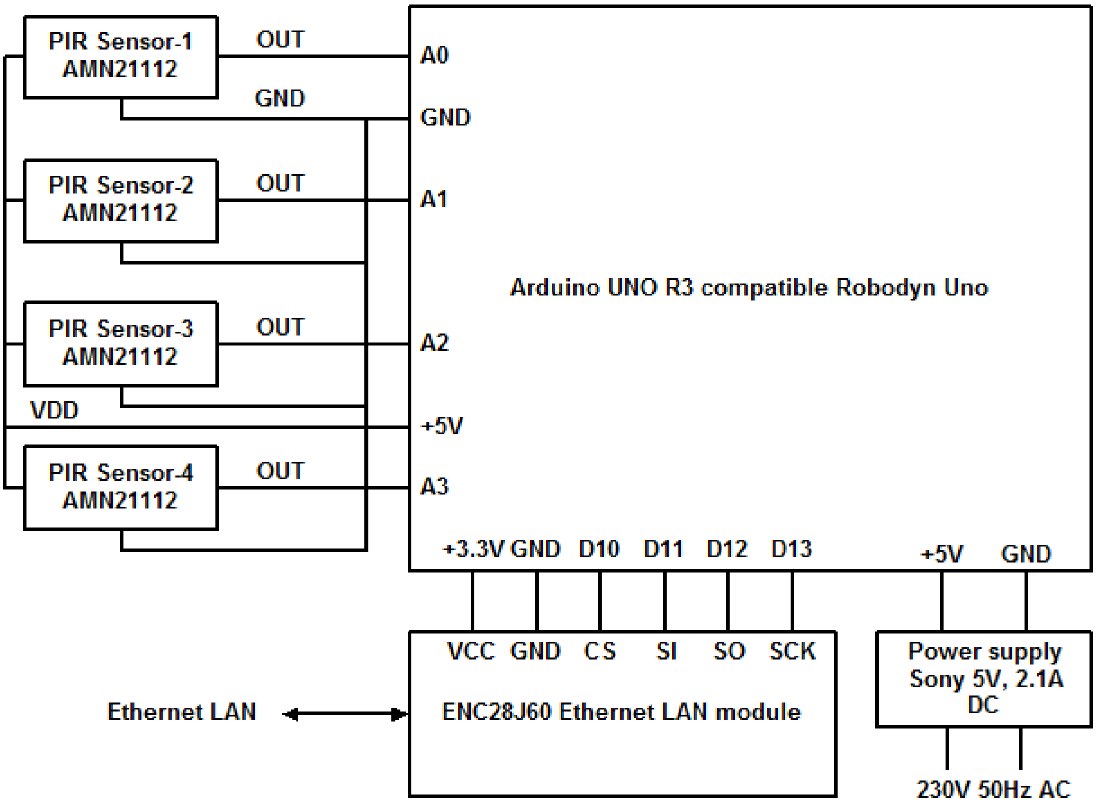
Fig. 4. 5. Pictorial representation of the PIR sensors used: (a) Top view of sensor array in movement tracking device, (b) Physical Layout, (c) Schematic, and d) Viewing range

micro USB connector whose input is 230 V, 50Hz AC. The schematic diagram of the data acquisition system is depicted in Fig. 4.6(b) developed by interfacing **PIR** sensors, Ethernet LAN module and power supply with the Robodyn Uno.

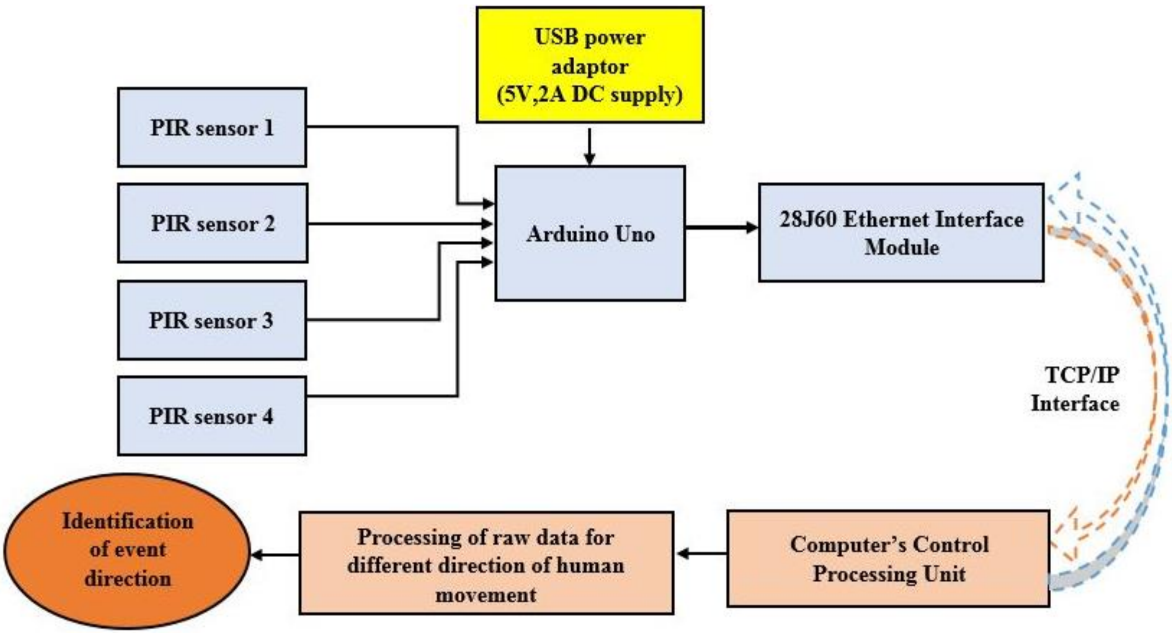
The complete schematic diagram of the human movement detection system is depicted in Fig. 4.6 (c) that comprises the hardware setup and the software modules that is capable of communicating with the hardware in real time from remote location. Here, A subject walking in eight different directions can be detected automatically by the sensor array. signals are acquired for walking in each one of the individual directions and these signals are transferred online to the PC via the Ethernet LAN module. Once data is acquired, Robodyn UNO communicates with the PC via this ethernet LAN module and transmits data to the PC after receiving a 'data send request' from the PC, utilizing a software module indigenously developed in the laboratory that uses Visual Basic and **TCP/IP**. The **GUI** developed at PC end in Visual Basic for real life is



(a)



(b)



(c)

Fig. 4. 6. (a) Top view of the developed experimental setup used in this work as a movement detecting device, (b) Pin diagram of PIR sensor with Robodyn UNO and ethernet module and (c) Block diagram of complete human movement detection system

presented in Fig. 4.7, online acquisition of signals from four PIR sensors. Here it is established that Robodyn UNO act as a server and it is monitoring a port and *Visual Basic* acts as a client which receives the signal value at each sampling instance using **TCP** interface with Robodyn UNO.

Once signal data are received at PC end, a novel dictionary learning algorithm, proposed in this Chapter and developed in **MATLAB**, communicates with Visual Basic using real life two-way handshaking to perform suitable classification and decision making to detect human movement in a specific direction, if any, and the result of the "Recognized Direction" is presented as the final result in **GUI**.

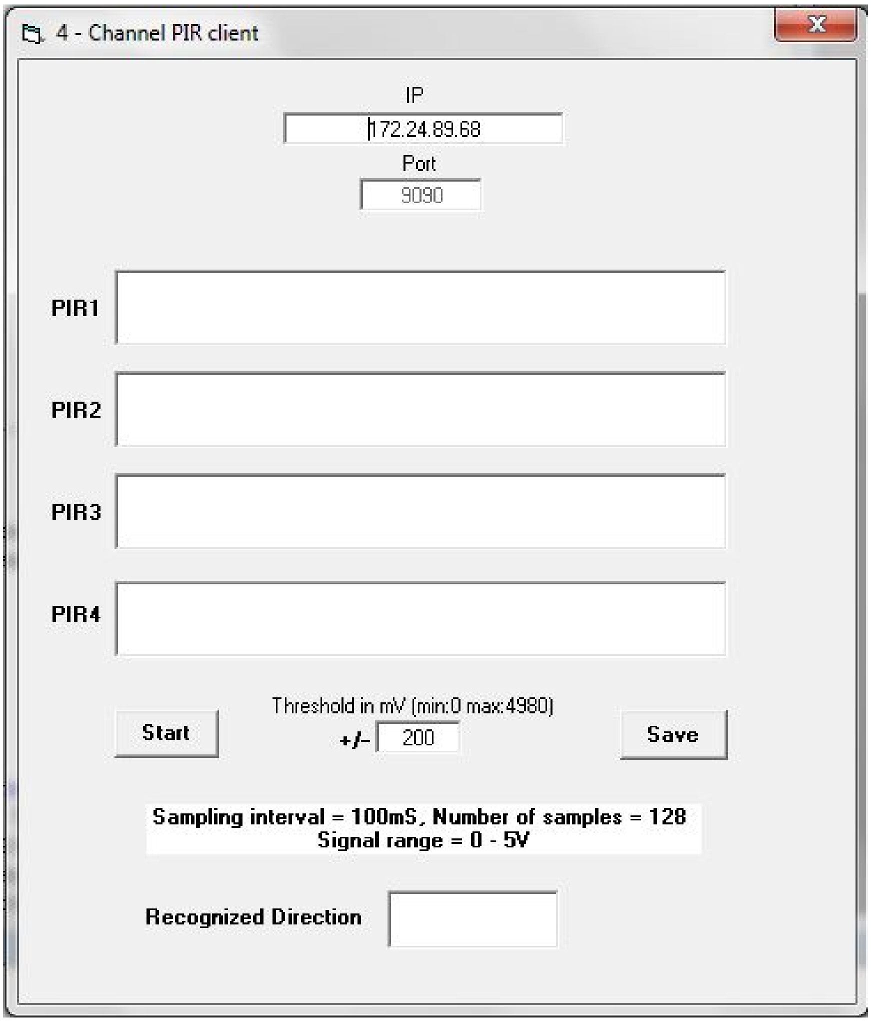


Fig. 4. 7. GUI developed at PC end for real time signal acquisition in remote mode and online display of recognized direction

4.4 Intelligent Movement Detection Using Modified MCP Based Dictionary Learning Algorithm

Once the signal(s) are acquired in real time, the intelligent movement detection is performed as a multiclass classification problem. In this Chapter, dictionary learning approach with sparse representation has been proposed to solve this problem. In sparse representation, any given signal is represented as a sparse combination of a few signals or atoms from an overcomplete dictionary [70],[55]. Usually, each atom in a dictionary is represented in terms of its Fourier or Wavelet basis [55], [71], [87]. Dictionary learning approaches are intended to learn a smaller dictionary from a larger initial database so that the computational burden involved in sparse representation can be significantly reduced, strictly maintaining the sparsity constraint [99] , [123].

It has already been mentioned that one of the most popular algorithms for designing over-complete dictionaries and suitably learning them using training signal database is the **K-SVD** algorithm [90]. **K-SVD** and hence many other algorithms have formulated the problem of dictionary learning as the minimization of an objective function, given as [117], [121], [91]:

$$\min_{\mathbf{D},\mathbf{X}} \left\|\mathbf{Y}-\mathbf{D}\mathbf{X}\right\| \quad subject\ to\ \left\|\mathbf{X}\right\|_p \le T \tag{4.1}$$

where N no of input signals or atoms are presented as $\mathbf{Y} \in \Re^{n\times N}$, each of dimension $n\times1$, the dictionary $\mathbf{D} \in \Re^{n\times K}$ is composed of K atoms, each of dimension $n\times1$, $\mathbf{X} \in \Re^{K\times N}$ is presented as a sparse coding matrix, where each column is constituted as a sparse coding vector, and $||\cdot||_p$ is presented as the l_p-norm. This optimization problem is essentially solved by executing a two-step process in an iterative fashion [90]:

a. Sparse coefficient matrix **X** is determined keeping the **D** fixed (known as *Sparse Coding* stage).

b. The new dictionary **D** is determined keeping **X** fixed as determined in step *a* (known as *Dictionary Updating* stage).

In the *Sparse Coding* stage, the problem is solved by solving *N* independent decoupled problems separately, given as:

$$\min_{\mathbf{x}_i} \|\mathbf{y}_i - \mathbf{D}\mathbf{x}_\mathbf{i}\|_2^2 \quad \textit{subject to} \quad \|\mathbf{x}_i\|_p \le t \tag{4.2}$$

where $\mathbf{y}_i$ and $\mathbf{x}_i$ give the ith columns of matrices **Y** and **X** respectively and *t* is the threshold considered for imposing sparsity in determining the ith sparse coding vector.

As mentioned in [90], the *Sparse Coding* stage can be implemented by employing any pursuit algorithm, and *Orthogonal Matching Pursuit* (**OMP**) algorithm is the most famous greedy algorithm for solving this stage iteratively. However, the computational burden of **OMP** can be significant, as only one dictionary atom is selected in each iteration. To overcome this problem, the *Multiple Clusters Pursuit* (**MCP**) algorithm was proposed in [123] to solve the *Sparse Coding* stage. **MCP** is primarily recognized for its sophisticated methodology for efficiently organizing the dictionary and selecting multiple numbers of atoms in each iteration, which significantly reduces the computational burden.

In the first stage, an efficient *K*-means strategy was utilized in **MCP** algorithm based on a correlation-based computation of similarity index which decomposes the training database into *K* clusters and computes *K* prototype atoms, $\mathbf{c}_j^* \ \left(j = 1, 2, \cdots, K\right)$, each prototype computed being a cluster center. In this case of *K*-means strategy, a two-step process is implemented in an iterative fashion [123].

a. each atom $\mathbf{d}_i$ is reallocated to the nearest cluster k based on maximum correlation between $\mathbf{d}_i$ and $\mathbf{c}_j^*(j=1,2,\cdots,K)$,and update each cluster sub-matrix.

b. Each prototype atom is recomputed as $\mathbf{c}_j^*$ $\left(j=1,2,\cdots,K\right)$ by computing dominant left singular vector of each updated cluster sub-matrix.

Once the organized dictionary structure is obtained, given by the collection of prototype atoms or cluster centers, the **MCP** algorithm enters into the searching phase of the sparse coding stage. Here, in each *k*th iteration, multiple prototype atoms $\mathbf{c}_j^*$, are selected first using the algorithm, which demonstrate correlation with the residual $\mathbf{r}_y^{k-1}$ being higher than a specified threshold.

This correlation is determined by calculating the corresponding inner product. Once the corresponding prototype atoms are selected, the algorithm visits each cluster sub-dictionary $\mathbf{U}_j$ associated with the selected jth cluster, containing dictionary atoms belonging to this jth cluster, and picks those atoms from each jth cluster which demonstrate highest correlation with residual $\mathbf{r}_y^{k-1}$ [123]. With this algorithm, multiple atoms can be selected in every iteration, and the convergence can occur much faster than with **OMP**. The sparse coding phase of **MCP** is shown in Algorithm 4.1.

In this Chapter, this **MCP** algorithm [123] is adopted in spirit to implement the intelligent human movement detection methodology and several modifications are also proposed in different stages to develop a *Modified MCP Algorithm* that has been successfully implemented in real-time to develop the intelligent decision-making module. The modifications have been proposed in three salient places: (*i*) the clustering methodology employed in step 1 and (*ii*) in step 2 and (*iii*) in step 5 in the sparse coding stage in **MCP** algorithm.

In the first modification, in applying *K-means* based clustering, a centre initialization method has been introduced to the modified **MCP** instead of using random signals from the training database to constitute K clusters. Here, at first, the database is partitioned into K number of divisions depending on the number of output classes contained in the database, and, from each division, the cluster centre atom is obtained by calculating the mean of each class. Then Euclidean distance is calculated between each cluster centre and each signal in the training database, then signals are regrouped based on least distance and again cluster centres are calculated. This process is continued until the distance between each pre calculated centre and it's corresponding newly calculated centre falls below a chosen threshold. The final cluster centers are chosen as the prototype atoms, $\mathbf{c}_j^*$, as used in the original **MCP** algorithm.

Algorithm 4.1: The Sparse Coding Stage in MCP Algorithm

BEGIN

Input: Training signal $\mathbf{y}_i$, cluster sub-dictionaries $\mathbf{U}_j$ and prototype atoms $\mathbf{c}_j^* (j = 1, 2, \cdots, K)$

Output: Sparse solution vector $\mathbf{x}_i$, index set of final chosen atoms $\mathbf{I}_i$

Step 1:

Initialization: Set $\mathbf{x}_i^0 = [\,]$, $\mathbf{r}_y^0 = y$, prototype atoms' index set $\mathbf{V}^0 = [\,]$, multiple selection atoms' index set $\mathbf{M}^0 = [\,], \mathbf{I}_i^0 = [\,], k = 1, v = 1, m = 1$, hard threshold $\varepsilon^0 = \max\left|\mathbf{c}_j^{*T} \mathbf{r}_y^0\right| \quad (j = 1, 2, \cdots, K)$

Step 2:

2.1 Compute *K* correlations $C_j^k = \left|\mathbf{c}_j^{*T}\mathbf{r}_y^{k\text{-}1}\right| \quad \left(j = 1, 2, \cdots, K\right)$

2.2 Populate $\mathbf{V}^k$ using indices of chosen prototype atoms as:

$$\mathbf{V}^k = \left\{q : C_j^k > \varepsilon^{k-1}\right\}$$

2.3 Compute new hard threshold:

$$\varepsilon^k = \mu\varepsilon^{k-1} \qquad \left(0 < \mu < 1\right)$$

Step 3:

FOR $\quad v = 1 \mathbf{:}\ size\left(\mathbf{V}^k\right)$

3.1 Search the atom in cluster sub-dictionary

$$\mathbf{U}_j\left(j = \mathbf{V}^k[v]\right)$$

which is best correlated with residual $\mathbf{r}_y^{k-1}$ and populate $\mathbf{M}^k$ as:

$$\mathbf{M}^k = \mathbf{M}^k \bigcup \left\{ r : \underset{r \in \mathbf{U}_j\left(j = \mathbf{V}^k[v]\right)}{\arg\max} \left|\mathbf{d}_r{}^T \mathbf{r}_y^{k-1}\right| \right\}$$

ENDFOR

3.2 Update the index set of final chosen atoms $\mathbf{I}_i$ as

$$\mathbf{I}_i^k = \mathbf{I}_i^{k-1} \bigcup \mathbf{M}^k$$

3.3 Reset $\mathbf{M}^k = []$

Step 4:

4.1 Update the sub-dictionary $\mathbf{D}_{\mathbf{I}_i^k}$ as:

FOR $\quad m = 1 \mathbf{:} size\left(\mathbf{I}_i{}^k\right)$

$$\mathbf{D}_{\mathbf{I}_i^k} = \mathbf{D}_{\mathbf{I}_i^k} \bigcup \mathbf{d}_{\mathbf{I}_i^k[m]}$$

ENDFOR

4.2 Update the sparse approximation $\mathbf{x}_i{}^k$ by projecting $\mathbf{y}_i$ on sub-dictionary $\mathrm{D}_{\mathbf{I}_i^k}$ as: $\mathbf{x}_i^k = \left(\mathbf{D}_{\mathbf{I}_i^k}{}^T \mathbf{D}_{\mathbf{I}_i^k}\right)^{-1} \mathbf{D}_{\mathbf{I}_i^k}{}^T \mathbf{y}_i$

4.3 Update the residual as: $\mathbf{r}_y^k = \mathbf{y}_i - \mathbf{D}\mathbf{x}_i^k$

Step 5:

IF $\left(\left(\left\|\mathbf{r}_y^k\right\|_2 < thresh\right) \text{ or } \left(size\left(\mathbf{I}_i^k\right) \geq count_{\max}\right)\right)$**,**
THEN
  STOP
ELSE
  $k = k + 1$
  GO TO STEP 2
ENDIF

END

---

calculated between each cluster centre and each signal in the training database, then signals are regrouped based on least distance and again cluster centres are calculated. This process is continued until the distance between each pre calculated centre and it's corresponding newly calculated centre falls below a chosen threshold. The final cluster centers are chosen as the prototype atoms, c_j^*, as used in the original **MCP** algorithm.

The next modifications are introduced in the searching process (in step 2) and in determination of the predefined threshold in the stopping criterion (in step 5) in Algorithm 4.1. As discussed in step 2.3, the final performance of the **MCP** algorithm is greatly influenced by how it computes the hard threshold depending on the initial choice of ε^0 and a proper choice of μ. In the original **MCP** algorithm, this has to be manually chosen and requires extensive trial-and-error approach to arrive at suitable values. In this proposed modification, this has been automated in three steps, for each iteration: (i) storing the maximum and the minimum values among all correlations computed, (ii) computing the difference between these two values, and (iii) choosing the best correlating atom from each chosen cluster, selected based on a percentage of this difference value-based threshold. It is also observed that this process results in a much faster speed of convergence and also gets rid of the tedious trial-and-error approach. In step 5 in Algorithm 4.1, the l_2-norm of $\mathbf{r}_y^k$ is expected to vary significantly for different datasets and hence the choice of the threshold *thresh* is also a tedious manual procedure for satisfactory operation. In the modified step 5, this process has been automated by choosing a stopping criterion on the basis of standard deviation of $\mathbf{r}_y^k$ computed over a moving analysis window.

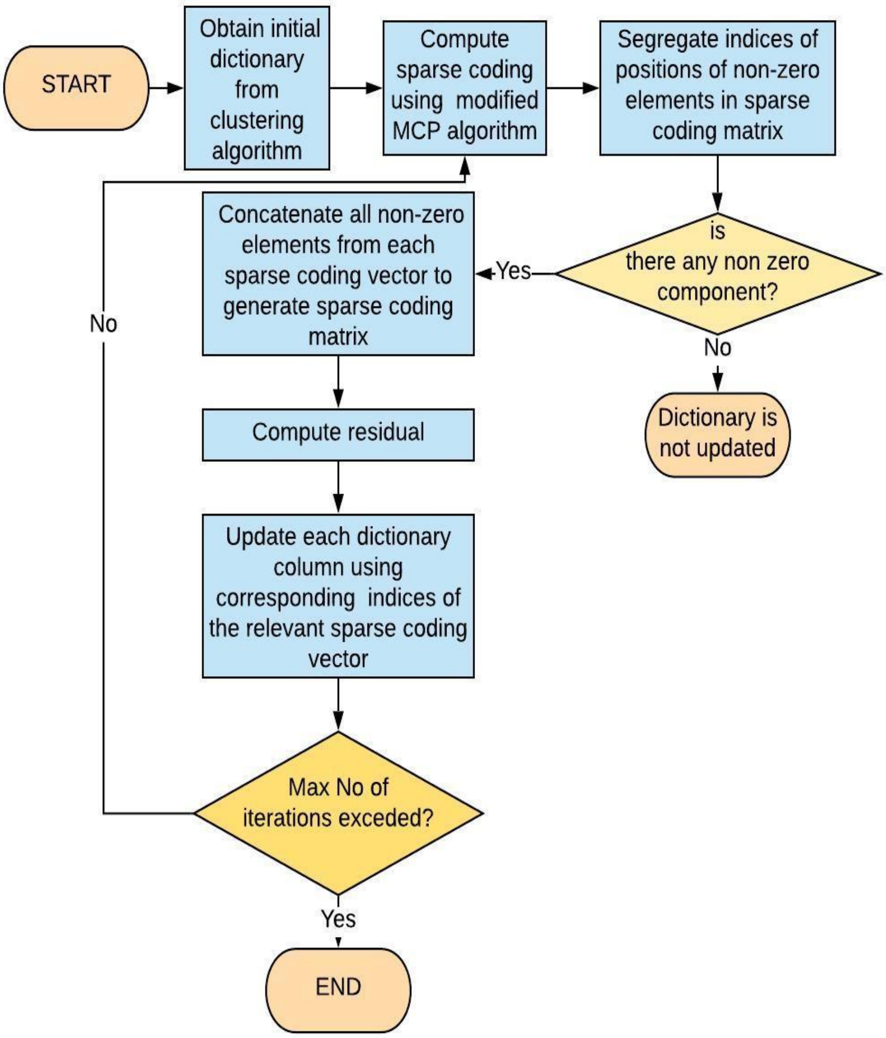


Fig. 4.8. The modified MCP based overall K-SVD dictionary learning algorithm

The algorithm will be stopped if $\mathbf{r}_y^k$ keeps decreasing over the moving window and if the standard deviation in this window falls below a threshold (*thresh_sd*). This value of *thresh_sd* can be much easily chosen as this is independent of the actual values of $\mathbf{r}_y^k$ over the iterations and a lower value attained essentially means that the residual has entered into a saturation phase, which, for all practical purposes, can be inferred as that the algorithm has reached steady state situation. Once the sparse matrix **X** is obtained, the dictionary **D** is updated next keeping **X** fixed. This process of obtaining **X** keeping **D** fixed, followed by updating **D** keeping obtained **X** fixed, is implemented in an iterative fashion. In the *dictionary update stage*, in each iteration, each column $\mathbf{d}_i$ is serially obtained one-by-one following the philosophy adopted in **K-SVD** algorithm. The proposed modified **MCP** algorithm based overall **K-SVD** dictionary learning algorithm is shown in Fig. 4.8.

4.5 Classification Based on Dictionary Learning

Once the dictionary has been suitably learned, this learned dictionary is used for identifying specific directions of human movement based on unknown signals acquired in real-life scenario in a continuous manner, using the indigenously developed experimental setup mentioned before. The problem essentially gets reduced to solving a real-life classification problem and it has been solved here using sparse representation based classification (**SRC**) theory.

4.5.1 Motion Detection based on Sparse Representation based Classification

As mentioned, each unknown signal **y** is acquired in real life and the human motion detection problem is solved as a multiclass classification problem. The **SRC** based classifier attempts to solve the optimization problem given as [87]:

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_p \ \textit{subject to} \ \|\mathbf{y}\text{-}\mathbf{D}\mathbf{x}\|_2 \leq \tau \qquad (4.3)$$

Both relaxation algorithms as well as greedy algorithms have been used here to solve (4.3) e.g., **MP, OMP, BP** and **IRLS** algorithms and their performances are compared with the performances achieved utilizing **MCP** based dictionary learning algorithm. The classification approach is discussed in detail in [117, 121].

4.5.2 MCP based Classification without Dictionary Learning

In this Chapter, another methodology of classifying motion in distinct directions has been investigated by using **MCP** based method, but without utilizing dictionary learning. Here, it is observed that an estimated dictionary is used instead of a trained dictionary to reduce the algorithm's complexity, and this strategy also explored the utility of redesigning dictionary from **MCP** algorithm. Here, a final dictionary is formed by using the concatenation of dictionaries obtained from each stage of **MCP** algorithm. A more extensive training database is represented in an organized form by using this dictionary which has been used to present each cluster individually. After constructing this concatenated dictionary, classification is carried out using **SRC**.

4.6 Experimental Result Analysis

Now, a detailed, systematic study of the performance evaluation carried out for the proposed approaches in real life situation vis-à-vis other competing algorithms is presented for the detection of movement direction problem under consideration.

4.6.1 Framework for Performance Study

The **PIR** sensors in the experimental setup developed, as shown in Fig. 4.4, are aligned towards the event direction. In this experiment, the observation area for movement tracking is considered as 1.98 m × 1.98 m in ground and the ceiling height is 2.59 m. Data from six different subjects have been acquired (comprising both male and female volunteers and volunteers having different walking patterns) walking in eight directions. it has been observed that the average weight of these subjects is 73 kg with a standard deviation of 7.74 kg (range 52 kg – 80 kg) and the average height of these subjects is 1.71 m with a standard deviation of 0.09 m (range 1.58 m – 1.82 m). Here, this hardware system has utilized 10bit ADC which is expected to have a maximum inaccuracy of the order of ±0.1%. Data for each direction have been collected on the basis of 30 sample signals per direction per person.

4.6.2 Performance Evaluation

At first a combination of **OMP** based basic **K-SVD** dictionary learning algorithm and **SRC** is used for the motion detection problem as reported in Table 4.1. It is evident that classification accuracy varies reasonably with dictionary size. However, even though the results obtained were not satisfactory enough, it was reasonable enough to encourage us that dictionary learning-based algorithms can be employed for developing feasible solutions. As the best results are obtained for a

TABLE 4. 1: PERFORMANCE ANALYSIS FOR RAW DATA SET USING BASIC K-SVD DICTIONARY LEARNING AND SRC

Clustering Size	**Recognition Accuracy (%)**
5%	42.00
10%	50.00
20%	65.67
50%	**74.00**
60%	65.00

clustering size of 50% in Table 4.1, keeping this value fixed for **K-SVD**, in the next step a detailed study of performance variations has been made with different variants of (**K-SVD**+**SRC**) combine, where different solution strategies are employed to obtain sparse solution for both **K-SVD** and **SRC**. Greedy algorithms like matching pursuit (**MP**), **OMP**, *Weak Matching Pursuit* (**WMP**), and relaxation algorithms like batch pursuit and *Iterative-Reweighed-Least-Squares* **(IRLS)** [121, 99] were employed in this study. From Table 4.2, it is observed that **IRLS** based sparse solution emerged as the best variant, providing an average detection accuracy of 82%.

Afterward, each signal vector is represented by a smaller feature vector, which makes the dictionary more overcomplete and hence potentially improves the

TABLE 4. 2: PERFORMANCE ANALYSIS FOR RAW DATA SET USING DIFFERENT VARIANTS OF (K-SVD+SRC) COMBINED

Method used to obtain Sparse Solution in K-SVD	**Method used to obtain Sparse Solution in SRC**	**Recognition Accuracy (%)**
MP	MP	65
WMP	WMP	60
OMP	OMP	74
IRLS	**IRLS**	**82**
BP	BP	66

performance of sparse representation. Each feature vector $\mathbf{f}_i$ is created by performing FFT of each signal atom $\mathbf{d}_i$ in the database and can be represented as: $\mathbf{f}_i = [\mathbf{PIR}_i(h_i(1)), \mathbf{PIR}_i(h_i(3)), \mathbf{PIR}_i(h_i(5)), \mathbf{PIR}_i(freq_i(1)), \mathbf{PIR}_i(freq_i(3)), \mathbf{PIR}_i(freq_i(5))]^T$ (i=1,2,3,4). Here, the Fourier transform coefficients corresponding to the fundamental, 3rd, and fifth harmonic of the signal, acquired from the ith **PIR** sensor, are represented as $\mathbf{PIR}_i(h_i(1))$, $\mathbf{PIR}_i(h_i(3))$ and $\mathbf{PIR}_i(h_i(5))$, respectively, and the fundamental, 3rd, and 5th harmonic frequency values of the signal are represented as $\mathbf{PIR}_i(freq_i(1))$, $\mathbf{PIR}_i(freq_i(3))$, and $\mathbf{PIR}_i(freq_i(5))$, respectively. Hence each signal atom $\mathbf{d}_i$ is represented by a much smaller feature vector $\mathbf{f}_i$ of size 24×1 which gives a more overcomplete dictionary.

A performance analysis similar to Table 4.2 has been presented in Table 4.3, but raw data has been replaced with feature data. As a result, it is reasonable to conclude that this could improve performance consistently for all sparse solution strategies, with **IRLS** still producing the best overall accuracy of 87.5%.

Next, **MCP** and modified **MCP** algorithms have been employed to obtain sparse solution in **K-SVD** using feature data set and the results are reported in Table 4.4. The performance can be enhanced by introducing **MCP** and modified **MCP** consistently enhanced performances and a significantly higher detection accuracy of 92.01% could be achieved using (**Modified MCP** based **K-SVD**+**IRLS** based **SRC**)

TABLE 4. 3: PERFORMANCE ANALYSIS FOR FEATURE DATA SET USING DIFFERENT VARIANTS OF (K-SVD+SRC) COMBINED

Method used to obtain Sparse Solution in K-SVD	Method used to obtain Sparse Solution in SRC	Recognition accuracy (%)
MP	MP	85.00
WMP	WMP	66.00
OMP	OMP	86.81
IRLS	**IRLS**	**87.50**
BP	BP	75.00

combined. Even **MCP** based classification without dictionary learning, an overall accuracy of 89.6% could be achieved that is better than performances achieved in Tables 4.1-4.3.

The confusion matrices achieved using modified **MCP** algorithm vis-à-vis basic **K-SVD** algorithm is depicted in Table 4.5. The quantitative performance measure of a classifier or classification model is presented by this confusion matrices. Here, each row is marked as the actual class label and each column is marked as the predicted class label. It is seen from Table 4.5 that the entries in the diagonal correspond to the situation when the actual class and predicted class are identical i.e., the classification is correct. A higher value in an entry in the diagonal means that particular class has been identified with higher accuracy. The summation of the entries in a given row will always be 100% for a specific class. By looking at the confusion matrix shown in Table 4.5, it can be easily seen that, for each class, the correct recognition accuracy obtained using modified **MCP** algorithm is higher than the corresponding value achieved using **K-SVD** algorithm. In Table 4.5, it is accomplished that modified **MCP** has 100% accuracy when recognizing direction **N-S**, i.e., class **D3**, whereas **K-SVD** has 97.2% accuracy and similarly in recognizing direction **SW-NE**, i.e., class **D7**, it also has been observed that the accuracy of modified **MCP** is 94.5% whereas the corresponding accuracy of **K-SVD** is 86.1%, and so on. It has been aptly demonstrated the utility of dictionary learning algorithms from these in-depth performance analyses carried out and also, the effectiveness of the proposed variant for real-life human movement detection in eight directions has also been established the effectiveness of the proposed variant for real-life human movement detection in eight directions has also been established.

It should be noted that the algorithm proposed in this Chapter has two modules. The first one is presented as the leaning module i.e., learning the dictionary and the second one is presented as the classification module i.e., performing the actual classification using the trained dictionary. The learning module has been implemented in offline mode, based on a training database created by acquiring real-life signals using the experimental setup developed and the classification of an unknown test signal has been carried out in online mode, using the same experimental setup. The average computation time taken to classify an unknown signal is found to be 1.404 ±0.108 sec, on the basis of 10 sample consecutive executions of the classification algorithm. Hence both offline and online mode of this algorithm can be implemented using a standard, low-cost, ordinarily

TABLE 4. 4: PERFORMANCE ANALYSIS FOR FEATURE DATA SET USING DIFFERENT VARIANTS OF (MCP BASED K-SVD+SRC) COMBINED

Dictionary Learning Algorithm	**Method used to obtain Sparse Solution in K-SVD**	**Classification**	**Method used to obtain Sparse Solution in SRC**	**Recognition Accuracy (%)**
K-SVD	**Modified MCP**	**SRC**	MP	88.50
			WMP	75.00
			OMP	90.20
			IRLS	**92.01**
			BP	85.06
	MCP	**SRC**	MP	87.50
			WMP	73.00
			OMP	89.60
			IRLS	**90.60**
			BP	84.06
MCP based Classification without using K-SVD				89.60

TABLE 4. 5: CONFUSION MATRICES OBTAINED FOR (A) MODIFIED MCP BASED CLASSIFICATION AND (B) BASIC K-SVD BASED CLASSIFICATION

Predicted→ Actual↓	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**
D1(EW)	**100**	0	0	0	0	0	0	0
D2(NEW)	5.5	**88.9**	5.6	0	0	0	0	0
D3(NS)	0	0	**100**	0	0	0	0	0
D4(NWSE)	0	0	11.1	**72.2**	0	0	0	16.7
D5(SENW)	5.5	0	0	0	**80.6**	11.1	2.8	0
D6(SN)	0	0	0	0	0	**100**	0	0
D7(SWNE)	0	0	0	0	0	0	**94.5**	5.5
D8(WE)	0	0	0	0	0	0	0	**100**

(A)

Predicted→ Actual↓	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**
D1(EW)	**94.5**	5.5	0	0	0	0	0	0
D2(NESW)	5.5	**80.6**	11.1	0	2.8	0	0	0
D3(NS)	0	2.8	**97.2**	0	0	0	0	0
D4(NWSE)	0	0	8.4	**72.2**	0	0	5.5	13.9
D5(SENW)	8.3	0	0	0	**80.6**	11.1	0	0
D6(SN)	0	0	0	0	2.8	**91.7**	5.5	0
D7(SWNE)	0	0	0	8. 4	0	0	**86.1**	5.5
D8(WE)	0	0	0	0	0	0	2.8	**97.2**

(B)

available computing platform and it does not require any powerful computer or an enterprise data server.

4.7 Summary

The present Chapter has shown how a state-of-the-art, low cost, integrated system can be developed using contemporary concepts in hardware and software designs for automated, intelligent human movement detection in eight directions in an indoor environment. The hardware setup is developed with remote monitoring facility and Ethernet Interference module and **TCP/IP** interface to the client end. This Chapter has shown how a recently proposed dictionary learning technique, called **MCP** algorithm, can be successfully employed to solve the real time human movement detection problem. This work has also proposed a new variant of **MCP** algorithm, called modified **MCP** algorithm, which could further improve the accuracy achieved using **MCP** algorithm.

Chapter 5

Regularized K-SVD based Dictionary Learning Approaches for PIR Sensor based Detection of Human Movement Direction

5.1 Introduction

It has been established in Chapter 4 that *Multiple Cluster Pursuit* (**MCP**) based DL and *Modified Multiple Cluster Pursuit* (**MMCP**) based **DL** algorithms can be suitably utilized for detection of human movement in eight directions in a smart home or indoor environment [128]. This has been experimentally achieved using an indigenously developed hardware-software combine setup in the laboratory using four **PIR** sensors, Arduino UNO hardware and other accessories. This system solution can be used to detect indoor movement in eight different directions with a spatial resolution of 45^0 (directions defined as **S-N, N-S, SE-NW, NW-SE, SW-NE, NE-SW, E-W**, and **W-E**). The best overall recognition performance achieved in Chapter 4 was 92.01% which was encouraging. However, it also meant that there is definite scope for further research in this problem domain so that more sophisticated **DL** based algorithms can be investigated, developed and implemented which can potentially provide superior recognition performance.

Encouraged by this development and understanding, further developments of sophisticated **DL** algorithms have been undertaken in conjunction with the multipurpose experimental setup developed in the laboratory. This experimental setup has been developed as a generic **AAL/ADL** device so that several **AAL/ADL** problems can be investigated in real life and corresponding experimental prototypes can be developed. This experimental system is now utilized for development of more sophisticated system solutions for detection of human movement direction by employing the regularization concept-based **K-SVD** algorithms (referred to as **RK-SVD** here) [127]. This concept of **RK-SVD** is a recently proposed technique in the domain of dictionary learning. In this context, it should be remarked that, to the best of the knowledge and belief, these are the first works where real-life, physical **AAL** systems for human movement detection in specific directions have been developed, utilizing both the concepts of **MCP** and **MMCP** based **DL** as well as regularization based **K-SVD** based **DL**. According to the concept of regularization, solutions with large values of sparse representation coefficients are penalized. In this Chapter it will be shown how both **RK-SVD** and **RAK-SVD** algorithms, proposed in [127], can be successfully implemented in the development of real **AAL** systems and it will be comfortably established that the performances achieved by both **RK-SVD** and **RAK-SVD** algorithms for the human movement detection problem can outperform the performances achieved by **MCP** and **MMCP** algorithms in conjunction with the four PIR sensor-based hardware system, discussed in Chapter 3 [128]. A novel modification for both **RK-SVD** and **RAK-SVD** algorithms has also been proposed, namely the **MRK-SVD** and **MRAK-SVD** algorithms, in which novel adaptation techniques for the regularization parameter have been introduced to further enhance the performance. Based on extensive experiments, it will be shown that the performance of **MRK-SVD** and **MRAK-SVD** can further improve over the performances achieved by **RK-SVD** and **RAK-SVD** algorithms, with the **MRAK-SVD** algorithm emerging as the best alternative for the problem under consideration.

A brief discussion of the experimental setup is presented in Section 5.2. In Section 5.3, dictionary learning has been introduced, then the regularized versions of the **K-SVD** algorithm and the **AK-SVD** algorithm are also discussed, and the modification has also been proposed for the regularization parameter. The classification part has also been discussed in Section 5.4 and the extensive real-life performance evaluations and analyses have been carried out in Section 5.5. The conclusion of this Chapter is presented in Section 5.6.

5.2 The Scheme for Detection of Human Movement Direction Problem

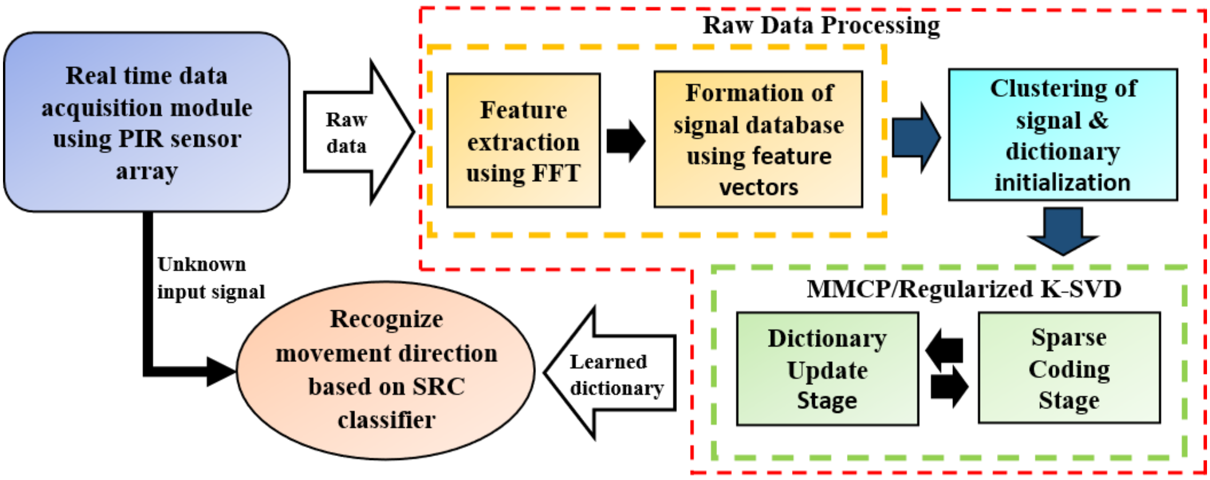


Fig. 5. 1. The overall scheme employed for the detection of human movement direction problem

The identification of human activity, human behavior, and the movement of humans within an AAL environment have recently been a thriving research interest [1], [45]. The human movement detection is considered very important for the independent living of senior residents and for remote monitoring, as discussed in Chapter 4. An overall scheme proposed for the human movement detection problem is depicted in Fig. 5.1. This scheme has also been followed by Chapter 4. In Chapter 4, **MCP** and **MMCP** based **DL** has been successfully employed for finding the solution of the problem under consideration and in this Chapter, for improving the performance furthermore, regularized **K-SVD** based **DL** has been proposed in place of **MMCP**.

The complete hardware-software combine based scheme, utilized here to solve the movement detection problem is presented in Fig. 5.2, essentially comprising five modules/stages. The experimental hardware-software hybrid system indigenously developed in the Electrical Measurement and Instrumentation Laboratory in Electrical Engineering Department, Jadavpur University, India [128] is presented in Module 1. The set-up has been composed of four **PIR** sensors for detecting human movement in eight particular directions

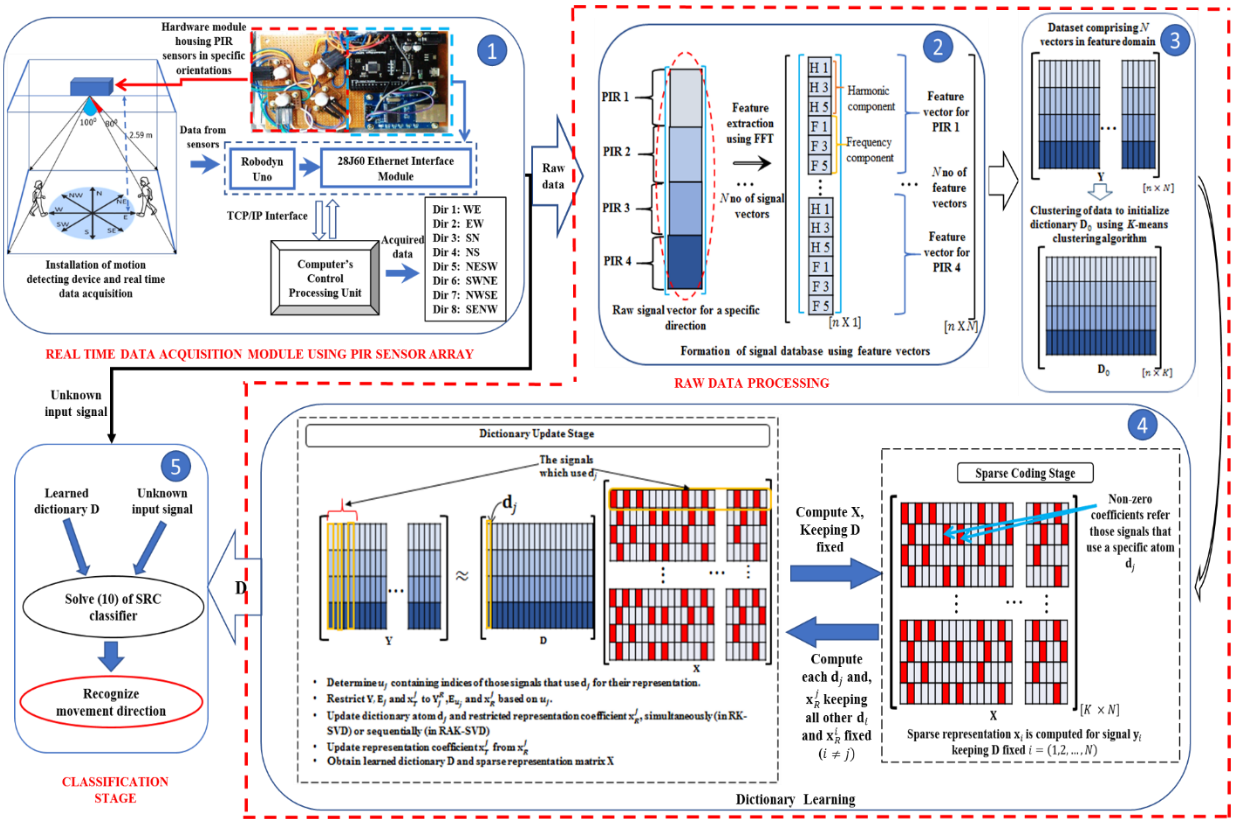


Fig. 5. 2. The complete scheme for the direction of human movement detection problem.

i.e., toward **N, S, NW, SE, SW, NE, W,** and **E**, in a hallway of specific dimensions. In Modules 2 and 3, from the real-life raw signals acquired from the four **PIR** sensors, feature vectors are formed using **FFT** and then the feature signal database is clustered to form the initial dictionary. The novel techniques of **DL** have been investigated in this Chapter i.e., regularized versions of **DL**, and this new version has been proposed and effectively utilized in this work to learn a smaller size dictionary **D** from feature signal database **Y**. This learned dictionary **D** has been utilized to detect any movement direction, in real time, using the **SRC**-based classification procedure which is presented in Module 4.

As discussed in Chapter 1, stationary objects can be distinguished quite effectively from movable objects using the PIR sensor. Construction-wise, **PIR** sensors are composed of two pyroelectric elements inside it, which are placed in the monitoring field in such a way so that the temperature variation can be detected due to any movement, e.g., the entry of a person, within its viewing range [125], [128], as discussed in Chapter 4. As shown in Fig. 4.4 of Chapter 4, a **PIR**-based movement detection device with four sensors has been developed for solving the human detection problem. This indigenously developed experimental device has been described in detail in Chapter 4, also used in this Chapter and this device is integrated with another indigenously designed **TCP/IP** based automatic, real life signal acquisition module, as shown in Module 1 of Fig. 5.2. The dimension of the area utilized for performing the experiment along with the viewing range of each **PIR** sensor is presented in the Module 1 of Fig. 5.2 which has been employed in Chapter 4 also. Overall data acquisition module as discussed in Chapter 4, is presented in Module 1 of Fig. 5.2 where **PIR** sensors are connected to a Robodyn Uno board which is interfaced with an ENC28J60 Ethernet LAN network module for real time transfer of signal data acquired over Ethernet LAN [128]. For the purpose of human movement detection problem, a final composite **GUI** has been developed in this chapter, which is presented in Fig 5.3. This **GUI** acquires data from four **PIR** sensors in real time at the PC end and utilizes this data to communicate with **MATLAB** where all competing experimental algorithms have been developed for human movement detection, using two-way handshaking. The Recognized Direction of human movement and the Representation Error for that Recognized Direction are also displayed in this developed **GUI**. Lower the Representation

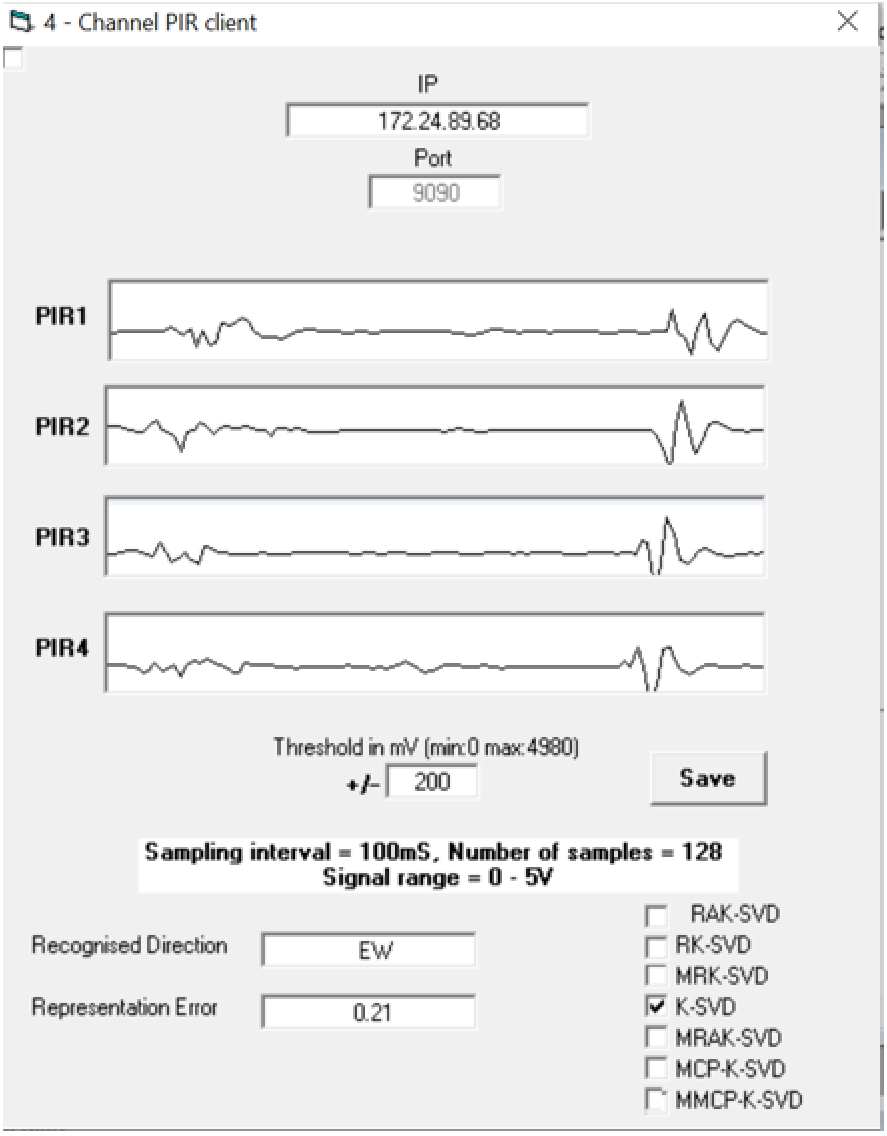


Fig. 5. 3. GUI developed at the PC end for the acquisition of real-time signals in remote mode and the online display of recognized direction of human movement

Error for the Recognized Direction using a particular dictionary, more efficient is the corresponding dictionary learning algorithm using which the dictionary has been learned. Fig.

5.4 shows the step-by-step procedure employed, in a flow chart form, for data transfer and the intelligent decision-making algorithm employed at PC end that has also been used in Chapter 4.

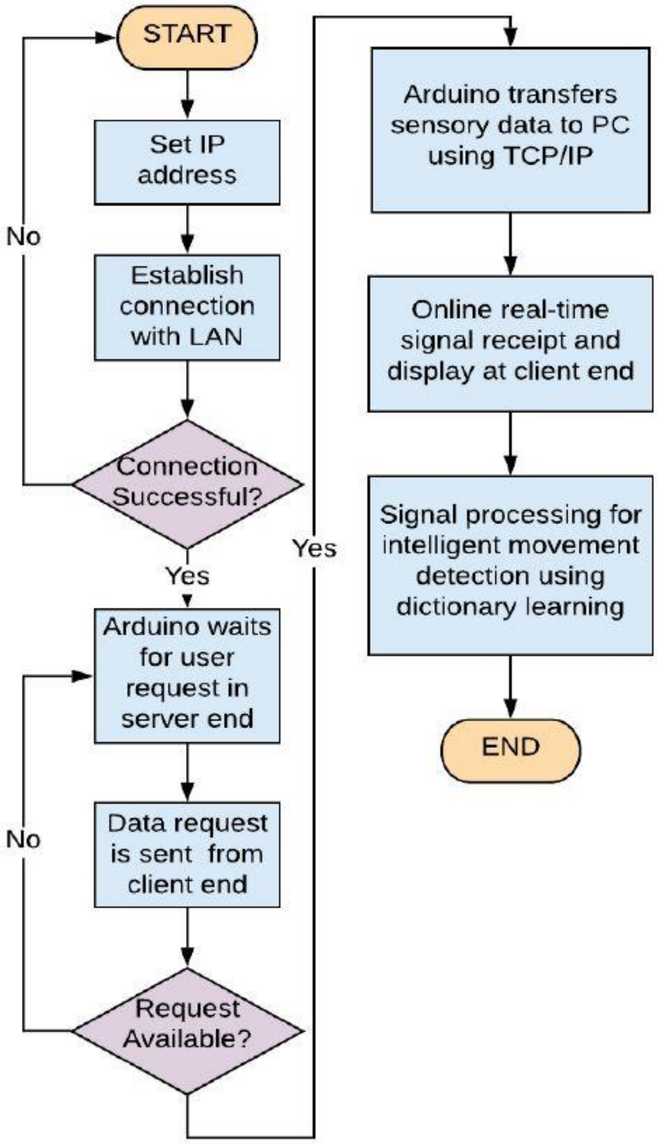


Fig. 5.4. Flow chart for sensory data transfer to PC using TCP/IP interface and subsequent signal processing

5.3 Detection of Human Movement using Regularised Versions of Dictionary Learning Algorithms

Based on the online acquisition of signals from four **PIR** sensors and subsequent transmission of those to the remote PC end, in this Chapter, a regularized **K-SVD** based DL approach has been proposed to detect human movement, in specific eight directions.

The fundamental idea of any **DL** algorithm is based upon sparse representation in which a given signal is represented as a combination of few atoms from an overcomplete dictionary [87], [90].

According to the objective of a dictionary learning approach, a dictionary is learned in a smaller form from a larger signal training database so that the subsequent computational burden can be reduced. Each column of the training database is made up of either an original signal or features extracted from that signal. It has been shown in this Chapter that an efficient dictionary learning approach-based solution can be proposed for movement detection. This approach has been implemented in real life using this indigenously developed system reported in [128].

5.3.1 Regularized K-SVD algorithm

According to the **K-SVD** algorithm,-the dictionary **D** is solved by utilizing the family of training signals which is assembled in a training database **Y**, as [90], [99], [127].

$$\min_{\mathbf{D},\mathbf{X}} \left\|\mathbf{Y}-\mathbf{D}\mathbf{X}\right\|_F^2 \quad \textit{subject to } \forall i,\ \left\|\mathbf{x}_i\right\|_p \le l \tag{5.1}$$

Here, the input training signal database is presented as $\mathbf{Y} \in \Re^{n \times N}$ which is made up of N no of input signals with the dimension of each signal being $n\times1$. The dictionary is constructed as $\mathbf{D} \in \Re^{n \times K}$ where the number of atoms in the dictionary ($K<N$) is depicted as K and sparse representation matrix is presented as $\mathbf{X} \in \Re^{K \times N}$ where each column presents the sparse representation vector corresponding to each input signal. The l_p norm is presented in $\|\cdot\|_p$ ($\|\cdot\|_0$ was considered in (5.1) for **K-SVD** algorithm which counts number of nonzero elements in a vector) and the Frobenius norm of the matrix is presented in $\|\cdot\|_F$. It is now well established that a dictionary must be true to the signal it represents and it must be reliable when recovering sparse representations. However, in some situations, the solutions for sparse coefficients can be appeared quite large, tantamount to nearly linearly dependent atoms from the dictionary contributing to the representation of the same signal. Due to this, it has been seen that the dictionary update stage of the **DL** algorithm becomes prohibitively slow [127]. For finding a convenient way to acquire strong guarantees of recovery, the **DL** optimization equation can be modified in such a way that the resulting dictionary is incoherent, meaning that ideally, it does not contain any group of linearly dependent atoms. This situation is taken care of by introducing a modification of the objective function in (5.1) by adopting a regularization term that punishes solutions comprising large sparse coefficient terms. This regularized **DL** problem can be written as:

$$\min_{\mathbf{D},\mathbf{X}} \left[\|\mathbf{Y} - \mathbf{D}\mathbf{X}\|_F^2 + \zeta \|\mathbf{X}\|_F^2 \right] \ \textit{subject to}\ \forall i,\ \|\mathbf{x}_i\|_p \le l \tag{5.2}$$

The relative weightage of the two terms in the objective function can be determined by a choice of regularization parameter ζ>0. In [127], how this regularized **DL** problem can be solved by incorporating the concept of basic **K-SVD**, has been discussed and their proposed algorithm was called regularized **K-SVD** (referred to henceforth as **RK-SVD**). In the *dictionary update* stage in basic **K-SVD** algorithm, one dictionary column is updated at a time and for a K-column dictionary, the algorithm performs K sweeps in this stage. Here, each column $\mathbf{d}_j$ in dictionary **D**, and the values of the non-zero coefficients in sparse matrix **X** corresponding to $\mathbf{d}_j$, i.e., in the jth row of **X**, are updated simultaneously in one sweep, keeping all other entries in **D** and $\mathbf{X}$ fixed. The **RK-SVD** algorithm was proposed following a similar concept, but in a modified form. Let us assume that all columns of **D** are fixed except $\mathbf{d}_j$. Let a set of those indices of the signals $\mathbf{y}_i$ (i=1, 2, …, N) that use $\mathbf{d}_j$ in their representation, be represented as u_j. The corresponding positions in the jth row of $\mathbf{X}$ having non-zero entries are denoted as $\mathbf{x}_T^j$. The representation error is denoted as [90]:

$$\left\|\mathbf{Y}\text{ - }\mathbf{DX}\right\|_F^2 = \left\|\mathbf{Y}\text{ - }\sum_{k=1}^{K}\mathbf{d}_k\mathbf{x}_T^k\right\|_F^2 = \left\|\left(\mathbf{Y}\text{ - }\sum_{\substack{k=1,\\k\neq j}}^{K}\mathbf{d}_k\mathbf{x}_T^k\right)-\mathbf{d}_j\mathbf{x}_T^j\right\|_F^2 = \left\|\mathbf{E}_j-\mathbf{d}_j\mathbf{x}_T^j\right\|_F^2 \qquad (5.3)$$

Then the transformed representation error that is restricted to those signals $\mathbf{y}_i$ only that use $\mathbf{d}_j$ in their representation, is denoted as:

$$\left\|\mathbf{E}_{u_j}-\mathbf{d}_j\mathbf{x}_R^j\right\|_F^2 = \left\|\mathbf{E}_j\mathbf{U}_j-\mathbf{d}_j\mathbf{x}_T^j\mathbf{U}_j\right\|_F^2 \qquad (5.4)$$

where $\mathbf{E}_{u_j} = \mathbf{E}_j\mathbf{U}_j$ = a restricted version of the error matrix $\mathbf{E}_j$, corresponding to those signals only which use $\mathbf{d}_j$ in their representation and $\mathbf{x}_R^j = \mathbf{x}_T^j\mathbf{U}_j$ is a restricted version of the row vector $\mathbf{x}_T^j$ containing the non-zero values only. The restriction matrix is presented as $\mathbf{U}_j$ which is a matrix of size $N\times|u_j|$ with ones in ($u_j(s)$, s) (s=1,2,

…, K), places and zeros in all other places. Then, from (5.2), the objective function to be minimized for the **RK-SVD** algorithm can be written as [127]:

$$\phi\left(\mathbf{d}_j, \mathbf{x}_R^j\right) = \left\| \mathbf{E}_{u_j} - \mathbf{d}_j \mathbf{x}_R^j \right\|_F^2 + \zeta \left\| \mathbf{x}_R^j \right\|^2 \tag{5.5}$$

Hence the regularized **K-SVD** problem, for obtaining each dictionary column $\mathbf{d}_j$ and its corresponding non-zero row sparse vector coefficients $\mathbf{x}_R^j$, can be written as [127]:

$$\min_{\mathbf{d}_j, \mathbf{x}_R^j} \phi\left(\mathbf{d}_j, \mathbf{x}_R^j\right) \text{ subject to } \left\| \mathbf{d}_j \right\| = 1 \tag{5.6}$$

As per the proposition given in [127], the solution of (5.6) is obtained by performing SVD of $\mathbf{E}_{u_j}$ as

$$\mathbf{E}_{u_j} = \sum_{m=1}^{r} \mathbf{u}_m \sigma_m \mathbf{v}_m^T \tag{5.7}$$

and assigning $\mathbf{d}_j = \mathbf{u}_1$ and $\mathbf{x}_R^j = \dfrac{\sigma_1 \mathbf{v}_1}{1+\zeta}$ (5.8)

Hence it can be easily seen that the sparse coefficients get diminished in magnitude compared to the basic **K-SVD** algorithm and hence the main objective behind proposing a regularized version of **K-SVD** gets fulfilled.

Although the *sparse coding* stage in basic **K-SVD** algorithm and in **RK-SVD** algorithm were solved using only *Orthogonal Matching Pursuit* (**OMP**) algorithm, in this present work, extensive modifications of the **RK-SVD** algorithm have been made by implementing both relaxation and greedy algorithms like **MP, OMP, WMP** and **IRLS** [99], to solve the *sparse coding* stage.

5.3.2 Modified Regularized K-SVD algorithm

In the original regularized **K-SVD** algorithm [127], the regularization parameter ζ has to be manually selected and it requires extensive trial and error methods to determine an appropriate value of ζ, for a particular problem at hand. Moreover, it has been seen that this ζ remains fixed during the *dictionary learning* stage. In this Chapter, a modified version of the **RK-SVD** algorithm is proposed, named as **MRK-SVD** algorithm, where the regularization parameter ζ is adapted in each iteration in the learning stage as a function of the *Root Mean Square Error* (**RMSE**), calculated in each iteration as: $RMSE = \frac{\|\mathbf{Y}-\mathbf{DX}\|_F}{\sqrt{n \times N}}$. The overall flowchart for this proposed **MRK-SVD** algorithm, which is utilized in this Chapter, is depicted in Fig. 5.5.

5.3.3 Regularized Approximated K-SVD algorithm and its Modified form

In this Chapter, another regularized version of **K-SVD** algorithm has also been implemented, called regularized approximated **K-SVD** algorithm (named here as **RAK-SVD** algorithm), proposed in [127]. The regularized version of the approximated **K-SVD** (**AK-SVD**) algorithm that is proposed in [129] is illustrated in this Chapter. Contrary to the basic **K-SVD**, where, in *dictionary update* stage, each dictionary column $\mathbf{d}_j$ and its corresponding row sparse coefficient vector $\mathbf{x}_T^j$ are updated simultaneously, in **AK-SVD**, $\mathbf{d}_j$ and its corresponding $\mathbf{x}_T^j$ are updated successively. An approximate, and not exact, solution of (5.6) is obtained by first performing minimization of (5.6) as a function of $\mathbf{d}_j$ and then performing minimization of same (5.6) as a function of $\mathbf{x}_R^j$ [127]. Hence, in each iteration, $\mathbf{d}_j$ is obtained first by keeping $\mathbf{x}_R^j$ fixed and then $\mathbf{x}_R^j$ is obtained by keeping the newly determined $\mathbf{d}_j$ fixed. The corresponding expressions of $\mathbf{d}_j$ and $\mathbf{x}_R^j$ are depicted as [127]:

$$\mathbf{d}_j = \frac{\mathbf{E}_{u_j}\mathbf{x}_R^j}{\left\|\mathbf{E}_{u_j}\mathbf{x}_R^j\right\|} \quad \text{and} \quad \mathbf{x}_R^j = \frac{\mathbf{E}_{u_j}{}^T\mathbf{d}_j}{1+\zeta} \tag{5.9}$$

As in **RK-SVD**, in **RAK-SVD** also the regularization parameter ζ has to be manually selected and it remains fixed during the *dictionary learning* stage. Like in **RK-SVD**, here also a modified version of **RAK-SVD**, named as **MRAK-SVD** algorithm has also been proposed, where ζ is adapted as a function of **RMSE**, as given before. The complete **MRAK-SVD** algorithm is presented in Algorithm 5.1, utilized in this work.

The reason why ζ is adapted as a function of **RMSE**, both in **MRK-SVD** and **MRAK-SVD** algorithms, is that as the learned dictionary-based representation **DX** more closely approximates **Y**, the **RMSE** decreases. Hence, when **RMSE** decreases, it is expected that diminishing $\mathbf{x}_R^j$ by a lesser amount from $\sigma_1\mathbf{v}_1$, i.e., the original proposal in basic **K-SVD** algorithm, should produce better performance and vice versa. Hence, a modification has been introduced to alter the denominator term in $\mathbf{x}_R^j = \frac{\sigma_1\mathbf{v}_1}{1+\zeta}$ in (5.8) by adapting ζ as a function of RMSE.

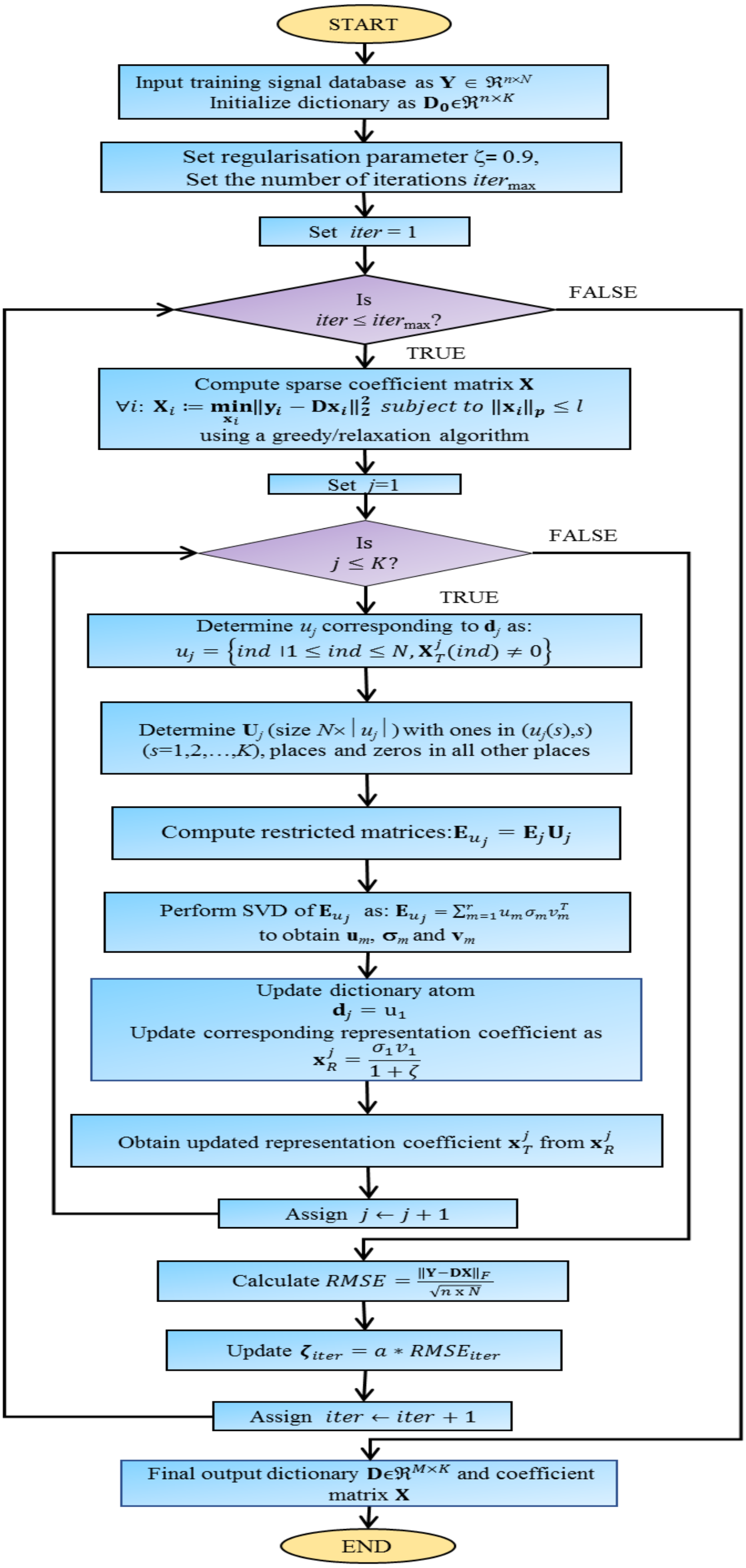


Fig. 5.5 Flowchart of Modified Regularized
K-SVD Algorithm

Algorithm 5.1: Modified Regularized AK-SVD Algorithm

BEGIN

Input: Training signal database $\mathbf{Y} \in \Re^{n\times N}$,

Initial dictionary $\mathbf{D}_0 \in \Re^{n\times K}$

Output: New dictionary $\mathbf{D} \in \Re^{n\times K}$,

Sparse coefficient matrix $\mathbf{X} \in \Re^{K\times N}$

Step 1:

Initialization: Set regularization parameter ζ, the number of iterations $iter_{\max}$, the sparsity level l.

Step 2:

FOR $iter = 1 : iter_{\max}$

Solve Sparse Coding stage:

FOR $i=1 : N$

- Compute sparse coefficient vector x_i

$$\mathbf{X}_i = \min_{\mathbf{x}_i} \left\| \mathbf{y}_i - \mathbf{D}\mathbf{x}_i \right\|_2^2 \quad \text{subject to} \quad \left\| \mathbf{x}_i \right\|_p \le l$$

using a greedy/relaxation algorithm

ENDFOR

Solve Dictionary Update Stage:

FOR $j=1:K$

- Determine u_j corresponding to d_j as: $u_j = \left\{ ind \middle| 1 \le ind \le N, \mathbf{x}_T^j(ind) \neq 0 \right\}$
- Determine U_j (size $N\times|u_j|$) with ones in $(u_j(s),s)$ ($s=1,2,\ldots,K$), places and zeros in all other places
- Compute restricted matrices:

$\mathbf{E}_{u_j} = \mathbf{E}_j \mathbf{U}_j$ and $\mathbf{x}_R^j = \mathbf{x}_T^j U_j$

- Update $\mathbf{d}_j = \dfrac{\mathbf{E}_{u_j}\mathbf{x}_R^j}{\left\|\mathbf{E}_{u_j}\mathbf{x}_R^j\right\|}$
- Update $\mathbf{x}_R^j = \dfrac{\mathbf{E}_{u_j}{}^T \mathbf{d}_j}{1+\zeta_{iter}}$
- Obtain $\mathbf{x}_T^j$ from $\mathbf{x}_R^j$

ENDFOR

- Calculate $RMSE_{iter} = \dfrac{\left\|\mathbf{Y}-\mathbf{D}\mathbf{X}\right\|_F}{\sqrt{n\times N}}$
- Update $\zeta_{iter} = a * RMSE_{iter}$

ENDFOR

END

5.4 Classification Based on Dictionary Learning

It has been shown in Module 5 in Fig. 5.2 that after constructing a suitable dictionary **D**, each unknown signal **y** is acquired in real time and the movement direction is detected solving a multiclass classification problem, using sparse representation-based classifier (**SRC**), which essentially solves the optimization problem [87], [44], [127]:

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_p \text{ subject to } \|\mathbf{y}\text{-}\mathbf{D}\mathbf{x}\|_2 \leq \tau \tag{5.10}$$

Similar to the methodology followed in [128], here also both greedy algorithms and relaxation algorithms have been implemented to solve (5.10) e.g., **MP, OMP, WMP** and **IRLS** algorithms enabling us to present a very detailed form of performance comparisons. The value of error tolerance is usually chosen as $\tau \in (0,1)$ i.e., it controls how much error is permitted to produce the sparse approximate solution of **x.** For **MP, OMP and WMP** algorithms, p is chosen as 0 and for **IRLS** algorithm p is chosen as 1.

5.5 Experimental Result Analysis

5.5.1 Experimental Platform

As mentioned before in Chapter 4, in Module 1 in Fig. 5.2, the area under observation is 1.98 m×1.98 m in ground and the ceiling height where the hardware system has been installed is 2.59 m. The training dataset has been developed by acquiring signals in real time from six different subjects of different height and weight, walking in eight different directions, specified before, having a spatial resolution of 45°

[128]. It is already well established [128] that usually an over-complete dictionary (where the number of columns is more than the number of rows) is able to achieve better sparse representation. However, one should keep in mind that the dictionary cannot be grown arbitrarily large as the atoms may start to become null or collinear. A signal, when represented in form of a smaller dimensional feature vector, usually helps to create an overcomplete dictionary.

Keeping this in mind, like in [128], in this Chapter also each signal vector has been represented by a smaller dimensional feature vector by performing **FFT** of each signal atom $\mathbf{d}_i$ and creating the corresponding feature vector f_i is developed as

$$f_i = \begin{bmatrix} S_i(H_i(1)), S_i(H_i(3)), S_i(H_i(5)), \\ S_i(F_i(1)), S_i(F_i(3)), S_i(F_i(5)) \end{bmatrix}^T$$

where $i = (1,2,3,4)$ corresponds to the number of the **PIR** sensor, the **FFT** coefficients corresponding to the fundamental, third and fifth harmonic of the signal acquired from ith sensor are presented as $S_i(H_i(1)), S_i(H_i(3)), S_i(H_i(5))$, respectively, and the frequency values corresponding to the fundamental, third and fifth harmonic are presented as $S_i(F_i(1)), S_i(F_i(3)), S_i(F_i(5))$, respectively. The training database **Y** has been built acquiring 30 real signals from each subject walking in a specific direction and each signal acquired from a **PIR** sensor comprises 128 samples. Hence, the original signal database of size ((128×4)×(30×6×8)) i.e. (512×1440), is obtained for six subjects walking in eight directions while four PIR sensors are in their position. Then six features are extracted from each 128 length signal acquired by a **PIR** sensor, as mentioned before, and the training database **Y** of size ((6×4)×(24×6×8)) i.e. (24×1152) is built. Utilizing different **DL** algorithms, the dictionary learning phase is executed based on this **Y** to create an appropriate **D** (and associated **X**) . Once this **D** is learned, the system is used online to perform live movement detection. Here at first signals are acquired online using four **PIR** sensors and features are extracted from it, as mentioned before, to create **y** and then the classification procedure mentioned in Section 5.5 is implemented using the learned **D**, online, to determine the direction of human movement.

In the next step the dictionary is initialized. Here, *K-means* clustering has been used for determining the initial dictionary and, encouraged by the results obtained in the previous work [128], here the clustering size of 50% has been chosen for this experimental analysis. The graphical representation of the clustering algorithm employed is presented in Module 3 in Fig. 5.2.

5.5.2 Performance Evaluation

As mentioned before, in this Chapter extensive experimentations have been conducted to investigate relative strengths and weaknesses of **RK-SVD** algorithm, when it utilizes various greedy algorithms like *Matching Pursuit* (**MP**), *Weak Matching Pursuit* (**WMP**), and relaxation algorithms like *Iterative-Reweighed-Least-Squares* (**IRLS**) in *sparse coding* stage, along with the conventional **OMP** method utilized in original **RK-SVD** algorithm in [127]. Similarly, in the **SRC** based classification stage where **OMP, MP, WMP, IRLS** etc. have also been employed. The performance analysis of representative variants of **RK-SVD** utilizing different fixed values of regularization parameter ζ in *dictionary learning* stage is presented in Table 5.1.

Actually, extensive experiments have been performed by considering all possible combinations of **OMP, MP, WMP, and IRLS** algorithms i.e., choosing all possible different combinations of "A" and "B". Each variant of **RK-SVD** utilized here has been denoted as **RK-SVD**$_{A\text{-}B}$ where *A* gives the solution algorithm used in sparse coding stage and *B* gives the sparse solution method utilized in **SRC**. These results are presented in Table 5.1 (a). However, the summarization of the result obtained in Table 5.1(a) is presented in Table 5.2 (a), showing four representative results. As

TABLE 5.1(a): PERFORMANCE ANALYSIS OF DIFFERENT VARIANTS OF RK-SVD KEEPING ζ FIXED

RK-SVD$_{A\text{-}B}$	**Recognition Accuracy (%)**					
	ζ=0	ζ=0.1	ζ=0.2	ζ=0.3	ζ=0.4	ζ=0.5
RK-SVD$_{OMP\text{-}OMP}$	86.10	89.50	90.00	89.90	91.60	**93.80**
RK-SVD$_{IRLS\text{-}IRLS}$	87.50	83.30	84.70	90.00	90.90	**94.70**
RK-SVD$_{MP\text{-}MP}$	85.00	86.80	87.50	88.20	89.00	**89.80**
RK-SVD$_{WMP\text{-}WMP}$	66.00	**83.30**	73.60	66.60	70.80	79.10
RK-SVD$_{MP\text{-}OMP}$	74.00	82.00	85.40	85.00	76.00	71.40
RK-SVD$_{MP\text{-}IRLS}$	79.50	85.00	**88.80**	86.10	86.40	76.70
RK-SVD$_{MP\text{-}WMP}$	45.12	46.80	**58.30**	58.60	48.60	52.00
RK-SVD$_{WMP\text{-}MP}$	48.60	62.50	76.50	78.80	**79.80**	78.80
RK-SVD$_{WMP\text{-}IRLS}$	65.60	72.90	73.20	77.00	76.70	**79.50**
RK-SVD$_{WMP\text{-}OMP}$	44.80	47.50	52.00	59.00	**62.50**	64.90
RK-SVD$_{OMP\text{-}IRLS}$	84.70	**87.50**	86.40	85.10	89.90	83.30
RK-SVD$_{OMP\text{-}MP}$	64.20	69.70	79.80	74.30	**82.90**	76.70
RK-SVD$_{OMP\text{-}WMP}$	60.70	66.00	67.70	**69.40**	46.10	46.80
RK-SVD$_{IRLS\text{-}MP}$	71.20	73.60	76.00	**86.80**	79.50	76.30
RK-SVD$_{IRLS\text{-}WMP}$	40.60	41.60	43.75	**61.80**	53.80	45.00
RK-SVD$_{IRLS\text{-}OMP}$	76.30	79.80	85.00	83.60	89.90	**90.60**

the best two results were obtained in Table 5.1(a) for **RK-SVD**$_{\text{IRLS-IRLS}}$ and **RK-SVD**$_{\text{OMP-OMP}}$ combinations, hence in this Chapter those representative variants were chosen where A=B.

TABLE 5.1 (b): PERFORMANCE ANALYSIS OF DIFFERENT VARIANTS OF RK-SVD CONSIDERING ζ FIXED FOR FIRST 250 ITERATIONS AND THEN MAKING ζ=0 FOR LAST 250 ITERATIONS

RK-SVD$_{A\text{-}B}$	Recognition Accuracy (%)				
	ζ=0.1	ζ=0.2	ζ=0.3	ζ=0.4	ζ=0.5
RK-SVD$_{\text{OMP-OMP}}$	86.80	85.40	85.80	87.80	**91.7**0
RK-SVD$_{\text{IRLS-IRLS}}$	83.30	87.50	89.60	92.40	**95.10**
RK-SVD$_{\text{MP-MP}}$	83.30	**90.60**	85.40	89.00	88.90
RK-SVD$_{\text{WMP-WMP}}$	72.00	75.70	**83.3**0	77.10	80.20
RK-SVD$_{\text{MP-OMP}}$	89.90	**91.00**	85.40	80.20	82.30
RK-SVD$_{\text{MP-IRLS}}$	89.00	**92.00**	88.90	89.20	78.80
RK-SVD$_{\text{MP-WMP}}$	47.20	**63.50**	51.40	48.00	49.50
RK-SVD$_{\text{WMP-MP}}$	77.10	82.50	83.00	**80.20**	79.90
RK-SVD$_{\text{WMP-IRLS}}$	74.20	75.70	80.00	77.10	**84.40**
RK-SVD$_{\text{WMP-OMP}}$	48.00	56.00	62.50	**67.00**	65.80
RK-SVD$_{\text{OMP-IRLS}}$	85.10	**89.90**	87.50	83.30	77.60
RK-SVD$_{\text{OMP-MP}}$	70.00	83.30	75.70	**84.70**	77.80
RK-SVD$_{\text{OMP-WMP}}$	64.20	66.00	**72.10**	48.00	45.00
RK-SVD$_{\text{IRLS-MP}}$	74.20	78.00	**88.90**	78.80	**79.50**
RK-SVD$_{\text{IRLS-WMP}}$	42.40	45.00	**64.80**	47.80	45.00
RK-SVD$_{\text{IRLS-OMP}}$	80.20	87.50	85.40	91.70	**93.10**

The corresponding variations in recognition accuracy with ζ are presented in Fig. 5.6 in graphical form. It can be seen from Table 5.2 (a) and Fig. 5.6 that, overall, a tendency of improvement in performance with an increase in regularization parameter ζ has been seen for all algorithms, and it has been found that a choice of **IRLS** algorithm for both A and B emerge as the best option with a recognition accuracy of 94.7%**.** Here the traditional **K-SVD** algorithm

TABLE 5.2 (a): PERFORMANCE ANALYSIS OF DIFFERENT VARIANTS OF RK-SVD KEEPING **ζ** FIXED THROUGHOUT

RK-SVD$_{A\text{-}B}$	Recognition Accuracy (%)					
	ζ=0	ζ=0.1	ζ=0.2	ζ=0.3	ζ=0.4	ζ=0.5
1 **RK-SVD$_{OMP\text{-}OMP}$**	86.1	**89.5**	**90.0**	89.9	**91.6**	93.8
2 **RK-SVD$_{IRLS\text{-}IRLS}$**	**87.5**	83.3	84.7	**90.0**	90.9	**94.7**
3 **RK-SVD$_{MP\text{-}MP}$**	85.0	86.8	87.5	88.2	89.0	89.8
4 **RK-SVD$_{WMP\text{-}WMP}$**	66.0	83.3	73.6	66.6	70.8	79.1

TABLE 5.2 (b): PERFORMANCE ANALYSIS OF RK-SVDs KEEPING **ζ** FIXED FOR FIRST 250 ITERATIONS AND THEN MAKING IT ZERO

RK-SVD$_{A\text{-}B}$	**Recognition Accuracy (%)**				
	ζ=0.1	ζ=0.2	ζ=0.3	ζ=0.4	ζ=0.5
1 **RK-SVD$_{OMP\text{-}OMP}$**	**86.8**	85.4	85.8	87.8	91.7
2 **RK-SVD$_{IRLS\text{-}IRLS}$**	83.3	87.5	**89.6**	**92.4**	**95.1**
3 **RK-SVD$_{MP\text{-}MP}$**	83.3	**90.6**	85.4	89.0	88.9
4 **RK-SVD$_{WMP\text{-}WMP}$**	72.0	75.7	83.3	77.1	80.2

corresponds to the case of ζ=0, and the corresponding results of this **K-SVD** algorithm were presented in Chapter 4. It can be easily seen that the incorporation of the concept of regularization (with non-zero values chosen for ζ) consistently helped in achieving better performances. In Table 5.1 (b), another concept has been implemented, presented in [127] where ζ is kept fixed to a non-zero value for first few iterations and then made zero for the remaining iterations. The results have been reported here considering regularization parameter ζ as a constant value for the first 250 iterations and then ζ has been made zero for the last 250 iterations.

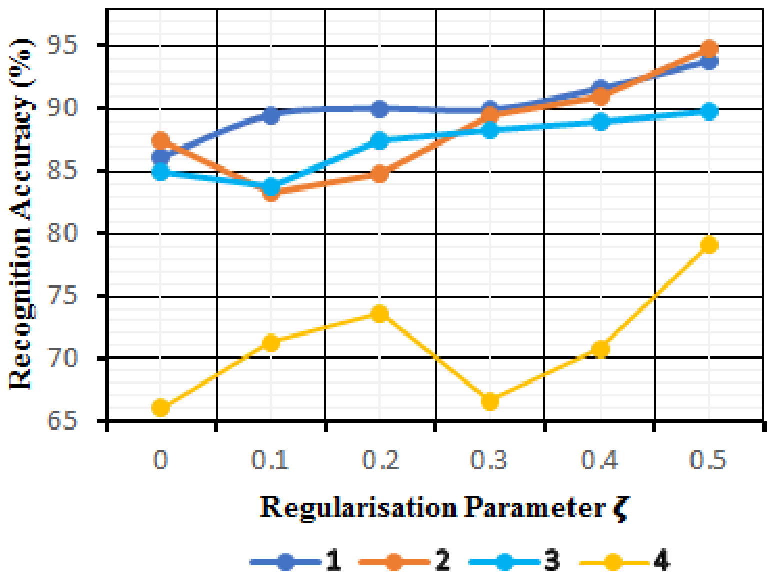


Fig. 5. 6. Performance variation of different variants of RK-SVD

Here also the results are finally summarized in Table 5.2(b) considering four best representatives chosen from Table 5.1(b). It can be seen that this procedure is able to marginally improve the performances of **RK-SVD** variants. Several other popular algorithms e.g., *Orthogonal Least Squares* (**OLS**), *Projection based Orthogonal Least Squares* (**POLS**), *Look-Ahead Orthogonal Least Squares* (**LAOLS**), *Projection Based Orthogonal matching pursuit* (**POMP**) algorithms etc., presented in [137], can also be potentially explored for solving similar dictionary learning problems.

TABLE 5.3 (a): PERFORMANCE ANALYSIS OF DIFFERENT VARIANTS OF MRK-SVD

MRK-SVD$_{A\text{-}B}$	**Recognition Accuracy (%)**
MRK-SVD$_{OMP\text{-}OMP}$	**94.1**
MRK-SVD$_{OMP\text{-}IRLS}$	91.7
MRK-SVD$_{OMP\text{-}MP}$	88.9
MRK-SVD$_{OMP\text{-}WMP}$	45.0
MRK-SVD$_{IRLS\text{-}IRLS}$	**95.8**
MRK-SVD$_{IRLS\text{-}OMP}$	90.6
MRK-SVD$_{IRLS\text{-}MP}$	79.5
MRK-SVD$_{IRLS\text{-}WMP}$	45.0
MRK-SVD$_{MP\text{-}MP}$	**90.2**
MRK-SVD$_{MP\text{-}IRLS}$	79.9
MRK-SVD$_{MP\text{-}OMP}$	80.2
MRK-SVD$_{MP\text{-}WMP}$	77.1
MRK-SVD$_{WMP\text{-}WMP}$	**82.0**
MRK-SVD$_{WMP\text{-}IRLS}$	80.6
MRK-SVD$_{WMP\text{-}OMP}$	75.8
MRK-SVD$_{WMP\text{-}MP}$	77.1
MRK-SVD$_{OLS\text{-}OLS}$	86.1
MRK-SVD$_{POMP\text{-}POMP}$	53.5
MRK-SVD$_{POLS\text{-}POLS}$	64.2
MRK-SVD$_{LAOLS\text{-}LAOLS}$	79.5
MRK-SVD$_{OLS\text{-}IRLS}$	**87.5**
MRK-SVD$_{OLS\text{-}MP}$	80.0
MRK-SVD$_{OLS\text{-}WMP}$	48.0
MRK-SVD$_{POMP\text{-}IRLS}$	**64.2**
MRK-SVD$_{POMP\text{-}MP}$	47.8
MRK-SVD$_{POMP\text{-}WMP}$	49.5
MRK-SVD$_{LAOLS\text{-}MP}$	83.3
MRK-SVD$_{LAOLS\text{-}IRLS}$	**85.1**
MRK-SVD$_{LAOLS\text{-}WMP}$	62.0
MRK-SVD$_{POLS\text{-}MP}$	77.0
MRK-SVD$_{POLS\text{-}WMP}$	56.0
MRK-SVD$_{POLS\text{-}IRLS}$	**79.5**

Next, the proposed modified version of **RK-SVD** algorithm was implemented, i.e., **MRK-SVD** algorithm, presented earlier in Fig. 5.6. Here the sensitivity of **MRK-SVD** has been extensively studied on suitable choices of the hyper-parameters, i.e., the initial value of ζ and a, by choosing initial value of ζ=0.8, 0.9, 1.0, and 2.0 and for each case varying a from 0.08 to 0.3. For **MRK-SVD** also, this experiments have been performed by

TABLE 5.3 (b): PERFORMANCE ANALYSIS OF MRK-SVD VARIANTS IN TERMS OF RECOGNITION ACCURACY (%)

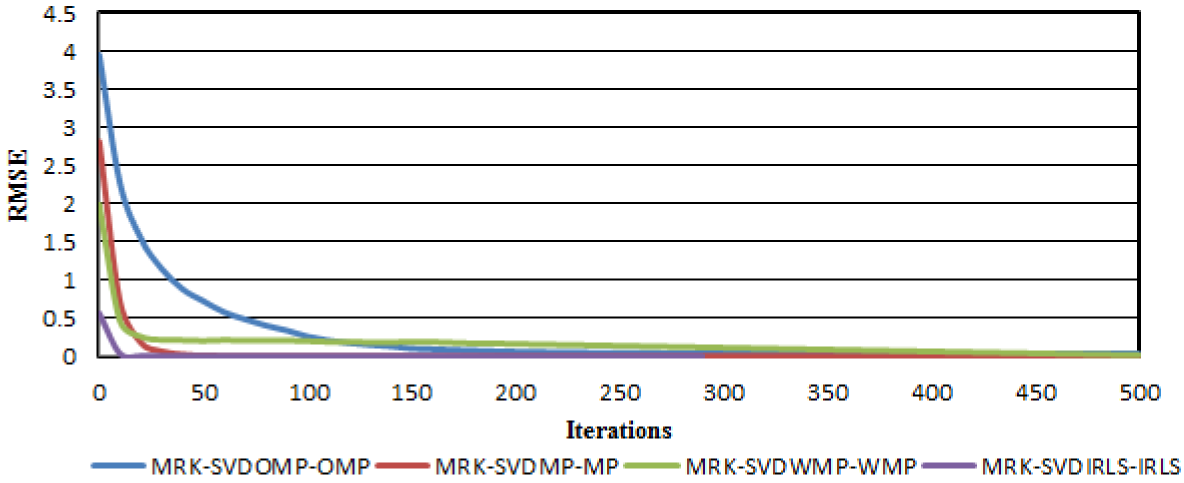
MRK-SVD performance (%) with initial ζ=0.8				
Method	a=0.08	a=0.1	a=0.2	a=0.3
MRK-SVD$_{\text{OMP-OMP}}$	89.9	90.6	79.2	75.0
MRK-SVD$_{\text{IRLS-IRLS}}$	89.5	94.0	86.1	79.8
MRK-SVD$_{\text{MP-MP}}$	88.5	89.5	85.5	83.3
MRK-SVD$_{\text{WMP-WMP}}$	80.5	81.0	80.5	78.8
MRK-SVD performance (%) with initial ζ=0.9				
MRK-SVD$_{\text{OMP-OMP}}$	88.9	**94.10**	79.2	75.0
MRK-SVD$_{\text{IRLS-IRLS}}$	90.2	**95.83**	86.1	79.8
MRK-SVD$_{\text{MP-MP}}$	89.5	**90.11**	85.5	83.3
MRK-SVD$_{\text{WMP-WMP}}$	81.9	**82.00**	80.5	78.8
MRK-SVD performance (%) with initial ζ=1.0				
MRK-SVD$_{\text{OMP-OMP}}$	87.5	91.2	77.8	76.3
MRK-SVD$_{\text{IRLS-IRLS}}$	86.1	92.0	87.5	77.0
MRK-SVD$_{\text{MP-MP}}$	88.8	89.9	83.3	78.1
MRK-SVD$_{\text{WMP-WMP}}$	80.5	78.9	75.0	79.5
MRK-SVD performance (%) with initial ζ=2.0				
MRK-SVD$_{\text{OMP-OMP}}$	82.9	90.2	72.2	72.0
MRK-SVD$_{\text{IRLS-IRLS}}$	84.2	92.0	84.1	75.8
MRK-SVD$_{\text{MP-MP}}$	86.1	88.9	84.5	81.2
MRK-SVD$_{\text{WMP-WMP}}$	78.0	77.8	71.5	64.0

considering all possible combinations of **OMP, MP, WMP,** and **IRLS** algorithms i.e. choosing all possible different combinations of "A" and "B". In addition, the algorithms proposed in [137] i.e., **OLS, POLS, LAOLS, POMP** algorithms etc., have also been considered.

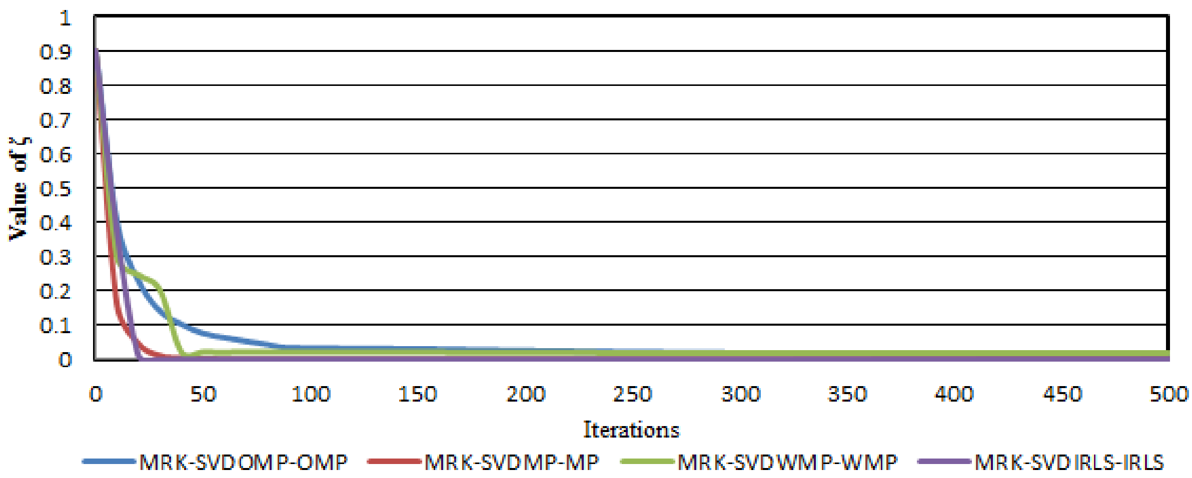
The corresponding results of extensive evaluation are reported in Table 5.3 (a) (by choosing the initial value of ζ=0.9 and $a = 0.1$). The corresponding summarization of this detailed study is reported in Table 5.3 (b) in which only those combinations are considered where A=B. This is because, from the results presented in Table 5.3 (a), here also it can be seen that the best two results were obtained for **MRK-SVD**$_{\text{IRLS-IRLS}}$ and **MRK-SVD**$_{\text{OMP-OMP}}$ combinations. It can be seen from Table 5.3 (b) that a choice of the initial value of ζ=0.9 gives consistently better results for different values of *a* and the best result is obtained when *a*=0.1. Here also different variants of **MRK-SVD** algorithms are denoted as **MRK-SVD**$_{A\text{-}B}$, following the same philosophy presented in Table 5.1 and Table 5.2. From this study it has been established that for each combination of *A*-*B*, the best **MRK-SVD** performance achieved was consistently better than the best results achieved with the corresponding **RK-SVD** variant.

Here also the best result for **MRK-SVD** has been achieved with the best recognition accuracy achieved being 95.83%.for a choice of IRLS algorithm for both A and B.

Figs. 5.7 (a) and 5.7 (b) show how RMSE and ζ vary with iterations, for the four variants of this proposed **MRK-SVD** algorithms, considered from Table 5.3(b). It can be seen that both RMSE and ζ overall decrease with iterations for all four variants considered.



(a)



(b)

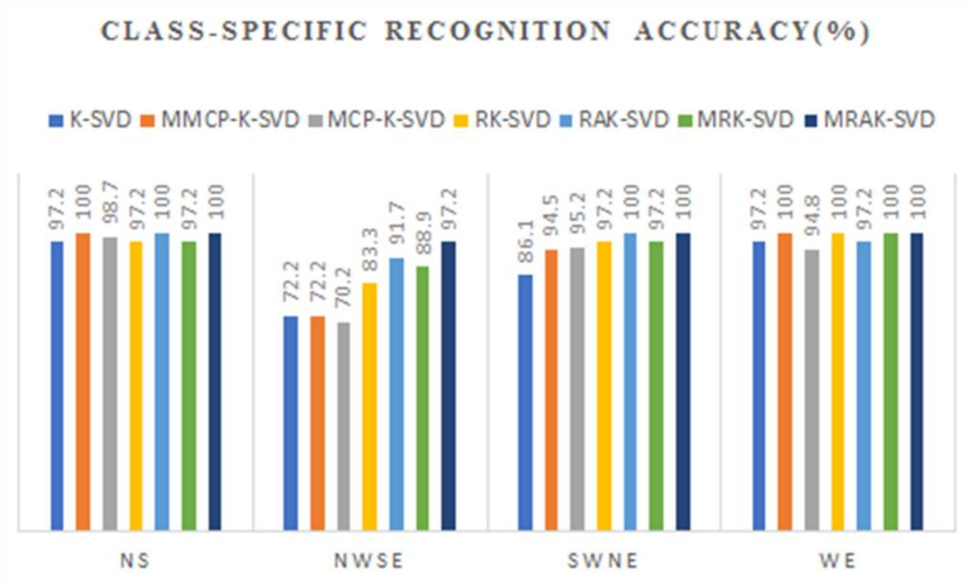
Fig. 5. 7. Graphical representation of variations of (a) RMSE and (b) ζ with iteration

This is in conformation with the proposal that with a decrease in RMSE, ζ should also be decreased and this helped each algorithm to perform better as iterations progress. However, it has been observed from the performance study that this rate of decrease is different for each algorithm, with the **IRLS-IRLS** variant showing the steepest fall.

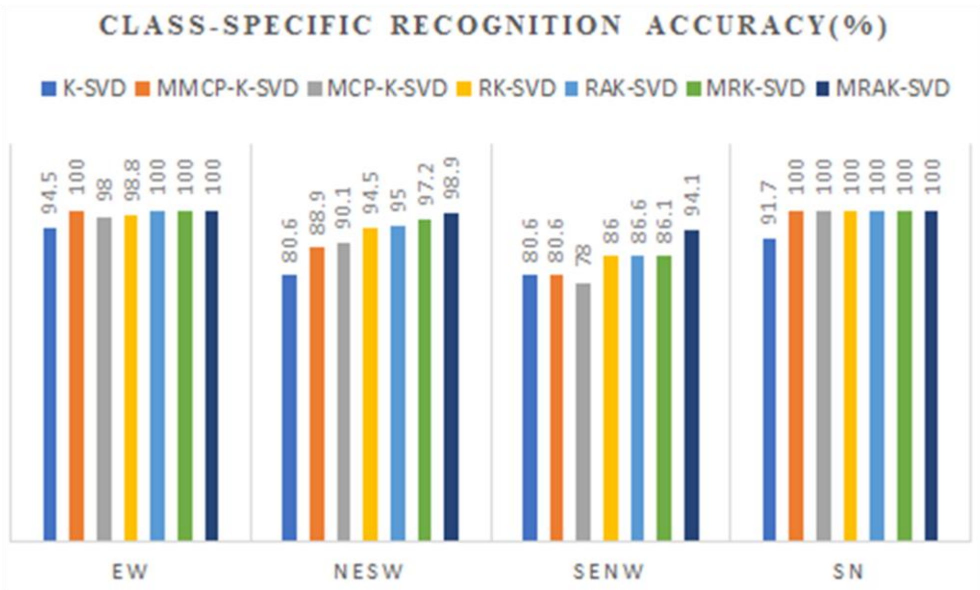
Next, a very comprehensive performance comparison is carried out and presented in Table 5.4 for several popular classification algorithms e.g. **SVM, KNN**, **SRC**, **CRC** etc. and all dictionary learning based algorithms utilized (i.e. **RK-SVD** and **RAK-SVD**) and proposed (**MRK-SVD** and **MRAK-SVD**) in this work for human movement detection in specific directions, vis-à-vis other state-of-the-art methods known for the same problem, recently proposed in [128], and also **AK-SVD**c algorithm [138] and recently proposed consistently adaptive sequential dictionary learning algorithm [132]. For each variant of the **RK-SVD** algorithm, the best result was achieved for the **IRLS-IRLS** combination and those corresponding results are reported here.

TABLE 5.4 PERFORMANCE COMPARISON WITH OTHER STATE- OF-THE-ART METHODS

Method	Recognized accuracy (%)
SVM	70.80
KNN	59.40
SRC	41.00
CRC-RLS	83.70
CASDL [132]	71.90
AK-SVDc [138]	77.80
K-SVD [128]	87.50
MCP-K-SVD [128]	90.60
MMCP-K-SVD [128]	92.01
RK-SVD	94.80
MRK-SVD	95.83
RAK-SVD	96.50
MRAK-SVD	**98.60**



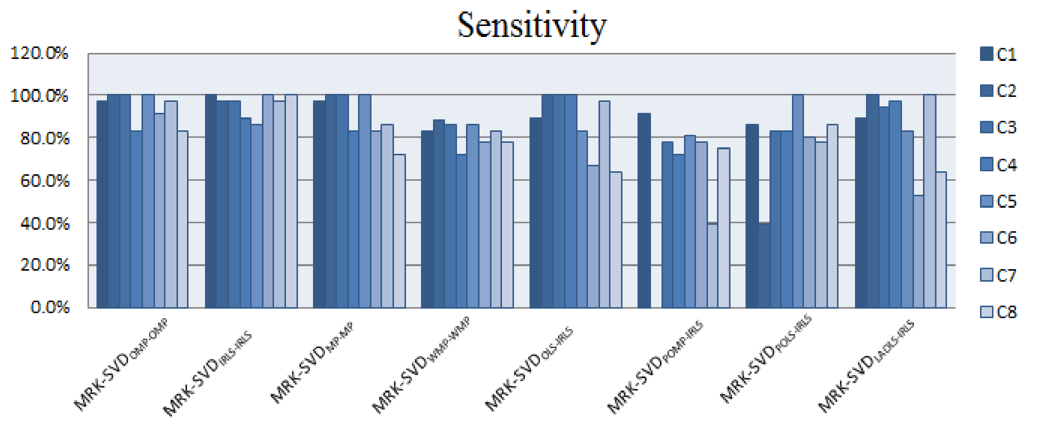
(a)



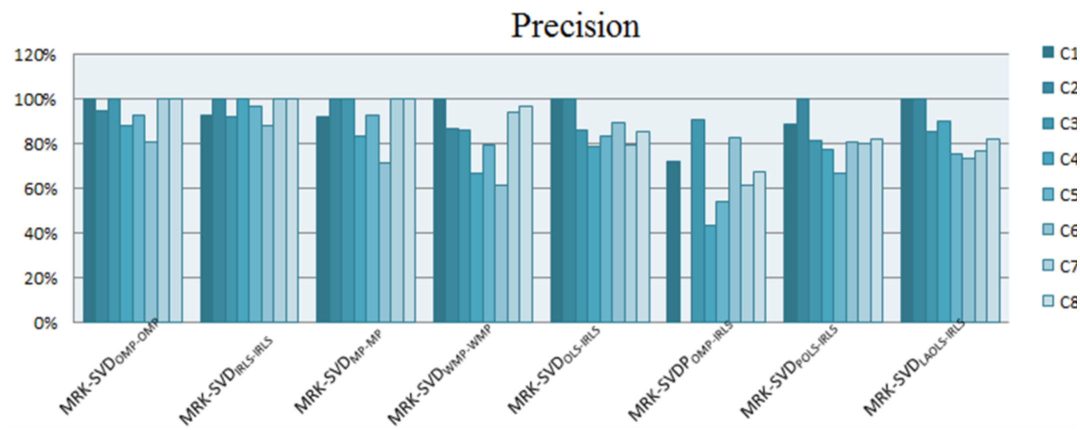
(b)

Fig. 5. 8. Class-specific performance analysis for eight individual directions: (a) towards east all possible directions and NS and (b) towards west all possible directions and SN

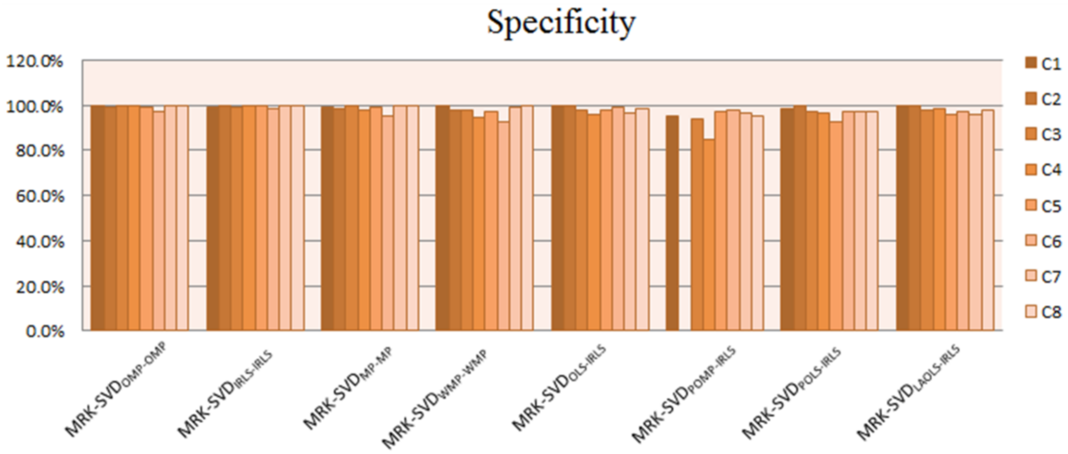
It can be seen that all of the **RK-SVD**, **RAK-SVD**, **MRK-SVD**, and **MRAK-SVD** algorithms achieved consistently better performances, while both modified algorithms proposed in this thesis produced better results compared to the corresponding versions proposed in [128]. Finally, it has



(a)

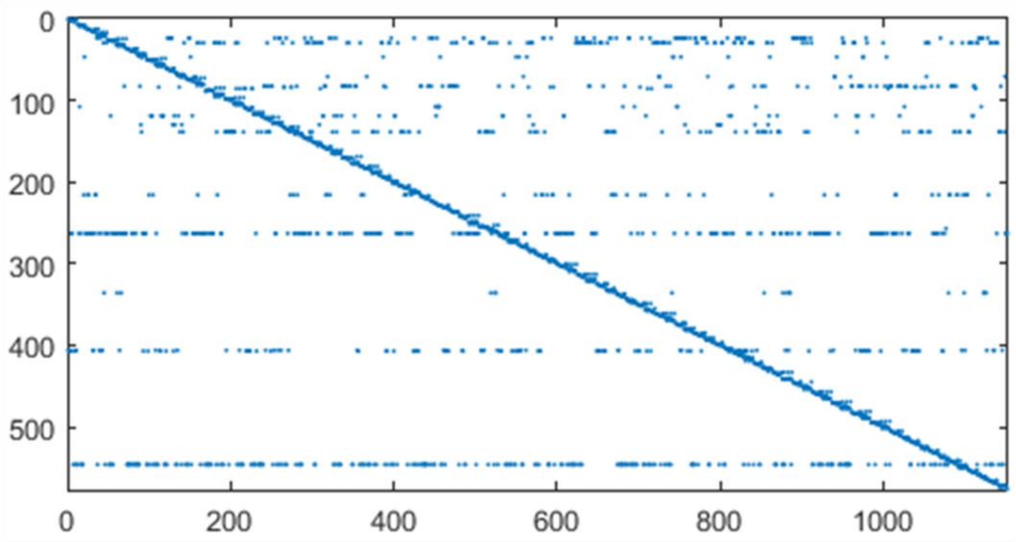


(b)

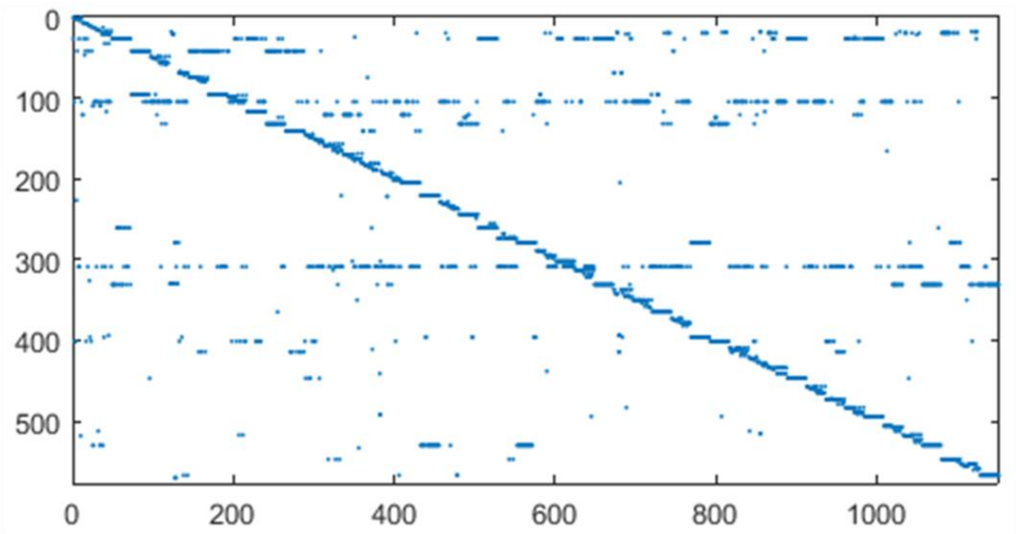


(c)

Fig. 5. 9. Performances of different MRK-SVD algorithms, in terms of (a) sensitivity, (b) precision, and (c) specificity



(a)



(b)

Fig. 5. 10. Sparsity pattern of coefficient matrix (a) with and (b) without employment of regularization parameter

been established that the **MRAK-SVD** algorithm emerged as the best candidate solution approach with a very impressive recognition accuracy of 98.60%.

TABLE 5.5 (a): CONFUSION MATRIX FOR THE MRK-SVD$_{OMP-OMP}$, MRK-SVD$_{IRLS-IRLS}$, MRK-SVD$_{MP-MP}$, MRK-SVD$_{WMP-WMP}$ ALGORITHM

MRK-SVD$_{OMP-OMP}$

A→ P↓	C1	C2	C3	C4	C5	C6	C7	C8
C1	97.2	0	0	0	0	0	0	0
C2	0	100	0	0	0	0	0	5.6
C3	0	0	100	0	0	0	0	0
C4	0	0	0	83.3	0	2.7	0	8.3
C5	2.8	0	0	0	100	5.6	0	0
C6	0	0	0	16.7	0	91.7	2.8	2.8
C7	0	0	0	0	0	0	97.2	0
C8	0	0	0	0	0	0	0	83.3

MRK-SVD$_{IRLS-IRLS}$

A→ P↓	C1	C2	C3	C4	C5	C6	C7	C8
C1	100	2.8	0	5.5	0	0	0	0
C2	0	97.2	0	0	0	0	0	0
C3	0	0	97.2	5.6	2.8	0	0	0
C4	0	0	0	88.9	0	0	0	0
C5	0	0	2.8	0	86.1	0	0	0
C6	0	0	0	0	11.1	100	2.8	0
C7	0	0	0	0	0	0	97.2	0
C8	0	0	0	0	0	0	0	100

MRK-SVD$_{MP-MP}$

A→ P↓	C1	C2	C3	C4	C5	C6	C7	C8
C1	97.2	0	0	0	0	8.3	0	0
C2	0	100	0	0	0	0	0	11.1
C3	0	0	100	0	0	0	0	0
C4	0	0	0	83.3	0	2.8	0	13.9
C5	2.8	0	0	0	100	5.6	0	0
C6	0	0	0	16.7	0	83.3	13.9	2.8
C7	0	0	0	0	0	0	86.1	0
C8	0	0	0	0	0	0	0	72.2

MRK-SVD$_{WMP-WMP}$

A→ P↓	C1	C2	C3	C4	C5	C6	C7	C8
C1	83.3	0	0	0	0	0	0	0
C2	0	88.9	0	0	13.8	0	0	0
C3	0	0	86.2	0	0	0	13.9	0
C4	0	11.1	0	72.2	0	11.1	0	13.9
C5	11.1	0	0	0	86.2	11.1	0	0
C6	0	0	13.8	25	0	77.8	2.8	8.3
C7	5.6	0	0	0	0	0	83.3	0
C8	0	0	0	2.8	0	0	0	77.8

While Tables 5.1-5.4 presented overall recognition accuracy for all eight directions, individual class or direction specific performance is shown in Fig. 5.8, for seven superior performing **DL** based competing algorithms considered in Table 5.4. It can be seen that **MRAK-SVD** algorithm produced the best recognition performance in detecting all individual directions, with 100% accuracy being achieved in five out of eight classes or directions under consideration. It has been aptly demonstrated that the remarkable performance could be achieved by using proposed **MRAK-SVD** algorithm.

TABLE 5.5 (b): CONFUSION MATRIX FOR THE MRK-SVD$_{OLS\text{-}IRLS}$, MRK-SVD$_{POMP\text{-}IRLS}$, MRK-SVD$_{POLS\text{-}IRLS}$, MRK-SVD$_{LAOLS\text{-}IRLS}$ ALGORITHM

MRK-SVD$_{OLS\text{-}IRLS}$

A→ P↓	C1	C2	C3	C4	C5	C6	C7	C8
C1	**88.9**	0	0	0	0	0	0	0
C2	0	**100**	0	0	0	0	0	0
C3	0	0	**100**	0	16.7	0	0	0
C4	0	0	0	**100**	0	16.7	0	11.1
C5	11.1	0	0	0	**83.3**	5.5	0	0
C6	0	0	0	0	0	**66.7**	2.8	5.6
C7	0	0	0	0	0	0	**97.2**	19.4
C8	0	0	0	0	0	11.1	0	**63.9**

MRK-SVD$_{POMP\text{-}IRLS}$

A→ P↓	C1	C2	C3	C4	C5	C6	C7	C8
C1	**91.7**	16.7	0	19.5	0	0	0	0
C2	0	**0**	0	0	0	0	0	0
C3	0	36.1	**77.8**	0	0	0	0	8.3
C4	0	47.2	0	**72.2**	19.4	0	38.9	0
C5	0	0	0	0	**80.6**	0	22.2	0
C6	0	0	0	0	0	**77.8**	0	16.7
C7	0	0	0	8.3	0	16.7	**38.9**	0
C8	8.3	0	22.2	0	0	5.5	0	**75**

MRK-SVD$_{POLS\text{-}IRLS}$

A→ P↓	C1	C2	C3	C4	C5	C6	C7	C8
C1	**86.1**	11.1	0	0	0	0	0	0
C2	0	**38.9**	0	0	0	0	0	0
C3	0	19.5	**83.3**	0	0	0	0	0
C4	2.7	0	16.7	**83.3**	0	0	5.5	0
C5	5.6	22.2	0	5.6	**100**	0	16.7	0
C6	5.6	0	0	0	0	**80.5**	0	13.9
C7	0	8.3	0	11.1	0	0	**77.8**	0
C8	0	0	0	0	0	19.5	0	**86.1**

MRK-SVD$_{LAOLS\text{-}IRLS}$

A→ P↓	C1	C2	C3	C4	C5	C6	C7	C8
C1	**88.9**	0	0	0	0	0	0	0
C2	0	**100**	0	0	0	0	0	0
C3	0	0	**94.4**	0	16.7	0	0	0
C4	0	0	0	**97.2**	0	0	0	11.1
C5	11.1	0	0	0	**83.3**	16.7	0	0
C6	0	0	5.6	0	0	**52.8**	0	13.9
C7	0	0	0	2.8	0	16.7	**100**	11.1
C8	0	0	0	0	0	13.8	0	**63.9**

In Figs. 5.9 (a)-5.9 (c), detailed performance evaluations of different **MRK-SVD** algorithms have been presented in terms of specificity, precision, and sensitivity. According to these plots and accuracy results, it is conclusively demonstrated that **MRK-SVD**$_{IRLS\text{-}IRLS}$ is the overall best superior variant among all **MRK-SVD** algorithms considered. The extensive computations of confusion matrices have been appended in Table 5.5 (a)-5.5 (b) for the different versions of **MRK-SVD** algorithms implemented and studied here for this real-life problem (*A* stands for the actual class and *P* stands for the predicted class). Also, to make a visual comparison of the sparse code matrix **X** obtained with and without the employment of additional regularization term, Fig. 5.10(a) and 5.10(b) are plotted for the sparsity patterns obtained with **MRK-SVD** and classical **K-SVD** algorithms. It is clearly demonstrated the advantages obtained in this context from the pattern obtained, while employing the regularization term. Based on 10 sample consecutive executions of the classification method in online/implementation mode, it is determined that the average computation time needed to classify an unknown signal is 0.51 ±0.025 sec for MRAK-SVD based solution of the motion detection problem.

5.6 Summary

In this Chapter, it has been seen that how recently proposed regularized versions of **K-SVD DL** algorithm can be successfully implemented in direction-specific human movement detection problems. The problem has been solved using an indigenously developed low-cost hardware system in the laboratory. Two such recent approaches, **RK-SVD** and **RAK-SVD**, have been successfully implemented and, for each, a modified version is proposed (**MRK-SVD** and **MRAK-SVD**) by varying ζ as a function of **RMSE**. The supremacies of the proposed and implemented **DL** methods have been established from extensive real-life experimentations.

Currently, movements in eight directions can be sensed by this system, based on the spatial resolution of 45° offered by the Panasonic AMN21112 sensors, the best resolution that analog PIR sensors available in the market can offer till now. However, the system can be suitably scaled in future to sense more than eight directions, if there is an availability of such sensors in market, with a better spatial resolution.

CHAPTER 6

PIR Sensor based Surveillance Tool for Intruder Detection in Secured Environment: A Label Consistency based Modified Sequential Dictionary Learning Approach

---

6.1 Introduction

The study presented in Chapters 2 and 3 has demonstrated the utility of the traditional **K-SVD** algorithm-based dictionary learning approach and its different variants for finding the solution to human behavior recognition problems. Inspired by these initial successes, further investigations have been conducted in Chapters 4 and 5 and the utility of dictionary learning-based approaches in solving another category of **ADL** problems, called detection of human movement direction problems, has been successfully established. In this context, modified *Multiple Cluster Pursuit* (**MCP**) based and modified regularized **K-SVD** based algorithms have been proposed in Chapters 4 and 5, respectively.

In this Chapter, the suitability of implementing dictionary learning-based approaches for solving another important problem from the genre of **AAL/ADL** problems i.e., intruder detection has been investigated. In this Chapter, motivated by some of the **IoT**-based state-of-the-art approaches for intruder detection purposes [75], [76], [130], a novel solution is presented for detecting an unwanted person in a restricted environment. The present research work presented in this Chapter aims at developing an **IoT**-based intelligent hardware-software combined real-life module based on a novel dictionary learning algorithm for finding the solution to intruder detection problems. A novel dictionary learning algorithm has been proposed and will be subsequently discussed in this Chapter which utilizes the concept of label consistency [131] in combination with consistent adaptive dictionary learning [132]. The concepts of label consistency constraint (i.e., discriminative sparse code error), the reconstruction error, and the classification error have been introduced in combination with the objective function of adaptive dictionary learning [132] to form a novel, integrated objective function. The Chapter will discuss how an efficient optimal solution can be obtained using adaptive learning where penalized rank one matrix approximation [132] has been introduced to jointly update a pair of a dictionary atom and its corresponding sparse code. Here, another novel modification has been proposed in finding a proper tuning parameter of rank one approximation that can further enhance performance. Several real-life experiments have been carried out to aptly demonstrate the utility of such a version of a **DL** algorithm when coupled with a real-life four **PIR** sensor-based **IoT** module, based on the same experimental setup described earlier. The Chapter will also demonstrate how the variant of the **DL** algorithm presented here could comfortably outperform the corresponding performances achieved using basic label consistent **K-SVD** [131], basic consistent adaptive dictionary learning [132] algorithm, and other established dictionary learning-based and non-dictionary learning-based classification algorithms.

The rest of this Chapter is organized as follows. The overall scheme of the intruder detection problem under discussion has been elaborated in Section 6.2. The indigenously developed hardware-software combined **IoT** module in the laboratory has been explained briefly in Section 6.3. The fundamentals of label consistent **K-SVD** [131], and consistent adaptive dictionary learning (**CAS-DL**) [132] have been discussed in Section 6.4 in detail, followed by modified **CAS-DL** introduced in this work and then the final proposed algorithm i.e., label consistency-based modified adaptive dictionary learning (**LC-MCAS-DL**) has been explained in detail, for the intruder detection problem. The classification methodologies used in this work have been described in Section 6.5. Several real-life performance evaluations have been carried out in Section 6.6 to establish the efficiency of the proposed algorithm. The summary of this Chapter is presented in Section 6.7.

6.2 Overall Scheme of Intruder Detection Problem

The development of smart home security, smart surveillance, and intruder detection systems has recently become a very important research topic under the scope of **IoT** applications [74], [75], [133]. The problem of intruder detection has been addressed in this Chapter under unmanned scenarios, such as at home or in the office. The detailed scheme of the multipurpose, two-stage, intelligent hardware-software combined **IoT** system utilized here has been developed in the Electrical Measurement and Instrumentation Laboratory in the Electrical Engineering Department, Jadavpur University and it has already been discussed and utilized in Chapters 4 and 5. As mentioned before, this general-purpose platform can be utilized for testing and proposing solutions for several **AAL/ADL**-related problems.

The overall scheme for the intruder detection system solution developed is shown in Fig. 6.1. A hardware-based real-life data acquisition module using four **PIR** sensors and other components, as described before, is shown in Stage 1. The four **PIR** sensors of the sensor array have been arranged in such a fashion that they can comfortably cover all the regions of a hallway under the glance of this developed surveillance tool. This **IoT**-based sensor module is integrated with an indigenously designed **TCP/IP** automatic, real-life signal acquisition module. Here, a sampling rate of 1.2 kHz has been used in the signal acquisition module.

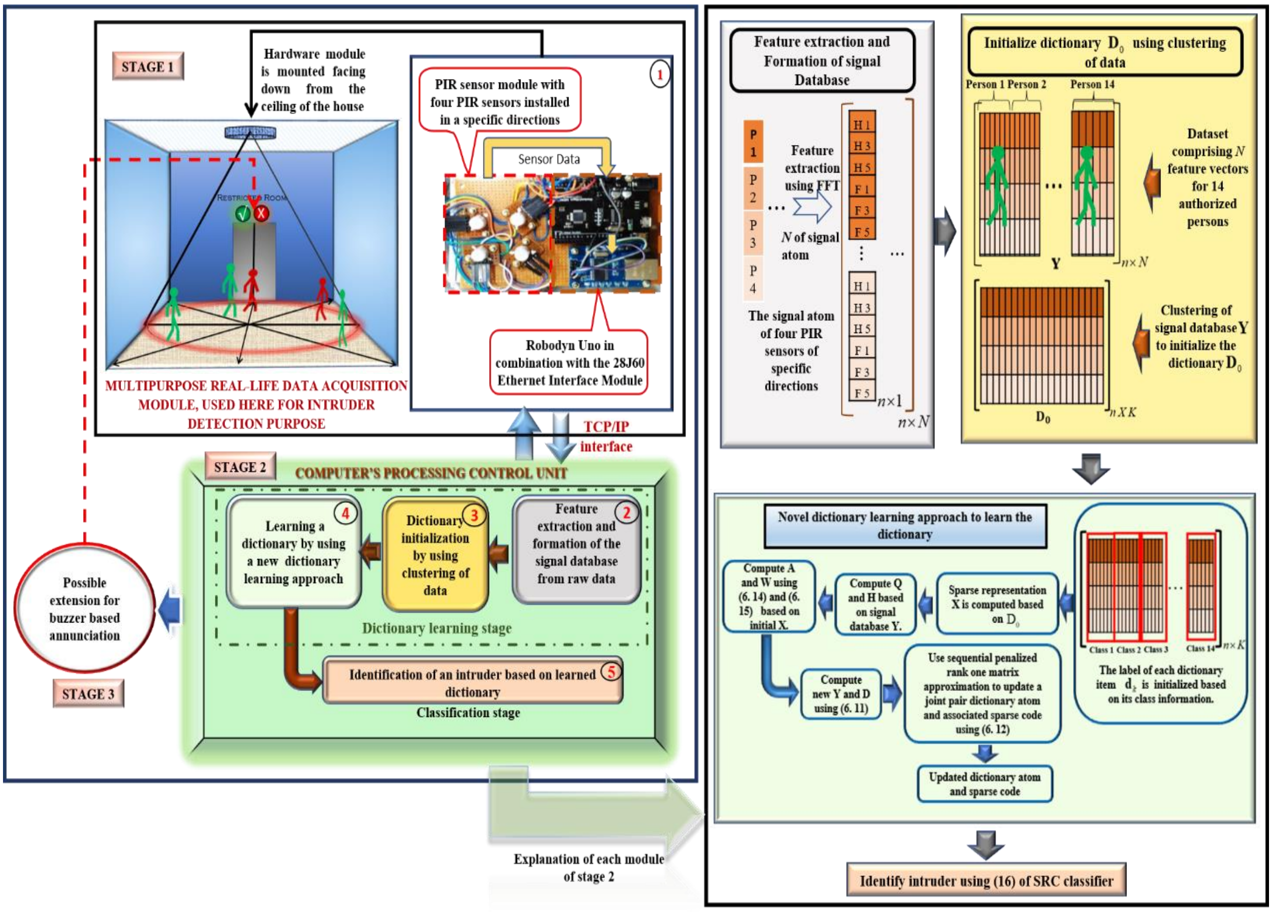
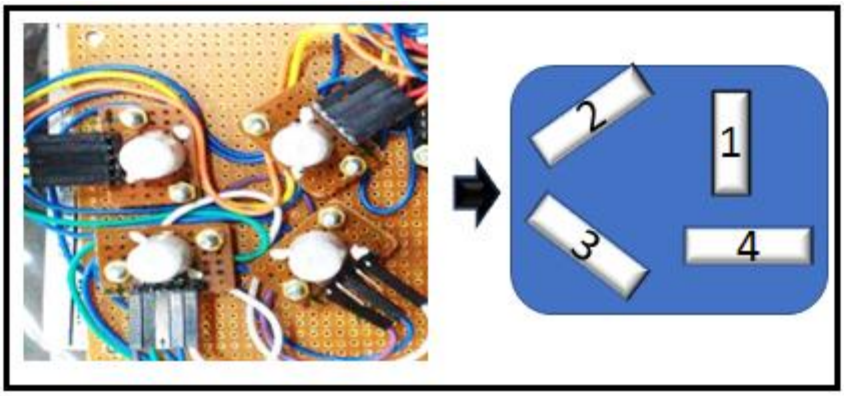


Fig. 6.1. The overall scheme of intruder detection problem

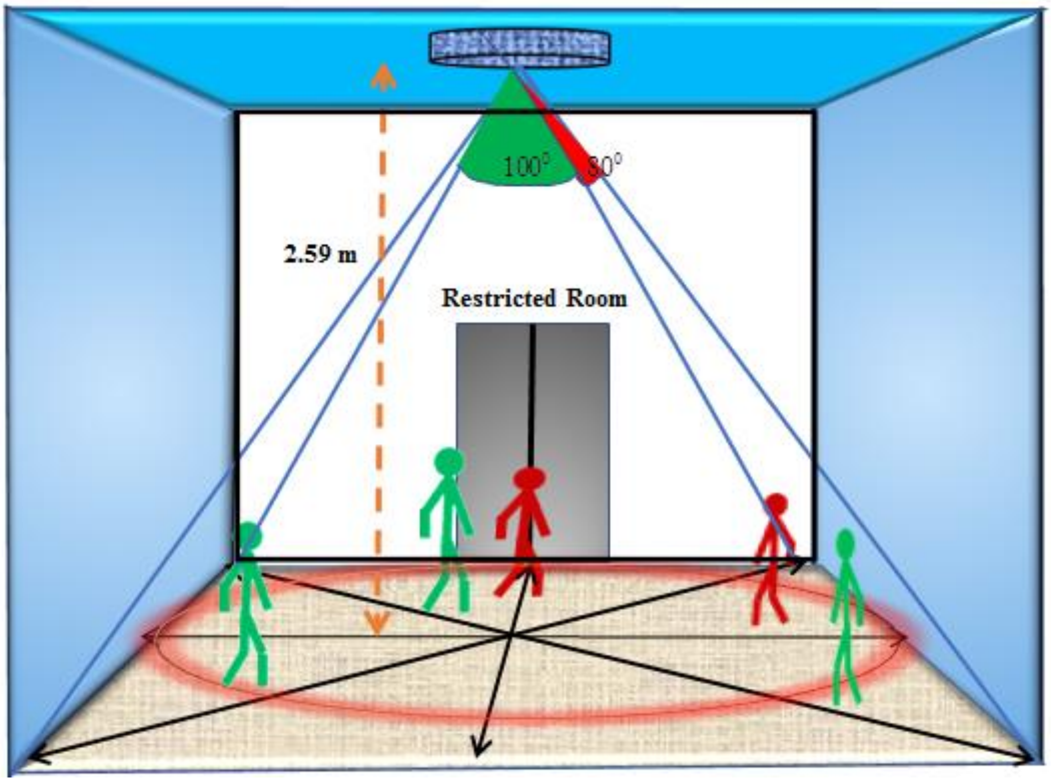
In this Chapter, the proposed software-based dictionary learning algorithm is presented in Stage 2 for online detection of intruders. At the remote **PC** end, a **GUI**-based software has been developed by using Visual Basic and **MATLAB**, thus enabling real-time communication with the hardware from a remote location. Essentially, the computer's processing control unit is made up of four modules. In Module 2, feature extraction is carried out from all four raw signals acquired from **PIR** sensors using **FFT** coefficients, and feature vectors are populated into the feature signal database. Next in Module 3, clustering of the feature signal database is carried out to form the initial dictionary to initiate the **DL** algorithm. The salient steps of this proposed dictionary learning algorithm (**LC-MCAS-DL**) have been established in Module 4 to learn a smaller size dictionary from the larger original feature signal database efficiently without compromising the quality of the dictionary. In Module 5, a classification algorithm based on a learned dictionary is presented for solving the intruder detection problem. An optional Stage 3 can be easily appended to this system where potentially an audio/visual based annunciation can be activated based on the output of this **DL**-based system. It is strongly believed that this proposed concept can also be easily integrated with the existing, reported approaches known in intruder detection problems e.g., automatic door control, and smartphone-based surveillance system, with an enhanced performance [73], [75], [133].

6.3 Development of the IoT-based Real-Time Intruder Detection System and Data Acquisition Procedure

As already acknowledged in [73], [74], [130], and [133], the use of **PIR** sensors has become very appropriate in developing surveillance tools because of their low cost, ability to sense infrared radiation within the viewing range, and also, due to the ability to discriminate stationary objects from movable ones. As mentioned previously, the fundamental structure of the **PIR** sensor [128], [135] consists of two pyroelectric elements inside it, which are aligned in such a way within the surveillance region that it can detect the temperature variation due to any movement within its viewing range. This detection technique of the **PIR** sensor has been used here for solving the problem of intruder identification. The nature of the signal received from **PIR** sensors varies due to the movement of different persons, the gap between the human



(a)



(b)

Fig. 6. 2. Pictorial representation of PIR sensors used: (a) alignment of PIR sensors inside the sensor array and (b) the viewing range of the sensor array

body and the **PIR** sensor, height of the person, the existence of different objects within the viewing range, and the walking speed of an individual. The indigenously developed four PIR sensor-based intruder detection module has been shown in stage 1 of Fig. 6.1. The detailed implementation of the alignment of four **PIR** sensors along with the viewing range is presented in Fig. 6.2. As discussed before, this system has been developed using four *Panasonic AMN21112* analog **PIR** sensors [124], [125] along with a *Robodyn Uno* board that has been interfaced with an *ENC28J60 Ethernet LAN* network module for transferring the real-time data under *Ethernet LAN*. The details of the hardware developed and the internal connections of this experiment module are presented in Chapter 4. In this work, the system is built based on a client-server architecture where the *Robodyn* Uno acts as a server and Visual Basic acts as a clie

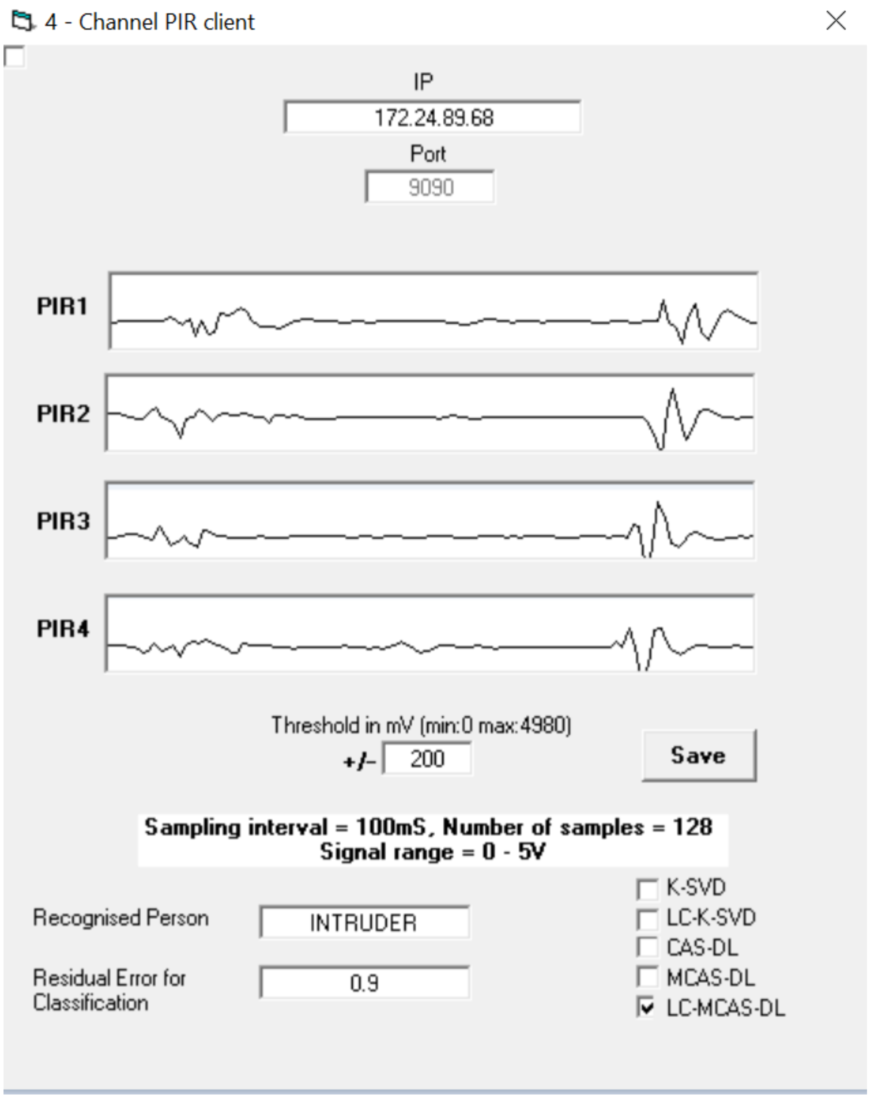


Fig. 6. 3. GUI developed at the PC end for the acquisition of real-time signals in remote mode and the online display of recognized person whether anyone is an intruder or not

The **GUI** developed for real implementation for this problem at hand is shown in Fig. 6.3. Using this **GUI** at the **PC** end, data is acquired from four **PIR** sensors in real-time, and this data has been used to communicate in real-time with **MATLAB** where this proposed **LC-MCAS-DL** algorithms and conventional **K-SVD** variants have been developed. In the recognized person Section, residual error of classification is used to determine whether the person is an intruder. The presence of an intruder is indicated by a moderately high residual error for entry of a particular individual. So, the detection of an intruder in specific regions is more effectively solved by using a specified dictionary learning algorithm that produces a higher residual error value.

6.4 Label Consistency-based Modified Adaptive Sequential Dictionary Learning Approaches

Representation of a signal as a combination of a few atoms from an overcomplete dictionary is the basic notion of sparse representation which is used as the essential foundation of the dictionary learning algorithm [87]. In this dictionary learning approach, a reduced-size dictionary is learned from a larger signal database in order to minimize the computational burden without losing any significant information of original data. In conventional dictionary learning, class information of the training data set is not used to learn a dictionary i.e., unsupervised learning is used [121]. In some of the earlier works [121] [128] [133], the effectiveness of such unsupervised learning has already been established for human movement detection problems. In [131], it has already been established that supervised dictionary learning shows better performance in classification compared to unsupervised learning. In this work, a new sophisticated **DL** algorithm has been proposed to solve the intruder detection problem more efficiently. In this present proposed approach, the knowledge of supervised learning has been combined with the concept of adaptive sequential learning, replacing the corresponding stages in a conventional **K-SVD** algorithm [90]. The **LC-K-SVD** method [131], which is based on the conventional **K-SVD** algorithm but incorporating with some useful modifications, is presented first in a nutshell, followed by a brief discussion on adaptive sequential dictionary [132] learning as an alternative to the conventional **K-SVD** algorithm. Subsequently, the modified version of **CAS-DL** is presented, followed by a detailed discussion of the proposed new algorithm **LC-MCAS-DL** where the concept of label consistency has been integrated with modified consistent adaptive sequential dictionary learning.

6.4.1 The Label Consistent K-SVD Algorithm

A supervised version of conventional **K-SVD** [90] [117] is named **LC-K-SVD** [131] which is aimed to use the class information of each training signal to learn a dictionary by introducing the power of reconstructive and discriminative properties. In **K-SVD**, the dictionary is learned from a larger signal database by solving the objective function:

$$\min_{\mathbf{D},\mathbf{X}} \left\|\mathbf{Y}-\mathbf{D}\mathbf{X}\right\|_F^2 \quad \textit{subject to } \forall i,\ \left\|\mathbf{x}_i\right\|_p \le l \tag{6.1}$$

Here, the signal database $\mathbf{Y}$ is expressed as $\mathbf{Y} \in \Re^{n \times N}$ i.e., set of N no. of signals with n dimensions each. Dictionary $\mathbf{D}$ is denoted as $\mathbf{D} \in \Re^{n \times K}$ i.e., K no. of dictionary atoms with n dimensions each. The sparse representation matrix is presented as

$\mathbf{X} \in \Re^{K \times N}$ (*K*<*N*). In **K-SVD**, (6.1) is solved to obtain $\mathbf{D}$ and $\mathbf{X}$ by minimizing the reconstruction error. The discriminative sparse code error is introduced in [131] to enforce the label consistency i.e., similar sparse code representations will be obtained for the signals with the same class identity. The objective function [131] has also been enhanced by incorporating the classification error into it. Hence, the objective function in **LC-K-SVD** is given as [131]:

$$\min_{\mathbf{D},\mathbf{W},\mathbf{A},\mathbf{X}} \left\|\mathbf{Y}-\mathbf{D}\mathbf{X}\right\|_F^2 + \alpha \left\|\mathbf{Q}-\mathbf{A}\mathbf{X}\right\|_F^2 + \beta \left\|\mathbf{H}-\mathbf{W}\mathbf{X}\right\|_F^2$$
$$\textit{subject to } \forall i,\ \left\|\mathbf{x}_i\right\|_p \le l \tag{6.2}$$

In (6.2), the classification error is expressed as $\left\|\mathbf{H}-\mathbf{W}\mathbf{X}\right\|_F^2$ where class labels of input signals are introduced as $\mathbf{H} \in \Re^{m \times N}$ to learn the linear classifier $\mathbf{W} \in \Re^{m \times K}$. $\mathbf{H}$ is called the label matrix representing the labels of *N* signals of database $\mathbf{Y}$ with *m* no of classes. Each column of label matrix $\mathbf{H}$ is denoted as a column vector e.g., $\mathbf{h}_i = [0, 0..., 1, ..., 0, 0]'$ having a non-zero value representing the class label of the signal $\mathbf{y}_i$. The discriminative sparse code error is expressed as $\left\|\mathbf{Q}-\mathbf{A}\mathbf{X}\right\|_F^2$ where discriminative sparse codes for the signal database $\mathbf{Y}$ are presented as $\mathbf{Q} = [\mathbf{q}_1 \ ... \ \mathbf{q}_N] \in \Re^{K \times N}$ and each column vector $\mathbf{q}_i$ is expressed corresponding to the signal $\mathbf{y}_i$. Each column vector $\mathbf{q}_i$ is expressed corresponding to each input signal $\mathbf{y}_i$ by indicating the non-zero quantities at certain indices where the same class label has been shared by both the training signal $\mathbf{y}_i$ and dictionary atom $\mathbf{d}_k$. Here, $\mathbf{A}$ is a linear transformation matrix. α and β both are the regularization parameters utilized to balance the contributions of discriminative and classification error in the objective function (6.2). In **LC-K-SVD**, the conventional **K-SVD** algorithm is used to solve (6.2) for learning the dictionary $\mathbf{D}$. The objective function can be modified as [131]:

$$\min_{\mathbf{D}_{lc},\mathbf{X}} \left\|\mathbf{Y}_{lc} - \mathbf{D}_{lc}\mathbf{X}\right\|_{\mathrm{F}}^{2} \quad s.t.\ \forall i,\ \left\|\mathbf{x}_i\right\|_{\mathrm{p}} \leq l \tag{6.3}$$

Where $\mathbf{Y}_{lc} = \begin{bmatrix} \mathbf{Y} & \sqrt{\alpha}\mathbf{Q} & \sqrt{\beta}\mathbf{H} \end{bmatrix}'$ $\mathbf{D}_{lc} = \begin{bmatrix} \mathbf{Y} & \sqrt{\alpha}\mathbf{A} & \sqrt{\beta}\mathbf{W} \end{bmatrix}'$.

In the next Subsection, a modified consistent adaptive sequential learning algorithm (**MCAS-DL**) has been proposed and the objective function (6.3) has been solved in a novel manner using **MCAS-DL** instead of using conventional **K-SVD**.

6.4.2 Modified Consistent Adaptive Sequential Dictionary Learning

The fundamental concept of **MCAS-DL** has been developed based on l_1 norm-based dictionary learning algorithm in which the sparsity is controlled by regularization parameter. In consistent adaptive dictionary learning algorithm [132], an automatic adjustment in each entry of sparse matrix $\mathbf{X}$ has been computed using adaptive penalization of each entry of $\mathbf{X}$. The objective function of consistent adaptive dictionary learning is formulated as [132]:

$$\min_{\mathbf{D}\in\mathbf{D},\mathbf{X}} \left\|\mathbf{Y} - \mathbf{D}\mathbf{X}\right\|_{F}^{2} + n\sum_{k=1}^{K}\sum_{i=1}^{N}\zeta_{ki}\left|\mathbf{x}_{ki}\right|,\ s.t.\left\|\mathbf{d}_j\right\|_2 = 1, \forall j \tag{6.4}$$

The objective function (6.4) is differed from the conventional norm-based dictionary learning algorithm by introducing the use of different regularization parameters in each entry of the sparse matrix $\mathbf{X}$. Instead of using the conventional approach of solving (6.4), here, in this case, at each iteration dictionary atom $\mathbf{d}_j$ is updated along with the respective sparse code $\mathbf{x}_T^j$ associated with it based on the objective function (6.5) where penalized rank-1 matrix approximation has been used.

$$(\mathbf{d}_j, \mathbf{x}_T^j) = \arg \min_{\mathbf{d}_j, \mathbf{x}_T^j} \left\| \mathbf{E}_j - \mathbf{d}_j \mathbf{x}_T^j \right\|_F^2 + n \sum_{i=1}^{N} \zeta_{ji} \left| \mathbf{x}_{ji} \right|, \quad s.t. \left\| \mathbf{d}_j \right\|_2 = 1 \tag{6.5}$$

Where $\mathbf{E}_j = \mathbf{Y} - \sum_{\substack{k=1, \\ k \neq j}}^{K} \mathbf{d}_k \mathbf{x}_T^k$ (6.6)

The concept of $(j = 1 \ldots K)$ penalized rank-1 matrix approximation to combine the sparse coding stage and dictionary update stage has been introduced by this algorithm in each iteration of the sequential algorithm. Update of $\mathbf{d}_j$ and $\mathbf{x}_T^j$ can be computed by performing the alternate iterative minimization of (6.5). Keeping $\mathbf{d}_j$ fixed, $\mathbf{x}_T^j$ can be obtained as in (6.7) by minimizing (6.5).

$$\mathbf{X}_T^j = \operatorname{sgn}(\mathbf{d}_j' \mathbf{E}_j) \circ \left(\left| \mathbf{d}_j' \mathbf{E}_j \right| - \frac{n \zeta_j}{2} \right)_+ \tag{6.7}$$

Here, the row vector of tuning parameters is denoted as ζ_j which has been used to selectively control the sparsity of $\mathbf{X}_T^j$ by introducing different threshold values for different entries of $\mathbf{X}_T^j$ [132]. To overcome the problem of tuning all the entries of sparse vector simultaneously, (6.8) has been proposed in [132] to promote sparsity of $\mathbf{X}_T^j$.

$$\zeta_{ji} = \frac{\zeta}{\left| \mathbf{X}_T^{ji} \right|^{\gamma}}, \gamma > 0 \tag{6.8}$$

As shown in equation (6.8), different weightages are assigned to different entries of **X**, with a higher weightage assigned to more significant entries and vice versa. In this Section, a modified version of this methodology has been proposed to solve (6.3) to strengthen the effect of sparsity along with the concept of reducing reconstruction error, discriminative error, and classification error. Here, a modification has been incorporated in the stage of selection of a vector of tuning parameter ζ_j in such a way that the values of the sparse entries are decreased exponentially, to provide different weightages in each entry of a sparse vector such that higher priorities will be assigned to significant entries over others. The modified version of (6.8) proposed in this work is given below:

$$\zeta_{ji} = e^{-\zeta\left|\mathbf{x}_T^{ji}\right|^{\gamma}}, \gamma > 0 \tag{6.9}$$

In Section 6.6, the effectiveness of the proposed idea of selecting tuning parameters has been established for solving the problem of intruder detection. It has also been established that (6.9) works more efficiently compared to (6.8) for learning a dictionary to solve the problem at hand. The proposed MCAS-DL algorithm is summarized in Algorithm 6.1.

Algorithm 6.1: Modified consistent adaptive sequential dictionary learning (MCAS-DL)

BEGIN

Input: Training signal database as $\mathbf{Y} \in \Re^{n \times N}$, Initial dictionary as $\mathrm{D}_0 \in \Re^{n \times K}$

Output: Output dictionary $\mathbf{D} \in \Re^{n \times K}$ and a coefficient matrix **X**.

Step 1:

Initialization: Initialize tuning parameter ζ, $\gamma > 0$, the maximum number of iterations $iter_m$ and $iter = 1$.**Step 2:**

FOR $iter = 1 : iter_m$

FOR $j = 1 : K$

- Compute $\mathbf{E}_j = \mathbf{Y} - \sum_{\substack{k=1, \\ k \neq j}}^{K} \mathbf{d}_k \mathbf{x}_T^k$
- Perform singular value decomposition of $\mathbf{E}_j$ to compute $\mathbf{d}_j$ and $\mathbf{x}_T^j$.
- Compute the vector ζ_j of tuning parameter ζ_{ji} using the proposed methodology (6.9).
- Update associated sparse coefficients as $\mathbf{X}_T^j = \mathrm{sgn}(\mathbf{d}_j' \mathbf{E}_j) \circ (\left| \mathbf{d}_j{}' \mathbf{E}_j \right| - \frac{n\zeta_j}{2})_+$
- Update dictionary atom $\mathbf{d}_j$ as $\mathbf{d}_j = \frac{\mathbf{E}_j \mathbf{x}_T^{j'}}{\left\| \mathbf{E}_j \mathbf{x}_T^{j'} \right\|_2}$

ENDFOR

IF $\left\| \mathbf{d}_{iter} - \mathbf{d}_{iter-1} \right\|_F > \varepsilon$

THEN

CONTINUE

ELSE

STOP

ENDIF

ENDFOR

END

6.4.3 Label Consistency Based Modified Adaptive Sequential Dictionary Learning

In this Subsection, the proposed **LC-MCAS-DL** algorithm has been discussed where the basic merits of the **LC-K-SVD** have been intelligently integrated with the concept of the modified adaptive sequential dictionary learning to find a superior solution for this intruder detection problem. Hence, the concept of supervised learning is introduced where discriminative sparse code error is introduced along with the reconstruction error and classification error to form a novel objective function (6.10) and this objective function has been solved by using the concept of adaptive sequential learning [132] to find a superior solution in classification. This new, integrated objective function is proposed as:

$$\begin{aligned} &\min_{\mathbf{D},\mathbf{W},\mathbf{A},\mathbf{X}} \|\mathbf{Y}-\mathbf{D}\mathbf{X}\|_F^2 + \alpha\|\mathbf{Q}-\mathbf{A}\mathbf{X}\|_F^2 + \beta\|\mathbf{H}-\mathbf{W}\mathbf{X}\|_F^2 + n\sum_{k=1}^{K}\sum_{i=1}^{N}\zeta_{ki}|\mathbf{x}_{ki}| \\ &s.t.\ \|\mathbf{d}_j\|_2 = 1, \forall j \end{aligned} \tag{6.10}$$

Keeping in mind the concept of penalized rank-1 approximation, (6.10) has been reformulated as (6.11) to incorporate penalization in each entry of sparse code matrix $\mathbf{X}$ to adjust the sparsity level adaptively:

$$\min_{\mathbf{D}_{LC},\mathbf{X}} \|\mathbf{Y}_{LC}-\mathbf{D}_{LC}\mathbf{X}\|_F^2 + n\sum_{k=1}^{K}\sum_{i=1}^{N}\zeta_{LCki}|\mathbf{x}_{ki}| \ \ s.t \|\mathbf{d}_{LCj}\|_2 = 1, \forall j \tag{6.11}$$

Where $\mathbf{Y}_{LC} = \begin{bmatrix}\mathbf{Y} & \sqrt{\alpha}\mathbf{Q} & \sqrt{\beta}\mathbf{H}\end{bmatrix}'$ and $\mathbf{D}_{LC} = \begin{bmatrix}\mathbf{Y} & \sqrt{\alpha}\mathbf{A} & \sqrt{\beta}\mathbf{W}\end{bmatrix}'$

The equation (6.10) has been developed by hybridizing two objective functions (6.3) and (6.4) in which the advantages of adaptive sequential dictionary learning along has been combined with the concept of label consistency. Here, due to the use of penalized rank-1 matrix approximation, each atom of dictionary $\mathbf{D}_{LC}$ i.e., $\mathbf{d}_{LCj}$ is updated sequentially along with $\mathbf{X}_T^{LCj}$ and equation (6.11) can be modified as

$$
\begin{aligned}
&(\mathbf{d}_{LCj}, \mathbf{x}_T^{LCj}) = \arg \min_{\mathbf{d}_{LCj}, \mathbf{x}_T^{LCj}} \left\| \mathbf{E}_{LCj} - \mathbf{d}_{LCj} \mathbf{x}_T^{LCj} \right\|_F^2 + n \sum_{i=1}^{N} \zeta_{LCji} \left| \mathbf{x}_{ji}^{LC} \right| \\
&s.t. \left\| \mathbf{d}_{LCj} \right\|_2 = 1
\end{aligned}
\tag{6.12}
$$

Here, another modification has also been proposed in (6.12) in selecting the tuning parameter ζ_{LC}. The ζ_{LC} for each entry is modified as:

$$
\zeta_{LCji} = e^{-\zeta_{LC} \left| \mathbf{x}_T^{LCji} \right|^{\gamma}}, \gamma > 0 \tag{6.13}
$$

In this proposed algorithm, the tuning parameter ζ_{LCj} has been used to endorse the best version of sparsity in each entry of sparse code matrix $\mathbf{X}$. To obtain the initial dictionary $\mathbf{D}_0$ several iterations of conventional **K-SVD** is performed for each sub-database containing original signals from a specific class and then the output of each **K-SVD** is combined to generate $\mathbf{D}_0$. This size of the dictionary is fixed throughout the learning process. Initialization of **A** and **W** is carried out using multivariate ridge regression model along with l_2 norm regularization, as follows [131]:

$$
\mathbf{A} = \mathbf{Q}\mathbf{X}'(\mathbf{X}\mathbf{X}' + \lambda_2 \mathbf{I})^{-1} \tag{6.14}
$$

$$
\mathbf{W} = \mathbf{H}\mathbf{X}'(\mathbf{X}\mathbf{X}' + \lambda_1 \mathbf{I})^{-1} \tag{6.15}
$$

Algorithm 6.2: Label consistency based modified consistent adaptive sequential dictionary learning (LC-MCAS-DL)

BEGIN

Input: Training signal database as $\mathbf{Y} \in \Re^{n \times N}$

Output: **O**utput dictionary $\tilde{\mathbf{D}} \in \Re^{n \times K}$ and a coefficient matrix **X**.

Step 1:

Initialization:

Initialize tuning parameter ζ_{LC}, set $\gamma > 0$ the maximum number of iterations $iter_m$ and $iter = 1$

Set **Q** as the discriminative sparse code of **Y** and **H** as class labels of input signal **Y**

Set α and β as the weightage of discriminative and sparse code error and initialize dictionary size *K.*

Step 2:

Compute initial Dictionary $\mathbf{D}_0 \in \Re^{n \times K}$ by grouping all the class specific dictionary obtained from each class using (6.1).

Step 3:

Initialize $\mathbf{x}_0$ by using l_0 *or* l_1 optimization approach and initialize $\mathbf{A}_0$ and $\mathbf{W}_0$ using (6.14) and (6.15).

Step 4:

Initialize $\mathbf{Y}_{LC} = \begin{bmatrix} \mathbf{Y} & \sqrt{\alpha}\mathbf{Q} & \sqrt{\beta}\mathbf{H} \end{bmatrix}'$ and $\mathbf{D}_{LC} = \begin{bmatrix} \mathbf{Y} & \sqrt{\alpha}\mathbf{A} & \sqrt{\beta}\mathbf{W} \end{bmatrix}'$

FOR $iter = 1 : iter_m$

- Update each atom of $\mathbf{D}_{LC}$ i.e., $\mathbf{d}_{LCj}$ by solving (6.12) using modified sequential learning given in Algorithm I.

ENDFOR

- Compute $\tilde{\mathbf{D}}, \tilde{\mathbf{A}}, \tilde{\mathbf{W}}$ using (6.17).

END

Initially $\mathbf{X}_0$ has been computed based on given initial class specific dictionary by using equation (6.1) where l_1 norm optimization has been utilized and it has been solved by **IRLS** algorithm. The final **LC-MCAS-DL** algorithm is presented in Algorithm 6.2. In this proposed algorithm, the final **D**, **A**, **W**, and **X** are obtained simultaneously, in which accommodating a larger number of classes by minimizing the chances of getting trapped in local minima is encouraged. In this algorithm, both the sparse code and associated dictionary atom have been updated sequentially by adopting block co-ordinate decent approach via penalized rank-1 approximation instead of conventional **K-SVD.**

6.5 Classification Approach based on Dictionary Learning

After learning the dictionary **D**, the next step, the classification problem is shown in the last Section of Stage 2 in Fig. 6.1 to detect an intruder based on that learned dictionary. In this classification part, a linear predictive classifier has been used to detect whether an unknown signal **y** is that of an intruder entering in the restricted area among other known people in real-time. Thus, the optimization problem [123] is essentially solved.

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{x}\|_p \text{ subject to} \|\mathbf{y}\text{-}\mathbf{D}\mathbf{x}\|_2 \leq \tau \tag{6.16}$$

Encouraged by the previous research efforts in [117][121][128][135], here also the performances of intruder detection systems have been extensively tested by using both relaxation and greedy algorithms based on the learned dictionary **D**.

As **D**, **A** and **W** are obtained from $\mathbf{D}_{LC}$ by using label consistency based sequential dictionary learning, where **D**, **A**, and **W** are l_2 normalized in $\mathbf{D}_{LC}$, the dictionary **D** cannot be used directly to solve the sparse code. To overcome this problem the actual dictionary $\tilde{\mathbf{D}}$, the transformation parameter $\tilde{\mathbf{A}}$ and the classification parameter $\tilde{\mathbf{W}}$ has been computed as follows [131].

$$\tilde{\mathbf{D}} = \left\{ \frac{\mathbf{d}_j}{\|\mathbf{d}_j\|_2} \right\}, \tilde{\mathbf{A}} = \left\{ \frac{a_j}{\|\mathbf{d}_j\|_2} \right\} \text{ and } \tilde{\mathbf{W}} = \left\{ \frac{\mathbf{w}_j}{\|\mathbf{d}_j\|_2} \right\}, \forall j \tag{6.17}$$

As a first step to identifying an intruder or a known person, at first, sparse code $\hat{\mathbf{x}}$ is first computed by using the equation (6.16) for the signal under consideration and then by using linear predictive classifier, the label vector **c** is computed as $\mathbf{c} = \tilde{\mathbf{W}}\hat{\mathbf{x}}$. The presence of a known person in the restricted area can be identified if a significantly large value is obtained for any entry of this vector corresponding to a specific class. Otherwise, if a significant difference is not obtained for all entries in vector c and a single value cannot be distinguished as significantly different from the other values in vector c, then the signal was acquired from an intruder instead of from an authorized person. Here, sparse representation classifier based on $\tilde{\mathbf{D}}$ can also be used to solve this classification problem. In the context of residual calculation for a signal **y** using the method of **SRC**, if the residual error for any one of the known classes is found extremely low compared to the residual error calculated for others, then the signal **y** would be associated with that class. The existence of an intruder is recognized if relatively high values are obtained in the estimated residual errors for the signal in each of the known classes.

6.6 Experimental Result Analysis

6.6.1 Experimental Framework for Intruder Detection Problem

To evaluate the performance of the developed module for intruder detection purposes, a certain area inside the laboratory has been utilized as a restricted access zone with the dimension of 1.98 m x 1.98 m in the ground and the hardware module has been installed at a height of 2. 59 m. This area was also used for the experimental purposes in Chapter 4 and Chapter 5. To form the signal database, real-life signals have been acquired using this experimental setup from twenty-one subjects of different height, weight, and walking patterns, roaming in different directions in the region under observation. The volunteers have been selected from a height range of 1.58 m - 1.82 m and a weight range of 52 kg - 80 kg for this experiment. Then, the intruder detection has been carried out in a complete online fashion, in a real-world scenario. To test the performance of the system developed, 14 people are considered authorized persons, and the signals acquired from the rest seven people are considered intruders. Hence the dictionary is learned based on signals acquired from 14 authorized persons. For each person 240 signals have been acquired walking in all directions i.e., a total of 5040 (=21×240) signals. Out of these 2688 (=14×192) signals acquired from 14 authorized persons have been used to create the training database and the rest are used for testing purpose.

Now each signal of the training and testing database is composed of readings acquired from all four **PIR** sensors. From each **PIR** sensor, 128 samples of data are acquired and those are concatenated to create a signal vector of (4×128) samples. As mentioned, several times before, it is well known that the fundamental concept of **DL** is based upon sparse representation in which better performance can be obtained for over-complete dictionaries. The performance of sparse representation will be enhanced with the increase of dictionary over-completeness. This requires that number of rows should be as small compared to the number of columns in the dictionary as possible. This was also experimentally validated in previous works [128], [135]. Hence, to make the dictionary overcomplete, each signal vector has been represented using a smaller dimensional feature vector f_i consisting of Fourier coefficients by executing **FFT** on each dictionary atom $\mathbf{d}_i$ where the number of PIR sensor is expressed as i.

$$f_i = \begin{bmatrix} S_i(H_i(1)), S_i(H_i(3)), S_i(H_i(5)), \\ S_i(F_i(1)), S_i(F_i(3)), S_i(F_i(5)) \end{bmatrix}^T, \tag{6.18}$$

where $i = (1, 2, 3, 4)$

Here, for the signal acquired from ith sensor, the Fourier coefficient magnitudes of fundamental, third, and fifth harmonic are shown in $S_i(H_i(1)), S_i(H_i(3)),$ and $S_i(H_i(5))$ respectively, while the corresponding frequency values are depicted in $S_i(F_i(1)), S_i(F_i(3)),$ and $S_i(F_i(5))$, i.e., 50 Hz, 150 Hz, and 250 Hz, respectively. Hence from each 128 data samples from a **PIR** sensor acquired, six features have been extracted and concatenated for four **PIR** sensors to generate a feature vector of size (24 × 1). In this feature extraction stage, the training signal database is reduced from (512 × 2688) to a training feature database of (24 × 2688). For generating the testing signal, similar logic is applied. Thus, a significantly overcomplete dictionary is created in a bid to enhance performance.

In this context, first, it should be mentioned that a very extensive experimental evaluation was first undertaken utilizing signals acquired from 21 subjects and performing feature extraction using **FFT** and **PCA**. For features generated using **FFT**, from each **PIR** signal six, or ten or fourteen features have been extracted considering odd harmonic components upto fifth, or ninth, or thirteenth harmonic components. Similarly, six, or ten or fourteen features are also considered from the principal components obtained for each **PIR** signal. In this manner, at first six datasets were created. Then to further introduce more variations in the experiments carried out, for each dataset four different combinations of training and testing signals have been created. Out of these 21 subjects, four specific combinations of authorized persons and intruders are considered i.e., 16/14/11/7 are considered as authorized persons and the rest 5/7/10/14 are considered as intruders. Then experiments based on 24 such datasets created were performed. The details of these datasets created are presented in Table 6.1.

TABLE 6. 1: DETAILED DATA SETS IN CONSIDERATION FOR EXPERIMENTS ON INTRUDER DETECTION

Dataset No.	Feature Extraction Methodology	No. of features extracted from each PIR signal	Signal feature database dimension	Dataset Description
DATA SET_1	**FFT**	3+3=06	(6×4)×5040 = 24×5040 [21 persons]	DATASET_1_A: 16 authorised persons+5 unauthorised persons Training dataset: (24×(16×192)) = (24×3072) Testing dataset: (24×(21×48)) = (24×1008)
				DATASET_1_B: 14 authorised persons+7 unauthorised persons Training dataset: (24×(14×192)) = (24×2688) Testing dataset: (24×(21×48)) = (24×1008)
				DATASET_1_C: 11 authorised persons+10 unauthorised persons Training dataset: (24×(11×192)) = (24×2112) Testing dataset: (24×(21×48)) = (24×1008)
				DATASET_1_D: 7 authorised persons+14 unauthorised persons Training dataset: (24×(7×192)) = (24×1344) Testing dataset: (24×(21×48)) = (24×1008)

Dataset No.	Feature Extraction Methodology	No. of features extracted from each PIR signal	Signal feature database dimension	Dataset Description
DATA SET_2	**FFT**	5+5=10	(10×4)×5040 = 40×5040 [21 persons]	DATASET_2_A: 16 authorised persons+5 unauthorised persons Training dataset: (40×(16×192)) = (40×3072) Testing dataset: (40×(21×48)) = (40×1008)
				DATASET_2_B: 14 authorised persons+7 unauthorised persons Training dataset: (40×(14×192)) = (40×2688) Testing dataset: (40×(21×48)) = (40×1008)
				DATASET_2_C: 11 authorised persons+10 unauthorised persons Training dataset: (40×(11×192)) = (40×2112) Testing dataset: (40×(21×48)) = (40×1008)
				DATASET_2_D: 7 authorised persons+14 unauthorised persons Training dataset: (40×(7×192)) = (40×1344) Testing dataset: (40×(21×48)) = (40×1008)

Dataset No.	Feature Extraction Methodology	No. of features extracted from each PIR signal	Signal feature database dimension	Dataset Description
DATA SET_3	**FFT**	7+7=14	(14×4)×5040 = 56×5040 [21 persons]	DATASET_3_A: 16 authorised persons+5 unauthorised persons Training dataset: (56×(16×192)) = (56×3072) Testing dataset: (56×(21×48)) = (56×1008)
				DATASET_3_B: 14 authorised persons+7 unauthorised persons Training dataset: (56×(14×192)) = (56×2688) Testing dataset: (56×(21×48)) = (56×1008)
				DATASET_3_C: 11 authorised persons+10 unauthorised persons Training dataset: (56×(11×192)) = (56×2112) Testing dataset: (56×(21×48)) = (56×1008)
				DATASET_3_D: 7 authorised persons+14 unauthorised persons Training dataset: (56×(7×192)) = (56×1344) Testing dataset: (56×(21×48)) = (56×1008)

Dataset No.	Feature Extraction Methodology	No. of features extracted from each PIR signal	Signal feature database dimension	Dataset Description
DATA SET_4	**PCA**	06	(6×4)×5040 = 24×5040 [21 persons]	DATASET_4_A: 16 authorised persons+5 unauthorised persons Training dataset: (24×(16×192)) = (24×3072) Testing dataset: (24×(21×48)) = (24×1008)
				DATASET_4_B: 14 authorised persons+7 unauthorised persons Training dataset: (24×(14×192)) = (24×2688) Testing dataset: (24×(21×48)) = (24×1008)
				DATASET_4_C: 11 authorised persons+10 unauthorised persons Training dataset: (24×(11×192)) = (24×2112) Testing dataset: (24×(21×48)) = (24×1008)
				DATASET_4_D: 7 authorised persons+14 unauthorised persons Training dataset: (24×(7×192)) = (24×1344) Testing dataset: (24×(21×48)) = (24×1008)

Dataset No.	Feature Extraction Methodology	No. of features extracted from each PIR signal	Signal feature database dimension	Dataset Description
DATA SET_5	**PCA**	10	(10×4)×5040 = 40×5040 [21 persons]	DATASET_5_A: 16 authorised persons+5 unauthorised persons Training dataset: (40×(16×192)) = (40×3072) Testing dataset: (40×(21×48)) = (40×1008)
				DATASET_5_B: 14 authorised persons+7 unauthorised persons Training dataset: (40×(14×192)) = (40×2688) Testing dataset: (40×(21×48)) = (40×1008)
				DATASET_5_C: 11 authorised persons+10 unauthorised persons Training dataset: (40×(11×192)) = (40×2112) Testing dataset: (40×(21×48)) = (40×1008)
				DATASET_5_D: 7 authorised persons+14 unauthorised persons Training dataset: (40×(7×192)) = (40×1344) Testing dataset: (40×(21×48)) = (40×1008)

Dataset No.	Feature Extraction Methodology	No. of features extracted from each PIR signal	Signal feature database dimension	Dataset Description
DATA SET_6	**PCA**	14	(14×4)×5040 = 56×5040 [21 persons]	DATASET_6_A: 16 authorised persons+5 unauthorised persons Training dataset: (56×(16×192)) = (56×3072) Testing dataset: (56×(21×48)) = (56×1008)
				DATASET_6_B: 14 authorised persons+7 unauthorised persons Training dataset: (56×(14×192)) = (56×2688) Testing dataset: (56×(21×48)) = (56×1008)
				DATASET_6_C: 11 authorised persons+10 unauthorised persons Training dataset: (56×(11×192)) = (56×2112) Testing dataset: (56×(21×48))=(56×1008)
				DATASET_6_D: 7 authorised persons+14 unauthorised persons Training dataset: (56×(7×192)) = (56×1344) Testing dataset: (56×(21×48)) = (56×1008)

6.6.2 Performance Evaluation

Next, a very comprehensive performance comparison is carried out among many varieties of competing, state-of-the-art, related algorithms for each of these datasets and the corresponding results are reported below in TABLE 6.2_DATASET_1_A to TABLE 6.2_DATASET_1_D (for DATASET_1), TABLE 6.2_DATASET_2_A to TABLE 6.2_DATASET_2_D (for DATASET_2), TABLE 6.2_DATASET_3_A to TABLE 6.2_DATASET_3_D (for DATASET_3), TABLE 6.2_DATASET_4_A to TABLE 6.2_DATASET_4_D (for DATASET_4), TABLE 6.2_DATASET_5_A to TABLE 6.2_DATASET_5_D (for DATASET_5), and TABLE 6.2_DATASET_6_A to TABLE 6.2_DATASET_6_D (for DATASET_6).

TABLE 6. 2: PERFORMANCE COMPARISON WITH OTHER COMPETING APPROACHES FOR DIFFERENT DATA SET

TABLE 6.2_DATASET_1_A

Method	Recognition Accuracy (%)
SVDD	82.14
OC-SVM	72.82
SVM	62.11
KNN	70.00
SRC	40.17
K-SVD [117]	88.29
MMCP-K-SVD [128]	89.09
MRK-SVD [135]	90.28
MRAK-SVD [135]	91.77
LC-K-SVD [131]	88.29
IDL [131]	87.90
CAS-DL [132]	69.64
MCAS-DL	85.71
LC-MCAS-DL	**93.35**

TABLE 6.2_DATASET_1_B

Method	Recognition Accuracy (%)
SVDD	73.80
OC-SVM	72.02
SVM	53.00
KNN	66.67
SRC	47.34
K-SVD [117]	83.13
MMCP-K-SVD [128]	86.90
MRK-SVD [135]	89.09
MRAK-SVD [135]	90.38
LC-K-SVD [131]	91.96
IDL [131]	86.30
CAS-DL [132]	78.86
MCAS-DL	85.12
LC-MCAS-DL	**93.55**

TABLE 6.2_DATASET_1_C

Method	Recognition Accuracy (%)
SVDD	68.75
OC-SVM	71.03
SVM	66.03
KNN	52.38
SRC	45.63
K-SVD [117]	82.14
MMCP-K-SVD [128]	84.23
MRK-SVD [135]	87.80
MRAK-SVD [135]	89.68
LC-K-SVD [131]	82.44
IDL [131]	79.76
CAS-DL [132]	56.65
MCAS-DL	86.48
LC-MCAS-DL	**90.77**

TABLE 6.2_DATASET_1_D

Method	Recognition Accuracy (%)
SVDD	61.70
OC-SVM	60.20
SVM	61.21
KNN	51.88
SRC	54.26
K-SVD [117]	71.72
MMCP-K-SVD [128]	74.60
MRK-SVD [135]	75.79
MRAK-SVD [135]	76.19
LC-K-SVD [131]	75.29
IDL [131]	75.00
CAS-DL [132]	64.48
MCAS-DL	77.18
LC-MCAS-DL	**83.03**

TABLE 6.2_DATASET_2_A

Method	Recognition Accuracy (%)
SVDD	79.96
OC-SVM	83.33
SVM	79.36
KNN	76.00
SRC	48.00
K-SVD [117]	68.45
MMCP-K-SVD [128]	71.43
MRK-SVD [135]	76.19
MRAK-SVD [135]	77.18
LC-K-SVD [131]	72.22
IDL [131]	88.59
CAS-DL [132]	86.31
MCAS-DL	88.69
LC-MCAS-DL	**89.78**

TABLE 6.2_DATASET_2_B

Method	Recognition Accuracy (%)
SVDD	67.56
OC-SVM	78.17
SVM	77.38
KNN	67.10
SRC	46.83
K-SVD [117]	60.71
MMCP-K-SVD [128]	62.50
MRK-SVD [135]	64.29
MRAK-SVD [135]	67.66
LC-K-SVD [131]	57.44
IDL [131]	81.45
CAS-DL [132]	82.14
MCAS-DL	84.23
LC-MCAS-DL	**86.81**

TABLE 6.2_DATASET_2_C

Method	Recognition Accuracy (%)
SVDD	64.98
OC-SVM	77.68
SVM	62.00
KNN	52.50
SRC	41.27
K-SVD [117]	48.21
MMCP-K-SVD [128]	52.38
MRK-SVD [135]	52.98
MRAK-SVD [135]	54.76
LC-K-SVD [131]	80.35
IDL [131]	77.28
CAS-DL [132]	80.65
MCAS-DL	81.55
LC-MCAS-DL	**84.32**

TABLE 6.2_DATASET_2_D

Method	Recognition Accuracy (%)
SVDD	64.98
OC-SVM	77.68
SVM	62.00
KNN	52.50
SRC	41.27
K-SVD [117]	48.21
MMCP-K-SVD [128]	52.38
MRK-SVD [135]	52.98
MRAK-SVD [135]	54.76
LC-K-SVD [131]	75.00
IDL [131]	77.28
CAS-DL [132]	80.65
MCAS-DL	81.55
LC-MCAS-DL	**82.14**

TABLE 6.2_DATASET_3_A

Method	Recognition Accuracy (%)
SVDD	79.26
OC-SVM	88.40
SVM	79.00
KNN	76.80
SRC	69.35
K-SVD [117]	70.63
MMCP-K-SVD [128]	71.43
MRK-SVD [135]	76.19
MRAK-SVD [135]	77.38
LC-K-SVD [131]	66.17
IDL [131]	86.51
CAS-DL [132]	76.79
MCAS-DL	88.98
LC-MCAS-DL	**89.29**

TABLE 6.2_DATASET_3_B

Method	Recognition Accuracy (%)
SVDD	73.11
OC-SVM	74.10
SVM	78.37
KNN	66.80
SRC	62.00
K-SVD [117]	61.90
MMCP-K-SVD [128]	64.29
MRK-SVD [135]	66.67
MRAK-SVD [135]	67.86
LC-K-SVD [131]	76.98
IDL [131]	82.84
CAS-DL [132]	67.56
MCAS-DL	84.92
LC-MCAS-DL	**85.91**

TABLE 6.2_DATASET_3_C

Method	Recognition Accuracy (%)
SVDD	62.59
OC-SVM	63.19
SVM	78.27
KNN	52.57
SRC	50.20
K-SVD [117]	60.41
MMCP-K-SVD [128]	61.21
MRK-SVD [135]	65.17
MRAK-SVD [135]	67.16
LC-K-SVD [131]	70.43
IDL [131]	77.28
CAS-DL [132]	55.16
MCAS-DL	73.15
LC-MCAS-DL	**79.06**

TABLE 6.2_DATASET_3_D

Method	Recognition Accuracy (%)
SVDD	60.09
OC-SVM	61.21
SVM	62.30
KNN	51.28
SRC	51.88
K-SVD [117]	59.82
MMCP-K-SVD [128]	62.20
MRK-SVD [135]	63.19
MRAK-SVD [135]	64.18
LC-K-SVD [131]	73.71
IDL [131]	75.69
CAS-DL [132]	55.16
MCAS-DL	75.00
LC-MCAS-DL	**76.19**

TABLE 6.2_DATASET_4_A

Method	Recognition Accuracy (%)
SVDD	28.57
OC-SVM	54.87
SVM	55.10
KNN	14.09
SRC	26.09
K-SVD [117]	52.38
MMCP-K-SVD [128]	54.86
MRK-SVD [135]	54.56
MRAK-SVD [135]	59.72
LC-K-SVD [131]	60.31
IDL [131]	62.30
CAS-DL [132]	61.40
MCAS-DL	62.50
LC-MCAS-DL	**67.95**

TABLE 6.2_DATASET_4_B

Method	Recognition Accuracy (%)
SVDD	38.57
OC-SVM	63.98
SVM	54.39
KNN	13.59
SRC	35.62
K-SVD [117]	52.87
MMCP-K-SVD [128]	53.57
MRK-SVD [135]	40.60
MRAK-SVD [135]	66.07
LC-K-SVD [131]	65.97
IDL [131]	63.19
CAS-DL [132]	52.38
MCAS-DL	65.67
LC-MCAS-DL	**66.36**

TABLE 6.2_DATASET_4_C

Method	Recognition Accuracy (%)
SVDD	52.38
OC-SVM	58.04
SVM	64.68
KNN	48.31
SRC	50.00
K-SVD [117]	51.48
MMCP-K-SVD [128]	53.57
MRK-SVD [135]	54.66
MRAK-SVD [135]	55.25
LC-K-SVD [131]	55.85
IDL [131]	56.84
CAS-DL [132]	50.09
MCAS-DL	64.18
LC-MCAS-DL	**66.00**

TABLE 6.2_DATASET_4_D

Method	Recognition Accuracy (%)
SVDD	60.91
OC-SVM	58.53
SVM	63.29
KNN	49.70
SRC	51.68
K-SVD [117]	52.18
MMCP-K-SVD [128]	59.42
MRK-SVD [135]	53.07
MRAK-SVD [135]	53.57
LC-K-SVD [131]	54.06
IDL [131]	58.33
CAS-DL [132]	56.25
MCAS-DL	62.59
LC-MCAS-DL	**64.38**

TABLE 6.2_DATASET_5_A

Method	Recognition Accuracy (%)
SVDD	59.22
OC-SVM	62.79
SVM	54.16
KNN	53.47
SRC	48.21
K-SVD [117]	53.96
MMCP-K-SVD [128]	51.09
MRK-SVD [135]	53.17
MRAK-SVD [135]	55.35
LC-K-SVD [131]	55.56
IDL [131]	58.63
CAS-DL [132]	56.84
MCAS-DL	57.93
LC-MCAS-DL	**63.29**

TABLE 6.2_DATASET_5_B

Method	Recognition Accuracy (%)
SVDD	36.80
OC-SVM	61.40
SVM	52.38
KNN	49.80
SRC	33.73
K-SVD [117]	39.68
MMCP-K-SVD [128]	50.70
MRK-SVD [135]	51.48
MRAK-SVD [135]	53.47
LC-K-SVD [131]	54.46
IDL [131]	54.66
CAS-DL [132]	52.77
MCAS-DL	54.26
LC-MCAS-DL	**61.70**

TABLE 6.2_DATASET_5_C

Method	Recognition Accuracy (%)
SVDD	41.37
OC-SVM	61.21
SVM	65.00
KNN	48.31
SRC	46.83
K-SVD [117]	48.81
MMCP-K-SVD [128]	51.78
MRK-SVD [135]	52.08
MRAK-SVD [135]	53.37
LC-K-SVD [131]	53.86
IDL [131]	54.36
CAS-DL [132]	49.40
MCAS-DL	55.95
LC-MCAS-DL	**61.30**

TABLE 6.2_DATASET_5_D

Method	Recognition Accuracy (%)
SVDD	48.31
OC-SVM	60.61
SVM	63.29
KNN	46.72
SRC	48.01
K-SVD [117]	47.81
MMCP-K-SVD [128]	51.88
MRK-SVD [135]	51.68
MRAK-SVD [135]	52.67
LC-K-SVD [131]	52.87
IDL [131]	54.76
CAS-DL [132]	49.20
MCAS-DL	54.86
LC-MCAS-DL	**60.71**

TABLE 6.2_DATASET_6_A

Method	Recognition Accuracy (%)
SVDD	57.53
OC-SVM	52.48
SVM	54.16
KNN	44.44
SRC	44.65
K-SVD [117]	49.40
MMCP-K-SVD [128]	52.38
MRK-SVD [135]	60.51
MRAK-SVD [135]	61.90
LC-K-SVD [131]	61.01
IDL [131]	62.20
CAS-DL [132]	62.20
MCAS-DL	59.82
LC-MCAS-DL	**63.78**

TABLE 6.2_DATASET_6_B

Method	Recognition Accuracy (%)
SVDD	49.50
OC-SVM	48.41
SVM	52.38
KNN	40.18
SRC	41.56
K-SVD [117]	44.64
MMCP-K-SVD [128]	45.53
MRK-SVD [135]	56.64
MRAK-SVD [135]	57.24
LC-K-SVD [131]	57.63
IDL [131]	58.13
CAS-DL [132]	49.30
MCAS-DL	59.92
LC-MCAS-DL	**62.30**

TABLE 6.2_DATASET_6_C

Method	Recognition Accuracy (%)
SVDD	38.29
OC-SVM	61.50
SVM	60.91
KNN	47.81
SRC	54.66
K-SVD [117]	49.70
MMCP-K-SVD [128]	40.47
MRK-SVD [135]	55.75
MRAK-SVD [135]	57.14
LC-K-SVD [131]	57.73
IDL [131]	59.22
CAS-DL [132]	54.66
MCAS-DL	58.43
LC-MCAS-DL	**61.60**

TABLE 6.2_DATASET_6_D

Method	Recognition Accuracy (%)
SVDD	37.40
OC-SVM	59.22
SVM	59.42
KNN	47.42
SRC	51.68
K-SVD [117]	49.10
MMCP-K-SVD [128]	49.90
MRK-SVD [135]	50.00
MRAK-SVD [135]	51.48
LC-K-SVD [131]	52.77
IDL [131]	53.07
CAS-DL [132]	52.67
MCAS-DL	54.46
LC-MCAS-DL	**60.41**

Both state-of-the-art dictionary-based algorithms and well-established non-dictionary based algorithms have been considered for comparison purposes and the overall supremacy of the proposed **LC-MCAS-DL** algorithm has been clearly established from these experimentations. From the results reported it can also be seen that when the feature extraction was carried out using **FFT**, for each same size of feature vector chosen, the corresponding results obtained using **LC-MCAS-DL** algorithm was uniformly superior to the results obtained using **PCA** based feature extraction. From these extensive studies carried out and performance evaluations obtained, it can be inferred that the supremacy of **FFT** based feature selection with a choice of 6 features per signal is firmly established. As the best recognition accuracy of 93.55% was achieved with **LC-MCAS-DL** using Dataset_1_B, henceforth all performance evaluations are carried out based on this dataset where **FFT** based feature selection was carried out and a concatenated feature vector of size (24×1) obtained from four PIR sensors were used for evaluating all dictionary-learning and non-dictionary-learning based algorithms.

Once the feature vectors are created and **Y** is formed, an important aspect is initialization of the dictionary in achieving good performance. Encouraged by the previous works [128], [135], *k*-means clustering has been used to initialize the dictionary $\mathbf{D_0}$ with a clustering size of 50%. As presented in Stage 2 of Fig. 6.1, in the next step, the dictionary **D** is learned based on $\mathbf{D_0}$ and **Y** using the **DL** algorithm presented in Section 6.4. Next, this dictionary **D** is used to detect the presence of an intruder, in online scenario, following the detection algorithm described in Section 6.5.

As mentioned before, initial experiments are conducted to study the performance of **LC-K-SVD** [131] for different variations of α and β to learn the dictionary **D**. Motivated by [128], [135], the *Iterative-Reweighed-Least-Squares* (**IRLS**) algorithm is used both in dictionary learning as well as classification stage to solve the sparse coding stage and obtain sparse solutions respectively. The quantitative and graphical performance analysis of **LC-K-SVD** for different α and β are presented in Table 6.3 and Fig. 6.4 respectively, in solving the intruder detection problem at hand. It can be seen that the recognition accuracy of **LC-K-SVD** gets improved until the value of α and β reach a certain level and then, the recognition accuracy starts to decrease. A choice of α=20 and β=5 are found as the best combination achieving the intruder detection accuracy of 91.96%.

TABLE 6. 3: PERFORMANCE ANALYSIS OF LC- K-SVD WITH DIFFERENT α AND β

$\beta\downarrow$ $\alpha\rightarrow$	Recognition Accuracy (%)					
	1	2	5	10	20	30
0.5	63.49	64.68	64.48	73.90	69.44	68.15
1	64.38	65.07	66.47	74.90	75.39	68.94
2	64.88	65.87	70.13	77.77	78.37	69.34
3	65.37	66.36	78.67	81.34	89.28	72.12
5	**68.35**	**73.41**	81.34	**84.32**	**91.96**	**76.09**
10	67.95	69.34	**82.14**	78.86	79.36	75.69
20	67.75	68.84	65.57	75.09	70.40	73.51

TABLE 6. 4: PERFORMANCE ANALYSIS OF CAS-DL AND MCAS-DL FOR DIFFERENT CHOICES OF ζ AND γ

Initial value of ζ	**Recognition Accuracy (%)**					
	γ=2		γ=3		γ=6	
	CAS-DL	**MCAS-DL**	**CAS-DL**	**MCAS-DL**	**CAS-DL**	**MCAS-DL**
1	62.40	65.27	64.48	65.47	63.78	77.28
2	62.89	66.76	64.98	67.46	64.18	79.06
5	63.19	69.44	65.37	70.83	65.37	79.36
10	64.18	70.43	65.57	71.23	77.08	81.05
15	**64.48**	**71.72**	**67.46**	72.22	**78.86**	**85.09**
20	63.59	71.32	67.06	**72.32**	76.48	81.25

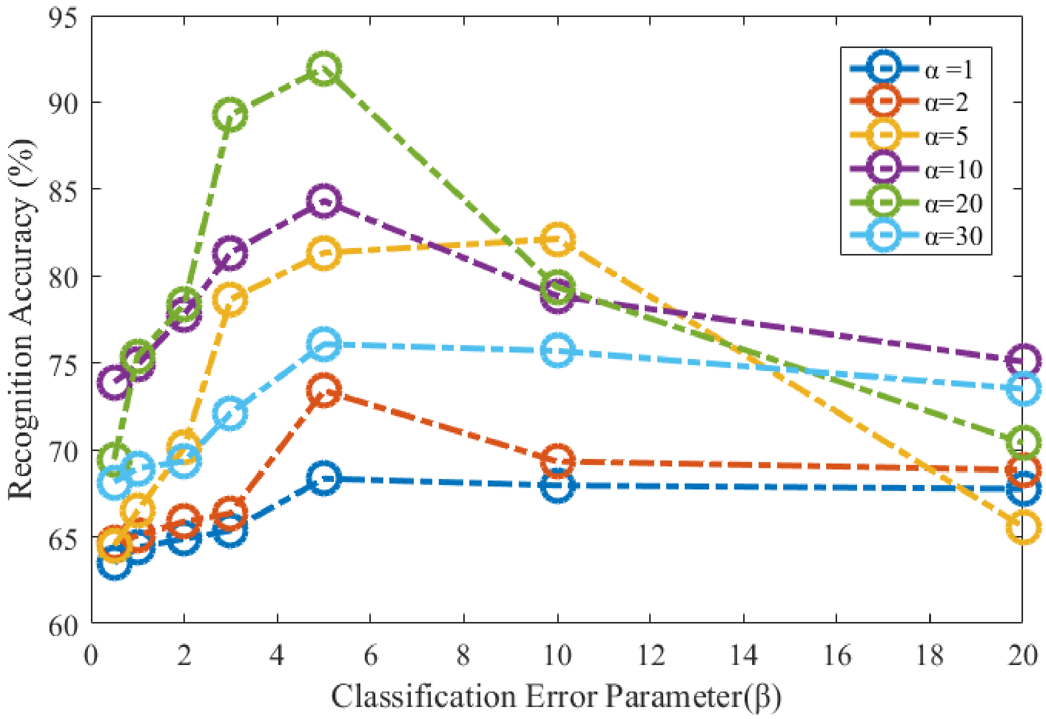


Fig. 6. 4. Performance variations in LC-K-SVD with α and β

Next, a detailed performance analysis and comparison of consistent adaptive sequential dictionary learning (**CAS-DL**) [132] and the modified version i.e., **MCAS-DL** algorithm is presented in Table 6.5, for different choices of the initial values of ζ and γ. Once **D** is learned, **SRC** based classifier is implemented for intruder detection. A limiting value of 0.4 is chosen for residual error in the detection stage. It can be seen that **MCAS-DL** consistently provided improved performances compared to **CAS-DL** and the best detection accuracy of 85.09% was achieved with a choice of γ=6 and ζ=15.

Armed with the reasonable success of **LC-K-SVD** and **MCAS-DL** algorithms as presented in Table 6.3 and Table 6.4, in the next step, a detailed performance analysis of the proposed **LC-MCAS-DL** algorithm for the purpose of intruder detection is presented in Table 6.5. Here, α=20 and β=5 are chosen fixed, obtained as the best combination in Table 6.3. From Table 6.4 the best recognition accuracy of 93.55% is obtained with α, β, ζ, and γ values of 20, 5, 15 and 6 respectively and when the initial dictionary is obtained using *k*-means algorithm.

TABLE 6. 5: PERFORMANCE ANALYSIS OF LC-MCAS-DL ALGORITHM FOR DIFFERENT CHOICES OF ζ AND γ

LC-MCAS-DL (D_0 obtained using *k*-means clustering)		**Recognition Accuracy (%)**	**LC-MCAS-DL (D_0 obtained using K-SVD [131])**		**Recognition Accuracy (%)**
γ=2	ζ=5	74.80	γ=2	ζ=5	77.28
	ζ=10	82.73		ζ=10	77.97
	ζ=15	84.72		ζ=15	86.40
	ζ=20	83.33		ζ=20	82.83
γ=3	ζ=5	73.41	γ=3	ζ=5	83.13
	ζ=10	82.83		ζ=10	85.81
	ζ=15	85.31		ζ=15	87.20
	ζ=20	84.82		ζ=20	83.63
γ=6	ζ=5	87.59	γ=6	ζ=5	84.42
	ζ=10	91.96		ζ=10	90.37
	ζ=15	**93.55**		ζ=15	**92.26**
	ζ=20	88.69		ζ=20	87.99

Finally, a comprehensive performance comparison of the proposed algorithms with other contemporary, state-of-the-art competing algorithms is shown in Table 6.6, both in terms of recognition accuracy and equal error rate (**EER**). Both well-established non-dictionary based algorithms and recently proposed related dictionary learning based algorithms have been used for the purpose of performance comparison. As mentioned before this comprehensive comparison has been reported on the basis of experiments carried out using Dataset_1_B. Hence these comprehensive performance results are presented based on 14 authorized persons and seven intruders, employing three-fold cross-validation mechanism. It has been firmly established in Table 6.6 that LC-**MCAS-DL** has emerged as the overall superior candidate algorithm for the intruder detection problem, both in terms of achieving highest recognition accuracy of 93.55% and lowest **EER** of 0.1%**.** In terms of recognition accuracy, **LC-K-SVD** emerged as the second best alternative with a recognition accuracy of 91.96%. In terms of **EER**, **MRAK-SVD** emerged as the second best alternative with an **EER** of 0.38%**.**

TABLE 6. 6: PERFORMANCE COMPARISON WITH OTHER COMPETING APPROACHES

Method	Recognition Accuracy (%)	Equal Error Rate (%)
SVDD	73.80	1.5
OC-SVM	72.02	1.8
SVM	53.00	3.4
KNN	66.67	2.8
SRC	47.34	4.5
CRC-RLS	61.50	2.5
K-SVD [117]	83.13	0.39
MMCP-K-SVD [128]	86.90	0.46
MRK-SVD [135]	89.09	0.49
MRAK-SVD [135]	90.38	0.38
LC-K-SVD [131]	91.96	0.41
IDL [131]	86.30	1.1
CAS-DL [132]	78.86	1.5
MCAS-DL	85.12	0.45
LC-MCAS-DL	**93.55**	**0.1**

Next, another detailed performance comparison of **LC-MCAS-DL**, **LC-K-SVD** and **MCAS-DL** in terms of accuracy, sensitivity, specificity, false positive rate (**FPR**), false rejection rate (**FRR**) and **EER** on the basis of Dataset_1_B is shown in Table 6.7. Here also, the supremacy of **LC-MCAS-DL** algorithm has been consistently established in terms of all performance metric considered. Fig. 6.5 shows the class specific performances for these three algorithms for the intruder detection problem at hand. Here also it can be seen that **LC-MCAS-DL** overall outperforms other two algorithms in recognizing both authorized persons and detecting presence of intruders in the restricted access area. Based on 10 sample consecutive executions of the classification method in online/implementation mode, it is determined that the average computation time required to detect an unauthorized/authorized person is 0.68 ±0.034 sec for LC-MCAS-DL based solution of the intruder detection problem.

TABLE 6. 7: PERFORMANCES COMPARISON IN TERMS OF ACCURACY, SENSITIVITY, SPECIFICITY, FPR, FRR AND EER

Method Used	**LC-MCAS-DL**	**LC-K-SVD**	**MCAS-DL**
Accuracy (%)	**93.55**	91.96	85.12
Sensitivity (%)	**93.55**	91.96	85.12
Specificity (%)	**99.68**	99.60	99.26
Precision (%)	**94.27**	92.79	87.68
False Positive Rate (%)	**0.32**	0.40	0.74
False Rejection Rate (%)	**6.48**	8.03	14.88
Equal Error Rate (%)	**0.10**	0.41	0.45

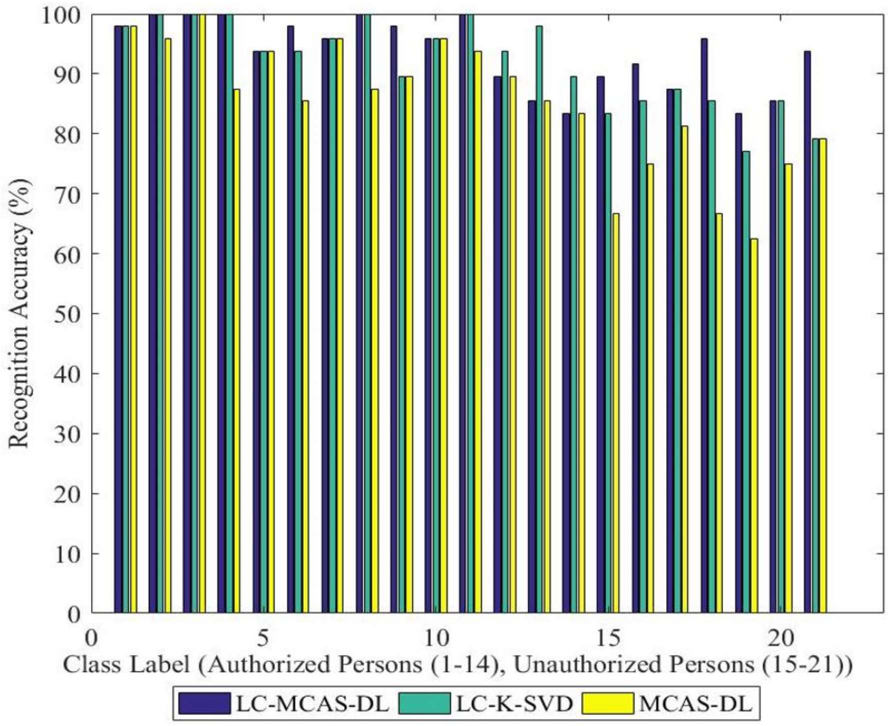


Fig. 6. 5. Class specific performances for fourteen authorized persons and seven unauthorized persons

6.7 Summary

In this Chapter, a novel **DL** algorithm called **LC-MCAS-DL** algorithm has been proposed for intruder detection problems in unmanned office or home environment. An indigenously developed low-cost hardware system, comprising four **PIR** sensors, a Robodyn Uno board, and an Ethernet interface module, is used in conjunction with a sophisticated software module, developed at the PC end, in real-time, in which the **LC-MCAS-DL** approach is implemented for intruder detection in a restricted access area. The **LC-MCAS-DL** algorithm has been developed by hybridizing the good features of **LC-K-SVD** and **CAS-DL** algorithms and proposing a modification in the **CAS-DL** module. According to extensive real-life experiments, it has been firmly established the supremacy of the proposed approach over several dictionary-based and non-dictionary-based state-of-the-art and well-established approaches.

CHAPTER 7

Conclusion

This present thesis work is focused on developing sensor based intelligent system incorporating sophisticated machine learning aided signal processing techniques with efficient decision making mechanism for monitoring **ADLs** in smart homes or in other indoor environment. This Chapter summarises the thesis work by drawing conclusions from the investigations covered in the earlier Chapters. Additionally, this thesis delineates a number of research directions for future studies.

7.1 Conclusion of the present Thesis Work

In this study, three prominent categories of **ADL** problems have been addressed. Those are human behavior identification problem, detection of the direction of human movement, and intruder detection. Several solution methodologies have been proposed for finding the solution of different **ADL** problems under consideration.

In this context, first, for finding the solution of human behavior identification problem, this present research work has proposed **K-SVD** dictionary learning based **SRC** classifier where sparse coding stage has been solved using **OMP** algorithm. In order to demonstrate the efficacy of this approach, an accelerometer data set with data corresponding to different human behaviors has been used. Furthermore, the proposed algorithm has demonstrated its efficiency in classifying/separating both bi-class behavior and multi-class behavior. Additionally, different variants of **K-SVD** algorithms by using different variation of greedy and relaxation algorithm, have been developed and successfully employed for human behavior recognition purposes. In order to establish more efficient **DL** algorithms for human behavior recognition, **IRLS** and **LS** based sparse coding stages have been hybridized with the **K-SVD** algorithm.

Next, the thesis work has shown how a general purpose low-cost, integrated system can be developed utilizing modern hardware and software designs for automated, intelligent monitoring of **ADL** activities in smart home or in indoor environment. This research work has shown how this module can be employed for developing low-cost **ADL** system.

In this regard, this research work has focused on another important category of **ADL** problem i.e., the human movement detection problem. This work has demonstrated how a recently proposed dictionary learning method, known as the **MCP** algorithm, can be effectively used to address the real-time detection of the direction of human movement detection problem. As part of this research, a new variant of **MCP** algorithm, referred as the modified **MCP** algorithm, is proposed, which can improve the accuracy of the **MCP** algorithm even further. The research has successfully shown how the performance of the **K-SVD** method can be enhanced by using the **MCP** algorithm and eventually improved more by employing the **MMCP** algorithm.

In this same context of detection of the direction of human movement, for improving the performance further, this research work has proposed another **DL** scheme based on the concept of regularization and established how this recently proposed regularised version of the **K-SVD** algorithm can be successfully applied to find an optimal solution. Both the **RK-SVD** and **RAK-SVD** have been successfully applied to the problem at hand and a modified version of both algorithms is proposed which uses novel methods for adapting the regularization parameter.

At last, this research work is focused on finding the solution of another important problem i.e., intruder detection in unmanned situation. Here, a novel **DL** algorithm called **LC-MCAS-DL** algorithm has been proposed and has been coupled with an indigenously developed low-cost hardware system in real time. **LC-MCAS-DL** is a hybrid algorithm that integrates the best features of **LC-K-SVD** and **CAS-DL**, and proposes modifications to the **CAS-DL** module.

7.2 Future Scope of Work

In the present scenario, being able to deliver a self-sufficient environment in the office or home by using an indigenously developed hardware-software combine module is considered as the fundamental requirement of any **AAL** system. In this context, it has been established that this sensor based integrated system coupled with several novel dictionary learning based approaches can be successfully employed to find the solution of many common **ADL** problems. Therefore, development of **DL** based systems for monitoring different activity in real environment are certain to have a positive influence on the workforce. Based on this premise, it can be concluded that research on such topics will gain popularity not just amongst academicians but also industrialists. This premise leads to the conclusion that research on such areas will become more popular among academics as well as businesspeople. Hence, it becomes necessary to keep improving the technologies associated with sensor based **ADL** monitoring system so that it can efficiently detect any kind of **ADL** activities in **AAL** environment. Several such ideas regarding future directions for research as an extension of the present work, are listed below.

- In this present work, the dictionary has been trained offline after creation of the training database using real signals acquired and then live **ADL** monitoring has been performed in real time based on the learned dictionary and high recognition accuracy has been achieved from performance analysis. In this context, in future, this work may focus on learning the dictionary for any **ADL** detection in online situation itself for the experimental platform developed in the laboratory and also, can investigate the real time recognition performance of such systems.

- Developing the sensor based integrated system with suitable scaling to sense more than eight directions in human movement detection problem, if there is an availability of such sensors in market, with a better spatial resolution.

- Developing similar low-cost, integrated systems in future, using new dictionary learning-based approaches for further improvement in sophistication and accuracy, will consider a variety of challenging situations like the observation area having obstacles in it, having different shapes etc. and also will investigate robustness for other classes of **AAL** problems like fall detection, human tracking, etc.

- The impact of limitation in the use of **PIR** sensor, possible noise causes and disturbance may have influence on the detection accuracy and that can be addressed in future for enhancing the performance of the system even further.

- Developing different new varieties of dictionary initialization methods by introducing e.g. different variants of *K-Medoid* clustering method such as distribution distance metrics based *K-Medoid, supervised similarity measure based K-Medoid, Tabu search based iterative K-Medoid clustering*, etc. and their modified versions so that the performance of **ADL** detection can be enhanced.

- In this present work, suitable values of hypermeters have been chosen based on extensive manual tuning to evaluate performance, for example as shown in Chapter 5 in pg.119 and in Chapter 6 in pg. 157. However, these hyper-parameters can also be obtained, in future, by configuring the problem as an optimization problem and then using e.g. a suitable metaheuristic/evolutionary algorithm to solve it. For example, Eq. 5.5 in Chapter 5 or Eq. 6.10 in Chapter 6 can be solved in this manner.

Bibliography

[1] C. Debes, A. Merentitis, and S. Sukhanov, “Monitoring Activities of Daily Living in Smart Homes: Understanding human behavior,” *IEEE Signal Processing Magazine*, vol. 33, no. 2, pp. 81-94, March., 2016. DOI:10.1109/MSP.2015.2503881

[2] F. Erden, S. Velipasalar, and A. Z. Alkar, “Sensors in assisted living: a survey of signal and image processing methods,” *IEEE Signal Processing Magazine*, vol. 33, no. 2, pp. 36-44, March. 2016. DOI:10.1109/MSP.2015.2489978

[3] A. Yazar, F. Keskin , B. U. Töreyin, A. Cetin “Fall detection using single-tree complex wavelet transform,” *Pattern Recognit. Lett.*, vol. 34, no. 15, pp. 1945–1952, 2013. https://doi.org/10.1016/j.patrec.2012.12.010

[4] B. Andò, S. Baglio, C. O. Lombardo, and V. Marletta, “RESIMA: Adaptive paradigms for the user localization in indoor environments,” in *Proc. IEEE Int. Instrum. and Meas. Technology Conf. (I2MTC)*, Italy, May, 2015. DOI: 10.1109/I2MTC.2015.7151411

[5] Q. Hao, D. J. Brady, B. D. Guenther, J. B. Burchett, M. Shankar, and S. Feller, “Human tracking with wireless distributed pyroelectric sensors,” *IEEE Sensors J.*, vol. 6, no. 6, pp. 1683–1696, Dec. 2006. DOI**:** 10.1109/JSEN.2006.884562

[6] B. Bruno, F. Mastrogiovanni, A. Sgorbissa, T. Vernazza, and R. Zaccaria, “Human motion modelling and recognition: A computational approach*,” in Proc. IEEE Int. Conf. Automation Science and Engineering (CASE)*, Aug. 2012, pp. 156-161. DOI: 10.1109/CoASE.2012.6386410

[7] Y. Wang, S. Cang and H. Yu, "A data fusion-based hybrid sensory system for older people’s daily activity and daily routine recognition", *IEEE Sensors J.*, vol. 18, no. 16, pp. 6874-6888, Aug. 2018. https://doi.org/10.1109/jsen.2018.2833745

[8] H. Gjoreski, M. Lustrek and M. Gams, "Accelerometer placement for posture recognition and fall detection", *Proc. 7th Int. Conf. Intell. Environments*, pp. 47-54, Jul. 2011. DOI: 10.1109/IE.2011.11

[9] L. Atallah, B. Lo, R. Ali, R. King and G.-Z. Yang, "Real-time activity classification using ambient and wearable sensors", *IEEE Transactions on Information Technology in Biomedicine*, vol. 13, no. 6, pp. 1031-1039, 2009. DOI: 10.1109/TITB.2009.2028575

[10] R.J. Lemmens, H. A. Seelen, A. A. Timmermans, M. L. Schnackers, A. Eerden, R.J. Smeets, et al., "To What Extent Can Arm-Hand Skill Performance of Both Healthy Adults and Children be Recorded Reliably Using Multiple Bodily Worn Sensor Devices?", *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 23, no. 4, pp. 581-590, 2015. DOI: 10.1109/TNSRE.2015.2396082

[11] N. A. Choudhury, S. Moulik and D. S. Roy, "Physique-based human activity recognition using ensemble learning and smartphone sensors", *IEEE Sensors J.*, vol. 21, no. 15, pp. 16852-16860, Aug. 2021. https://doi.org/10.3390/s22093401

[12] R. Amstutz et al., "Performance analysis of an hmm-based gesture recognition using a wristwatch device", *IEEE CSE*, Aug 2009. DOI: 10.1109/CSE.2009.58

[13] G. Paolini, D. Masotti, F. Antoniazzi, T. Salmon Cinotti and A. Costanzo, "Fall Detection and 3-D Indoor Localization by a Custom RFID Reader Embedded in a Smart e-Health Platform", *IEEE Transactions on Microwave Theory and Techniques*, vol. 67, no. 12, pp. 5329-5339, December 2019. DOI: 10.1109/TMTT.2019.2939807

[14] A. K. Triantafyllidis, V. G. Koutkias, I. Chouvarda and N. Maglaveras, "A Pervasive Health System Integrating Patient Monitoring Status Logging and Social Sharing", *IEEE Journal of Biomedical and Health Informatics*, vol. 17, no. 1, pp. 30-37, 2013. DOI:10.1109/TITB.2012.2227269

[15] A. Fleury, M. Vacher and N. Noury, "SVM-based multimodal classification of activities of daily living in health smart homes: Sensors algorithms and first experimental results", *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 2, pp. 274-283, Mar. 2010. DOI: 10.1109/TITB.2009.2037317

[16] L. F. Xiong and J. Liu, "Fusion of different height pyroelectric infrared sensors for person identification", *IEEE Sensors J.*, vol. 16, no. 2, pp. 436-446, Jan. 2016. DOI: 10.1109/JSEN.2015.2454000

[17] S. O. Al-Jazzar, S. A. Aldalahmeh, D. McLernon and S. A. R. Zaidi, "Intruder localization and tracking using two pyroelectric infrared sensors", *IEEE Sensors J.*, vol. 20, no. 11, pp. 6075-6082, Jun. 2020. DOI: 10.1109/JSEN.2020.2974633

[18] Y. W. Bai, Z. L. Xie, and C. C. Cheng, "New approach to passive infrared motion sensors signal processing for Ambient Assisted Living Applications," *Proc. IEEE Int. Instrum. and Meas. Technology Conf.*, Austria, July, 2012. DOI: 10.1109/I2MTC.2012.6229464

[19] U. Gopinathan, D. J. Brady, and N. P. Pitsianis, "Coded apertures for efficient pyroelectric motion tracking," *Optics Express*, vol. 11, no. 18, pp. 2142-2152, Sept. 2003. https://doi.org/10.1364/OE.11.002142

[20] M. Shankar, J. B. Burchett, Q. Hao, B. D. Guenther, and D. J. Brady, "Human-tracking systems using pyroelectric infrared detectors," *Opt. Eng.*, vol. 45, no. 10, pp. Oct. 2006. DOI:10.1117/1.2360948

[21] Q. Hao, F. Hu, and Y. Xiao, “Multiple human tracking and identification with wireless distributed pyroelectric sensor systems,” *IEEE Sensors J*, vol. 3, no. 4, pp. 428–439, Dec. 2009. DOI: 10.1109/JSYST.2009.2035734

[22] P. Zappi, E. Farella, and L. Benini, “Tracking motion direction and distance with pyroelectric IR sensors,” *IEEE Sensors J.*, vol. 10, no. 9, pp. 1486–1494, Sep. 2010. DOI: 10.1109/JSEN.2009.2039792

[23] J. Yun, and M.H. Song, “Detecting Direction of Movement Using Pyroelectric Infrared Sensors,” *IEEE Sensors J.*, vol. 14, no. 5, pp. 1482–1489, May. 2014. DOI: 10.1109/JSEN.2013.2296601

[24] X. Jin, S. Sarkar, A. Ray, S. Gupta, and T. Damarla, “Target Detection and Classification Using Seismic and PIR Sensors,” *IEEE Sensors J.*, vol. 12, no. 6, pp. 1709–1718, June. 2012. DOI: 10.1109/JSEN.2011.2177257

[25] L. Vuegen, B. Van Den Broeck, P. Karsmakers, H. Van Hamme and B. Vanrumste, "Automatic monitoring of activities of daily living based on real-life acoustic sensor data: A preliminary study", *Proc. Workshop on Speech and Language Processing for Assistive Technologies*, vol. 4, pp. 113-118, 2013. ISBN: 978-1-937284-93-0

[26] K. Doughty and J. Costa, “Continuous automated telecare assessment of the elderly,” *J. Telemed. Telecare*, vol. 3, no. 1, pp. 23–25, 1997. DOI: 10.1258/1357633971930247

[27] K. Z. Haigh, L. M. Kiff, and G. Ho, “The independent lifestyle assistant: Lessons learned,” *Assist. Technol.*, vol. 18, no. 1, pp. 87–106, 2006. DOI:10.1080/10400435.2006.10131909

[28] J. Han and B. Bhanu, “Human activity recognition in thermal infrared imagery,” *Proc. IEEE Computer Society Conf. Computer Vision and Pattern Recognition*, 2005, pp. 17–17. DOI: 10.1109/CVPR.2005.469

[29] P. Hevesi, S. Wille, G. Pirkl, N. Wehn, and P. Lukowicz, “Monitoring household activities and user location with a cheap, unobtrusive thermal sensor array,” *Proc. ACM Int. Joint Conf. Pervasive and Ubiquitous Computing*, 2014, pp. 141–145. https://doi.org/10.1145/2632048.2636084

[30] Y. Zigel, D. Litvak, and I. Gannot, “A method for automatic fall detection of elderly people using floor vibrations and sound - proof of concept on human mimicking doll falls,” *IEEE Trans. Biomed. Eng.*, vol. 56, no. 12, pp. 2858–2867, 2009. DOI: 10.1109/TBME.2009.2030171

[31] S. S. Intille, K. Larson, J. S. Beaudin, J. Nawyn, E. M. Tapia, and P. Kaushik, “A living laboratory for the design and evaluation of ubiquitous computing technologies,” *Proc. CHI’05 Extended Abstracts on Human Factors in Computing Systems*, 2005, pp. 1941–1944. https://doi.org/10.1145/1056808.1057062

[32] T. Tsukiyama, “Ambient sensor system for in-home health monitoring,” *Proc. The 4th Int. Conf. Ambient Computing, Applications, Services and Technologies*, 2014, pp. 47–50. DOI:10.1016/j.eswa.2012.01.153

[33] L. Hu, Y. Chen, S. Wang, and L. Jia, “A nonintrusive and single point infrastructure-mediated sensing approach for water-use activity recognition,” *Proc. IEEE Int. Conf. Embedded and Ubiquitous Computing*, 2013, pp. 2120–2126. DOI: 10.1109/HPCC.and.EUC.2013.304

[34] J. H. Lim, H. Jang, J. Jang, and P. Soo-Jun, “Daily activity recognition system for the elderly using pressure sensors,” *Proc. Engineering in Medicine and Biology Society*, 2008, pp. 5188–5191. DOI: 10.1109/IEMBS.2008.4650383

[35] A. Glascock and D. Kutzik, “Behavioral telemedicine: A new approach to the continuous nonintrusive monitoring of activities of daily living,” *Telemed. J.*, vol. 6, no. 1, pp. 33–34, 2004. DOI:10.1089/107830200311833

[36] A. Fleury, N. Noury, M. Vacher, H. Glasson, and J. F. Seri, “Sound and speech detection and classification in a health smart home,” in *Proc. 30th Annu. Int. Conf. Engineering in Medicine and Biology Society, 2008, pp.4644–4647.* DOI: 10.1109/IEMBS.2008.4650248

[37] G. C. Franco, F. Gallay, M. Berenguer, C. Mourrain, and P. Couturier, “Non invasive monitoring of the activities of daily living of elderly people at home—A pilot study of the usage of domestic appliances,” *J. Telemed. Telecare*, vol. 14, no. 5, pp. 231–235, 2008. DOI: 10.1258/jtt.2008.071207

[38] Y.W. Bai, Z. L. Xie, and C. C. Cheng, “Use of a multi-frequency relay of ultrasonic sensors with PIR sensors to extend the sensing range of an embedded surveillance system,” in *Proc. IEEE Int. Instrum. and Meas. Technology Conf.*, Austria, July, 2012. DOI: 10.1109/I2MTC.2012.6229206

[39] Z. Han, R. X. Gao, and Z. Fan, “Occupancy and indoor environment quality sensing for smart buildings,” in *Proc. IEEE Int. Instrum. and Meas. Technology Conf.*, Austria, July, 2012. DOI: 10.1109/I2MTC.2012.6229557

[40] M. Chan, D. Estve, C. Escriba and E. Campo, "A review of smart homes—present state and future challenges", *Comput. Methods Programs Biomed.*, vol. 91, no. 1, pp. 55-81, 2008. https://doi.org/10.1016/j.cmpb.2008.02.001

[41] P. Rashidi and D. J. Cook, "Keeping the resident in the loop: Adapting the smart home to the user," *IEEE Trans. Syst. Man Cybern. Part A Syst. Hum.*, vol. 39, no. 5, pp. 949–959, 2009. DOI: 10.1109/TSMCA.2009.2025137

[42] C. Lin-Wu, "Nonparametric activity recognition system in smart homes based on heterogeneous sensor data," *IEEE Transactions on Automation Science and Engineering*, vol. 16, no. 2, pp. 949–959, April. 2019. DOI: 10.1109/TASE.2018.2846795

[43] "Ambient Assisted Living [Guest editors' introduction]", *IEEE Intelligent Systems*, vol. 30, no. 4, pp. 2-6, Jul.-Aug. 2015. DOI: 10.1109/MIS.2015.63

[44] C. Will, P. Vaishnav, A. Chakraborty and A. Santra, "Human target detection tracking and classification using 24-GHz FMCW radar", *IEEE Sensors J.*, vol. 19, no. 17, pp. 7283-7299, Sep. 2019. DOI: 10.1109/JSEN.2019.2914365

[45] B. Andò, S. Baglio, C. O. Lombardo, and V. Marletta, "An Event Polarized Paradigm for ADL Detection in AAL Context," *IEEE Trans. Instrum. Meas.*, vol. 64, no. 7, pp. 1814-1825, July. 2015. DOI: 10.1109/TIM.2014.2385144

[46] M. J. Rantz, M. Skubic, S. J. Miller, C. Galambos, G. Alexander, J. Keller, and M. Popescu, "Sensor technology to support aging in place," *J. Amer. Med. Dir. Assoc.*, vol. 14, no. 6, pp. 386–391, 2013. DOI:10.1016/j.jamda.2013.02.018

[47] T. L. M. Van Kasteren, A. Noulas, G. Englebienne, and B. J. A.Kröse, “Accurate activity recognition in a home setting,” *Proc. ACM Int. Joint Conf. Pervasive and Ubiquitous Computing*, 2008,pp. 1–9. https://doi.org/10.1145/1409635.1409637

[48] S. Chen, H. Xu, D. Liu, B. Hu and H. Wang, “A vision of IOT: Applications challenges and opportunities with China perspective,” *IEEE Internet Things J.*, vol. 1, no. 4, pp. 349-359, Aug. 2014. DOI: 10.1109/JIOT.2014.2337336

[49] M. Handte, S. Foell, S. Wagner, G. Kortuem and P. J. Marrón, "An Internet-of-Things enabled connected navigation system for urban bus riders,” *IEEE Internet Things J.*, vol. 3, no. 5, pp. 735-744, Oct. 2016. DOI: 10.1109/JIOT.2016.2554146

[50] S. Kumar, S. Swetha, V. T. Kiran and P. Johri, "IoT based smart home surveillance and automation", in *Proc. Int. Conf. Comput. Power Commun. Technol. (GUCON)*, Sep. 2018, pp. 786-790. DOI: 10.1109/GUCON.2018.8674999

[51] Y.W. Bai and Y.T. Ku, “Automatic room light intensity detection ancontrol using a microprocessor and light sensors,” *IEEE Trans. Consum. Electron*., vol. 54, no. 3, pp. 1173-1176, Aug. 2008. DOI:10.1109/ISCE.2008.4559538

[52] E. Zdravevski, P. Lameski, V. Trajkovik, A. Kulakov, I. Chorbev; R. Goleva; N. Pombo, and N. Garcia, “Improving Activity Recognition Accuracy in Ambient-Assisted Living Systems by Automated Feature Engineering,” *IEEE Access* 2017, 5, 5262–5280. DOI: 10.1109/ACCESS.2017.2684913

[53] Al Machot, F.; Haj Mosa, A.; Ali, M.; Kyamakya, K. “Activity Recognition in Sensor Data Streams for Active and Assisted Living Environments,” *IEEE Trans. Circuits Syst. Video Technol*. 2018, 5, 951–953. DOI: 10.1109/TCSVT.2017.2764868

[54] J. Yu, "Health Condition Monitoring of Machines Based on Hidden Markov Model and Contribution Analysis," *IEEE Trans. Instrum. Meas.,* vol. 61, no. 8, pp. 2200-2211, Aug. 2012. DOI: 10.1109/TIM.2012.2184015

[55] G. Panahandeh, N. Mohammadiha, A. Leijon, and P. Händel, "Continuous Hidden Markov Model for Pedestrian Activity Classification and Gait Analysis," *IEEE Trans. Instrum. Meas.,* vol. 62, no. 5, pp. 1073-1083, May. 2013. DOI: 10.1109/TIM.2012.2236792

[56] P. Turaga, R. Chellappa, V. S. Subrahmanian, and O. Udrea, "Machine recognition of human activities: A survey," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 18, no. 11, pp. 1473–1488, Nov. 2008. DOI: 10.1109/TCSVT.2008.2005594

[57] X. Li, "HMM-based action recognition using oriented histograms of optical flow field," *Electron. Lett*., vol. 43, no. 10, pp. 560–561, 2007. DOI:10.1049/el:20070027

[58] R. Amstutz, O. Amft, and B. French, "Performance Analysis of an HMM-Based Gesture Recognition Using a Wristwatch Device," in *Proc. Int. Conf. Computational Science and Engineering (CSE),* Vancouver, BC, Canada, Aug. 2009, pp. 303-309. DOI: 10.1109/CSE.2009.58

[59] K. Bousmalis, S. Zafeiriou, L. Morency, and M. Pantic, "Infinite Hidden Conditional Random Fields for Human Behavior Analysis," *IEEE Trans. Neural Networks and Learning Systems*, vol. 24, no. 1, pp. 170-177, Jan. 2013. DOI: 10.1109/TNNLS.2012.2224882

[60] E. Nazerfard, B. Das, L. B. Holder, and D. J. Cook, "Conditional random fields for activity recognition in smart environments," in *Proc. 1st ACM International Health*

Informatics Symposium, Nov. 2010, pp. 282-286. https://doi.org/10.1145/1882992.1883032

[61] Mitchell, T. Machine Learning; McGraw Hill: New York, NY, USA, 1997. ISBN 0070428077.

[62] Bishop, C. Pattern Recognition and Machine Learning; Springer: Berlin/Heidelberg, Germany, 2006. ISBN-13: 978-0387-31073-2

[63] B. Bruno, F. Mastrogiovanni, A. Sgorbissa, T. Vernazza, and R. Zaccaria, “Analysis of human behavior recognition algorithms based on acceleration data,” in *Proc. IEEE Int. Conf. Robotics and Automation (ICRA)*, Germany, May 2013, pp. 1602-1607. DOI: 10.1109/ICRA.2013.6630784

[64] G. Donaj, M.S. Maučec, “Extension of HMM-Based ADL Recognition With Markov Chains of Activities and Activity Transition Cost,” *IEEE Access* , vol. 7, pp. 130650–130662, Aug. 2019. DOI: 10.1109/ACCESS.2019.2937350

[65] F. Martinez-Contreras, C. Orrite-Urunuela, and E. Herrero-Jaraba, “Recognizing Human Actions Using Silhouette-based HMM,” in *Proc. 6th IEEE Int. Conf. Advanced Video and Signal Based Surveillance(AVSS)*, Genova, Italy, Sept. 2009, pp. 43-48. DOI: 10.1109/AVSS.2009.46

[66] V. Vapnik, The nature of statistical learning theory. New York: Springer, 1995. http://dx.doi.org/10.1007/978-1-4757-2440-0

[67] S. Chernbumroong, S. Cang, A. Atkins, and H. Yu, “Elderly activities recognition and classification for applications in assisted living,” Expert Syst. Appl., vol. 40, no. 5, pp. 1662–1674, 2013. https://doi.org/10.1016/j.eswa.2012.09.004

[68] T. Huy`nh, U. Blanke, and B. Schiele, “Scalable recognition of daily activities with wearable sensors,” in *Proc. Location-and Context-Awareness,* 2007, pp. 50–67. DOI:10.1007/978-3-540-75160-1_4

[69] M. Skubic, R. D. Guevara and M. Rantz, "Automated health alerts using in-home sensor data for embedded health assessment", *IEEE Journal of Translational Engineering in Health and Medicine*, vol. 3, pp. 1-11, 2015. DOI: 10.1109/JTEHM.2015.2421499

[70] A. Julazadeh, M. Marsousi and J. Alirezaie, "Classification based on sparse representation and euclidian distance", *Proc. Vis. Commun. Image Process.*, pp. 1-5, 2012. DOI:10.1109/VCIP.2012.6410815

[71] N. H. Dardas, N. D. Georganas, “Real-Time Hand Gesture Detection and Recognition Using Bag-of-Features and Support Vector Machine Techniques,” *IEEE Trans. Instrum. Meas.*, vol. 60, no. 11, pp. 3592-3607, Nov. 2011. DOI: 10.1109/TIM.2011.2161140

[72] A. H. Sanoob, J. Roselin and P. Latha, "Smartphone enabled intelligent surveillance system,” *IEEE Sens. J.*, vol. 16, no. 5, pp. 1361-1367, Mar. 2016. DOI: 10.1109/JSEN.2015.2501407

[73] S. Nico and W. Ridwan, "Design of Smart Home Security System using Object Recognition and PIR Sensor", *Procedia Computer Science, vol. 135, pp. 465-472, 2018.* https://doi.org/10.1016/j.procs.2018.08.198

[74] D. Yang, W. Sheng and R. Zeng, "Indoor human localization using PIR sensors and accessibility map,” *Proc. IEEE Int. Conf. Cyber Technol. Automat. Control Intell. Syst. (CYBER)*, Jun. 2015, pp. 577-581. DOI: 10.1109/CYBER.2015.7288004

[75] L. Hu and Q. Ni, "IoT-driven automated object detection algorithm for urban surveillance systems in smart cities," *IEEE Internet Things J.*, vol. 5, no. 2, pp. 747-754, Apr. 2018. DOI: 10.1109/JIOT.2017.2705560

[76] B. Mukhopadhyay, S. Anchal and S. Kar, "Detection of an intruder and prediction of his state of motion by using seismic sensor," *IEEE Sens. J.*, vol. 18, no. 2, pp. 703-712, Jan. 2018. DOI: 10.1109/JSEN.2017.2776127

[77] Aggarwal, C.C. Neural Networks and Deep Learning; Springer: Berlin/Heidelberg, Germany, 2018. ISBN: 978-3-319-94463-0

[78] R. Mojarad, F. Attal, A. Chibani and Y. Amirat, "Automatic classification error detection and correction for robust human activity recognition", *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 2208-2215, 2020. DOI: 10.1109/LRA.2020.2970667

[79] V. Bianchi, M. Bassoli, G. Lombardo, P. Fornacciari, M. Mordonini and I. De Munari, "IoT wearable sensor and deep learning: An integrated approach for personalized human activity recognition in a smart home environment", *IEEE Internet Things J.*, vol. 6, no. 5, pp. 8553-8562, Oct. 2019. DOI: 10.1109/JIOT.2019.2920283

[80] A. Chowdhury, S. Bhattacharya, A. Ghose, B. Krishnan, "Early Detection of Mild Cognitive Impairment using Pervasive Sensing," *Proc. of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Berlin, Germany, 23–27 July 2019. DOI: 10.1109/EMBC.2019.8856435

[81] P. Gupta, R. McClatchey and P. Caleb-Solly, "Tracking changes in user activity from unlabelled smart home sensor data using unsupervised learning methods", *Neural Computing and Applications*, 2020. https://doi.org/10.1007/s00521-020-04737-6

[82] B. Ni, G. Wang and P. Moulin, "RGBD-HuDaAct: A color-depth video database for huamn daily activity recognition", *Proc. IEEE Workshop Consum. Depth Cameras Comput. Vision*, pp. 1147-1153, 2011. DOI:10.1109/ICCVW.2011.6130379

[83] E. Ramanujam, T. Perumal and S. Padmavathi, "Human activity recognition with smartphone and wearable sensors using deep learning techniques: A review", *IEEE Sensors J.*, vol. 21, no. 12, pp. 13029-13040, Jun. 2021. DOI: 10.1109/JSEN.2021.3069927

[84] E. De-La-Hoz-Franco, P. Ariza-Colpas, J. M. Quero and M. Espinilla, "Sensor-based datasets for human activity recognition—A systematic review of literature", *IEEE Access*, vol. 6, pp. 59192-59210, 2018. DOI: 10.1109/ACCESS.2018.2873502

[85] H. Elahi, A. Castiglione, G. Wang and O. Geman, "A Human-centered artificial intelligence approach for privacy protection of elderly App users in smart cities", *Neurocomputing*, vol. 444, pp. 189-202, Jul. 2021. DOI:10.1016/j.neucom.2020.06.149

[86] P. Lameski, A. Dimitrievski, E. Zdravevski, V. Trajkovik and S. Koceski, "Challenges in data collection in real-world environments for activity recognition", *Proc. IEEE 18th Int. Conf. Smart Technol. (EUROCON)*, pp. 1-5, Jul. 2019. DOI: 10.1109/EUROCON.2019.8861964

[87] J. Wright, A. Yang, A. Ganesh, S. Sastry, and Yi Ma, "Robust Face Recognition via Sparse Representation," *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 31, no. 2, pp. 210-227, Feb. 2009. DOI: 10.1109/TPAMI.2008.79

[88] J.Yang, J.Wang, and T. Huang, "Learning the sparse representation for classification," *IEEE Int. Conf. Multimedia and Expo (ICME)*, Sep. 2011. DOI: 10.1109/ICME.2011.6012083

[89] M. Elad and M. Aharon, "Image Denoising Via Sparse and Redundant Representations Over Learned Dictionaries," *IEEE Trans. Image Processing*, vol. 15, no. 12, pp. 3736-3745, Dec. 2006. DOI: 10.1109/TIP.2006.881969

[90] M. Aharon, M. Elad, and A. Bruckstein, "K-SVD: An Algorithm for Designing Overcomplete Dictionaries for Sparse Representation", *IEEE Trans. Signal Processing*, vol. 54, no. 11, pp. 4311-4322, Dec. 2006. DOI: 10.1109/TSP.2006.881199

[91] I. Tošić and P. Frossard, "Dictionary learning", *IEEE Signal Processing Magazine*, vol. 28, no. 2, pp. 27-38, 2011. DOI:10.1109/MSP.2010.939537

[92] R. Rubinstein, A. M. Bruckstein and M. Elad, "Dictionaries for sparse representation modeling", *Proc. IEEE*, vol. 98, no. 6, pp. 1045-1057, Jun. 2010. http://dx.doi.org/10.1109/JPROC.2010.2040551

[93] B.A. Olshausen and D.J. Field, "Emergence of Simple-Cell Receptive Field Properties by Learning a Sparse Code for Natural Images", *Nature*, vol. 381, pp. 607-609, 1996. DOI:10.1038/381607a0

[94] S. Joardar, A. Chatterjee, and A. Rakshit, "Real-time NIR imaging of Palm Dorsa subcutaneous vein pattern based biometrics: An SRC based approach," *IEEE Trans. Instrum. Meas.*, vol. 19, no. 2, pp. 13-19, April. 2016. DOI: 10.1109/MIM.2016.7462787

[95] K. Engan, S. O. Aase and J. H. Hakon-Husoy, "Method of optimal directions for frame design", *IEEE Int. Conf. Acoust. Speech Signal Process.*, vol. 5, pp. 2443-2446, 1999. DOI: 10.1109/ICASSP.1999.760624

[96] K. Engan, B. D. Rao and K. Kreutz-Delgado, "Frame design using focuss with method of optimal directions (mod)", *Norwegian Signal Process. Symp.*, vol. 65-69, 1999. https://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.719.8961.

[97] S. Lesage, R. Gribonval, F. Bimbot and L. Benaroya, "Learning unions of orthonormal bases with thresholded singular value decomposition", *Proc. IEEE Int. Conf. Acoust. Speech Signal Process. (ICASSP)*, pp. v/293, Mar. 2005. DOI: 10.1109/ICASSP.2005.1416298

[98] R. Vidal, Y. Ma and S. Sastry, "Generalized principal component analysis (GPCA)", *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 27, no. 12, pp. 1945-1959, Dec. 2005. DOI: 10.1109/CVPR.2003.1211411

[99] M. Elad, Sparse and Redundant Representations: From Theory to Applications in Signal and Image Processing, Springer, 2010. DOI: 10.1007/978-1-4419-7011-4

[100] Y. Kong, T. Wang, F. Chu, Z. Feng and I. Selesnick, "Discriminative dictionary learning-based sparse classification framework for data-driven machinery fault diagnosis", *IEEE Sensors J.*, vol. 21, no. 6, pp. 8117-8129, Mar. 2021. DOI: 10.1109/JSEN.2021.3049953

[101] H. Chen and S.-J. Kim, "Robust RF mixture signal recognition using discriminative dictionary learning", *IEEE Access*, vol. 9, pp. 141107-141120, 2021. DOI:10.1109/access.2021.3120635

[102] G. Tauböck, S. Rajbamshi and P. Balazs, "Dictionary learning for sparse audio inpainting", *IEEE Journal of Selected Topics in Signal Processing*, vol. 15, no. 1, pp. 104-119, 2021. DOI: 10.1109/JSTSP.2020.3046422

[103] Z. Yang, J. Deng and A. Nallanathan, "Moving target recognition based on transfer learning and three-dimensional over-complete dictionary", *IEEE Sensors J.*, vol. 16, no. 14, pp. 5671-5678, Jul. 2016. DOI: 10.1109/JSEN.2016.2568462

[104] A. He, G. Wei, J. Yu, Z. Tang, Z. Lin and P. Wang, "A novel dictionary learning method for gas identification with a gas sensor array", *IEEE Trans. Ind. Electron.*, vol. 64, no. 12, pp. 9709-9715, Dec. 2017. DOI: 10.1109/TIE.2017.2748034

[105] S. Singh, R. S. Anand, “Multimodal Medical Image Sensor Fusion Model Using Sparse K-SVD Dictionary Learning in Nonsubsampled Shearlet Domain,” *IEEE Trans. Instrum. Meas.* (early access), pp. 1-15, April. 2019. DOI: 10.1109/TIM.2019.2902808

[106] H. Li, Y. Wang, Z. Yang, R. Wang, X. Li, and D. Tao, “Discriminative dictionary learning-based multiple component decomposition for detail-preserving noisy image fusion,” *IEEE Trans. Instrum. Meas.* (early access), April. 2019. DOI: 10.1109/TIM.2019.2912239

[107] I. Diamant, E. Klang, M. Amitai, E. Konen, J. Goldberger and H. Greenspan, "Task-driven dictionary learning based on mutual information for medical image classification", *IEEE Trans. Biomed. Eng.*, vol. 64, no. 6, pp. 1380-1392, Jun. 2017. DOI: 10.1109/TBME.2016.2605627

[108] X. Gong, W. Chen and J. Chen, "A low-rank tensor dictionary learning method for hyperspectral image denoising", *IEEE Trans. Signal Process.*, vol. 68, pp. 1168-1180, 2020. DOI: 10.1109/TSP.2020.2971441

[109] A.K. Seghouane and A. Iqbal, "Sequential dictionary learning from correlated data: Application to fMRI data analysis", *IEEE Trans. Image Process.*, vol. 26, no. 6, pp. 3002-3015, Jun. 2017. DOI: 10.1109/TIP.2017.2686014

[110] R. Rosas-Romero, "Remote detection of forest fires from video signals with classifiers based on K-SVD learned dictionaries", *Eng. Appl. Artif. Intell.*, vol. 33, pp. 1-11, Aug. 2014. DOI:10.1016/j.engappai.2014.03.011

[111] K. Engan, S. O. Aase and J. Husøy, "Multi-frame compression: Theory and design", *Signal Process.*, vol. 80, no. 10, pp. 2121-2140, Oct. 2000. https://doi.org/10.1016/S0165-1684(00)00072-4

[112] Y.S. Lee and S.B. Cho, "Activity recognition using hierarchical hidden markov models on a smartphone with 3D accelerometer," in *Proc. Springer Int. Conf. Hybrid Artificial Intelligence Systems (HAIS),* 2011, pp. 460-467. DOI:10.1007/978-3-642-21219-2_58

[113] UCI Machine Learning Repository. Dataset for ADL Recognition with Wrist-worn Accelerometer Data Set.

https://archive.ics.uci.edu/ml/datasets/Dataset+for+ADL+Recognition+with+Wrist-worn+Accelerometer.

[114] J. A. Tropp, "Greed is good: Algorithmic results for sparse approximation," *IEEE Trans. Inf. Theory*, vol. 50, pp. 2231–2242, Oct. 2004. DOI: 10.1109/TIT.2004.834793

[115] D.L. Donoho, Y. Tsaig., "Fast solution of L1-norm minimization problems when the solution may be sparse," Stanford University, Technical Report, 2006. DOI: 10.1109/TIT.2008.929958

[116] A.Y. Yang, S.S. Sastry, A. Ganesh and Y. Ma, " Fast ℓ 1 -minimization algorithms and an application in robust face recognition: A review ", *in 2010 IEEE International Conference on Image Processing*, pp. 1849-1852, 2010. DOI: 10.1109/ICIP.2010.5651522

[117] P. De, A.Chatterjee and A.Rakshit," Recognition of Human Behavior for Assisted Living Using Dictionary Learning Approach", *IEEE Sensor Journal*, vol. 18, no. 6, pp. 2434–2441, Mar. 2018. DOI: 10.1109/JSEN.2017.2787616

[118] S.J. Kim, K. Koh, M. Lustig, S. Boyd and D. Gorinevsky, " An interior-point method for large-scale l_1 regularized least squares ", *IEEE J. Sel. Topics Signal Process.*, vol. 1, no. 4, pp. 606-617, Dec. 2007. DOI: 10.1109/JSTSP.2007.910971

[119] M. A. Figueiredo, R. D. Nowak and S. J. Wright, "Gradient projection for sparse reconstruction: Application to compressed sensing and other inverse problems", *IEEE J. Sel. Top. Signal. Process.*, vol. 1, no. 4, pp. 586-597, Dec. 2007. DOI: 10.1109/JSTSP.2007.910281

[120] L. Zhang, M. Yang, and X. Feng, "Sparse Representation or Collaborative Representation Which Helps Face Recognition?" in *Proc. ICCV*, 2011. DOI:10.1109/ICCV.2011.6126277

[121] P. De, A. Chatterjee, and A. Rakshit, "A hybrid IRLS-KSVD based dictionary learning algorithm for human behavior recognition," in *Proc. IEEE Appl. Signal Process. Conf. (ASPCON)*, Kolkata, India, Dec. 2018, pp. 234–239. DOI: 10.1109/ASPCON.2018.8748744

[122] C. M. Perez, J. R. Magdaleno, H. P. Barreto, and J. P. A. Sanchez, "Incipient Broken Rotor Bar Detection in Induction Motors Using Vibration Signals and the Orthogonal

Matching Pursuit Algorithm,” *IEEE Trans. Instrum. Meas.*, vol. 67, no. 9, pp. 2058-2068, Sept. 2018. DOI: 10.1109/TIM.2018.2813820

[123] S. Li, L. Fang, and H. Yin, “An Efficient Dictionary Learning Algorithm and Its Application to 3-D Medical Image Denoising,” *IEEE transactions on biomedical engineering*, vol. 59, no. 2, Feb. 2012. DOI: 10.1109/ICICES.2013.6508257

[124] MP Motion Sensor (AMN1,2,4).

(Online)Available:https://www.mouser.com/datasheet/2/315/panasonic_amn1_2_4-1196943.pdf.

[125] INFRARED PARTS MANUAL, Glolab Corporation,2003. (Online). Available: https://www.bucek.name/pdf/re200b.pdf

[126] B. Dumitrescu and P. Irofti, Dictionary Learning Algorithms and Applications, Springer, 2018. ISBN: 978-3-319-78674-2

[127] B. Dumitrescu and P. Irofti, *"*Regularized K-SVD*"*, *IEEE Signal Processing Letters,* vol. 24, no. 3, pp. 309-313, 2017. DOI: 10.1109/LSP.2017.2657605

[128] P. De, A.Chatterjee and A.Rakshit, “PIR Sensor based AAL Tool for Human Movement Detection: Modified MCP based Dictionary Learning Approach”, *IEEE Trans. Instrum. Meas.*, vol. 69, no. 10, pp. 7377-7385, Oct. 2020. DOI: 10.1109/TIM.2020.2981106

[129] R. Rubinstein, M. Zibulevsky and M. Elad, "Efficient implementation of the **K-SVD** algorithm using batch orthogonal matching pursuit" in Tech. Rep. CS-2008-08, Technion–Computer Science Department, Apr. 2008. https://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.182.9978

[130] Z. Zhang, Y. Cao, M. Ding, L. Zhuang and W. Yao, "An intruder detection algorithm for vision based sense and avoid system," in *Proc. Int. Conf. Unmanned Aircr. Syst. (ICUAS)*, Jun. 2016, pp. 550-556. DOI: 10.1109/ICUAS.2016.7502521

[131] Z. Jiang, Z. Lin and L. S. Davis, "Label consistent **K-SVD**: Learning a discriminative dictionary for recognition", *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 35, no. 11, pp. 2651-2664, Nov. 2013. DOI: 10.1109/TPAMI.2013.88

[132] A. K. Seghouane and A. Iqbal, "Consistent adaptive sequential dictionary learning," *Signal Process.*, vol. 19, pp. 300-310, Jul. 2018. https://doi.org/10.1016/j.sigpro.2018.07.018

[133] M. Moghavvemi and L. C. Seng, "Pyroelectric infrared sensor for intruder detection," in *Proc. IEEE Region 10 Conf. (TENCON 2004)*, vol. 4, Nov. 2004, pp. 656-659. DOI: 10.1109/TENCON.2004.1415018

[134] A. H. Sanoob, J. Roselin and P. Latha, "Smartphone enabled intelligent surveillance system," *IEEE Sens. J.*, vol. 16, no. 5, pp. 1361-1367, Mar. 2016. DOI: 10.1109/JSEN.2015.2501407

[135] P. De, A. Chatterjee, and A. Rakshit, "Regularized K-SVD-Based Dictionary Learning Approaches for PIR Sensor-Based Detection of Human Movement Direction," *IEEE Sens. J.*, vol. 21, no. 5, pp. 6459 -6467, Mar. 2021. DOI: 10.1109/JSEN.2020.3040228

[136] P. De, A. Chatterjee and A. Rakshit, "Human Behavior Recognition: An l1 – ls KSVD-Based Dictionary Learning and Collaborative Representation-Based Classification", in *Advances in Control, Signal Processing and Energy Systems*, 1st Ed., Vol. 591, Tapan Kumar Basu, Swapan Kumar Goswami, and Nandita Sanyal, Ed. Singapore: Springer, 2020, pp. 97-105. DOI: 10.1007/978-981-32-9346-5_8

[137] P. Irofti and B. Dumitrescu, "Overcomplete dictionary design: the impact of the sparse representation algorithm," in *Proc. 2015 20th International Conference on Control Systems and Science*, 27-29 May 2015, pp. 901-908, Bucharest, Romania. DOI: 10.1109/CSCS.2015.50

[138] P. Irofti and B. Dumitrescu, "Regularized algorithms for dictionary learning," in *Proc. 2016 International Conference on Communications (COMM)*, 9-10 June 2016, pp. 439-442, Bucharest, Romania. DOI: 10.1109/ICComm.2016.7528326

[139] P. De, A. Chatterjee, and A. Rakshit, "PIR Sensor based Surveillance Tool for Intruder Detection in Secured Environment: A Label Consistency based Modified Sequential Dictionary Learning Approach", *IEEE Internet of Things Journal* (Early Access), DOI: 10.1109/JIOT.2022.3178160. DOI: 10.1109/JIOT.2022.3178160

Signature of the Candidate: ......Pubali De......

(Pubali De)

Date: ...27.09.2022...