Electrooculographic Interface(s) for Rehabilitative Aid(s)

Thesis submitted by

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2016

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INDEX NO. 108/13/E

1. **Title of the thesis:** Electrooculographic Interface(s) for Rehabilitative Aid(s)

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3. **List of Publications:**

I. Journal Publications

i. **Anwesha Banerjee**, Shreyasi Datta, Amit Konar, D.N. Tibarewala, *"*A Computational Approach to Bimodal Cognitive Activity Recognition", Journal on Multimodal User Interfaces, Springer. *[Under Review]*
ii. Sananda Paul, **Anwesha Banerjee**, Rana Ghoshal, DN Tibarewala, "Development of ultrasonic tachography system for gait analysis", International Journal of Biomedical Engineering and Technology, vol. 20, no. 1, pp. 66-95, 2016.
iii. **Anwesha Banerjee,** Monalisa Pal, Shreyasi Datta, D. N. Tibarewala, Amit Konar, "Voluntary Eye Movement Controlled Electrooculogram based Multitasking Graphical User Interface", International Journal of Biomedical Engineering & Technology, Inderscience Publishers, vol. 18, no. 3, pp.254–271, 2015.
iv. **Anwesha Banerjee**, Monalisa Pal, Shreyasi Datta, D.N. Tibarewala, Amit Konar, *"*Electrooculography Based Reading Speed Analysis as an Assistive Tool", Biomedical Engineering: Applications, Basis & Communication, World Scientific, Vol. 27, No. 2, 2015.
v. **Anwesha Banerjee**, Monalisa Pal, Shreyasi Datta, D.N. Tibarewala , Amit Konar, "Eye Movement Sequence Analysis using Electrooculogram to Assist Autistic Children", Biomedical Signal Processing and Control, Elsevier, Vol. 14, pp 134-140, 2014.
vi. **Anwesha Banerjee,** Shreyasi Datta, Monalisa Pal, Amit Konar, D. N. Tibarewala, and R. Janarthanan. "Classifying Electrooculogram to Detect Directional Eye Movements." Procedia Technology, volume 10, pp: 67-75, 2013.
vii. **Anwesha Banerjee**, Shounak Datta, Amit Konar, D.N. Tibarewala, " Development strategy of eye movement controlled rehabilitation aid using Electro-oculogram", International Journal of Scientific and Engineering Research (IJSER), ISSN-2229-5518, Volume 3, Issue 6, 2012.

II. List of Book chapters

i. **Anwesha Banerjee**, Ankita Mazumder, Poulami Ghosh, D.N. Tbarewala, “Visual Perception from Object Scanning as revealed by Electrooculography”, Biomedical Image Analysis and Mining Techniques for Improved Health Outcomes in Advances in Bioinformatics and Biomedical Engineering (ABBE) Series, IGI Global, 2015.
ii. Poulami Ghosh, **Anwesha Banerjee**, Ankita Mazumder, D.N. Tibarewala, “Electromyography based Functional Electrical Stimulation (FES) in Rehabilitation”, Biomedical Image Analysis and Mining Techniques for Improved Health Outcomes in Advances in Bioinformatics and Biomedical Engineering (ABBE) Series, IGI Global, 2015.
iii. **Anwesha Banerjee**, Shreyasi Datta, Amit Konar, D.N. Tibarewala and R. Janarthanan, “Cognitive Activity Recognition based on Electrooculogram analysis”, Advanced Computing, Networking and Informatics-Volume 1, pp. 637-644. Springer International Publishing, 2014.
iv. **Anwesha Banerjee,** Anilesh Dey, Shreyasi Datta, D.N. Tibarewala, “Effect of Audio Cue on Electrooculogram-Based Eye Movement Analysis of Visual Memory Recall”, Computational Advancement in Communication Circuits and Systems, pp. 471-477, Springer India, 2015.
v. Anilesh Dey, **Anwesha Banerjee,** D.K. Bhattacharya, D.N. Tibarewala, “Does Music Affect HRV Impulse? A Time Domain Study”, Computational Advancement in Communication Circuits and Systems, pp. 453-461, Springer India, 2015.
vi. **Anwesha Banerjee**, Amit Konar, R. Janarthana, and D. N. Tibarewala. "Electro-oculogram Based Classification of Eye Movement Direction." Advances in Computing and Information Technology, Volume 178, pp. 151-159. Springer Berlin Heidelberg, 2013.
vii. **Anwesha Banerjee**, Pratyusha Das, Shounak Datta, Amit Konar, R. Janarthanan, and D. N. Tibarewala. "Real Time Electro-Oculogram Driven Rehabilitation Aid." Advances in Intelligent Systems and Computing, Volume 174, pp. 435-440. Springer India, 2012.

4. List of Patents: NIL

5. List of Presentations in National/ International Conferences:

i. Arnab Rakshit, **Anwesha Banerjee** and D.N. Tibarewala, “Electro-oculogram based Digit Recognition to Design Assitive Communication system for Speech Disabled Patients”, International Conference on Microelectronics, Computing and Communication (MicroCom), January 23-25, 2016.
ii. **Anwesha Banerje**, D.N. Tibarewala, “Electrooculogram based Approach for Prevention of Dry Eye Condition in Computer Users”, International Conference on control, Measurement & Instrumentation (CMI), January 8-10, 2016.
iii. **Anwesha Banerjee**, Arnab Rakshit, D.N. Tibarewala, “Application of Electrooculography to Estimate Word Count While Reading Text”, International Conference on Systems in Medicine and Biology (ICSMB), January 04-7, 2016.

iv. **Anwesha Banerjee**, Monalisa Pal, Shreyasi Datta, D.N. Tibarewala, Amit Konar, “Electrooculogram based Blink Detection to Limit the Risk of Eye Dystonia”, Eighth International Conference on Advances in Pattern Recognition(ICAPR), January 04-07, 2015.

v. **Anwesha Banerjee**, Shreyasi Datta, Amit Konar, D.N. Tibarewala and R. Janarthanan, “Electrooculogram based Detection of Visual Memory Recall Process”, IEEE International Conference on Communication and Signal Processing (ICCSP), Tamilnadu, April 3-5, 2014.

vi. Shreyasi Datta, **Anwesha Banerjee**, Monalisa Pal, Amit Konar, D.N. Tibarewala and R. Janarthanan, "Blink Recognition to Detect the Possibility of Eye Dystonia based on Electrooculogram Analysis", International Conference on Control, Instrumentation, Energy and Communication (CIEC), Kolkata, India, January 31- February 2, 2014.

vii. Shreyasi Datta, **Anwesha Banerjee**, Amit Konar and D.N. Tibarewala, "Electrooculogram Based Cognitive Context Recognition", International Conference on Electronics, Communication and Instrumentation (ICECI), Kolkata, India, January 16-17, 2014.

viii. Monalisa Pal, **Anwesha Banerjee**, Shreyasi Datta, Amit Konar, D.N. Tibarewala and R. Janarhanan, "Electrooculography based Blink Detection to Prevent Computer vision Syndrome", International Conference on Electronics, Computing and Communication Technologies (CONECCT), Bangalore, India, January 6-7, 2014.

ix. **Anwesha Banerjee,** Sumantra Chakraborty, Pratyusha Das, Shounak Datta, Amit Konar, D.N. Tibarewala, R. Janarthanan,, "Single channel electrooculogram(EOG) based interface for mobility aid," Intelligent Human Computer Interaction (IHCI), 2012 4th International Conference on, vol., no., pp.1,6, 27-29 Dec. 2012.

x. **Anwesha Banerjee**, Shounak Datta, Pratyusha Das, Amit Konar, D.N. Tibarewala, R. Janarthanan, "Electrooculogram Based Online Control Signal Generation for Wheelchair," Electronic System Design (ISED), International Symposium on , vol., no., pp.251-255, 19-22 Dec. 2012.

xi. **Anwesha Banerjee**, Amit Konar, D.N. Tibarewala, R. Janarthanan, “Detecting Eye Movement Direction from stimulated Electro-oculogram by Intelligent Algorithms”, Proceedings of IEEE International Conference on Computing, Communication And Networking Technology(ICCCNT 2012), Tamilnadu, India, July 26 – 28, 2012.

xii. **Anwesha Banerjee**, Amit Konar, R. Janarthanan, D.N. Tibarewala,”Identification of Eye Movement from EOG by SVM and KNN techniques”, Proceedings of International conference on Advancements in Engineering & Management (ICAEM 2012), Hyderabad, India, February 28-29, 2012.

xiii. **Anwesha Banerjee**, D. N. Tibarewala, 'Electro-oculogram and Its Implementation in various Biomedical Applications : A Review', Proceedings of the AICTE sponsored National Seminar on Biomedical Engineering Research and Its Application (BERA 2011), pp 183-188, Kalyani, West Bengal, India, July 29-30, 2011.

Certificate from the Supervisor

*This is to certify that the thesis entitled "***Electrooculographic Interface(s) for Rehabilitative Aid(s)***" Submitted by* ***Smt. Anwesha Banerjee****, who got her name registered on 10.01.2013 for the award of* ***Ph.D. (Engineering)*** *degree of Jadavpur University is absolutely based upon her own work under the supervision of* ***Prof. D.N. Tibarewala*** *and that neither her thesis nor any part of the thesis has been submitted for any degree/diploma or any other academic award anywhere before.*

Signature of the Supervisor
and date with office seal

Acknowledgement

"To be inspired is great, to inspire is incredible"

I am availing this opportunity to express my gratitude to everyone who has supported me throughout the course of my Ph.D. tenure. I am thankful for their aspiring guidance, invaluably constructive criticism and friendly advice during this duration. I am sincerely grateful to them for their truthful and illuminating views on a number of issues related to this Ph.D. research.

I would like to express my earnest gratitude & sincere thanks to my supervisor Prof. D. N. Tibarewala, School of Bioscience and Engineering, Jadavpur University, for giving me the opportunity to work under him and inspiring me to explore the interesting fields of Biomedical Instrumentation and Human Computer Interfaces. I am indebted to him for his patient guidance, critical and constructive views and untiring support that shaped my work. The past years have been a remarkable experience in terms of gaining knowledge and skill that I hope to carry on and develop further.

I am exceedingly grateful to Prof. Amit Konar, Department of Electronics & Telecommunication Engineering, Jadavpur University, who has provided great help, guidance and invigorating suggestions for my work.

It is an honour to express my sincere appreciation to Prof. Asis Goswami of Ramakrishna Mission Vivekananda University, Belur for his valuable guidance and support.

I convey my regards and respect to the faculty members of School of Bioscience & Engineering, Jadavpur University, Prof. D.K. Bhattacharya, Prof. Abhijit Chanda, Prof. Monisha Chakraborty, Prof. Himadri Chattopadhya , Prof. Manish Bagchi and present Director Prof. Piyali Basak, for their help and support.

I am thankful to the associates of School of Bioscience and Engineering, Jadavpur University Mr. Sundar Mondal and Mr. Prabir Pramanik for their support and assistance.

The work would not have been possible without the whole-hearted co-operation from fellow researchers and students of our lab for making my stay *enjoyable and memorable. I am grateful to put on record the contribution of Shreyasi, Monalisa, Anwesha di, Saugat da, Dwaipayan, Debobrata, Sananda, Poulami, Ankita, Priyanka, Arnab, Anilesh da, Rohit, Arup da, Anisha di, Anuradha di, both Pratyusha Das & Pratyusha Rakshit, Sriparna, Reshma, Shounak, Sanchita mam and Ramadoss Janarthanan in this regard.*

I am extremely grateful to Dr. Sharada Fatehpuria, Secretary General of Manovikas Kendra, Kolkata for allowing me to involve with some special kids in her esteemed organization. A special thank to Ms. Arundhati Sarkar, Head, Manochetna Academic and Research Centre (a wing of Manovikas Kendra) for the support, assistance and belief in the research work.

I would also like to thank Council of Scientific and Industrial Research (CSIR), India for their financial aid.

Last but not the least I am immensely indebted to my parents, Mr. Tarun Banerjee and Mrs. Lakshmi Banerjee, for their continuous support and encouragement that made me believe in myself. I am taking this opportunity to thank my husband Mr. Abhishek Chakraborty for providing me the strength to work hard. I want to pay my sincere gratitude to my dadubhai Mr. Amalendu Sengupta, parents-in-law Mr. Dulal Chakrabourty and Mrs. Gouri Chakraborty, sister Ms. Aritri Banerjee, family and friends for being an inevitable part of my life.

Finally, I thank all my well wishers who have contributed directly and indirectly towards the completion of this work and the almighty for everything.

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Preface

The current research on Bio-robotics is centered on the design and development of new robotic equipments for possible applications as rehabilitative aids to the people suffering from neurological/congenital/muscle failures. Bio-potential signals provide measurements about the degree of functionality or degradation of biological organs of the humans and other advanced creatures. Several electronic/mechanical/electro-mechanical aids are currently being employed on human subjects as rehabilitative aids. Some of the common aids for example include pace makers as the replacement of hearts, artificial kidneys in place of malfunctioning kidneys and electromechanical humanoid arms for the amputees.

Besides the above, the current research findings paved a new way for the people suffering from neurological disorders by replacement of their damaged limbs by neuro-prosthetic devices. Traces of such research in the said area are also noticed in different research laboratories in India.

The idea behind the development of next generation Human Computer Interfaces (HCI) is to provide healthy individuals an easier and better life while providing diseased individuals assistance and rehabilitation. Such devices are based on some form of input bio-modality that is processed efficiently to provide the desired results while being interfaced with the computer. HCI based control of rehabilitative aids, communicative devices and robotic equipments are gaining a tremendous significance as observed from recent literature.

Bio-signals such as EMG (Electromyography), EEG (Electroencephalography), EOG (Electrooculogram) and ECG (Electrocardiogram) have been organized to develop control systems for improving the life quality of disabled and elderly people. In the near future we will see highly robust and flexible bio-control systems, which are based on various bio-signals such as voice, muscle contractions, brain waves and gestures. These bio-control systems will have ability to understand human intentions and emotions, and adapt the dynamic changes in the real-world. The design of bio-control systems has four stages: data acquisition and segmentation, feature extraction, classification and control.

This project investigates the potential uses of EOG for real life problems of rehabilitation. The objective is to improve the control capability of the eye movement signal, thus positively contributing to the development of bio-signal controlled assistive devices. Different aspects of

HCI applications for rehabilitation are presented using eye movements through electrooculogram.

EOG is a measure of the potential difference between the front (positive pole formed by cornea) and the back (negative pole formed by retina) of the eye ball. This potential difference between the cornea and the retina is due to the large presence of electrically active neurons in the retina compared to the front of the eye. EOG is detected by the skin electrodes placed around the eye socket. Experiments reveal that there exists a linear relation between eye movements and EOG amplitude up to a certain degree. A change in potential is detected as the poles come closer or move away from the electrodes while moving the eyes. The sign of the change depends on the direction of the movement. EOG measurements can be affected by artifacts arising from muscle potentials and small electromagnetic disturbances due to cables or surrounding power line interference.

Chapter 1 presents a brief overview of human computer interactive systems as rehabilitation aids based on electrooculogram. Major research works in the field of electrooculographic interfaces are outlined in this chapter. The overview of the objective and approach of the work undertaken in this thesis are also addressed in this chapter.

In chapter 2, the first primary work for the accomplishment of this thesis is discussed. The objective of the work presented in this chapter is to design an acquisition circuit for EOG and indentify directional eye movements. A dual channel circuit is designed to collect both horizontal and vertical eye movement data. In the preliminary stage Ag-AgCl disposable surface electrodes has been placed around the eye socket region to receive EOG signal. Later, a wearable EOG glass is implemented with stainless steel electrodes. The final phase deals with classification of right, left, up, down eye movement and blink from the recorded EOG signal.

Biopotential signals provide measurements about the degree of functionality or degradation of biological organs of the humans and other advanced creatures. Eye Movements are a great source of information. In chapter 3, research is done to extract the useful details from EOG and implement it as assistive tool. This chapter is divided into four sections. In first and second sections, assistance schemes are proposed to follow progress of autistic and reading disabled children respectively, analyzing their eye tracking data. The second scheme of reading speed evaluation is done by studying EOG data of three children having specific learning disorder. In third and fourth section, strategies as precautionary measure for computer vision syndrome and eye dystonia respectively are presented based on blink detection.

Control strategies for Assistive Devices based on electrooculogram are presented in Chapter 4. In this chapter we aim to classify the eye movements of right, left, up, down directions along with blink and utilize them to control human computer interactive systems having different rehab purpose. The chapter proposes three novel approaches towards EOG-driven rehabilitative aids with can lead to smart homes. In the first proposed scheme, a multitasking graphical user interface (GUI) is designed by controlling the position of a computer cursor using eye movements. Each and every icon of the GUI can be accessed online by just selecting them and thus the particular function can be performed. Second, a scheme is proposed to recognize the pattered eye movements of some known digits, letters and shapes and those are generated on the computer screen. In the last and third approach, movements of a motorized wheelchair, i.e., forward, backward, right, left in a particular speed and start-stop operation are controlled in real time by EOG with predefined eye commands.

Recognition of a person's cognitive context has been done in chapter 5 from EOG based eye movement data and also in combination with brain activity from EEG signal. This chapter accounts for the combination of information from brain signals using EEG and eye movements using EOG for cognitive context recognition. It introduces multimodal data analysis using EEG and EOG signals as sources of cognitive context recognition information. It illustrates the architectures of feature and decision level fusion for constructing a bimodal cognitive context recognition platform.

Chapter 6 revisits the primary goal of the thesis and briefly highlights the findings and contributions of the work to substantiate the extent to which the objective of the thesis is accomplished. Following this, the future course of the work is discussed which are open for research as extension of the work done as a part of this thesis.

The work presented in this thesis, to the best of author's knowledge, is a distinctive work in EOG acquisition, its analysis for various rehabilitative applications and at the same time eye movement directed assistive device control. This work has achieved all the primary objectives necessary for developing electrooculographic intelligent system.

This work can find its application in rehabilitation, for at home analysis of autistic and reading disabled child, for eye care at IT organization, road safety of drivers, for more comfortable lifestyle and freedom from attendant in case of physically challenged or injured persons, HCI applications using artificial limbs and various fields of eye movement research. This work is highly valuable in the field of biomedical engineering as it can be implemented for tracking the progress and gives feedback to special kids and may be beneficial for them and also for other human computer interface based control devices.

The studies have been carried out jointly in the Bio-signal Processing and HCI Lab of School of Bioscience and Engineering, Control lab of the department of Electronics & Telecommunication Engineering, Jadavpur University and Manovikas Kendra, Kolkata. The

research work has been partially funded by Jadavpur University and Council of Scientific and Industrial Research, India.

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"Eyes are windows to our soul"

~ William Shakespeare

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Introduction to Human Computer Interfaces in Rehabilitation

The aim of rehabilitation is to maximize the potential to restore a person who has an impairment, or an incapacity for service or work, as a result of a service injury or disease to at least the same physical and psychological state, and at least the same social, vocational and educational status, as he or she had before the injury or disease. The people suffering from sensory motor impairments having spinal cord injury or those who are paralyzed or who have diseases with unconventional eye movements are needed to be assisted with some technologically advanced human computer interactive tools. This work is undertaken towards the development of electrooculogram based eye movement controlled rehabilitative aid(s), which will improve the life of the aforementioned. This chapter provides an insight into the fundamentals of Human Computer Interfaces (HCI) and human computer interactions along with the relevance and applicability of Electrooculography for different rehabilitative applications. Major research works in the field of electrooculographic interfaces are outlined in this chapter. The overview of the objective and approach of the work undertaken in this thesis are also addressed in this chapter.

1.1 Human Computer Interfaces

A Human Computer Interface (HCI) provides a platform for man-machine interaction and is aimed at a large number of applications [1-2]. The user interacts directly with the hardware through an interface. The user-machine environment has an input-output flow maintained by some form of feedback that evaluates and controls the information flowing from the user to the computer and back in the form of a loop.

Human computer interactive devices are not limited to ordinary computers that take in user data and provide the necessary outputs. These devices are being advanced further with the aims of user end customization and embedded computation. User end customization aims to provide users the ability to tailor applications according to their needs. Embedded computation refers to embedding computers within all objects in the environment, or the development of pervasive computing systems. When this is associated with proper networking, these devices will be able to communicate with each other as well as the user.

An important aspect of next generation HCI is the control of devices or communication through the use of bio-signals. Such HCI devices can be efficiently utilized in rehabilitation, robotic applications, gaming or in context aware pervasive computing systems [3]. Bio-signals modulated by the different physiological processes of the human body are important in such cases. These signals when processed can generate accurate control or communication signals for use in the HCI devices. The focus of this work is on the efficient utilization of the various bio-modalities for the development of useful HCI systems that can be applied in rehabilitation, robot aided systems, etc. For that purpose the interpretation of the bio-modalities for specific tasks through Today robots are expected to fulfill a growing number of roles in society, from being industrial tool to service applications to medical care and entertainment. While robots were initially used in repetitive tasks mainly in industrial purposes, they are becoming involved in increasingly more complex and less structured tasks and activities, including interactions with people. The technology involved in making these robots to perform different tasks to assist human beings is called Human-Robot Interaction (HRI) of which Human-Computer Interface (HCI) is an integral part [4-5].

Another very important application of robotics is in case of assistive robots. The term assistive robot is generally thought to be synonymous with rehabilitative robots. But assistive robots have a wider field of applications. These can perform various tasks like tutoring, physical therapy, daily life assistance etc. [6-7]. They can even be used for expressing emotions when the subject is incapable of such expression, for example children with autism spectrum disorders, cardiac failure etc. [8-9].

1.2 Rehabilitation & Available Rehabilitation Aids

Rehabilitation refers to restoration of something to its original form. In medical science rehabilitation is a treatment(s) designed to facilitate the process of recovery from injury, illness or disease to as normal condition as possible [10].

From the statistical records given in Census of India, 2011, it is evident that the population of disabled person (fig. 1.1) is gradually increasing. Hence the need of intelligent rehabilitation is an important matter of concern in near future [11]. As well as by observing the chart given for type of disability (fig. 1.2) it can be easily understood that eye movement is the least affected system of human body by any kind of impairment.

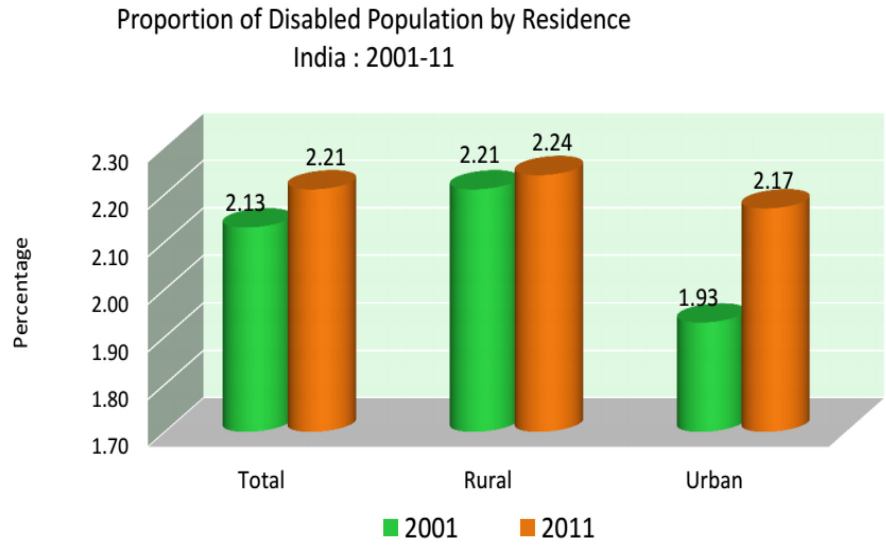


Fig. 1.1 Proportion of disabled population in India [source: C-Series, Table C-20, Census of India, 2011]

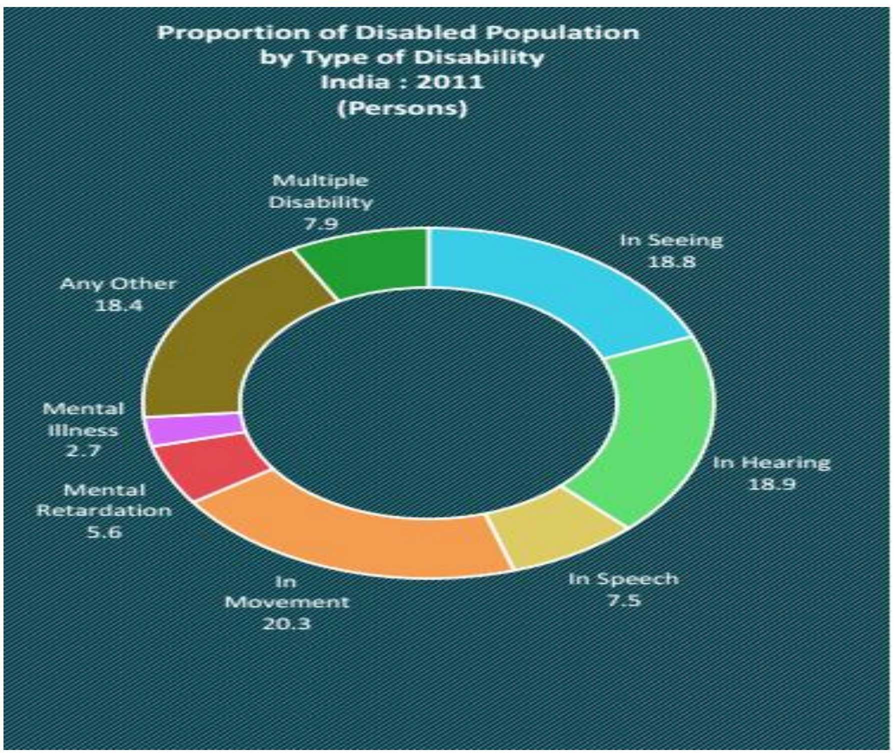


Fig. 1.2 Proportion of Disabled Population by Type of Disability in India [source: C-Series, Table C-20, Census of India, 2011]

HCI can provide rehabilitation to patients with severe motor disabilities as discussed above. Not only for neuro-motor disabilities but BCI based devices can also control artificial limbs in patients with damaged or lost body parts [12]. Apart from using brain activity, eye movements can also be used in many cases where the body is paralyzed but the ocular functions are unhampered. For example eye movements can be efficiently used for the control of the direction of an electric wheelchair [13]. All these techniques can be used as rehabilitative aids.

Human-machine interface (HMI) allows easy, intuitive control of any device with a large number of commands and allows disabled people to control devices for rehabilitative purposes like virtual keyboard, cursor, biofeedback chair, ocular implants, finger exoskeleton, neuro-prosthetic devices, mobility aids and robotic arms [14]. Basically HMI converts the bio signals coming from the subject to signals which can be used to drive the devices [15]. Not only rehabilitative devices, HMI can be used to provide post-stroke rehabilitation [16] through virtual environment and haptics [17]. Research is going on to provide rehabilitation by providing the patient with sense of touch specially for amputees so that they can feel the touch sensation using different techniques like electrically stimulating sensory nerve fibre [18], using artificial tactile sensation which converts the mechanical stimuli experienced by the device to such a form that the subject experiences the corresponding somatic sensations.

1.3 Electrooculography: Physiological Basis

The eye is a seat of a steady electric potential field that is quite unrelated to light stimulation [19]. In fact, this field may be detected with the eye in total darkness and/or with the eyes closed. It can be described as a fixed dipole with positive pole at the cornea and negative pole at the retina [20]. It is not generated by excitable tissue but, rather, is attributed to the higher metabolic rate in the retina. The polarity of this potential difference in the eyes of invertebrates is opposite to that of vertebrates. This potential difference and the rotation of the eye are the basis for a signal measured at a pair of surface electrodes. The signal is known as the electrooculogram (EOG) [21]. The chief application of the EOG is in the measurement of eye movement.

1.3.1 The Resting Potential

All cells have voltages across their plasma membranes. Voltage is electrical potential energy-a separation of opposite charges. The cytoplasm is negative in charge relative to the extracellular fluid because of an unequal distribution of anions and cations on opposite sides of the membrane. The voltage across a membrane, called a membrane potential, ranges from about - 50 to – 200 mill volts (the minus sign indicates that the inside of the cell is negative relative to the outside). When the membrane potential of a cell can go for a long period of time without changing significantly, it is referred to as a resting potential [22].

The membrane potential acts like a battery, an energy source that affects the traffic of all charged substances across the membrane. Because the inside of the cell is negative compared with the outside, the membrane potential favors the passive transport of cations into the cell and anions out of the cell. This difference in ionic concentration that exists between the inside and outside of this membrane can be related to the diffusion potential – also known as the Nernst Potential. The diffusion potential level across a membrane that exactly opposes the net diffusion of a particular ion through the membrane is called the Nernst potential for that ion. The magnitude of this Nernst potential is determined by the ratio of the concentrations of that specific ion on the two sides of the membrane [25-26]. The following equation, called the Nernst equation, can be used to calculate the Nernst potential for any univalent ion:

$$E_{eq.K+} = \frac{RT}{zF} \ln \frac{[K+]_{out}}{[K+]_{in}} \quad (2.1)$$

Where:

• $E_{eq, K+}$ is the equilibrium potential for potassium, measured in volts
• R is the universal gas constant, equal to 8.314 joules·K-1·mol-1
• T is the absolute temperature, measured in Kelvin
• z is the number of elementary charges of the ion in question involved in the reaction
• F is the Faraday constant, equal to 96,485 coulombs·mol-1
• [K+] out is the extracellular concentration of potassium, measured in mol·m-3
• [K+] in is likewise the intracellular concentration of potassium

1.3.2 The Resting Potential in the Human Eye

The eyeball may actually be regarded as a small battery, with a positive pole in the cornea and a negative pole in the retina although its mechanics are slightly more complex than in the case of a single cell, neuron or muscle fiber as has been discussed so far [23]. In the eye most of the resting potential has been attributed to the retina although some research has been done which proves the lens and maybe the cornea also play important roles.

The corneo-retinal potential is roughly aligned with the optic axis. Hence it rotates with the direction of gaze. Changes in the position of the eyeball cause changes in potential at the skin surface around the eye socket which can be measured by surface electrodes placed on the skin around the eyes. To have a better understanding of the generation of EOG a look inside the eyes is a must.

1.3.3. Inside The Eyes

Our ability to "see" starts when light reflects off an object at which we are looking and enters the eye. As it enters the eye, the light is unfocused. The first step in seeing is to focus the light rays onto the retina, which is the light sensitive layer found inside the eye. Once the light is focused, it stimulates cells to send millions of electrochemical impulses along the optic nerve to the brain [24]. The portion of the brain at the back of the head (the visual cortex) interprets the impulses, enabling us to see the object.

Light entering the eye is first bent, or refracted, by the cornea -- the clear window on the outer front surface of the eyeball. The cornea provides most of the eye's optical power or light-bending ability.

After the light passes through the cornea, it is bent again -- to a more finely adjusted focus – by the crystalline lens inside the eye. The lens focuses the light on the retina. This is achieved by the ciliary muscles in the eye changing the shape of the lens, bending or flattening it to focus the light rays on the retina.

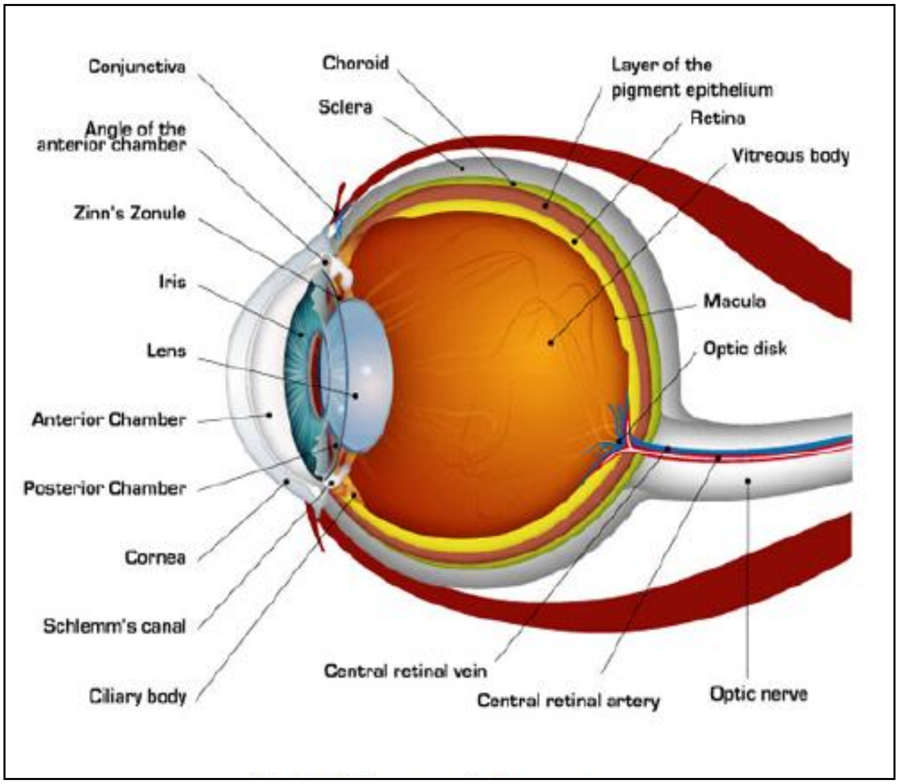


Fig. 1.3 Diagram of a human eye

This adjustment in the lens, known as accommodation, is necessary for bringing near and far objects into focus. The process of bending light to produce a focused image on the retina is called "refraction".

Two types of receptors, rods and cones, are present. Rods are mainly found in the peripheral retina and enable us to see in dim light and to detect peripheral motion. They are primarily responsible for night vision and visual orientation. Cones are principally found in the central retina and provide detailed vision for such tasks as reading or distinguishing distant objects. They also are necessary for colour detection. These photoreceptors convert light to electrochemical impulses that are transmitted via the nerves to the brain. Millions of impulses travel along the nerve fibers of the optic nerve at the back of the eye, eventually arriving at the visual cortex of the brain, located at the back of the head. Here, the electrochemical impulses are unscrambled and interpreted.

Light enters from the top and passes through the neural structure to the photoreceptors, which are the rods and cones. Just behind the rods and cones is the retinal pigment epithelium (RPE). Its major function is to supply the metabolic needs (as well as other supportive functions) of the photoreceptors. The rods respond to dim light, whereas the cones contribute to vision in bright light and in color [25]. This area is the site of visual excitation [26].

The lens of the eye brings the illuminated external scene to a focus at the retina. The retina is the site of cells that are sensitive to the incident light energy; as with other peripheral nerve cells, they generate receptor potentials. The collective behavior of the entire retina is a bioelectric generator, which sets up a field in the surrounding volume conductor. This potential field is normally measured between an electrode on the cornea (contact-lens type) and a reference electrode on the forehead. The recorded signal is known as the electroretinogram (ERG) [27]. It may be examined both for basic science studies and for clinical diagnostic purposes.

In literature, it was observed that the cornea of the eye is electrically positive relative to the back of the eye [28]. Since this potential was not affected by the presence or absence of light, it was thought of as a resting potential. It is not constant but slowly varying and is the basis for the electro-oculogram (EOG).

This source behaves as if it were a single dipole oriented from the retina to the cornea. Such corneoretinal potentials are well established and are in the range of 0.4 - 1.0 mV. Eye movements thus produce a moving (rotating) dipole source and, accordingly, signals that are a measure of the movement may be obtained.

The measurement of horizontal eye movements can be done by the placement of a pair of electrodes at the outside of the left and right eye. With the eye at rest the electrodes are effectively at the same potential and no voltage is recorded [29]. The rotation of the eye to the right results in a difference of potential, with the electrode in the direction of movement (i.e., the right canthus) becoming positive relative to the second electrode. (Ideally the difference in potential should be proportional to the site of the angle.) The opposite effect results from a rotation to the left. The calibration of the signal may be achieved by having the patient look consecutively at two different fixation points located a known angle apart and recording the concomitant EOGs. Typical achievable accuracy is ±2°, and maximum rotation is ±70° however, linearity becomes progressively worse for angles beyond 30°. Typical signal magnitudes range from 5-20 μV/° [30].

Electrooculography has both advantages and disadvantages over other methods for determining eye movement. The most important disadvantages relate to the fact that the corneoretinal potential is not fixed but has been found to vary diurnally, and to be affected by light, fatigue, and other qualities. Consequently, there is a need for frequent calibration and recalibration. Additional difficulties arise owing to muscle artifacts and the basic nonlinearity of the method [31]. The advantages of this technique include recording with minimal interference with subject activities and minimal discomfort. Furthermore, it is a method where recordings may be made in total darkness and/or with the eyes closed.

1.3.4 Characteristics of EOG

The characteristics of EOG signal are:

- ✓ The EOG signal has a pulse shape with the pulse duration approximately 200ms on the average.
- ✓ When eye ball is moved one side the voltage remains positive (or negative) and returns to zero when looking straight.
- ✓ When measuring horizontal movement, the potential caused by vertical movement on the horizontal electrodes is less significant compared to horizontal potential.
- ✓ Movement of the patient's head or body alters the DC level of the signal.
- ✓ The pulse produced by leftward movement is nearly the same as produced by rightward movement in both amplitude and pulse duration.
- ✓ Even with the eye closed, the potential was observed to be the same.
- ✓ Depending on the angle through which the eyeball was moved, the amplitude of the EOG signal changed.

✓ Typical signal magnitudes range from 5-20 μV per degree of eye ball movement.

So, Electrooculography is, in simple words, the science of measuring the resting potential of the eye and its variations [32-33].

1.4 Different types of Eye Movements

Human ocular movement has been widely studied in neurophysiology and psychology. These studies indicate that the extra-ocular muscles work together to achieve four basic types of eye movements [34]: saccades, smooth pursuit movements, vergence movements, and vestibulo- ocular movements.

- **Saccades**

Saccades are rapid, ballistic movements of the eyes that abruptly change the point of fixation. They range in amplitude from the small movements to the much larger movements made while gazing around a room. Saccades can be voluntary, but occur reflexively whenever the eyes are open, even when fixated on a target.

- **Smooth pursuit movements**

Smooth pursuit movements are much slower tracking movements of the eyes designed to keep a moving stimulus on the fovea.

- **Vergence movements**

Vergence movements align the fovea of each eye with targets located at different distances from the observer. They involve either a convergence or divergence of the lines of sight of each eye to see an object that is nearer or farther away.

- **Vestibo-ocular movements**

Vestibulo-ocular movements stabilize the eyes relative to the external world, thus compensating for head movements. These reflex responses prevent visual images from “slipping” on the surface of the retina as head position varies.

1.5 State of the art research on Electrooculogram

Eye movement detection can be done using many techniques [29] such as Infrared Video System (IRVS), Infrared Oculography (IROG), Search Coil (SC), Optical type Eye Tracking System, Purkinje dual Purkinje image (DPI) and Electroculography (EOG) [35]. EOG has proved to be the simplest of all these techniques. An EOG system is fairly easy to construct using surface electrodes that are placed around the eye socket and is simple to work with in real time. Thus we can employ an electrooculographic system to predict the presence of diseases whose symptoms are heavily characterized by eye movements in a cost-effective and simple way.

Different characteristics of EOG reveal its potential to be implemented for controlling different rehabilitation aids. EOG is important for both clinicians and scientists as it provides abundant neuropathological information. EOG is also an efficient alternative for HCI without speech or hand movements.

The main applications of EOG signal include detection and assessment of many ophthalmological diseases such as Retinitis Pigmentosa [36] and Best's disease [37] as well as degenerative muscular disorders and neural diseases like Parkinson's disease [38]. Drowsiness detection and cognitive process modeling are also different applications of EOG analysis [39]. Eye movement controlled human computer interfaces based on EOG are the major interests of recent HCI research. Several instances of EOG based control of neuro-prosthetic devices are found in the literature [40-42], including controlling motion of computer cursor [43] and controlling wheelchair system for rehabilitation [44]. There have been different strategies of analyzing [45] and implementing EOG in the field of robotics [46]. Researchers have shown blink detection using various methods with applications in different events like fatigue monitoring [47], consciousness analysis during driving, etc. [48].

EOG controlled device are gaining popularity in recent times. Devices such as robotic aids [49], rehabilitation aids [50], computer control [51], etc. are being achieved using EOG signal. Choice of EOG over other possible methods is probably based on the ease of usage and the low cost-of-production. Bulling et al. used a wearable EOG unit in recognition of different activities [52]. The recognition algorithms were successfully evaluated in an experiment performed with eight subjects while reading, copying a text, taking notes, watching video and net surfing. This shows that EOG is a potentially robust technique for activity recognition across a number of typical daily situations. With each passing day, research is going on in the field of electrooculogram and its utilization for human computer interfacing. New approaches have come up. Some are software based [53] and some of them are hardwired or embedded systems [54]. The application of EOG has been done on home appliances also [55]. EOG based systems have been experimented to produce eye movement controlled wheelchairs [44, 56-58] to give the severely paralyzed patients a way to move without the help of others. As this was being implemented, the problems regarding such applications were discovered. There is a long journey ahead to make such work worthy.

In the work by L. D. Lledó, [59] an application of EOG controlled internet browsing has been demonstrated. The study involves eye movement controlled writing, searching and mouse controlling tasks. Five eye movements viz. left, right, up, down and blink are encoded as commands to control the mouse pointer. However, the application is only restricted to internet browsing activity, involves calculation of moving average and derivative as signal processing to detect change in eye movement direction and uses market-made circuitry which is costlier and less flexible than laboratory-made circuits. Thus, there is a need to focus on a general purpose GUI rather than only on internet browsing, using a more cost-effective circuitry to detect EOG signals and process the signals using less number of signal processing steps to make it suitable for real-time applications. A virtual keyboard is mapped to eye movements by Z. Jin [60]. In this work, the eye movements are linearly mapped pixel coordinates of the keyboard. Hence, moving far from current position required a stretched eye movement in the required direction which can not only be imprecise but also can stress the eye muscles than normal amount. This limitation indicates a need to formulate a way to make the movement of cursor not proportional to the extent of eye movement. The different cursor control methods basically involves tracking the eye movement followed by encoding the eye movements as control signals for the cursor. In the work by T. Kasahara [61], the eye movement is detected by tracking the movement of the pupil. For this, an infra-red camera has been used which is not only a costlier device but also processing images captured by the camera requires more amount of memory and computation. Hence, the measurement made by the sensor for such real-time application of eye movement controlled GUI should also be optimized in terms of the cost of the sensor as well as in terms of the memory required to store the raw measured data [62].

The main purpose of our work is to create a reliable, affordable and easy-to-use eye controlled human-computer interface that will enable the paralyzed or differentially abled people to use computers independently. This would provide a large number of people the chance to engage more easily and powerfully in productive activity. The work illustrates an application of precise control of the computer cursor using specific permutations of eye movements of the user as a rehabilitative platform.

Table 1.1 Highlights of recent EOG research

Author & Year of publication	**Highlights of work done**
ER Powsner and KS Lion, 1950 [63]	Testing of eye muscles from electronics equivalent point of view
Glenn O Dayton et al., 1964 [64]	Study of coordinated eye movements in the human infant
J Francois, A De Rouck, and D Fernandez-Sasso, 1967 [65]	Electro-oculography in vitelliform degeneration
AF Deutman, 1969 [66]	Electro-oculography in families with vitelli form dystrophy
TH Kirkham, AC Bird, and MD Sanders , 1972 [67]	Electro-oculographic study for Divergence paralysis
Hewitt D Crane and Carroll M Steele, 1985 [68]	Eye Tracker design
Thomas E Hutchinsonmet al., 1989 [69]	Human-computer interaction using eye-gaze input
Carol L Rosen, Lynn Dandrea, and Gabriel G Haddad, 1992 [70]	Sleep apnea study from eye movements
Jacob, R. J. K. , 1993 [71]	Non-command interface design using eye movements
Kazushi Hyoki et al., 1998 [72]	Quantitative EOG and EEG as indices of alertness
Simon K Rushton and Patricia M Riddell, 1999 [73]	Developing visual systems for virtual reality
Liversedge, S. P., and Findlay, J. M. , 2000 [74]	Eye movement analysis for cognition
Chun, M. M. , 2000 [75]	Contextual cueing of visual attention
Melcher, D , 2001 [76]	Visual memory analysis
Majaranta, P., and Räihä , 2002 [77]	Eye typing
Katarzyna Chawarska et al., 2003 [78]	Eye movement analysis of children related to autism

Shell, J. S. et al., 2003 [79]	Attention-seeking devices that respond to visual attention
Zhiwei Zhu and Qiang Ji, 2004 [80]	Eye and gaze tracking for interactive graphic display
Vehkaoja, A. T. et al., 2005 [81]	Wireless Head Cap for EOG
Qvarfordt, P., and Zhai, S. , 2005 [82]	Eye gaze pattern based conversation
Wijesoma, W. S., Kang et al., 2005 [83]	EOG based control of mobile assistive platforms
Carlos H Morimoto and Marcio RM Mimica [84]	Interactive Application Using Eye Tracking
Manabe, H., and Fukumoto, M, 2006 [85]	Wearable headphone-type gaze detector
Hori, J. et al., 2006 [86]	Communication Control System Based on EOG and Voluntary Eye Blink
Manu Kumar etal., 2007 [87]	Gaze-based password entry system
Claudia Ehmke and Stephanie Wilson, 2007 [88]	Web usability problems from eye-tracking
Jussi Virkkala et al., 2007 [89]	Sleep stage classification using electro-oculography
Drewes, H., and Schmidt A., 2007 [90]	Interacting with the Computer Using Gaze Gestures
David M Hoffman et al., 2008 [91]	Vergence– accommodation conflicts
Porta, M., Turina, M. , 2008 [92]	Full-screen input modality for pure eye-based communication
Keith Rayner, 2009 [93]	Eye movements and attention in reading, scene perception, and visual search
Bulling, Andreas, Daniel Roggen, and Gerhard Tröster , 2009 [94]	Context-awareness in everyday environments
Alain Forget, Sonia Chiasson, and Robert Biddle, 2010 [95]	Shoulder-surfing resistance with eye-gaze entry
Jeffrey Michael Klingner, 2010 [96]	Study of Cognitive load during visual tasks by eye movements
T. Gandhi et al., 2010 [96]	Eye movement controlled multitasking gadget
Z.-P. Wei and B.-L. Lu, 2012 [98]	Eye movements based vigilance analysis
Dereck Toker et al., 2013 [99]	Information visualization through eye tracking
A. Ubeda, E. Ianez, J. M. Azorin, 2013 [100]	Bimodal Interface to Support Robotic Arm Control
M. Juhola, Y. Zhang, J. Rasku, 2013 [101]	Eye movements based biometric verification
Shoya Ishimaru et al., 2015 [102]	Smart eyewear design
S Kanoh et al., 2015 [103]	Development of an eyewear
Kai Kunze et al., 2015 [104]	Smart glasses to promote healthy habits
Kai Kunze et al., 2015 [105]	Counting the number of words a user reads using electrooculography
J. A Müller et al., 2016 [106]	Measuring individual sentence comprehension duration
F. Fang et al., 2016 [107]	Eye Motion Sequence Recognition
K. Tabal et al., 2016 [108]	Wearable Drowsiness Detection System

A. Dasgupta et al., 2016 [109]	Identification of eye saccadic signatures
W.D. Chang et al., 2016 [110]	Removing the Interdependency between Horizontal and Vertical Eye-Movement Components
K.R. Lee et al., 2016 [111]	'Eye-writing' recognition in real time
V.S. Arthi et al., 2016 [112]	Interface and Control of Appliances
C. Derchi et al., 2016 [113]	A new empirical perspective on intentional action of eye blink
T. Liang et al., 2016 [114]	Detection of myasthenia gravis
C.G. Altintop et al., 2016 [115]	Analysis of electrooculogram signals from students before and after exam
K. Archawut et al., 2016 [116]	FIR system characterizing eye movement
J. Shimizu et al., 2016 [117]	Eye movement interactions in google cardboard
T. Pfeiffer et al., 2016 [118]	Model-based real-time analysis of mobile eye-tracking in static and dynamic three-dimensional scenes
A. Leroy et al., 2016 [119]	Gaze-controlled text size control, and methods for gaze-based measuring of a text reading speed
R.A. Becerra-García et al., 2017 [120]	Identification of non-spontaneous saccadic movements
D. Alvarez-Estevez et al., 2017 [121]	Derivation and modeling of two new features for the characterization of rapid and slow eye movements during sleep

1.6 Scope of the Thesis

The idea behind the development of next generation Human Computer Interfaces (HCI) is to provide healthy individuals an easier and better life while providing diseased individuals assistance and rehabilitation. Such devices are based on some form of input bio-modality that is processed efficiently to provide the desired results while being interfaced with the computer. HCI based control of rehabilitative aids, communicative devices and robotic equipments are gaining a tremendous significance as observed from recent literature.

Bio-signals such as EMG (Electromyography), EEG (Electroencephalography), EOG (Electrooculogram) and ECG (Electrocardiogram) have been organized to develop control systems for improving the life quality of disabled and elderly people. In the near future we will see highly robust and flexible bio-control systems, which are based on various bio-signals such as voice, muscle contractions, brain waves and gestures. These bio-control systems will have ability to understand human intentions and emotions, and adapt the dynamic changes in the real-world. The design of bio-control systems has four stages: data acquisition and segmentation, feature extraction, classification and control.

This project investigates the potential uses of EOG for real life problems of rehabilitation. The objective is to improve the control capability of the eye movement signal, thus positively contributing to the development of bio-signal controlled assistive devices. Different aspects of HCI applications for rehabilitation are presented using eye movements through electrooculogram.

1.7 Organization of the Thesis

The present research is aimed at development of interface based on electrooculography for rehabilitative applications as discussed in the previous section. The physiological basis of electrooculographic signal and its characteristics have been described in this chapter to provide the reader, an insight into the genesis of the signal. An overview of the background research and development in this field has also been included here (chapter 1) to facilitate understanding of further research needs.

The first and foremost requirement for working with this signal is to acquire, collect and store the signal. The details of the developed EOG acquisition system have been discussed in chapter 2. The first section of chapter 2 explains all the details associated with the design and development of the signal conditioning circuit and data acquisition. Although disposable self-adhesive surface electrodes were used for EOG signal acquisition initially, a wearable glass frame with inbuilt electrodes has been designed to make the system user friendly as well as comfortable and portable.

EOG signal is basically the signal produced by eye ball movements in different directions. In the next section of chapter 2, emphasis has been given to different feature extraction and classification algorithms to explore relationship between EOG signal and eye movements in various directions. This was considered necessary to use this signal as control signal; and, to optimize the control algorithms.

Eyes convey much useful information related to a person's ophthalmic disease or cognitive or mental state or any disability or any physical condition. One important objective of this work is to extract relevant parameters that can be observed by eye movement analysis about a person's condition and provide a feedback mechanism that can be used as an assistive tool or supportive device. The research and development related to implementation of EOG in this domain have been discussed in chapter 3.

This chapter is divided into four sections. In first section, assistance scheme is proposed to follow progress of autistic children. Autism is a disease characterized by abnormal eye movements and an inability to follow a pattern of object movement in different directions. Eye movement data is recorded from normal individuals over a period of five days. Hjorth Parameters are used as signal features. Eye movement directions in response to a visual stimulus for tracking an object are classified using ensemble classifiers based on bagging and adaptive boosting algorithms. Maximum classification accuracies of 83.09%, 90.27%, 80.75% and 92.27% were achieved on Hjorth Parameters as features using Bagging Ensemble classifier while tracking four different sequences. The individuals are trained by repeated tracking of the sequences such that there is an improvement in tracking over time. The system is designed to measure the tracking accuracy of following four different sequences of movement of an object in different directions as shown in a cue in a predetermined interval of time. The average tracking accuracy over ten normal subjects considering all the four sequence stimuli improves from 78.64% to 90.96% in five days which is accompanied with a decrease in staring errors from 6.36% to 1.29%. This would enable convenient detection of eye fixations/staring errors in Autistic people along with the provision of gradual improvements when the tracking sequences are not followed in 50% of the cases through consequent training.

The second section of third chapter deals with reading disabled children, analyzing their eye tracking data. This section describes how reading speed can be conveniently decoded from recorded EOG. It is common that the reading speed of dyslexic patients is lower than their normal counterparts, because of slow letter and word processing. Eye movements in dyslexic patients are significantly different from that of normal individuals, in terms of the presence of frequent fixations and stares in the former. Eye movement data for different reading speeds is recorded. From the data, Adaptive Autoregressive (AAR) parameters, Band Power Estimates and Wavelet Coefficients are extracted as signal features. Reading speeds are classified using different pattern classifiers from which an average accuracy of 94.67% over all classes and participants is obtained using Radial Basis Function (RBF) Support Vector Machine (SVM) Tree classifier and AAR Parameters as features. Friedman test is done to select the best classifier. The trained classifier is used to recognize the reading speeds of a set of new normal individuals. If the reading speeds are less than a preset threshold, that individual is trained repeatedly for 10 days for improvement. An improvement of reading speed is observed by the decrease in the misclassification rate from 45.1% to 9.92% in 10 days for the fastest speed (1 sentence/2 s) over all the subjects.

This scheme of reading speed evaluation is carried out on three children having specific learning disorder. The number of children are too less to come to any conclusion. However, the results reveal that the proposed system may also be used for training and assisting children with dyslexia or other similar reading disabilities.

In third section, strategy as precautionary measure for computer vision syndrome is presented based on blink detection. Feature extraction was accomplished by level 4 wavelet decomposition of the EOG signal using Haar and order 4 Daubechies as mother wavelets. In the offline mode, binary classification was performed on the two acquired set of detail coefficients to distinguish between blinks and non-blink eye movements using linear, polynomial and Radial Basis Function (RBF) kernelized Support Vector Machine (SVM) classifier. The best classification accuracy of 95.83% was achieved haar as the mother wavelet and polynomial-SVM as the classifier. This trained classifier was chosen for real-time classification of EOG signals. The system causes the computer to go to a standby mode when the desired number of blinks is not attained over a predetermined period of time, thereby allowing the computer user to rest his/her eyes. Real-time implementation of the proposed algorithm was carried out on 10 subjects. The performance of the system was validated by noting that the AER over each 30 minutes interval and the POC over each subject reduces as time progresses.

In last part of this chapter a layout of electrooculogram based eye dystonia prevention method is put forward. By classifying EOG into blinks and non-blinks and counting the number of blinks over a period of time, development of an intelligent automatic eye dystonia indicator based on EOG for cost-effective assistance in diagnosis of the disease has been experimented. Feature extraction was accomplished by AR parameters, Hjorth Parameters and Power Spectral Density. Binary classification was performed on the two acquired feature sets (AR+PSD) and (Hjorth+PSD) to distinguish between blinks and non-blink eye movements using linear, polynomial and Radial Basis Function (RBF) kernelized Support Vector

Machine (SVM) classifier. The best classification accuracy of 93.40% was achieved on AR (5) +PSD feature space and using RBF-SVM as the classifier. The present work has been carried out on normal individuals, and future scopes include implementation of this scheme to assist patients suffering from eye dystonia.

The persons who are congenital amputee, or those who have lost their limb(s) or paralyzed due to accident or trauma are unable to move freely without the help of an assistant. This mobility problem is also applicable for elderly people. Most of the commercially available rehabilitative aids cannot provide full control to operate any household gadget alone or communicate with people. Thus there is a need to develop a technology for the movement disabled to improve their lifestyle. From previous research work it is evident that EOG signal has the potential to control any device. In this research work, it has been investigated that how much effectively, accurately and precisely EOG signal may be employed to control any rehabilitative device. Development of an intelligent interface capable of controlling assistive or daily need based electronic devices through eye movements alone has been another main object of this present research. Therefore, three novel approaches towards EOG-driven rehabilitative aids which can lead to smart homes have been proposed in chapter 4.

In the first proposed scheme, a multitasking graphical user interface (GUI) is designed by controlling the position of a computer cursor using eye movements. Each and every icon of the GUI can be accessed online by just selecting them and thus the particular function can be performed. Here eye movements are classified using standard classification algorithms as well as a custom made routine. The signals were classified based on their amplitudes to generate control commands to drive a GUI. Finally the application of the GUI is tested with six healthy subjects by performing different icon selection by controlling the mouse pointer with eye movements. The users completed the testing process in a reasonable time and the speed improves with training. For the real time control of the GUI, the proposed approach yields 95.83% accuracy.

Second approach proposed is chapter 4 is to recognize the patterned eye movements of some known digits, letters and shapes. Eyeball movements intended to draw a pattern (numeric digit, alphabet or geometric shape) have been recorded. The extracted signal has been processed and classified successfully with more than 90% accuracy rate. Here Power spectral density has been used as feature extractor and support vector machine with multilayer perceptron kernel function has been used as classifier. Performance of other classifiers also has been compared here. Five healthy subjects took part in experiment and their eyeball movement signal has been acquired for distinguishing different numerical digits that are frequently needed for communication to external world.

In the last and third approach, movements of a motorized wheelchair, i.e., forward, backward, right, left in a particular speed and start-stop operation are controlled in real time by EOG with predefined eye commands. This section presents the three modules of this work, where the first module deals with detection of eye movement direction from the EOG data. The second module is the wireless transmission of the classified signal. The third module manages pulse width modulated signal generation to control the driving motors of the wheelchair.

As said earlier, eye movements itself act as a rich source of information about a person’s memory as well as cognition. Combination of information from brain signals using EEG and eye movements using

EOG for cognitive context recognition has been illustrated in chapter 5. The first subsection introduces multimodal data analysis using EEG and EOG signals as sources of cognitive context recognition information. The experimental design and data analyses are explained in the next subsection. After that an illustration of the architectures of feature and decision level fusion for constructing a bimodal cognitive context recognition platform is given. The final subsection of chapter 5 provides the results and discussions.

Chapter 6 provides a thorough self-review of the reported work with an aim to test the major claims introduced in different parts of the thesis. It also summarizes the main results obtained experimentally and proposes the possible direction of future research.

Thus this work implements various approaches of application of EOG in different rehabilitative purposes. The approaches are implemented in real time with available human subjects and assessed over a period of time to evaluate the efficacy, robustness and repeatability of the systems.

References

[1] Karray, F. at al. (2008) 'Human-computer interaction: overview on state of the art', International Journal on Smart Sensing and Intelligent Systems, Vol. 1 No. 1.

[2] Dix, A. (2009). *Human-computer interaction* (pp. 1327-1331). Springer US.

[3] Jacko, J. A. (Ed.). (2012). *Human computer interaction handbook: Fundamentals, evolving technologies, and emerging applications*. CRC press.

[4] Kosuge, K., & Hirata, Y. (2004, August). Human-robot interaction. In *Robotics and Biomimetics, 2004. ROBIO 2004. IEEE International Conference on* (pp. 8-11). IEEE.

[5] Murphy, R. R., Nomura, T., Billard, A., & Burke, J. L. (2010). Human–robot interaction. *IEEE robotics & automation magazine*, *17*(2), 85-89.

[6] Kutner, N. G., Zhang, R., Butler, A. J., Wolf, S. L., Alberts, J. L., & Merians, A. S. (2010). Quality-of-Life Change Associated With Robotic-Assisted Therapy to Improve Hand Motor Function in Patients With Subacute Stroke: A Randomized Clinical Trial/Invited Commentary/Author Response. *Physical therapy*, *90*(4), 493.

[7] Broadbent, E., Stafford, R., & MacDonald, B. (2009). Acceptance of healthcare robots for the older population: review and future directions. *International Journal of Social Robotics*, *1*(4), 319.

[8] Scassellati, B., Admoni, H., & Matarić, M. (2012). Robots for use in autism research. *Annual review of biomedical engineering*, *14*, 275-294.

[9] Kang, K. I., Freedman, S., Mataric, M. J., Cunningham, M. J., & Lopez, B. (2005, June). A hands-off physical therapy assistance robot for cardiac patients. In *Rehabilitation Robotics, 2005. ICORR 2005. 9th International Conference on* (pp. 337-340). IEEE.

[10] Deegan, P. E. (1988). Recovery: The lived experience of rehabilitation. *Psychosocial Rehabilitation Journal*, *11*(4), 11.

[11] Census of India, 2011(http://censusindia.gov.in/)

[12] Stephanidis, C. (Ed.). (2000). *User interfaces for all: concepts, methods, and tools*. CRC Press.

[13] Yanco, H. A. (1998). Wheelesley: A robotic wheelchair system: Indoor navigation and user interface. In *Assistive technology and artificial intelligence* (pp. 256-268). Springer Berlin Heidelberg.

[14] Navarro, X., Krueger, T. B., Lago, N., Micera, S., Stieglitz, T., & Dario, P. (2005). A critical review of interfaces with the peripheral nervous system for the control of neuroprostheses and hybrid bionic systems. *Journal of the Peripheral Nervous System*, *10*(3), 229-258.

[15] Moon, I., Lee, M., Chu, J., & Mun, M. (2005, April). Wearable EMG-based HCI for electric-powered wheelchair users with motor disabilities. In *Robotics and Automation, 2005. ICRA 2005. Proceedings of the 2005 IEEE International Conference on* (pp. 2649-2654). IEEE.

[16] Matarić, M. J., Eriksson, J., Feil-Seifer, D. J., & Winstein, C. J. (2007). Socially assistive robotics for post-stroke rehabilitation. *Journal of NeuroEngineering and Rehabilitation*, *4*(1), 5.

[17] Srinivasan, M. A., & Basdogan, C. (1997). Haptics in virtual environments: Taxonomy, research status, and challenges. *Computers & Graphics*, *21*(4), 393-404.
[18] El Saddik, A. (2007). The potential of haptics technologies. *IEEE Instrumentation & Measurement Magazine*, *10*(1), 10-17.
[19] Berg, P., & Scherg, M. (1991). Dipole models of eye movements and blinks. *Electroencephalography and clinical neurophysiology*, *79*(1), 36-44.
[20] Mowrer, O. H., Ruch, T. C., & Miller, N. E. (1935). The corneo-retinal potential difference as the basis of the galvanometric method of recording eye movements. *American Journal of Physiology--Legacy Content*, *114*(2), 423-428.
[21] Thakor, N. V. (2015). Biopotentials and Electrophysiology Measurements. In *Telehealth and Mobile Health* (pp. 555-574). CRC Press.
[22] Huxley, A. F., & Stämpfli, R. (1951). Direct determination of membrane resting potential and action potential in single myelinated nerve fibres. *The Journal of physiology*, *112*(3-4), 476.
[23] Mowrer, O. H., Ruch, T. C., & Miller, N. E. (1935). The corneo-retinal potential difference as the basis of the galvanometric method of recording eye movements. *American Journal of Physiology--Legacy Content*, *114*(2), 423-428.
[24] Dawkins, M. S. (1993). *Through our eyes only?*. WH Freeman.
[25] Lythgoe, J. N. (1988). Light and vision in the aquatic environment. In *Sensory biology of aquatic animals* (pp. 57-82). Springer New York.
[26] Wald, G. (1968). The molecular basis of visual excitation. *Nature*, *219*, 800-807.
[27] Brown, K. T. (1968). The electroretinogram: its components and their origins. *Vision research*, *8*(6), 633-IN6.
[28] Marg, E. (1951). Development of electro-oculography: Standing potential of the eye in registration of eye movement. *AMA archives of ophthalmology*, *45*(2), 169-185.
[29] Young, L. R., & Sheena, D. (1975). Survey of eye movement recording methods. *Behavior research methods & instrumentation*, *7*(5), 397-429.
[30] Brown, M., Marmor, M., Zrenner, E., Brigell, M., & Bach, M. (2006). ISCEV standard for clinical electro-oculography (EOG) 2006. *Documenta ophthalmologica*, *113*(3), 205-212.
[31] Gratton, G. (1998). Dealing with artifacts: The EOG contamination of the event-related brain potential. *Behavior Research Methods, Instruments, & Computers*, *30*(1), 44-53.
[32] Peters, J. F. (1967). Surface electrical fields generated by eye movements. *American Journal of EEG Technology*, *7*(2), 27-40.
[33] Miles, W. R. (1939). The steady polarity potential of the human eye. *Proceedings of the National Academy of Sciences*, *25*(1), 25-36.
[34] Rayner, K. (1998). Eye movements in reading and information processing: 20 years of research. *Psychological bulletin*, *124*(3), 372.
[35] Young, L. R., & Sheena, D. (1975). Eye-movement measurement techniques. *American Psychologist*, *30*(3), 315.
[36] Stavrou, P., Good, P. A., Broadhurst, E. J., Bundey, S., Fielder, A. R., & Crews, S. J. (1996). ERG and EOG abnormalities in carriers of X-linked retinitis pigmentosa. *Eye*, *10*(5), 581-589.
[37] Weleber, R. G. (1989). Fast and slow oscillations of the electro-oculogram in Best's macular dystrophy and retinitis pigmentosa. *Archives of Ophthalmology*, *107*(4), 530-537.
[38] Shibasaki, H., Tsuji, S., & Kuroiwa, Y. (1979). Oculomotor abnormalities in Parkinson's disease. *Archives of Neurology*, *36*(6), 360-364.
[39] Bartholow, B. D., Fabiani, M., Gratton, G., & Bettencourt, B. A. (2001). A psychophysiological examination of cognitive processing of and affective responses to social expectancy violations. *Psychological science*, *12*(3), 197-204.
[40] Veraart, C., Wanet-Defalque, M. C., Gerard, B., Vanlierde, A., & Delbeke, J. (2003). Pattern recognition with the optic nerve visual prosthesis. *Artificial organs*, *27*(11), 996-1004.
[41] Kilgore, K. L., Peckham, P. H., Crish, T. J., & Smith, B. (2015). *U.S. Patent No. 9,108,060*. Washington, DC: U.S. Patent and Trademark Office.
[42] Mcfarland, D. J., & Wolpaw, J. R. (2010). Brain–computer interfaces for the operation of robotic and prosthetic devices. *Advances in Computers*, *79*, 169-187.
[43] Norris, G., & Wilson, E. (1997, May). The eye mouse, an eye communication device. In *Bioengineering Conference, 1997., Proceedings of the IEEE 1997 23rd Northeast* (pp. 66-67). IEEE.

[44] Hashimoto, M., Takahashi, K., & Shimada, M. (2009, July). Wheelchair control using an EOG-and EMG-based gesture interface. In *Advanced Intelligent Mechatronics, 2009. AIM 2009. IEEE/ASME International Conference on* (pp. 1212-1217). IEEE.

[45] Wissel, T., & Palaniappan, R. (2013). Considerations on strategies to improve EOG signal analysis. In *Investigations into Living Systems, Artificial Life, and Real-World Solutions* (pp. 204-217). IGI Global.

[46] IáñEz, E., Úbeda, A., Azorín, J. M., & Perez-Vidal, C. (2012). Assistive robot application based on an RFID control architecture and a wireless EOG interface. *Robotics and Autonomous Systems*, *60*(8), 1069-1077.

[47] Sommer, D., & Golz, M. (2010). Evaluation of PERCLOS based current fatigue monitoring technologies. In *Engineering in Medicine and Biology Society (EMBC), 2010 annual international conference of the IEEE* (pp. 4456-4459). IEEE.

[48] Chieh, T. C., Mustafa, M. M., Hussain, A., Hendi, S. F., & Majlis, B. Y. (2005, November). Development of vehicle driver drowsiness detection system using electrooculogram (EOG). In *Computers, Communications, & Signal Processing with Special Track on Biomedical Engineering, 2005. CCSP 2005. 1st International Conference on* (pp. 165-168). IEEE.

[49] Chen, Y., & Newman, W. S. (2004, April). A human-robot interface based on electrooculography. In *Robotics and Automation, 2004. Proceedings. ICRA'04. 2004 IEEE International Conference on* (Vol. 1, pp. 243-248). IEEE.

[50] Ten Kate, J. H., & Hepp, B. (1989). Optical and eye-controlled communication aids. *Journal of medical engineering & technology*, *13*(1-2), 63-67.

[51] Patmore, D. W., & Knapp, R. B. (1998, January). Towards an EOG-based eye tracker for computer control. In *Proceedings of the third international ACM conference on Assistive technologies* (pp. 197-203). ACM.

[52] Bulling, A., Ward, J. A., Gellersen, H., & Troster, G. (2011). Eye movement analysis for activity recognition using electrooculography. *IEEE transactions on pattern analysis and machine intelligence*, *33*(4), 741-753.

[53] Kaufman, A. E., Bandopadhay, A., & Shaviv, B. D. (1993, October). An eye tracking computer user interface. In *Virtual Reality, 1993. Proceedings., IEEE 1993 Symposium on Research Frontiers in* (pp. 120-121). IEEE.

[54] Bulling, A., Roggen, D., & Tröster, G. (2009). Wearable EOG goggles: Seamless sensing and context-awareness in everyday environments. *Journal of Ambient Intelligence and Smart Environments*, *1*(2), 157-171.

[55] Lin, C. T., Chang, C. J., Lin, B. S., Hung, S. H., Chao, C. F., & Wang, I. J. (2010). A real-time wireless brain–computer interface system for drowsiness detection. *IEEE Transactions on Biomedical Circuits and Systems*, *4*(4), 214-222.

[56] Tsui, C. S. L., Jia, P., Gan, J. Q., Hu, H., & Yuan, K. (2007, December). EMG-based hands-free wheelchair control with EOG attention shift detection. In *Robotics and Biomimetics, 2007. ROBIO 2007. IEEE International Conference on* (pp. 1266-1271). IEEE.

[57] Wei, L., Hu, H., & Yuan, K. (2009, February). Use of forehead bio-signals for controlling an intelligent wheelchair. In *Robotics and Biomimetics, 2008. ROBIO 2008. IEEE International Conference on* (pp. 108-113). IEEE.

[58] Wang, H., Li, Y., Long, J., Yu, T., & Gu, Z. (2014). An asynchronous wheelchair control by hybrid EEG–EOG brain–computer interface. *Cognitive neurodynamics*, *8*(5), 399-409.

[59] Lledó, L. D., Ubeda, A., Iáñez, E., & Azorín, J. M. (2013). Internet browsing application based on electrooculography for disabled people. *Expert Systems with Applications*, *40*(7), 2640-2648.

[60] Jin, Z., & Laszlo, S. (2014). *U.S. Patent Application No. 14/533,617*.

[61] Kasahara, T. (1991). *U.S. Patent No. 5,070,883*. Washington, DC: U.S. Patent and Trademark Office.

[62] Gandhi, T. (2007). Design of an electro-oculogram (EOG) based assistive computer system for the rehabilitation of severely disabled. *Int. J. Tech., Knowledge Soc.*, *2*(8), 101-106.

[63] Powsner, E. R., & Lion, K. S. (1950). Testing eye muscles. *Electronics*, *23*(March), 96.

[64] Dayton, G. O., Jones, M. H., Aiu, P., Rawson, R. A., Steele, B., & Rose, M. (1964). Developmental study of coordinated eye movements in the human infant: I. Visual acuity in the newborn human: a study based on induced optokinetic nystagmus recorded by electro-oculography. *Archives of Ophthalmology*, *71*(6), 865-870.

[65] Francois, J., De Rouck, A., & Fernandez-Sasso, D. (1967). Electro-oculography in vitelliform degeneration of the macula. *Archives of Ophthalmology*, *77*(6), 726-733.

[66] Deutman, A. F. (1969). Electro-oculography in families with vitelliform dystrophy of the fovea: detection of the carrier state. *Archives of ophthalmology*, *81*(3), 305-316.

[67] Kirkham, T. H., Bird, A. C., & Sanders, M. D. (1972). Divergence paralysis with raised intracranial pressure. An electro-oculographic study. *The British journal of ophthalmology*, *56*(10), 776.

[68] Crane, H. D., & Steele, C. M. (1985). Generation-V dual-Purkinje-image eyetracker. *Applied Optics*, *24*(4), 527-537.

[69] Hutchinson, T. E., White, K. P., Martin, W. N., Reichert, K. C., & Frey, L. A. (1989). Human-computer interaction using eye-gaze input. *IEEE Transactions on systems, man, and cybernetics*, *19*(6), 1527-1534.

[70] Rosen, C. L., D'Andrea, L. Y. N. N., & Haddad, G. G. (1992). Adult criteria for obstructive sleep apnea do not identify children with serious obstruction. *Am Rev Respir Dis*, *146*(5 Pt 1), 1231-1234.

[71] Daugman, J. G. (1993). High confidence visual recognition of persons by a test of statistical independence. *IEEE transactions on pattern analysis and machine intelligence*, *15*(11), 1148-1161.

[72] Hyoki, K., Shigeta, M., Tsuno, N., Kawamuro, Y., & Kinoshita, T. (1998). Quantitative electro-oculography and electroencephalography as indices of alertness. *Electroencephalography and clinical Neurophysiology*, *106*(3), 213-219.

[73] Rushton, S. K., & Riddell, P. M. (1999). Developing visual systems and exposure to virtual reality and stereo displays: some concerns and speculations about the demands on accommodation and vergence. *Applied Ergonomics*, *30*(1), 69-78.

[74] Liversedge, S. P., & Findlay, J. M. (2000). Saccadic eye movements and cognition. *Trends in cognitive sciences*, *4*(1), 6-14.

[75] Morimoto, C. H., Koons, D., Amir, A., & Flickner, M. (2000). Pupil detection and tracking using multiple light sources. *Image and vision computing*, *18*(4), 331-335.

[76] Melcher, D. (2001). Persistence of visual memory for scenes. *Nature*, *412*(6845), 401-401.

[77] Majaranta, P., & Räihä, K. J. (2002, March). Twenty years of eye typing: systems and design issues. In *Proceedings of the 2002 symposium on Eye tracking research & applications* (pp. 15-22). ACM.

[78] Shell, J. S., Vertegaal, R., & Skaburskis, A. W. (2003, April). EyePliances: attention-seeking devices that respond to visual attention. In *CHI'03 extended abstracts on Human factors in computing systems* (pp. 770-771). ACM.

[79] Chawarska, K., Klin, A., & Volkmar, F. (2003). Automatic attention cueing through eye movement in 2-year-old children with Autism. *Child development*, *74*(4), 1108-1122.

[80] Ji, Q., & Zhu, Z. (2002, June). Eye and gaze tracking for interactive graphic display. In *Proceedings of the 2nd international symposium on Smart graphics* (pp. 79-85). ACM.

[81] Vehkaoja, A. T., Verho, J. A., Puurtinen, M. M., Nojd, N. M., Lekkala, J. O., & Hyttinen, J. A. (2006, January). Wireless head cap for EOG and facial EMG measurements. In *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the* (pp. 5865-5868). IEEE.

[82] Qvarfordt, P., & Zhai, S. (2005, April). Conversing with the user based on eye-gaze patterns. In *Proceedings of the SIGCHI conference on Human factors in computing systems* (pp. 221-230). ACM.

[83] Wijesoma, W. S., Wee, K. S., Wee, O. C., Balasuriya, A. P., San, K. T., & Soon, K. K. (2005, July). EOG based control of mobile assistive platforms for the severely disabled. In *Robotics and Biomimetics (ROBIO). 2005 IEEE International Conference on* (pp. 490-494). IEEE.

[84] Morimoto, C. H., & Mimica, M. R. (2005). Eye gaze tracking techniques for interactive applications. *Computer vision and image understanding*, *98*(1), 4-24.

[85] Manabe, H., & Fukumoto, M. (2006, April). Full-time wearable headphone-type gaze detector. In *CHI'06 Extended Abstracts on Human Factors in Computing Systems* (pp. 1073-1078). ACM.

[86] Hori, J., Sakano, K., Miyakawa, M., & Saitoh, Y. (2006, July). Eye movement communication control system based on EOG and voluntary eye blink. In *International Conference on Computers for Handicapped Persons* (pp. 950-953). Springer Berlin Heidelberg.

[87] Kumar, M., Garfinkel, T., Boneh, D., & Winograd, T. (2007, July). Reducing shoulder-surfing by using gaze-based password entry. In *Proceedings of the 3rd symposium on Usable privacy and security* (pp. 13-19). ACM.

[88] Ehmke, C., & Wilson, S. (2007, September). Identifying web usability problems from eye-tracking data. In *Proceedings of the 21st British HCI Group Annual Conference on People and Computers: HCI... but not as we know it-Volume 1* (pp. 119-128). British Computer Society.

[89] Virkkala, J., Hasan, J., Värri, A., Himanen, S. L., & Müller, K. (2007). Automatic sleep stage classification using two-channel electro-oculography. *Journal of neuroscience methods*, *166*(1), 109-115.

[90] Borghetti, D., Bruni, A., Fabbrini, M., Murri, L., & Sartucci, F. (2007). A low-cost interface for control of computer functions by means of eye movements. *Computers in Biology and Medicine*, *37*(12), 1765-1770.

[91] Hoffman, D. M., Girshick, A. R., Akeley, K., & Banks, M. S. (2008). Vergence–accommodation conflicts hinder visual performance and cause visual fatigue. *Journal of vision*, *8*(3), 33-33.

[92] Porta, M., & Turina, M. (2008, March). Eye-S: a full-screen input modality for pure eye-based communication. In *Proceedings of the 2008 symposium on Eye tracking research & applications* (pp. 27-34). ACM.

[93] Rayner, K. (2009). Eye movements and attention in reading, scene perception, and visual search. *The quarterly journal of experimental psychology*, *62*(8), 1457-1506.

[94] Bulling, A., Roggen, D., & Tröster, G. (2009). Wearable EOG goggles: Seamless sensing and context-awareness in everyday environments. *Journal of Ambient Intelligence and Smart Environments*, *1*(2), 157-171.

[95] Forget, A., Chiasson, S., & Biddle, R. (2010, April). Shoulder-surfing resistance with eye-gaze entry in cued-recall graphical passwords. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 1107-1110). ACM.

[96] Klingner, J. (2010). *Measuring cognitive load during visual tasks by combining pupillometry and eye tracking* (Doctoral dissertation, Stanford University).

[97] Gandhi, T., Trikha, M., Santhosh, J., & Anand, S. (2010). Development of an expert multitask gadget controlled by voluntary eye movements. *Expert Systems with Applications*, *37*(6), 4204-4211.

[98] Wei, Z. P., & Lu, B. L. (2012, June). Online vigilance analysis based on electrooculography. In *Neural Networks (IJCNN), The 2012 International Joint Conference on* (pp. 1-7). IEEE.

[99] Toker, D., Conati, C., Steichen, B., & Carenini, G. (2013, April). Individual user characteristics and information visualization: connecting the dots through eye tracking. In *proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 295-304). ACM.

[100] Ubeda, A., Iánez, E., & Azorin, J. M. (2013). An integrated electrooculography and desktop input bimodal interface to support robotic arm control. *IEEE Transactions on Human-Machine Systems*, *43*(3), 338-342.

[101] Juhola, M., Zhang, Y., & Rasku, J. (2013). Biometric verification of a subject through eye movements. *Computers in biology and medicine*, *43*(1), 42-50.

[102] Ishimaru, S., Kunze, K., Tanaka, K., Uema, Y., Kise, K., & Inami, M. (2015, April). Smart eyewear for interaction and activity recognition. In *Proceedings of the 33rd Annual ACM Conference Extended Abstracts on Human Factors in Computing Systems* (pp. 307-310). ACM.

[103] Kanoh, S., Ichi-Nohe, S., Shioya, S., Inoue, K., & Kawashima, R. (2015, August). Development of an eyewear to measure eye and body movements. In *Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE* (pp. 2267-2270). IEEE.

[104] Kunze, K., Inoue, K., Masai, K., Uema, Y., Tsai, S. S. A., Ishimaru, S. & Inami, M. (2015, July). MEME: smart glasses to promote healthy habits for knowledge workers. In *ACM SIGGRAPH 2015 Emerging Technologies* (p. 17). ACM.

[105] Kunze, K., Katsutoshi, M., Uema, Y., & Inami, M. (2015, March). How much do you read?: counting the number of words a user reads using electrooculography. In *Proceedings of the 6th Augmented Human International Conference* (pp. 125-128). ACM.

[106] Müller, J. A., Wendt, D., Kollmeier, B., & Brand, T. (2016). Comparing eye tracking with electrooculography for measuring individual sentence comprehension duration. *PloS one*, *11*(10).

[107] Fang, F., Shinozaki, T., Horiuchi, Y., Kuroiwa, S., Furui, S., & Musha, T. (2016). Improving Eye Motion Sequence Recognition Using Electrooculography Based on Context-Dependent HMM. *Computational intelligence and neuroscience*, *2016*.

[108] Tabal, K. M. R., Caluyo, F. S., & Ibarra, J. B. G. (2016). Microcontroller-Implemented Artificial Neural Network for Electrooculography-Based Wearable Drowsiness Detection System. In *Advanced Computer and Communication Engineering Technology* (pp. 461-472). Springer International Publishing.

[109] Dasgupta, A., Chakraborty, S., Mondal, P., & Routray, A. (2016). Identification of eye saccadic signatures in electrooculography data using time-series motifs. In *India Conference (INDICON), 2016 IEEE Annual* (pp. 1-5). IEEE.

[110] Chang, W. D., Cha, H. S., & Im, C. H. (2016). Removing the Interdependency between Horizontal and Vertical Eye-Movement Components in Electrooculograms. *Sensors*, *16*(2), 227.

[111] Lee, K. R., Chang, W. D., Kim, S., & Im, C. H. (2016). Real-time 'eye-writing'recognition using electrooculogram (EOG). *IEEE Transactions on Neural Systems and Rehabilitation Engineering*.

[112] Arthi, S. V., & Norman, S. R. (2016). Interface and Control of Appliances by the Analysis of Electrooculography Signals. In *Artificial Intelligence and Evolutionary Computations in Engineering Systems* (pp. 1075-1084). Springer India.

[113] Derchi, C., Casarotto, S., Comanducci, A., Mazza, A., Marchello, A., Fecchio, M. & Sinigaglia, C. (2016). Behind an eye blink: A new empirical perspective on intentional action. *Gait & Posture*, *49*, S27.

[114] Liang, T., Boulos, M. I., Murray, B. J., Krishnan, S., Katzberg, H., & Umapathy, K. (2016). Detection of myasthenia gravis using electrooculography signals. In *Engineering in Medicine and Biology Society (EMBC), 2016 IEEE 38th Annual International Conference of the* (pp. 896-899). IEEE.

[115] Altıntop, Ç. G., Latifoğlu, F., & Esas, M. Y. (2016). Analysis of electrooculogram signals from students before and after exam. In *Medical Technologies National Congress (TIPTEKNO), 2016* (pp. 1-4). IEEE.

[116] Archawut, K., Tangsuksant, W., Thumwarin, P., Sangworasil, M., & Matsuura, T. (2016). Realization of FIR system characterizing eye movement based on electrooculogram. In *Biomedical Engineering (BME-HUST), International Conference on* (pp. 23-26). IEEE.

[117] Shimizu, J., & Chernyshov, G. (2016). Eye movement interactions in google cardboard using a low cost EOG setup. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct* (pp. 1773-1776). ACM.

[118] Pfeiffer, T., Renner, P., & Pfeiffer-Leßmann, N. (2016). EyeSee3D 2.0: model-based real-time analysis of mobile eye-tracking in static and dynamic three-dimensional scenes. In *Proceedings of the Ninth Biennial ACM Symposium on Eye Tracking Research & Applications* (pp. 189-196). ACM.

[119] Leroy, A., Fleureau, J., & Guillotel, P. (2016). "Method for gaze-controlled text size control, and methods for gaze-based measuring of a text reading speed and of a number of visual saccades per text line."*U.S. Patent No. 9,256,285*. Washington, DC: U.S. Patent and Trademark Office.

[120] .Becerra-García, R. A., García-Bermúdez, R. V., Joya-Caparrós, G., Fernández-Higuera, A., Velázquez-Rodríguez, C., Velázquez-Mariño, M., & Rodráguez-Labrada, R. (2017). Data mining process for identification of non-spontaneous saccadic movements in clinical electrooculography. *Neurocomputing*.

[121] Alvarez-Estevez, D., van Velzen, I., Ottolini-Capellen, T., & Kemp, B. (2017). Derivation and modeling of two new features for the characterization of rapid and slow eye movements in electrooculographic sleep recordings. *Biomedical Signal Processing and Control*, *35*, 87-99.

2

Development of Acquisition Device & Wearable Glasses for Electrooculogram

As indicated in the previous chapter, the first module for electroocugraphic artificial interface deals with procurement of eye tracking signal and detection of different eye movements from by analyzing it. The objective of the work presented in this chapter is to design an acquisition circuit for EOG and indentify directional eye movements. A dual channel circuit is designed to collect both horizontal and vertical eye movement data. In the preliminary stage Ag-AgCl disposable surface electrodes has been placed around the eye socket region to receive EOG signal. Later, a wearable EOG glass is implemented with stainless steel electrodes. The final phase deals with classification of right, left, up, down eye movement and blink from the recorded EOG signal.

2.1 Introduction

The foremost requirement for eye movement detection from EOG signals is the EOG device to record the EOG signals related to emotion. The commercially available EOG devices are very costly. A data acquisition system has been designed for EOG that will be user friendly, simple and portable. The details of development of a multi-channel EOG amplifier suitable for eye movement tracking and EOG signal acquisition is presented in this chapter.

Electrodes, amplifier, signal conditioning and acquisition are the major parts of an EOG system [1, 2]. The electrodes are the sensors that detect the signal from the surrounding region of eye, the microvolt signals are brought into the measurable range where they can be digitized accurately by the amplifiers, the filters remove the unwanted artifacts and noise from the desired signal, analogue to digital converter converts the acquired analogue signal into digital form to be stored, displayed and analysed in computers.

This work aimed at developing the EOG amplifier; digitize the analogue EOG signal thus obtained and then acquiring the EOG signal into for storage, display and further analysis. The schematic of the EOG system development is presented in figure 2.1.

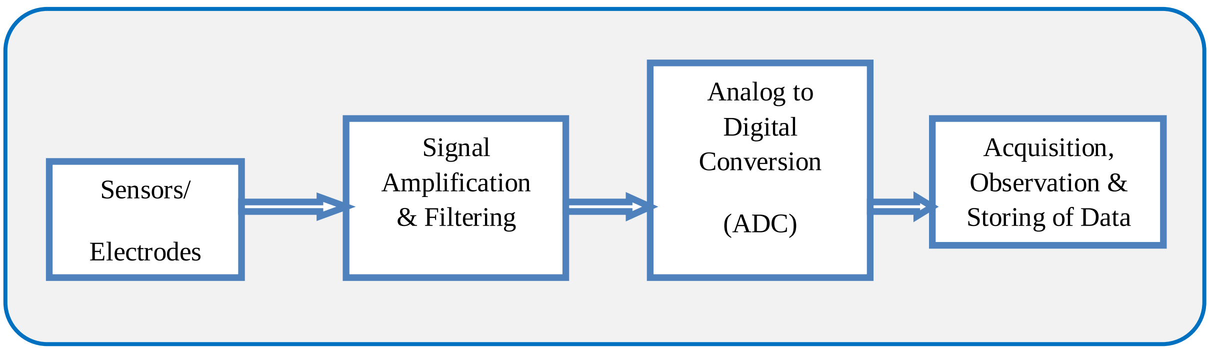


Fig. 2.1 Schematic of the data acquisition system

The chapter is mainly divided in four sections for design of EOG acquisition circuit, processing & storage in LabView, development of wearable EOG glass & procedure for detection of directional eye movements. The concluding section summarizes the total method of EOG data acquisition, processing & analysis.

2.2 Development of Two Channel EOG Acquisition Circuit

The previous studies on EEG based emotion recognition and the experimental procedures applied in this work and the results and observations thus obtained, as reported in the literature [3-5], the parameters for development of an EOG device for emotion recognition can be outlined as follows:

- Amplitude of the EOG signal ranges in few micro volts. The EOG amplifier has high gain of approximately two thousand.
- The frequency band needed for eye movement detection is 1-15 Hz. Therefore the bandwidth of the filter is 1-20 Hz.
- Proper signal conditioning is provided to remove the base line drift, the 50Hz power line interference and other unwanted artifacts.

The basic block diagram of EOG circuit is shown in Fig. 2.2.

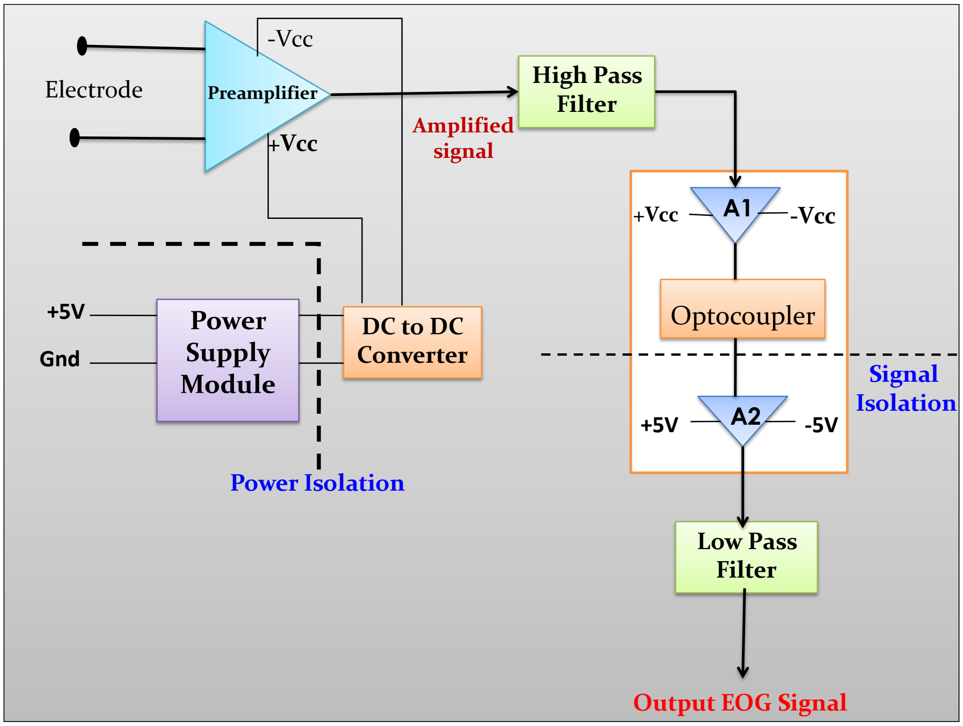


Figure 2.2. Block diagram of the EOG circuit design

2.2.1 Preamplifier

The preamplifier is the first block in the system. It amplifies the EOG signal and eliminates the common mode signals [6]. The gain in range of thousands is required for the EOG amplifier [7]. The developed system has a total gain of 1000. The gain is given in two stages. The gain of the preamplifier is 100. The rest of the gain is given in the signal isolation stage. To eliminate the possibility of signal saturation in the preamplifier stage due to various interferences the gain is provided in two stages. Here IC AD620 [10] an instrumentation amplifier with very high input impedance and CMRR, is used for pre-amplification. Pin diagram and basic configuration of IC AD620 is given in Fig. 2.3 and 2.4 respectively.

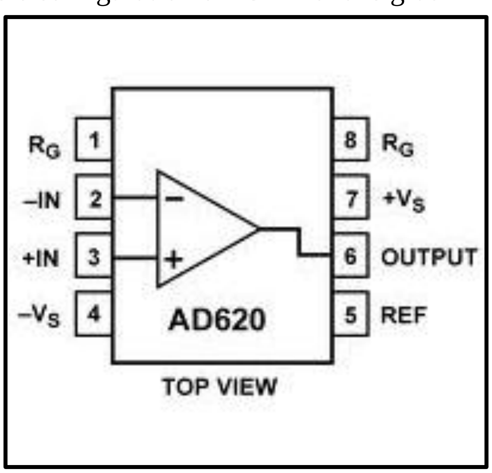


Fig. 2.3 Pin diagram of IC AD620

The AD620 is a low cost, high accuracy instrumentation amplifier that requires only one external resistor to set gains of 1 to 1000. It only needs 1.3mA max supply current. It a good fit for battery powered, and portable applications. The low noise, low input bias current and low power of the AD620 make it well suited for biosignals.

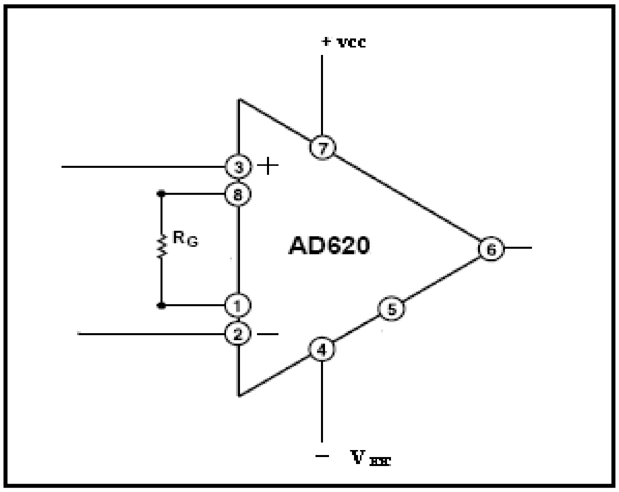


Fig 2.4. Basic Configuration of AD 620

The gain equation of AD620 is given by,

$$R_G = \frac{49.4\ k\Omega}{G-1} \tag{2.1}$$

According to the equation 2.1, for gain G=100, the gain resistance R_G is found out to be 470Ω. The gain resistance is connected across the pin number 1 and 8 of AD620. In the system AD620 is driven at the voltage of ±12V. The two electrodes are connected to pin number 2 and 3. The ground electrode is connected with pin number 5 which is the circuit ground.

2.2.2 Safety Measures

Safety measures for both the patient and device are required to be taken to protect them from the electrical hazards. In addition to good grounding, insulation of the device and the wires, incorporating fuses or circuit breakers, shock preventers the devices like EOG that are directly connected with the patient's body require certain other safety features to be incorporated. To achieve the safety measures for the device and the patient, power and signal isolation are required.

2.2.2.1 Power Isolation

Power isolation isolates the total device from the power supply side. This can be achieved in many the following ways:

- Power from batteries: This is the best method for power isolation which eliminates the possibilities of shock hazard from the power supply. But the disadvantage is that it requires regular monitoring.
- Using photovoltaic cells.
- DC to DC converter: It uses isolation transformer to isolate power.

In this work a dual output DC/DC converter IC MAU108 [8] is used for power isolation. Basic configuration of MAU 108 is shown in figure 2.5. The isolation is achieved by an inbuilt step up isolation transformer. It operates at an input voltage of 5V and provides an isolated dual output of ±12V.

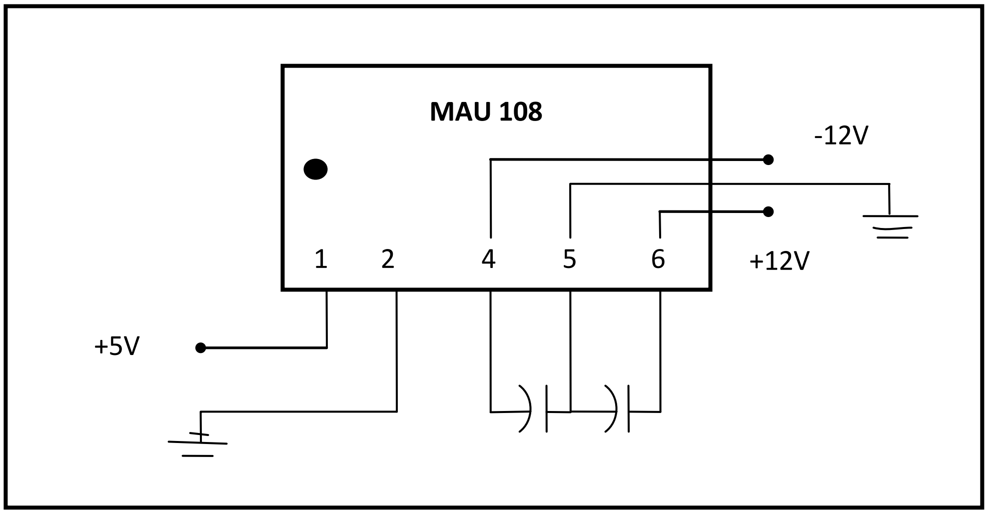


Fig. 2.5 Basic configuration of MAU 108 for power isolation

2.2.2.2 Signal Isolation

Nowadays signal isolation is most commonly achieved by optocoupler device, which consists of LED (light emitting diode) and photodiode (PD). When the photodiode is illuminated by the LED, it can conduct in the reverse direction. The maximum current conducted by the photodiode depends on the intensity of the radiation that falls on it.

In this work the signal isolation is achieved by using the high linear optocoupler IC HCNR200 [9-10]. It is a high-linearity optocoupler comprising a high performance AlGaAs, (aluminium, gallium, and arsenide) LED which illuminates two closely matched photodiodes.

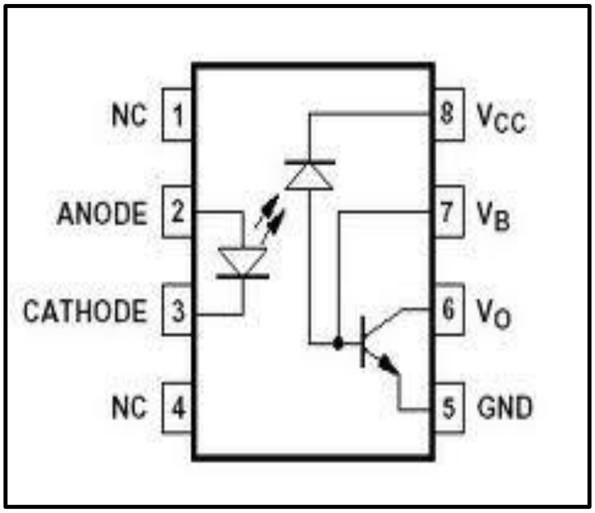


Fig. 2.6 Pin diagram of HCNR 200

The Figure 2.6 presents the actual circuit diagram of signal isolation. R1=1MΩ and R2=10MΩ is chosen so that the gain of the signal isolation stage G2=10. A gain of the preamplifier stage was G1=100. Thus the total gain of the whole system becomes 1000. Ultra low offset voltage (75µV) IC OP07 [8] (Figure 2.7) is used as both the input and output stage opamps A1 and A2. OP07 has a wide input voltage range of 3-18V, with a CMRR of 106dB and high input impedance.

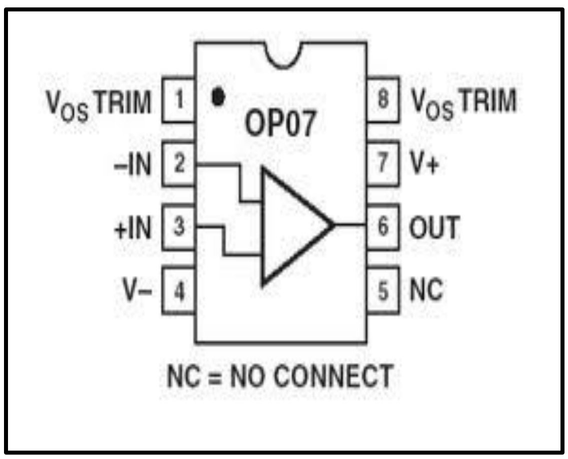


Fig. 2.7 Pin connections of OP07

The input opamp of signal isolation is driven by ±12V provided by the output of MAU108. The output opamp is driven by the ±5V of the power supply.

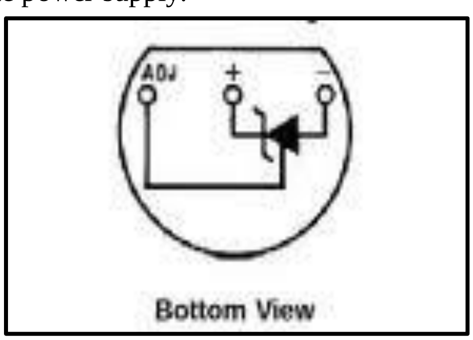


Fig. 2.8 Pin connections of LM336

IC LM336 [11] (Figure 2.8) is a 2.5V reference diode, which is used in both input and output side, with a combination of 220kΩ resistances to add some positive signal in the input side and subtract it from the output side to make the circuit work for both positive and negative signals.

2.2.3 Filtering

The bandwidth of the developed EOG system is 0.1Hz to 20Hz. To attain this requirement analogue passive HPF and LPF are implemented in the circuit. This filtering arrangement provides us the signal of the required bandwidth as well as eliminates the artifacts present in the recorded signal [12-14].

The low cut off frequency is set as 0.1Hz, which eliminates the base line drift and the low frequency artifacts. The passive HPF is implemented at the output of the preamplifier, followed by a passive second order LPF implemented in the signal isolation stage. The high cut off of the LPF is set as 20Hz.The cut off frequency of the filters is given by (2.2) Where, R is the resistance and C is the capacitance.

$$f_c = \frac{1}{2\pi RC} \tag{2.2}$$

According to the equation 2.2, a capacitor, C=0.32μF is connected in series with the resistance R1=1MΩ to obtain the HPF configuration of cut off frequency 0.1Hz. For the 2nd order LPF of cut off frequency 20 Hz, a combination of R=47kΩ, C=0.1μF in the input side and a combination R=10MΩ, C=10pF is connected in parallel. The LPF ensures that the 50Hz power line interference is eliminated from the signal.

2.2.4 Power Supply

The EOG system needed to be portable. The battery powered devices require continuous monitoring. In the developed system the power is provided by the USB port of the PC or laptops used for storage, display and analysis of EOG signal. The USB port provides +5V power supply. Using ICL7660 [15] the +5V from the USB is converted to -5V which drives the output op amp of the signal isolation part (shown in Figure 2.9. The +5V obtained from the power supply is given as the input to MAU108 which isolates the power. The circuit diagram and the developed circuit for EOG acquisition can be seen in Figure 2.10 and 2.11 respectively.

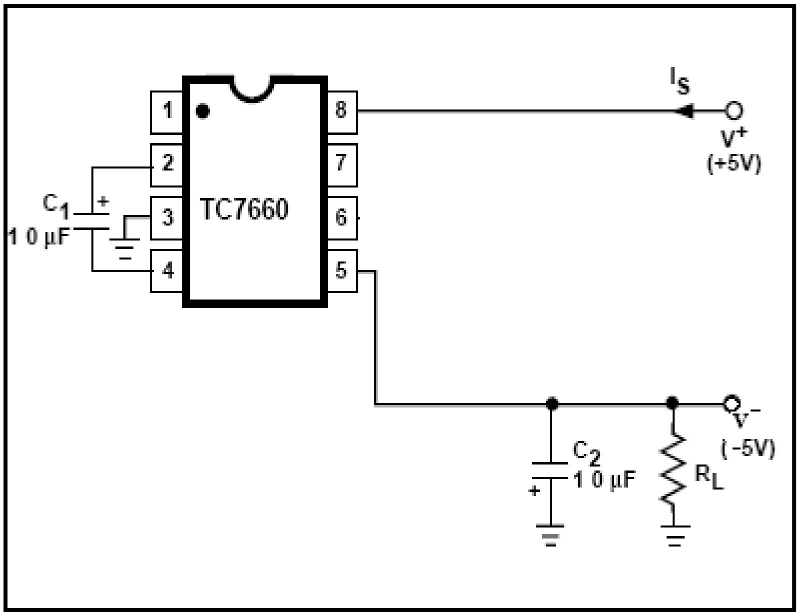


Fig. 2.9 Connection of IC 7660 for -5V generation

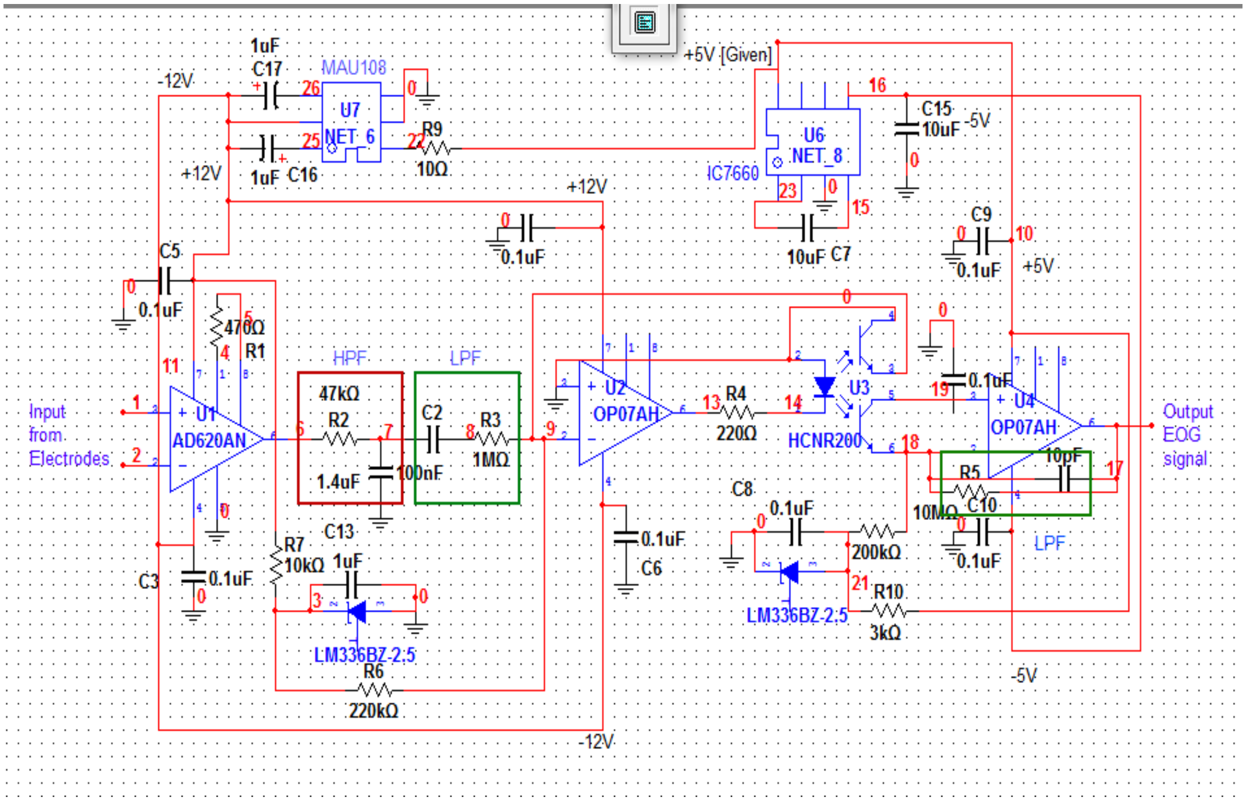


Fig. 2.10 Circuit diagram of single channel data acquisition system

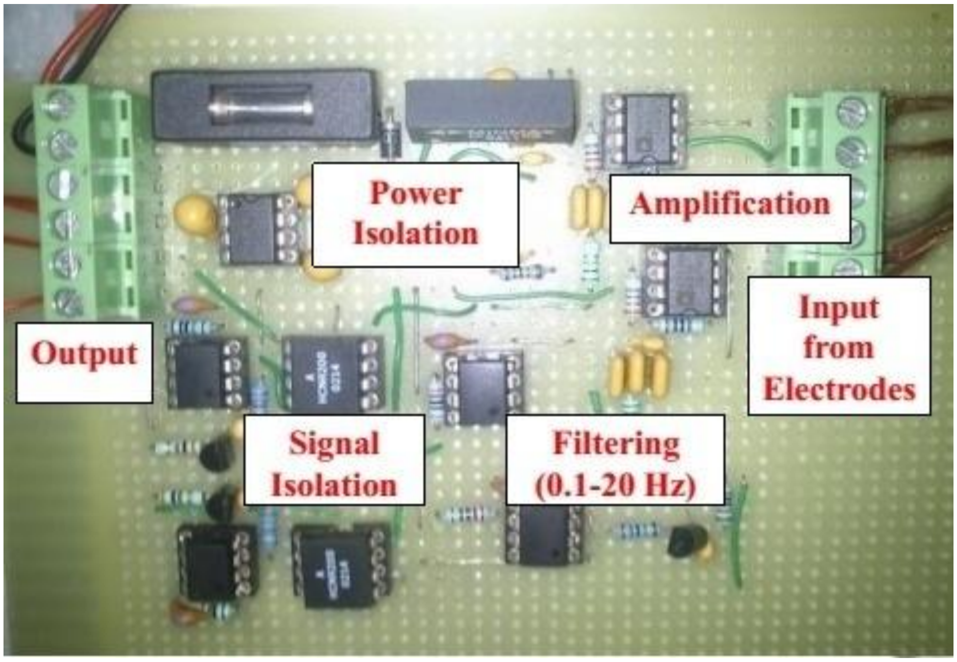


Fig. 2.11 The developed two channel EOG acquisition system

2.3 Choice of Electrodes and Their Positioning

The first stage of our system design is the electrodes. The electrodes were chosen with the concern of protecting the eyes from hazardous elements. Silver/Silver-Chloride electrodes were chosen because the half-cell potential of this variety of electrodes is low and, remain steady. Electrodes with the smallest amount of time variation in half-cell potential are desirable because they cause the least amount of offset. By definition, the hydrogen electrode has a zero half-cell potential, but due to the gaseous nature, they cannot be feasibly used. Although lead electrodes have a lower half-cell potential than the Ag/Ag- Cl electrodes, lead is hazardous to the health and thus is avoided [13]. The choice of electrodes has taken into account low cost and proper signal pick-up along with ease in mounting electrodes at desired locations without any specific accessories. Thus keeping all this factors in mind, disposal electrodes were chosen. They satisfy all the condition stated above and at the same time, are easily available.

The next task that needed proper emphasis was the placement of this electrode. Two electrodes could be placed in the region adjoining the eye depending upon the movement (vertical, horizontal or both) for which signal detection is desired. But placement of ground electrode was a matter of concern. Placing them in the front lobe of brain sometime resulted in the excitation of some sensory neuron, perhaps due to some leakage of signal which may be due to the contact between the body and the ground. But such an occurrence was to be avoided.

At the same time placing of ground electrode in lower part of the body resulted in increase of the noise level. Thus an optimization between signal quality and the safety of the subject was to be considered. The best suitable location in such a scenario was the lower end of external pinna. But due to the size of the electrode we opted for, it was not feasible. Hence, the neck region was selected for placement of ground electrode. The output was considerably noise free without any compromise regarding safety & comfort level of subjects.

2.4 EOG Signal Acquisition in LabVIEW

Since EOG signal remains contaminated with various artifacts and noises like eye blink, head movement artifacts, environmental noise, power line interferences etc.; the filters need to be implemented in the hardware and also in the software platform for acquisition with high Q.

Only four electrodes are sufficient to measure the signal, which have to be placed on the surrounding region of eye to detect horizontal eye movements. These few numbers of electrodes will also reduce the complexity of the device, will make it user friendly and can be easily implemented. The ground electrode is placed on the neck.

EOG signal acquisition is performed in the LabVIEW software platform. The analogue EOG signal obtained from the developed circuitry is digitized using analogue to digital converter (ADC). The digitized signals obtained from the ADC are acquired in the LabVIEW platform. Once the data is stored digital filters are implemented in the LabVIEW program. The data is stored in files using LabVIEW program which can be retrieved using LabVIEW programming for display and offline analysis. In the preliminary stage, NI"s (National Instrument's) USB6008 is used as ADC. Its specifications and its analogue pin assignments are provided in Figure 2.12 and 2.13 respectively.

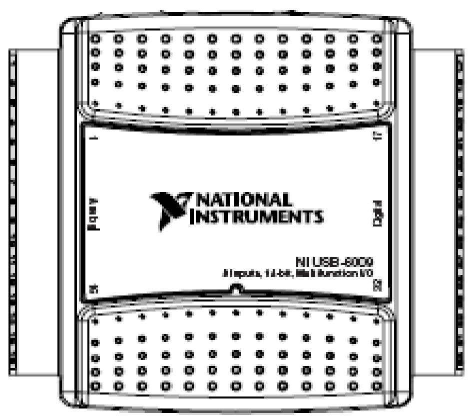
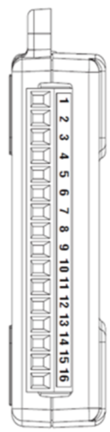


Fig. 2.12 National Instruments USB-6008 DAQ

Module	Terminal	Signal, Single-Ended Mode	Signal, Differential Mode
	1	GND	GND
	2	AI 0	AI 0+
	3	AI 4	AI 0–
	4	GND	GND
	5	AI 1	AI 1+
	6	AI 5	AI 1–
	7	GND	GND
	8	AI 2	AI 2+
	9	AI 6	AI 2–
	10	GND	GND
	11	AI 3	AI 3+
	12	AI 7	AI 3–
	13	GND	GND
	14	AO 0	AO 0
	15	AO 1	AO 1
	16	GND	GND

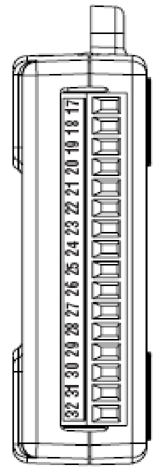
Module	Terminal	Signal
	17	P0.0
	18	P0.1
	19	P0.2
	20	P0.3
	21	P0.4
	22	P0.5
	23	P0 6
	24	P0.7
	25	P1.0
	26	P1.1
	27	P1.2
	28	P1.3
	29	PFI 0
	30	+2.5 V
	31	+5 V
	32	GND

Fig. 2.13 Analog & Digital terminal assignment of NI USB 6008

The LabVIEW program using NI DAQ data assistant VI used as the 1st block for acquiring EOG data using NI USB 6008 ADC. The AI channel of the ADC is chosen in the LabVIEW platform, as shown in Figure 2.14. Recording of EOG data in LabVIEW is shown in figure 2.15. An infinite impulse response (IIR) BPF of cut off 1-15Hz of Butterworth topology of order 10 is implemented. The filtered signal is displayed in the waveform chart and is saved in a file using the block "write to measurement file" VI.

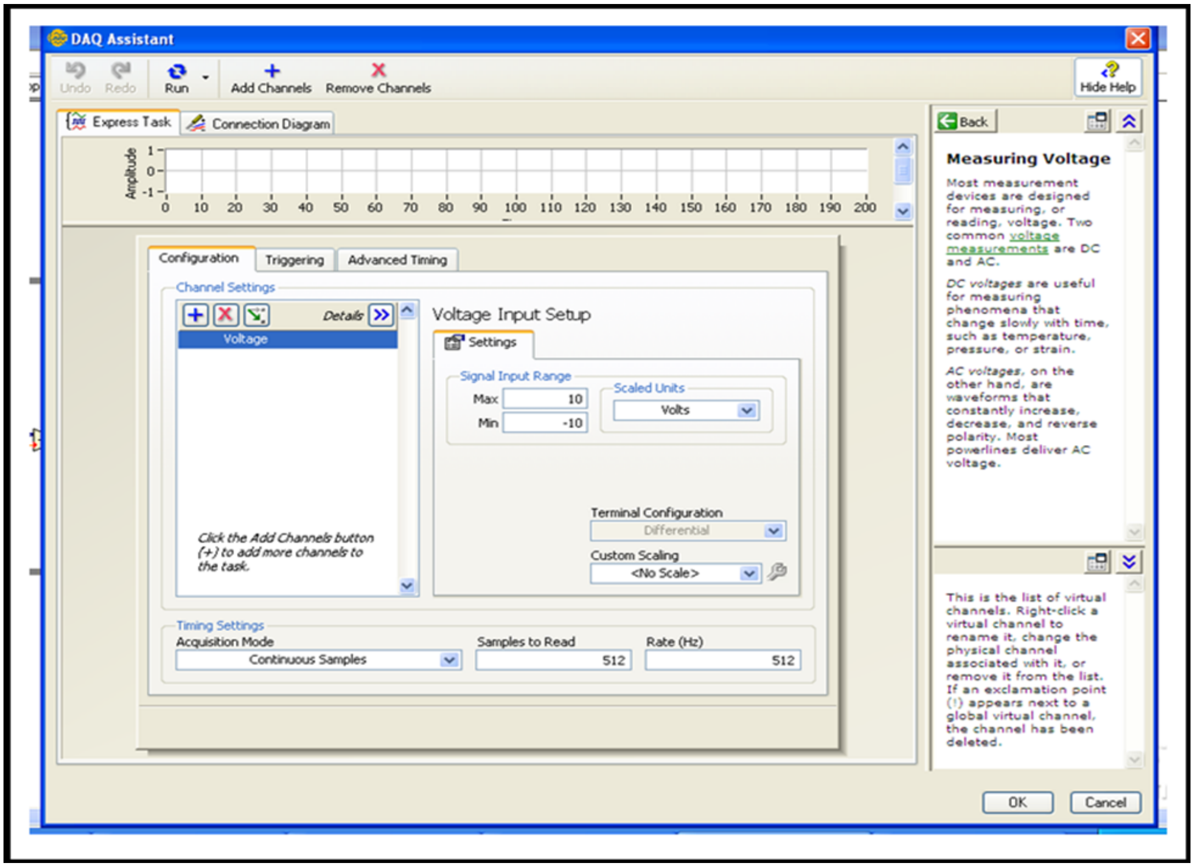


Fig. 2.14 NI DAQ assistant VI configuration

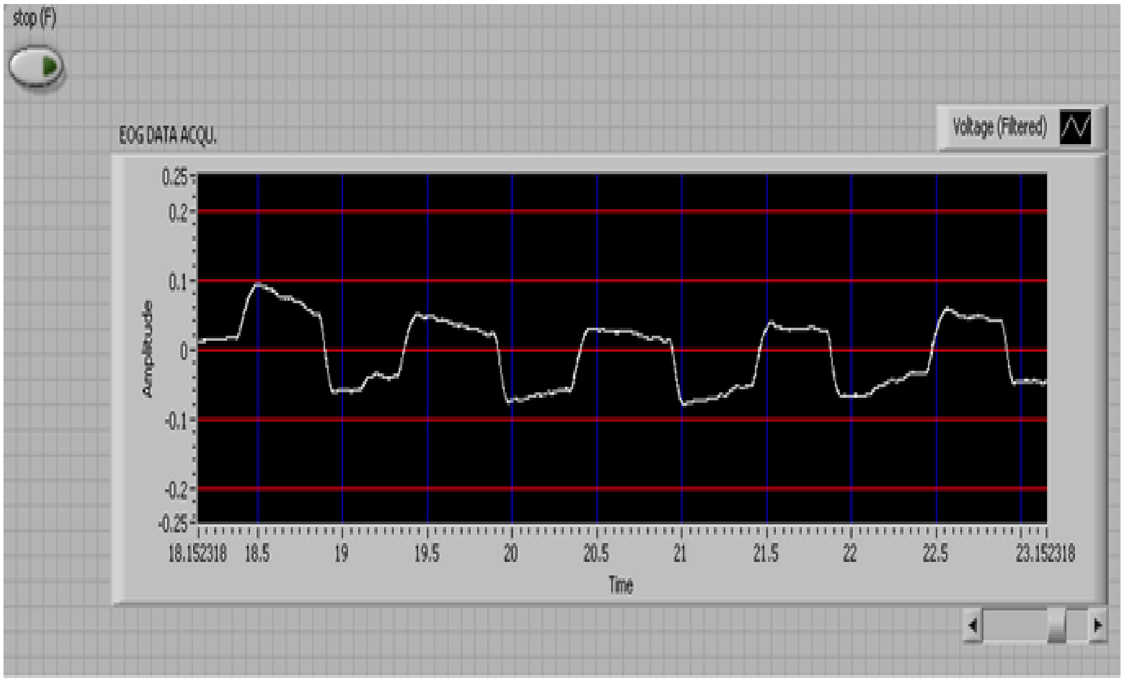


Fig. 2.15 Recording of EOG data in LabVIEW

2.5 Wearable EOG Glass Development

A comfortable wearable spectacle system has been developed for EOG signal acquisition with attached electrodes. The picture of the proposed eye glass system for EOG is shown in Figure 2.16. The wearable EOG goggles were designed to fulfill the following requirements:

- ✓ To achieve a convenient and unobtrusive implementation and minimize user distraction the device needs to be wearable and lightweight.
- ✓ To allow for autonomous long-term use in daily life the device needs to be low-power.
- ✓ The device needs to provide adaptive real-time signal processing capabilities to allow for context-aware interaction.
- ✓ To compensate for EOG signal artifacts caused by physical activity

The spectacle contains dry EOG electrodes attached to the glasses frame. Four electrodes are arranged around the left eye and mounted on flat springs to achieve good skin contact. A fifth sensor near right side of the neck region provides the reference signal.

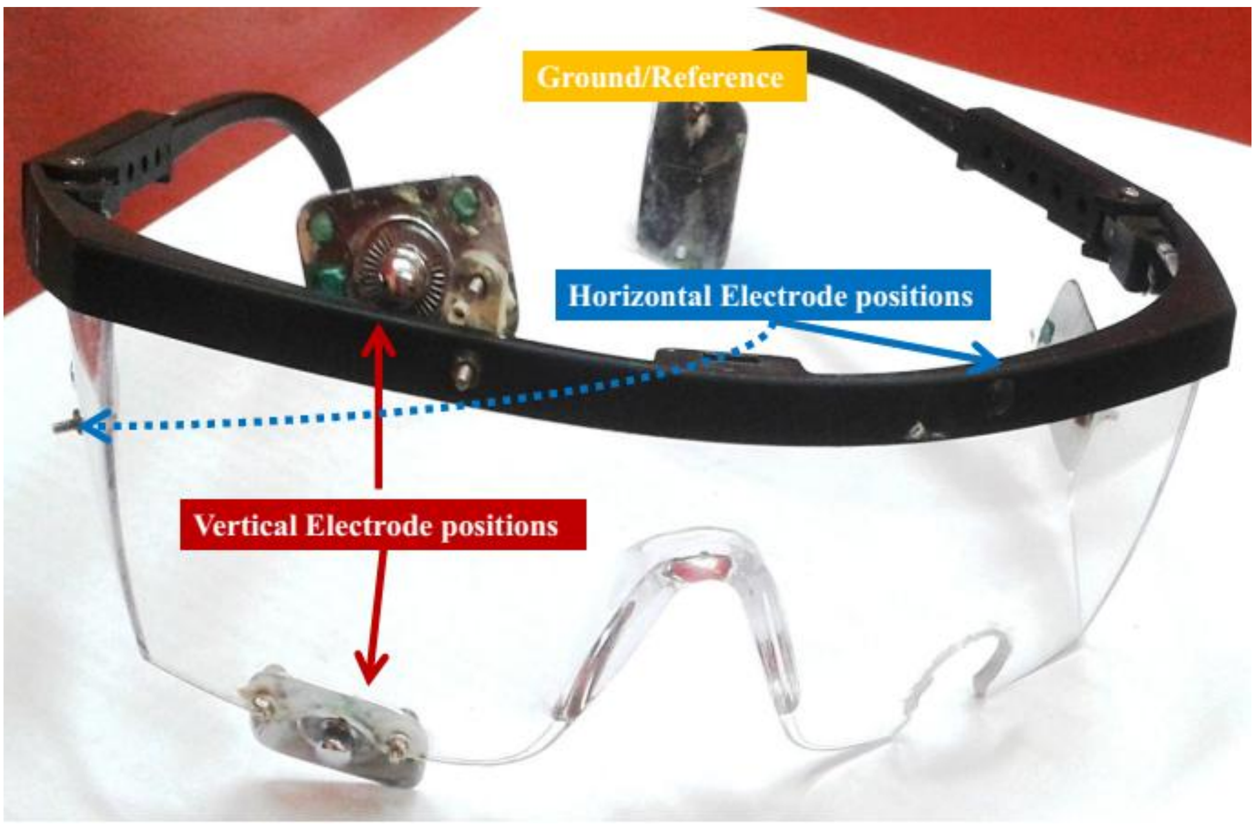


Fig. 2.16 Developed Wearable EOG glass

To further improve this spectacle system for more accurate EOG recording, to compensate changes in ambient light an accelerometer and a light sensor need to be added. Moreover, to make the eye glass system fit to every user irrespective of face size and shape the system must be made of some flexible material that can be adjusted according to requirement.

2.6 Classification of Eye Movements

The detection of the actual direction of eye movements is the basic and most important criteria to apply EOG to control devices. The potential of EOG changes, when unintentional eye movement occurs. Hence to generate the control commands of any device from EOG signal the directional eye movements must be accurately classified.

Controlling Human Computer Interface (HCI) by any bio-potential comprises of three main steps: feature extraction, classification, and control signal coding [16-20].

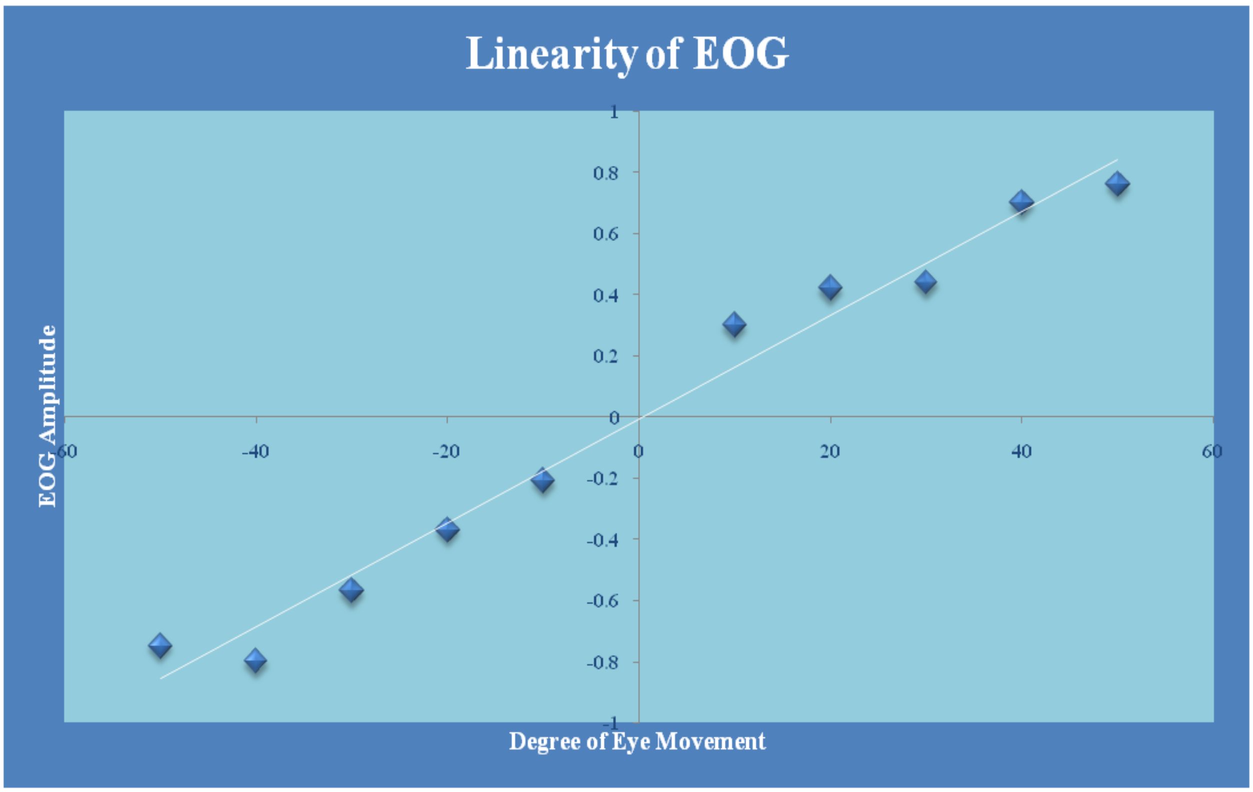


Fig. 2.17 Linearity of EOG signal in Horizontal Direction

First of all the linearity of EOG signal has been checked with the recorded EOG signal using the developed acquisition system. EOG signal for +10 to +60 and -10 to -60 in horizontal direction. Similarly, in vertical direction +10° to +30° and -10° to -30°. These EOG data have plotted to observe the behaviour of EOG signal (Figure 2.17). It is noticed that up to ±50° in horizontal direction EOG signal maintains linearity and in vertical direction up to± 30° the EOG signal is linear. These degree wise measurements have been done assuming that when looking straight it is zero degree and in one direction is positive and negative in reverse direction.

Here, power spectral density (PSD), wavelet detail coefficients, Auto Regressive (AR) coefficients and combinations of these are taken as sets of features. After feature extraction, the band pass filtered

EOG signals are classified according to different directions of eye movements i.e., right, left, up, down, blink and straight or no movement. These can be used to generate control signals to simulate the movement of rehabilitation aids. The present work has been developed in an offline environment, but it has opened the door towards the real time control of HCI using EOG in future.

2.6.1 Experimental Paradigm

Experiments were conducted with two females and two males in the age group of 23±2 years as subjects, who were asked to move their eye balls according to a visual cue. In the visual stimulus, a ball in the middle of a screen was displayed in the first 10 seconds. After that they were asked to track the movement of the ball in different directions (left-right-up-down) and blink their eyes when it is displayed to do so in the screen.

2.6.2 Eye Movement Detection Methodology

The raw EOG data obtained is subjected to the following processes: Filtering, feature extraction and finally classification. The methodology is shown in the following block diagram (Figure 2.18).

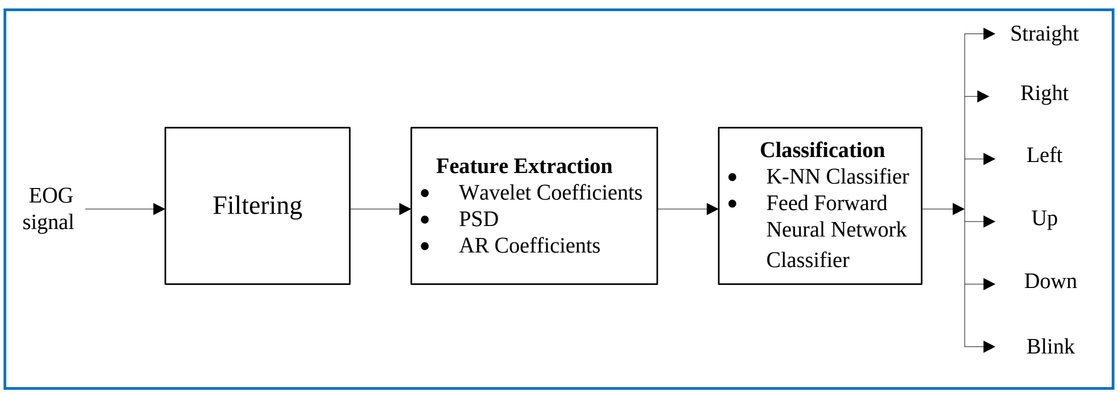


Fig. 2.18 Flowchart depicting the course of work

2.6.2.1 Feature Extraction

Any signal can be represented by means of some attributes. Such attributes can be used as features to distinctly characterize the signal. In the present work we have performed classification with Auto-Regressive parameters, Power Spectral Density (PSD) and Wavelet Coefficients as features of the EOG signal.

2.6.2.1.1 Auto Regression (AR) Model

The AR Model can also be called infinite impulse response (IIR) filter or all-pole filter or maximum entropy model [22-23]. It is used to model any stationary stochastic time-series. Wide-sense stationary means the mean of the data is constant and the autocorrelation depends only on the time lag Eq. (2.3).

$$< x_t > = \text{constant}; \quad < x_t x_{t+k} > = r_k \tag{2.3}$$

The autoregressive model of order p, AR (p), is given by

$$x_t = \sum_{i=1}^{p} a_i x_{t-i} + \varepsilon_t \tag{2.4}$$

Where a_i is the AR coefficients, x_t is the series under observation and ε_t is the residue term which is Gaussian White Noise. By convention, the series x_t is assumed to have zero mean [24-25].

For calculating the AR coefficients, among the different methods the two algorithms that we have followed are:

- Yule-Walker Method
- Burg Method

2.6.2.1.1.1 Yule Walker Method

The method involves multiplying the Eq. (2.2) by x_{t-d}, where d is the delay; then averaging and normalizing the result. Repeating the process for d=1 to p, yields the following set of linear equations called the Yule-Walker equations.[26] The matrix form of the Yule-Walker Equations is given by Eq. (2.5)

$$\begin{bmatrix} 1 & r_1 & r_2 & \cdots & r_{p-1} \\ r_1 & 1 & r_1 & \cdots & r_{p-2} \\ r_2 & r_1 & 1 & \cdots & r_{p-3} \\ \vdots & \vdots & \vdots & & \vdots \\ r_{p-1} & r_{p-2} & r_{p-3} & \cdots & 1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \\ a_p \end{bmatrix} = \begin{bmatrix} r_1 \\ r_2 \\ r_3 \\ \vdots \\ r_p \end{bmatrix} \tag{2.5}$$

Here, a_i (i=1 to p) are the required AR coefficients for an AR (p) process.

2.6.2.1.1.2 Burg Method

If we are provided with N discrete values, we can approximate the values using k coefficients by forward linear prediction Eq. (2.5) or by backward linear prediction Eq. (2.6).

$$y_n = -\sum_{i=1}^{k} a_i x_{n-i} \tag{2.6}$$

$$z_n = -\sum_{i=1}^{k} a_i x_{n+i} \tag{2.7}$$

The forward prediction and backward prediction selects a_i such that the forward error F_k and backward error B_k are minimized. Eq. (2.8) & (2.9)

$$F_k = \sum_{n=k}^{N} (x_n - y_n)^2 = \sum_{n=k}^{N} (x_n - (-\sum_{i=1}^{k} a_i x_{n-i}))^2 \tag{2.8}$$

$$B_k = \sum_{n=0}^{N-k} (x_n - z_n)^2 = \sum_{n=0}^{N-k} (x_n - (-\sum_{i=1}^{k} a_i x_{n+i}))^2 \tag{2.9}$$

In Levinson Durbin recursion

$$A_{k+1} = A_k + \mu V_k \tag{2.10}$$

Where $A_{k+1}= [1\ a_1\ a_2\ \dots\ a_k\ 0]^T$ and $V_{k+1}=[0\ a_k\ \dots\ a_2\ a_1\ 1]^T$

In Burg's method, μ is so calculated that F_k+B_k are minimized. With the initial condition of A_0= [1] and iterating Eq. (2.9) from k=0 to p-1, we can obtain the AR coefficients for an AR (p) process [25].

In our work, we have fitted the data using an AR (4) model. So we have 5 coefficients for each data point.

2.6.2.1.2 Power Spectral Density Estimation using Yule-Walker Method

Non-parametric power spectral density estimation involves computing the Fourier Transform of the data or the auto-correlation function of the data. On the other hand, parametric power spectral density estimation involves fitting an appropriate model to the data, a parametric estimation method to calculate the values of the parameters of the model and the frequency response evaluation of the model which gives an estimate of the PSD of the data.

The method, used in this work, is a parametric power spectral density estimation method [26].

Rearranging Eq. (2.2), we can write

$$x_t - \sum_{i=1}^{p} a_i x_{t-i} = (1 - \sum_{i=1}^{p} a_i z^{-i}) x_t = \varepsilon_t$$

$$\Rightarrow \frac{x_t}{\varepsilon_t} = \frac{1}{1 - \sum_{i=1}^{p} a_i z^{-i}} = H(z)$$

$$\Rightarrow H(f) = \frac{1}{1 - \sum_{i-1}^{p} a_i e^{-ji(2\pi f)T}} \tag{2.11}$$

This is the transfer function of the system Eq. (2.11), where the AR coefficients, a_i, are given by the Yule-Walker Equation Eq. (2.3).

The power spectrum, $P_x(f)$, of the time series x_t is given by Eq. (2.12). This is related to the power spectral density of the white noise, $P_\varepsilon(f)$, which is its variance, σ^2.

$$P_x(f) = |H(f)|^2\, P_\varepsilon(f) = \frac{\sigma^2}{\left|1 - \sum_{i=1}^{p} a_i e^{-ji(2\pi f)T}\right|^2} \tag{2.12}$$

We have used a 129-point discrete approximation of the power spectrum.

2.6.2.1.3 Wavelet Features

Wavelet transform [27, 28], an efficient technique to represent the characteristics of a signal, is based on small waves called wavelets having variable frequency and limited duration. The discrete wavelet transform (DWT) analyzes the signals by decomposing the signal into approximation and detail information, called approximation and detail coefficients respectively.

The outputs of the first decomposition level provide the detail D1 and approximation A1 coefficients, respectively. The first approximation A1 is further decomposed into second approximation A2 and detail D2 and the process continued, until the desired result is obtained.

In the present study, Daubechies (db) mother wavelet of order 4 have used. After trials with the filtered EOG data, the detail coefficients from level 5 are selected as features.

2.6.2.2 Classification

Classification is carried out on each of the different feature spaces obtained from the raw EOG signal as described above using two different classification techniques: k-NN Classifier and a feed- forward neural network and the corresponding classification accuracies are compared.

2.6.2.2.1 k-NN Classifier

K Nearest Neighbour is a classification algorithm where a test point is put into the class which is the most common among its k nearest neighbours [29-30]. The measure of nearness is some form of distance which can be calculated using different methods, such as Euclidean distance, Mahalanobis distance, Manhattan distance etc.

In our experiments, k-NN algorithm has been run with different values of k ranging from 2 to 7. Euclidean distance with k=5 have been selected as it produces the best results.

2.6.2.2.2 Feed Forward Neural Net Classifier

Artificial Neural Networks [31-32] comprise of artificial neurons following the principle of biological neural networks. A feed forward neural network consists of a number of layers of neurons connected such that information can flow only in the forward direction. The initial layer is the input layer and the final layer is the output layer. All the other layers are hidden layers. For each neuron the weighted sum of the inputs are passed through some non-linearity to obtain the outputs. According to the principle of supervised learning, during the training phase, for an initial set of weights of the neural network, the output is calculated and the error is computed for a known target. According to the computed error the weights are adapted. The process is continued as long as the error is reduced below a certain predetermined small value.

In the present work we have used a feed forward network with 10 hidden layers where weight adaptation is done on the basis of Levenberg-Marquardt method [33].

2.6.2.3 Performance Analysis

The classification results obtained are compared in terms of the classification accuracies and the computational time for each classification method. The classification accuracies are computed using confusion matrices.

Table 2.1 and Table 2.2 show the classification performance using Wavelet Detail Coefficients and Power Spectral Density (PSD) as features respectively.

Table 2.1. Classification Results for Wavelet Detail Coefficients as Features

	k-NN with k=5		Feed Forward Neural Network	
	Classification Accuracy	Time (Sec)	Classification Accuracy	**Time (Sec)**
Subject 1	56.67%	0.5634	70.00%	**25.0183**
Subject 2	56.67%	0.5792	72.00%	**26.3662**
Subject 3	56.67%	0.5951	70.00%	**34.8541**
Subject 4	56.67%	0.5766	73.30%	**34.8165**
Average	**56.67%**	**0.578575**	**71.33%**	**30.26378**

Table 2.2 Classification Results for PSD as Features

	k-NN with k=5		Feed Forward Neural Network	
	Classification Accuracy	Time (Sec)	Classification Accuracy	**Time (Sec)**
Subject 1	66.67%	1.5175	83.30%	**86.6939**
Subject 2	73.33%	0.5901	83.30%	**126.3032**
Subject 3	60.00%	0.6731	70.00%	**92.3123**
Subject 4	66.67%	0.6899	76.70%	**78.2909**
Average	**66.67%**	**0.86765**	**78.33%**	**95.90008**

Table 2.3 Classification Results for Wavelet Detail Coefficients + PSD as Features

	k-NN with k=5		Feed Forward Neural Network	
	Classification Accuracy	Time (Sec)	Classification Accuracy	**Time (Sec)**
Subject 1	60.00%	0.6398	70.00%	**287.3973**
Subject 2	70.00%	0.6554	76.70%	**259.3699**
Subject 3	56.67%	0.6734	76.70%	**284.115**
Subject 4	66.67%	0.6575	77.70%	**296.0901**
Average	**63.34%**	**0.656525**	**75.28%**	**281.7431**

. Table 2.3 shows the classification results when both Wavelet Detail Coefficients and PSD are used to construct the feature space. A feature vector from the feature space representing the two channels of EOG signal formed by only Wavelet Detail Coefficients, only PSD and Wavelet Detail Coefficients + PSD have dimensions of 1×172, 1×258 and 1×430 respectively. As is clear from these three tables, the average classification accuracy is increased to 63.34% for k-NN classifier when Wavelet Detail Coefficients and PSD are together used as features.

Table 2.4 Classification Results for AR Coefficients (Yule Walker Method + Burg Method) as Features

	k-NN with k=5		Feed Forward Neural Network	
	Classification Accuracy	Time (Sec)	Classification Accuracy	**Time (Sec)**
Subject 1	51.00%	0.6647	90.00%	**5.1052**
Subject 2	53.33%	0.6899	73.30%	**4.967**
Subject 3	50.00%	0.648	73.30%	**4.9705**
Subject 4	56.67%	0.6491	83.30%	**5.0177**
Average	**52.75%**	**0.662925**	**79.98%**	**5.0151**

Table 2.4 shows the classification results obtained by taking the AR coefficients as features. The feature space is constructed by concatenating the feature spaces obtained from calculating AR coefficients by Yule Walker method and Burg Method respectively, the corresponding feature vector having dimension of 1×20.

Table 2.5 Classification Results for AR Coefficients (Yule Walker Method) + PSD as Features

	k-NN with k=5		Feed Forward Neural Network	
	Classification Accuracy	Time (Sec)	Classification Accuracy	**Time (Sec)**
Subject 1	63.33%	0.6495	80.00%	**105.5567**
Subject 2	80.00%	0.6111	86.70%	**105.839**
Subject 3	66.67%	0.6498	73.30%	**91.762**
Subject 4	66.67%	0.651	80.00%	**123.87**
Average	**69.17%**	**0.64035**	**80.00%**	**106.7569**

Table 2.5 shows the classification results obtained by taking AR coefficients from Yule Walker method and PSD together to form the feature space so that a feature vector in this case would have a dimension of 1×268.

There is clear improvement of classification accuracy in the latter case. It is increased 69.17% for k-NN classifier and 80% for the Neural Network Classifier.

2.7 Summary

A portable, low powered, USB driven two channel EOG amplifier is designed and developed. A two channel EOG amplifier circuit has been developed using instrumentation amplifier. Necessary filters for artifact elimination has been incorporated both in the hardware and software platform. The circuit is developed maintaining the safety measures by incorporating power and signal isolation in the hardware circuitry. The circuit is driven by USB power from the PC/laptop used for signal acquisition, display and storage. The EOG signal recorded and amplified by the developed circuit is acquired in LabVIEW platform after digitization of the analogue EOG signal by a 12bit ADC. The acquired signal is stored for further analysis. The two channel EOG amplifier is cost efficient and the complexity of large number of channels in EEG recording for practical purpose is eliminated with the developed circuit. Thus developed two channels EOG system has enhanced portability and optimized cost-performance.

After that, the different types and directions (straight, up, down, right, left, and blink) of eye movement has been classified from acquired EOG signal by k-NN and feed forward Neural Network classifiers. The features used for classification are Wavelet Detail Coefficients, PSD and AR Coefficients and combinations of these. It has been observed that in all cases the neural network classifier performs better with average classification accuracies greater than 65%.

References

[1] Bronzino, J. D. (1999). *Biomedical engineering handbook* (Vol. 2). CRC press.

[2] Pallás-Areny, R. (1998). A design study of a bioelectric amplifier and improvement of its parameters. *Journal of medical engineering & technology*, *23*(4), 152-153.

[3] Spinelli, E. M., Martinez, N. H., & Mayosky, M. A. (2001). A single supply biopotential amplifier. *Medical engineering & physics*, *23*(3), 235-238.

[4] Tietze U and Schenk C., (1990) "Measurement Circuits," *Electronic Circuits Design and Application*, 767-778.

[5] Kim, J., & Pedrotti, K. (2010). A low-power self-biased neural amplifier for implantable EEG recording system ICs. In *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE* (pp. 1573-1576). IEEE.

[6] Yin, M., & Ghovanloo, M. (2007). A low-noise preamplifier with adjustable gain and bandwidth for biopotential recording applications. In *Circuits and Systems, 2007. ISCAS 2007. IEEE International Symposium on* (pp. 321-324). IEEE.

[7] Holleman, J., & Otis, B. (2007). A sub-microwatt low-noise amplifier for neural recording. In *Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE* (pp. 3930-3933). IEEE.

[8] Harrison, R. R. (2007). A versatile integrated circuit for the acquisition of biopotentials. In *Custom Integrated Circuits Conference, 2007. CICC'07. IEEE* (pp. 115-122). IEEE.

[9] García, P. A., Haberman, M., & Spinelli, E. M. (2010). A versatile hardware platform for brain computer interfaces. In *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE* (pp. 4193-4196). IEEE.

[10] Low cost, low power instrumentation amplifier. AD620," Datasheet, Analog Devices
[11] "1W, Miniature SIP, Single & Dual Output DC/DC Converters. MAU Series", Datasheet, MINMAX
[12] "High-Linearity Analog Optocouplers. HCNR200," Technical data, Hewlett Packard
[13] "Ultralow offset voltage operational amplifier. OP07", Datasheet, Analog Devices
[14] "Reference diode. LM336-2.5V", Datasheet, National Semiconductors
[15] "Switched capacitor voltage converter. ICL7660," Datasheet, Maxim Integrated Products.
[16] Cincotti, F., Mattia, D., Aloise, F., Bufalari, S., Schalk, G., Oriolo, G., ... & Babiloni, F. (2008). Non-invasive brain–computer interface system: towards its application as assistive technology. *Brain research bulletin*, *75*(6), 796-803.
[17] Barea, R., Boquete, L., Mazo, M., & López, E. (2002). System for assisted mobility using eye movements based on electrooculography. *IEEE transactions on neural systems and rehabilitation engineering*, *10*(4), 209-218.
[18] Keegan, J. A., Burke, E., Condron, J., & Coyle, E. (2011). On Improving Electrooculogram-based Computer Mouse Systems: the Accelerometer Trigger.
[19] Barea, R., Boquete, L., Mazo, M., & López, E. (2002). Wheelchair guidance strategies using EOG. *Journal of Intelligent & Robotic Systems*, *34*(3), 279-299.
[20] Wissel, T., & Palaniappan, R. (2013). Considerations on strategies to improve EOG signal analysis. In *Investigations into Living Systems, Artificial Life, and Real-World Solutions* (pp. 204-217). IGI Global.
[21] Deng, L. Y., Hsu, C. L., Lin, T. C., Tuan, J. S., & Chang, S. M. (2010). EOG-based Human–Computer Interface system development. *Expert Systems with Applications*, *37*(4), 3337-3343.
[22] Nijholt, A., Tan, D., Pfurtscheller, G., Brunner, C., Millán, J. D. R., Allison, B. & Müller, K. R. (2008). Brain-computer interfacing for intelligent systems. *IEEE intelligent systems*, *23*(3).
[23] Choudhury, S. R., Venkataramanan, S., Nemade, H. B., & Sahambi, J. S. (2005). Design and development of a novel EOG biopotential amplifier. *IJBEM*, *7*(1), 271-274.
[24] Eshel, G. (2003). The yule walker equations for the AR coefficients. *Internet resource*, *2*, 68-73.
[25] Hurvich, C. M., & Tsai, C. L. (1989). Regression and time series model selection in small samples. *Biometrika*, 297-307.
[26] Bezerra, M. I. S., Iano, Y., & Tarumoto, M. H. (2008). Evaluating some Yule-Walker Methods with the maximum-likelihood estimator for the spectral ARMA model. *Trends in Applied and Computational Mathematics*, *9*(2), 175-184.
[27] Bruce, A., Donoho, D., & Gao, H. Y. (1996). Wavelet analysis [for signal processing]. *IEEE spectrum*, *33*(10), 26-35.
[28] Hazarika, N., Chen, J. Z., Tsoi, A. C., & Sergejew, A. (1997). Classification of EEG signals using the wavelet transform. *Signal processing*, *59*(1), 61-72.
[29] Dietterich, T. G. (1997). Machine-learning research. *AI magazine*, *18*(4), 97.
[30] Li, B., Yu, S., & Lu, Q. (2003). An improved k-nearest neighbor algorithm for text categorization. *arXiv preprint cs/0306099*.
[31] Konar, A. (2006). *Computational intelligence: principles, techniques and applications*. Springer Science & Business Media.
[32] Haykin, S., & Network, N. (2004). A comprehensive foundation. *Neural Networks*, *2*(2004), 41.
[33] Moré, J. J. (1978). The Levenberg-Marquardt algorithm: implementation and theory. In *Numerical analysis* (pp. 105-116). Springer Berlin Heidelberg.
[34] Barea, R., Boquete, L., Rodriguez-Ascariz, J. M., Ortega, S., & López, E. (2010). Sensory system for implementing a human—computer interface based on Electrooculography. *Sensors*, *11*(1), 310-328.
[35] Itakura, N., & Sakamoto, K. (2010). A new method for calculating eye movement displacement from AC coupled electro-oculographic signals in head mounted eye–gaze input interfaces. *Biomedical Signal Processing and Control*, *5*(2), 142-146.
[36] Gandhi, T., Trikha, M., Santosh, J., & Anand, S. (2007, December). VHDL based electro-oculogram signal classification. In *Advanced Computing and Communications, 2007. ADCOM 2007. International Conference on* (pp. 153-158). IEEE.

3

Rehabilitative Applications using Eye Movement Analysis

The idea behind the development of next generation Human Computer Interfaces (HCI) is to provide healthy individuals an easier and better life while providing diseased individuals assistance and rehabilitation. Such devices are based on some form of input bio-modality that is processed efficiently to provide the desired results while being interfaced with the computer as biopotential signals provide measurements about the degree of functionality or degradation of biological organs of the humans and other advanced creatures. Eye Movements are a great source of information. In this chapter research is done to extract the useful details from EOG and implement it as assistive tool. This chapter is divided into four sections. In first and second sections, assistance schemes are proposed to follow progress of autistic and reading disabled children respectively, analyzing their eye tracking data. The second scheme of reading speed evaluation is done by studying EOG data of three children having specific learning disorder. In third section, strategy as precautionary measure for computer vision syndrome is presented based on blink detection. In last part of this chapter a layout of electrooculogram based eye dystonia prevention method is put forward.

3.1 Introduction

As discussed in chapter 1, the main applications of EOG signal include detection and assessment of many ophthalmological diseases such as Retinitis Pigmentosa and Best's disease [1] as well as degenerative muscular disorders and neural diseases like Parkinson's disease [2].

This chapter consists of different projects that investigate the potential uses of EOG for real life problems of rehabilitation. The objective is to improve the control capability of the eye movement signal, thus positively contributing to the development of bio-signal controlled assistive devices. Different aspects of HCI applications for rehabilitation are presented using eye movements through electrooculogram.

3.2 Analysis of Eye Movement Sequence to Assist Autistic Children

Autism is a neurological disorder featuring lack of social interaction and communication abilities [3-5]. The onset of the disease is detected in children prior to 3 years of age. The affected children show restricted and repetitive behavior and avoid eye contact. Execution of core activities involving eye movement tasks such as reading, concentrating on a pattern etc. helps in improving visual discrimination, strengthening of memory, tracking and focusing abilities of such individuals although that never reaches typical adult levels [6-10].

The present work proposes a scheme to assist autistic children having abnormalities in eye movement related to continuous tracking of an object using EOG analysis. EOG is recorded using a two channel data acquisition system from ten subjects over a period of 6 minutes each for 5 days using a visual stimulus. Hjorth Parameters [11] are extracted as features from the acquired EOG. Ensemble (Bagging and Boosting) classifiers [12-13] are trained to distinguish eye movements in different directions as well as fixed gaze. The trained classifiers are used to classify different eye movement directions using a test visual stimulus that involves tracking a ball on the computer screen. The performance of the ensemble classifiers in distinguishing the eye movement directions is analyzed. The best classifier is then used to find the tracking accuracy of an individual where successful tracking of a complete sequence is considered. If the tracking accuracy is lesser than 50%, it can be concluded that the person cannot trace the movement of the ball and is likely to be affected by autism. If a subject is detected to be Autistic, he/she is asked to use the system daily until the tracking accuracy improves more than 50% and the staring errors decreases below 20%.

3.2.1 Principles and Methodology

The present work proposes a system for assistance of Autistic children by analysis of eye movements. Autism is a disease characterized by abnormal eye movements and an inability to follow a pattern of object movement in different directions. Eye movement data is recorded from normal individuals over a period of five days using an Electrooculogram signal acquisition system developed in the laboratory. Hjorth Parameters are used as signal features. Eye movement directions in response to a visual stimulus for tracking an object are classified using Ensemble classifiers based on bagging and adaptive boosting algorithms. Maximum classification accuracies of 83.09%, 90.27%, 80.75% and 92.27% were achieved on Hjorth Parameters as features using Bagging Ensemble classifier while tracking four different sequences. The individuals are trained by repeated tracking of the sequences such that there is an improvement in tracking over time. The system is designed to measure the tracking accuracy of following four different sequences of movement of an object in different directions as shown in a cue in a predetermined interval of time. This would enable convenient detection of eye fixations/staring errors in Autistic people along with the provision of gradual improvements when the tracking sequences are not followed in 50% of the cases through consequent training.

3.2.1.1 Feature Extraction

Hjorth Parameters [11], namely activity (A), mobility (M) and complexity(C) are time domain features extracted from a signal. For an input signal *x(n)* of length *N*, these can be defined by (3.1) to (3.3).

$$A(x) = \mathrm{var}(x) \tag{3.1}$$

$$M(x) = \sqrt{A(x')/A(x)} \tag{3.2}$$

$$C(x) = M(x')/M(x) \tag{3.3}$$

Where x' denotes the first derivative of the signal $x(n)$ and $\mathrm{var}(x)$ denotes the biased variance of signal $x(n)$ with mean value $\bar{x}$, given by (3.4).

$$\mathrm{var}(x) = \sum_{n=1}^{N} \left(x(n) - \bar{x}\right)^2 \Big/ N \tag{3.4}$$

Hjorth Parameters are relevant in case of biosignals because they help in reducing the non-stationarities and capturing the stationarities through the use of higher order derivatives of the input signal [21]. In order to represent the stationarities, Hjorth Parameters are computed over small overlapping windows of equal lengths and then for a particular instance, all the parameters over all windows for that instance are averaged. For each instance of each of the two channels of the EOG signal, we have obtained three values corresponding to activity, mobility and complexity representing the Hjorth Parameters. Concatenating the features per channel we obtain six features per instance. For our work, the length of the window is experimentally chosen to be 16 i.e. Hjorth Parameters are evaluated over 10 instants of an observation, at a time, followed by moving the window over the next set of 16 instants considering 50% overlap with the previous window.

3.2.1.2 Classification

Ensemble classifier [12-13] is a family of classifiers whose individual predictions are combined (weighted voting) to decide the class of the test samples. It is more accurate to rely on the decision that is made by a group of classifiers rather than by a single classifier. So, we use ensemble classifier in our work. Two important criteria must be satisfied in selecting the classifiers: the classifiers must be accurate (error rate better than random guess; also called weak learners) and diverse (different error on new dataset). We have used 'tree' classifier as the weak learner in this work. Each node of the tree classifier operates on each of the features in the dataset to predict the class of a sample. There are several algorithms to implement the ensemble classifiers. Two such popular methods are bagging and boosting which have been used in this work.

In case of bagging, classifiers are trained by dataset obtained from bootstrapping the original dataset. While bootstrapping, a subset of the dataset is created by randomly drawing (with replacement) n samples from the original dataset. The diversity among the weak classifiers is obtained by resampling procedure. The resampling is decided to take place T times. Finally, majority voting is employed to infer the class of an unknown sample.

AdaBoost refers to adaptive boosting [14]. If the process is iterated T times, each time AdaBoost creates a new weak classifier using the whole dataset and the weights for all samples are updated, which is initially equal for all instances. The weights of the samples misclassified are increased and the weights of the samples correctly classified are decreased. It is called adaptive because it is focuses on those samples which are misclassified in previous iterations. The weighted voting mechanism decides the class of a new sample.

For our work, the value of T in both the algorithms is taken to be 100. The bootstrap size (n) for the bagging algorithm is considered to be 30% of the total dataset. AdaBoostM1 extension of the AdaBoost algorithm is chosen for the concerned application and the classification is performed in a one-versus-one framework.

3.2.2 Autism Assistance

A brief description of the circuit used for acquiring the data and the different steps taken in the course of experimentation in a laboratory environment are briefly outlined in this section.

3.2.2.1 Data Acquisition

The layout of the data acquisition module and the total arrangement for gathering the data for the experiment has been addressed to in this section.

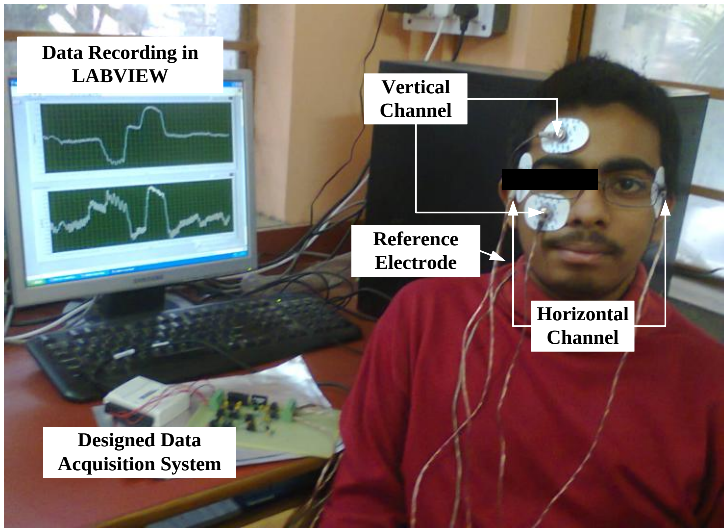
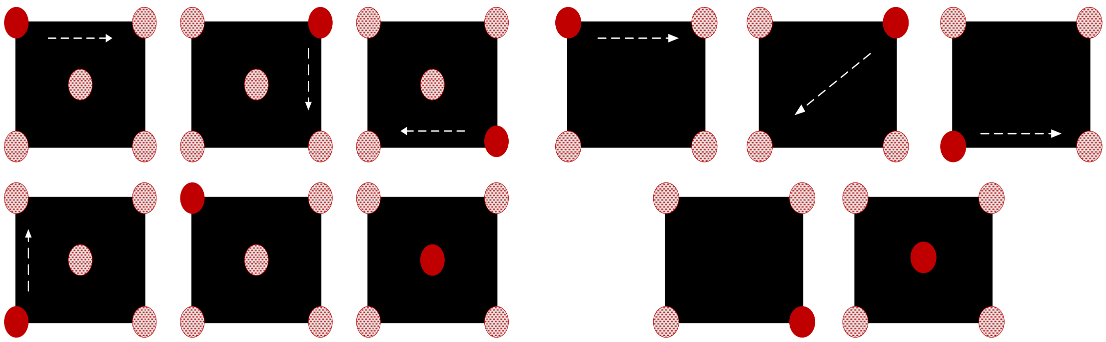


Fig. 3.1 EOG Signal Acquisition and Experimental Setup

The EOG data is collected from twenty subjects, ten male and ten female in the age group of 25±3 years with the laboratory developed acquisition system. The electrode placement is illustrated in Fig. 3.1. The data acquisition is done for 5 days with one day interval in between, to include any variation caused by the weather, the surrounding environment as well as possible allergy or temporary infections to the eyes of the subjects. After explaining the procedure and the objective of study, a consent form is signed by all the subjects. An audio visual stimulus is shown to the subjects for acquiring EOG data for classification.

We consider four different visual cues in the form of the movement of a ball in a specified path. In the first cue the displayed sequence is right, down, left, up followed by a stare in the middle. In the second one, the previous cue is back tracked i.e., down, right, up, left and stare. The third cue traces a ‘Z’ in the screen where the ball moves in the right side in the top of the screen, then, coming down along the off diagonal and again, moving in the right side in the bottom of the screen followed by a stare i.e. right, off-diagonal down, right, stare. The fourth cue is just opposite of the third one, where the ball moves in the order left, off diagonal up, left, stare. The first and the third cues are illustrated in Fig. 3.2(a) and Fig. 3.2(b) respectively. For each sequence of pattern, a particular direction of movement is of duration 2s. Each stimulus is traced ten times by each subject with sufficient rest periods in between to produce a dataset of large number of instances for training/testing. Data was acquired in an airy room where the stimulus was shown on a screen using a projector.



(a) (b)

Fig. 3.2 Visual Cues showing the path of the ball along the sides of a rectangle and stare at the center for the sequences corresponding to (a) Stimulus 1: Right, Down, Left, Up, Stare and (b) Stimulus 3: Right, Off Diagonal Down, Right, Stare

3.2.2.2 Filtering

In the present experiments it was found that the EOG power spectrum showed significant variations below 10Hz which concludes that no necessary information is prevalent in the 10-20Hz region. To eliminate undesirable noise and obtain EOG in the frequency range of 0.1 to 10Hz, the range where maximum information is contained [10, 30], we implement band pass filtering using a Butterworth band pass filter in the specified frequency range.

3.2.2.3 Training of classifier

EOG for eye movements over an interval of approximately 6 minutes are recorded and processed for training the classifiers. Experiments are carried out using Hjorth parameters as the signal features. Different Ensemble classifiers are trained for classification. Classification is carried out using 5-fold cross-validation and following a one-versus-one strategy. After classification, percentage accuracy (5) is noted as a performance metric using the number of samples classified as true positive (TP), true negative (TN), false positive (FP) and false negative (FN) according to the resulting confusion matrix.

$$Accuracy = \left[TP + TN \,/\, TP + FN + TN + FP \right] \times 100\% \tag{3.5}$$

3.2.2.4 Assistance to the Autism Affected

Ten new subjects, who are unaware of the pattern in the visual cue, are asked to provide data in a manner similar to the previous case. The trained classifiers are used to classify the gaze direction. The resulting classification accuracy gives a measure of how correctly the sequence is tracked and is termed as tracking accuracy, henceforth. The number of eye movements (left, right, up, down or diagonals) misclassified as looking straight are referred to as staring errors.

After consulting with professionals working with autistic children, taking a safe margin we have set the value of greater than 50% tracking accuracy and less than 20% staring error for healthy individuals in properly conditioned light and air in following the sequence of movements as shown in the visual cues.

Hence we can say that autistic people will fail to follow a pattern in 50% of the cases and mostly maintain a fixed gaze at the screen where the cue is shown.

We understand that the opinion of professionals, not being based on any objective study, is likely to have a subjective component. Therefore, the actual threshold values for determining tracking accuracies and staring errors may differ from the values set in our study and we also intend to find them out through experiments with autistic children in future. Thus the threshold values may be modified accordingly. The proposed methodology to be followed during assistance to autistic persons been illustrated in Fig. 3.3.

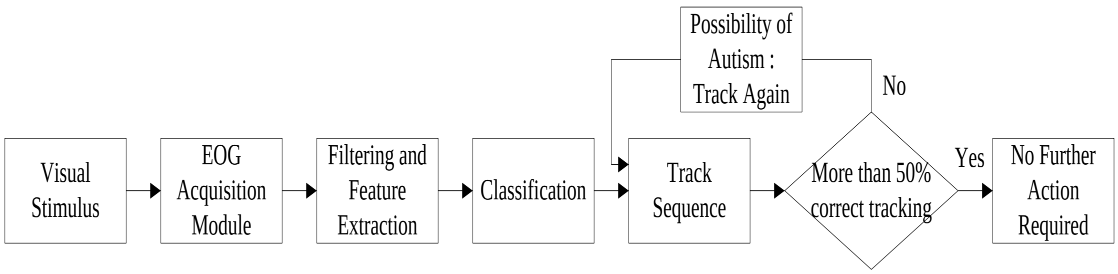


Fig. 3.3 Flowchart depicting course of work

3.2.3 Experimental Results

The EOG signal acquired while tracking the first sequence once is plotted against time in Fig. 3.4(a-b). The obtained signal is then filtered using a band pass Butterworth filter. The filtered signal is shown in Fig. 3.4(c-d).

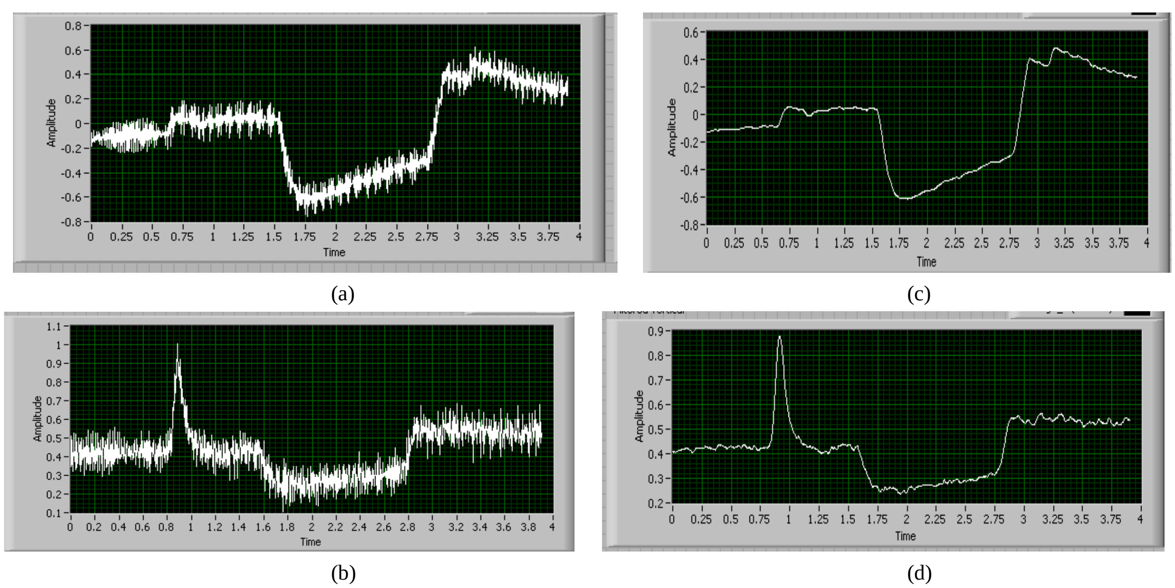
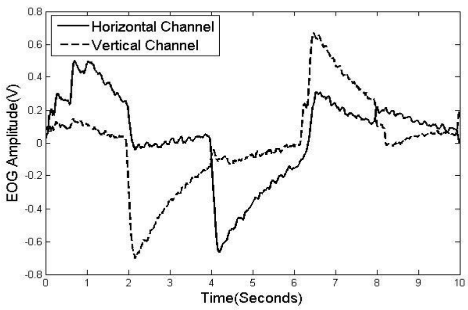
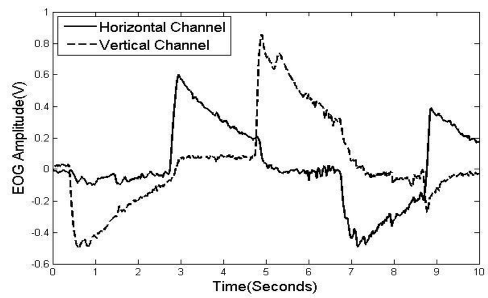


Fig. 3.4 EOG signals acquired in LABVIEW from Subject 1 corresponding to (a) Horizontal Channel : Raw (b) Vertical Channel : Raw (c) Horizontal Channel : Filtered (d) Vertical Channel : Filtered

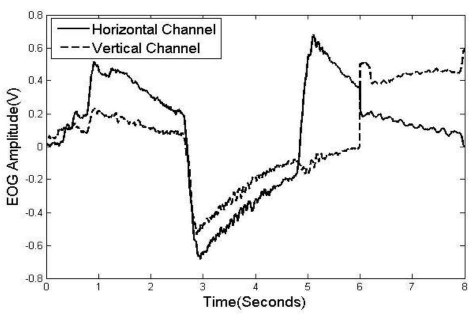
The time required to execute each eye movement is 2 seconds. Such eye movement tracings of the four different stimuli separately have been illustrated in Fig. 3.5(a)-(d) showing the horizontal and vertical channel signals in each case. From these plots it is observed how the horizontal channel data discriminates between the right/left directions and the vertical channel data discriminates the up/down or diagonal up/down movements clearly. For example the pattern in Fig. 3.5(a) clearly illustrates the tracing of right (a high positive horizontal signal)-down (a high negative vertical signal)-left (a high negative horizontal signal)-up (a high positive vertical signal)-stare (almost zero amplitudes in both channels) with respect to the time axis.



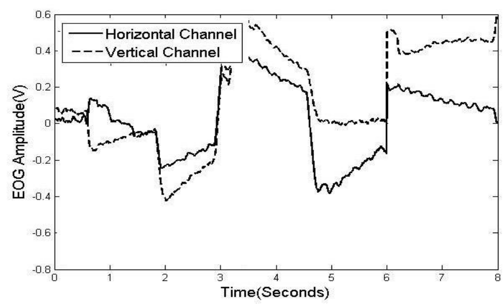
(a)



(b)



(c)



(d)

Fig. 3.5 EOG signals aquired from Subject 1 for different eye movements while tracking (a) stimulus 1, (b) stimulus 2 , (c) stimuls 3 and (d) stimulus 4

The average classification accuracy along with the timing complexity over 20 subjects obtained while training the classifier is noted in Table 3.1. As we note from Table 3.1, classification using Bagging outperforms the other and hence is considered further. To bring out the relevance of the use of Ensemble methods rather than standard procedures, a statistical validation test is carried out to rank Ensemble (Bagging and Boosting), Support Vector Machine (SVM) [31] , Naïve Bayes [31,32] and *k* nearest neighbor (*k*-NN) [32] classifiers with respect to their Accuracy (%) in classification.

Table 3.1 Classification Results: Average over Twenty Subjects

Stimulus	Ensemble Classifier	Classification	
		Accuracy (%)	*Time (Seconds)*
1	Bagging	83.09	17.6976
	Boosting	74.91	49.736
2	Bagging	90.27	17.3454
	Boosting	77.26	48.3352
3	Bagging	80.75	20.1218
	Boosting	79.59	60.1906
4	Bagging	92.27	19.6406
	Boosting	89.32	60.1380

All classifications are carried out in one-vs.one method and average results are used. For SVM a Radial Basis Function (RBF) kernel is used with the width of the Gaussian taken as 1 and it is tuned with a cost parameter of 100. The Naïve Bayes classifier is used with the assumption that the features have a normal distribution whose mean and covariance are learned during the process of training. For *k*-NN the value of *k* is taken as 3 and Euclidean distance as the distance measure with majority voting is used for determining the class of the test samples. All these parameters are determined experimentally after noting the best performances on an average. Friedman Test [33] has been carried out taking the mean classifier accuracy for each classification algorithm used, as shown in Table 3.2. The null hypothesis states that all the classification algorithms are equivalent. The Friedman statistic is given by (3.6).

$$\chi_F^2 = \frac{12N}{K(K+1)}\left[\sum_{j=1}^{K} R_j^2 - \frac{K(K+1)^2}{4}\right] \tag{3.6}$$

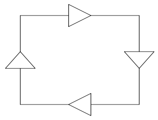
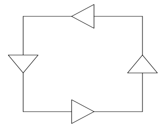
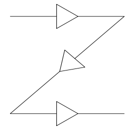
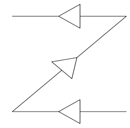
It is distributed according to χ_F^2 with *K*-1 degrees of freedom. Here *K* is the number of algorithms used which in our case is 5. The null hypothesis is rejected if evaluated $\chi_F^2 > \chi_{4,0.95}^2 = 9.49$, which indicates, for 4 degrees of freedom, the null hypothesis is correct to an extent of only 5%. The test is carried out on the twenty databases corresponding to the twenty subjects and the ranks are evaluated with respect to the average classification accuracies over all stimuli presentation. In this case χ_F^2 is found to be 91 hence the null hypothesis is rejected and the classifier performance is evaluated by its rank, showing the superiority of the bagging ensemble classifier followed by boosting ensemble classifier.

Table 3.2 Table for Classifier comparison through Friedman Test

Test Parameters	**Classifiers**				
	Ensemble Bagging	**Ensemble Boosting**	**SVM**	***k*NN**	**Naïve Bayes**
Mean Accuracy (%)	86.60	80.27	78.25	72.66	75.84
Mean Rank	1.25	2	3.50	4	4.75

Tracking accuracy measures the percentage of occasions when a complete sequence is correctly identified out of total number of such sequences followed by the subject. Staring error is defined as the percentage of occasions when a non-stare class is classified as a stare.

Table3.3 Eye Movement Analysis Results for Day 1

Sequence	**Right, Down, Left, Up, Stare** 		**Down, Right, Up, Left, Stare** 		**Right, Off Diagonal Down, Right, Stare** 		**Left, Off Diagonal Up, Left, Stare** 	
Subject	Tracking Accuracy (%)	Staring Errors (%)	Tracking Accuracy (%)	Staring Errors (%)	Tracking Accuracy (%)	Staring Errors (%)	Tracking Accuracy (%)	Staring Errors (%)
1	65.45	9.72	72.31	6.91	83.45	3.63	81.74	11.82
2	83.42	3.53	79.55	5.97	77.08	4.28	85.12	2.05
3	69.5	5.67	80.23	10.11	73.55	13.23	72.22	4.5
4	74.17	6.32	82.01	2.54	71.23	8.24	93.49	1.92
5	82.45	3.87	81.45	9.67	72.43	8.1	86.76	3.25
6	73.17	5.57	80.92	7.89	78.5	7.89	85.34	4.98
7	79.84	7.78	77.78	5.48	77.89	5.13	81.04	5.18
8	72.34	4.92	78.34	9.21	79.7	8.27	83.74	4.6
9	74.89	5.72	79.49	7.63	80.45	7.33	81.81	4.91
10	69.82	7.47	80.16	5.82	78.71	8.09	84.26	5.04

The tracking accuracy and the staring errors are mentioned in Table 3.3 when the proposed system was tested on healthy individuals for a single day. The tracking accuracy should be high so as to indicate a good ability to track a specified sequence. A low value of staring error indicates the absence of unnecessary staring and hence is mandatory to prove that the person is free from autism.

As observed from Table 3.3, the high performance of the proposed system indicates its applicability for the mentioned purpose of assisting Autistic children. Table 3.4 illustrates the gradual improvement in tracking all the four stimuli in average over a period of 5 days while training 10 normal individuals using the proposed system. There is evident improvement in tracking in healthy individuals according to the obtained results. However, when the system will be used on autistic persons, the accuracies are likely to deteriorate with larger amounts of staring errors. But it can be justifiably claimed that the trend in improvement with time will exist.

Table 3.4 Average improvements observed over ten subjects

Performance Parameters	Day 1	Day 2	Day 3	Day 4	Day 5
Tracking Accuracy (%)	78.64	84.09	87.78	89.53	90.96
Staring Errors (%)	6.36	5.95	3.78	3.50	1.29

In our previous works, we have successfully demonstrated EOG signals for classification of different types of eye movements using various features and standard pattern classifiers achieving high accuracies [15-18]. a microprocessor based control of motors using EOG based commands has been illustrated in a literature [19]. Such works show that EOG can successfully be utilized in eye movement recognition. It has also been observed in previously published work [20] that EOG signal analysis has been used for assisting the improvement of speed and accuracy of visual attention. This has been implemented by predicting the gaze positions while subjects play a computer game through wavelet denoising and subsequent target position estimation by least squares error from the linear transformation of EOG data into target positions [21]. However, the present work, to the best of the authors' knowledge, for the first time incorporates extensive experimental procedures to determine the relations of EOG signals with tracking four specific eye movement sequences and implements the results to estimate the improvements in tracking accuracy of subjects over time, achieving remarkable results.

The proposed methodology can be utilized in developing an intelligent automatic concept for behavioral intervention system for autistic children based on EOG signal analysis for cost-effective assistance in eye movement based sequence following training. The final strategy has to be designed working with autistic children. Moreover, the system needs to be made portable and wireless so that it can be useful to use at home also.

3.3 Estimating Reading Speed and Word Count to Support Reading Disabled

Reading speed is a characteristic trait of every individual and varies from person to person. One's ability to read quickly can be improved by repeated training at a given speed over several days. Some well-known disorders like Dyslexia involves difficulty in fluent reading, decoding and processing of words despite adequate intelligence [22]. Lower than average reading speed of such individuals can be because of slow letter and word processing. Reading speed can be related to the eye movements [23-24]. Eye movements in dyslexic patients are significantly different from normal individuals, in terms of presence of frequent fixations and stares in the former. The flowchart of the work is shown in Fig. 3.6.

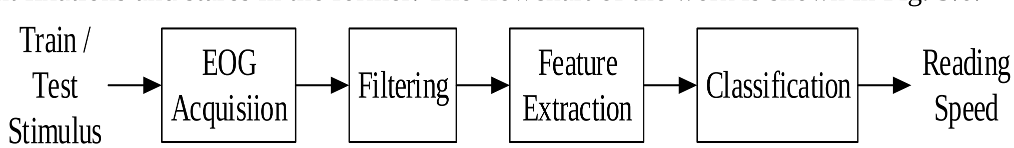


Fig. 3.6 Flowchart showing EOG Signal Processing and Classification

3.3.1 Experimental Paradigm

EOG data is collected from ten healthy subjects, five male and five female in the age group of 25±5 years, in a properly lit and airy room. After explaining the procedure and the objective of study, a consent form was filled up by all the subjects that collected information about the presence of any possible vision related ailments.

An audio visual stimulus was shown to the subjects for acquiring EOG data. The stimulus consisted of English sentences with an average number of five words per sentence. Each sentence of the stimulus appears on a screen in front of the subject in a character-wise manner. The subjects were instructed to read out loudly the sentences in order of appearance of the words. The predetermined reading speed is decided by the time taken for the complete sentence to appear. The duration was varied from 2 seconds to 10 seconds with an interval of 2 seconds. Thus, we have five different speeds viz. 1 sentence in 2 seconds (Speed-1), 4seconds (Speed-2), 6 seconds (Speed-3), 8 seconds (Speed-4) and 10 seconds (Speed-5).

Training of classifiers was done using EOG data of 10 subjects. EOG signal was collected from both the vertical and the horizontal channels. The whole process was repeated for 5 times for each subject to obtain a large database containing 10×5×5=250 observations. The threshold for reading speed was kept at 4 seconds per sentence. During testing phase ten new subjects were tested with different instances of sample reading speeds. If the subjects could not read at speeds greater than the threshold speeds then they were given assistance for improving their reading speeds by repeated trials for 10 days with sentences appearing at speeds greater than the threshold.

3.3.2 Pre-Processing

To eliminate undesirable noise and to obtain EOG in the frequency range of 0.1 to 15 Hz, the range where maximum information is contained, we implement band pass filtering. Chebyshev band pass filter [25] of order 6 in the specified frequency range has been used for this purpose for its superior transition from passband to stopband.

3.3.3 Feature Extraction

Classical Autoregressive (AR) model is an efficient technique for describing the stochastic behavior of any stationary time series [26]. However, EOG signals are time varying or non-stationary in nature, and hence the AR parameters for representing EOG signals should be estimated in a time-varying manner. As a result, Adaptive Autoregressive (AAR) model [27] of order *p* is described by (3.7) and (3.8).

$$y_k = a_{1,k} * y_{k-1} + \ldots + a_{p,k} * y_{k-p} + x_k \tag{3.7}$$

$$x_k = N\{0,\ \sigma^2_{x,k}\} \tag{3.8}$$

Where x_k is a zero-mean-Gaussian-noise process with variance $\sigma^2_{x,k}$; the index k is an integer to denote discrete, equidistant time points. y_{k-i} with i = 1to p are the p previous sample values, p is the order of the AAR model and $a_{i,k}$ are the time-varying AAR coefficients.

In the present work, AAR parameter model was chosen to be of order 6 and AAR estimation was done using Kalman filtering with an update coefficient of 0.0085. The feature space for the EOG data is constructed by taking EOG signals over the duration assigned for reading one sentence as a single observation. For each channel of EOG signal, 6 AAR parameters are computed, hence taking both the channels into consideration each feature vector is of dimensions 1×12.

3.3.4 Reading Speeds Detection

The classification of reading speeds was carried out using three different classifiers and the one with maximum performance out of the three was used for assistance to improve reading speed.

3.3.4.1 Neural Network with Back Propagation Learning

The Back propagation learning algorithm [28] is one of the most popular supervised learning algorithms used in artificial neural networks with a feed-forward topology of neurons. The adaptation of network weights is carried out using Gradient Descent Search algorithm [29].

3.3.4.2 Naïve Bayesian Classifier

Bayes' theorem (3) from classical probability theory is a well-known method for parametric decision making [30]. However, addressing the joint distribution, $p(x|C_i)$, for feature vector x and class C_i for $i=1$ *to* n, of all the features given a particular class, is in itself a complex task. A simple roundabout method to determine $p(x|C_i)$ is to treat all the features to be independent within a particular class (4). For any feature, the Naïve Bayes classifier evaluates $P(C_i|x)$ for all the known n classes and classifies the sample vector to the class C_i which yields the highest $P(C_i|x)$.

$$P(C_i \mid x) = \frac{P(C_i)\,p(x \mid C_i)}{\sum_{j=0}^{1} P(C_j)\,p(x \mid C_j)} \tag{3.9}$$

$$p(x \mid C_i) = p(x_1, x_2, \ldots x_d \mid C_i) = \prod_{j=1}^{d} p(x_j \mid C_i) \tag{3.10}$$

3.3.4.3 Binary Tree Support Vector Machine

Support vector machine (SVM) is a well-known binary supervised learning algorithm capable of classifying some test data in two different classes [31]. Linear SVM can be successfully used only in those cases where the data are linearly separable. This limitation of Linear SVM can be overcome by mapping the data into another much larger dimensional space using a kernel function, $K(x,y)$, such that the data points become linearly-separable. The radial basis function (RBF) kernel [32] has been used in the present work.

In the present work we investigate the one-against-all (OVA) classification accuracies i.e. binary classification results with a particular reading speed as a class and all the other speeds comprising another class. The concept of OVA classification can be extended to form a tree-like classification structure, whereby, at each level of classification the test instances are classified into belonging to a particular class of speed or not.

3.3.5 Assistance for Reading Speed Improvement

The scheme for assisting persons with reading problems and thereby having a possibility to be affected by dyslexia from analysis of EOG signals is depicted in Fig. 3.7.

As mentioned before, the classifiers were first trained to classify reading speeds using AAR parameters of EOG signal from 10 subjects. Testing was performed with 10 new subjects using the best classifier. On the first day, each subject was instructed to read out loudly the English sentences appearing at five different speeds. The threshold speed was fixed at 1sentence/4seconds. From the classification results the speeds that were misclassified were noted down. If it was observed that a minimum of 85% of the speeds greater than the threshold are correctly classified, it was concluded that no further assistance is required. Otherwise the process was repeated the next day and so on till ten days. In absence of significant improvement after ten days i.e. when accuracy is below 85%, participants are advised to consult doctors.

3.3.6 Results

Experiments were conducted in two phases as mentioned before. The first phase consisted of testing the performance of the several classifiers. In the second phase the best classifier was used to provide aid in improving the reading speed.

The filtered EOG corresponding to 20 seconds of data acquired from subject 1 for two different reading speeds is shown in Fig. 3.8. The steep changes in the horizontal signal correspond to the eye sweep from right to left on completion of each sentence. At a higher speed, these changes are frequent than that in slower speed as evident from Fig. 3.8(a) and 3.8(b).

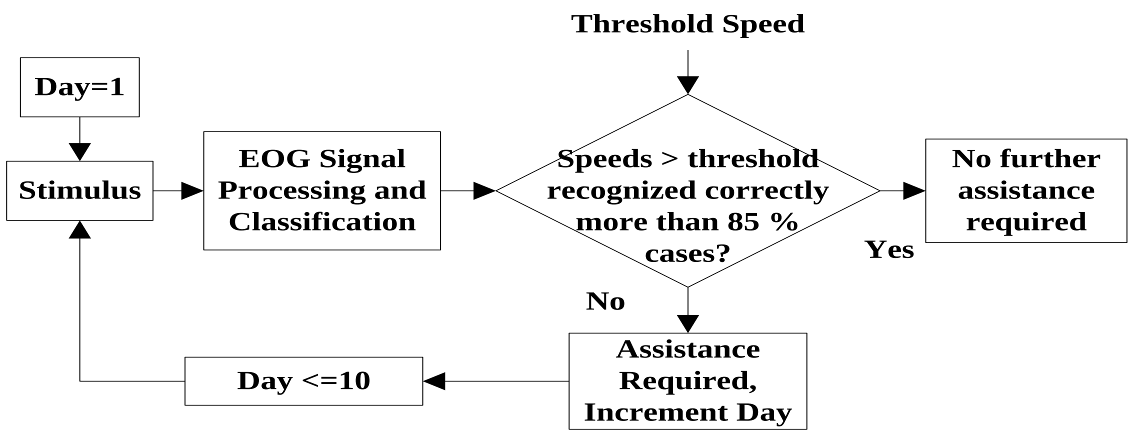


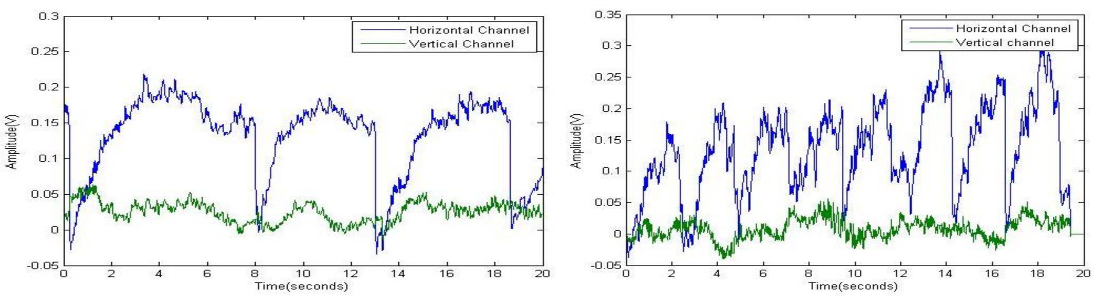
Fig. 3.7 Scheme for training to improve reading speed

The classification results for the first 10 subjects are tabulated in Table 3.5. The SVM classifiers are implemented using the binary tree approach as mentioned in Section II.

Table 3.5 Classification Results

Classifier	Average Performance over ten subjects	
	Accuracy (%)	Time (seconds)
Linear SVM Tree	91.78	0.9832
RBF SVM Tree	94.67	0.5244
BPNN	91.82	0.4528
Naïve Bayesian	90.33	0.0367

From Table 3.5 it is seen that RBF-SVM gives the best classification accuracy and hence it is selected for the assistance approach discussed below. A diagrammatic representation of the tree based classification using RBF-SVM on EOG data from a single subject is illustrated in Fig. 3.9.



(a) (b)

Fig. 3.8 Filtered EOG data from subject 1 for two different reading speeds (a) 1 sentence/6 seconds and (b) 1sentence/2 seconds

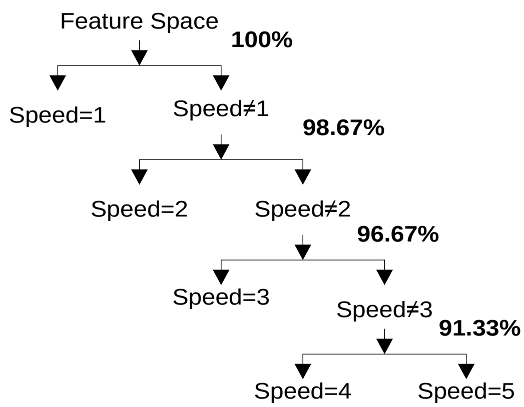


Fig. 3.9 Scheme of Tree Based Classification (with RBF-SVM on EOG of Subject 1) showing the classification accuracies at each level, the speeds are in increasing order

Bar charts illustrating the improvement in average reading speed over ten subjects with respect to results obtained from day 1, day 5 and day 10 are shown in Fig. 3.10. Here percentage of error is directly proportional to the inability to read at that particular speed. As is evident from Fig. 3.10, the average percentage of error over all the subjects reduces by repeated training from day 1 to day 10 by an amount of 35.18% for the fastest speed (1 sentence/2 seconds).

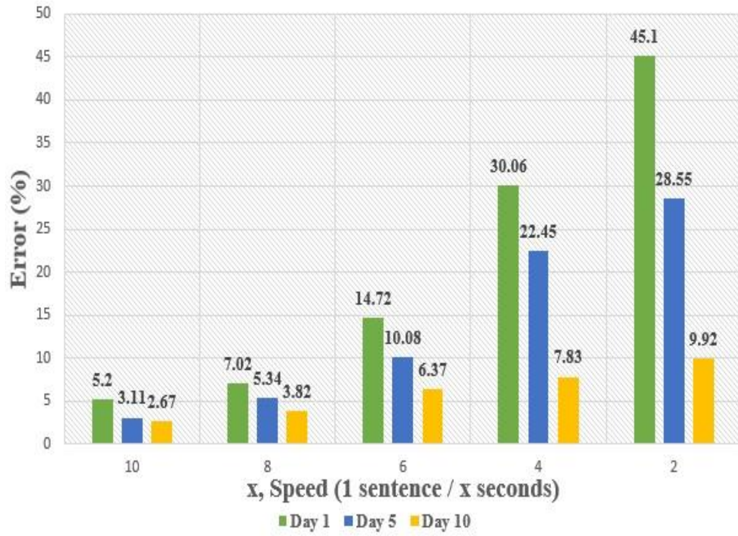


Fig. 3.10 Average Percentage Error over 10 subjects at different speeds for day 1, day 5 and day10

The ultimate aim of this study is to build an assistive system for dyslexic children who cannot read properly at an average reading speed of a normal individual of 1sentence/4 seconds.

The above mentioned work is carried out on healthy individuals. However, the results reveal that the proposed system can also be used for training and assisting dyslexic children. Actually dyslexic children may not show significant improvement in reading speed within a span of ten days. In such cases, this kind of assistance should be continued for some more days. This work can also find application in counting no. of words/no of lines while reading a document.

3.4.7 Case Study

In case study three children suffering from specific learning disorder have been observed by the proposed mechanism. Manovikas Kendra, Kolkata supported us in this case study. The sudy was done for two consequetive days.
The experimental observations are as follows:

Case 1: Patient 1

Gender: Male. Age: 17yrs

He is suffering from Specific Learning Disorder(Primarily Dyslexia with comprehension difficulty).His IQ is very good. He studies in a Bengali Medium School. He often has Attacks of Epileptic seizure. Takes Medicines related to that. He is Under training of MANOCHETNA for 2 years. He has Shown accuracy of 81.54% and 85.71% in consecutive two days reading task of difficulty level easy and medium respectively. He was able to follow all the instructions given during the study and completely read all the shown sentences/paragragh.

Case 2: Patient 2

Gender: Female. Age: 8 yrs

She is suffering from Specific Learning Disorder. She also has speech disorder and auditory impairment. Her IQ is good. She studies in an English medium school. She is an emotionally neglected child of her family. She is very sensitive. She is under training of MANOCHETNA for 1 and a half years. She has shown accuracy of 73.50 and 61.01% in consecutive two days reading task of difficulty level easy and medium respectively. As the difficulty level was increased, she could not complete sentences on second day.

Case 3: Patient 3

Gender: Male. Age: 14yrs.

He is one of twins. His brother is conventionally normal child. He is suffering from Specific Learning Disorder. He also has ophthalmological problem and related headache. His IQ is very good. He is good at computer programming. He studies in an English medium school. He has language and communication problem. He is under training of MANOCHETNA for 6-7 months. He has shown accuracy of 79.63% and 82.33% in consecutive two days reading task of difficulty level easy and medium respectively.

To actually come to a conclusion in dyslexia related cases, atleast 100 children must be observed. Hence, from this little observation it seems that this proposal may help them for better reading and communication.

3.4 Preventive Measure of Computer vision Syndrome/Dry Eyes

Computer Vision Syndrome (CVS) [33] is a well known ocular disorder that affects majority of the working professionals and students who spend a considerable amount of time at a stretch on the computer. Prolonged focus of eyes on the computer display causes the cornea to dry up leading to eye strain, headaches, dizziness, blurred vision and fatigue [34-35]. A possible therapy for avoiding CVS while not disturbing a person's working schedule is to blink more often and include breaks. Frequent blinking prevents the eyes from drying up quickly.

The present work proposes a scheme to detect the number of blinks of an individual working on a computer, over a certain period of time using EOG analysis and logging off the computer if a desirable number of blinks do not occur in that time interval.

3.4.1 Signal Conditioning

3.4.1.1 Feature Extraction: Wavelet Transform

For extracting feature, we have concentrated on discrete wavelet transform [36]. Wavelet transform is used to overcome the shortcoming of Fourier transform. On one hand, Fourier transform provide frequency domain analysis at a constant resolution on the frequency scale. On the other hand, Wavelet transform provides both frequency as well as time-domain analysis and at multiple resolution. Wavelet is a localized wave as the name suggests and thus convolution of a wavelet with the signal can be used to analyze the transient behavior of the concerned signal. The wavelet transform is given by (3.11).

$$X_{WT}(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t).\psi^{*}\left(\frac{t-\tau}{s}\right) dt \tag{3.11}$$

Here, $x(t)$ is the signal to be analyzed and $\psi(t)$ is the mother wavelet. The analysis is done by translation (shifting) and scaling (dilation and compression) of the mother wavelet. Shifting the wavelet by τ amount helps in time-domain analysis and the scaling parameter, s=1/frequency, helps in frequency-domain analysis. The detailed information is obtained using dilation operation whereas compression provides global information.

The sampled version of (1) results in Wavelet series. However, depending on the resolution, this takes up lot of time and resources. Thus, we rely on Discrete Wavelet Transform where the signals are passed through filters with different cutoff frequencies and different scales. The number of filter stages used gives the level of the transform. There are several mother wavelets. Depending on application and required resolution, the mother wavelet and the level of the transform are selected [36].

3.4.1.2 Classification: Support Vector Machine

Support vector machine (SVM) is a well-known binary supervised learning algorithm capable of classifying some test data in two different classes [31].

Linear SVM (LSVM) works on the principle of separating two classes of data by constructing a hyper plane within the training data points. The hyperplane is specified by ‘support vectors’ that are the training data points closest to the hyperplane belonging to the two different classes. The hyperplane is constructed such that the distance margin between the support vectors, and hence the two classes is maximized.

However, Linear SVM can be successfully used only in those cases where the data are linearly separable. This limitation of Linear SVM can be overcome by mapping the data into another much larger dimensional space using a kernel function, $K(x,y)$, such that the data points become linearly-separable. The frequently used kernel functions are polynomial and radial basis function (RBF) kernel [32]. The polynomial kernel is defined by (2) where d is the order of the polynomial and c is a constant trading off the influence of higher-order versus lower-order terms in the polynomial. The RBF or Gaussian kernel is defined by (3) where σ denotes the width of the Gaussian. In (3.12) and (3.13), x and y are two feature vectors.

$$K(x, y) = (x^{T} y + c)^{d} \tag{3.12}$$

$$K(x, y) = \exp\left(\frac{-\|x-y\|^{2}}{2\sigma^{2}}\right) \tag{3.13}$$

3.4.2. CVS Detection Procedure

The methodology followed during the course of work has been illustrated in Fig.3.11.

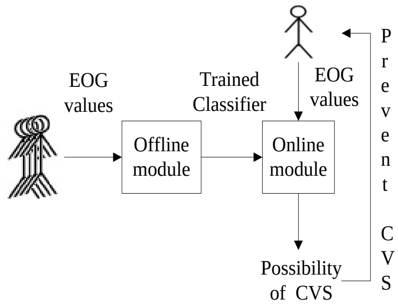


Fig. 3.11 Flowchart depicting course of work

3.4.2.1 Experimental Paradigm

The EOG data is collected from ten subjects, five male and five female in the age group of 25±3 years. The data acquisition was done for 5 consecutive days to include any variation caused by human factor in the data-set used for training the classifier. Following the training, ten people are monitored who daily work more than three hours on the computer. After explaining the procedure and the objective of study, a consent form was filled up by all the subjects.

An audio visual stimulus is shown to the subjects for acquiring EOG data for training the classifiers. As the EOG signal from the vertical channel can discriminate blinking from staring, looking up and looking down, we consider the cue in the form of 10 consecutive samples of blink, followed by 10 consecutive samples of no-blink (stare/up/down alternatively) i.e. in the sequence blink-stare-blink-up-blink-down. For each eye movement sample, EOG values of 1 second duration are recorded. Thus, we have a large database for training consisting of 5×10×6×10=3000 samples. The data was acquired in an airy room where the stimulus was shown on a screen using a projector.

3.4.2.2 Offline Training

For our application, we note that the EOG signal consists of pulses and different times corresponding to different eye movements. Thus, we have used Haar as the mother wavelet for constructing one feature set. Haar is known to belong to the family of Daubechies wavelet. Haar is the simplest Daubechies wavelet of order 1. Another feature-set is also constructed using Daubechies wavelet of order 4. The sampling rate of EOG device is 256 Hz. But we note that most of the useful information is limited to the band of 0.1-15Hz. Thus, a four-level transform on the filtered EOG signal from vertical channel provides us with the required information. We have used the detail coefficients at this level as a feature.

During the training phase, the different SVM classifiers (linear SVM, polynomial kernel SVM, RBF-kernel SVM) are trained for binary classification. For polynomial kernel, the order of polynomial, d, is considered to be 2 and the constant, c, is assumed to be zero. For RBF kernel σ is considered as 1. The two classes in which the data is classified are Blink and No-Blink. After classification, from the resulting confusion matrix, several performance indicators are noted. Second order Polynomial Kernel SVM was found to provide the optimum results with the feature set obtained using haar as the mother wavelet. The training of the classifier is demonstrated in Fig. 3.12.

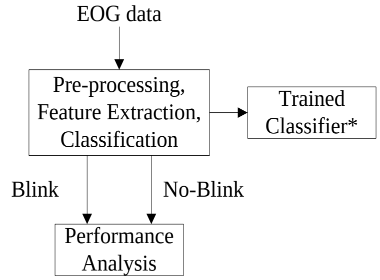


Fig. 3.12 Training module

3.4.2.3 Online Blink Detection

The algorithm adopted during the recognition and prevention of CVS in real-time scenario is outlined in Fig. 3.13. The execution of the module begins with the computer startup. The eye movements are monitored over an interval (θ) of approximately 30 minutes (30×60=1800seconds). The number of blinks made by the person in that duration is counted using the counting module called with θ=1800. A healthy individual in properly conditioned light and air blinks 18-22 times in a minute while at rest. People afflicted by CVS have reduced blink rate of around 6-7 blinks per minute [28]. Thus, a threshold of 10 blinks per minute is chosen to prevent CVS for a person working on computer in a concentrated manner. If the count of blinks in 30 minutes exceeds 300 (10×30=300), the person is unlikely to be afflicted by CVS. In case the count does not exceed 300, the person is alerted to blink 10 times in the next 10 seconds. For counting the number of blinks the counting module is called again with θ=10. If there is at least 80% success rate, the process continues to iterate in a similar manner. If the count is 7 or less, the computer goes to stand-by mode forcing the subject to break concentration and simultaneously saving the state of work in the computer. When the computer is again manually unlocked, the process resumes.

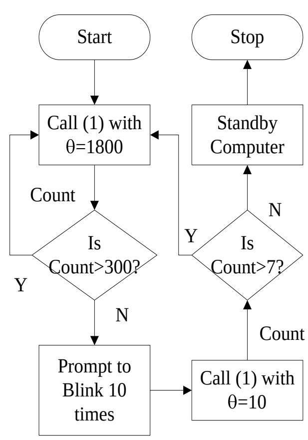


Fig. 3.13 Flowchart of the online module

The block used for counting the number of blinks within an interval of slightly more than θ seconds is illustrated in Fig. 4. EOG data of 1sec is acquired; filtered and discrete wavelet transform is applied. The classifier trained offline is used to classify whether an eye movement is a blink or not. If it is blink the count is incremented by 1. The process loops until time-out occurs which is decided by the θ value. The count is returned the program calling this module (figure 3.14).

3.4.3 Performance Analysis

After classification, the confusion matrix is constructed. From the confusion matrix, the accuracy , sensitivity and specificity are noted as performance metrics. For good classification, the accuracy is close to 100%, the sensitivity and the specificity tends to 1.

In (4-6), the terms represent the number of samples classified as true positive (TP), true negative (TN), false positive (FP) and false negative (FN). For good results, the Sensitivity specifies how much perfectly the classifier can identify a blink as blink. While the precision with which a non-blink movement of the eye is classified as no-blink is indicated by Specificity. If detected number of blinks is more than its actual number of occurrence, CVS detection is skipped. It is less detrimental to detect CVS when it is absent than to skip the detection when it actually occurs. The performance of the system can be enhanced if most of the non-blink movements are correctly identified. Thus, for the concerned work, the specificity is a much more important metric than sensitivity.

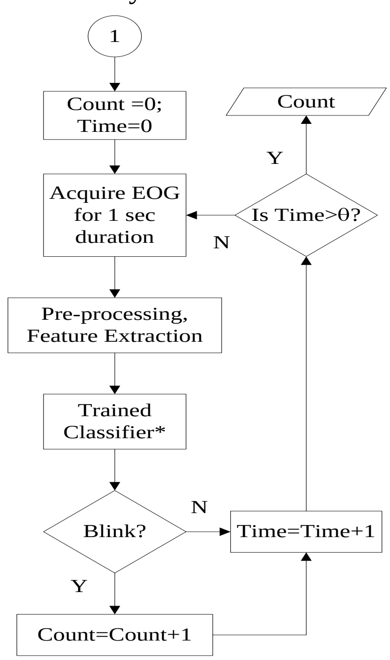
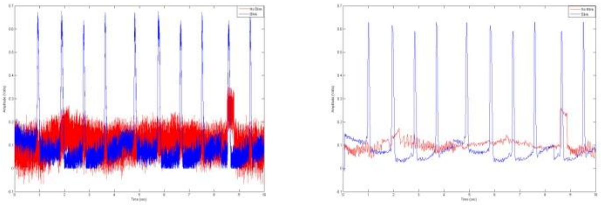


Fig. 3.14 Module for counting blinks

3.4.4 Experimental Results

The EOG acquired in the training phase has 10 second duration of blinks followed by 10 second duration of non-blink eye movement. The acquired EOG signal of two such observations is plotted against time in Fig. 3.15a.



(a) (b)

Fig. 3.15 EOG signals from Subject 1 over a duration of 10 seconds (a)Acquired EOG and (b)Filtered EOG

The obtained signal is then filtered using a band-pass Butterworth filter. The amplitude versus time plot of the signal obtained after filtering is shown in Fig. 3.15(b) for 10 consecutive blinks and no-blinks samples.

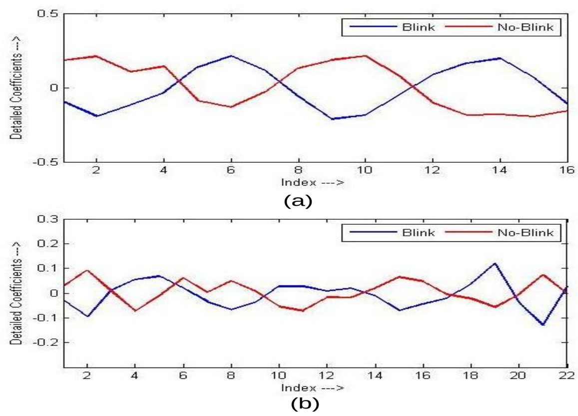


Fig. 3.16 Wavelet detail coefficients at level 4 decomposition of EOG from Subject 1, (a)using Haar and (b)Daubechies order 4 mother wavelet

Table 3.6 Offline Results

Feature (mother wavelet)	Classifier	Accuracy (%)	Sensiti-vity	Specifi-city	Time (s)
haar	LSVM	85.00	0.8	0.9	0.9503
	Poly-SVM	95.83	0.917	1	0.8110
	RBF-SVM	81.67	0.9	0.767	0.7722
db4	LSVM	76.67	0.8	0.733	0.9697
	Poly-SVM	82.00	0.9	0.7	0.7797
	RBF-SVM	72.50	0.767	0.6	0.7074

Discrete wavelet transform is applied on the filtered data as a feature extraction algorithm. The variation of detail coefficients for a blink and a no-blink trial, obtained from level-4 decomposition using Haar as the mother wavelet is plotted Fig. 3.16(a). A similar plot for coefficients considering db4 as mother wavelet is shown in Fig. 3.16(b).

The feature-sets are then classified into blink and no-blink class using the following classifiers, LSVM, Poly-SVM and RBF-SVM; and the average value of the performance metrics along with the timing complexity are noted in Table 3.6.

As we note from Table 3.6, feature-set produced with haar and classified using second-order polynomial kernel SVM outperforms the other algorithms considered.

The classifier trained in the offline mode is used for online classification of blink to detect the possibility of CVS. In the online mode, a web camera is used to track the actual blinks of the individual.

The actual and the detected number of blinks for ten subjects over two consecutive 30 minutes intervals are plotted in Fig.3.17 and in Fig. 3.18. The values over each of the double bar in the graph in Fig. 3.17 indicates the error rate which is given by the ratio of absolute value of the difference between actual and detected samples to the actual number of samples and is expressed as a percentage. The average error rate (AER) over the ten subjects is also noted for each of the 30 minutes duration. We note that the error rate decreases as the subject gets adapted to the system.

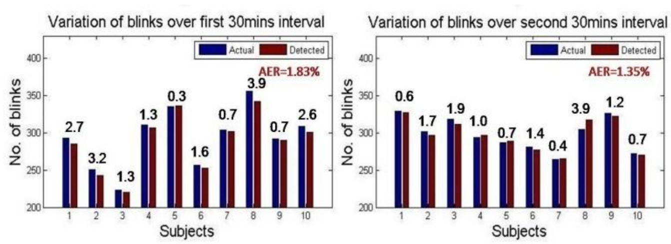


Fig. 3.17 Actual and classified number of blinks and AER

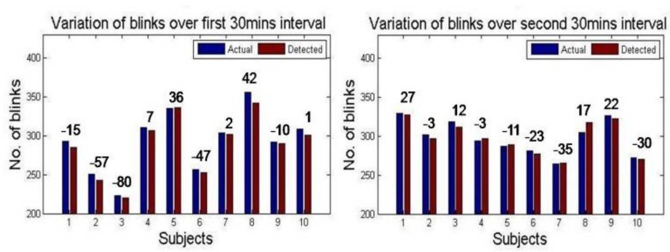


Fig. 3.18 Actual and classified number of blinks and POC

Similarly, the double bars in Fig. 3.18 are labeled with the possibility of CVS (POC) which is the difference between classified number of samples and the selected threshold of 300 blinks. A positive POC indicates that CVS can be avoided with a degree proportional to its magnitude. A negative POC recognizes a subject as CVS-prone. We note the subjects for whom CVS is detected in the first 30 minutes span tend to blink more often in the next 30 minutes period to avoid CVS [58].

3.5 Limiting the possibility of Eye Dystonia

An increase in eye blinking frequency is related to a well known neural disorder called eye dystonia [37]. Focal dystonia is a disease that causes involuntary muscular contractions in a particular body part. Blepharospasm, popularly known as eye dystonia [38] is a type of focal dystonia that affects the human eyes, and is characterized by excessive blinking and involuntary closure of the eyelids [39].

3.5.1 Experimental Setup

The EOG data is collected from ten subjects, five male and five female in the age group of 55±5 years. Though the designed system has two channels, the data collected from the vertical channel is further processed, as blinks are detected in this data.The data acquisition is done for 5 days with one day interval in between, to include any variation caused by the weather, the surrounding environment as well as possible allergy or temporary infections on the subjects. After explaining the procedure and the objective of study, a consent form is signed by all the subjects. An audio visual stimulus is shown to the subjects for acquiring EOG data for classification. As the EOG signal from the vertical channel can discriminate blinking from staring, looking up and looking down, we consider the cue in the form of blink, followed no-blink (stare/up/down alternatively) i.e. in the sequence blink-stare-blink-up-blink-down. The data is acquired in a properly lit and airy room.

3.5.2 Filtering

To eliminate undesirable noise and obtain EOG in the frequency range of 0.1 to 15Hz, the range where maximum information is contained, we implement band pass filtering. A Butterworth band pass filter in the specified frequency range has been used for this purpose.

3.5.3 Detection of Blinks

EOG for eye movements over an interval of approximately 30 minutes (30×60=1800seconds) are recorded and processed for feature extraction. Experiments are carried out using three different features, AR parameters [26-27], Hjorth Parameters [40] and PSD [41]. Two feature spaces are constructed. The first feature space is constructed from AR (5) parameters+PSD having a dimension of (5+129) =134 and the second feature space is constructed from Hjorth parameters+PSD having a dimension of (3+129) =132. The different SVM classifiers (linear SVM, polynomial kernel SVM, RBF-kernel SVM) [31-32] are trained for binary classification. For polynomial kernel, the order of polynomial, d, is considered to be 2 and the constant, c, is assumed to be zero. For RBF kernel the value of σ is taken as 1. The two classes in which the data is classified are Blink and No-Blink. After classification, from the resulting confusion matrix, several performance indicators are noted.

The number of blinks made by each subject is counted from the results of classification. A healthy individual in properly conditioned light and air blinks 18-22 times in a minute while at rest [39]. So taking a safe margin, we can assume that people afflicted by eye dystonia have increased blink rate of around 30 blinks per minute. If the count of blinks for the classification of EOG data in 30 minutes exceeds 900 (30×30=900), it is concluded that the person is likely to be afflicted by eye dystonia. The methodology followed during the course of work has been illustrated in Fig.3.19.

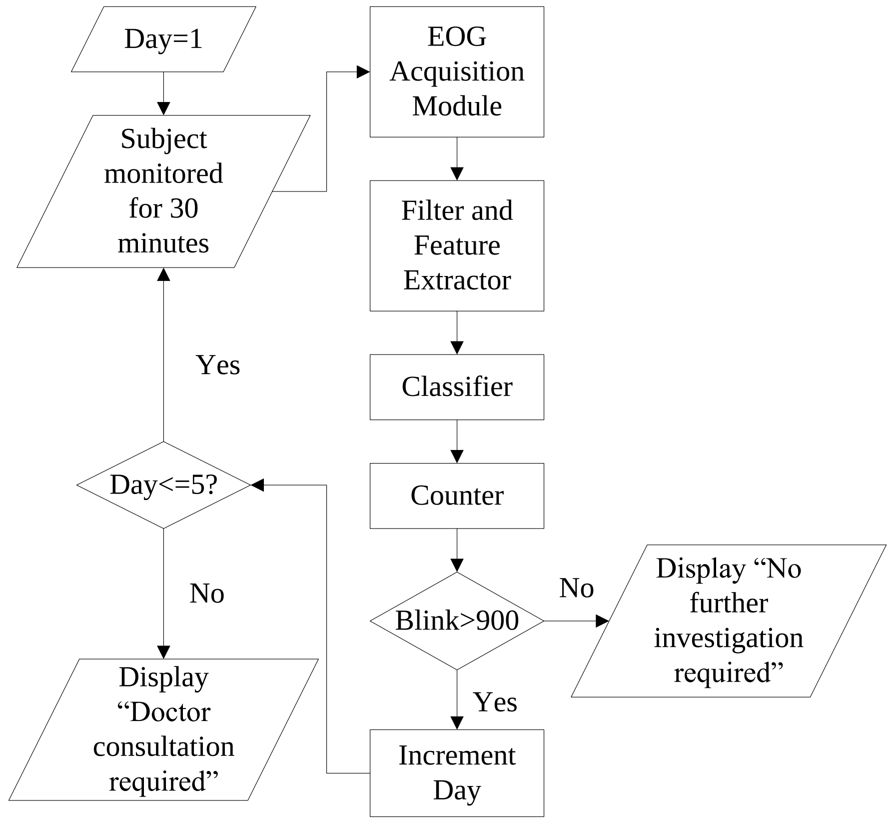


Fig. 3.19 Flowchart depicting course of work

3.5.4 Experimental Results

The EOG data acquired for 30 minutes has alternates of blink and no-blink eye movements.

Table 3.7 Classification Results

Feature	Classifier	Accuracy (%)	Sensitivity	Specificity	Time (sec)
AR(5)+ PSD	LSVM	83.33	0.733	0.933	1.1401
	Poly-SVM	76.67	0.733	0.8	1.1559
	RBF-SVM	93.40	0.91	0.958	1.0907
Hjorth + PSD	LSVM	86.67	0.867	0.867	1.1711
	Poly-SVM	73	0.667	0.8	1.1438
	RBF-SVM	90	0.8	1	1.1458

The results of classification in terms of the average value of the performance metrics along with the timing complexity over 10 subjects are noted in Table 3.7. A confusion matrix is constructed from each classification result to evaluate the accuracy, sensitivity and specificity as performance metrics.

As we note from Table 3.7, feature-set produced with AR (5) +PSD and classified using RBF kernel SVM outperforms the other algorithms considered.

3.6 Summary

This chapter is divided into four sections. Each section describes the application of EOG signal in five different areas of rehabilitation.

The first part of this third chapter describes a system for assistance of Autistic children by analysis of eye movements. Autism is a disease characterized by abnormal eye movements and an inability to follow a pattern of object movement in different directions. Eye movement data is recorded from normal individuals over a period of five days using an Electrooculogram signal acquisition system developed in the laboratory. Hjorth Parameters are used as signal features. Eye movement directions in response to a visual stimulus for tracking an object are classified using ensemble classifiers based on bagging and adaptive boosting algorithms. Maximum classification accuracies of 83.09%, 90.27%, 80.75% and 92.27% were achieved on Hjorth Parameters as features using Bagging Ensemble classifier while tracking four different sequences. This may enable convenient detection of eye fixations/staring errors in Autistic people along with the provision of gradual improvements when the tracking sequences are not followed in 50% of the cases through consequent training.

In second part, EOG was recorded using a two-channel data acquisition system from ten subjects while they continuously read English sentences on the computer screen. The sentences were produced at different speeds. Adaptive Auto-regressive parameters were extracted as features from the acquired EOG and classification was carried out, to distinguish various reading speeds, using Neural Network Classifier based on Back-propagation learning as well as Binary Tree Support Vector Machine and also Naïve Bayesian Classifier. Average classification accuracy greater than 90% indicated that reading speeds can be successfully classified from EOG signals. Using this information, for ten new subjects, if reading speeds were found to be lesser than a particular threshold, they were trained over a period of ten days to read the sentences at the same speeds repeatedly. Thus this scheme can be implemented for developing an artificial aid for assisting dyslexic children to improve their reading abilities over time.

A simple and novel scheme is proposed to prevent CVS by detecting and counting blinks over a period of time, analyzing the EOG signal in the third part of this chapter. Feature extraction was accomplished by level 4 wavelet decomposition of the EOG signal using Haar and order 4 Daubechies as mother wavelets. In the offline mode, binary classification was performed on the two acquired set of detail coefficients to distinguish between blinks and non-blink eye movements using linear, polynomial and Radial Basis Function (RBF) kernelized Support Vector Machine (SVM) classifier. The best classification accuracy of 95.83% was achieved haar as the mother wavelet and polynomial-SVM as the classifier. This trained classifier was chosen for real-time classification of EOG signals. The system causes the computer to go to a standby mode when the desired number of blinks is not attained over a predetermined period of time, thereby allowing the computer user to rest his/her eyes. Real-time implementation of the proposed algorithm was carried out on 10 subjects. The performance of the system was validated by noting that the AER over each 30 minutes interval and the POC over each subject reduces as time progresses.

Fourth part of this chapter proposes a simple scheme to detect the possibility of eye dystonia by classifying EOG into blinks and non-blinks and counting the number of blinks over a period of time. Feature extraction was accomplished by AR parameters, Hjorth Parameters and Power Spectral Density. Binary classification was performed on the two acquired feature sets (AR+PSD) and (Hjorth+PSD) to distinguish between blinks and non-blink eye movements using linear, polynomial and Radial Basis Function (RBF) kernelized Support Vector Machine (SVM) classifier. The best classification accuracy of 93.40% was achieved on AR (5) +PSD feature space and using RBF-SVM as the classifier. The present work has been carried out on normal individuals, and future scopes include implementation of this scheme to assist patients suffering from eye dystonia. In that case the entire scheme must provide good results, if not better, to justify the applicability of the proposed methodology so that it can be utilized in developing an intelligent automatic eye dystonia indicator based on EOG for cost-effective assistance in diagnosis of the disease.

References

[1] Pagon, R. A. (1988). Retinitis pigmentosa. *Survey of ophthalmology*, *33*(3), 137-177.

[2] Economou, S. G., & Stefanis, C. N. (1978). Changes of electrooculogram (EOG) in Parkinson's disease. *Acta Neurologica Scandinavica*, *58*(1), 44-52.

[3] Howlin, P., & Moore, A. (1997). Diagnosis in autism: a survey of over 1200 patients in the UK. *autism*, *1*(2), 135-162.

[4] Gillott, A., Furniss, F., & Walter, A. (2001). Anxiety in high-functioning children with autism. *Autism*, *5*(3), 277-286.

[5] Weiss, M. J. (2002). Hardiness and social support as predictors of stress in mothers of typical children, children with autism, and children with mental retardation. *Autism*, *6*(1), 115-130.

[6] Howlin, P. (2000). Outcome in adult life for more able individuals with autism or Asperger syndrome. *Autism*, *4*(1), 63-83.

[7] Higgins, D. J., Bailey, S. R., & Pearce, J. C. (2005). Factors associated with functioning style and coping strategies of families with a child with an autism spectrum disorder. *Autism*, *9*(2), 125-137.

[8] Silver, M., & Oakes, P. (2001). Evaluation of a new computer intervention to teach people with autism or Asperger syndrome to recognize and predict emotions in others. *Autism*, *5*(3), 299-316.

[9] S. Fletcher-Watson, S. R. Leekam, V. Benson, M. C. Frank, J. M. Findlay, Eye-movements reveal attention to social information in autism spectrum disorder, Neuropsychologia, 47(1) (2009) 248-257.

[10] C. Kemner, M. N. Verbaten, J. M. Cuperus, G. Camfferman, H. Van Engeland, Abnormal saccadic eye movements in autistic children, Journal of Autism and Developmental Disorders, 28(1) (1998) 61-67.

[11] Robert, C., Guilpin, C., & Limoge, A. (1998). Review of neural network applications in sleep research. *Journal of Neuroscience methods*, *79*(2), 187-193.

[12] Dietterich, T. G. (2000). An experimental comparison of three methods for constructing ensembles of decision trees: Bagging, boosting, and randomization. *Machine learning*, *40*(2), 139-157.

[13] Opitz, D., & Maclin, R. (1999). Popular ensemble methods: An empirical study. *Journal of Artificial Intelligence Research*, *11*, 169-198.

[14] Zhu, J., Zou, H., Rosset, S., & Hastie, T. (2009). Multi-class adaboost. *Statistics and its Interface*, *2*(3), 349-360.

[15] Banerjee, A., Chakraborty, S., Das, P., Datta, S., Konar, A., Tibarewala, D. N., & Janarthanan, R. (2012, December). Single channel electrooculogram (EOG) based interface for mobility aid. In *Intelligent Human Computer Interaction (IHCI), 2012 4th International Conference on* (pp. 1-6). IEEE.

[16] Banerjee, A., Datta, S., Pal, M., Konar, A., Tibarewala, D. N., & Janarthanan, R. (2013). Classifying electrooculogram to detect directional eye movements. *Procedia Technology*, *10*, 67-75.
[17] Banerjee, A., Konar, A., Tibarewala, D. N., & Janarthanan, R. (2012, July). Detecting eye movement direction from stimulated Electro-oculogram by intelligent algorithms. In *Computing Communication & Networking Technologies (ICCCNT), 2012 Third International Conference on* (pp. 1-6). IEEE.
[18] Banerjee, A., Konar, A., Janarthana, R., & Tibarewala, D. N. (2013). Electro-oculogram based classification of eye movement direction. In *Advances in Computing and Information Technology* (pp. 151-159). Springer Berlin Heidelberg.
[19] Rajan, A., Shivakeshavan, R. G., & Ramnath, V. J. (2006, December). Electrooculogram based instrumentation and control system (IC system) and its applications for severely paralysed patients. In *Biomedical and Pharmaceutical Engineering, 2006. ICBPE 2006. International Conference on* (pp. 1-4). IEEE.
[20] Allison, B. Z., Brunner, C., Kaiser, V., Müller-Putz, G. R., Neuper, C., & Pfurtscheller, G. (2010). Toward a hybrid brain–computer interface based on imagined movement and visual attention. *Journal of neural engineering*, *7*(2), 026007.
[21] J. Rapela, T. Y. Lin, M. Westerfield, T. P. Jung, J. Townsend, Assisting autistic children with wireless EOG technology, In 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (2012) 3504-3506.
[22] Vellutino FR, Dyslexia: Theory and research, Cambridge, MA: MIT press, pp. 74-81, 1979.
[23] Eden GF, Stein JF, Wood HM, Wood FB, Differences in eye movements and reading problems in dyslexic and normal children, Vision Res, 34:1345, 1994.
[24] Rayner K, Eye movements in reading and information processing, Psycho bulletin 85:618, 1978.
[25] Parks, T., & McClellan, J. (1972). Chebyshev approximation for nonrecursive digital filters with linear phase. *IEEE Transactions on Circuit Theory*, *19*(2), 189-194.
[26] Akaike, H. (1969). Fitting autoregressive models for prediction. *Annals of the institute of Statistical Mathematics*, *21*(1), 243-247.
[27] Pfurtscheller, G., Neuper, C., Schlogl, A., & Lugger, K. (1998). Separability of EEG signals recorded during right and left motor imagery using adaptive autoregressive parameters. *IEEE transactions on Rehabilitation Engineering*, *6*(3), 316-325.
[28] Jacobs, R. A. (1988). Increased rates of convergence through learning rate adaptation. *Neural networks*, *1*(4), 295-307.
[29] Møller, M. F. (1993). A scaled conjugate gradient algorithm for fast supervised learning. *Neural networks*, *6*(4), 525-533.
[30] Murphy, K. P. (2006). Naive bayes classifiers. *University of British Columbia*.
[31] Suykens, J. A., & Vandewalle, J. (1999). Least squares support vector machine classifiers. *Neural processing letters*, *9*(3), 293-300.
[32] Scholkopf, B., Sung, K. K., Burges, C. J., Girosi, F., Niyogi, P., Poggio, T., & Vapnik, V. (1997). Comparing support vector machines with Gaussian kernels to radial basis function classifiers. *IEEE transactions on Signal Processing*, *45*(11), 2758-2765.
[33] J. Anshel, "Computer vision syndrome", Visual Ergonomics, vol. 23, 2001.
[34] C. Blehm, S. Vishnu, A. Khattak, S. Mitra and R.W. Yee," Computer vision syndrome: a review", Survey of ophthalmology, vol. 50, no. 3, pp. 253-262, 2005.
[35] N. A. Charpe and V. Kaushik, "Computer vision syndrome (CVS): recognition and control in software professionals". Journal of Human Ecology, vo. 28, no. 1, pp. 67-69, 2009.
[36] Daubechies, I. (1990). The wavelet transform, time-frequency localization and signal analysis. *IEEE transactions on information theory*, *36*(5), 961-1005.
[37] Krack, P., & Marion, M. H. (1994). "Apraxia of lid opening," a focal eyelid dystonia: clinical study of 32 patients. *Movement disorders*, *9*(6), 610-615.
[38] J. Jankovic, W. E.Havins, and R. B. Wilkins, "Blinking and blepharospasm", JAMA: the journal of the American Medical Association, vol.248, no.23, pp.3160-3164, 1982.
[39] A. R. Bentivoglio, S. B. Bressman, E. Cassetta, D. Carretta, P. Tonali, and A. Albanese, "Analysis of blink rate patterns in normal subjects". Movement Disorders, vol.12, no.6, pp.1028-1034, 1997.
[40] Hjorth, B. (1970). EEG analysis based on time domain properties. *Electroencephalography and clinical neurophysiology*, *29*(3), 306-310.
[41] Marple, S. L. (1987). *Digital spectral analysis: with applications* (Vol. 5). Englewood Cliffs, NJ: Prentice-Hall.

4

Controlling Assistive Devices based on Electrooculogram

Recent research in Assistive Devices is aimed at designing rehabilitative aids for improving the life quality of disabled and elderly people. In this chapter we aim to classify the eye movements of right, left, up, down directions along with blink and utilize them to control human computer interactive systems having different rehab purpose. The chapter proposes three novel approaches towards EOG-driven rehabilitative aids which can lead to smart homes. In the first proposed scheme, a multitasking graphical user interface (GUI) is designed by controlling the position of a computer cursor using eye movements. Each and every icon of the GUI can be accessed online by just selecting them and thus the particular function can be performed. Second, a scheme is proposed to recognize the pattered eye movements of some known digits, letters and shapes. In the last and third approach, movements of a motorized wheelchair, i.e., forward, backward, right, left in a particular speed and start-stop operation are controlled in real time by EOG with predefined eye commands.

4.1 Introduction

Human Computer Interfacing enables the control of a wide variety of devices ranging from computers to wheelchairs by different types of biological signals [1]. Human Computer Interfacing (HCI) devices are, as quite evident, very significant for rehabilitation. Such devices enable the physically challenged people to lead a better life to a certain extent. Diseases like Amyotrophic Lateral Sclerosis (ALS), brain or spinal cord injury, cerebral palsy, muscular dystrophies, to mention a few, can completely damage the patient's peripheral and central motor nervous systems however, keeping certain sensory or cognitive functions unhampered [1]. Apart from these diseases, with age, motor and nervous system capabilities degenerate, sometimes making people handicapped. Thus there is a need for them to communicate effectively without using speech or limb movements through the use of appropriate HCI devices [2] i.e. communicating while bypassing the inherent neuro-muscular pathway.

Bio signals are basically the changes in electric currents produced by the sum of electrical potential differences across a specialized tissue, organ or cell system like the nervous system [3]. The most commonly known bio signals that are extensively used in design of rehabilitative aids based on HCI include Electroencephalogram (EEG) [4], Electromyogram (EMG) [5], Electrocardiogram (ECG) [6] and Electrooculogram (EOG) [7]. As well-known from various research works, these bio signals can be used individually or in suitable combinations as the means to control artificial limbs, computers or various devices depending on the nature of application as well as the nature of paralysis [8].

Effect of an accident or trauma could lead to the loss of limbs, paralysis of the motor capabilities, hamper of muscular movement as well as cerebral damage leading to improper or limited functioning of the human brain. However the vision system may not be damaged and the ability to move one's eyeballs may be present. Eye movement is proved to have a linear relation with Electrooculogram (EOG) amplitude up to a certain degree from literature study [9]. In such cases, measuring the EOG signal and utilizing it for human computer interaction is the best possible solution for rehabilitation. Apart from this fact, when compared with other biopotentials like EEG, EMG or ECG, acquisition as well as processing of EOG is relatively easier and simpler with the added advantage of less expense and real time application friendliness [10]. This makes EOG a suitable candidate as an effective biopotential for HCI not only in specific cases, but also in general.

4.2 Multitasking GUI for Paralyzed

The main purpose of our work is to create a reliable, affordable and easy-to-use eye controlled human-computer interface that will enable the paralyzed or differentially abled people to use computers independently. This would provide a large number of people the chance to engage more easily and powerfully in productive activity. The work illustrates an application of precise control of the computer cursor using specific permutations of eye movements of the user as a rehabilitative platform.

4.2.1 Experimental Paradigm

The entire course of work has been illustrated in Fig. 4.1. Each of the blocks are explained in detail in the different sub-sections of this section.

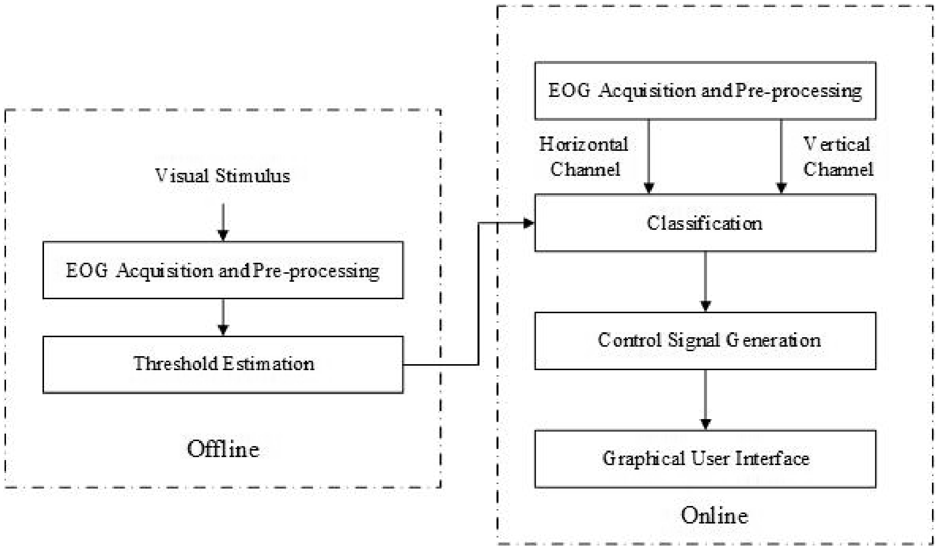


Figure 4.1 Block diagram illustrating the course of work

4.2.2 EOG Acquisition

Experiments are conducted with three female and three male subjects in the age group of 23±2 years with their consent. The purpose of the experiment and the meaning of the stimulus is informed in details to the subjects as well as to the institutional committee, which they have agreed upon. The devices used in the experiment and the procedure of the experiment are not only non-invasive but also follow all safety norms to assure the protection of the subjects. Thus, the ethical issues for dealing with human subjects for experimental purpose have been abided according to the Helsinki Declaration of 1975, revised in 2000 [11].

4.2.2.1 Acquisition for the Offline Experiment

In the first phase of the experiments, these subjects were asked to move their eye balls according to a visual cue. In the visual stimulus, a ball in the middle of a screen was displayed in the first 2 seconds. After that they were asked to track the movement of the ball in different directions (left-right-up-down) and blink their eyes when it is displayed to do so in the screen for a specific duration.

For movement of the ball in different directions, the ball starts to move from the middle of the screen, reaches the extreme position in a particular direction (left/right/up/down) on the screen and then returns to the middle of the screen. This back and forth movement for every direction is accomplished in 2 seconds. The corresponding EOG signals from both the horizontal and the vertical channels are acquired using the DAQ system mentioned before. A time frame representation of the stimulus is shown in Fig. 4.2. Each eye movement type constitutes one class and its corresponding stimulus is given for a duration of 2 seconds. All the classes are repeated to obtain 10 instances of each class of eye movement.

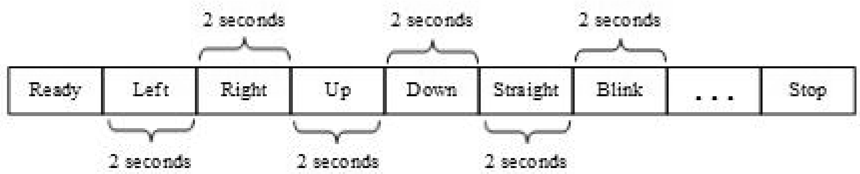


Figure 4.2 Time frame representation of the stimulus

4.2.2.2 Acquisition for the Online Experiment

During the second phase, the subjects are seated with the electrodes around their eyes in front of the computer screen with the GUI displayed (Fig. 4.6) and instructed to move the computer cursor and select the four icons at the extreme corners (i.e. 'Call Nurse', 'Game: Minesweeper', 'Emergency Alarm', 'Internet Browsing') starting from the center of the screen (i.e. at the 'Shut Down' icon) with the help of their eye movements while the EOG data at intervals of 2 seconds with 2 seconds of rest in between are classified based on the pre-computed threshold values. With each eye movement i.e. left, right, up or down the cursor has been programmed to move one icon to the left, right, up or down, respectively, if possible in the allowed screen dimensions. This stimulus for 2 second of 'act' phase followed by 2 second of 'relax' phase is intimated to the subjects through audio commands.

4.2.3 Pre-processing, Threshold Estimation and Classification

It has been experimentally determined that the most relevant information from recorded EOG lies in the frequency range of 0.1 to 15 Hz. To minimize undesirable noise and redundant information thereby obtaining signals only in the frequency range of 0.1 to 15Hz band pass filtering has been implemented on the acquired EOG data [12]. For its superior filtering abilities with respect to a fast transition between pass and stop bands an Elliptical band pass filter [13] of order 6 in the specified frequency range has been used for this purpose.

A number of standard feature extraction methods from bio-signals are available in the literature. Some of the well-known methods include estimation of power spectral density [14], Time-domain Parameters [15], Auto-regressive parameters [16], Approximate Entropy [17] and Wavelet based features [18]. However, these methods require large amounts of complex computations and transformations of the input signal. In the present work, our ultimate aim is the real time classification of EOG signals so as to control the computer cursor with eye movements. For that purpose the course of processing of the EOG signals acquired must not only be as fast as possible but also must produce very accurate results. The amplitude of the EOG signal is a very efficient indicator of the direction of eye movement. Also use of the amplitude as the feature eliminates the need of time-consuming feature extraction methods and is therefore the best option in the real time environment. Hence the amplitude itself is used as a feature in the present work.

For each type of eye movement for duration of 2 seconds the filtered EOG signals are shown in Fig. 4.3. The horizontal channel data can mainly discriminate among left, right and straight directions whereas the vertical channel data distinguishes the up and down directions as well as blinks from the rest.

For each subject, from the observation of the amplitude plots for each channel of EOG signal, certain thresholds are estimated to classify eye movement directions and blinks. The thresholds are evaluated in a trial and error basis while classifying the EOG dataset for each evaluated threshold and observing the classification accuracies. The classification accuracy is computed from a confusion matrix according to Eq. (4.1).

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \times 100\% \tag{4.1}$$

In Eq. (4.1), TP, TN, FP and FN denote the number of samples classified as true positive, true negative, false positive and false negative respectively. For good results, the Accuracy must be close to 100%.

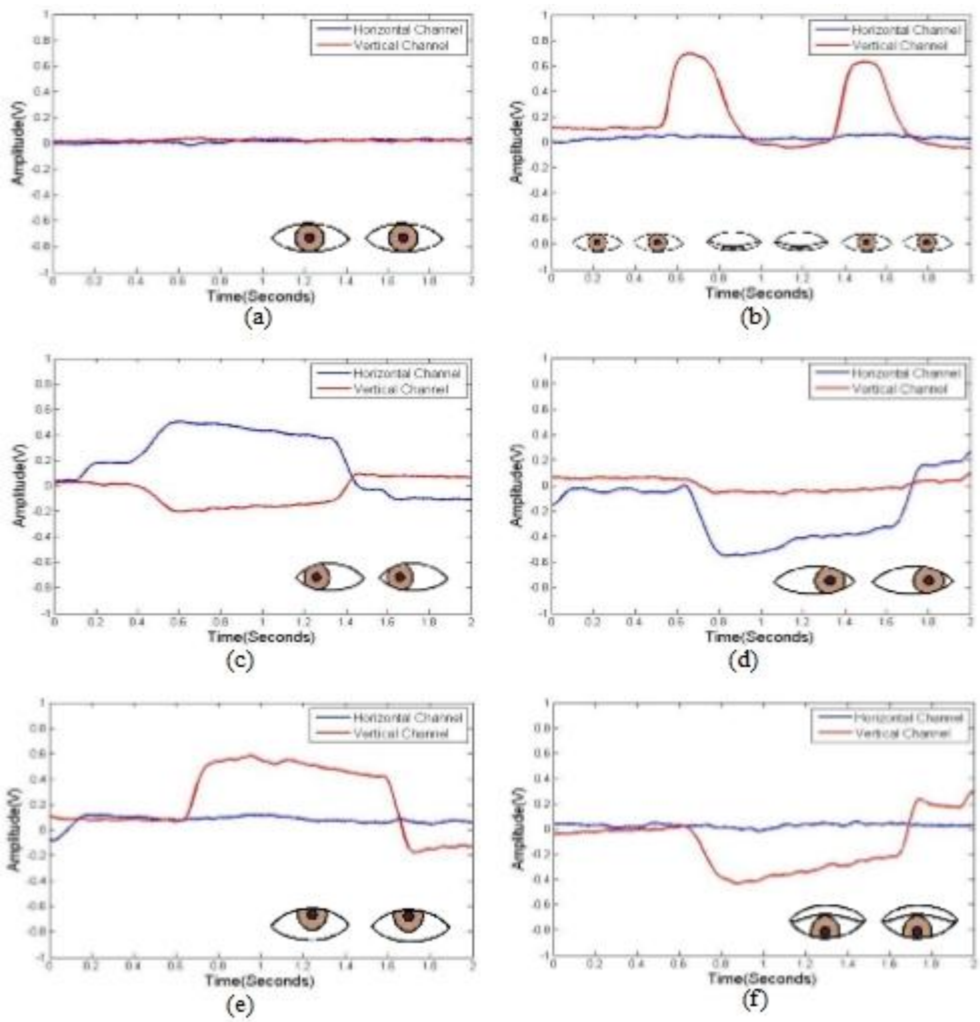


Figure 4.3 Filtered EOG signals corresponding to 2 seconds of each eye movement, (a) Straight (b) Blink (c) Right (d) Left (e) Up (f) Down

The process of classification is hierarchical based on a series of if-else conditions. A tree based structure showing the classification of the horizontal and the vertical channel data (averaged over 2 seconds) into the six different classes on the basis of the threshold values for each type of eye movement is shown in Fig. 4. 4. Here, TR, TL, TU, TB and TD are the computed threshold values for right, left, up, blink and down movements. The horizontal EOG classifies eye movements into right (R), left (L) or straight (S) classes and the vertical EOG classifies eye movements into up (U), down (D), blink (B) or straight (S) classes. Now, in order to determine the correct class of a particular instance of eye movement the classification results from the two channels (CH and CV according to Fig. 4.) must be combined.

As seen from Fig. 4.6 if a both the channels detect the class straight, then the outcome is that the person has looked straight in the window of 2 seconds. For other different outcomes from the two channels, the absolute deviations of the EOG data (averaged over the 2 second window) from the thresholds of the observed classes (two classes from the two channels) are considered and decision favors that class for which the absolute deviation is larger. Thus, at a time only one of the classes appears at the output. Situations involving diagonal directions like right-down, right-up, left-down and left-up are ignored.

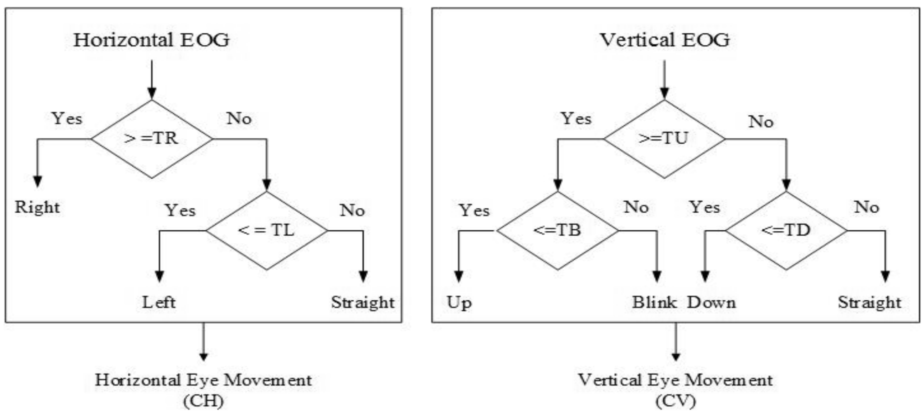


Figure 4.4. Schematic of the steps used for classifying eye movement directions from horizontal and vertical channel

For each subject an optimum value of threshold for each level is obtained and the minimum absolute value for that particular threshold over all subjects is evaluated. These minimum values of the thresholds along with the corresponding signs are used during real time classification. The estimated values of the thresholds that provide the maximum classification accuracy of 95.83%, taking minimum thresholds over six subjects are tabulated in Table 4.1. The minimum absolute threshold values over all the subjects appended with the corresponding sign are chosen to be ultimate threshold values as this method avoids most of the false negatives.

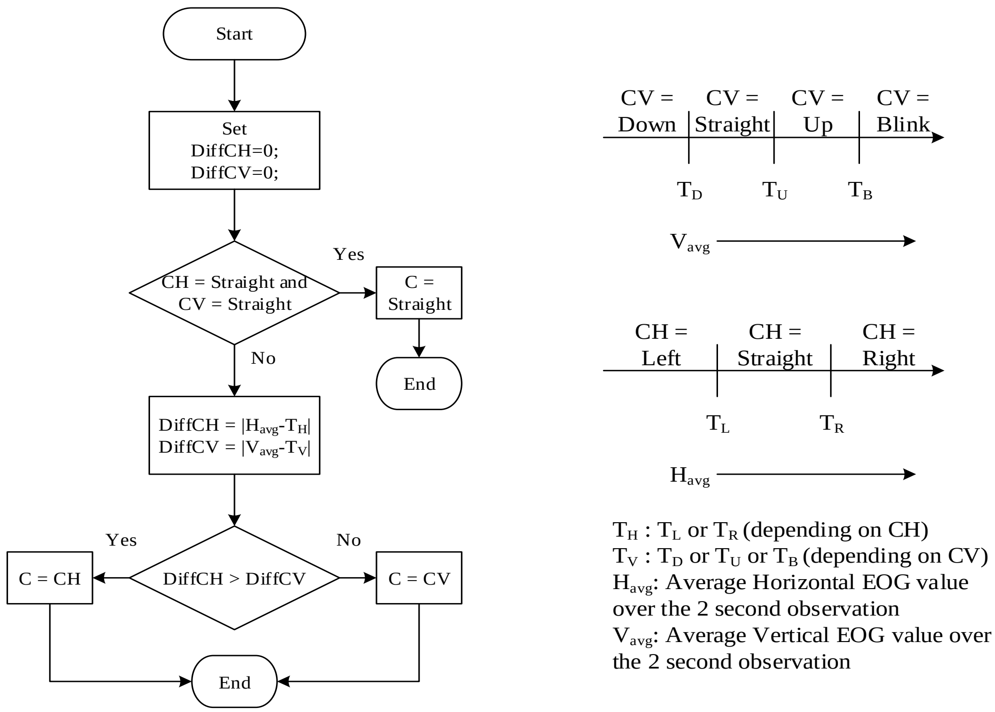


Fig. 4.5 Flowchart to detect the eye movement direction

4.2.4 GUI Development and Cursor Control Signal Generation

The developed GUI is aimed to provide assistance to patients with body and brain damage and allows to perform basic tasks, such as text writing, internet browsing, gaming, playing video and songs, sending emails, calling the nurse and alarm generating in case of emergency situation (as shown in Fig. 4.6).

The users move around the interface by performing eyes movements in the correct direction and blinking twice when they want to select an option. The user starts from the centre of the screen i.e. with the cursor placed on the ‘Shut Down’ icon and from there the cursor can be moved to the desired location. An Up/Down movement of eye-ball corresponds to moving the cursor to upper/lower row of icons. Similarly, a Left/Right movement of eye-ball corresponds to moving the cursor to the left/right columns of icons. When at an extreme row or column, further commands that would have caused the cursor to move outside the icon set are ignored. The users can move the cursor and select icons related to the specified tasks by ocular movements. Blinking twice is kept as a selection command as false alarms of blinking or false detection of blinks are less likely to occur twice consecutively.

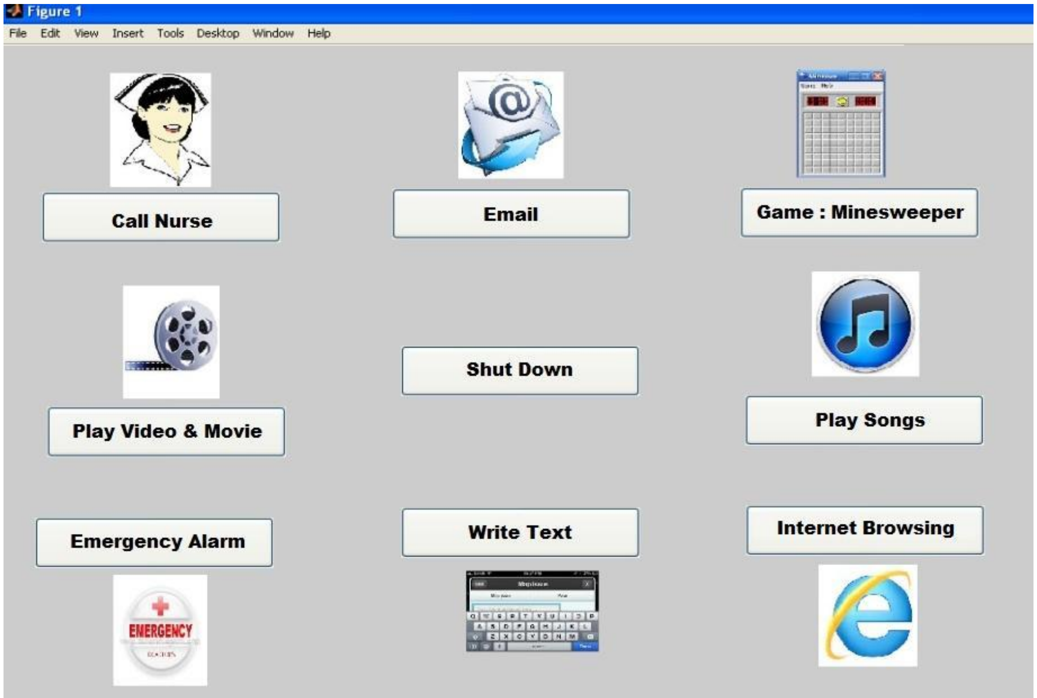


Figure 4.6 A snapshot showing the GUI screen for cursor control by eye movements for assisting paralyzed patients

In literature it is found that EOG has been utilized to control computer mouse (Kwon and Kim, 1999; Lacourse and Hludik, 1990; Norris and Wilson, 1997; Tecce et al., 1998) and to browse internet (Lledó et al., 2013), but in our work we have combined many functions that can be executed with eye movement control.

The GUI interface has been developed using MATLAB. It allows the user to perform different tasks by only using eyes movements. With this interface it is possible to:

- Call the nurse
- Send Email
- Play Game (Minesweeper)
- Play videos or movies
- Shut Down the system
- Play songs
- Emergency Alarm Generation
- Text writing (using virtual keyboard)
- Net surfing

By further improvement, rehabilitation aids and home appliances can also be connected with the GUI and can lead to an eye movement controlled smart home. The selection of a particular option is implemented by blinking twice consecutively. Results in Section 5 have analyzed the GUI control using eye-movement in synchronous real-time environment. It is to be mentioned here that the offline phase should be performed before the online implementation of the GUI. This is because as the same individuals would be using the GUI and hence, the offline phase has a two-fold purpose of providing the training to the users (getting accustomed with the time stamping while following the stimulus) as well as tuning the classification parameters (different thresholds) specific to the user who will be using the GUI in online phase.

4.3.5 Results

The threshold estimated for the six subjects is presented in Table 4.1. These are essentially the average amplitude value for the different eye movements. For the sake of completeness the amplitude of horizontal and vertical EOG while looking straight are also mentioned, here. The choice of the final threshold is the minimum of all the thresholds of the different subjects. This reduces the chances of false positives.

Table 4.1. Estimation of Thresholds

Subject ID	Threshold Voltage (V)						
	Right (TR)	**Left (TL)**	**Up (TU)**	**Down (TD)**	**Blink (TB)**	**Straight Horizontal**	**Straight Vertical**
S01	0.45	-0.37	0.40	-0.44	0.58	0.12	0.06
S02	0.45	-0.42	0.42	-0.43	0.62	0.07	-0.02
S03	0.45	-0.39	0.39	-0.41	0.59	-0.03	-0.01
S04	0.43	-0.40	0.38	-0.47	0.62	0.09	0.07
S05	0.44	-0.42	0.42	-0.49	0.61	0.06	-0.04
S06	0.49	-0.39	0.43	-0.45	0.58	0.04	0.05
Minimum	**0.43**	**-0.37**	**0.38**	**-0.41**	**0.58**	**-0.03**	**-0.01**

During the second phase of the experiment, EOG samples are collected online from each subject at intervals of 2 seconds duration, while they sit in front of the computer screen with the GUI displayed so as to move the cursor to the desired positions (selecting four corner icons starting from the middle of the screen) with eye movements. For each interval of 2 seconds EOG data is acquired and in the next 2 seconds the subject are asked to relax while the classification is done and the cursor is moved.

The test data is classified to belong to a particular direction or to be a blink according to the hierarchical classification method mentioned before by the use of the pre-computed thresholds at each level. The eye movement commands are up, down, left and right for moving the computer cursor in the respective directions. For selection of a particular option, a person needs to blink twice. A single blink and straight vision are not considered as any control signal.

The results of online classification for the six subjects at a particular trial (calling the nurse, ideally requiring 4 eye movements in the sequence up-left-blink-blink) have been shown in Table 4.2. Due to space constraint the details of only one icon selection is shown in Table 4.2.

Table 4.2. Online Classification Results (Performance for moving cursor and selecting icon 'Call Nurse'

Intervals	S01		S02		S03		S04		S05		S06	
	Ac[a]	**Pr**[b]	**Ac**	**Pr**	**Ac**	**Pr**	**Ac**	**Pr**	**Ac**	**Pr**	**Ac**	**Pr**
1	U[e]	U	U	R	U	U	U	U	U	R	U	S
2	L	D	L	L	L	L	L	D	L	D	U	U
3	U	U	U	U	B	D	U	U	L	L	L	D
4	L	L	L	D	U	U	L	L	U	U	U	B
5	B	S	U	B	B	U	B	B	U	U	U	R
6	B	R	U	U	B	B	B	R	L	S	L	S
7	L	L	L	L	B	B	L	L	L	L	L	L
8	B	L	B	S	-	-	B	B	B	S	U	U
9	B	B	B	B	-	-	B	B	B	B	L	L
10	B	B	B	B	-	-	-	-	B	B	B	B
11	-	-	-	-	-	-	-	-	-	-	B	B
MCR[c] (%)	**40.00**		**40.00**		**28.57**		**22.22**		**40.00**		**45.45**	
Err[d]	**6**		**6**		**3**		**5**		**6**		**7**	

a. Actual or Desired eye movement
b. Predicted or Classified eye movement from EOG data
c. Misclassification Rate = % of eye movements misclassified out of the total # movements executed
d. Error = excess steps undergone w. r. t. ideally required # steps i.e. 4 (Up-Left-Blink-Blink)
e. U: Up; D: Down; L: Left; R: Right; B: Blink; S: Straight

The other possible eye movement sequences to reach this particular option are not considered for performance analysis. Here, MCR denotes the misclassification rate computed as the percentage of eye movements misclassified out of the total number of movements executed and Error denotes the excess steps undergone because of misclassification with respect to the maximum number of steps i.e. 4. Thus, MCR indicates the performance of the classification approach undertaken whereas Error indicates how well the learning occurs for each of the subject. A balance among these two determines the performance of the proposed architecture in the mentioned GUI. Similar performance results for the other three icon selection are mentioned Table 4.3.

Table 4.3 Online Classification Results (Moving Cursor and Selecting four extreme icons of the GUI)

Subject ID	S01		S02		S03		S04		S05		S06	
Selecting Icons	**MCR[a] (%)**	**Err[b]**	**MCR (%)**	**Err**	**MCR (%)**	**Err**	**MCR (%)**	**Err**	**MCR (%)**	**Err**	**MCR (%)**	**Err**
‘Call Nurse’	40.00	6	40.00	6	28.57	3	22.22	5	40.00	6	45.45	7
‘Game: Minesweeper’	37.32	5	32.33	5	35.81	4	20.00	4	35.46	7	49.73	8
‘Emergency Alarm’	39.61	5	37.85	6	34.72	4	26.55	5	38.92	5	46.43	7
‘Internet Browsing’	42.22	6	31.09	5	27.63	3	24.38	5	40.00	6	41.66	8

Following this, the average classification accuracies for all the classes, the overall results for all the subjects and the classification accuracy as well as computation time considering the amplitudes as feature are mentioned in Fig. 7. The different classifiers with which the results are compared includes Linear Support Vector Machine (LSVM having cost=100), Support Vector Machine with Radial Basis Function as the kernel (RBF-SVM having kernel width=1 and cost=100), k-nearest neighbor (kNN having k=3, distance metric=Euclidean) and Naïve Bayesian (probability density function=Gaussian distribution) (Theodoridis and Koutroumbas, 2009). One-versus-all approach has been adopted in testing the Support Vector Machines.

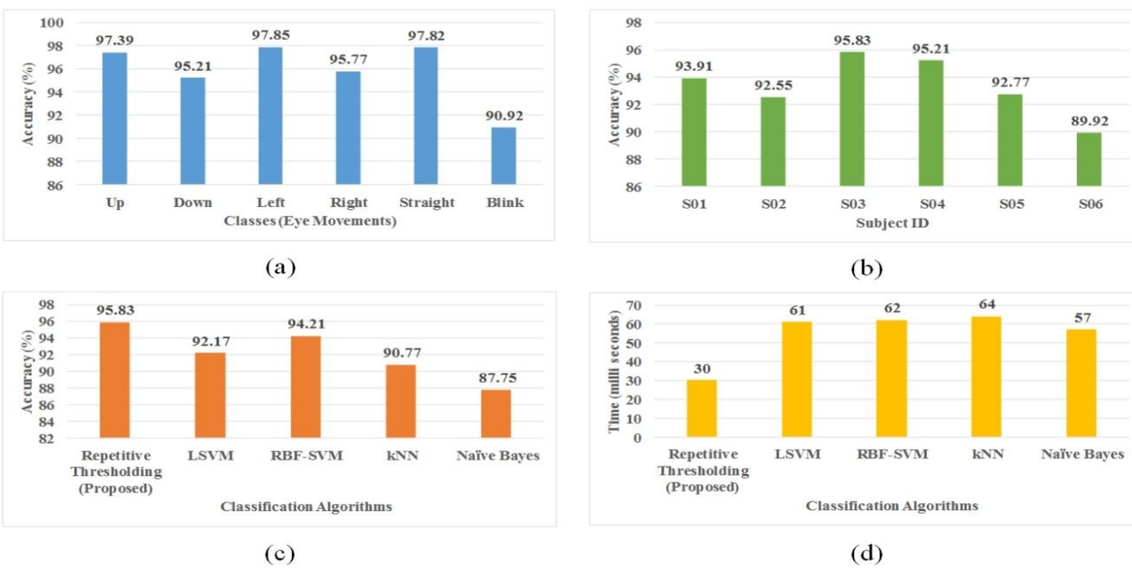


Figure 4.7 Classification Results: (a) Class-wise offline classification result with the proposed approach; (b) Subject-wise offline classification result with the proposed approach; (c) Overall offline classification results with the proposed algorithm and various other standard classifiers; (d) Computation time of the proposed algorithm and various other standard classifiers (executed on MATLAB R2012b on an Intel Core i3 64-bit processor having 4GB RAM)

The work presented here presents a fast yet accurate classification method to discriminate between different eye direction which has then been encoded for real-time control of the movement of the mouse pointer in a GUI. The small time requirement has been achieved by using the raw EOG i.e. the amplitude values directly for classification bypassing the feature extraction step. Even the classification has been done by repetitive thresholding which is faster as well as simpler than other conventional supervised algorithms. This low processing time and ease of implementation makes our proposed algorithm a good candidate for real-time applications. The approach to classify eye movements from EOG signal has been used to control mouse pointer which can assist differentially abled person to perform different functions as indicated by the different icons of the GUI.

The proposed theory has been practically applied in a real-time application i.e. the GUI controlled by voluntary eye movements and yielded accurate results validating the work. Yet some limitations of the presented theory and/or the application have been observed during the course of the work. The threshold obtained vary from subject to subject. In this work, the threshold values have been set as the minimum values after observing the thresholds of different subjects. But for practical applications, this calls for a mandatory offline training session before any real-time application. Secondly, only horizontal and vertical eye movements are considered in this work i.e. diagonal eye movements have been ignored so that there are lesser number of control commands and also less stress on human eyes.

However, the move diagonally across the screen this takes more number of eye movements which is an added load on the human eye. Thirdly, the EOG values need to be stored for a pre-defined period (2 second in pur work) before it can be processed. For any application that requires or builds a stand-alone system, this storing of EOG values calls for two buffers for the two channels. However, a duration of 2 second is not much and hence, the memory contraint presented by the proposed work is not impractical. Finally, the 2 second EOG values are averaged before comparison by thresholding which will lead to inaccurate values if there are a few unwanted spikes in the EOG signal caused by involuntary blinks or other signal interference. In our future work, we will address each of these problems in detailed to present an improved eye movement controlled interface for assisting the disabled people.

The proposed classification strategy has been compared with other standard classifiers in Fig. 4.7(c). For validation of the classification result Friedman Test (Demšar, 2006) is performed, here. The classifiers are ranked according to classification accuracy for every subject (dataset) and then the ranks are averaged as noted in Table IV. According to the null hypothesis, all the classifiers are equivalent and hence, they will have the same ranks. Friedman statistics for (K-1) degrees of freedom is distributed according to the chi-square statistics as given by (2) where N is the number of datasets (=6, here), K is the number of classifiers (=5, here) and R_j is the average rank of the j-th classifier. The null hypothesis is rejected if evaluated $\chi_F^2 > \chi_{4,0.05}^2 = 9.49$, which indicates, for 4 degrees of freedom, the null hypothesis is correct to an extent of only 5%.

$$\chi_F^2 = \frac{12N}{K(K+1)}\left[\sum_{j=1}^{K} R_j^2 - \frac{K(K+1)^2}{4}\right] \tag{4.2}$$

When chi-square is evaluated from Table IV, it is found to be 19.59 which is greater than 9.49. Hence, the null hypothesis is rejected which means that the classifiers are not equivalent but are ranked according to the ranks in Table 4.4. This validates that the proposed classification strategy outperforms the standard ones.

Table 4.4: Statistical Analysis: Friedman Test

Classifiers / Datasets	Repetitive threshold (Proposed)	LSVM	RBF-SVM	kNN	Naive Bayes
S01	1	3	2	4	5
S02	1	4	2	3	5
S03	1	2	3	4	5
S04	2	3	1	5	4
S05	2	3	1	4	5
S06	1	4	2	3	5
Average Ranks, R_j	1.33	3.17	1.83	3.83	4.83

In this study, Electrooculogram (EOG) signal is used to control the movement of computer cursor using eye movements. A simple yet effective strategy has been used to implement an eye movement based control system. The performance of the system is experimented in real time with normal subjects.

The proposed system is comparatively cheap and easy to design rehabilitative interface that can be controlled using subject's own EOG which will help severely paralyzed patients.

One important factor to be considered for real time implementation of an EOG based control system is that the user should be trained properly and the control commands should be chosen in a way so that the user feels comfortable. Future scopes of work include the incorporation of further sophisticated yet computationally simple signal processing algorithms for better accuracy and precision in the development of such control devices. This work has been carried out on healthy individuals. As a future work, we would like to test the same architecture with disabled individuals to address the problems that can rise when the targeted patients use this system.

4.3 Digit, Shape & Letter Recognition for Speech Disabled

This work is aimed to provide novel approach of rehabilitative HCI where it successfully classify the numerical digits drawn by subject's eye movement and for achieving the result, electroocculography sensors (dual channel) and amplifier has been designed, which is able to extract the sharp change of corneo-retinal potential due to eyeball movement intended to draw a pattern (numeric digit, alphabet). The extracted signal has been processed and classified successfully with more than 90% accuracy rate. Here Power spectral density has been used as feature extractor and support vector machine with multilayer perceptron kernel function has been used as classifier. Performance of other classifiers also has been compared here. Five healthy subjects took part in experiment and their eyeball movement signal has been acquired for distinguishing different numerical digits that are frequently needed for communication to external world.

4.3.1 Data Collection

EOG data has been acquired from 5 healthy subjects who have not gone through any eye disease any recent past, and all of them have nearly 6-6 vision or corrected to it. Among them 3 persons were male and 2 were female within age group (20- 28). At first all experimental procedures and purpose of the study were made clear to all subjects and a consent form stating the willingness of them to take part in this experiment was signed. All other safety and ethics related issues have been dealt according to Helsinki Declaration of 1975, revised in 2000 by World Medical Association (WMA) [11].

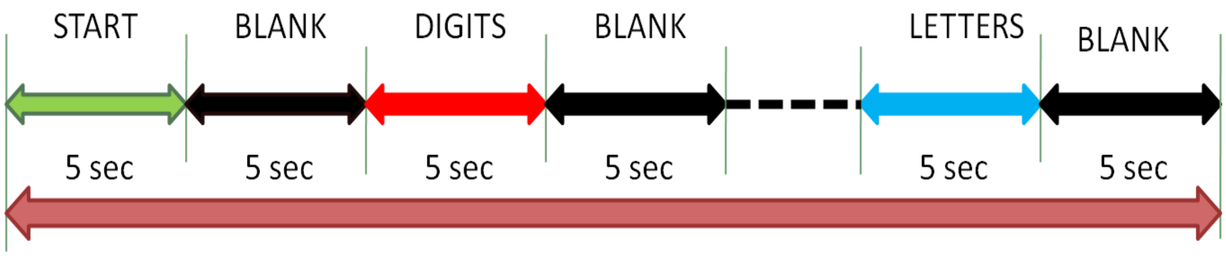


Fig. 4.8 Stimulus for data collection of digit, shape and letter tracking eye movements

The experiment consists of 20 trials in each session, i.e. each digit will come 20 times in each session. Total experiment is of 100 seconds. Subjects were presented visual stimuli on monitor to perform the eye movement task in synchronized manner. At beginning a 'start' screen appears on screen followed by a blank screen of 5 seconds to allow subject to concentrate on experiment. Each eye movement task is of 5 seconds where subject has to draw digits 1 to 9 by movement of his/her eyes and a ball moves on screen according to corresponding digit (Fig. 4.8). Each eye movement task is of 5 seconds. Nine digits, seven letters and six shapes have been tracked by each subject.

It is done to assist the subject to move eyes in synchronized manner; subject has to only follow the moving ball. EOG data was acquired by 2 channel EOG amplifier made in our lab and signal was recorded in LabVIEW platform through Analog to Digital converter made by National Instruments (Fig. 4.9). All the electrodes used here is made of Ag/AgCl and attached to a spectacle for ease of use. The sampling frequency of amplifier is 256 Hz.

4.3.2 EOG Data Processing Methodology

In the said experiment two days data of same subject is considered, so the extracted features have been normalized within (0, 1), before it is applied to classifier. New normalized signal will have zero mean and unity class variance. The feature set has been cross validated k fold such that (k-1) fold data will be used for training purpose and rest of data will be used for testing purpose. Extracted features have been classified by SVM classifier [19] using multilayer perceptron kernel function [20] and a comparative study is done to compare the results of different classifier based on same feature extractor. The result section is described in two sub sections, first performance is compared based on accuracy metric and second all the classifiers used here have been validated statistically.

Here in this experiment all the computation has been done in MATLAB 2015(a) software .The computer has the specification of windows 10 OS, Intel i7 processor, 64 bit.

Figure 4.9. EOG Recording

Classifier performance is evaluated based on Accuracy which ultimately measures the degree to which the result of the experiment conforms to the correct value. Accuracy has been obtained from confusion matrix. Confusion matrix generates a 2 x 2 matrix whose elements are identified as True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN) values.

Table 4.5. Classification Accuracy (%)

	Classification Accuracy (%)									Avg (%)
Digits	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	
	90.8	93.3	87.5	88.8	89.9	87.3	89.6	**92.8**	90.3	90.33
Letters	**S**	**M**	**Z**	**C**	**N**	**O**	**L**			
	86.73	82.5	83.46	80.5	85.33	83.5	82.71			83.53
Shapes	▲	▰	●	⬟	●	★				
	87.5	88.66	87.75	**88.9**	86.33	87.21				87.73

Here all the data has been cross validated 10 folds, i.e. 5 days data of same subject was used for training purpose, so before it is applied to classifier, the extracted feature was normalized such that it has zero mean and unity class variance. It is evident from accuracy table that SVM classifier with 'multilayer perceptron' worked best to distinguish between digits, it has got highest classification accuracy of 93.3% recognizing digit two. Average accuracy of SVM classifier is 90.33% where kNN [21] and ensemble classifier [22] has got average accuracy of 87.32% and 88.75% respectively (listed in Table 4.5). Here ensemble classifier is used as binary classifier with 'subspace' method and 'kNN' as weak learner. All the accuracies got here has been averaged over all the subjects.

A new approach of EOG based communication where subject draws different numerical digit by his/her eye movement which successfully interprets and result through computer is provided. Different number is used here because of its frequent use for communication to external world. These digits may also serve as password or may be involved in basic calculation. Here communication signal has been generated by combining different movement of eye and following some points has been noted, i.e. movement of eye is restricted to some angle, blinking artifacts must be removed for better accuracy, head or body movement alters the DC level of the signal. It has also been voted that EOG signal differs from subject to subject even in time to time for same subject. The system though works satisfactorily but still some issues must be addressed like miniaturization of circuit, real time reconstruction of digit and optimization between classifier performance and processing time. Still it can be concluded that eye movement triggered signal can be used successfully for controlling assistive device or to make interface between human and computer specially designed for patients with neuro-muscular disorder.

4.3 EOG Interface for Motorized Wheelchair Control

Today, approximately 10 percent of the world's population is over 60 years of age; by 2050 this proportion will have more than doubled and the greatest rate of increase is amongst the oldest of the old, i.e. people aged 85 and more. The population of elderly people in the world is increasing. With the increase in the number of senior citizens, there is a growing demand for welfare robotic devices. Wheelchair is the most common among such devices. However, for severely disabled people it needs to be further improved by considering the disability of the user. Usually, the control of wheelchair is realized by a joystick, but good motor functionality of hand muscles is needed to cope with the surrounding dynamic environments [23-25]. A survey has shown 41% of elderly people have difficulties in accomplishing fine movement of joysticks [26-27].

The main purpose of our work is to create a reliable, affordable and easy-to-use eye based human-computer interface that will enable the previously mentioned people to move independently. This would provide to a large number of people the chance to engage more easily and powerfully in productive and fulfilling activity. The aim of this work is to improve the quality of life of those people with disabilities and providing them with a more independent life style. The idea of wheelchair control using EOG has been tried in many laboratories [28-38]. But nowhere it has been accurate enough to be used by patients in real life scenario.

This section of this chapter provides a simple scheme for wheelchair control using EOG signals corresponding to the directional motion of eye balls. This can be used as a rehabilitative aid for the people suffering from neuro-motor disability.

The wheelchair used in this experiment is marketed by M/S Karma Healthcare, model no. is KP-25.2 (Fig. 4.10). The wheelchair has a overall width of 59cm. It is basically controlled by a joystick that operates with the help of VR2 controller. Weight of the wheelchair is 70 Kg. It has two 12 Volts 50 Ah batteries. IT has two motors of 200W but the maximum level of the motors is 420W.

Fig. 4.10 Picture of the Wheelchair used in our experiment

4.3.1 Methodology

Our experiment aims to control a small mobile robot entirely with eye movements and blinks. For example, if the eyes are moved left/right the robot turns left/right, if eyes are pointed upwards/downwards it accelerates/decelerates accordingly. This simple eye movement classification can be of great use to wheel chair guidance.

This section presents the three modules of this work, where the first module deals with detection of eye movement direction from the EOG data. The second module is the wireless transmission of the classified signal. The third module manages PWM or pulse width module signal generation to the motors of the wheelchair.

4.3.1.1 Eye movement direction detection from EOG data

This module classifies five eye movement directions (right, left, up, down and blink) which are classified by a Arduino based classifier. The module can be represented by the following block diagram (Fig. 4.11).

Fig. 4.11 Block diagram of Module 1 of the proposed Wheelchair control mechanism

4.3.1.1.1 EOG signal acquisition

15 subjects (10 female and 5 male) and in the age group 25±3 years took part in the experiments. Aim and procedure of the experiments are explained to them, and they are also given refreshments after the completion of each day's experiments.

EOG is acquired with the developed EOG acquisition system discussed in chapter 2. Ethical norms are followed concerning the subjects' safety, privacy and willingness. The subjects sign consent forms before the experiments. The institutional committee is informed in details about the experimental objective and procedure, which they have agreed upon. Thus all ethical issues are considered relating to human subject experiments. All procedures are non-invasive and all safety norms are abided, assuring protection of the subjects. All these 15 subjects participated in the data acquisition for real time assessment of the system.

4.3.1.1.2 Signal Pre-Processing and Feature Extraction

The EOG signal obtained from the previous step is amplified with amplitude ranging from 0-4.7v DC, but also crude and noisy. Thus the signal needs precise filtering and reconstruction before appearing at the classifier input.

In this section our approach is totally digital. A digital platform provides all the features and flexibilities of signal processing with required precision. Output devices like LEDs and motor control also becomes easy. Moreover, recent advancements like today's microcontrollers have almost all features integrated within, that a digital system needs—RISC Processor, huge memories (Static RAM + Flash ROM + CPU registers + E^2PROM), peripherals like multiple hardware timers, A/D converters, PWM for motor control, serial comm. and many others. Thus interfacing the analog signal properly with the MCU, and programming it accordingly is enough to support all the tasks from filtering to classification and motor control as required for our project.

- *Signal digitization and buffering:*

Digital processing of an analog signal requires the signal to be discretized (sampled) and converted to binary, it is exclusively done by a data sampler followed by an analog to digital converter (ADC). The ADC we used here is the internal ADC of the MCU so the analog signal can directly be interfaced to the MCU with proper voltage levels (0 – 5v). Here signal is sampled in 128 samples/second, converted to binary and stored in a buffer of size N (located in RAM space). Every sampling interval, i.e. 1/128 s, the oldest value (N^{th}) leaves the buffer, the remaining values are shifted by one position and the new sample is stored at 1^{st} position.

A convenient way of de-noising and reconstruction of random analog signal is filtering. Moreover digital filtering promotes precise signal filtering and reconstruction. Digital filters are primarily of two types, FIR (Finite Impulse Response) and IIR (Infinite Impulse Response). IIR filters are characterized by sharp cutoff and smaller order relative to FIR but having a non-linear phase (so different phase-delay for different frequency components) which often distorts the data pattern. Whereas FIR filters need a relatively higher order to have a moderate roll-off at cutoff frequencies but has an advantage over IIRs that it has a linear phase characteristics so time domain patterns of data are retained with a finite delay.

Since the eye movement patterns of the EOG is well embedded in its time domain representation, so the filtering must preserve the original signal pattern. As discussed earlier FIR filtering retains original signal pattern with a constant finite delay due to its linear phase characteristics. Here we have used a FIR filter of order N=31, whose coefficients are calculated and optimized using Least Pth Norm Algorithm so as to get steepest cutoff and flattest band possible at the order specified. It was verified in MATLAB that the pattern defining pulses are well below of 10Hz band. So, the filter specifications are kept as, 31 order FIR filter, 128Hz sampling rate,10Hz bandwidth. Since this filter has a large gain, filtered data have to be rescaled properly for saving memory space.

In actual implementation both input and output data are to be kept in buffers of 31 memory locations wide (in other words considering a window length same as filter order itself).

- Filter complexity calculation

Output is calculated as linear convolution of coefficient vector H and input vector x. Due to absence of MAC (Multiply and Accumulate) unit within the processor used, the filter complexity becomes N signed multiplications and N-1 signed additions, per sample per sampling interval. Some additional operations like N-1 shifts in both data buffers, scaling the output before putting it into output buffer, are also performed in the same sampling interval. The data scaling is computed as follows-

Let output be y_i from filter stage on application of inputs x_i to x_{i-30} where $x_i$and $y_i$are ith input and output samples respectively. Then y_i is scaled as

$$y_{i_{SCALED}} \leftarrow y_i * 0.75 + \mathrm{B} \tag{4.3}$$

Where B is a bias to convert the result to unsigned integer and determined experimentally. Since the processor used here have a fixed point architecture, we have to approximate the floating point multiplication as multiple shifting and adding operations. In our case-

$$\begin{aligned} 0.75\, y_i &= \frac{3}{4} * y_i \\ &= \frac{1}{2} y_i + \frac{1}{4} y_i \\ &= y_i >> 1 + y_i >> 2 \end{aligned} \tag{4.4}$$

It is true that un-scaled y_i is output as 16 bit signed integer. So three 16-bit shifts and a 16-bit addition (or six shifts and two additions according to present processor architecture) are performed and added with B (from (1)) to assign it to unsigned 8-bit integer data and get final scaled output $y_{i_{SCALED}}$. Thus space complexity of filtering part is a little higher than 2N main-memory locations. As there are two independent EOG signals (horizontal component a vertical component), every complexity is just doubled for this filter implementation.

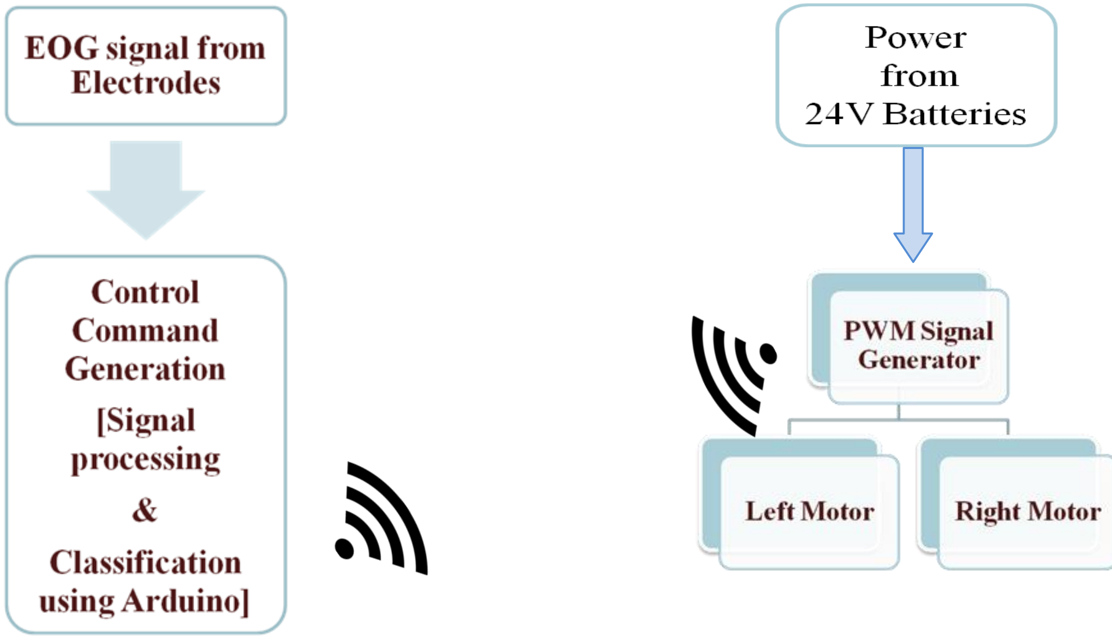


Fig. 4.12 Schematic representation of wheelchair control methodology

4.3.1.1.3 Eye Movement Classification

This work primarily deals with five classes – Up, Down, Right, Left and Blink as far as our classification problem is concerned. Final output is defined as – both motors of the bot are initially at halt. Two blinks start the bot and it waits for any further input. Generally Up gazes increases the bot speed forward in steps and down gazes reduce the speed. If the bot is stopped a down gaze will make it move backwards and increase speed downwards in steps after receiving more similar gazes. Left and right gazes make left and right turns respectively. Schematic representation of wheelchair control methodology is given in Fig. 4.12.

In our work, Up, Down, Blink and Left, Right classification is done independently from their independent characterizing signals viz. Horizontal and Vertical components of EOG signal respectively.

Signal (or real-time information data) inherently contains large amount of noise and various interferences, which cannot be easily removed with higher precision. Moreover output classes are poorly defined by the signals in their raw time-domain format, as signal characteristics for different classes often reside so close that class discrimination is hard. So for all these reasons data space is generally mapped to some higher dimensional space, called 'feature space', to maximize the distance between the feature points of different classes thus well discriminating between the classes and reducing probability of error.

This particular experiment deals with a rather simple bio-potential signal or EOG, where we can find out its basic classes (←, →, ↑, ↓ and blink) only by observing raw/filtered signal (eye estimation)—this is referred to as PROBLEM1. But we cannot accurately determine the angle of gaze, as specified by different voltage levels, referring to as PROBLEM2. In this case different angle of gazes are not clearly defined, or it varies extensively on the nature of analog circuit as well as the person of concern.

Generally complex problems, where the data tend to deviate from a predefined hypothesis, need a learning algorithm to specify the output classes in the feature space. PROBLEM2, as discussed above, will require such a complex learning process for classification. Our concern here particularly deals with a mobile robot guidance system by EOG, where angle classification of different gazes isn't necessary, so we stick to PROBLEM1 only.

- Features

The classification problem remains simple even in the filtered EOG signal. Signal feature here includes a 30 sample difference signal which best differentiates a sudden change in signal on onset of a gaze, from other small changes. From that difference signal we determine to find out the output classes with the help of embedded C-language on a microcontroller based embedded platform.

- Intuitive Classification on the basis of thresholds

Initially raw EOG datasets of different persons are acquired with the analog amplifier followed by a data acquisition device to the computer. These datasets are analyzed with the help of MATLAB, operations like filtering, fixed point quantization, and threshold level normalizations are done before realizing in the embedded domain.

Classification part in the embedded C-program consists of a FSM state model based decision making and realized similar to that of SWITCH –CASE statements in C. The FSM is explained below-
Final classification is realized in form of a C-routine 'class'. It is described as follows

Feature vector (dimension N=31) of horizontal and vertical EOG are input to this function as $\overrightarrow{\mathrm{d}H}$ and $\overrightarrow{\mathrm{d}V}$ respectively. For horizontal classification

Step1:

Initializing state $0 \rightarrow S_H$ for the first time only.

Step2:

Switch to different cases according to S_H values

<u>Case 0:</u> Checking new value of $\overrightarrow{\mathrm{d}H}$ whether it satisfies $\overrightarrow{\mathrm{d}H} \geq H_T$, where H_T stands for threshold of an RIGHT (→) gaze, or $\overrightarrow{\mathrm{d}H} \leq -H_T$ for a LEFT (←) gaze, accordingly $1 \rightarrow S_H$ or $-1 \rightarrow S_H$ decision is undertaken.

<u>Case 1:</u> Checks for negative change i.e. $\overrightarrow{\mathrm{d}H} \leq -H_T$ so as to go to state 10 or $10 \rightarrow S_H$.

<u>Case 10:</u> If a small negative change ($\square \frac{1}{2} H_T$) is encountered $0 \rightarrow S_H$.

<u>Case -1:</u> Checks for positive change i.e. $\overrightarrow{\mathrm{d}H} \geq H_T$ so as to go to state -10 or $-10 \rightarrow S_H$.

<u>Case -10:</u> If a small positive change ($\square \frac{1}{2} H_T$) is encountered $0 \rightarrow S_H$.

Step3:

Similar switching for S_V values

Case 0: Checking new value of $\overrightarrow{\mathrm{dV}}$ whether it satisfies $\overrightarrow{\mathrm{dV}} \geq V_T$, where V_T stands for threshold of an UP (↑) gaze, or $\overrightarrow{\mathrm{d}H} \leq -H_T$ for a down (↓) gaze, accordingly $1 \to S_V$ or $-1 \to S_V$ decision is undertaken, along with the above if $\overrightarrow{\mathrm{dV}} \geq \mathrm{V}_B$, where V_B stands for threshold of a blink state changes to 2.

Cases 1, 10, -1, -10 have same state transitions as in case of S_H .

Case 2: If a moderate negative change occurs state changes to -2.

Case -2: S_V changes to 0 if $\overrightarrow{\mathrm{dV}} \geq 0$

Each sampling interval the above routine class is run so that the whole process becomes dynamic.

4.3.1.2 Wireless Transmission of Classified Signals

The information of the classified directional eye movements is transferred wirelessly to the controller part of the wheelchair using ATMEL RF (radio frequency) module [39-40]. Two units are there. One is Transmitter and another is Receiver. Both units are based around ATmega16 MCU(microcontroller unit) on external 16MHz crystal. On the Transmitter unit one port will act as input. While in Receiver unit the same port will act as output. The value at that of Transmitter unit is constantly sent over the air to the Receiver unit where it is latched on its aforementioned port. That means whatever value you put in the port of Transmitter station is available on the exact port of Receiver station (8bits or 1 byte).

4.3.1.3 Generation of Control Signals

The classified eye movements from EOG data are required to be conveyed to the conveyed to the control unit part. Control signals are generated with microcontroller programming. The control commands are preset and the motor driving unit moves the motors accordingly.

In the microcontroller unit that uses ATMEGA the control logic for the movement of the wheelchair is set. As per the control logic looking straight refers to no movement of the wheelchair unit. All the control logics are listed in table 4.6.

The wheelchair unit uses four induction type motors for the movement of the two wheels. According to the set control commands when eye movement is classified as right then the right wheel is fixed, only the left wheel moves and the wheelchair thus moves towards right. Similarly to move the wheelchair forward the user need to look upwards. Whenever any eye movement is detected the corresponding movement of the wheelchair is executed for 5 seconds, during this time span no other eye movement is taken as command and for further movement of the wheelchair user has to make eye movements after this time.

The output of the system is PWM signals with duty varying according to the classifier output UP or DOWN. LEFT or RIGHT provokes a constant duty PWM to a single motor to rotate the bot accordingly. the PWM signals are fed to the inbuilt motor driver circuit of the wheelchair.

Table 4.6 Preset Eye Movement commands and corresponding Control Logic

Eye Movement	Motor Movement
Looking Straight	No Movement
Once left, then straight	Left turn
Once right, then straight	Right turn
Once up, then straight	Forward
Once down, then straight	Stop

4.4 Summary

This chapter deals with the control application of EOG signal. Utilization of EOG signal in three different control systems is done. A multitasking user interface has been designed and controlled by eye movements by correlating eye ball movement with mouse cursor. A system is developed to detect and recognize various digits, letters and shapes by analyzing eye ball movement patterns. This system can be helpful for eye writing purpose. Movement of a wheelchair is linked with directional eye movements, based on EOG. All the three applications can be useful for paralyzed persons.

References

[1] Daly, J. J., & Wolpaw, J. R. (2008). Brain–computer interfaces in neurological rehabilitation. The Lancet Neurology, 7(11), 1032-1043.

[2] Jovanov, E., Milenkovic, A., Otto, C., & De Groen, P. C. (2005). A wireless body area network of intelligent motion sensors for computer assisted physical rehabilitation. *Journal of NeuroEngineering and rehabilitation*, *2*(1), 6.

[3] Neuman, M. R. (1998). Biopotential amplifiers. *Medical instrumentation: application and design*, 292-296.

[4] Gao, X., Xu, D., Cheng, M., & Gao, S. (2003). A BCI-based environmental controller for the motion-disabled. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *11*(2), 137-140.

[5] Moon, I., Lee, M., Chu, J., & Mun, M. (2005, April). Wearable EMG-based HCI for electric-powered wheelchair users with motor disabilities. In *Robotics and Automation, 2005. ICRA 2005. Proceedings of the 2005 IEEE International Conference on* (pp. 2649-2654). IEEE.

[6] Karthikeyan, P., Murugappan, M., & Yaacob, S. (2012). ECG signal denoising using wavelet thresholding techniques in human stress assessment. *International Journal on Electrical Engineering and Informatics*, *4*(2), 306.

[7] Deng, L. Y., Hsu, C. L., Lin, T. C., Tuan, J. S., & Chang, S. M. (2010). EOG-based Human–Computer Interface system development. *Expert Systems with Applications*, *37*(4), 3337-3343.

[8] Carroll, J. M. (Ed.). (2003). *HCI models, theories, and frameworks: Toward a multidisciplinary science*. Morgan Kaufmann.

[9] Barea, R., Boquete, L., Mazo, M., & López, E. (2002). System for assisted mobility using eye movements based on electrooculography. *IEEE transactions on neural systems and rehabilitation engineering*, *10*(4), 209-218.

[10] Lv, Z., Wu, X. P., Li, M., & Zhang, D. (2010). A novel eye movement detection algorithm for EOG driven human computer interface. *Pattern Recognition Letters*, *31*(9), 1041-1047.

[11] World Medical Association. (2001). World Medical Association Declaration of Helsinki. Ethical principles for medical research involving human subjects. *Bulletin of the World Health Organization*, *79*(4), 373.

[12] Wijesoma, W. S., Wee, K. S., Wee, O. C., Balasuriya, A. P., San, K. T., & Soon, K. K. (2005). EOG based control of mobile assistive platforms for the severely disabled. In *Robotics and Biomimetics (ROBIO). 2005 IEEE International Conference on* (pp. 490-494). IEEE.

[13] Johnson, D. E., Johnson, J. R., & Moore, H. P. (1980). *A handbook of active filters*. Prentice Hall.

[14] Stoica, P., & Moses, R. L. (1997). *Introduction to spectral analysis* (Vol. 1, pp. 3-4). Upper Saddle River: Prentice hall.

[15] Hjorth, B. (1970). EEG analysis based on time domain properties. *Electroencephalography and clinical neurophysiology*, *29*(3), 306-310.

[16] Pfurtscheller, G., Neuper, C., Schlogl, A., & Lugger, K. (1998). Separability of EEG signals recorded during right and left motor imagery using adaptive autoregressive parameters. *IEEE transactions on Rehabilitation Engineering*, *6*(3), 316-325.

[17] Pincus, S. M. (1991). Approximate entropy as a measure of system complexity. *Proceedings of the National Academy of Sciences*, *88*(6), 2297-2301.

[18] Do, M. N., & Vetterli, M. (2002). Wavelet-based texture retrieval using generalized Gaussian density and Kullback-Leibler distance. *IEEE transactions on image processing*, *11*(2), 146-158.

[19] Schuldt, C., Laptev, I., & Caputo, B. (2004). Recognizing human actions: A local SVM approach. In *Pattern Recognition, 2004. ICPR 2004. Proceedings of the 17th International Conference on* (Vol. 3, pp. 32-36). IEEE.

[20] Freund, Y., & Schapire, R. E. (1999). Large margin classification using the perceptron algorithm. *Machine learning*, *37*(3), 277-296.

[21] Zhang, M. L., & Zhou, Z. H. (2007). ML-KNN: A lazy learning approach to multi-label learning. *Pattern recognition*, *40*(7), 2038-2048.

[22] Shen, H. B., & Chou, K. C. (2006). Ensemble classifier for protein fold pattern recognition. *Bioinformatics*, *22*(14), 1717-1722.

[23] Fattouh, A., Sahnoun, M., & Bourhis, G. (2004, October). Force feedback joystick control of a powered wheelchair: Preliminary study. In *Systems, Man and Cybernetics, 2004 IEEE International Conference on* (Vol. 3, pp. 2640-2645). IEEE.

[24] Kuno, Y., Shimada, N., & Shirai, Y. (2003). Look where you're going [robotic wheelchair]. *IEEE Robotics & Automation Magazine*, *10*(1), 26-34.

[25] Seki, H., Ishihara, K., & Tadakuma, S. (2009). Novel regenerative braking control of electric power-assisted wheelchair for safety downhill road driving. *IEEE Transactions on Industrial Electronics*, *56*(5), 1393-1400.

[26] Fisk, A. D., Rogers, W. A., Charness, N., Czaja, S. J., & Sharit, J. (2009). *Designing for older adults: Principles and creative human factors approaches*. CRC press.

[27] Eby, D. W., Trombley, D. A., Molnar, L. J., & Shope, J. T. (1998). The Assessment of Older Driver's Capabilities: A Review of the Literature. *Ann Arbor*, *1001*, 48109.

[28] Barea, R., Boquete, L., Mazo, M., & López, E. (2002). Wheelchair guidance strategies using EOG. *Journal of Intelligent & Robotic Systems*, *34*(3), 279-299.

[29] Purwanto, D., Mardiyanto, R., & Arai, K. (2009). Electric wheelchair control with gaze direction and eye blinking. *Artificial Life and Robotics*, *14*(3), 397.

[30] Yathunanthan, S., Chandrasena, L. U. R., Umakanthan, A., Vasuki, V., & Munasinghe, S. R. (2008, December). Controlling a wheelchair by use of EOG signal. In *Information and Automation for Sustainability, 2008. ICIAFS 2008. 4th International Conference on* (pp. 283-288). IEEE.

[31] Wei, L., Hu, H., & Yuan, K. (2009, February). Use of forehead bio-signals for controlling an intelligent wheelchair. In *Robotics and Biomimetics, 2008. ROBIO 2008. IEEE International Conference on* (pp. 108-113). IEEE.

[32] Simpson, R. C. (2005). Smart wheelchairs: A literature review. *Journal of rehabilitation research and development*, *42*(4), 423.

[33] Yamagishi, K., Hori, J., & Miyakawa, M. (2006, August). Development of EOG-based communication system controlled by eight-directional eye movements. In *Engineering in Medicine and Biology Society, 2006. EMBS'06. 28th Annual International Conference of the IEEE* (pp. 2574-2577). IEEE.

[34] Wijesoma, W. S., Wee, K. S., Wee, O. C., Balasuriya, A. P., San, K. T., & Soon, K. K. (2005, July). EOG based control of mobile assistive platforms for the severely disabled. In *Robotics and Biomimetics (ROBIO). 2005 IEEE International Conference on* (pp. 490-494). IEEE.

[35] Al-Haddad, A. A., Sudirman, R., & Omar, C. (2011, September). Guiding wheelchair motion based on eog signals using tangent bug algorithm. In *Computational Intelligence, Modelling and Simulation (CIMSiM), 2011 Third International Conference on* (pp. 40-45). IEEE.

[36] Kuo, C. H., Chan, Y. C., Chou, H. C., & Siao, J. W. (2009, October). Eyeglasses based electrooculography human-wheelchair interface. In *Systems, Man and Cybernetics, 2009. SMC 2009. IEEE International Conference on* (pp. 4746-4751). IEEE.

[37] Arai, K., & Mardiyanto, R. (2011). A prototype of electric wheelchair controlled by eye-only for paralyzed user. *Journal of robotics and mechatronics*, *23*(1), 66.

[38] Cinar, E., & Sahin, F. (2009, September). EOG controlled mobile robot using Radial Basis Function Networks. In *Soft Computing, Computing with Words and Perceptions in System Analysis, Decision and Control, 2009. ICSCCW 2009. Fifth International Conference on* (pp. 1-4). IEEE.

[39] Ganesan, P., Venugopalan, R., Peddabachagari, P., Dean, A., Mueller, F., & Sichitiu, M. (2003, September). Analyzing and modeling encryption overhead for sensor network nodes. In *Proceedings of the 2nd ACM international conference on Wireless sensor networks and applications* (pp. 151-159). ACM.

[40] Maletsky, K. D. (1999). *U.S. Patent No. 5,945,920*. Washington, DC: U.S. Patent and Trademark Office.

5

Cognitive Context Recognition

This chapter accounts for the combination of information from brain signals using EEG and eye movements using EOG for cognitive context recognition. It introduces multimodal data analysis using EEG and EOG signals as sources of cognitive context recognition information. It illustrates the architectures of feature and decision level fusion for constructing a bimodal cognitive context recognition platform.

5.1. Introduction to Cognitive Context

Cognition is the method of information processing that involves attention, working memory, sensory stimulation, decision making and problem solving [1]. Whether it is the processing of words or numbers, sensory-motor actions, logical reasoning, pattern recognition or memory testing; all involve cognitive activities [2-3]. It is very obvious that the brain signals convey a large amount of information regarding a person‘s mental state and cognition [4]. It has been found that eye movements also are a rich source of information about a person‘s cognitive activities [5]. Hence analysis of brain signals and eye movements for various dimensions of perception of stimuli form the basis of this work.

Recognition of the users’ context has potential applications in the development of context aware human computer interaction (HCI) based computing systems. Context awareness can be implemented in two ways, either by mounting sensors on the user that will detect the user’s context or by developing a pervasive computing environment with computers embedded in the surrounding everyday objects that will adapt to the user’s need [3]. In both the cases, interpretation of the user’s context is important. These systems can be used for assisted living for normal individuals as well as those in need of rehabilitation; say by assessing a paralyzed user’s intended direction, a wheelchair can be turned. Such systems also are germane in capturing information in a particular setting and transferring it to a remote location like in providing security.

Cognitive context recognition finds applications in pervasive or ubiquitous computing [1]. A wide variety of sensors can help to detect physical activities of human beings. Human activities can directly convey information about their location and cognitive state. The sensors for detecting cognitive context may be based on different types of bio-signals.

The present work is related to the process of cognitive information processing. The objective of this work is to provide a preliminary insight towards the development of a system capable of understanding a user’s context by analyzing his/her bodily responses while performing different activities. Various sources of information can directly relate to human activities, like heart rate, body temperature, emotional state, cognitive load in the brain, as well as eye movements. The present work deals with only cognitive activities and as brain responses can directly convey the mental load related to different states of cognition the analysis of brain signals is an obvious choice [2, 5]. Literature reveals that eye movements also convey a lot of information regarding a person’s cognitive state and hence also accounts for consideration in the present work [4-5]. Three types of eye movements, namely, saccades, fixations and blinks can convey information regarding a person’s ongoing activity [4-5]. The human eyes move constantly in saccades to build a ‘mental map’ of the visuals that is seen. Fixations are the eyes’ focus on a particular location in between saccades. Blinks are short duration pulses of relatively higher magnitude that are heavily characterized by environmental conditions and mental workload.

Different brain activity measuring techniques can estimate the neuronal activities inside the brain. These include invasive techniques like Electrocorticography (ECoG) and non-invasive techniques like functional Magnetic Resonance Imaging (fMRI), functional Near Infrared Spectroscopy (fNIRs), Magnetoencephalogram (MEG) and Electroencephalogram (EEG) [2, 6]. ECoG has advantages of high spatial resolution but requires surgical implantation of the electrodes directly on the brain surface. fMRI measures brain activity by detecting changes in blood oxygen level through the blood-oxygen-leveldependent (BOLD) contrast. fNIRs uses the NIRS (near-infrared spectroscopy) for functional neuroimaging. MEG maps brain activity by recording magnetic fields produced by the natural electrical currents in the brain through sensitive magnetometers. EEG is a measure of the electrical charges generated by firing neurons and their volume conduction. The use of Electroencephalography in BCI is popular because of the simple acquisition and processing, non-invasiveness, high temporal resolution and ease of real time implementations associated with EEG signals. Hence EEG signals are used as the bio-modality for brain activity analysis in this work. Table 5.1 lists the other well known brain signal measuring techniques along with their relative disadvantages.

Table 5.1 Relative disadvantages of brain signal measuring techniques other than EEG

Modality	Disadvantages
Magnetoencephalography (MEG)	Exposure to high-intensity (>1 Tesla) magnetic fields, bulky and immobile equipment
Functional magnetic resonance (fMRI)	Expensive, bulky and immobile equipment, can aggravate claustrophobia in subjects during measurement
Functional near-infrared spectroscopy (fNIRs)	Poor temporal resolution, less depth of penetration, small area of brain activity can be captured
Electrocorticography (ECoG)	Invasive, requires surgical implantation of electrodes on the brain surface

Techniques for eye movement measurement include Infrared Video System (IRVS), Infrared Oculography (IROG), Search Coil (SC), Optical-type Eye Tracking System (OETS), dual Purkinje-image (DPI) and Electrooculography [7-8]. Electrooculography is the simplest method among all of them. It is non-invasive and cost effective. Hence it is used as the bio-modality for the measurement of eye movements. The Electrooculogram (EOG) signal, a measure of the potential difference between the cornea and the retina of the human eyes, is simple to acquire and process in real time. Table 5.2 enlists the eye movement measuring techniques other than EOG and their relative disadvantages.

Table 5.2 Relative disadvantages of eye movement measuring techniques other than EOG

Modality	Disadvantages
Infrared Video System (IRVS)	Low tolerance to head movements, must be calibrated repeatedly for each individual
Infrared Oculography (IROG)	Harm may be caused by the infrared light to the eyes
Search Coil (SC)	Influence of magnetic field on the eyes
Optical-type Eye Tracking System (OETS)	Weight of the apparatus and the source of bright light on the eyes make user uncomfortable
Dual Purkinje-image (DPI)	Expensive

5.2. Eye movements for Cognitive Context Analysis

To recognize different human cognitive activities by analysis of eye movements is the aim of the present work. Such a work can be utilized in the development of a ubiquitous computing environment that is aware of people's cognitive context by only studying eye movements. A two-channel Electrooculogram signal acquisition system developed in the laboratory is used to record Eye movements by surface electrodes from ten subjects while they performed eight different activities. The acquired EOG signals are filtered and four features are extracted, two time domain features, Adaptive Autoregressive Parameters and Hjorth Parameters, a frequency domain feature Power Spectral Density and a time-frequency domain feature space of Wavelet Coefficients. These features are used independently as well as in combinations to classify the EOG signals using a Support Vector Machine with Radial Basis Function kernel, successfully recognizing the different cognitive activities.

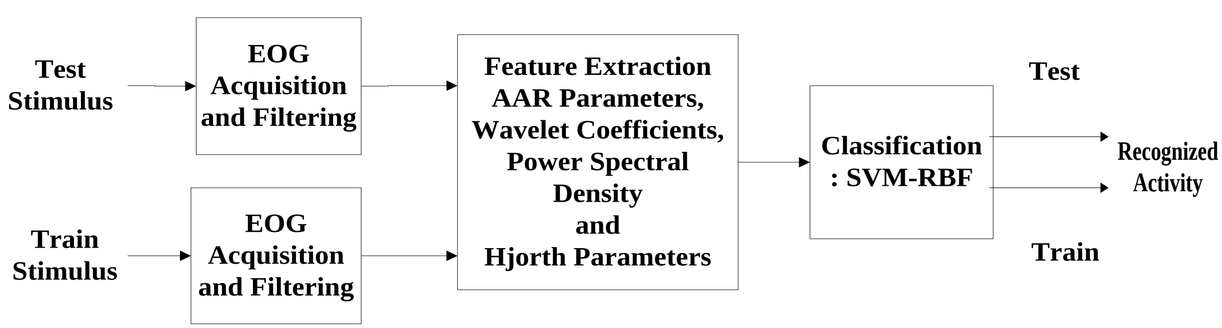


Fig. 5.1 Flowchart showing EOG Signal Processing and Classification

5.2.1 Experimental Procedure

EOG data is collected from ten healthy subjects, five male and five female in the age group of 25±5 years. Necessary audio visual stimuli/environment is provided according to eight activities, namely reading, writing, copying text, web browsing, watching video, playing game, searching for words in a word maze and relaxing, while acquiring EOG data.

5.2.2 Observations

The classifier is trained to recognize these eight activities using features from 60 seconds EOG data of each activity per subject. In the second phase the trained classifier is tested with unknown test stimuli. Classification accuracies are computed from respective confusion matrices.

The results of classification in terms of classification accuracy and computation time (including feature extraction and classification) have been tabulated in Table 5.3 and 5.4, mentioning each feature vector dimension (in parenthesis), for two channels of EOG and indicating the maximum accuracy in bold for each class.

Table 5.3
Classification results using SVM-RBF on Single Feature Spaces

Class of Activity	Average Performance over ten subjects							
	AAR (12)		Wavelet (32)		PSD (30)		Hjorth (6)	
	Accuracy (%)	Time (s)	Accuracy (%)	Time (s)	Accuracy (%)	Time (s)	Accuracy (%)	Time (s)
Reading	67.08	47.4801	87.92	0.2358	59.38	1.2815	90.02	0.7002
Writing	57.71	42.7067	87.71	0.1203	53.75	1.2574	84.58	0.6051
Copying	56.67	42.3419	88.33	0.1102	73.75	1.2538	93.33	0.6011
Web Browsing	72.92	42.3738	91.04	0.8873	72.75	1.2693	89.38	0.5978
Watching Video	69.37	43.3074	87.29	0.7786	73.75	1.2615	89.58	0.6074
Playing Game	50.83	42.5047	90.21	0.7687	52.71	1.2689	91.04	0.6384
Word Search	67.08	41.9151	78.54	0.8010	60.62	1.2404	82.08	0.6328
Relaxing	77.29	42.6593	87.71	0.7648	74.17	1.2571	90.83	0.6026

It is observed that using single feature spaces Hjorth Parameters provide highest average accuracy of 88.855% over all classes of activities. Thus other features are combined with Hjorth Parameters thereby showing a significant increase in classification accuracy as is evident from Table 5.4. The combination of all the four features produces the highest mean classification accuracy of 90.39% in 41.60 seconds on an average over all classes of activities.

The recognition of eight human cognitive activities on the basis of eye movement analysis using Electrooculogram signals is the main concern of the present work. AAR Parameters, Power spectral density, Hjorth Parameters and Wavelet Coefficients have been used as signal features and classification of the EOG signals to identify the activities is done using SVM-RBF classifier achieving a maximum average accuracy of 90.39% over eight classes of cognitive activities.

Table 5.4
Classification results using SVM-RBF on combined feature spaces

Class of Activity	Average Performance over ten subjects							
	AAR+Hjorth (18)		Wavelet+Hjorth (38)		PSD+Hjorth (36)		AAR+Wavelet+PSD + Hjorth (80)	
	Accuracy (%)	Time (s)	Accuracy (%)	Time (s)	Accuracy (%)	Time (s)	Accuracy (%)	Time (s)
Reading	88.12	53.8342	90.83	0.8146	75	1.4	90.42	41.3734
Writing	87.50	47.5630	91.46	0.8839	86.88	1.3446	90.42	41.6432
Copying	91.04	44.0070	93.33	0.8372	89.38	1.3046	92.08	41.3488
Web Browsing	90.00	45.4924	91.25	0.8706	85.62	1.3116	90.63	41.4337
Watching Video	86.46	46.7490	91.04	0.8258	58.13	1.334	90.21	41.9159
Playing Game	65.83	46.0374	92.71	0.8408	53.54	1.3404	93.13	41.544
Word Search	72.08	45.2229	92.71	0.8552	50.00	1.3446	87.08	41.728
Relaxing	84.17	46.5651	90.63	0.8407	67.50	1.33	89.17	41.8736

5.3. EEG and its relation to Cognitive Context

Brain Computer Interfacing (BCI) technology provides a communication pathway between the human brain and external devices and attempts to provide assistance to patients in need of rehabilitation from neuro-motor or sensory motor diseases. Electroencephalogram (EEG) analysis has found significant importance in BCI research [5, 6 , 9].

5.3.1 Electroencephalogram

Billions of electrically charged neurons located within the brain constantly exchange ions with the extracellular environment to maintain resting potential and to propagate action potentials. The volume conduction of these ions by means of their mutual interactions can be measured by electrodes on the brain surface. The difference in the voltages between any two electrodes can be recorded over time by a voltmeter giving the EEG signal. However the electric potential generated by an individual neuron is too small to be picked up. EEG is obtained as the linear combination of the synchronous activities of several thousands of neurons with similar spatial orientation within the brain.

The cerebral cortex covering the outer portion of the cerebrum, where most information processing occurs, is divided into lobes each of which has a specific function. It is necessary to understand the functions of various regions of the cerebral cortex in order to acquire EEG signals from the correct regions upon particular activations [10].

- Frontal lobe: conscious though, attention, working memory, emotion. The pre-frontal region is responsible for behavior, planning and short term memory.
- Parietal lobe: integration of various sensory information and manipulation of objects, decision making, visuospatial processing
- Somatosensory Cortex: Perception of somatosensations
- Motor Cortex: movement co-ordination
- Occipital lobe: sense of sight or vision
- Temporal lobe: senses of smell and sound and processing of complex stimuli like faces and scenes.

The main characteristics of the EEG signals are listed below [10-12]:

- Because of the asynchronous firing of the neurons over time EEG signals are non-stationary in nature.
- EEG signals are non-periodic and non-gaussian.
- Instantaneous EEG magnitudes range between (-10μV,10μV)
- The bandwidth of normal EEG signals is 0.5-70 Hz, comprising of distinct bands, namely, delta (0.5-4Hz), theta (4-8Hz), alpha (8-13Hz), beta (13-30Hz) and gamma (above 30 Hz) band [10]. Table 5.5 enlists these bands and the implication of the corresponding EEG signals.

Table 5.5
EEG Frequency Bands

Band Frequency (Hz)	Implication
Delta up to 4	Sleep, continuous-attention tasks, low arousal levels, no movements
Theta 4 – 8	Drowsiness, recall, imagery, creative mental states
Alpha 8 – 13	relaxation, meditation, tranquil conditions, associated with inhibition control
Beta 13 – 30	Alert, active, busy, or anxious thinking, active concentration, movement, sensorimotor rhythms
Gamma above 30	cross-modal sensory processing, short-term memory matching of recognized objects

A number of EEG signal modalities are used in BCI studies, depending upon the nature of stimulus presented and the observed EEG waveforms. The most commonly used modalities include P300, slow cortical potential (SCP), steady state visually evoked potential (SSVEP), event related desynchronization/synchronization (ERD/S), etc [10].

- The P300 is an event related potential that is associated with a person‘s reaction/decision making related to a stimulus. It is measured as a positive deflection in voltage with the delay between stimulus presentation and the response being around 250 to 500ms. These are observed in the somatosensory cortex/parietal region.
- Slow Cortical Potential (SCP) are regular changes in the membrane potentials of the cortical dendrites that last from 300 ms to several seconds from the stimulus presentation. These are commonly observed in the motor cortex.
- Steady State Visually Evoked Potentials (SSVEPs) are natural responses to visual stimuli at specific frequencies. SSVEPs provide a means to characterize preferred frequencies of neocortical dynamic processes. These are generally observed in the occipital cortex upon visual stimuli presentation.
- ERD/S refers to the relative decrease/increase in the EEG signal power in a certain frequency range during dynamic cognitive processes upon excitation with stimuli. For example Alpha-band

ERD/S is commonly observed in the somatosensory cortex in responses to tactile stimulations. Motor imagery tasks produce ERD/S in the motor cortex.

5.4. Cognitive Context Combining EEG & EOG:

In the first stage of experiments, EEG and EOG signals are separately subjected to signal processing algorithms to extract discriminating features between the signals for four different cognitive activities, namely, reading, solving a word puzzle, web browsing and relaxing. Support Vector Machine (SVM) [13], is implemented to classify the feature spaces.

In the second phase, feature level fusion of the features from EEG signals and those from EOG signals is done that produces overall higher recognition accuracy. Decision level fusion is implemented on the classification outputs of several separately implemented classifiers to provide a joint decision that also tend to provide better recognition accuracy than the two bio-modalities separately. The main contributions of the work amount to the study of individual performances of EEG and EOG in cognitive activity recognition, evaluating the best signal features common to both modalities for discriminating between cognitive activities, development of a hierarchical coupled one-vs.-all (OVA) and one-vs.-one (OVO) classification scheme to tackle multiclass problem with SVM and implementing feature and decision level fusion on EEG and EOG data to produce a bimodal cognitive activity recognition system.

5.4.1 Experimental Design and Data Analysis

The materials for EEG and EOG acquisition, experimental paradigm and the methods for signal processing and classification follow in this section.

5.4.1.1 EEG Acquisition and Pre-processing

For EEG acquisition selection of the electrode positions and the frequency band are important considerations. EEG is acquired using a 14-channel Emotiv Headset [14] at a sampling rate of 128Hz with the electrodes placed according to the 10/20 international system [15] of electrode placement as shown in Figure 5.2. The experiments concern detection of brain responses to cognitive activities in the presence of visual stimulus such as reading a piece of text or solving a word search puzzle. Such stimuli are supposed to activate the prefrontal, frontal, parietal and occipital regions to a greater extent [15-18] and hence signals from these regions are acquired through electrodes AF3, AF4, F3, F4, F7, F8, P7, P8, O1 and O2.

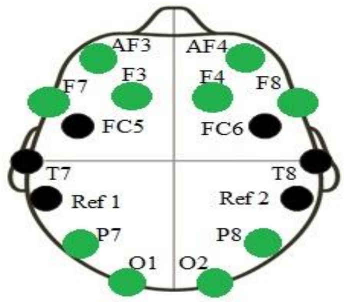


Fig 5.2. Electrode Placement for EEG Acquisition showing the selected electrodes in green, Ref1 and Ref2 are used as reference electrodes

Pre-processing of EEG signals involve frequency domain filtering and spatial filtering. The normal EEG bandwidth ranges between 0.5-70 Hz and is made up of the delta (0.5-4Hz), theta (4-8Hz), alpha (8-13Hz), beta (13-30Hz) and gamma (above 30 Hz) bands [15, 18]. It is experimentally found that the significant changes in the EEG spectrum for decoding the four activities never surpass to 1-30 Hz, hence we have considered EEG signals in the delta, theta, alpha and beta bands mainly for our work. To extract the EEG signals in the desired frequency range, the acquired EEG is filtered using an Elliptical Band pass filter of order 6 with 1dB passband ripple and 50 dB stopband ripple and bandwidth 1-30Hz. An elliptical filter is used because of its steeper roll-off characteristics and equiripple behavior in the passband and the stopband as compared to the other standard filters of the same order.

Common average referencing has been performed on the acquired EEG signals for spatial filtering to remove the effect of interference between the signals of adjacent channels [16]. In this technique, for each EEG channel, all the channels equally weighted are subtracted to eliminate the commonality of that channel with the rest and preserve its specific temporal features.

5.4.1.2 Experimental Paradigm

Experiments are conducted on 6 healthy subjects, 3 male and 3 female, in the age group 25±5 years with their consent. The subjects are instructed to comfortably sit on a chair while the stimulus is presented on a screen using a projector. Four cognitive activities are considered in this work, that include reading a piece of English text, playing a word-search game that consists of searching for English words from a word maze, browsing the internet and relaxing with closed eyes. In the first three cases the necessary stimulus is presented while in the last case the subject is instructed to sit and relax with closed eyes. The time frame for the presentation of the stimulus follows the pattern shown in Figure 5.3.

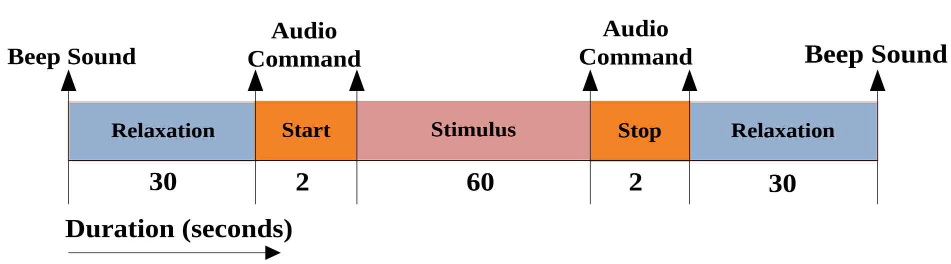


Fig 5.3. Time frame of stimulus presentation for data acquisition

For each subject and each day of experiment, initially 30s of relaxation is used to bring the EEG and EOG to the baseline conditions. This is followed by the presentation of the stimulus for 60s during which EEG and EOG are simultaneously acquired using the acquisition techniques mentioned before. Each stimulus is followed by a 30s relaxation period preceding the next stimulus.

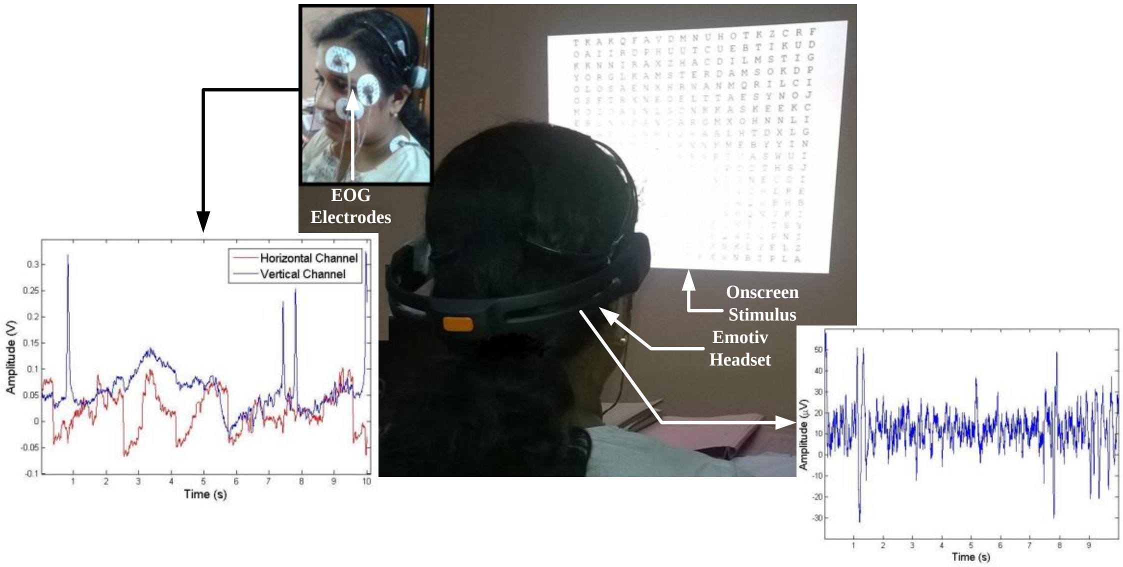


Fig 5.4. Experimental Setup showing a subject with Emotiv headset [14] and EOG electrodes (clearly in the inset) while she concentrates on the word search game and samples of acquired EEG signals (right) and EOG signals (left)

This procedure is carried out for 5 days of experimentation on each subject, to include the possible variations in the bio-modalities over different days. The set up of experimentation is shown in Figure 5.4 along with instances of acquired EEG and EOG signals.

5.4.1.3 Feature Extraction

A number of well known standard bio-signal based features exist in literature, like Autoregressive and Adaptive Autoregressive Parameters [16, 19], Power Spectral Density or Band power estimates [17], Hjorth Parameters [20], Hurst Exponents [20], Wavelet features [21-22] to mention a few. In the present work, experiments conducted with several such features on both pre-processed EEG and EOG signals show that maximum discrimination between the classes of cognitive activities from each of the bio-modalities is obtained either using Band Power Estimate or Wavelet decomposition based features.

5.4.1.3.1 Band Power Estimate

It is experimentally found that both EEG and EOG signals in response to different cognitive activities correspond to different amounts of signal power at different frequencies. Power Spectral Density (PSD) [23] of a wide sense stationary signal is the Fourier transform of its autocorrelation function, given by $R(l)$ for a discrete time signal $x(n)$ according to (5.1). The Discrete Fourier Transform of $R(l)$ of length L that gives the PSD estimate is given by (5.2).

$$R(l) = \sum_{n=-\infty}^{\infty} x(n)x(n-l) \tag{5.1}$$

$$S(k) = \sum_{l=0}^{L-1} R(l)e^{-j2\pi kl/L} \tag{5.2}$$

Both EEG as well as EOG signals are non-stationary in nature, thus for such time varying signals, the complete time series should be divided into segments to determine its PSD. In the present work PSD has been evaluated using Welch Method [23-24] that splits the input signal into overlapping segments, computes the periodograms of the overlapping segments from their Fourier Transforms, and averages the resulting periodograms to produce the power spectral density estimate.

Band Power Estimate (BPE) is an evaluation of the power content computed from PSD at different frequency bands. In the present work, PSD is computed using Welch Method with a Hamming window and with 50% overlap between the signal segments. After noting the most significant frequencies of activation, both EEG and EOG signals are found to be actively differentiable between different cognitive tasks in the range below 15Hz. Hence for both the signals BPE is evaluated using the signal power content at the 15 integer frequency points between 1-15 Hz.

5.4.1.3.2 Wavelet Decomposition

Though Fourier transform can efficiently represent a signal in the frequency domain, it fails to provide the variation in the frequency content of the signal with time. The loss of temporal frequency related information in not acceptable, especially in case of non-stationary signals such as EEG and EOG. In such signals, the variation in the frequency content with time is one of the most important information to be captured. Wavelet transform provides both frequency and time-domain information at multiple resolutions [21, 25] and is hence a suitable technique to represent the non-stationary signals. It evaluates the transient behaviour of a signal by convoluting it with a localized wave called wavelet. In Discrete Wavelet Transform (DWT) the signals are passed through high and low pass filters in several stages. In every stage the signal is passed through a high pass filter *h [.]* and a low pass filter *g [.]* which are related to each other and are known as the quadrature mirror filters. At the i^{th} stage, each filter output is down sampled by two to produce the approximate (*Ai*) coefficient (from the low pass filter) and the detail coefficient (*Di*) (from the high pass filter). Accordingly for an input signal *x[n]*, the downsampled outputs from the low pass and high pass filters will be given by (5.3) and (5.4) respectively yielding the Approximation and Detail Coefficients.

$$y_{low}[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n-k] \tag{5.3}$$

$$y_{high}[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n-k] \tag{5.4}$$

The approximation coefficient is then decomposed again, the process is repeated to get the approximate and detail coefficients of the subsequent stages. After trials with different mother wavelets, in the present work, Daubechies order 4 mother wavelet (for EEG)/Haar mother wavelet (for EOG) and the third (for EEG as well as EOG) level approximate coefficients of discrete wavelet transform have been used as features. The choice of the mother wavelets has been done on the basis of literature [21] guided experimental trials. The choice of the level of decomposition is guided by the availability of the maximum of the desired frequency range as shown in Figure 5.5, where *Ai* and *Di* denote the approximation and detail coefficients at the i^{th} level.

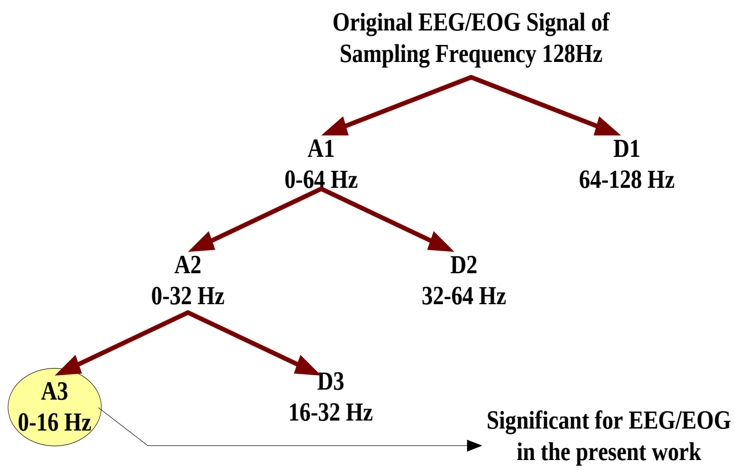


Fig 5.5. Signal Decomposition showing the significant levels for EEG/EOG to match the desired frequency range

5.4.1.4 Classification

Classification is carried out using Support Vector Machine (SVM) classifier [13]. SVM is inherently capable of binary classification only. In this work four classes of activities can be recognized by performing the one-vs.-all classification (OVA) as well as one-vs.-all (OVO) classifications using SVM among each of the four different classes. However, in a practical scenario, such mechanisms of classification is not justifiable, therefore we develop a hierarchical coupled OVA-OVO scheme of multiclass classification with SVM (HCM-SVM). In the training phase, four SVM classifiers are trained to recognize the respective OVA classifications with one class as the positive class and all others forming the negative class. Another ${}^4C_2$=6 OVO classifiers are trained to discriminate between each pair of activity. In the testing phase, the scheme illustrated in Figure 5 is followed where for the i^{th} class *i* denotes classification in that class and $\bar{i}$ denotes the classification into the other class than *i*. The test feature vector is first classified by each of the four OVA classifiers.

In the all correct case it will be classified to belong to one of the classes by a particular OVA classifier and for the rest of the OVA classifiers it will be classified to their respective negative classes. In case it is classified to belong to a positive class by more than one OVA classifier, it is sent over to the next stage consisting of OVO classifiers, where it is classified by those OVO classifiers which correspond to all the classes that the feature vector is classified to belong in the first stage. The outcome of the second stage is decided by majority voting on the OVO classifier outputs and ties are broken randomly. In case when the feature vector is classified into all negative classes in the first stage then the classification outcome is decided solely by the OVO classifiers in the second stage. This scheme helps to overcome the binary limitation while requiring the optimum time for classification and proceeds to subsequent levels only in case of conflicts in decision. Classification is performed by Linear as well as Radial Basis

Function Kernel SVM (RBF-SVM) and the latter shows overall better results, mainly because of the non-linearly separable nature of the signal features.

5.4.2 Information Fusion

For enhanced recognition performance, bimodal cognitive activity recognition is investigated with feature level and decision level fusion [26-27] in classification of EEG and EOG signals. The architectures for such information fusion are illustrated in Figure 5.6. In feature level fusion the filtered EEG and EOG for each class of activity are subjected to feature extraction separately and the features in feature space are normalized following a predetermined rule and concatenated. Classification is carried out on this combined feature space to produce the joint decision. In decision level fusion the decisions of the classification of the EEG and EOG feature spaces for different sets of features are combined to produce a joint decision.

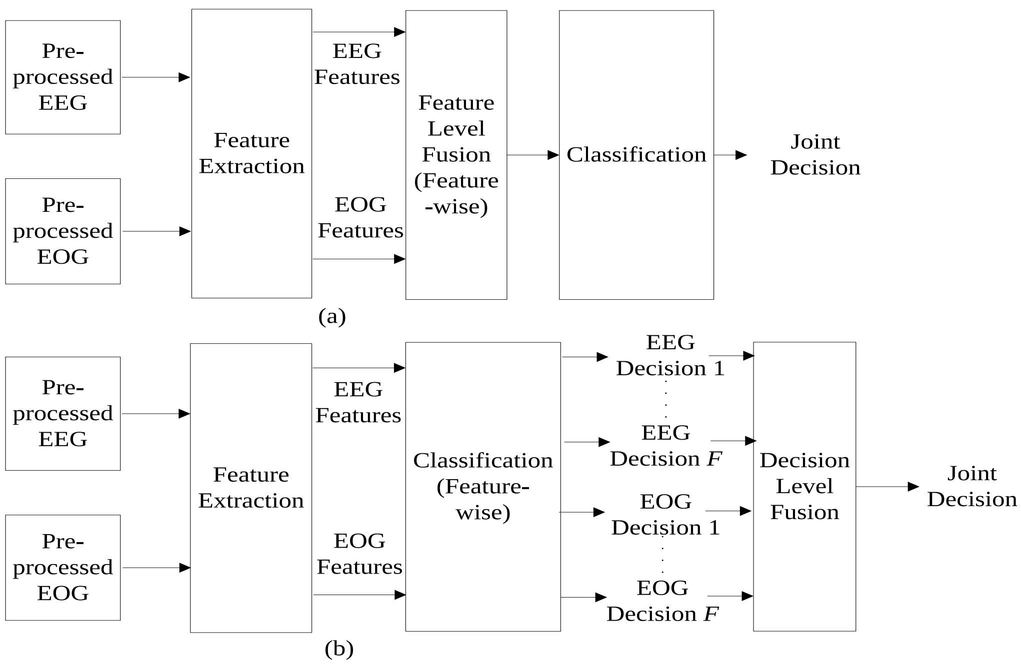


Fig 5.6. Schemes of information fusion for Bimodal Activity Recognition (a) Feature Level Fusion and (b) Decision Level Fusion, where F denotes the total number of feature sets considered

The combination of decision is based on majority voting. However in case of a conflict, the decision is based on a weighted voting scheme. The weight is decided by the individual classification accuracy of the modality-feature set pair in conflict i.e. suppose that EEG-BPE and EOG-BPE produce classification output as activity 1 while EEG-Wavelet and EOG-Wavelet produce classification output as activity 2 then decision is given in favour of activity 1 if the average individual classification performances of EEG-BPE and EOG-BPE surpass that of EEG-Wavelet and EOG-Wavelet and vice versa.

$$f_{i,j} \leftarrow \frac{f_{i,j} - f_{i,\min}}{f_{i,\max} - f_{i,\min}} \tag{5.5}$$

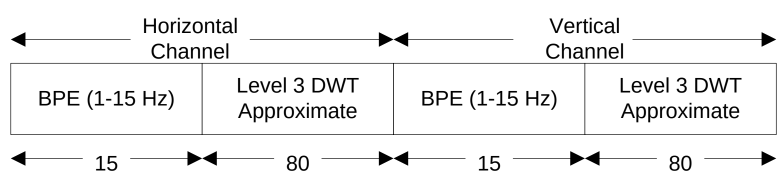
Information fusion is presented as a study to investigate how well the joint effects of multiple sources of information contribute to the recognition performance. This study can facilitate further analysis on multi-sensor wearable device based applications for cognitive context recognition from bio-modalities for enhanced recognition performance.

5.4.3 Performance Analysis

5.4.3.1 Data Processing

For each class of activity for both EEG and EOG from the 5 days of experimentations are used for creating the feature spaces. For either type of the bio-signals, 5s of data correspond to a single instance for data analysis. Therefore for a single day 12 such instances are available and over 5 days 60 instances are available from each subject. Feature extraction is done over these 60 instances of each class of data for either bio-signal. For creating either of the feature sets from EEG/EOG data, for each of the acquired channel (from the 10 channels for EEG and 2 channels for EOG) of data, the feature space is created. Then the features of all the channels are concatenated together. The available feature space is cross validated prior to each classification by 5-fold cross validation to determine the training and testing instances.

(a)



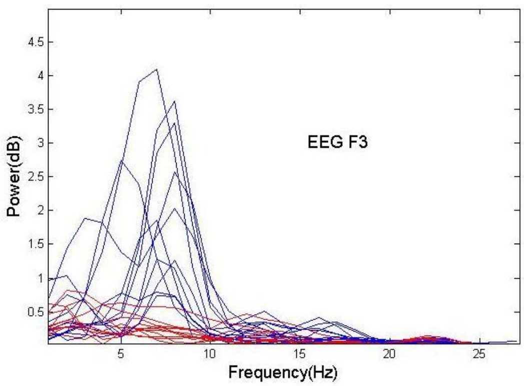
(b)

Fig 5.7. Feature vector showing dimension of each feature (a) for EEG Signals and (b) for EOG Signals

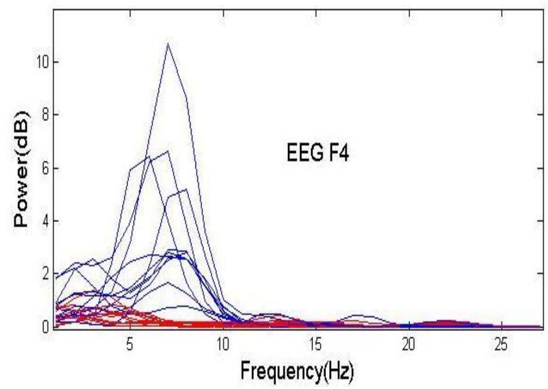
Signal powers at the integer frequencies from 1 to 15Hz were used as features for each type of signal. Therefore the feature size is 15×10=150 for EEG (EEG: 10 channels) and 15×2=30 for EOG (EOG: 2 channels). For both the signals a 5 second window comprises 128 (sampling frequency) × 5 (seconds) =640 data points. The wavelet transform on each instance is computed upon these 640 data points. For EOG, level 3 Haar based transform results in 80 approximate coefficients for each channel hence the feature vector is 80×2=160. For EEG, level 3 Daubechies order 4 wavelet based transform results in 86 approximate coefficients for each channel hence the feature vector is 86×10=860. Hence for EOG the total feature vector is of dimensions (30+160) =190 and that for EEG is (150+860)=1010. The feature vector is illustrated in Figure 5.7.

All analysis has been carried out in a MATLAB R2012b environment running on an Intel core i3 processor with Windows 7 64 bit operating system.

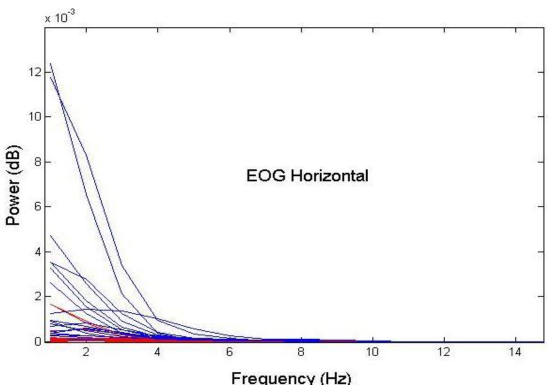
Figure 5.8 (a) and (b) illustrate the changes in the EEG power spectrum of F3 and F4 electrodes with different cognitive tasks for some instances of a particular subject's data. A pair of tasks is shown together instead of all to maintain clarity in the plots. Similarly, Figure 5.8 (c) and (d) illustrate the changes in the EOG power spectrum for the horizontal and the vertical channels with different two different cognitive tasks. It is observed that in each case the major variations in power content between the two classes of activities do not exceed 15 Hz. Also the variations in power content of the signals for two different classes of activities are quite distinctly different, thereby making this a suitable feature to be used.



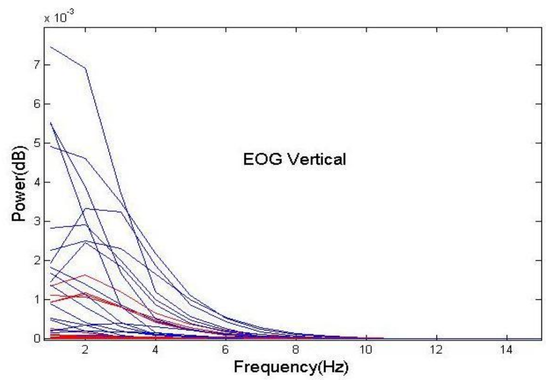
(a)



(b)



(c)



(d)

Fig 5.8. Variation in EEG power spectrum for EEG data from two electrodes (a) F3 and (b) F4 for a particular subject showing two tasks Reading (blue) and Relaxing (Red) in each graph and Variation in EOG power spectrum for data from two channels (c) horizontal and (d) vertical for a particular subject showing two tasks Reading (blue) and Relaxing (Red) in each graph

5.4.3.2 Performance Metrics

The classification results are tabulated in the form of a $N\times N$ confusion matrix [16] *CM* for an *N* class (in our case N=4) problem. The classification accuracy (CA) of each class C_i is computed from (5.6), $CM(i,j)$ denotes the number of samples of class C_i that are classified as class Cj.

$$CA(C_i) = \frac{CM(i,i)}{\sum_j CM(i,j)} \tag{5.6}$$

Two other commonly used metrics that can be easily derived from the confusion matrix are precision and recall [9]. These are usually applicable in a two-class problem. In the present context, an $N \times N$ confusion matrix is available from which for each class a binary confusion matrix is created as shown in Figure 5.9. Then precision and recall for each class is computed and the average precision (AP) and recall (AR) is computed for all classes. The F1 score of classification is then computed using (5.7).

$$F1 = 2\frac{AR * AP}{AR + AP} \tag{5.7}$$

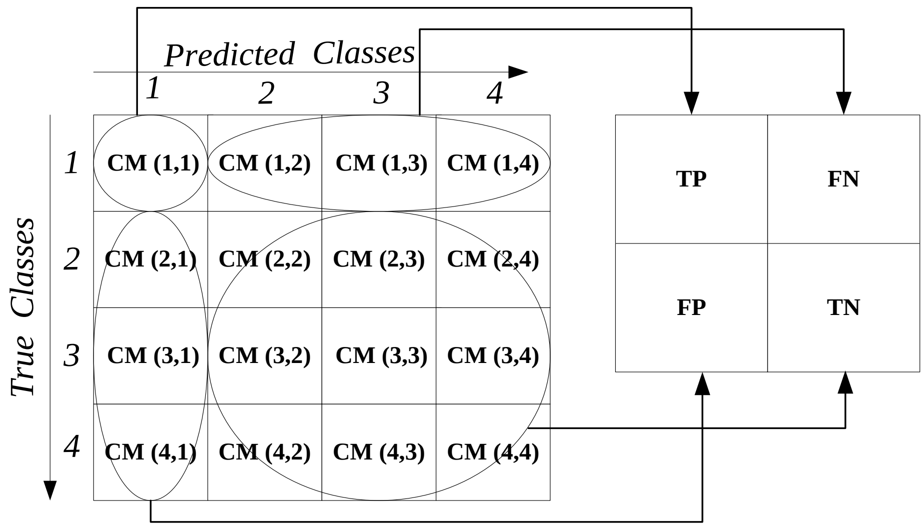


Fig 5.9. Estimating a binary confusion matrix for class 1 from the multiclass confusion matrix for evaluating precision and recall, TP, FN, FP and TN denote the true positive, false negative, false positive and true negative samples

5.4.4 Results

The results of classification are tabulated in Table 5.6 separately for EEG and EOG. These results are shown for an average performance with each of the feature spaces (BPE and Wavelet Coefficients) separately for each subject. CA denotes the average classification accuracy over all the four classes while F1 denotes the F1 score calculated from the average precision and recall over all classes. The table provides the values of the performance metrics over each subject along with the mean and the standard deviations over all the subjects.

Table 5.6
Individual Performances of EEG and EOG classifications

Subject ID	EEG Results		EOG Results	
	CA	**F1**	**CA**	**F1**
S1	0.8250	0.8372	0.6250	0.5714
S2	0.7750	0.7568	0.7500	0.7368
S3	0.8000	0.8095	0.7250	0.7442
S4	0.7750	0.7805	0.6750	0.6486
S5	0.8250	0.8205	0.6500	0.6500
S6	0.7500	0.7500	0.7750	0.7805
Mean	0.7917	0.7924	0.7000	0.6886
SD*	0.0303	0.0355	0.0529	0.0783

.[*Standard Deviation]

The results of classification after information fusion are illustrated in Table 5.7. For feature level fusion results are shown for an average performance with each of the feature spaces (BPE and Wavelet Coefficients) separately for each subject. Decision level fusion reports the results with majority voting over classifications with the four feature sets: EEG-BPE, EEG-Wavelet, EOG-BPE and EOG-Wavelet. In a 4-0 or 3-1 voting, the scheme has no conflicts; however majority voting fails when a 2-2 vote occurs. In that case the result of that feature set is given predominance which individually gives the better results, as mentioned previously.

Table 5.7
Performances of Information fusion from EEG and EOG

Subject ID	Feature Level		Decision Level	
	CA	**F1**	**CA**	**F1**
S1	0.8750	0.8718	0.8650	0.8250
S2	0.7500	0.7826	0.8440	0.8350
S3	0.8000	0.8000	0.7850	0.8150
S4	0.8250	0.8372	0.8050	0.8450
S5	0.8250	0.8205	0.8580	0.8670
S6	0.8550	0.8105	0.7950	0.7550
Mean	0.8217	0.8204	0.8253	0.8237
SD*	0.0438	0.0312	0.0345	0.0381

[*Standard Deviation]

5.4.5 Discussion

From Table 5.6 it is observed that for EEG classification, the values of classification accuracy and F1 score are always above 0.75 for all subjects. The mean values of classification accuracy and F1 score in this case are 0.7917 and 0.7924 respectively. The discriminating capability of EOG signals is somewhat lower in comparison, as from Table 5.6 it is observed that the mean values of classification accuracy and F1 score for EOG classification are 0.7000 and 0.6886 respectively. However in both the cases the standard deviation of the performance metrics over different subjects is lower than 0.1, indicating that inter subject variation regarding this scheme is not significant, and hence a subject invariant recognition platform can be proposed. Table 5.7 presents the performance metrics after information fusion from the two sources, EEG and EOG. The average values show that both feature level fusion and decision level fusion show significantly enhanced performance when compared with individual performances as observed in Table 5.6. The maximum values of classification accuracy and F1 score reach 0.8253 and 0.8237 respectively for decision level fusion, over all subjects. The standard deviation values of the performance metrics over different subjects is lower than 0.05 for each case of information fusion.

In an attempt to validate the justification of the use of the proposed HCM-SVM classifier, comparisons are made with standard pattern classifiers such as k-NN (k= 2 to 8) with Euclidean Distance as the similarity measure, Artificial Neural Network (ANN) with back propagation learning based on gradient descent search with 10 neurons in the hidden layer as well as a linear discriminant analysis (LDA) classifier [20]. The results are tabulated in Table 5.8 show that the proposed technique provides the most promising results in the present context.

Table 5.8
Comparison of CAs different classifiers

Subject ID	EEG Results				EOG Results			
	HCM-SVM	*k*-NN (average results for *k*=2 to 8)	LDA	ANN	HCM-SVM	*k*-NN (average results for *k*=2 to 8)	LDA	ANN
S1	0.8250	0.7890	0.7140	0.6825	0.6250	0.6520	0.6035	0.5810
S2	0.7750	0.7500	0.7200	0.7750	0.7500	0.6880	0.7115	0.5875
S3	0.8000	0.7800	0.6555	0.7380	0.7250	0.7020	0.7280	0.7120
S4	0.7750	0.7245	0.8470	0.8125	0.6750	0.6100	0.6550	0.6125
S5	0.8250	0.8020	0.8625	0.6620	0.6500	0.6225	0.5715	0.5800
S6	0.7500	0.7810	0.7400	0.7175	0.7750	0.7125	0.6525	0.6830
Mean	0.7917	0.7711	0.7565	0.7312	0.7000	0.6645	0.6536	0.6260

There have been various previous works that show that cognitive activities can indeed be recognized from EEG signals as well as EOG signals. The use of EEG for decoding mental activities has been noticed in literature [19, 24, 27]. A fuzzy clustering approach to discriminate between EEG responses to different levels of cognitive loads [19] has been presented by C Vidaurre et. al. (2009). The use of EOG in decoding context related information from eye movements have been presented in a research paper [1] that particularly focus on how activities can be recognized by tracking eye movements, also including reading and visual memory related applications. A. Bulling et. al. (2011) reported the decoding of five types of activities including copying a text, reading a printed paper, taking handwritten notes, watching a video, and browsing the Web, from 90 EOG features derived using saccade, fixation and blink characteristics that lead to recall and precision rates of the order of 70% [3]. In another work published by A. Bulling et. al. (2008), the authors have presented the decoding of reading activities during sitting, standing, walking etc from EOG signals through string matching as well as using Hidden Markov Models achieving 80.2% recognition rate [4]. However, the goal of the present paper is to build a common-features based platform for decoding some basic activities from both EEG and EOG as well as extending the work towards a multi-sensor activity recognition platform.

5.5 Summary

This chapter illustrates that while EEG and EOG data can individually distinguish between four classes of cognitive activities, an enhanced recognition performance is noticed upon information fusion. Thus a simple and efficient bimodal cognitive activity recognition platform using brain responses and eye movement information has been proposed.

The present work has successfully illustrated that EEG and EOG data with the same set of features (Band Power estimates and Wavelet Coefficients) can individually distinguish between four classes of cognitive activities, and an enhanced recognition performance is noticed upon information fusion. It is found that indeed feature level and decision level fusion tend to produce slightly better results in recognition of the activities than the individual modalities alone. This finding can facilitate the development of multi-sensor based bio-modality analysis for improvement of cognitive context aware systems. Thus a simple and efficient bimodal cognitive activity recognition platform using brain responses and eye movement information has been proposed, achieving sufficiently high recognition accuracy in the order of 80%.

However, the present system has been implemented for recognition of a very limited number of activities and the proposed approach is entirely offline. Such a platform can be extended further for recognition of a larger number of activities or complicated activities in future. This would probably require better signal processing and classification algorithms. Also we intend to implement the entire system in real time in future. Such an integrated system can be implemented to transfer real time information regarding a person's context from body worn bio-sensors to remote locations for various applications.

References

[1] Bulling, A., Roggen, D., & Troester, G. (2011). What's in the Eyes for Context-Awareness?. *IEEE Pervasive Computing*, *10*(2), 48-57.

[2] Siegelbaum, S. A., & Hudspeth, A. J. (2000). Principles of neural science (Vol. 4, pp. 1227-1246). E. R. Kandel, J. H. Schwartz, & T. M. Jessell (Eds.). New York: McGraw-hill.

[3] Bulling, A., Ward, J. A., Gellersen, H., & Troster, G. (2011). Eye movement analysis for activity recognition using electrooculography. *IEEE transactions on pattern analysis and machine intelligence*, *33*(4), 741-753.

[4] Bulling, A., Ward, J. A., Gellersen, H., & Tröster, G. (2008). Robust recognition of reading activity in transit using wearable electrooculography. In International Conference on Pervasive Computing (pp. 19-37). Springer Berlin Heidelberg.

[5] Acharya, R., Faust, O., Kannathal, N., Chua, T., & Laxminarayan, S. (2005). Non-linear analysis of EEG signals at various sleep stages. *Computer methods and programs in biomedicine*, *80*(1), 37-45.

[6] Haynes, J. D., & Rees, G. (2006). Decoding mental states from brain activity in humans. *Nature Reviews Neuroscience*, *7*(7), 523-534.
[7] Barea, R., Boquete, L., Mazo, M., & López, E. (2002). Wheelchair guidance strategies using EOG. *Journal of Intelligent & Robotic Systems*, *34*(3), 279-299.
[8] Deng, L. Y., Hsu, C. L., Lin, T. C., Tuan, J. S., & Chang, S. M. (2010). EOG-based Human–Computer Interface system development. *Expert Systems with Applications*, *37*(4), 3337-3343.
[9] Dornhege, G. (2007). *Toward brain-computer interfacing*. MIT press.
[10] Sanei, S., & Chambers, J. A. (2013). *EEG signal processing*. John Wiley & Sons.
[11] Pfurtscheller, G., & Neuper, C. (2001). Motor imagery and direct brain-computer communication. *Proceedings of the IEEE*, *89*(7), 1123-1134.
[12] Mitchell, T. M., Hutchinson, R., Niculescu, R. S., Pereira, F., Wang, X., Just, M., & Newman, S. (2004). Learning to decode cognitive states from brain images. *Machine learning*, *57*(1-2), 145-175.
[13] Fukunaga, K. (2013). *Introduction to statistical pattern recognition*. Academic press.
[14] Gevins, A., & Smith, M. E. (1999). Detecting transient cognitive impairment with EEG pattern recognition methods. *Aviation, space, and environmental medicine*, *70*(10), 1018-1024.
[15] Alkan, A., & Yilmaz, A. S. (2007). Frequency domain analysis of power system transients using Welch and Yule–Walker AR methods. *Energy conversion and management*, *48*(7), 2129-2135.
[16] Cona, F., Zavaglia, M., Astolfi, L., Babiloni, F., & Ursino, M. (2009). Changes in EEG power spectral density and cortical connectivity in healthy and tetraplegic patients during a motor imagery task. *Computational intelligence and neuroscience*, *2009*.
[17] Freeman, W. J., Ahlfors, S. P., & Menon, V. (2009). Combining fMRI with EEG and MEG in order to relate patterns of brain activity to cognition. *International journal of psychophysiology*, *73*(1), 43-52.
[18] Huan, N. J., & Palaniappan, R. (2005, March). Classification of mental tasks using fixed and adaptive autoregressive models of EEG signals. In *Neural Engineering, 2005. Conference Proceedings. 2nd International IEEE EMBS Conference on* (pp. 633-636). IEEE.
[19] Vidaurre, C., Krämer, N., Blankertz, B., & Schlögl, A. (2009). Time domain parameters as a feature for EEG-based brain–computer interfaces. *Neural Networks*, *22*(9), 1313-1319.
[20] Rafiee, J., Rafiee, M. A., Prause, N., & Schoen, M. P. (2011). Wavelet basis functions in biomedical signal processing. *Expert Systems with Applications*, *38*(5), 6190-6201.
[21] Subasi, A. (2007). EEG signal classification using wavelet feature extraction and a mixture of expert model. *Expert Systems with Applications*, *32*(4), 1084-1093.
[22] Welch, P. (1967). The use of fast Fourier transform for the estimation of power spectra: a method based on time averaging over short, modified periodograms. *IEEE Transactions on audio and electroacoustics*, *15*(2), 70-73.
[23] Das, D., Chatterjee, D., & Sinha, A. (2013, November). Unsupervised approach for measurement of cognitive load using EEG signals. In *Bioinformatics and Bioengineering (BIBE), 2013 IEEE 13th International Conference on* (pp. 1-6). IEEE.
[24] Mallat, S. G. (1989). A theory for multiresolution signal decomposition: the wavelet representation. *IEEE transactions on pattern analysis and machine intelligence*, *11*(7), 674-693.
[25] Llinas, J., & Hall, D. L. (1998, May). An introduction to multi-sensor data fusion. In *Circuits and Systems, 1998. ISCAS'98. Proceedings of the 1998 IEEE International Symposium on* (Vol. 6, pp. 537-540). IEEE.
[26] Petrantonakis, P. C., & Hadjileontiadis, L. J. (2010). Emotion recognition from EEG using higher order crossings. *IEEE Transactions on Information Technology in Biomedicine*, *14*(2), 186-197.
[27] Vuckovic, A., Radivojevic, V., Chen, A. C., & Popovic, D. (2002). Automatic recognition of alertness and drowsiness from EEG by an artificial neural network. *Medical engineering & physics*, *24*(5), 349-360.

6

Conclusion & Future Directions

A self-review of the thesis and the future prospects of possible research in the field of electrooculography analysis and based control applications is presented in this chapter. The major research outcomes of the works undertaken in this thesis are outlined here, with emphasis on the accomplishment of the primary objectives of this thesis. The concluding section of this chapter indicates the open research areas which can be further attended in future.

6.1. Conclusions

With technological growth, concept of touch and multi-touch screens have arisen which changed the smart phone industry dramatically. Hence it opened up the dimension for new reliable input modalities that have the potential to lead to significant advancement in technology. As a result, a significant amount of research energy has been put into creating input modalities that allow for more natural interaction with users. One such category of input modalities that is becoming more relevant is those that make use of the human eye. Similarly, innovative human-computer interaction paradigms with minimum motor control provide realistic interactions and have potential to be used in assistive technologies. Among the human modalities, the eyes are one of area with minimum motor requirements. Most of the existing assistive technologies based on tracking the eyes are intrusive, limited to the laboratory environment and restrictive or are not accurate enough for real-life applications. Moreover, vision being human's primary sense to obtain and perceive information about the surrounding world, movements of the eyes provides acts as a rich source of information about human beings.

In this project, basically the efficacy of electrooculography for real life problems is investigated. In addition to analyzing the real time classification of directional eye movements and implementing them to control supportive systems, this thesis tries to explore the potential uses of EOG within the realm of Human Computer Interaction in rehabilitation.

Chapter 1 briefly overviews the human computer interactive systems as rehabilitation aids that involves electrooculogram. In this chapter, an outline is given of the major research works already done in the field of electrooculographic interfaces. This chapter also addresses the objective and undertaken approach of the performed experimental work presented in this thesis.

The primary work for the accomplishment of this thesis is discussed in chapter 2. Design and development of an acquisition circuit for EOG and identification directional eye movements is the main objective of the work discussed in this chapter. A two channel circuit is designed to collect both horizontal and vertical eye movement data. In the preliminary stage, EOG signal is picked up by placing Ag-AgCl disposable surface electrodes around the eye socket region. Later, a wearable EOG glass is implemented with stainless steel electrodes. In second phase of this chapter, classification of right, left, up, down eye movement and blink from the recorded EOG signal is done by implementing various soft computing algorithms.

Eye Movements are a great source of information about a person. Physiological signals provide measurements about the degree of functionality or degradation of biological organs of the humans and other advanced creatures. In chapter 3, research is done to extract the useful details from EOG and implement it as assistive tool. This chapter is divided into five sections. In first section, assistance schemes are proposed to follow progress of autistic children by analyzing their eye tracking data. The second scheme of reading speed evaluation is proposed by studying EOG data for providing assistance to reading disabled children. The performance of this novel proposal is validated by the assessment of three children having specific learning disorder. In third section, strategy as precautionary measure for computer vision syndrome is presented based on blink detection. A simple approach to detect the possibility of eye dystonia is suggested in fourth section. The last part of this chapter gives a layout of electrooculogram based mental fatigue detection method.

In Chapter 4, Electrooculogram based Control strategies are presented for eye movement directed Assistive Devices. Work discussed in this chapter aims to classify the eye movements of right, left, up, down directions along with blink and utilize them to control human computer interactive systems solving different purposes in rehabilitation. The chapter proposes three novel approaches towards EOG-driven rehabilitative aids with can lead to intelligent homes environment. A multitasking graphical user interface (GUI), designed by controlling the position of a computer cursor using eye movements, is the first proposal given in this chapter. Each and every icon of the GUI can be accessed online by just selecting them and thus the particular function can be performed. The Second proposal is a scheme to recognize the pattered eye movements of some known digits, letters and shapes and those are generated on the computer screen. The last and third approach describes how the directional movements of a motorized wheelchair, i.e., forward, backward, right, left in a particular speed and start-stop operation are controlled in real time by EOG with predefined eye commands.

in chapter 5, research work has been done to recognise a person's cognitive context from EOG based eye movement data and also in combining eye movement information with brain activity from EEG signal. This chapter accounts for the combination of information from brain signals using EEG and eye movements using EOG for cognitive context recognition. It introduces multimodal data analysis using EEG and EOG signals as sources of cognitive context recognition information. It illustrates the architectures of feature and decision level fusion for constructing a bimodal cognitive context recognition platform.

The work presented in this thesis, to the best of author's knowledge, is a distinctive work in the field of eye movement analysis and at the same time application in various rehabilitation purposes, be it controlling assistive devices or preventing a typical eye disorder or helping the autistic/reading disabled with a feedback approach. This work has experimented all the phases of eye movement research and developed an interface for assistive devices in real time, one wheelchair for physically challenged and one for special kids having specific learning disorder and another for long time computer users for computer vision syndrome prevention which is first of their kinds. All of These works can find its application in rehabilitation. This work is highly valuable in biomedical engineering domain as it can be implemented for providing improved lifestyle and more freedom where the user is unable to move, for a remedial method of learning as a helping hand to autistic and dyslexic children, for safety of drivers in long journey and also for other human computer interface based control as well as assistive devices.

6.2. Future Prospects

The works discussed in this thesis have introduced novel a areas of research in the field of HCI as well as eye movement analysis. Experiments must be conducted further to extract maximum relevant information from eye movements to improve the therapeutic feedback approach by eye movement analysis. Studies on employment of eye movement combinations in control mechanism are to be performed in future along with directional movement control. Studies related to different attributes of movements such as speed, position will be conducted for more accurate and robust control of the assistive or prosthetic devices.

Further work includes implementation of new algorithms to improve the performance of control scheme and/or eye tracking proposal in terms of accuracy and computational time, making it feasible to work in real-time scenarios. Moreover, some changes or modification can be made in the design systems to make it more reliable and comfortable to use as well as better in aesthetic sense, such as the wearable EOG glass can be made more flexible such that it can be adjusted according to face shape or structure. The autism proposal must be tested in real life condition with affected children. The wheelchair unit can be accompanied with a desktop to combine the use of the multitasking GUI and a robotic arm can also be implemented with it which can be controlled with EOG itself or other biopotentials, e.g., EEG, EMG, can be incorporated.

After studying all the characteristics of EOG signal, in future an optimal feature extraction-selection-classification algorithm can be developed only for EOG for real-time control. Non-invasive bio-potential signals or physiological parameters such as electroencephalography (EEG) [1, 2], electromyography (EMG) [3-5], galvanic skin resistance (GSR) or any other eye movement tracking method [6] may be implemented with the proposed systems to make its functioning more improved as well as to detect or prevent or track progress of any disease [7-8] and it may open new directions for application of eye movement related information.

Final aim of this work is to attempt all the proposed schemes and approaches in an embedded platform and to provide feasible solutions to real world rehabilitation problems. The schemes would be further modified accordingly after studying with concerned specially-abled users.

References

[1] Slanzi, G., Balazs, J. A., & Velásquez, J. D. (2017). Combining eye tracking, pupil dilation and EEG analysis for predicting web users click intention. *Information Fusion*, *35*, 51-57.

[2] Tagluk, M. E., Sezgin, N., & Akin, M. (2010). Estimation of sleep stages by an artificial neural network employing EEG, EMG and EOG. *Journal of medical systems*, *34*(4), 717-725.

[3] Hashimoto, M., Takahashi, K., & Shimada, M. (2009, July). Wheelchair control using an EOG-and EMG-based gesture interface. In *Advanced Intelligent Mechatronics, 2009. AIM 2009. IEEE/ASME International Conference on* (pp. 1212-1217). IEEE.

[4] Paul, G. M., Cao, F., Torah, R., Yang, K., Beeby, S., & Tudor, J. (2014). A smart textile based facial EMG and EOG computer interface. *IEEE Sensors Journal*, *14*(2), 393-400.

[5] Jang, G., Kim, J., Lee, S., & Choi, Y. (2016). EMG-based continuous control scheme with simple classifier for electric-powered wheelchair. *IEEE Transactions on Industrial Electronics*, *63*(6), 3695-3705.

[6] Van der Geest, J. N., & Frens, M. A. (2002). Recording eye movements with video-oculography and scleral search coils: a direct comparison of two methods. *Journal of neuroscience methods*, *114*(2), 185-195.

[7] Liaska, A., Petrou, P., Georgakopoulos, C. D., Diamanti, R., Papaconstantinou, D., Kanakis, M. G., & Georgalas, I. (2016). β-Thalassemia and ocular implications: a systematic review. *BMC ophthalmology*, *16*(1), 102.

[8] Stuart, S., Hickey, A., Galna, B., Lord, S., Rochester, L., & Godfrey, A. (2016). iTrack: instrumented mobile electrooculography (EOG) eye-tracking in older adults and Parkinson's disease. *Physiological Measurement*, *38*(1), N16.