BIOLOGICAL AND COGNITIVE COMMUNICATION USING MACHINE INTELLIGENCE TECHNIQUES

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CERTIFICATE

This is to certify that the dissertation "**Biological and Cognitive Communication Using Machine Intelligence Technique.**" has been carried out by **Snehalika Lall (University Registration No: 128928of 14-15)** under my guidance and supervision and be accepted in partial fulfillment of the requirements for the degree of Master of Electronics and Telecommunication Engineering of Jadavpur University. The research results presented in the thesis have not been submitted to any other University/Institute for the award of any Degree or Diploma.

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The foregoing thesis is hereby approved as a creditable study of an Engineering subject, carried out, and presented in a manner satisfactory to warrant its acceptance as a prerequisite to the degree for which it has been submitted. It is understood that by this approval the undersigned do not necessarily endorse or approve any statement made, opinion expressed or conclusion drawn therein but approve the thesis only for the purpose for which it has been submitted.

Final examination and evaluation
Of the Thesis of
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DECLARATION OF ORIGINALITY AND COMPLIANCE OF

ACADEMIC THESIS

I hereby declare that this thesis titled "**Biological and Cognitive Communication Using Machine Intelligence Technique."** contains literature survey and original research work by the undersigned candidate, as a part of his degree of **Master of Electronics and Telecommunication Engineering of Jadavpur University.**

All information have been obtained and presented in accordance with academic rules and ethical conduct.

I also declare that, as required by these rules and conduct, I have fully cited and referenced all the materials and results that are not original to this work.

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LIST OF PUBLICATIONS BY THE AUTHOR

1. **Snehalika Lall**, Arup Kumar Sadhu, Amit Konar, Kalyan Kumar Mallik, Sanchita Ghosh, "Multi-agent Reinforcement Learning for Stochastic Power Management in Cognitive Radio Network," *IEEE Microcom Conference*, NIT Durgapur, India, Jan 1-3, 2016.

2. **Snehalika Lall**, Anuradha Saha, Amit Konar, Mousumi Laha, Anca L. Ralescu, Kalyan kumar Mallik, Atulya K. Nagar, "EEG-based Mind Driven Type Writer by Fuzzy Radial Basis Function Neural Classifier," *IEEE International Conference of World Congress Conferences*, Canada, Vancouver, July 24-26, 2016. (accepted).

PREFACE

A machine is called intelligent when it is capable to thinking and acting like a human being. Machine intelligence is a vast discipline of knowledge dealing with the process of making a machine smart like a human being by empowering it to perform at least by one of the following few activities, namely reasoning, learning, planning, and perception. Reasoning is concerned with automated generation of inference from a given set of facts and rules. Learning deals with autonomous ability extract knowledge from raw real world data. Planning includes the inherent skill of a machine to generate a sequence of tasks autonomously to reach a definite pre-defined goal. Perception is primarily responsible for sensing and interpretation of raw real world data/information. Machine intelligence is a vast discipline of knowledge that covers the principles and methodology of the above realization of the biological processes indicated above.

Cognitive science includes the physiological and psychological processes involved to understand the human mind. Although there is an overlap between machine intelligence and cognitive science, there exists a fundamental difference between the two. While cognitive science attempts to understand the biological traits, machine intelligence aims at representing the biological processes on a computational platform so as make an inanimate machine act like an animated one. The thesis aims at dealing with biological and cognitive communications using machine intelligence. Biological communications include cellular communications, where one cell transmits a chemical signal to a desired cell, where modulation is used in the transmitting cell and demodulation at the receiving cell to get back the transmitted chemical signal. Cognitive communications on the other hand deal with communications performed using the human brain as part of the communication process. Maybe the brain acts as a receiving agent, while a particular organ may be the recipient, but the brain acts as the main controlling agent for signal transfer. The thesis deals with both biological and cognitive communications with special reference to its electrical analogue in cognitive radio.

The thesis includes five chapters. Chapter 1 deals with a brief discussion on the scope of the thesis. Chapter 2 covers a thorough discussion on cognition, primarily focusing on cognitive processes, cognitive communication and how cognition is connected with memory and learning. Lastly, the chapter examines possible exploration of cognition in non-biological system, such as cognitive networking. Chapter 3 deals with power optimization problem in a cognitive radio network using reinforcement learning techniques. In Chapter 4, a detailed discussion is given on the design and realization of EEG-driven typewriter. It may be added here that the advent of EEG-driven type-writer lies in automatic communication of mental imagery about vowel sounds to a computer without uttering the vowels. In Chapter 5, an overview of biological communication is described with special emphasis on biological modulation/demodulation. Chapter 6 provides conclusive remarks about the thesis.

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Chapter 1

Introduction and Scope of the Thesis

1.1 Scope of Thesis

The thesis deals with application of well-known techniques of machine intelligence in the field of cognitive and biological communications Primary motivation of this thesis is to develop intelligent models of computations, by introducing a sense of autonomous learning in communication systems.

Three distinct problems of communication have been addressed in the thesis.

The first problem of this thesis is that, an overview of power-management in a cognitive radio network. In a cognitive radio, the unlicensed users selectively utilize the radio spectrum over time to maintain essential services. Selection of frequency band from non-utilized spectrum and power level from the available list of power bands are the primary focus of research in Cognitive Radio. In the present context, the selection of power levels are emphasized while transmitting the modulated carrier. Reinforcement learning is used to learn to select appropriate power levels for communication at specific (unlicensed) frequency bands by adaptively forming the Q-table from the experimental instances of agent-power–level as the reward. After the learning algorithm converges, the Q-table is used for prediction of power-level at a selected channel.

The other important aspect of the thesis includes human-machine interactive communication, where the acquired brain signals are pre-processed for noise filtering, feature extraction and classification and then transmission to a receiver computer for generation of control command to an external actuator/robotic device. In many brain-computer interfacing application, control command generation is not required as the primary motivation. There is necessity to decode the brain signals only. One specific problem to be undertaken in the second chapter is to communicate mind-uttered alphabets to a remote computer connected through a radio network. A new classification model has been developed to deal with EEG based decoding of mental imagery about vowel sounds mentally uttered by a subject. It has been observed that even when the subjects do not literally pronounce the vowel sounds, the mentally uttered vowel sounds can be detected by the machine. A simple three lettered coding, vowel sound followed by a space vowel sound, has been adapted to represent and decode consonant sounds using vowel sounds as well.

The last and the most important work undertaken in the thesis is the third problem, which deals with a problem of biological cellular communication mechanism, where the principles of the biological diffusion, modulation and demodulation are modeled by novel techniques. This model has a great impact to understand the detailed mechanism of biological communication undertaken by cell and also (sub-cellular substances) Biochemical injected into muscles for being applied to a non-accessible location (say brain or lungs) of the human physique, support the mechanism of biological communication. Here, Protein plays a vital role to form a bonding with the bio-chemicals added as drug. A binding is formed between the protein and the injected bio-chemical molecule. The overall molecule, called modulated chemical as carrier molecule, is passed on to the desired location through blood cavities and other pathways. Diffusion plays a vital role in molecular communication of bio-materials. The thesis emphasizes on new models of diffusion and examines its scope in the biological communication process. Demodulation takes place in the receiving end to retrieve the bio-chemical drug.

In this thesis, Chapter 2 describes the brief overview of cognitive process. Chapter 3 describes power optimization in a cognitive radio network, using reinforcement learning technique. Chapter 4 deals with EEG based decoding of mental imagery about vowel sounds mentally uttered by a subject. In Chapter 5 mechanism of biological communication including biological diffusion, modulation and demodulation are modeled. Conclusion of the thesis including future scope has been discussed in Chapter 6.

Chapter 2

Brief Overview of Cognitive Processes

Cognition refers to the art of perceiving, understanding and interpreting the world of a subject. It also helps a person to translate his thoughts into actions by utilizing the external actuators and limbs, control his gesture and or body language to convey his intention to his fellow beings and understand the interaction process among team members to plan and execute a complex task. This chapter provides a thorough understanding of the cognitive processes and their interaction to understand the human behavior to execute a complex task.

2.1 Cognitive Process

In engineering science, a *process* is represented by two main attributes: i) the input and the output variables and ii) the principles used to transform the given input variables to obtain the desired output variables. For example a heating coil may be called a process. Here, the current passing through the coil for some time duration is the input and the heat generated may be treated as the output. A heater is an example of a simple process. There exists complexity, when two or more processes are coupled. For example, the heating process when coupled with a heat transfer from a given source to a detector, together becomes a complex process.

To design engineering system, the physical/chemical processes involved in the system need to be modeled first. Next, the behavior of the models are analyzed and compared to that of the other models. If the model has more than one parameter, intelligent selection of their range is an important issue to study the dynamic behavior of the model. System identification techniques here serve an important purpose to determine the parameters of that model.

2.2 The States of Cognition

2.2.1 Sensing:

In engineering sciences, sensing refers to the reception and transformation of signal into a measurable form. However, sensing has a wider perspective in cognitive science. It represents all the above together with pre-processing (filtering from stray information) and extraction of features from the received information. For example, visual information on reception is filtered from undesirable noise [1] and the elementary features like size, shape, color, etc. are extracted for storing into the Short-term memory (STM).

2.2.2 Acquisition:

In the acquisition process, the response of the STM is compared with the existing information stored the long term memory (LTM). In case there is similarity between the two, the stored information in LTM is strengthened. Otherwise, the old information is sometimes replaced by the new, when the certainty of the new information exceeds to that of the old information. This updating of information in LTM is performed by Unsupervised Learning. The learning process that helps updating information is called unsupervised as the subject performs the information-update by himself without the assistance/support of a supervisor.

2.2.3 Perception:

While the acquisition state engages itself to extract low level features of the world around us, the perception state extracts high level features and sometimes knowledge to understand the environment. For example, to recognize a 3D scene, the acquisition state extracts and stores only 2D gray image intensities, while the perception state derives 3D information to understand the 3D surfaces and edges of the object that we are inspecting. This 3D information are then used to understand the object by comparing it with the stored information about similar 3D objects. Similarly, to recognize a natural language, we do primitive operations like pre-processing and information extraction in the acquisition state, whereas we derive the semantics of the statement in the perception state. In brief, the perception state does higher order information/knowledge extraction, whereas the acquisition state only deals with low level information extraction [2,3].

2.2.4 Planning:

This state of cognition is used to derive a plan to successfully complete a pre-defined goal with the knowledge already acquired in the perception state. The primary motivation of planning is to identify a sequence of rules that together offers a smooth journey towards a fixed goal from a pre-defined starting state. In many real world problems, such as driving from office to home, we often utilize the roadmap as the knowledge source and use incidental data, such a possible mob in a street, to avoid unwanted roads to reach our destination.

It may be noted that both planning and reasoning although share common formalisms, have a fundamental difference with respect to their nomenclature. The reasoning may be continued with sequence of execution of the actions, while in planning, the schedule of actions are derived and executed in a later phase.

2.2.5 Action:

This state mainly determines the control commands to execute the schedule of the action-plan for a given problem. It is generally carried out through a process of supervised learning, with the required action as input stimulus and the strength of the control signals as the response.

The states of this cognitive process are shown in below Fig.2.1.

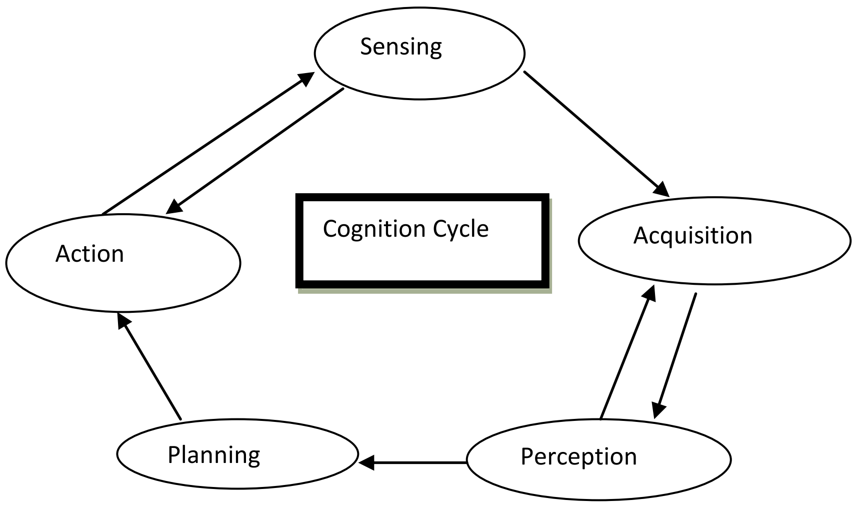

Fig.2.1. State of Cognition Process

2.3 External world Cognitive Communication

Cognitive Radio Network (CRN) is the practical application of cognitive communication. CRN is an intelligent wireless communication system which is sensible about its surroundings. In order to overcome the overcrowded spectrum problem CRN is used as an emerging technology to effectively exploit the under-utilized spectrum [4]. Due to the advancement of wireless systems, the demand for wireless spectrums has resulted in spectrum scarcity based on the conventional fixed allocation schemes. Even with the extensive usage of frequency spectrums, it has been studied that [5] that 62% of spectrum still remains unoccupied by the licensed primary user (PU). The PU is users under licensed spectrum. The users under this cognitive radio network (CRN) are called Cognitive Users (CU). A CRN is constructed by allowing the Cognitive users (CUs) in a secondary communication network (SCN) to opportunistically operate in the frequency bands originally which is allocated to a primary communication network (PCN). CRN may also be built by allowing SCN to coexist with the primary users (PUs) in PCN until the interference caused by SCN to each PU is properly regulated [6]. The primary aim of this CRN is efficiently choosing the RADIO Spectrums sharing with PUs as the radio spectrum is naturally limited resource needed for wireless communication systems.

This CRN uses the intelligent Cognitive process technique to choose spectrums. The CRN first sense the unoccupied spectrum bands and then learn the environment and choose the available spectrums, then share the spectrums with other cognitive users (CU). One challenge in CRN is to select power by unlicensed users or cognitive users for the usage of unutilized spectrum holes, within the tolerable limit of interference between cognitive user and licensed user. In this thesis, we focus on cognitive radio network stochastic power management in multi user environment using mixed strategies. The performance is evaluated by ratio of transmitting signal power with interference with SU to PU power level, called SNR. Each SU perform as a learning agent and chooses power and transmit the signal to receiver. The sender SU receives a feedback from environment according to SNR level and again updates its power. The goal is to find an optimal strategy of each SU, that all can transmit above the threshold level without interrupting the licensed users. The transmitting power allocation is important to discuss because using high transmitting power, we can get higher SNR and better performance but it causes also higher interferences with others SUs and PUs and higher power consumption cost. So a proper allocation scheme is needed. In wireless system, different power levels can also affect another protocol layer. There are several methods exist about it [7-9]

A machine intelligence technique [12] is applied in this thesis to overcome the power allocation problem. The reinforcement learning technique is used to complete the cognitive process during power allocation. The techniques of all such machine learning are discussed. The overview of CRN network and spectrum hopping technique are given in below Fig. 2.2 and Fig. 2.3.

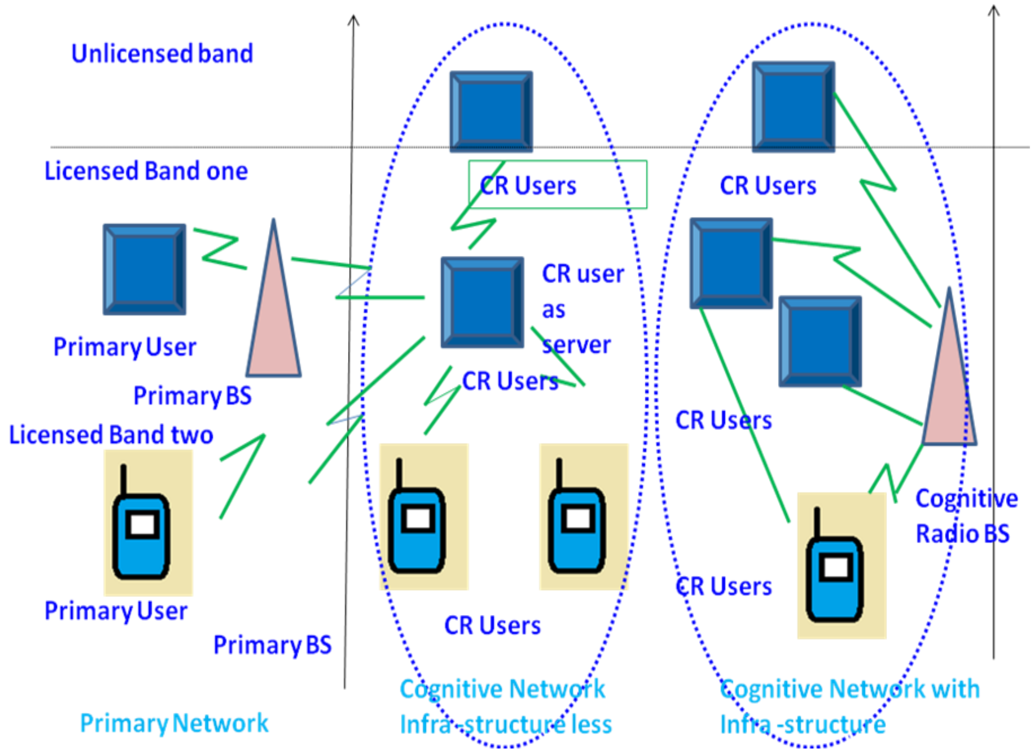

Fig.2.2. The architecture of Cognitive Radio Network

In the above Fig. 2.2, two type of CRN architecture are showed. One is infrastructure less another is with infrastructure. In infrastructure based CRN, there is a cognitive base station where it is the central element and controlling the entire cognitive user node. In infrastructure less CRN, there is no such cognitive base station. Each node is controlling itself. All CUs share the spectrum with PUs licensed band. The Fig. 2.3 describes the spectrum sharing technique of CRN.

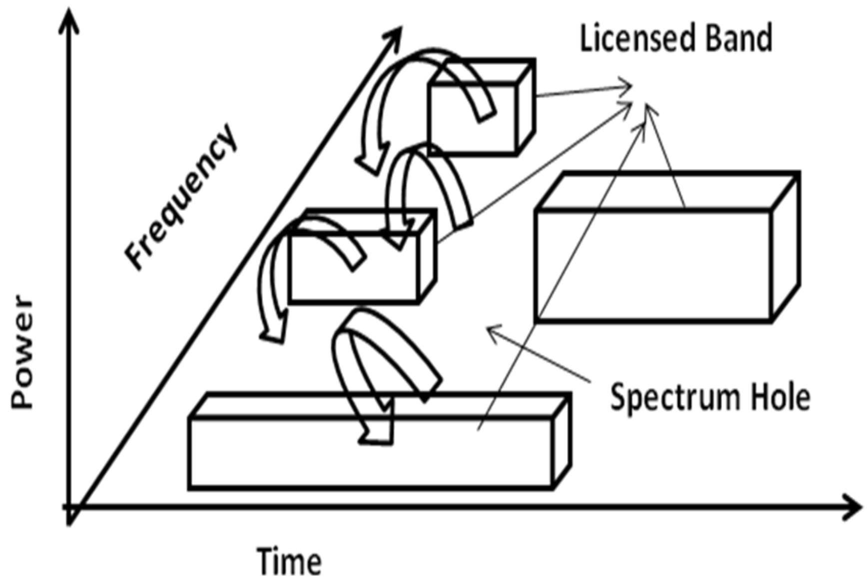

Fig.2.3. Spectrum Sharing Technique

The above Fig. 2.3 describes the spectrum sharing technique of CRN. The network always finds a spectrum hole from the licensed frequency band with hopping technique. The machine leaning technique is used in this spectrum allocation and sensing method which is described in this chapter.

2.4 Introduction to Reinforcement Learning

In Reinforcement learning (RL) [10,11], a controller (agent, decision maker) interacts with a process (environment), by means of a three parameters: state, action and reward. State describes the position/situation of an agent in the process. An action is executed by a controller, which allows the controller to influence the process and the controller moves to the next state in the same process. A scalar signal, which is received from the process as a feedback to the controller measures the quality of the state-action pair. The above situation is illustrated graphically in Fig. 2.4.

In this chapter, the performance of the cognitive radio network communication is being improved by employing the reinforcement learning. The synergism of the reinforcement learning and the cognitive radio network communication leads to better performance in terms of power adaption.

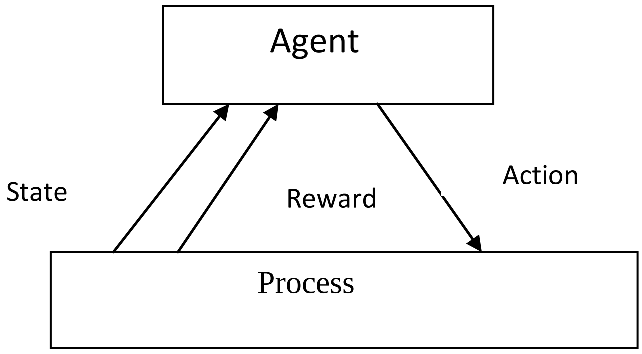

Fig.2.4. Block diagram of Reinforcement Learning

2.5 Connecting Cognition with Learning

As discussed previously, cognition involves quite a few biological processes, including sensory perception, reasoning, planning and execution of a plant. Leaning appears in two phases. Occasionally, we learn the sensory action patters by experiencing them from real world. Normally, a child prefers to store sensory-action doublets as they need not understand the essence of the action for a given sensory perception. For instance, the mother usually makes a child aware of the knowledge to make away when he/she finds a possible encounter with a strange creature. A baby then unwelcome system as they seem to be strange for him/her.

Adults usually prefer semi supervised or unsupervised leaning as they can identify the similarity between a set of objects/concepts, thereby clusters them into one group. Reinforcement learning is comparatively more real life and real time learning prediction as the subjects gradually can update their knowledge about the leaned experience.

It is apparent that learning needs memory for encoding and necessary recalls. Human like most of the advance mammals store their learned experience in the hippocampus region inside the brain. The hippocampus is located almost at the centre of the brain, surrounding the cerebra spinal fluid sources. It is found that most of the supervised learning based knowledge acquisition is performed by the hippocampus region of the brain.

The other brain region that keeps track of essential knowledge we learn through an experience, is temporal region located near the ear region. It is true that most of the mammalian memory is concentrated around these two brain module.

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Chapter 3

Cognitive Radio Network power control using Reinforcement Learning

Frequency spectra are nowadays getting overcrowded because of increasing cell phone users. Cognitive radio network offers an alternative modality to utilize unused spectra efficiently among unlicensed users. This chapter attempts to allocate transmission power among cognitive users in an efficient way without creating interference to the licensed users. Multi-agent reinforcement learning is used for cooperative power allocation in cognitive radio network. Multi-agent learning is here used to handle stochastic behavior of the environment. Three mixed strategies (Correlated equilibrium) are used to control transmission power in multi-agent learning. After the learning algorithm converges, we obtain the optimum power level under different situations for subsequent use in power utilization during communication. Experimental results indicate that the proposed algorithm outperforms its classical counterparts by a significant margin.

3.1 Introduction

The electromagnetic radio frequency is the most valuable resource, in wireless communications. Radio frequencies are regulated by governmental agencies on a long-term basis to all licensed users in large geographical regions. There hardly exists unused frequency band for wireless services due to the overcrowding of the spectrum. However, due to the fixed spectrum allocation policy, there exist lots of unutilized spectrums. According to a report obtained from Federal Communication commission [1], 62% of the allocated spectrum in the United States remains under-utilized in most of the time, thereby causing inefficient spectrum uses in limited available spectrum range. This observation calls for designing an efficient strategy of new communication paradigm to explore the existing wireless spectrum opportunistically [2]. In recent times, researchers are taking keen interest to introduce new approaches, including opportunistic spectrum access (OSA) and dynamic spectrum access (DSA) to optimize time and space based on potential spectrum efficiency. The OSA [3] is a part of DSA. In wireless communication, the OSA techniques are widely used. The OSA technique includes a device to sense the spectrum first. Next it recognizes the presence of any primary user in the spectrum. In absence of any primary users, the device finds spectrum holes, representing unused frequency band and then transmits using those opportunities in such a way to cancel the interference that might have been introduced by primary users. Such opportunistic spectrum access enhances spectrum utilization. Cognitive radio network (CRN) is a promising radio technique which explore these unused spectrum holes by sensing a wide range of the frequency bands. As stated by J. Mitola [4], “wireless personal digital assistants and the related networks were sufficiently computationally intelligent about radio resources, to detect user needs as a function of use context, and to provide radio resources and wireless services most appropriate to those needs". Cognitive radio is an example of agent technology in telecommunications. The compendium, Intelligent Agents for Telecommunications Applications [24] and the feature topic on Mobile Software Agents for Telecommunications of the IEEE Communications Magazine [25] summarize the state of the art in applying automated reasoning to telecommunications. Mobility aspects are couched in terms of network applications of “autonomous, interactive, reactive” software objects. Goal-orientation, mobility, planning, reflection, and cooperation are described as additional attributes of agents that distinguish them from other types of software. Although wireless is mentioned in some of the papers, none of the contributions describes anything approaching cognitive radio. It begins with an illustration of how capabilities that are missing from current wireless nodes can be embedded in a model-based reasoning framework to enhance the effectiveness of service delivery. In order to extend this concept to include interaction with the environment, a cognition cycle is introduced. This is the top-level control loop for cognitive radio. Cognitive radio's potential abilities require an organization of radio knowledge. In order to address this issue systematically, this chapter identifies four areas of wireless on which cognitive radio could have an impact. These are radio resource management, network management, services delivery, and download certification. Today's digital radios have considerable flexibility, but they have little computational intelligence. For example, the equalizer taps of a GSM SDR reflect the channel impulse response. If the network wants to ask today's handsets "How many distinguishable multipath components are in your location?" two problems arise. First, the network has no standard language with which to pose such a question. Second, the handset has the answer in the structure of its time-domain equalizer taps internally, but it cannot access this information. It has no computationally accessible description of its own structure. Thus, it does not "know that it knows." To be termed "cognitive," a radio must be self-aware. It should know a minimum set of basic facts about radio and it should be able to communicate with other entities using that knowledge. For example, it should know that an equalizer's time domain taps reflect the channel impulse response. The radio hardware consists of a set of modules: antenna, RF section, modem, INFOSEC module, baseband/ protocol processor, and user interface. This could be a software radio, SDR, or PDR. In addition, however, a cognitive radio contains an internal model of its own hardware and software structure. The model of the equalizer shown would contain the codified knowledge about equalizers, including how the taps represent the channel impulse response. Variable bindings between the equalizer model and the software equalizer establish the interface between the reasoning capability and the operational software. The model-based reasoning capability that applies these RKRL frames to solve radio control problems gives the radio its "cognitive" ability. Cognitive Radio identifies unused spectrum bands and establishes a communication by an opportunistically overlaying manner [5], which indicates that cognitive users (SU) use a portion of the spectrum, not used by licensed users. CRN self organizes itself in frequency spectrum scarcity. It is a special type of wireless communication in which the transmission or reception parameters are adapted to communicate efficiently without interfering with licensed users. CRN is aware of its surrounding environment to learn from the environment for adaptation its internal states to statistical variations in incoming transmitted signals by making following changes in certain operating parameters (including, carrier frequency, modulation strategy and transmit power) at real time. The cognitive radio power management using multi-agent reinforcement learning method [6] is the main aim. The research on CRN has already been employed in different parts of wireless networks, covering many fields of wireless communications like wireless channel capacity, spectrum allocations etc. [7], [8].

Reinforcement learning [14], [15], [16], [17] employs a learning paradigm satisfying the principles of reward and penalty (Fig. 1). In a single agent learning [18], [19], the agent adapts the qualitative learning space based on its own actions at specific states. In multi-agent reinforcement leaning [20], [21], [22] the agents learn through interactions among them based on a policy, involving the rewards earned by individual agents. Three different policies [22], namely Egalitarian, Utilitarian and Republican have been introduced to compare their relative merits in multi-agent learning.

Q-learning is one such reinforcement learning. In Multi-agent Q-learning (MAQL), the state-action value (Q-value) function is designed at a joint state –action space of all the participating agents following one of the equilibrium (Nash equilibrium (NE) o (correlated equilibrium (CE)) among others I cooperative situation. The former equilibria are employed to evaluate the discounted expected future reward in MAQL. A brief description of CE (EE, UE and RE) is given below. A novel cooperative power management model is used here for cognitive radio users (SUs) to learn the optimal strategy and control the transmission power with cooperating neighbors using multi-agent reinforcement learning (RL).

Cooperative network are designed based on the model of parallel fusion networks in distributed systems [9], where all the cooperating SUs take local decisions and send those simultaneously to a controlling node called fusion centre (FC) for making global decisions. Each fusion center is located in the controlling base station of the cognitive users. The modality of communication between a pair of cognitive users is briefly outlined below. First, a local cognitive user sends a request to FC, which allocates a spectrum band to establish a communication. Next, both the users randomly choose a transmission power. Each user being an intelligent node, learns the environment from the information broadcasted by the FC, and updates its power level using reinforcement learning algorithm. After the learning algorithm converges, users achieve their optimum power level and start communication. The environment in the present context being stochastic justifies the use of cooperative multi-agent learning to achieve the best policy for efficient power management.

Cognitive radio offers technology-based mechanisms for supporting the social contracts in a way that enhances the utilization of the radio spectrum. One fundamental issue in the application of this technology is the tradeoff between intelligence in the network infrastructure and intelligence in the mobile devices. An assumption of this use case is that there are few limits on the computational capacity of infrastructure. The focus then shifts to the mobile devices.

In general, cognitive radio can apply its awareness of the local radio environment and communications context to enhance efficiency. This section therefore begins with a parametric analysis of spectrum pooling, a spectrum-rental arrangement that requires radio etiquette offered by cognitive radio that has not been feasible with conventional radio technology. Since the parametric analysis is promising, it includes a statistical analysis of demand offered over space and time. This leads to the identification of specific steps that can be taken to shape demand in the market transition towards greater use of email and multimedia in wireless. The initial analysis of demand uncertainty motivates the use-case analysis of profiling demand at the source.

Spectrum pooling [26], is the arrangement under which current owners of spectrum agree to rent it to each other for some time. Let this be as brief as one second. Spectrum that could be made available for pooling includes those bands already allocated to mobile terrestrial uses. The large radiation patterns and rapid movement of aircraft and satellites essentially preclude the use of these bands in spectrum pools. In addition, radio navigation and radar bands are not considered in the readily pooled spectrum.

One of the critical challenges in CRN is how to design an efficient power distribution scheme for the proper usage of available unused spectrums among the all secondary users (SUs). It is also necessary to mitigate the interferences with spectrums sharing with the neighboring primary users (PUs) and the secondary users. A perfect design is needed to maximize the network performance without disturbing the PU transmissions and minimize the signal-to--noise ratio (SNR) [10] of the SUs' transmission connections. Control of transmission power is an efficient approach to overcome the above problems in real dynamic environment.

The reinforcement learning model employed here includes three important terminologies (Fig.3.1), called state, action and reward. In the present context, state designates usable frequency bands (busy/idle), actions of a cognitive user include selection of one from a set of power levels, and reward here indicates the number of packets successfully received at the receiving end. In a dynamic cognitive network, there exist a number of paired users, each using a specific channel at a selected power level. The motivation of the present research is to jointly determine the channels and power levels for efficient communication, measured by a reward function of signal to noise ratio. Several strategies of multi-agent cooperation are available in the literature. We here select three specific correlated strategies, popularly referred to as Egalitarian, Utilitarian, Republican strategies. In Egalitarian strategy, the joint action is selected so as to maximize the reward of the weakest cognitive agent. In Utilitarian learning, aim is to maximize the reward functions of the sum of all agents. Lastly, in Republican strategy, aim is to maximize the largest reward obtained by an agent. In this chapter, the relative merits of the three strategies are compared in Cognitive Radio network. Experimental results reveal that total energy efficiency increases with iterations. In the experimental section, the effect of variation of learning rate and discounting factor is studied on cognitive performance of the radio network.

In general, psychological (cognitive) processes of the human beings are much more complex than any engineering processes. Some example of well-known cognitive processes consist of the act of i) memorizing (encoding) and recall, ii) recognizing visual, auditory, touch, taste and smell stimuli, iii) translating and rotating visual images in the human mind, and iv) forming ideas about size and shape of the objects. These elementary processes are the heart of the complex human thought processes such as reasoning, learning, planning, perception building, understanding and coordinating multiple tasks. To model these types of complex systems, conventional tools and techniques are preferable which are usually used in modeling of engineering systems.

To model an engineering system, familiarization of behavioral characteristics of it is important. Similarly, for modeling a cognitive system, familiarization with the cognitive processes is the first task. There are two main approaches for understanding the behavior of the cognitive processes. At first step, a questionnaire has to be developed to collect the response of the individuals for studying each cognitive process. This is very time-consuming and not feasible in real life situation. An alternative way to do this is to take the classical models of cognitive processes which are developed by the philosophers and the psychologists over the past few decades. Though, there are several controversies among the models, but those models are accepted, which are free from any controversies.

The chapter is divided into four sections. In Section 3.2, the proposed model is presented, algorithm and analysis of the cognitive radio power management. In Section 3.3, the experiments and results are explained. Conclusions and Future direction are listed in Section 3.4.

3.2 Problem Formulation

Here, a multi-user cooperative system is assumed. Each SU serves as a learning agent. Each user adapts its transmission power based on rewards or feedback received from the stochastic environment to reach at optimal strategy where receiver gain is maximum and communication between agents are noiseless.

In this section, power allocation system model is described first, which takes the energy efficiency as reward parameter. The power allocation problem is considered through stochastic learning process based on the reward action state model as reinforcement learning.

3.2.1 Reinforcement Learning and Multi-Agent Strategies

In reinforcement learning [14], [15], [16], [17], an agent i receives a reward or penalty $r_i(s_i, a_i)$ from the environment at the current state $s_i \in S_i$ because of the state transition caused by an action $a_i \in A_i$. The sequence of state-transitions caused by the an autonomous agent i leads it towards the final destination of the agent from a randomly initialized starting state following the maximum cumulative reward.

Based on the number of agents involved in the learning process reinforcement learning is of two types 1) single agent Q-learning and 2) multi-agent Q-learning. In single agent Q-learning, the cumulative reward (Q-value) of an agent i, $Q_i(s_i, a_i)$ is the summation of the individual reward $r_i(s_i, a_i)$ and the optimal future reward $Q_i(s_i^/, a_i^*)$ scaled by a factor $\gamma \in (0,1]$ at the next-state $s_i^/ \in S_i$. The block diagram of reinforcement learning [30] is given as shown in Fig. 1. The single agent Q-learning update rule for agent i is given by (1) [18].

$$Q_i(s_i, a_i) = r_i(s_i, a_i) + \gamma \underset{a_i^/}{Max} Q_i(s_i^/, a_i^/) \tag{3.1}$$

The single agent Q-learning in stochastic situation is given by

$$\begin{aligned} Q_i(s_i, a_i) &= (1-\alpha)Q_i(s_i, a_i) + \\ &\alpha[r_i(s_i, a_i) + \gamma \sum_{\forall s_i^/} P_i[s_i^/ \mid (s_i, a_i)] Q_i(s_i^/, a_i^*)] \end{aligned} \tag{3.2}$$

where, $\alpha \in (0,1]$ is the learning rate and $P_i[s_i^/ \mid (s_i, a_i)]$ is the state transition probability of agent i from state s_i to the next state $s_i^/$ because of action a_i.

However, in the multi-agent Q-learning [26], the cumulative reward obtained by an agent i depends on the actions of other mobile agents $(-i)$ in the environment. The non-stationary behavior of the environment is handled by considering the cumulative rewards of an agent i, $Q_i(S, A)$ at joint state $S = \times_{i=1}^{m} S_i$ because of a joint action $A = \times_{i=1}^{m} A_i$. Like single agent Q-learning [28], $Q_i(S, A)$ is the summation of individual immediate reward $r_i(S, A)$ and the Δ equilibrium based joint future reward $\Delta Q_i(S^/)$ scaled by a factor $\gamma \in (0,1]$ of agent i at the joint next-state $S^/ \in \{S\}$. Where Δ is the Correlated equilibrium (CE). The multi-agent Q-learning update rule for agent i is given by (3) [21], [22].

$$Q_i(S, A) = r_i(S, A) + \gamma \Delta Q_i(S^/) \tag{3.3}$$

The multi-agent Q-learning in stochastic situation is given by

$$Q_i(S,A) = (1-\alpha)Q_i(S,A) + \alpha[r_i(S,A) + \gamma \sum_{\forall S^{/}} P_i[S^{/} \mid (S,A)]\Delta Q_i(S^{/})] \tag{3.4}$$

where, $\Delta \in \{\text{EE, UE, RE}\}$ and $P_i[S^{/} \mid (S,A)]$ is the joint state transition probability of agent i from joint state S to the joint next state $S^{/}$ because of action A.

The Definition of CE [22] (i.e., Egalitarian equilibrium (EE) Utilitarian equilibrium (UE) and Republican Equilibrium (RE)) is given below.

Correlated equilibrium (CE): In *Correlated equilibrium* (CE) [29], each agent selects the joint action corresponding to the maximum of the $\Psi = \{\underset{\forall i}{Min}, \sum_{\forall i}, \underset{\forall i}{Max}\}$ of individual rewards given by.

$$CE = \arg\max_{A}[\Psi(Q_i(S,A)] \tag{3.5}$$

The correlated mixed strategy is given by

$$\beta = \arg\max_{\beta}[\Psi(\sum_{\forall A} \beta(A)Q_i(S,A)] \tag{3.6}$$

$\beta = \{\beta_i\}_{i=1}^{m},\ \beta_i : \{a_i\} \rightarrow [0,1]$ and $\underset{\forall i}{Min}, \sum_{\forall i}$ and $\underset{\forall i}{Max}$ are the operations for EE, UE and RE respectively.

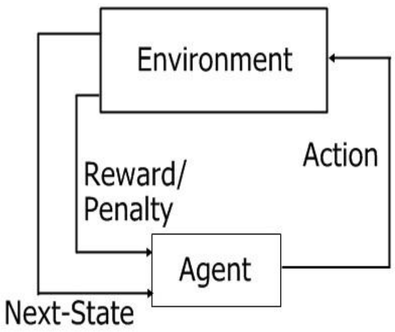

Fig.3.1. Reinforcement Learning block diagram

3.2.2 System Model

A group of SUs are forming a CRN. As indicated in Fig. 3.2, the network consist a primary network where more than one PU may appear which are using licensed channels. Each user operates in a half-duplex manner, which means SU cannot transmit any signal when it is receiving with another and vice versa. The total interference noise includes PU-to-SU interference, SU-to-SU interference, and the Additive White Gaussian Noise (AWGN).

The structure of environment where the cognitive radio users play an intelligent role is described below. A slotted time structure spectrum access is considered for SUs and PUs. The cooperative power control (CPC) is represented by a quadruple $\langle S, A, r, \Pr \rangle$ as described below.

3.2.2.1. State

A state of the CPC is the status of user channel either busy or ideal. The status of the channel is then reported to its neighbor, which includes cooperating SUs and the observations from the other PU signal. $s_i \in S^N = (I_i, a_i)$, I_i ε {0,1} is the information whether the received SNR (Signal to noise ratio) is greater than threshold SNR or not. If it is true then I_i =1, and the state is valid, otherwise I_i =0 and state is invalid for user.

3.2.2.2. Action

A discrete power profile is considered $p_i \forall i$ for agent $i \in [1, N]$ N is the number of cognitive users. $p^{\max}$ is the maximum power allotted for the cognitive users and $p^{\min}$ is the minimum power required for communication. The joint actions are considered, $a_i \in \times_{i=1}^{N} A_i = \{1, 2, 3 ... m_i\}$, m_i is number of available power level for i^{th} user.

3.2.2.3. Reward

A cognitive user uses a cognitive radio link between a pair of users. Here, $P = \left[P^{\max}, P^{\min} \right], \mu_i$ are the available power range and signal to noise (SNR) value of the i^{th} user respectively. The channel gain is g_{ij} between the transmitter node i and receiving node j for the link ij. The channel gain changes slowly with the changes of SNR. The SNR expression is given by

$$\mu_i(p_i) = \frac{p_i}{\sigma + \omega + \sum_{j \in N} g_{ij} p_i} \tag{3.7}$$

where σ is the Additive white Gaussian noise (AWGN) and ω the primary user interference for the cognitive user i. The main aim of the power allocation is to maintain that no user SNR should not fall the below threshold level, means that $\mu_i \geq \mu_i^*$ for successful transmission. μ_i^* is the threshold SNR for successful transmission.

Thus the reward function is the function of SNR value which means how many packets are received successfully per unit transmitted energy [11]. The reward function mainly measures the energy efficiency in terms of Mbps/mW of the transmitter and it is expressed as

$$r_i(p_i) = \frac{B\log_2(1+\mu_i(p_i))}{p_i} \tag{3.8}$$

3.2.2.4. Transition probability

The transition probability function is a mapping function given by

$$\Pr : S \times A \times S^{/} \rightarrow [0,1] \tag{3.9}$$

$\Pr$ is the transition probability from current state $s_i \in S_i \in S$ to the next state $s_i^{/} \in S_i \in S$ because of an action $a_i \in A_i \in A$. $\Pr$ is not known by users, so $\Pr$ as same as action selection probability, which is given below.

3.2.3 Proposed Algorithm

Based on the CPC model, the reinforcement learning algorithm learns the environment by iteratively choosing actions, receiving rewards, and deciding action selections with the objectives of maximizing received rewards without fall of SNR value for transmission.

In the following, action selection strategy is considered , state-action value updates for action evaluation and algorithm analysis.

3.2.4 Action selection strategy

The action selection strategy indicates the policy which the cognitive user adapts to choose an action and interact with the environment. Here, the softmax approach is employed based on Boltzmann distribution [12], [23] for individual user action selections. The action a_i is selected with a probability $\delta_i(s_i, a_i)$ at state s_i is given below

$$\delta_i(s_i, a_i) = \frac{e^{Q_i(s_i, a_i)/T}}{\sum_{j=1}^{|A|} e^{Q_i(s_i, a_i)/T}} \tag{3.10}$$

$Q_i(s_i, a_i)$ is the state action value (Q-value), which measures the quality of choosing an action a_i at state s_i. T is a parameter called temperature that controls the degree of exploration/exploitation. For large values of T, all actions can be chosen equally. In this case, the centre control detects the opportunities of more uncorrelated cooperating SUs to get higher detection probability in the future with large T. for small T, the action with maximum Q value is favored. Hence, the agent exploits the current knowledge of best selections of cooperating SUs to get highest detection probability with small T. As a result, T remains a large value for exploration in highly dynamic environment [13]. To get the good convergence value in a certain number of episodes, a linear function is used for the value of T over episodes as follows:

$$T^t = T^0 - T^0 \times (t/\tau) \tag{3.11}$$

T^0 is the initial temperature and τ is total number of learning epoch.

3.2.5 State Action value update

The quality measure of action selection is done by a table which is known as Q table for all state-action pairs. The size of Q table is $|S| \times |A|$. It is used to store the Q values for each joint state s_i and because of joint action A_i. For each user there will be a separate Q table. There are separate Q-tables at joint state-action space for each cognitive user. The joint Q-value updated rule for agent *i* is given in (4).

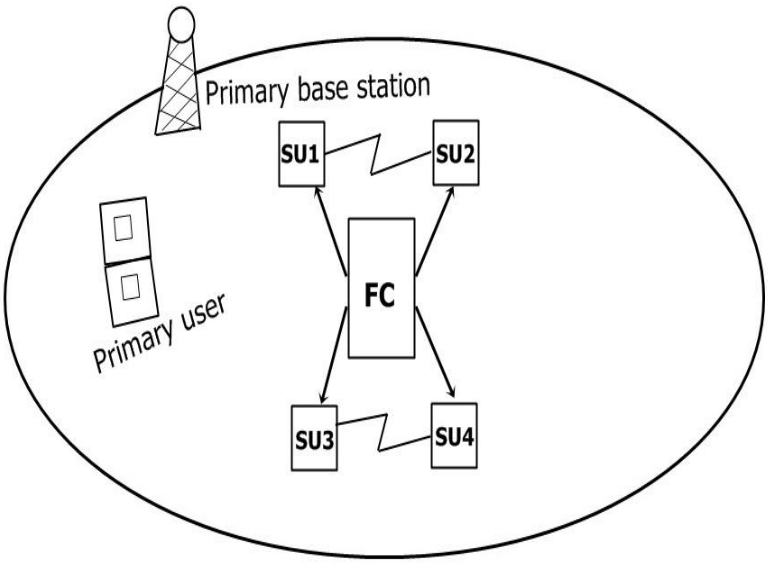

Fig.3.2. Cooperative control based Cognitive Radio Network

Algorithm 3.1

Cooperative power control in stochastic system employing multi-agent Q-Learning Algorithm
Input: discount factor $\gamma = [0,1]$, Learning rate $\alpha = [0,1]$ and, convergaence limit $\varepsilon \to 0$; **Output:** optimal Q value $Q_i^*(S,A), \forall i;$ **Initialization:** $Q(S,A) \to 0, \forall i;$ **Begin** Randomly choose a state $s_i, \forall i;$ Select action $a_i, \forall i$ by (3.10); Evaluate next state for agent i, $s_i^/, \forall i$ according to (3.10); Evaluate the SNR for agent i, μ_i by (3.7); **If** $\mu_i > \mu_i^*$ **Then** receive an immediate reward $r_i(S,A)$ by (3.8); **Else** $r_i(S,A) = 0;$ **Update** $Q_i(S,A), \forall i$ by (3.4); $Q_i^/(S,A) \leftarrow Q_i(S,A), \forall i;$ **Until** $\left\| Q_i^/(S,A) - Q_i(S,A) \right\| \le \varepsilon, \forall i;$ **end.**

The CPC algorithm (code is given in Appendix-A) adapts the state action value $Q_i(S,A), \forall i$ is given below. The algorithm begins with initialization of Q-values of the cognitive agents as zero, learning rate, discounting factor, convergence limit $\varepsilon \to 0$. It then selects an action a_i with a random action selection probability. Next it selects a joint state and action and updates Q-table and action selection probability until convergence is attained. The algorithm returns optimal Q-values of all agents, which are used later for best power selection for fixed channels at a given time.

3.3 SIMULATION AND RESULTS

In this section, the proposed and contender algorithm (epsilon-Greedy) is simulated to test the power management in cognitive radio networks. Also the convergence in terms of reward is mentioned.

3.3.1 Experimental Setup

Matlab is being used for experiments considering different values of discounting factor and learning rate in the range of 0 to 1. A 500 m $\times$ 500 m area is considered, where the users are distributed in maintaining uniform distance among themselves. The minimum distance between a transmitter and a receiver should not be more than 50 meter for successful data transfer. The cognitive users are sharing the same frequency bands as described in opportunistic spectrum access(OSA) approach, where the total shared bandwidth is B= 2 MHz. The total time slot is divided in duration of 10 ms. In each slot PU or SU can be present. The AWGN is a Gaussian noise, where $\sigma = 10^{-7}$ mW and one primary user are assumed having power level 200 mW. The maximum power is $p^{\max} = 600$ mW for all cognitive radio users. The gain between transmitter and receiver is maintained as constant throughout the all experiments.

The results are taken as expected average reward over 1000 episodes. Initially the starting state is chosen randomly. During the planning phase the optimal power transmission configuration is reached because of a mixed strategy in a single step.

Here, the convergence of expected average reward has been shown considering the variation of learning rate, discount factor and strategies. The cognitive radio users have 5 power level $\{100,\ 200,\ 300,\ 400,\ 500\}$ (action pool) and number of cognitive radio user is initially two and the threshold of SNR is 0 db.

3.3.2 Experimental Results

Optimal solutions of all the mixed strategies are further evaluated by the expected cumulative rewards, learning epoch and they are discussed below with figures and table.

3.3.3 Expected Average reward

The Expected Average reward (EAR) is the performance metric to analyse the cognitive radio network. It indicates that total number received packets at the receiver successfully per unit delivered power. The EAR reaches an upper bound after convergence of the algorithm. Two states are considered for each cognitive radio user in the experiments. Fig.3.3 indicates the simulation results of expected reward (ER) verses learning epoch with three types of mixed strategies (EE, UE and RE) employed in reinforcement learning. 1000 learning epoches are considered and only one agent as transmitter. The discount factor γ as 0.8 is chosen in the experiment and observe the result in different learning rate α.

In EE, it has been shown that after 400 iterations the learning algorithm converges and expected reward reaches its highest value of 1.51 with α=0.9. As α decreases, the expected reward decreases, because of more exploration rate though better power level is achieved. It is observed that using the mixed strategy (EE) the algorithm converges faster than the contender algorithm (epsilon-Greedy) for multi cognitive radio users in the stochastic environment. In other two mixed strategies (UE and RE) converge within 200 iterations, so exploration cannot dominate the exploitation. Hence, best power level is achieved faster than EE. However, all the strategies (EE, UE and RE) are giving better result in power management in stochastic environment.

Fig. 3.4, indicates the simulation results of the expected reward verses learning epoch for three mixed strategies (EE, UE and RE) employed in reinforcement learning. 1000 iterations are considered here and only one agent as transmitter and one for receiver. The result is obtained by fixing the learning rate α at 0.9 and varying the discounting factor γ in the experiment. It is observed that all the three mixed strategies converges within 150 learning epoch and the highest expected reward reaches its upper bound 1.86 at α=0.9. As γ decreases, reward also decreases, because of more exploration rate though better power level is achieved. Also the same conclusions are observed in Fig. 2.4 as it is observed in Fig. 3.3.

Fig.3.5 shows the simulation results of expected reward verses the primary user power in mW. Her, three SUs are considered in the experiment. The initial control parameters are taken as γ=0.8 and α=0.9. 1000 learning epochs are considered. It is observed that as the PUs power level increases, the expected reward decreases. PUs has higher priority than SUs. So, when PUs power level increase, each SU get a interference with PUs, and the reward indicates the packet receives at receiver decreases. The EE is considered for these experiments. The highest reward is 1.210 at Pus power level 100 mW, and the lowest reward is 0.100 at PUs power level 600 mW.

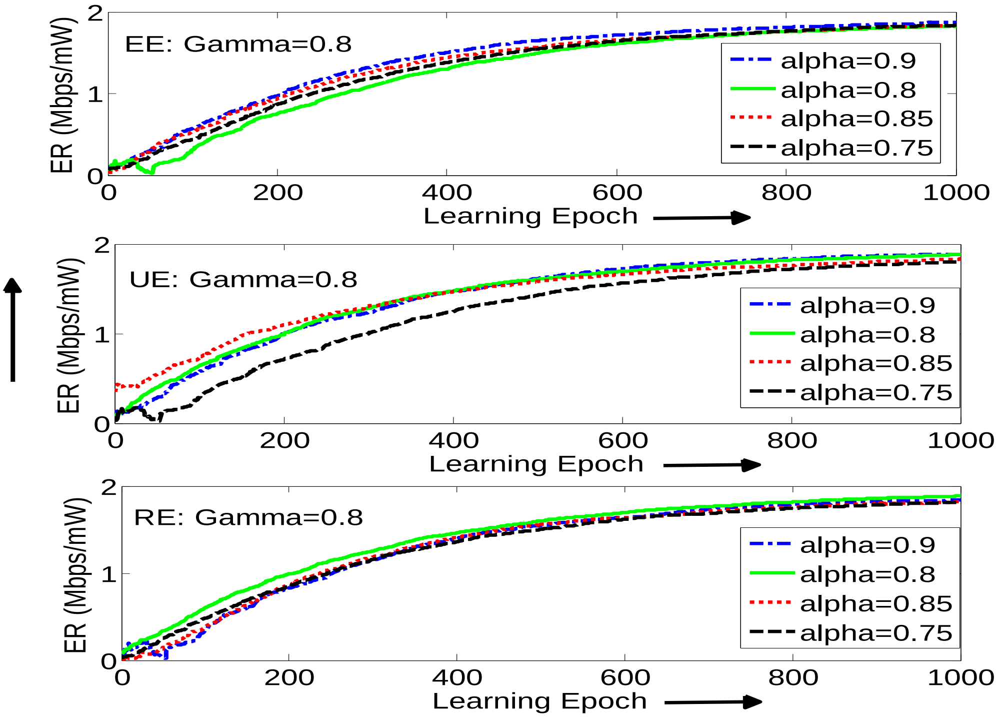

Fig.3.3. Expected Reward with vary Gamma in three mixed strategy.

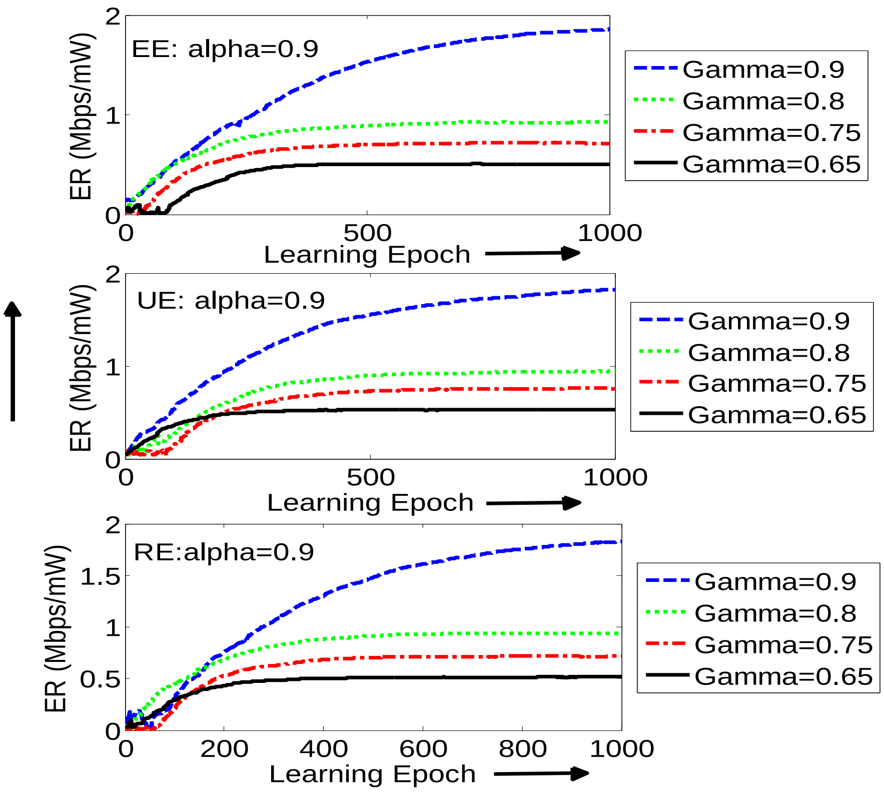

Fig. 3.4. Expected Reward with vary alpha in three mixed strategy

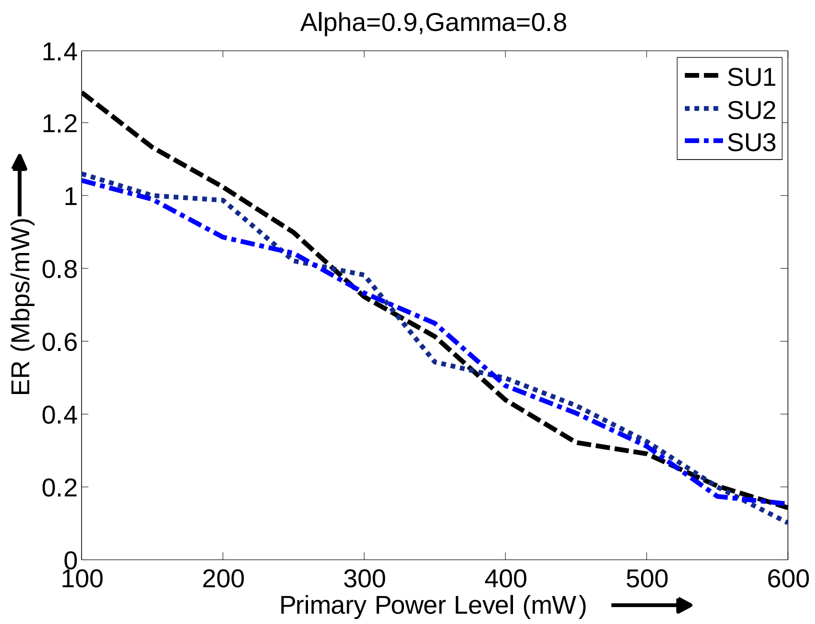

Fig.3.5. Variation of three Agents Expected Rewards with Egalitarian Strategy

TABLE 3.1

Performance Analyses of CPC Algorithm

Strategies	Epoch	Run Time (second)		Expected Reward (Mbps/mW)
		/ Epoch	Total	
Egalitarian	200	0.0183	180.13	1.78
Utilitarian	100	0.0198	198.34	1.88
Republican	200	0.0175	175.65	1.95
Epsilon-greedy	210	0.0191	207.96	1.69

The learning epoch is shown in Table 3.1. It is described as the converging number of epoch for Q learning algorithm in three strategies (EE, UE and RE) is less than the contender algorithm (epsilon-Greedy). As the algorithm converges faster than the contender algorithm (epsilon-Greedy) there is a good tradeoff between exploration and exploitation. The computation time is also less for using these strategies for power management in CRN.

3.4 Conclusions And Future Direction

In this chapter, a cooperative power management model is proposed in stochastic environment with multi agent reinforcement learning algorithm. It is done to maximize the energy efficiency with a method of machine learning technique. Three mixed strategies are compared in Q learning for multi users. Better convergence result is obtained in each experiment. The proposed multi agent RL algorithm is capable of converging to the optimal solution and is adaptable to the stochastic environment. Due to its learning capability, this work is extended to consider the movement of SUs, the change of PU models, and the data falsification problem such as learning the malfunctioning (noise) of SUs and the attacks of malicious users that compromise the accuracy of cooperative power management.

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Chapter 4

Brain Signal Processing and Classification for Design of Mind Driven Type Writer

EEG based vowel classification is currently gaining importance for its increasing applications in the next generation mind-driven type-writing. This chapter addresses a novel approach to classify the mentally uttered alphabets in a specific three lettered format, where the first and the last letter represent two vowel sounds and the middle is a space, where no character is imagined. Such formatting helps recognizing 26 alphabets in English language using seven vowels sounds only. To eliminate the possible infiltration of noise by parallel thoughts a specialized neuro-fuzzy classifier is used, where the first layer of the classifiers realized with fuzzy logic eliminates the possible creeping of noise due to side active channel interference. Two models of fuzzy pre-processing are used. The first one is realized with type-1 fuzzy logic, whereas the second model is realized with interval type-2 fuzzy sets. The latter model can take care of both intra- and inter-personal level uncertainty in measurements. Experiments undertaken reveal that the proposed type-2 fuzzy classifier outperforms both type-1 and traditional neural classifiers by a significant margin.

4.1 INTRODUCTION

4.1.1. Human Cognitive Communication

The human cognitive communication occurs from one brain to another. Human sensory and motor systems provide the natural means for the exchange of information between individuals. Most of the technological developments have focused on advancing human communication. From telegraph to the Internet, the primary means of these game-changing innovations has been to increase the range of audiences that an individual can reach. However, most recent methods for communicating are still limited by the words and symbols available to the sender and understood by the receiver. At the time of non-verbal content (as in the case of visual and auditory information), communication constraints can be severe. A great deal of the information that is available to our brain is not introspectively available to our consciousness, and thus cannot be voluntarily put in linguistic form. For instance, knowledge about one's own fine motor control is completely opaque to the subject [1], and thus cannot be verbalized. The recent development of brain-computer interfaces (BCI) [2-3] has provided an important element for the creation of brain-to-brain communication systems. Brain stimulation techniques are also now available for the realization of non-invasive computer-brain interfaces (CBI). These technologies, BCI and CBI, can be combined to realize the vision of non-invasive, computer-mediated brain-to-brain (B2B) communication between subjects [4-7]. Pseudo-random binary streams encoding words were transmitted between the minds of emitter and receiver subjects separated by great distances, representing the realization of the first human brain-to-brain interface. Electroencephalographic (EEG) device can be used to decode the signal from transmitter person and a non invasive Transcranial Magnetic Simulation (TMS) device to decode the modulated signal to receiver person brain.

The overview of this human brain cognitive communication is shown in Fig. 4.1.

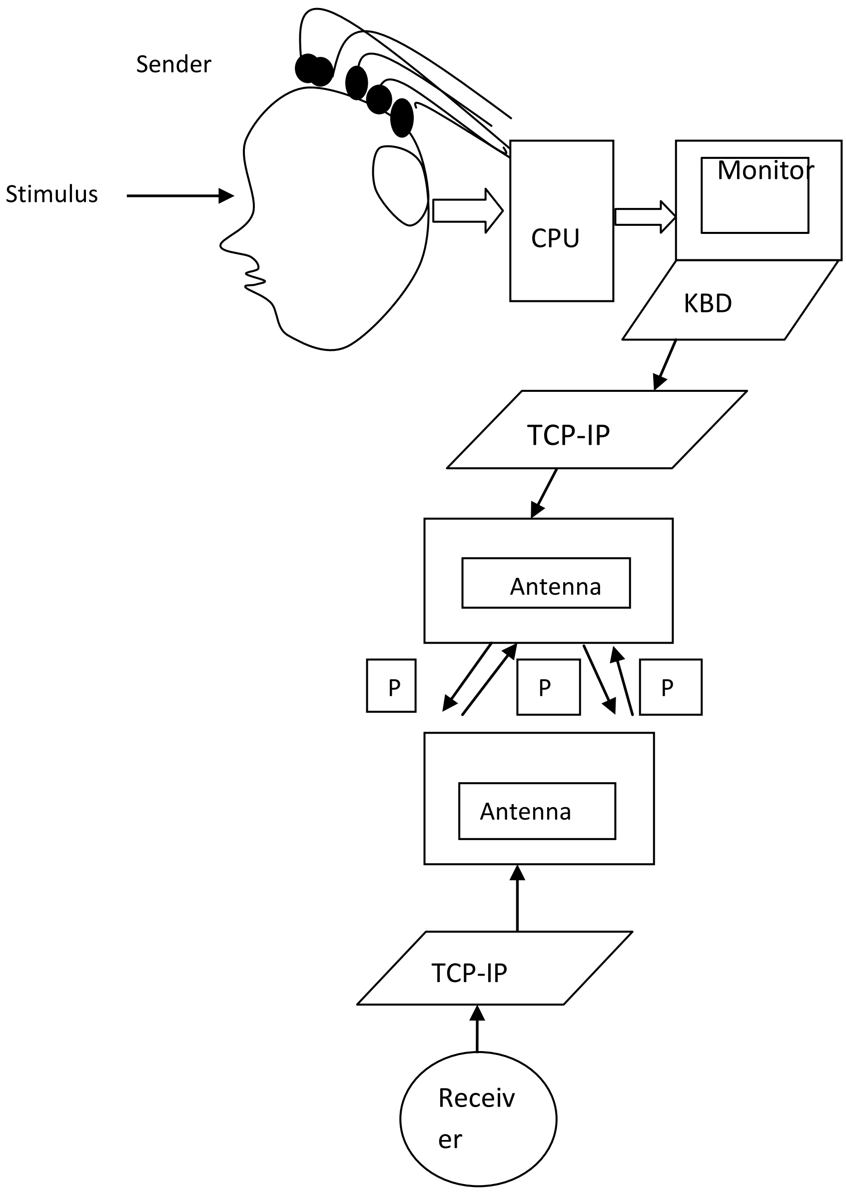

Fig.4.1. Overview of human and machine Communication

4.1.2 Supervised learning Using Neural Network

An artificial neural net is an electrical analogue of a biological neural net [8]. The cell body in an artificial neural net is modeled by a linear activation function. The activation function, in general, attempts to enhance the signal contribution received through different dendrons. The action is assumed to be signal conduction through resistive devices. The synapse in the artificial neural net is modeled by a non-linear inhibiting function, for limiting the amplitude of the signal processed at cell body. Artificial neural nets have successfully been used to recognize objects from their feature patterns. For classification of patterns, the neural networks should be trained prior to the phase of recognition process. The process of training a neural net can be broadly classified into three typical categories, namely, Supervised learning, Unsupervised learning, Reinforcement learning. The supervised learning process (Fig.4.1, Fig 4.2) requires a trainer that submits both the input and the target patterns for the objects to get recognized. For example, to classify objects into "ball", "skull", and "apple", one has to submit the features like average curvature, the ratio of the largest solid diameter to its transverse diameter, etc. as the input feature patterns. On the other hand, to identify one of the three objects, one may use a 3-bit binary pattern, where each bit corresponds to one object. Given such input and output patterns for a number of objects, the task of supervised learning calls for adjustment of network parameters (such as weights and non-linearity), which consistently [9] can satisfy the input-output requirement for the entire object class (spherical objects in this context). Among the supervised learning algorithms,

Most common are the back-propagation training [10] and Widrow-Hoff's MADALINEs [11].

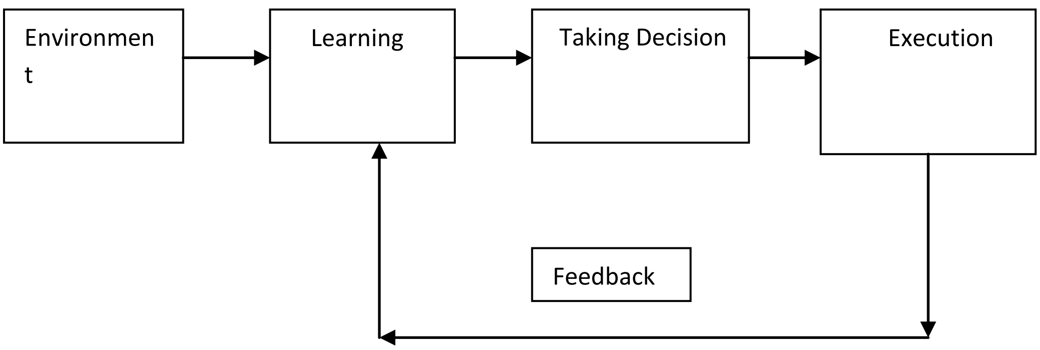

Fig.4.2. Overview of Supervised Machine Learning

In this thesis, this supervised neural network is employed to classify the brain signal acquired from EEG device. The brain signal processing is observed during imagery vowel sound classification experiment.

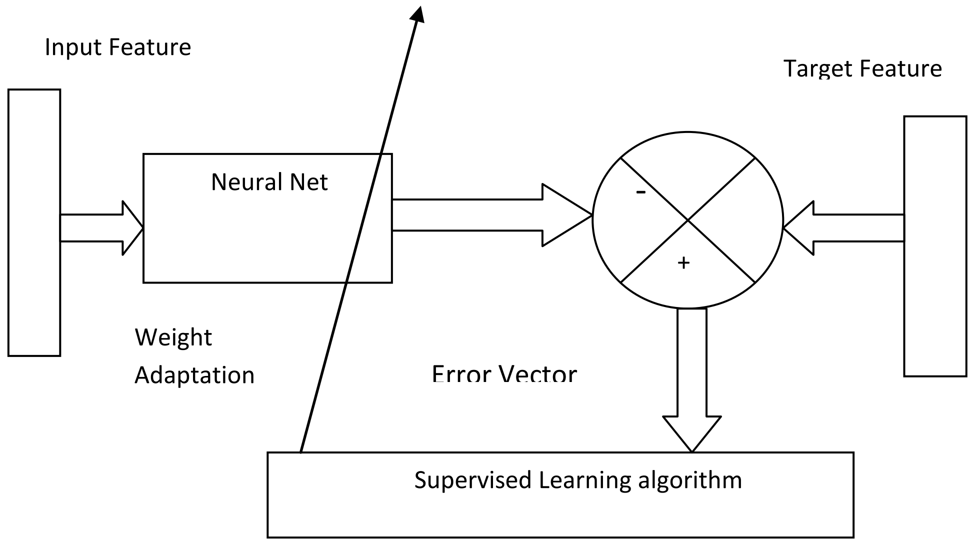

Fig.4.3. Neural Network Process

Mind-driven type-writing (MD-TW) is one of the cutting edge technological innovations of modern Brain-Computer Interfacing (BCI) [12]. Although commercial product level design of MD-TW is still far from reality, the innovations of MD-TW at research level cannot be denied. Previously, there exists various works on EEG based vowel/word classification. However, our proposed techniques and classifiers that have been used in this chapter are new. In a recent work by DaSalla [13], classification of imagery speech vowel ‘a’ and ‘u’ has been done using EEG signals, where common spatial pattern (CSP) is used to extract necessary EEG features. In addition, nonlinear support vector machine (SVM) is used for decoding the vowels, which gives an accuracy of 56-82%.

In another work by Iqbal *et al.* [14], EEG has been recorded to decode vowels ‘a’ and ‘u’, where variance, mean and normalized energy are considered as important features. Classification has been done using linear, quadratic and nonlinear SVM, where non linear SVM classifier outperforms with classification accuracy of 77.5-100 %. Besides the above two researches, some other works have done by Kamalakkannan *et al.* [15], Riaz *et al.* [16] and Kim *et al.* [17] need special mention. In [15] EEG features including variance, mean and standard deviation are extracted for five imagery vowels ‘a’, ‘e’, ‘i’, ‘o’, ‘u’, after which bipolar neural network is used for classification. In [16], large pools of EEG features are extracted using a variety of feature-extraction techniques using Mel Frequency Cepstral Coefficients (MFCCs) and log variance Auto Regressive (AR) coefficients. Classifier performance is compared between three standard classifiers: i) SVM, ii) Hidden Markov Model (HMM) and iii) k-nearest neighbor (k-NN). Experimental result reveals that their HMM attains the reasonably highest classification accuracy. Lastly, In [17], multivariate empirical mode decomposition (MEMD) [18] and common spatial pattern are used as feature extractor, whereas linear discriminant analysis (LDA) classifier is used to decode three vowels: ‘a’, ‘i’, ‘u’.

This chapter attempts to bridge the gap between the research and product level outcomes of this new device. The present work was inspired from an interesting biological observation that the vowel sounds are pronounced by controlling the tongue position inside the mouth and also the mouth-opening. This requires different motor actions in phases for pronouncing a different vowel sounds. Because of such variation in motor activity and their phasing, significant difference in the signals acquired from the parietal, temporal, and motor cortex region. In this chapter, we attempt to detect mental imagery of vowel sounds from the above three regions on the scalp. It is observed that EEG signals acquired during MD-TW of a normal and healthy subject have significant difference in features, and thus are easily separable.

The above principle works well for individual vowel sounds. To include consonants in print, a data dictionary is developed for each consonant represented by two vowel sounds in just-apposition. For example, A_A denotes one consonant, that includes two A and one space (blank) between the two uttering of A. Seven vowel sounds (A, AA, Aea, EE, UU, Ae, O) are presumed here. However, by combining two vowel sounds we can have as many as ${}^{7}C_{2}$ =21 consonants. Thus, 26 characters can be covered as consonant. The ultimate aim of the chapter is to design and develop a stand-alone mind driven type writer. The EEG signals acquired in 0.5 to 70 Hz would be used to classify an alphabet from a mental imagery of two vowel sounds separated by a space (no thought for vowels) to determine the intension about the desired alphabet. The proposed system should be smart enough to complete the classification of individual vowel sounds within an expected duration of 10 ms, so that the user does not have any trouble to complete the imagination task of a character within 30 ms, considering three time slots for a character, as introduced before.

The classifier to be designed should be able to classify seven classes (A, AA, Aea, EE, UU, Ae, O) based on input EEG features. The number of classes being fewer, apparently we can use any standard supervised learning classifier to serve the purpose. Experiments undertaken across different experimental instances on a subject and across different subjects, however, reveal that the feature variance within a class even for the same subject is high (on an average 20-30% of the feature mean). This calls for one level of normalization of features, which in this chapter has been performed using a fuzzy mapping of individual feature into a membership value in [0, 1]. Such non-linear mapping helps eliminating the effect of intra-subjective variations in features. Next normalized features are fed to the input of a 2-layered Radial Basis Function (RBF) neural net, where the RBF neurons are tuned to the mean feature vector of individual class. Naturally, when a feature vector matches with the tuned mean vector of a class then the RBF neuron triggers with an output close to one. Thus the right RBF neuron describing a particular class can be identified. The last layer in the RBF neural net is designed with perceptron neurons. This layer is used to produce a binary encoded class for different mental imageries. The encoding is required to keep a few (three) neurons at the output layer.

Experiments have been undertaken to examine the performance of the proposed classifier with standard back-propagation classifier, recurrent neural classifiers and hierarchical support vector machine classifier. Experimental results envisage that the RBF based classification outperforms traditional classifiers by mean classification accuracy.

The chapter is divided into six sections. Section 4.2 introduces the overall system integration. In Section 4.3, the details are presented on classifier design. Experimental details are introduced in Section 4.4. Performance analysis is undertaken in section 4.5. Conclusions are listed in Section 4.6.

4.2 SYSTEM OVERVIEW

This section introduces an overview of vowel classification technique using EEG signal analysis. The block diagram of the overall system is given in Fig.4.3. EEG signals are recorded from the electrodes placed on the scalp of human subjects, when they are asked to observe a set of visual stimulus, each containing one specific vowel sound. As the stimulus appears on the computer screen, subjects are advised to imagine uttering the vowel sounds.

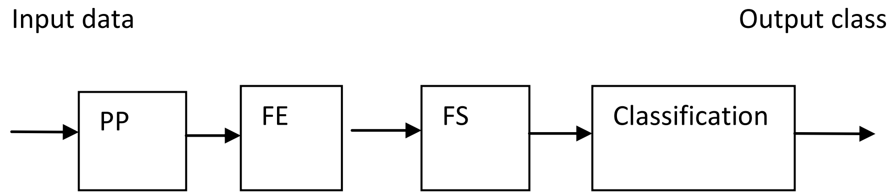

Fig.4.4. EEG based vowel classification analysis: PP is Pre-Processing, FE is Feature Extraction, DPS is Data Point Selection, FS is Feature Selection

First, the acquired EEG signals are pre-processed (PP)/filtered to remove eye-blinking artifacts and other line noise. Next, the pre-processed signal is used to extract its independent features by using Feature extraction (FE) technique [26]. In this chapter, Approximate Entropy (ApEn) [19] and Power Spectral Density (PSD) [20] are used as important features. Since, all extracted features do not contain important information; Principal Component Analysis (PCA) [21] is applied to select most significant features as well as to remove the unwanted features. Lastly, selected EEG features are applied to classify vowel sounds using two proposed methods: i) type 1 fuzzy radial basis function (RBF)[22] induced perceptron neural network (PNN)[23] and ii) type 2 fuzzy radial basis function (RBF) induced perceptron neural network (PNN).

4.3 Classifier Design

This section introduces the architecture of two proposed Neuro-fuzzy classifiers.

4.3.1 Model I

The first classifier, called Type-1 fuzzy-RBF classifier includes three layers. The first layer includes type-1 fuzzy membership functions (MFs) to process n dimensional features into n membership values in [0, 1]. Gaussian type MFs is used here, where the mean and the variance of the Gaussian MFs are obtained from the feature mean and variance for a given set of training samples for a given class. The second layer is an RBF layer, where the RBF neurons produce an output close to one, when the input feature vector for an unknown class component-wise matches with the mean vector of an RBF neuron. The response of the *i-th* RBF neuron is given by equation (4.1):

$$y_i = \exp\left(-\left\|X_i - \bar{X}_i\right\|\right)^2 \tag{4.1}$$

It is apparent from the RBF response that if $\bar{X}_i$ approaches to X_i, then y_i approaches 1. On the other hand, when the difference between the above vectors is component-wise large, y_i is small. Thus only one RBF neuron, whose mean vector matches sufficiently close to the input vector only triggers to produce an output equal to 1.

The third layer in the classifier includes 7 perceptron neurons with step type non-linearity. It produces encoded binary classes at the output of this layer. For instance, if the class is 6, it produces the binary code of 6 at the uses the binary code of 6 at the output. The schematic diagram of model I is given in Fig. 4.4.

4.3.2 Model II

The second model also includes three layers, where the first layer comprises interval type-2 fuzzy MFs (IT2FMFs) [25]. The second and the third layer are similar with that of Model I. The IT2FMFs layer in Model 2 helps in reducing both intra- and inter-personal level uncertainty, whereas the type-1 MF in Model-I takes care of intra-personal level uncertainty only. Construction of IT2MF largely depends on individual type-1 MFs obtained from individual subjects. In fact, the footprint of uncertainty is obtained by taking union of all the type-1 MFS. Let $\mu_A^1(f_i)$, $\mu_A^2(f_i)$, … $\mu_A^n(f_i)$, be the type-1 MFs obtained from n subjects for feature *i*, where the fuzzy set A represents CLOSE_TO the middle of the parametric range of variable f_i. The interval type-2 fuzzy set is defined by upper membership function (UMF) with equation 4.2 and lower membership function (LMF) with equation 4.3, where

$$UMF_i = \max_i \left\{\mu_A^1(f_i), \mu_A^2(f_i), \ldots\ldots, \mu_A^n(f_i)\right\}, \tag{4.2}$$

$$LMF_i = \min_i \left\{\mu_A^1(f_i), \mu_A^2(f_i), \ldots\ldots, \mu_A^n(f_i)\right\}. \tag{4.3}$$

Thus for m features, IT2FS with UMF_i and LMF_i for $i=1$ *to* m.

Now given an unknown measurement of the features:

$f_1', f_2', \ldots\ldots, f_m'$. The average degree of membership for the measured feature f_j' as (UMF_i + LMF_i)/2 is obtained. This average degree of membership is transferred to the input of all RBF neurons in the next layer. The schematic diagram of the proposed neuro-fuzzy classifier of model I and Model II are given in Fig. 4.4 and Fig.4.5.

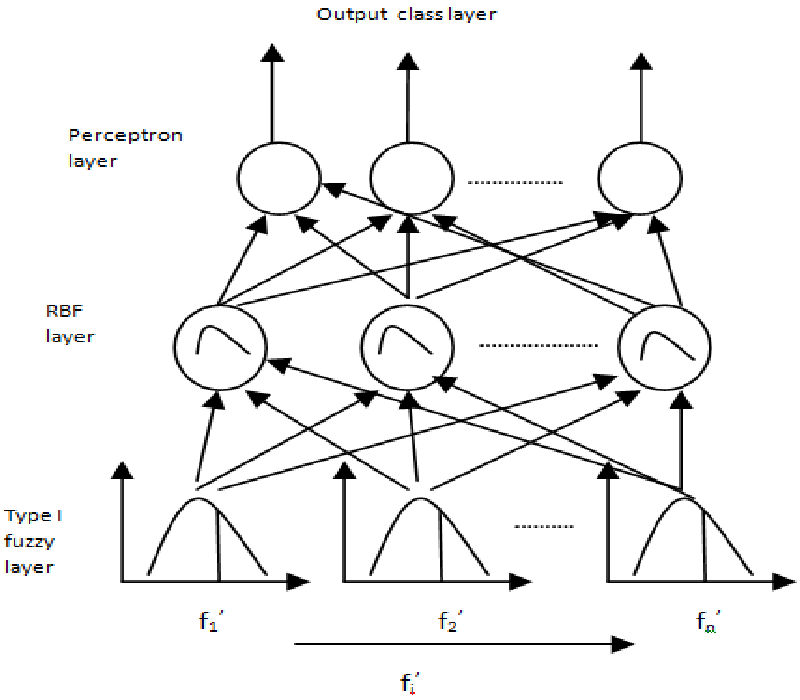

Fig.4.5. Schematic diagram of three layered Neuro-fuzzy classifier using model I.

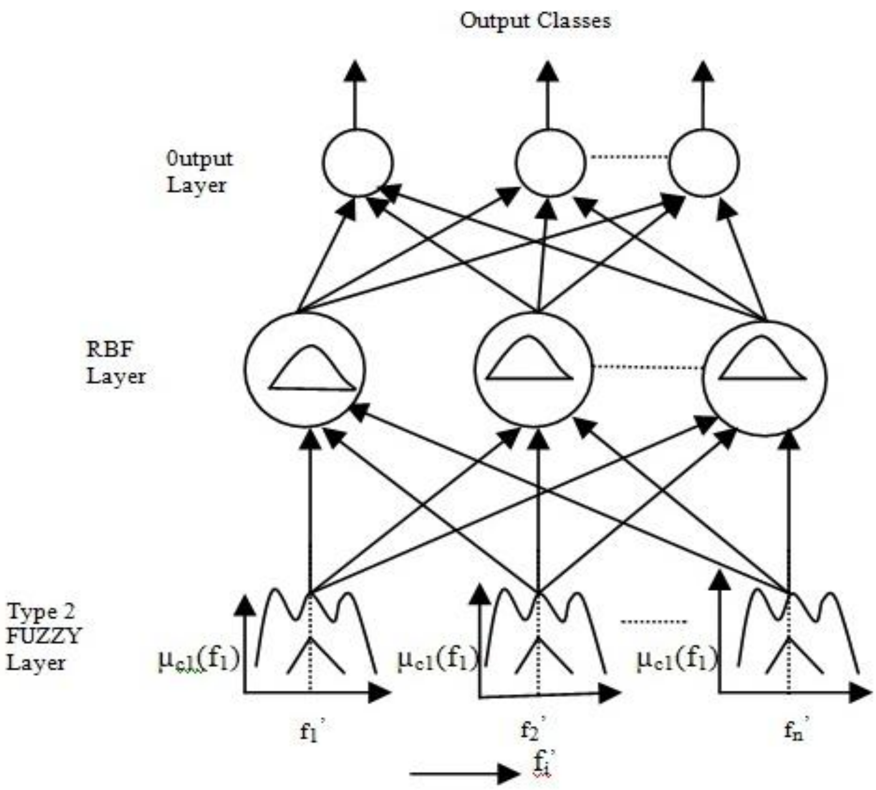

Fig.4.6. Schematic diagram of three layered Neuro-fuzzy classifier using model II

4.4 EXPERIMENTS AND RESULTS

This section includes two following experiments: i) selection of brain regions, ii) selection of EEG features.

4.4.1 Experimental framework

This section includes three following experiments: i) selection of brain regions, ii) selection of EEG features and iii) classifier performance.

The experiment has been performed at Artificial Intelligence Lab, Jadavpur University, where the framework includes a 21-channel stand-alone EEG device having a sampling rate of 200 Hz and resolution of 100μ (Fig. 4.6). Twelve volunteers with 10 healthy and normal and 2 patients suffering from ear-loss have participated in our said experiments. Of the 10 healthy normal subjects, 6 men and 4 women in the age group 22-35 years are selected. The two subjects with partial ear-loss are both men. They are advised to sit on a comfortable chair with armrest and restrict their movement to eliminate movement-related artifacts. Subjects are shown visual stimuli containing instruction to try to pronounce the specific vowel at a time.

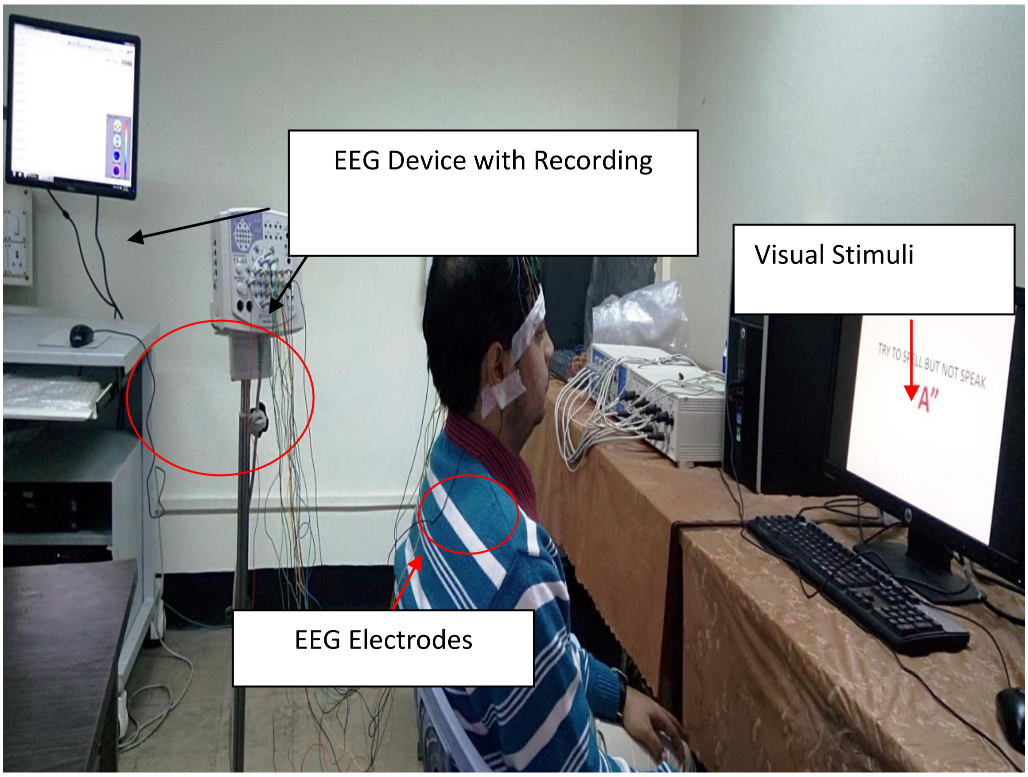

Fig.4.7. An Experimental set up: EEG signal acquisition from the scalp of human subject during experiment

4.4.1.1 Experiment 1:Selection of Brain Regions

EEG signals are captured from 21 electrode positions and are recorded on a separate computer having 8 GB RAM with CPU clock of 3.4 GHz. Fig. 4.7 shows the scalp maps of the two randomly selected subjects (here, S_4 and S_6), as have been recorded during the experiment. It can be observed from the Fig. that pre-frontal, motor cortex, parietal and occipital lobes exhibit significant activations during the experiment. Here, occipital lobe is found active because of the visual signal processing, whereas slight activation in the pre-frontal region is associative with eye-blinking. Besides these, parietal and motor cortex regions are found to take significantly active participation during the experiment. Additionally, literature [12-18] reveals that temporal lobe is highly associated with human speech signal processing. Therefore, P_3, P_4 and P_z (from parietal lobe), T_1, T_2, T_3, T_4, T_5 and T_6 (from temporal lobe) and C_3, C_4 and C_z (from motor cortex region) are used for extracting necessary information by applying signal processing techniques.

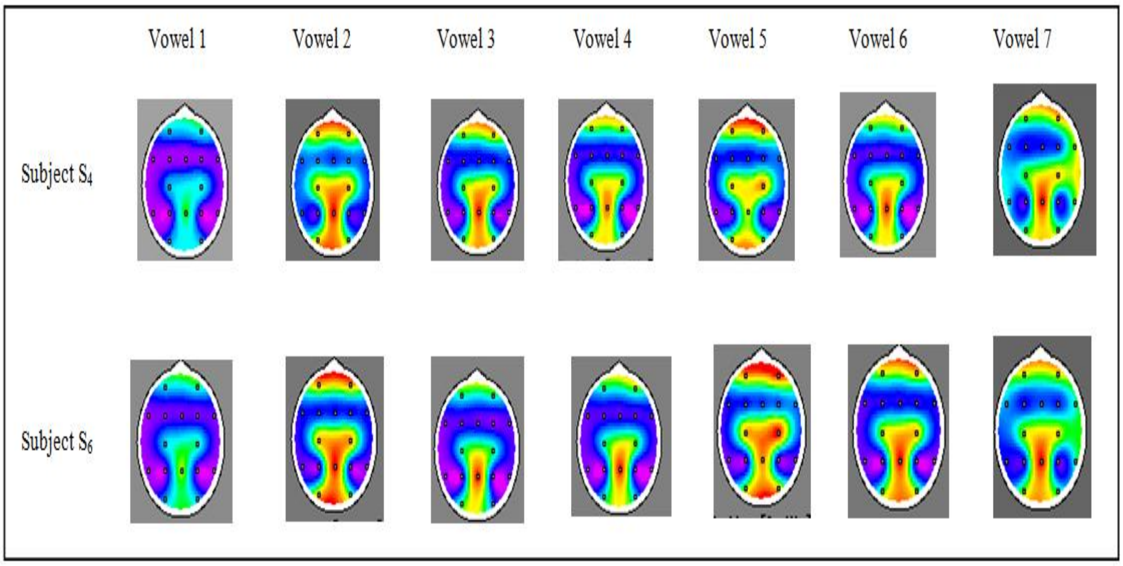

Fig.4.8. Selection of brain regions and frequency bands from scalp maps of subject S_4 and S_6 for all 7 vowel sounds

4.4.1.2 Experiment 2: Selection of EEG Features

Selection of correct features is important for EEG classification problem for accurate decoding of mental tasks. Literature reveals a variety of time domain (e.g., Hjorth parameters [24], Autoregressive parameters [27]), frequency domain (e.g., power spectral density) and time-frequency correlated (e.g., Discrete wavelet transform [28]) EEG features. To select the right EEG features for the present problem, first the EEG signal pattern are plotted which are recorded from the specific brain regions. Fig. 3.6 presents the raw EEG signal acquired from the temporal region during visual stimuli containing 7 different vowel sounds.

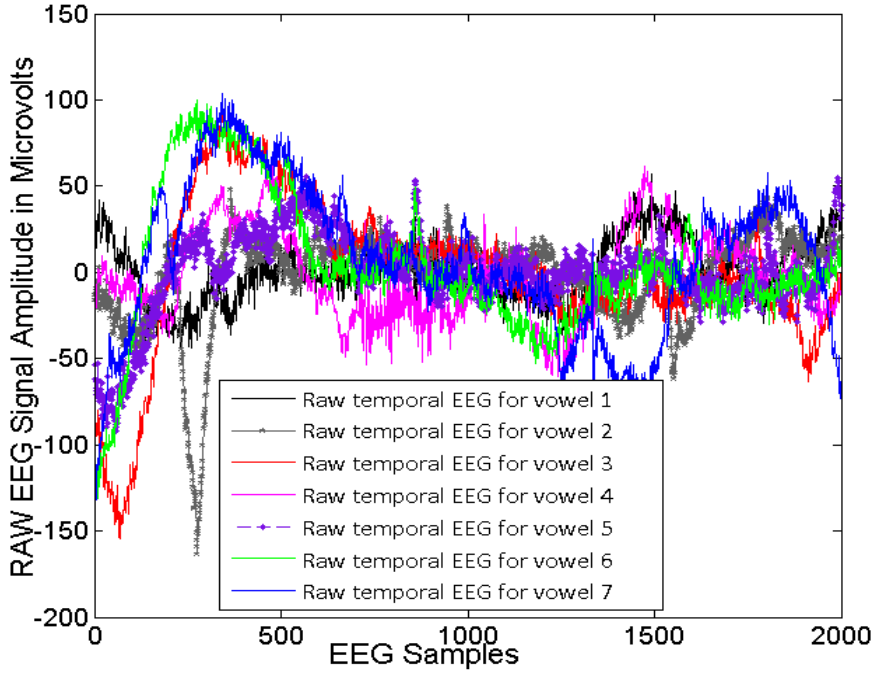

Fig.4.9. Raw EEG signal from temporal lobe during vowel sounds

It is important to note from Fig. 4.7, that EEG signal amplitude is enhanced at around certain EEG samples (here, around 250th sample) for every vowel sounds. Therefore, it is necessary to extract information that results in the rise in signal amplitude. Power spectral density (PSD), which is a well-known frequency-domain EEG feature to extract signal power distribution, is applied on the filtered EEG signal acquired from the parietal, temporal and motor cortex regions. Besides PSD, a special kind of EEG features is too extracted namely approximate entropy (ApEn), which can accurately quantify the unpredictable fluctuations of EEG samples. It is important to mention here that filtering of EEG signal is done by using a standard Elliptic band pass infinite impulse response (IIR) filter of order 4, which has the pass band frequency of 0.5-70 Hz. The selection is made so because of the superior performance of Elliptic filter as compared to its standard counterparts including Butterworth and Chebyshev[18]. Now, for each subject and each vowel sound, PSD and ApEn extract 10×12×253 and 10×12×1 feature sets respectively (since, here, experiment is repeated 10 times and number of selected electrodes 12). Fig.4.8, 4.9, and 4.10 present the PSD features extracted from the above brain regions.

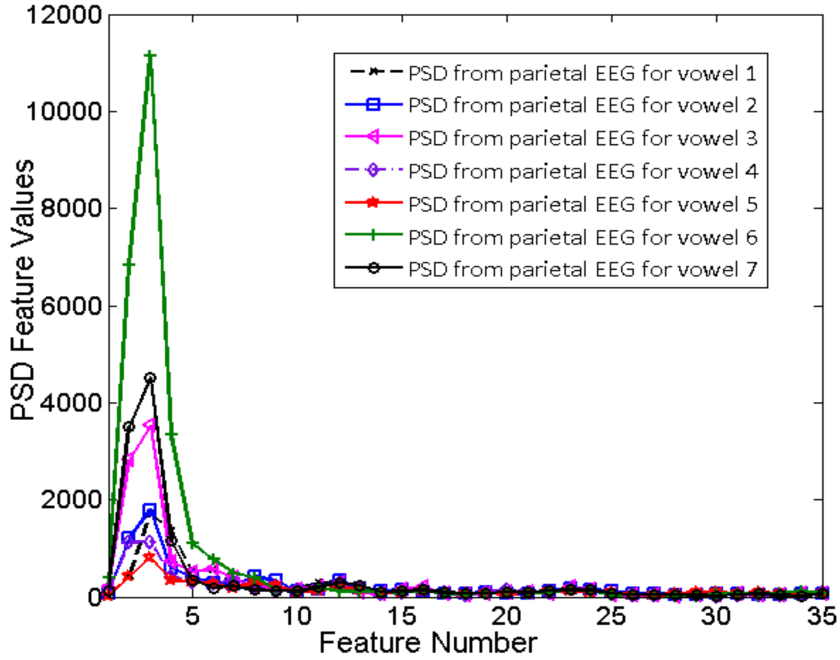

Fig.4.10. PSD features extracted from parietal EEG signals during 7 distinct vowel sounds

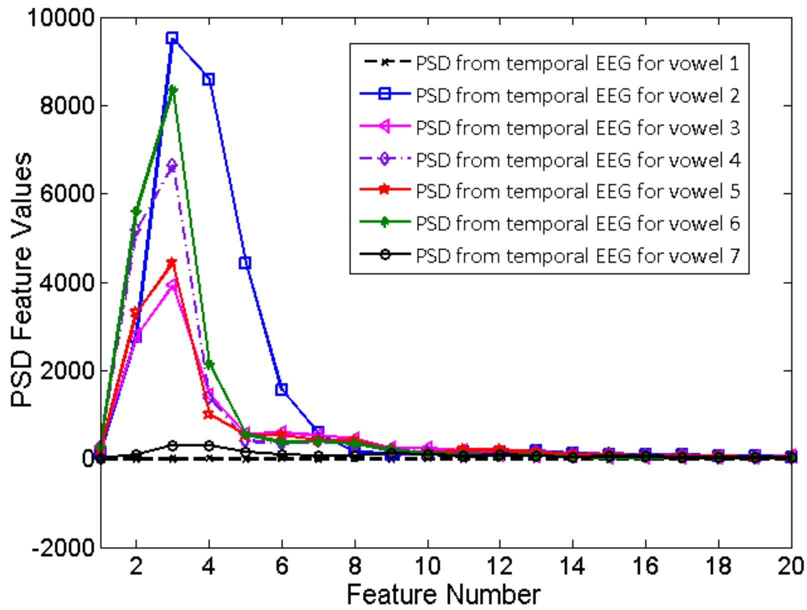

Fig.4.11.. PSD features extracted from temporal EEG signals during 7 distinct vowel sounds

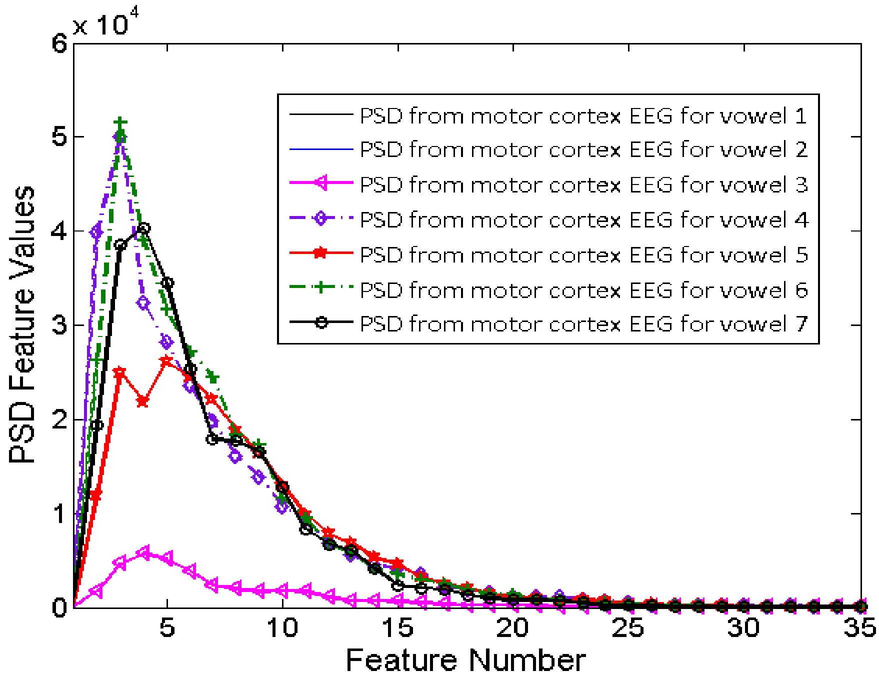

Fig.4.12. PSD features extracted from motor cortex EEG signals during 7 distinct vowel sounds

It has been observed from Fig.4.8, 4.9 and 4.10 that although PSD extracts 253 features for a particular vowel sound, only a fewer features (e.g., 3rd, 4th, 5th) can discriminate vowel sounds jointly. In this manner, 12 such features are obtained that can be fed to the classifier to decode the vowel sound.

4.4.1.3 Classifier Performance

The classification accuracy is examined of the proposed classifier techniques by observing i) individual class performance during the classifier training and ii) overall classifier performance during testing phase.

4.4.1.4 Individual Class Performance During Training

For individual class performance of different genres, the proposed classification algorithms are trained with 840 trials, one for each vowel sound, repeated ten times on each of 12 subjects. A standard ten-fold cross validation technique is employed to check the consistency of the data [29], where nine out of ten folds are applied for training purposes and the remaining one fold is used for the validation purposes. Table 4.1 provides the individual class performance of 7 vowel sounds.

Table 4.1

Classification Performance analysis with both two proposed model

Vowel Sound	Classification Accuracy (%) using Model 1 for			Classification Accuracy (%) using Model 2 for		
	Worst	Average	Best	Worst	Average	Best
Vowel 1(A)	62.50	74.16	80.33	70.83	79.16	91.66
Vowel 2(AA)	60.00	69.66	78.33	65.00	76.66	83.33
Vowel 3(AeA)	64.16	70.83	81.66	70.00	80.83	92.50
Vowel 4(EE)	63.33	68.33	77.50	71.66	75.33	90.80
Vowel 5(O)	61.66	73.33	79.16	69.66	82.50	89.16
Vowel 6(Ae)	65.00	76.66	82.50	73.33	87.50	94.16
Vowel 7(UU)	60.80	67.50	76.66	68.33	85.00	95.00

4.4.1.5 Overall Classifier Performance During Testing Phase

To study the relative performance, the following two standard classifiers are considered: 1) support vector machine (SVM) [30] and back propagation neural network (BPNN) [31] along with our two proposed methods. Table 4.2 provides the average percentage classification accuracies, where from it can be concluded that the proposed model II outperforms the existing BPNN, SVM and Model I by a significant margin.

Table 4.2

Proposed classifier comparison with existing standard classifier

Vowel Sound	Subjective Average Classification Accuracies (%) for			
	SVM	BPNN	Proposed Model 1	Proposed Model 2
Vowel 1(A)	71.66	74.16	74.34	79.43
Vowel 2(AA)	73.33	76.66	69.66	76.83
Vowel 3(AeA)	68.33	82.50	70.37	80.40
Vowel 4(EE)	65.00	75.83	68.76	75.33
Vowel 5(O)	65.33	77.33	73.52	82.54
Vowel 6(Ae)	67.50	82.50	76.66	87.50
Vowel 7(UU)	73.33	80.00	67.50	85.08
Consonant using Vowel-blank-Vowel format	63.33	71.66	68.33	74.16

Table 4.3 and 4.4 present the statistical test results by applying well-known McNemar's test[32] using model I and model II algorithms respectively. The z value in McNemar's test is given by the equation 4.4:

$$z^2 = \frac{\left(|m-n|-1\right)^2}{m+n} \tag{4.4}$$

Table 4.3

Statistical performance test for Model I algorithm with McNemar's Test

Classifier name	McNemar's constant (m)	McNemar's constant (n)	z	P
SVM	6	12	1.14	<0.0001
BPNN	7	10	1.45	<0.0012

Table 4.4

Statistical performance test for Model II algorithm with McNemar's Test

Classifier name	Mcnemar's constant (m)	Mcnemar's constant (n)	Z	P
SVM	4	17	2.61	<0.0006
BPNN	5	21	2.94	<0.0017

From Table 4.3 and 4.4 , *z* value describes that our proposed model I and II outperform the above two standard classifiers with a wider margin.

Table 4.5 shows Friedman test [33] performance using the proposed algorithms: Model I and Model II. Based on Friedman test, if there is $x_{n\times t}$ data, where *n* is number of samples and *t* is dimension of features, then the statistical measure *Q* is given by (4.5-4.9).

$$\bar{x}_t = \frac{1}{n}\sum_{i=1}^{n} x_{nt}$$
$$\bar{x} = \frac{1}{nt}\sum_{i=1}^{n}\sum_{j=1}^{t} x_{nt} \qquad (4.5\text{-}4.6)$$

$$Q_1 = n\sum_{j=1}^{t}(\bar{x}_t - \bar{x})^2$$

$$Q_2 = \frac{1}{n(t-1)}\sum_{i=1}^{n}\sum_{j=1}^{t}(x_{nt} - \bar{x})^2 \qquad (4.7\text{-}4.8)$$

$$Q = \frac{Q_1}{Q_2} \qquad (4.9)$$

From Table 4.5, it can be concluded that our proposed Model I and Model II algorithms also provide superior performance than SVM and BPNN in Friedman test.

Table 4.5

Statistical performance test for Model I and Model II algorithm with Friedman Test

Classifier name	Q	P
SVM	5.64	0.002
BPNN	5.02	0.012
Model I	3.28	<0.0001
Model II	2.83	<0.0001

Table 4.6 describes the performance analysis of our model algorithms with previous existing methods. The model I, II classifiers outperform the other existing methods with a wider margin.

Table 4.6

Performance comparison with previous works

Methods	Accuracy (%)
DaSalla method(SVM)[2]	82
S.Iqbal (non linear SVM)[3]	77.5
Kamalakkannan(Bipolar NN)[4]	44
Our Model I and II	85-90

4.5 CONCLUSIONS

The Chapter to the best of the authors' knowledge is one of the early researches on mentally imagined alphabet classification using EEG as the modality. Classical fuzzy and IT2FS are induced RBF neural nets for classification of both vowel and consonant sound imageries using a three elemental codes, containing vowel, followed by a space, followed by a second vowel. The IT2FS induced RBF neural technique outperforms its type-1 fuzzy induced counterpart, BPNN and SVM classifier based classification by a significant margin. The work is also compared with existing works in classification accuracy, and the results are acceptable with reference to the present technology in EEG research and pattern classifiers.

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Chapter 5

Diffusion Dynamics Using Molecular Communication System

Inspired by biological communication systems, molecular communication has been proposed as a viable scheme to communicate between nano-sized devices separated by a very short distance. Molecular Communication (MC) is a communication paradigm based on the exchange of molecules. The implicit biocompatibility and nano-scale feasibility of MC make it a promising communication technology for nano-networks. Here, molecules are released by the transmitter into the medium, which are then sensed by the receiver. This chapter develops a preliminary version of such a communication system focusing on the release of either one or two molecules into a fluid medium with drift. A new diffusion dynamics is discussed between transmitter cell and the receiver cell when information means the protein molecules are encoded during transmission and decoded again inside the receiver cell in the time of release of the molecule. Simplifying assumptions are required in order to calculate the mutual information, and theoretical results are provided to show that these calculations are also applicable in practical cell diffusion.

5.1 INTRODUCTION

5.1.1 Biological Process

A process can be defined as a sequence of inter-related events involving multiple agents leading to an effective outcome. For example, product manufacturing, economical developments, various phenomena in biological and social sciences can be viewed as sums of different inter-related processes [1]. Biological processes are necessary for a living organism. These are consisting of different cellular and biochemical reactions inside living bodies. In other words a biological process can be defined as complex and inter-related phenomena involving sequence of events. Here, some of the important biological process can be mentioned that includes some obvious processes like respiration, osmosis, blood flow, digestion, absorption [2]. Including those mentioned above, some other bio-physiological processes are enlisted below.

Digestion: The physiological process by which food is break down into absorbable smaller entities. As for example the daily carbohydrate intakes are converted into mono and di-saccharides that is easily absorbed from intestine. The fate of proteins and fats produces almost similar outcomes.

Blood Flow: The dynamic process through which blood flows inside the human body through blood vessels..

Osmosis: The biological process in which molecules dissolved in body fluid passes from higher concentration to lower concentration according to concentration gradient considering some other physiological parameters..

Absorption: The process of uptake of molecules from higher concentration to lower concentration. The process of nutrient uptake into body follows the absorption process – nutrients (body fuels) get absorbed from the gastrointestinal tract after the completion of digestion process.

Adaptation: It is the process through a living organism changes its biological and environmental needs according to changing situation.

Agglutination: A process of combating antigenic molecules (bacteria, virus and other pathogens) by producing an aggregating clump of invading pathogens through antigen-antibody reaction. Agglutination is also useful to clot blood and preventing continuous bleeding.

Respiration: A process consisting of two sub process – inspiration and expiration. It is the most required biological process of gaseous exchange inside and outside of the body.

Carbon cycle: An organic cycle of carbon assimilation from the environment into organisms and back again to the environments.

Metabolism: As like respiration this process too consists of two different process – Anabolism and Catabolism. Anabolism refers to the energy gaining process and the process of new molecular synthesis whereas catabolism signifies the conversion of stored energy into externally usable entity. One example of catabolism is the process of thermoregulation (mostly specific for mammals including us) – the production of body heat.

Crossing over: A process of interchanging of chromosomal sections between pairing homologous chromosomes during the prophase of meiosis.

Glycogenesis: A process of conversion of excess body glucose in to glycogen that to be stored in liver (most profoundly) and other body parts for future use..

Heredity: The biological process whereby genetic factors are transmitted from one generation to the next generation. Genetic traits are transmitted from parents to child with the embedded codes of survival.

The important biological processes are shown in a pie chart below in Fig.5.1.

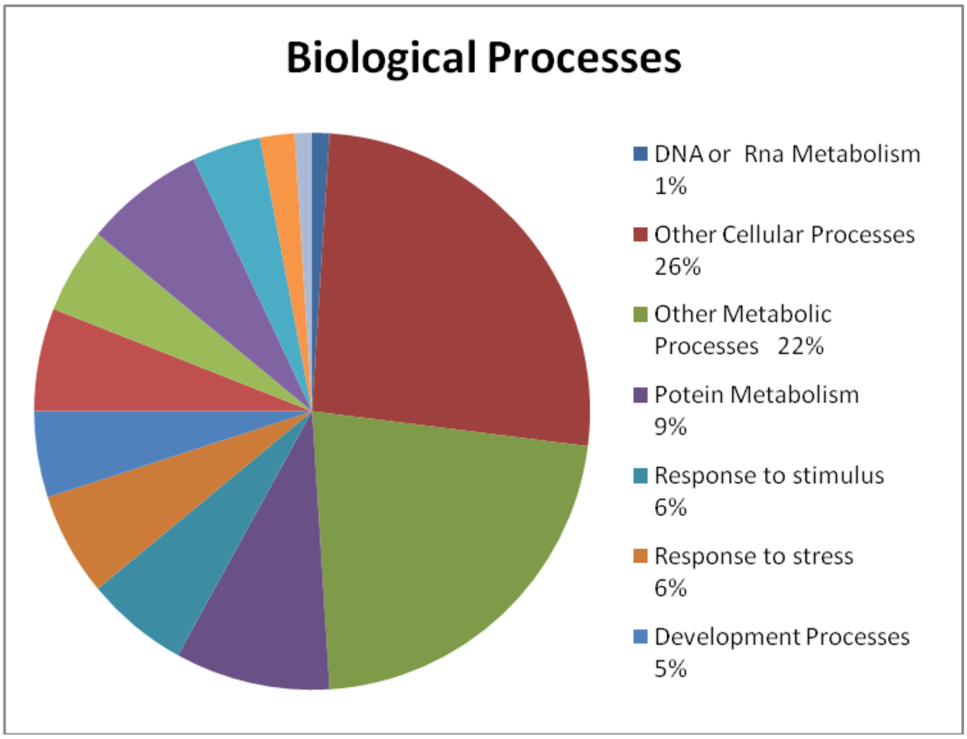

Fig.5.1. Different biological processes in a pie graph

The biological processes can be described as mathematical models for ease in analyzing the parameter values within it. It is beneficial to use mathematical models which facilitate the understanding of the experimental data in a systematic way and also in a less complex manner..

The mathematical biological process is given below in Fig.5.2.

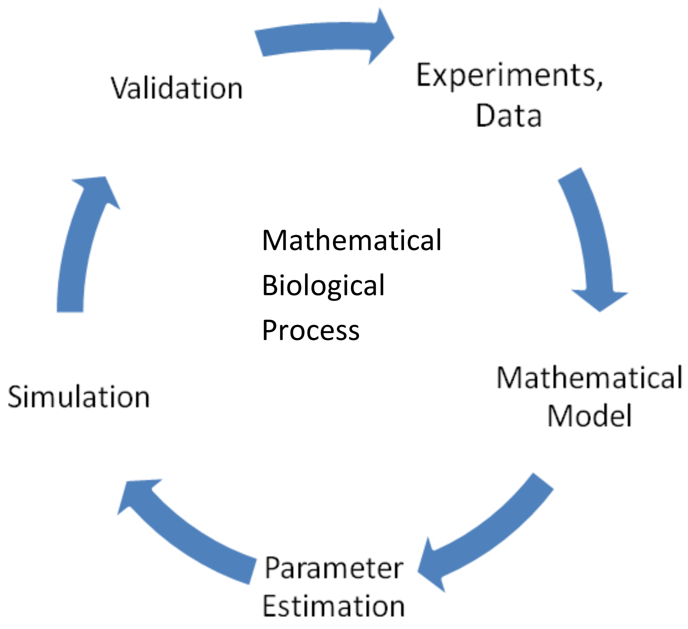

Fig.5.2. the mathematical model of biological processes.

5.1.2 Biological Communication

Molecular communication (MC) is a promising area for communication in biological cell, where the applicability of classical communication technologies is limited.

MC is based on the exchange of molecules, through which information is transmitted, propagated, and received. This approach well studied in biology since it is successfully adopted by cells for intra- and intercellular communication [6], where message-carrying molecules are synthesized, emitted, collected, and converted to cellular responses through biochemical processes.

Molecular Communication is a new interdisciplinary research area including the nanotechnology, biotechnology, and communication technology [7]. In nature, molecular communication is the most important biological function in living organisms to enable biological phenomena to communicate with each other. For example, in an insect colony, insects communicate with each other by means of pheromone molecules. When an insect emits the pheromone molecules, some of them bind the receptors of some insects in the colony and these insects convert the bound pheromone molecules to biologically meaningful information. This enables the insects in the colony to communicate with each other. Similar to insects, almost all of the biological systems in nature perform intra-cellular communication through vesicle transport, inter-cellular communication through neurotransmitters, and inter-organ communication through hormones [8].

In Molecular communication (MC), transmission and reception of information are realized through molecules, as it naturally occurs within the living organisms. The characterization of MC mechanisms, the definition of molecular channel models and the development of architectures and protocols for nano-networks are new challenges need to be solved in the research world. Communication based on electromagnetic waves, using either wired or wireless links, may not be directly applicable. Given the size of nano-machines, wiring a large quantity of them is unfeasible and, due to the size and current complexity of electromagnetic transceivers, these cannot be easily integrated into nano-machines. Only the development of nano-structures based on carbon electronics (e.g., graphene and carbon nanotubes) may be able to provide the ICT community with a new set of tools to develop tiny EM transceivers (starting with the development of nano-antennas, for example). However, the power consumption is still a problem to be solved. Regarding acoustic communication, it is the size of acoustic transducers why the transmission of ultrasonic waves among nano-machines is not feasible. In the case of mechanical communication among nano-machines, i.e., the transmission of information through linked devices at nano-level, it is clear that both their size and random deployment limit the usefulness of this approach.

The main aim of molecular communication is to characterize propagation of molecules (nano-scale particles) through the medium [9]. For MC the three main nano-network architectures are based on the type of molecule propagation. In the conventionalarchitectures, the molecules propagate through re-defined pathways connecting the transmitter to the receiver by using carrier substances, such as molecular motors [10]. In the flow-based architectures, the molecules propagate through diffusion in a fluidic medium whose flow and turbulence are guided and predictable. The hormonal communication through blood streams inside the human body is an example of this type of propagation of molecular information (hormones). An example of this MC architecture is given by pheromonal communication in an ant colony. In the diffusion-based architectures, the molecules propagate through their spontaneous diffusion in a fluidic medium [11]. In this case, the molecules can be subject solely to the laws of diffusion or can also be affected by non-predictable turbulence present in the fluidic medium. Example of diffusion-based architecture is Pheromonal communication. When pheromones are released into a fluidic medium [12], such as air or water Pheromonal communication happened. Another example of this kind of transport is calcium signaling among cells [13].

The architecture of this MC is shown in Fig.5.3. Disease control and infectious agent detection [14], smart drug delivery systems [15], bacterial bio film monitoring and control [16], and automated surveillance systems against biological and chemical attacks are among the potential practical applications of molecular communication [17-18]. Cognitive communication has to do with how a person or outside environment understands the world and acts in it. It is the set of mental or network abilities or processes that are part of nearly every action while the things are active. The cognition communication is two types. One is inside human and another is in outside environment.

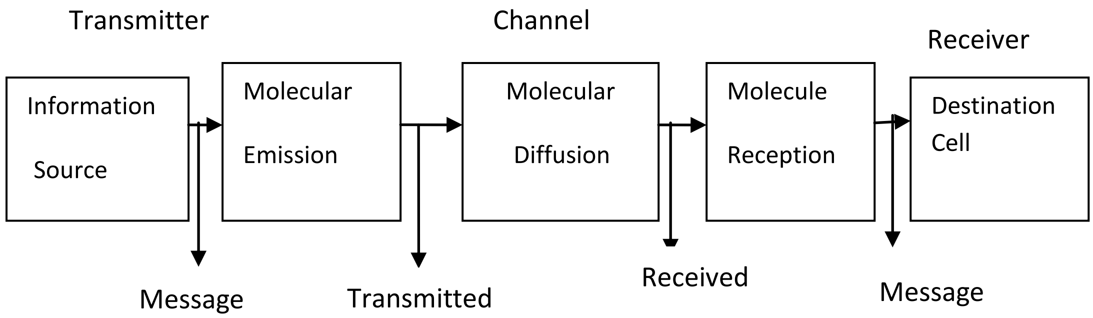

Fig.5.3. Diffusion based Molecular Communication Approach

A cell's most important activities are its interaction with the environment. Living cells are encased within a lipid membrane (also known as plasma membrane) contains protein passage-ways that permit specific substances to move in and out of the cell and allow the cell to exchange information with its environment. The movement or translocation of drug molecules across biological membrane (biological membrane spanning of average 10 nm) has the following underlying mechanisms – (a) passive diffusion, (b) career mediated diffusion which includes – facilitated diffusion and active transport, (c) phagocytosis and pinocytosis and (d) filtration. Polar compounds like sugar, amino acids and certain drug molecules of therapeutic interest cannot penetrate through membrane by passive diffusion but can only be moved by carriers present on the cell membrane. Career molecules bind with the drugs to form a complex and gets dissociated from the drug after transporting it to the inner membrane side and the career returns to its original site. Career mediated translocation of molecules need no energy [19] and translocate the substrate in the direction of electrochemical gradient [20]. As for example, the role of GLUT transporters can be considered as enhancing the transport of glucose across muscle cell membrane. Active transport is energy dependent and hence works against the concentration gradient [19].

Diffusion is considered as the mass transfer of individual molecules brought about random molecular motion and associated with a active driving force known as concentration gradient [21]. There are two kinds of facilitated diffusion - through career proteins and ion channels. Transmembrane proteins those are also known as permease are specific to bind a complementary molecule. On the outer membrane side (high concentration of ligands) the molecules bind to the carrier protein [22]. The carrier changes conformational shape, moving the binding site from one side of the membrane to the other to release the molecules on the inner side of the membrane (to the lower concentration) [23]. Ion channel proteins have gate to control the passage of substances across the cell membrane down their electrochemical gradient usually by ligands gated ion channels, voltage gated ion channels or intracellular messenger-gated ion channel [24].

Facilitated diffusion is regulated by following factors – (a) concentration gradient across cell membrane, (b) specific careers and transporters (receptors) availability, (c) available surface area for diffusion, (d) plasma membrane (cell membrane) thickness, (e) temperature sensitivity, as careers get desensitized at higher temperature, (f) time taken for the molecule to bind with the carrier protein, (g) affinity of the carrier protein for its substrate molecule. Some of the limiting factors in molecular transport after certain time window are mostly related to (a) competition of substances with structural similarity, (b) saturation which leads to a decrease in transport across the membrane, (c) inhibition or activation of transporter due to drug activity [20]. Molecular property of the diffusive molecules is also considered to be a major factor in molecular transport.

Diffusion of molecules through membrane is a process of considerable importance in pharmaceutical science. Many drugs need to pass through one or more cell membranes to reach their site of action. A common feature of all cell membranes is a phospholipid bilayer, about 10 nm thick, arranged with the hydrophilic heads on the outside and the lipophilic chains facing inwards. Spanning this bilayer or attached to the outer or inner leaflets are glycoproteins, which may act as ion channels, receptors, intermediate messengers (G-proteins) or enzymes. Facilitated diffusion produces a diffusion rate faster than passive diffusion alone. Examples of this process include the absorption of steroids and amino acids from the gut lumen. The absorption of glucose, a very polar molecule, would be relatively slow if it occurred by diffusion alone and requires facilitated diffusion to cross membranes (including the BBB) rapidly [25].

Human cells, including erythrocytes, are exposed to extracellular glucose concentrations that are higher than those inside the cell, so facilitated diffusion results in the net inward transport of glucose. When glucose is taken up by these cells it is rapidly metabolized, so intracellular glucose concentrations remain low (that produces a sink condition) and glucose continues to be transported into the cell from the extracellular fluids (blood, plasma). Conformational changes of the glucose transporter are reversible, so, glucose can be transported in the opposite direction simply by reversing the steps. Reverse transport of glucose occurs in liver cells, in which glucose is synthesized and released into the circulation [26].

Diffusion of drugs across biological membrane (cell membrane) is essential for a drug molecule to be absorbed, metabolized and eliminated. Most desired role of biological membrane in drug action is related to reaching the site of action [21]. The half-life of drug and the desired therapeutic concentration in blood and plasma depends on different molecular transport parameters and limiting factors those are mostly related to membrane transport. Passive diffusion of drug molecules cover less than 1 % of total diffusion where as ion channels are involved in the transportation of weakly acidic or basic drug molecules across the membrane.

A molecular communication model can be developed that can optimize the rate of diffusion across the cell membrane considering various regulating and limiting factors. Rate of diffusivity can be maintained in a controlled manner that will reach the desired molecular concentration that will help to maintain the bioavailability of a drug in body fluid, half life and therapeutic window.

There are several works in designing of MC network through diffusion process [27-36]. In work by Adam Noel [27], they design a diffusion based MC network and estimate the joint channel parameter using Fisher information matrix. In another work by Chun Tung Chou [28], they consider diffusion based MC system and design an optimal demodulator using Markovian approach and maximum posteriori probability. In another work by Sachin Kadloor [29], they develop a diffusion based MC network using Brownian motion with drift. They also calculate the mutual information between transmitter and receiver. Other work by Massimiliano Pierobon [30], their work provides the information capacity value in a freely diffusive medium. An analysis of the molecular achievable rate is done by B. Atakan [31] they consider a single instantaneous emission of molecules from the transmitter, a deterministic diffusion channel, and chemical model of the receiver, but effects of transmitted molecules concentration over time is not considered. A complete overview of MC is given in work by I. Akyildiz and by S. Hiyama in [32-36].

In our proposed work, a MC system is designed with a transmitter and receiver section, where the diffusion dynamics of propagation of molecule in blood medium are studied. A variable diffusion co-efficient is used during diffusion. This co-efficient is a function of concentration. A binary concentration modulation is employed encoding the molecular information, and then diffuse in blood medium with protein carrier ligand. At the receiver, threshold detector is used to decode the original molecular information. The channel diffusion dynamics is observed in our work.

The variations of concentration function over time due to variable diffusion co-efficient are observed.

The Chapter is divided into five sections. Section 5.2 introduces the overall system overview. In Section, 5.3 the details on diffusion dynamics is discussed. Experimental results are introduced in Section 5.4. Conclusions are listed in Section 5.5.

5.2 Problem Formulation

This section describes the overview of MC system and its components. The MC is analogous of general telecommunication system. Only the characteristics are different like signal types, speed, range and features. The Fig. 5.4 describes MC overview.

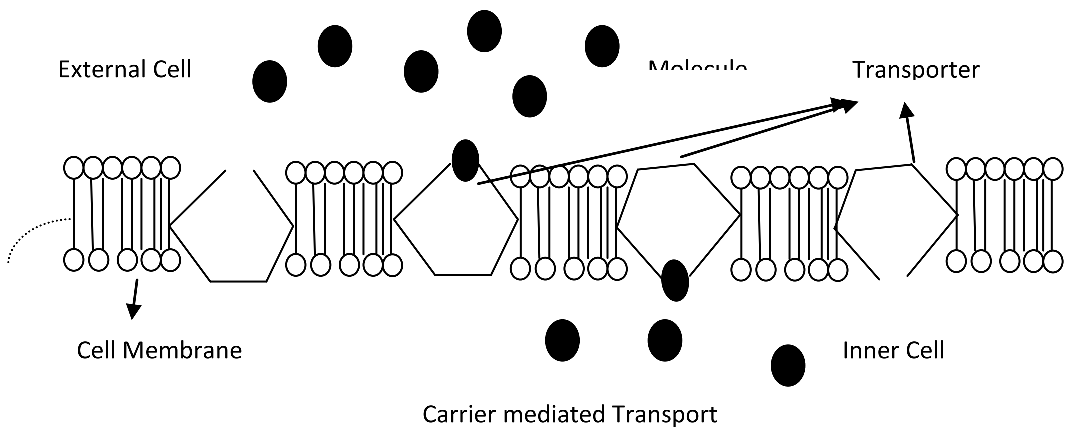

Fig.5.4. Molecular Communication Overview

5.2.1 Communication Model.

5.2.1.1 Encoding

Encoding is a process in which the information molecule is translated into other molecule. Encoding is done into communication process due to security of information. In biological system, encoding is also used during food or water molecule transformation from cell to cell.

In this work, glucose is considered as information molecule and Glut 1, Glut 2 protein as transporter. This protein is used as carrier of glucose molecule. The protein transfer glucose to another molecule through reaction. And it release glucose molecule at destination cell after propagation through blood medium.

5.2.1.2 Sending

Binary concentration modulation (BCM) is employed as modulation scheme. The carrier protein amplitude is varying with concentration of molecule released from source to the blood medium. Binary carrier protein molecule is used as carrier molecule. When information molecule concentration crosses the threshold, the protein carrier amplitude is one, otherwise zero.

5.2.1.3 Propagation

Propagation is a stage in which the molecule moves from source to destination cell. This propagation occurs through diffusion. The diffusion may be passive means without any chemical energy. The diffusion may be facilitated means diffusion with carrier protein. A facilitated diffusion model is assumed in this chapter.

After BCM, the information molecules diffuse through blood medium with carrier protein. A new diffusion dynamics is discussed here. The whole process is shown in a block diagram in Fig. 5.5.

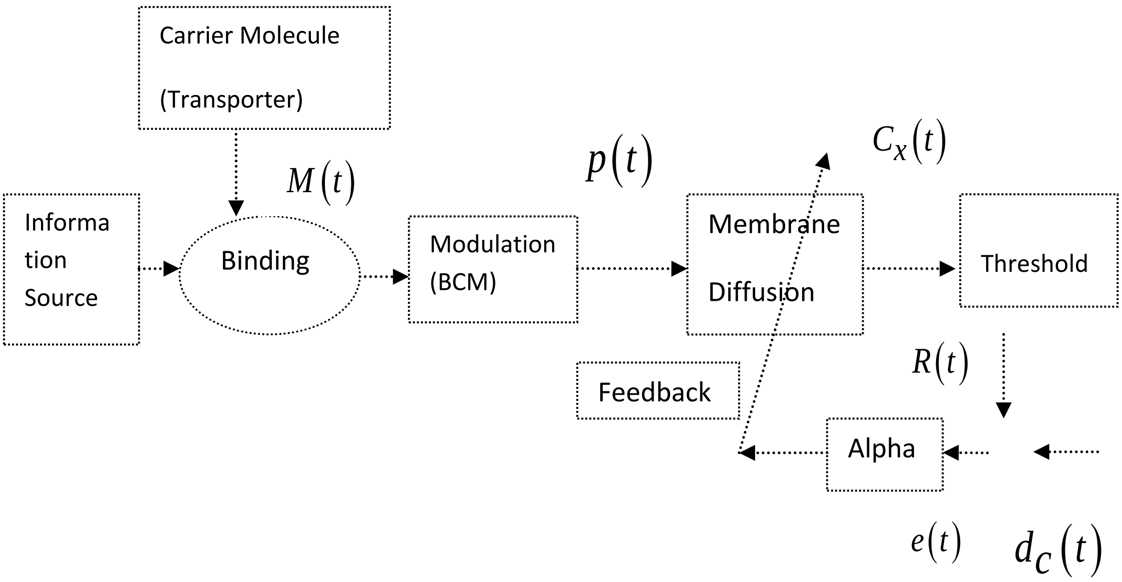

Fig.5.5. Communication model with diffusion Dynamics. $M(t)$ is message concentration, $p(t)$ is modulated carrier molecule concentration, $C_X(t)$ is diffused molecule concentration, $R(t)$ is received molecule concentration, $d_C(t)$ desired cell level

5.2.1.4 Receiver

Receiver is the destination of communication system. In this stage, the transmitted messages are captured into destination network.

Decoding of transmitted message is done in receiver system. And then original message is extracted at the receiver section. In our work, the diffused molecule is received at destination cell. Information molecule is extracted in receiver cell using a decoding process. Threshold detector method is used at the receiver section to demodulate the diffused molecule. The decoding process and demodulator process are described in next section.

5.2.2 Binary Concentration Modulation(BCM)

Digitized carrier signal is considered which depends on the concentration of transmitted molecule from source. If the concentration of transmitted molecule from source exceeds threshold τ, then the carrier amplitude is 1 otherwise 0. The meaning of amplitude of carrier molecule 0 is, the concentration of transmitted molecule from source is very low. That low concentration does not transmit due to noise in biological communication. The noise in biological communication is destroying of molecule due to reaction.

The modulation technique is shown below in Fig.5.6.

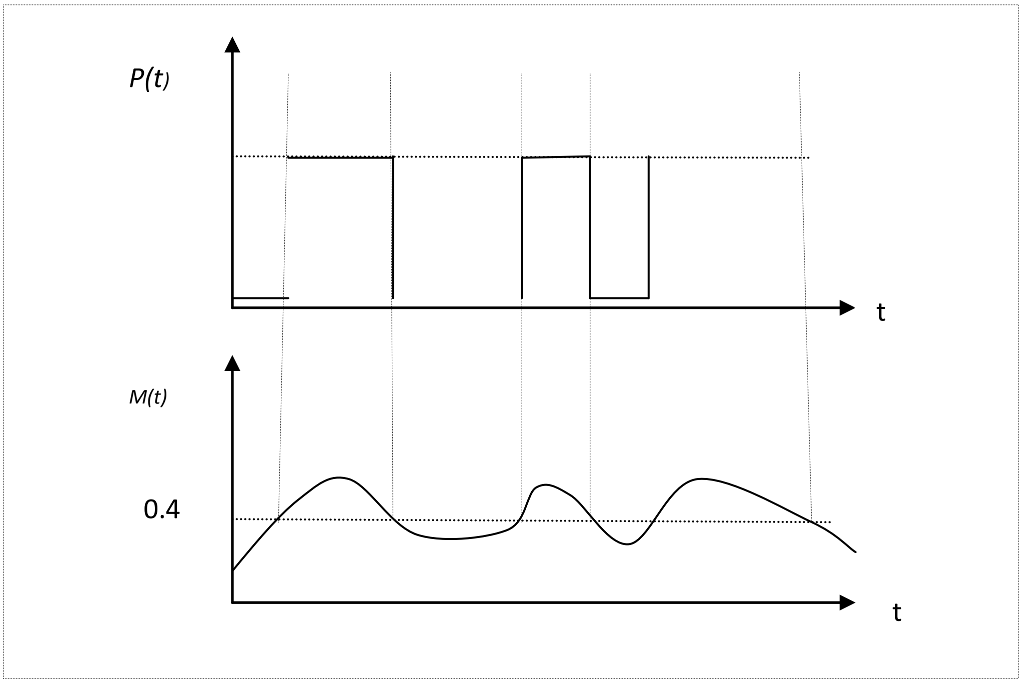

Fig.5.6. Concentration modulation graph, p(t) is carrier concentration, M(t) is normalized message molecule Concentration.

This modulated carrier signal is transmitted through blood medium with diffusion process. This carrier signal $p(t)$ is also a parameter of concentration of the diffusion medium.

5.3 Channel Diffusion Dynamics

A continuous time propagation model is assumed in Fig. 5.3. Our proposed diffusion dynamics is a feedback controlled diffusion mechanism. This feedback is sent from the destination cell. The feedback controls the diffusion damping behavior. Let $C_{ax}(t)$, $C_{bx}(t)$ are the concentration function of diffusion flow with variable time t and for a fixed length of diffusion x of two drug molecule A and B. Two drug molecules A and B are entering into a same cell through cell membrane from blood medium.

So, the change of concentration of molecules through cell membrane with time can be written as:

The concentration gradient = The outer cell membrane concentration - The inner cell concentration though carrier mediated diffusion $\pm$ the correction factor.

So, the change of concentration for drug molecule A

$$\frac{dC_{ax}(t)}{dt} = d_{ca} - C_{ax}(t) + f_a(t) \tag{5.1}$$

d_{ca} is the outer cell means blood medium concentration. It should be greater than inner cell concentration $C_{ax}(t)$ for forward diffusion otherwise reverse diffusion will start.

$f_a(t)$ is the correction factor, the controlling part of the diffusion.

$$f_a(t) = k_{fa}\, P_t\, M_{ta} - k_{ar}\, C_{ax}(t) + F_{fa}(t) + k_1\, C_{bx}(t)$$

(5.2)

$F_{fa}(t)$ = Rate of diffusion into the inner cell from the cell membrane of drug molecule A.

k_{fa} = binding reaction rate with protein carrier molecule at time t of drug molecule A.

P_t = modulating binary carrier signal, it is 1 when M_{ta} is greater than threshold τ, otherwise 0

M_{ta} = information molecule (Glucose) concentration at time t of drug molecule A.

k_{ra} = molecule release rate from protein carrier molecule at time t of drug molecule A .

$C_{ax}(t)$ = diffused molecule concentration at time t of drug molecule A.

k_1 is the factor that effect the binding of drug molecule A due to presence of drug molecule B.

Putting the value of $f_a(t)$ in equation (5.1)

$$\frac{dC_{ax}(t)}{dt} = -(1+k_{ar})\ C_{ax}(t) + k_1\ C_{bx}(t) + d_{ca} + k_{fa}\ P_t\ M_{ta} + F_{fa}(t)$$

$$\frac{dC_{ax}(t)}{dt} = -(1+k_{ar})\ C_{ax}(t) + k_1\ C_{bx}(t) + D_a + F_{fa}(t)$$

(5.3)

Where, $D_a = d_{ca} + k_{fa}\ P_t\ M_{ta}$ is a constant value at each instant of time t.

Similarly, the change of concentration for drug molecule B

$$\frac{dC_{bx}(t)}{dt} = d_{cb} - C_{bx}(t) + f_b(t)$$

(5.4)

d_{cb} is the outer cell means blood medium concentration. It should be greater than inner cell concentration $C_{bx}(t)$ for forward diffusion otherwise reverse diffusion will start.

$f_b(t)$ = It is the correction factor, the controlling part of the diffusion.

$$f_b(t) = k_{fb}\ P_t\ M_{tb} - k_{rb}\ C_{bx}(t) + F_{fa}(t) + k_2\ C_{ax}(t)$$

(5.5)

Putting the value of $f_b(t)$ in equation (5.4)

$$\frac{dC_{bx}(t)}{dt} = -(1+k_{br})\ C_{bx}(t) + k_1\ C_{bx}(t) + d_{cb} + k_{fb}\ P_t\ M_{tb} + F_{fb}(t)$$

$$\frac{dC_{bx}(t)}{dt} = -(1+k_{br})\ C_{bx}(t) + k_2\ C_{ax}(t) + D_b + F_{fb}(t) \qquad (5.6)$$

Where, $D_b = d_{cb} + k_{fb}\ P_t\ M_{tb}$ is a constant value at each instant of time *t*.

$F_{fb}(t)$ = Rate of diffusion into the inner cell from the cell membrane of drug molecule B.

k_2 is the factor that effect the binding of drug molecule A due to presence of drug molecule A.

Let the equation (5.3) and (5.6) can be written as the following

$$\frac{dC_{ax}(t)}{dt} = a_1\, C_{ax}(t) + k_1\, C_{bx}(t) + D_a + F_{fa}(t) \tag{5.7}$$

$$\frac{dC_{bx}(t)}{dt} = a_2\, C_{bx}(t) + k_2\, C_{ax}(t) + D_b + F_{fb}(t) \tag{5.8}$$

Where , $a_1 = -(1+k_{ar})$ and $a_2 = -(1+k_{br})$ in above equation.

Taking Laplace transform of equation (5.7) and (5.8)

$$(s-a_1)C_{ax}(s) = k_1\, C_{bx}(s) + F_{fa}(s) + \frac{D_a}{s} \tag{5.9}$$

$$(s-a_2)C_{bx}(s) = k_2\, C_{bx}(s) + F_{fa}(s) + \frac{D_b}{s} \tag{5.10}$$

Now, if the Rate of diffusion into the inner cell from the cell membrane of drug molecule B and molecule A are $F_{fa}(t)$ and $F_{fb}(t)$ respectively, be unit step and other else as shown in Fig.5.7 function. Where $c_a = (1+D_a)$

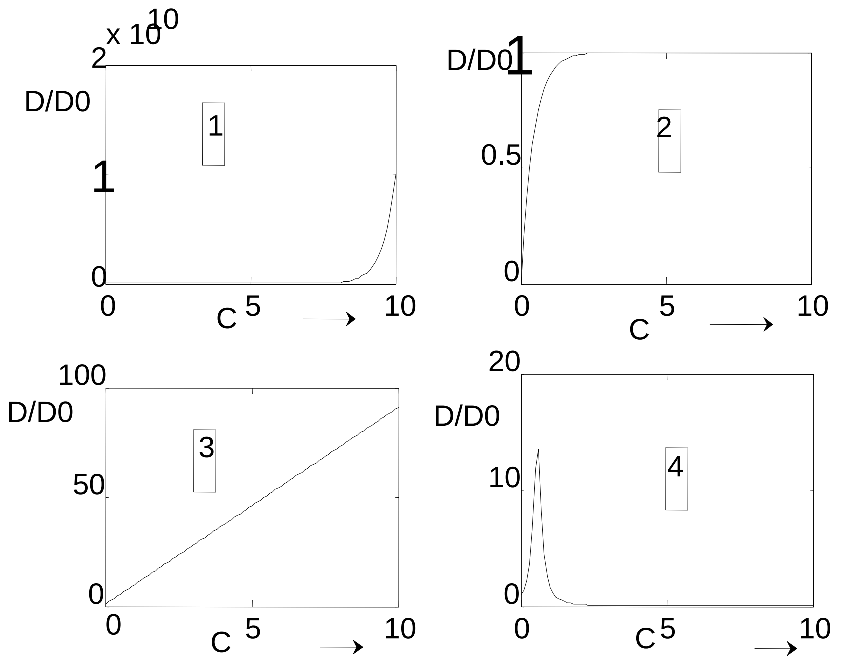

Fig.5.7. Different variable diffusion rate coefficient graphs

Now, the input case 3 is considered as a step input function.

Then equation (5.9) can be written as

$$(s-a_1)C_{ax}(s)=k_1\ C_{bx}(s)+\frac{1}{s}+\frac{D_a}{s}$$

$$(s-a_1)C_{ax}(s)=k_1\ C_{bx}(s)+\frac{c_a}{s}\quad\left[c_a=(1+D_a)\right] \tag{5.11}$$

Similarly, equation (5.10) can be written as,

$$(s-a_2)C_{bx}(s)=k_2\ C_{ax}(s)+\frac{c_b}{s}\quad\left[c_b=(1+D_b)\right] \tag{5.12}$$

Solving the two equation (5.11) and (5.12)

$$C_{ax}(s)=\frac{1}{s}\frac{c_a(s-a_2)+c_b\ k_1}{((s-a_2)(s-a_1)-k_1\ k_2)} \tag{5.13}$$

Similarly, $$C_{bx}(s)=\frac{1}{s}\frac{c_b(s-a_1)+c_a\ k_2}{((s-a_2)(s-a_1)-k_1\ k_2)} \tag{5.14}$$

The equation is a second order equation with unit step input function.

So, the characteristics equation is

$$(s-a_2)(s-a_1)-k_1\ k_2=0$$

$$s^2-(a_1+a_2)s+a_1\ a_2-k_1\ \mathrm{k}_2=0 \tag{5.15}$$

This is similar to second order characteristics equation,

$$s^2+2\ \delta\ \omega\ \mathrm{s}+\omega^2=0$$

Here, δ is the damping factor to control the over damping and under damping. ω is the natural frequency.

So, the condition for the under damped behavior is $\delta<1$

The condition for over damped behavior is $\delta>1$

The condition for critical damping is $\delta=1$

The value of δ in equation (15) is

$$\delta = \frac{-(a_1 + a_2)}{2\sqrt{(a_1\ a_2 - k_1\ \mathrm{k}_2)}} \tag{5.16}$$

Now, $a_1 = -(1 + k_{ar})$ and $a_2 = -(1 + k_{br})$ where k_{ar} and k_{br} is the drug molecule release rate of A and B respectively.

Considering, $k_{br} \to 0$ due to more concentration of drug molecule A and greater affinity of molecule A to protein transporter molecule. So, the condition for under damping condition is $k_{ar} < 2\sqrt{(k_1\ \mathrm{k}_2)}$

So, the equation (5.16) can be written as

$$\delta = \frac{-(a_1)}{2\sqrt{(k_1\ \mathrm{k}_2)}}$$

$$\delta = \frac{1 + k_{ar}}{2\sqrt{(k_1\ \mathrm{k}_2)}}$$

$$\delta = \frac{k_{ar}}{2\sqrt{(k_1\ \mathrm{k}_2)}} \qquad [k_{ar} >> 1]$$

So, the condition for under damping condition is $k_{ar} < 2\sqrt{(k_1\ \mathrm{k}_2)}$,

So, $k_{ar}(\mathrm{max}) = 2\sqrt{(k_1\ \mathrm{k}_2)}$

Now, different values of k_1 ,k_2 are applied and different stability systems graph of diffusion dynamics can be observed. The result is shown in next section.

5.4 Experiments and Results

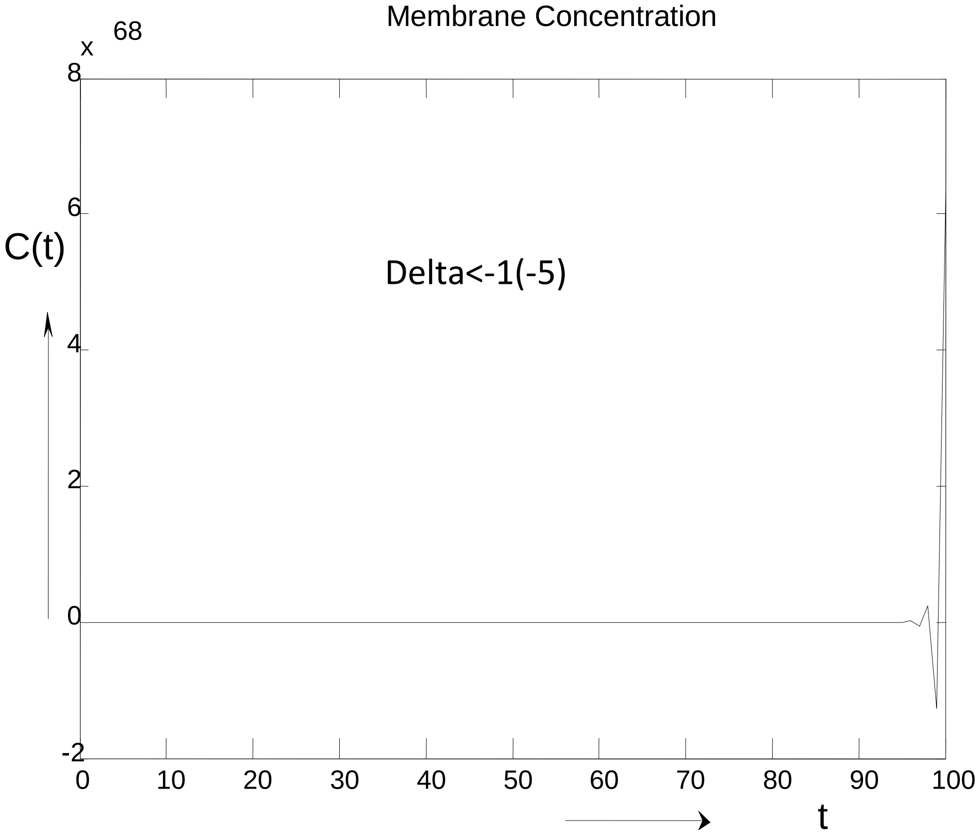

Fig.5.8. Concentration variation graph with time when root δ<-1

The results graph, Fig. 5.8 shows the concentration of the molecule in cell membrane due to diffusion. The parameter change in the solution of second order ordinary differential solution in equation (5.10) shows the different graphs.

When the control parameter Delta is below -1, then the concentration graph is unstable and it is oscillating after time epoch 90 ms, as shown in Fig. 5.8.

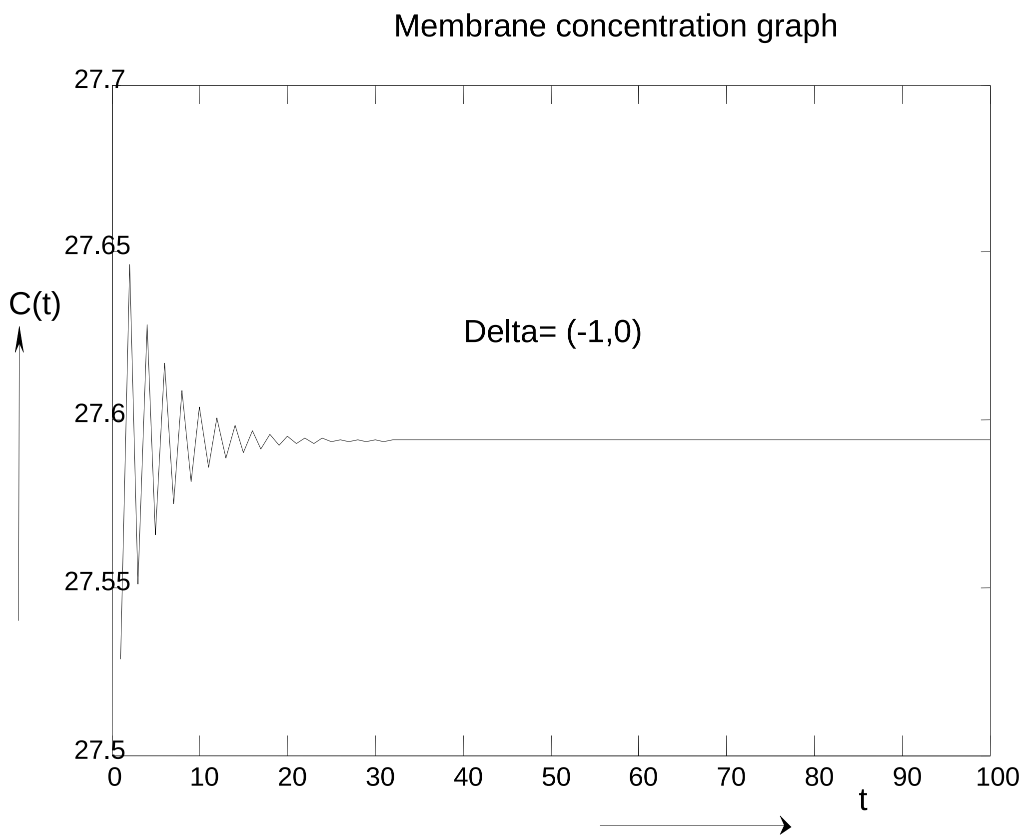

Fig.5.9. Concentration variation graph with time when root δ is (-1,0).

The results graph, Fig. 5.9 shows the concentration of the molecule in cell membrane due to diffusion. The parameter change in the solution of second order ordinary differential solution in equation (5.10) shows the different graphs.

When the control parameter Delta is between (-1,0), then the concentration graph is unstable and it is oscillating after time epoch around 0 ms, as shown in Fig. 5.9.

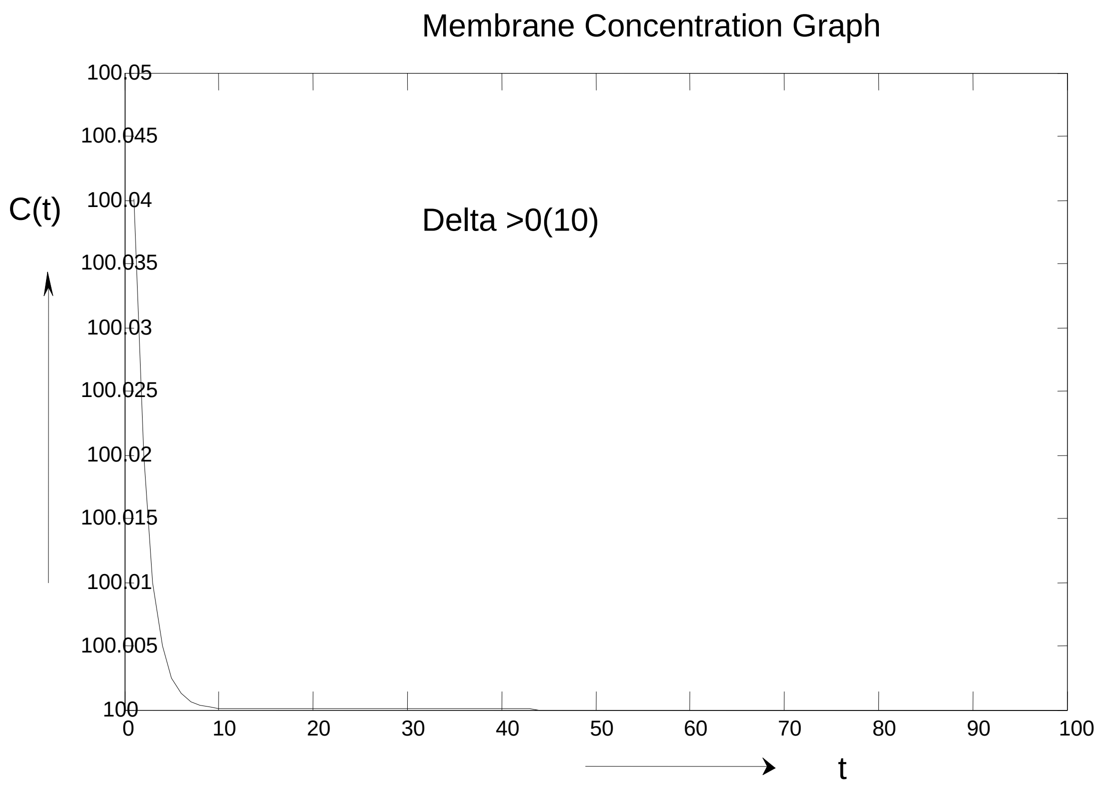

Fig. 5.10. Concentration variation graph with time when root δ is (0,1).

The results graph, Fig. 5.10 shows the concentration of the molecule in cell membrane due to diffusion. The parameter change in the solution of second order ordinary differential solution in equation (5.10) shows the different graphs.

When the control parameter Delta is between (0,1), then the concentration graph is stable and it is converging to 0 after time epoch 10 ms, as shown in Fig. 5.10.

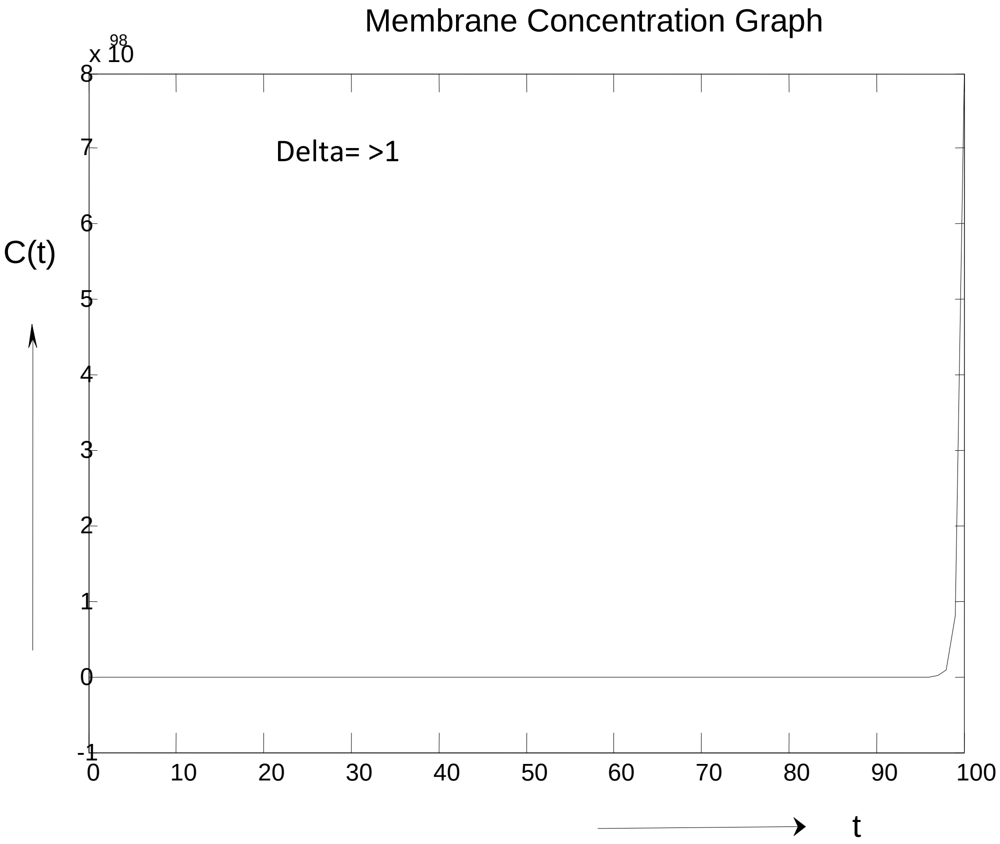

Fig.5.11. Concentration variation graph with time when root δ >1

The results graph, Fig.5.11 shows the concentration of the molecule in cell membrane due to diffusion. The parameter change in the solution of second order ordinary differential solution in equation (5.10) shows the different graphs.

When the control parameter Delta is above 1, then the concentration graph is unstable and it is diverging to infinity after time epoch 90 ms, as shown in Fig. 5.10.

5.5 Conclusion

In this chapter, a new diffusion dynamics is studied by us inside the biological cell. There are two critical points of control parameter, -1 and 1. The concentration rate can be controlled in fluid medium of biological cell using the control parameter. Practical proof of this diffusion dynamics can't be given so much in this chapter. Future direction is to apply this diffusion dynamics into practical data set of diffusion experiments.

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Chapter 6

Conclusions and Future directions

It can be concluded that from this thesis that, using machine learning technique several problems of and biological cognitive communication problem can be solved. New models are discussed in chapter 3, 4 and 5 in communication field. A better performance can be achieved using new models in cognitive and biological communication area. A brief introduction of cognitive processes and its stages are discussed in 2nd chapter.

6.1 Highlights of current research

In the third chapter, the most challenging problem of power optimization in CRN is solved using reinforcement learning technique. Cooperative learning process is used to learn the environment and efficiently choose a power band. It is shown in result that after some steps, learning stops and a saturation state occur, means optimal power spectrum is reached. Reinforcement learning shows an efficient learning and adaptation efficiency in this power allocation problem.

In the fourth chapter, a new classifier model is designed to perfectly classify the mentally imagery vowel sound. The communication path from human brain to external world machine is also shown in that chapter using EEG signals. EEG signals have fascinated researchers from different fields, whether for medical diagnostic purposes, design of rehabilitative brain computer interfaces or other interfaces that require or work well with brain signals. The concept of signal processing in human brain using EEG to evaluate a person's mental state or activities is well established. This thesis extends this idea to build the above interesting application. The classifier performance is very well to classify the brain computer interaction. The classifier accuracy is around 96% in this mental imagery vowel sound classification.

The last work done in this thesis is designing of a model of diffusion based communication in biological communication. The condition of stability for which diffusion through the cell membrane will be stable is derived. It is found that the stability value of the damping co-efficient remain between 0 to 1. Otherwise the model becomes unstable. A new modulation technique (Binary Concentration modulation) is used for communicate the protein carrier molecule to the receiver cell. This modulation techniques works well for bio-molecule communication inside our body.

6.1 Future Directions

All the works carried out have significant scopes of extension in future. These include:

- Implementation of a cognitive radio network with optimized time delay and better spectrum and power efficiency.
- An amazing human machine interaction with mental imagery sentence detection.
- A new biological model with cognition to find the cognitive pathway inside human body for any cognitive task, especially, injection of a new drug, attraction with a new thing.

Appendix A

User Guide to Run Computer Codes

This Appendix provides a guide to execute the computer codes used in this work provided in the accompanying CD. The codes are meant to be executed in the MATLABR2012b environment.

A.1 Associated Software Installation

- Install MatlabR2012b for all computations.
- EEGLAB (eeglab10.2.24b) provided in the CD is required for EEG analysis related to viewing scalp source/sink components, event related potentials, etc. In order to use it save the EEGLAB path to the MATLAB. To use EEGLAB, along with the data file, event files containing information about the class, duration of stimulus and time stamps, and associated channel locations (.locs) file have to be supplied.

A.2 EEG Preprocessing and Feature Extraction

- The M file EEG_feature_extraction.m is used for EEG pre-processing and feature extraction.
- The necessary data file has to be loaded, that must include the EEG data arranged in the matrix form of samples×channels. The data must be accompanied by the event information as given in the target files. Samples of such data are provided in the associated folder. The code is written for 14 channels of the Emotiv. If fewer channels or the Neurowin system is to be used, the channel names have commented out/ modified accordingly.
- The filtering is done by an elliptical filter followed by common average referencing. Filtered EEG signals can be viewed by running the associated lines of code (Fig. A.1).

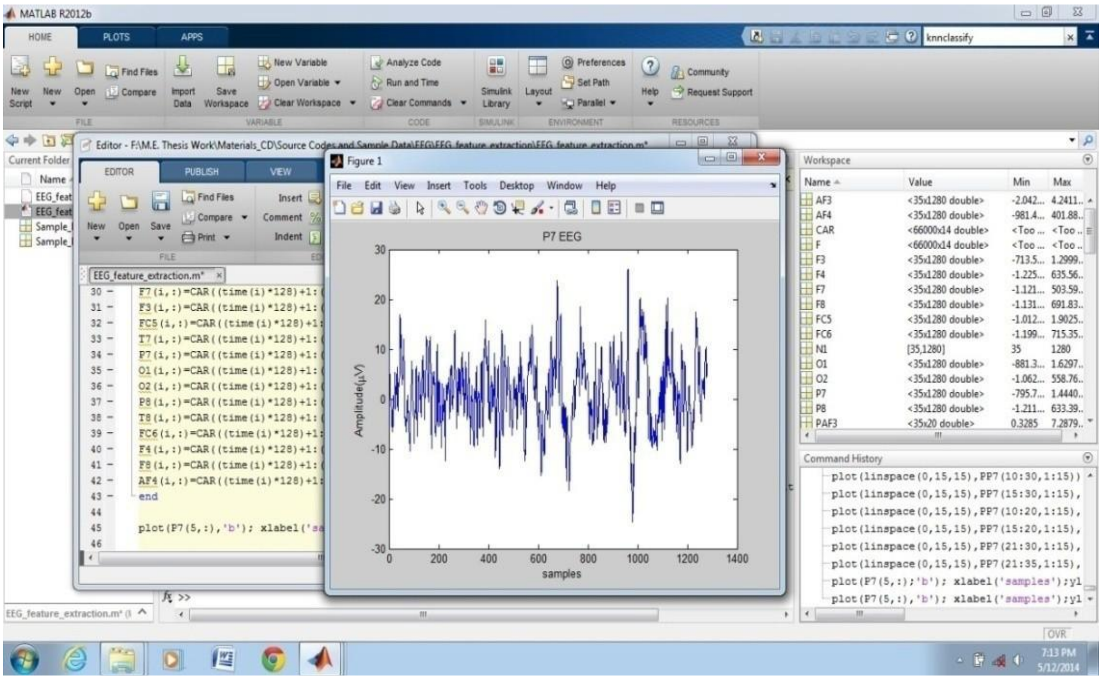

Fig.A.1 Plotting the pre-processed EEG signal

- Features that are included here are Adaptive Autoregressive Parameters, Hjorth Parameters, Wavelet based features, temporal differences, Power spectral density/Band Power Estimates. The associated function files are given in the EEG_feature_extraction folder along with the sample datasets for haptic task recognition and cognitive activity recognition. For AAR parameters the order and value of update coefficient can be changed by editing the MODE.MOP and MODE.UC variables respectively. For Power Spectral Density using Welch method the width of the Hamming window and the percentage overlap can be modified. The frequency range of power spectrum has to be changed according to the desired value. The power spectrum can be plotted to view the range of the spectrum. Such an instance is depicted in Fig. A.2. For wavelet features the order of decomposition and the mother wavelet has to be changed according to the requirement. The featnormalize.m file is used for feature normalization.
- The codes for channel similarity feature extraction are provided separately in Channel Similarity folder. Before running the code, the feature set for which similarity features are to be found have to be loaded into the workspace and indicated to by editing the necessary portions of the code.

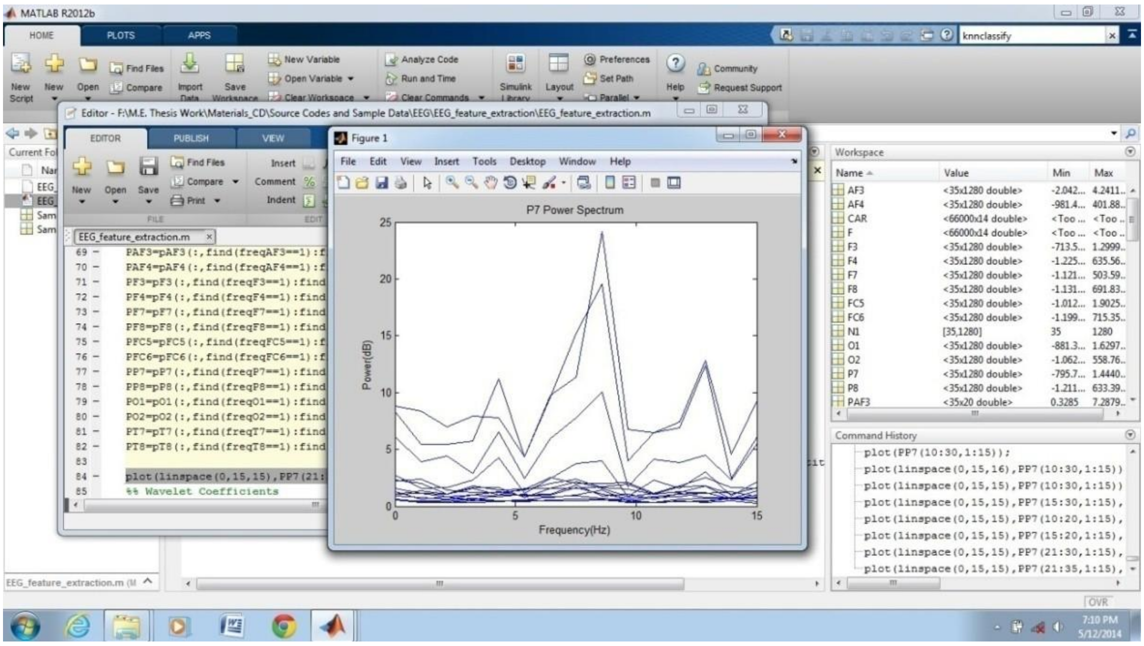

Fig.A.2. Plotting the EEG power spectrum

A.3 Classification

- The M file classification process.m is used for classifying any set of data. All standard pattern classifiers SVM, k-NN, Naïve Bayes, LDA or neural networks can be used. The classifiers other than which the result is required have to be commented out. The extracted features have to be first divided into training and testing sets through cross validation or, if two different datasets are to be used for training and testing the *Xtr* and *Xte* variables have to be assigned accordingly. The target class labels that are known before hand for the training dataset have to be supplied.
- Features can be selected using PCA by giving the desired feature space as input to FeatSel_PCA.m prior to classification.

- The classification performance can be viewed using classification accuracy, sensitivity, specificity, or area under the region of convergence curve on the command window. The classification can also be viewed. (Fig. A.4).

A.4 Classification using Neural Networks

- Regression using Back-propagation neural networks can be done using the regNN.m file. All data and codes for this purpose are provided in the Regression folder. These include prediction of parietal/motor cortex EEG features as well as joint co-ordinates from occipital EEG features. The network inputs and targets have to be specified in each case.
- The weight adaptation algorithm can be modified within the code to view the results for different learning algorithms. A snapshot of the neural network training is illustrated in Fig. A.3.

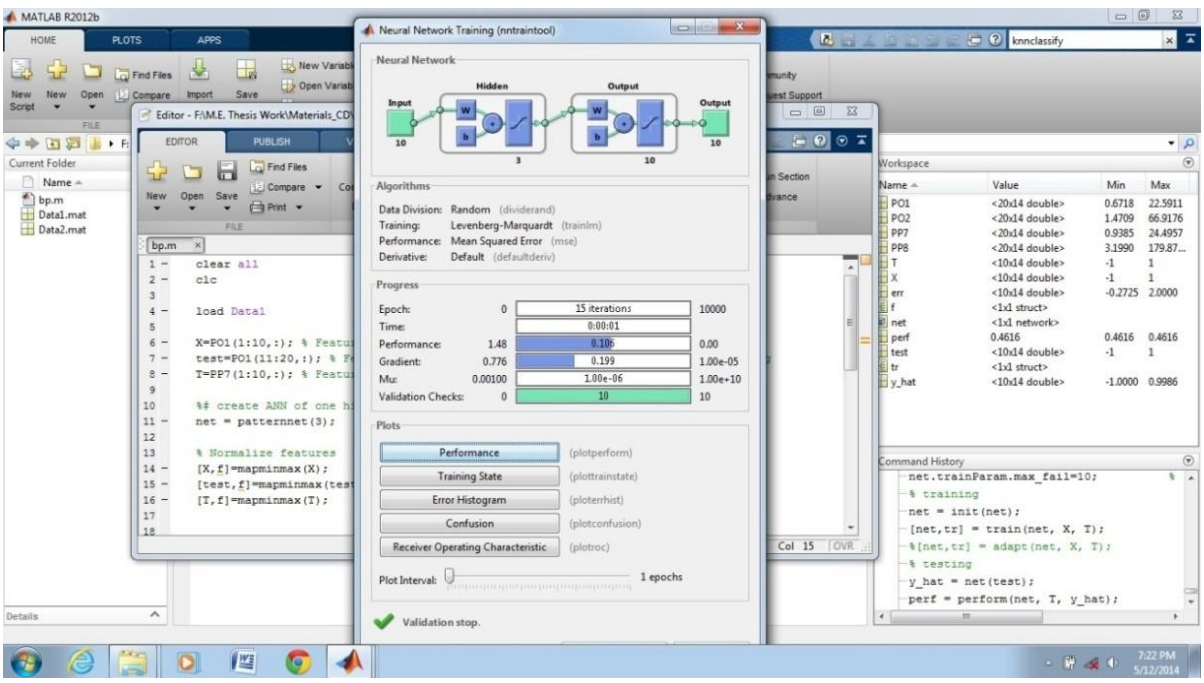

Fig.A.3. Neural Network Training

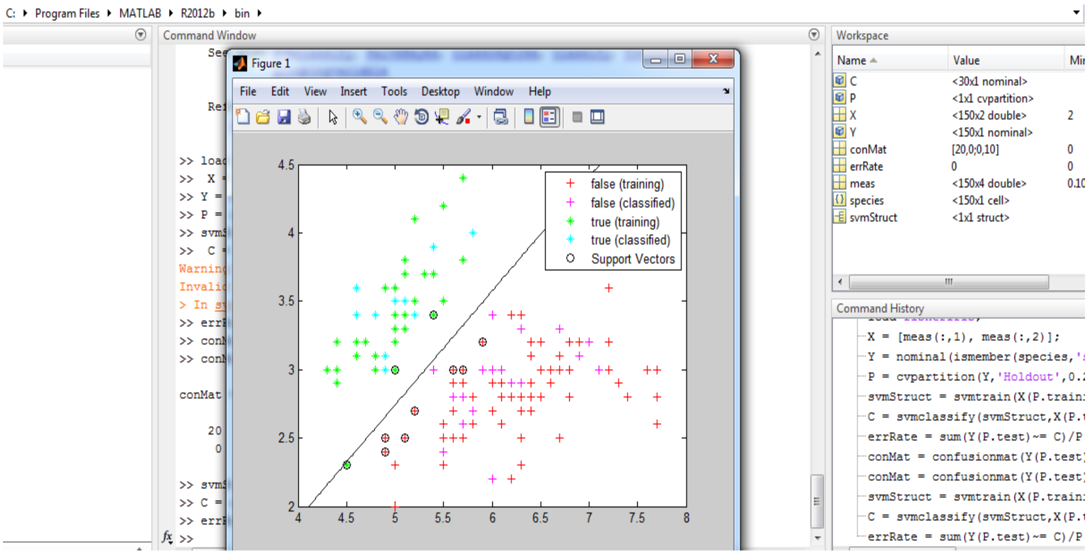

Fig.A.4. Classification Results

A.5 EEG Scalp Map Generation

- From the selected scalp locations the corresponding source activations within the brain can be viewed. EEGLAB has to be initiated by typing eeglab in the command window. The data and the channel location file have to be loaded into eeglab (Fig. A.5). Then ICA has to be run to find the source components corresponding to the channel components provided. One such sample is illustrated in Fig. A.6.

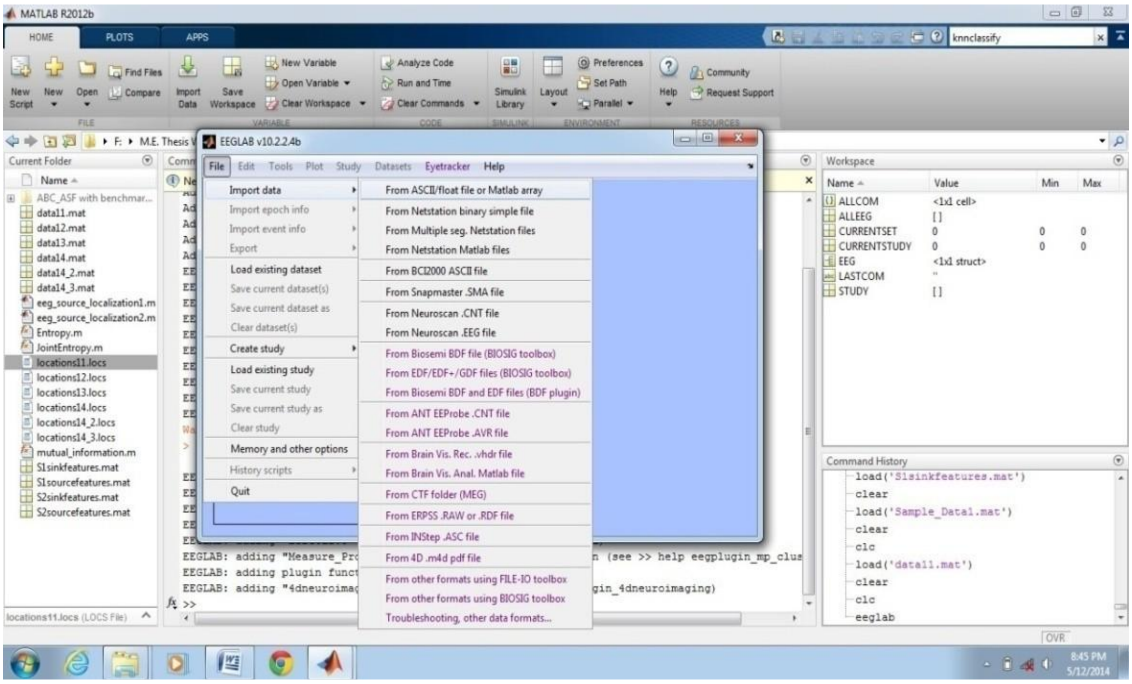

Fig.A.5. importing data into EEGLAB

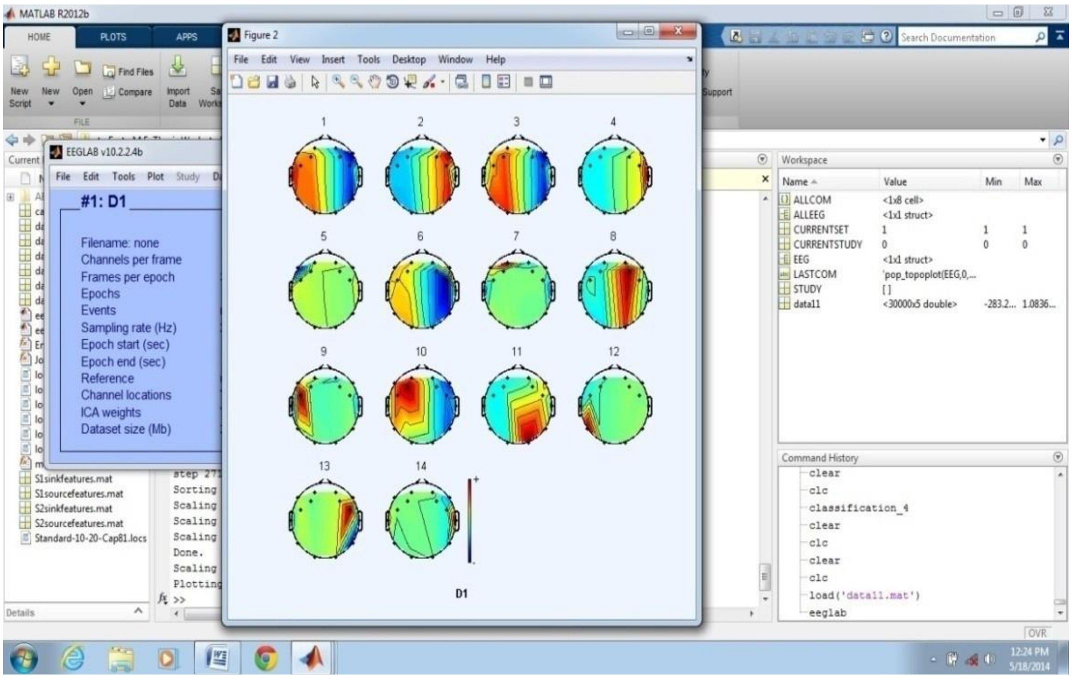

Fig.A.6. Viewing Source Components after performing ICA

A.6 Generation of Reward time Graph using Reinforcement Learning

The code of cooperative Reinforcement learning code is given here to run the program of power optimization with co-related Anti-Egalitarian Strategy. The input is only the discount rate may be 0.9 or 0.85. The output is the Q table and the Reward –Time Graph.

function [Q1,Q2,V1,V2,result1] = pomdp_qlearningmulti2mixed(discount)

```
%   Detailed explanation goes here summary of this function goes here
%with convergence checking, with pure strategy
%discount=0.9;
result1=zeros(1,2000);
result2=zeros(1,2000);

% initialisation
S = 9;    %  no of states
A = 25;  % no of action
Z=16 ;    % no of obsevation
Q1 = zeros(S,A);
```

```
Q2 = zeros(S,A);

sum2=zeros(1,Z);
power=[100 200 300 400 500];

% generation of transition probability matrix
T=rand(A*S,S);
rowsum = sum(T,2);
T= bsxfun(@rdivide, T, rowsum);
V1 = zeros(S,1);
V2 = zeros(S,1);



% generation of observation probability matrix
O=rand(A*S,Z);
rowsum = sum(O,2);
O = bsxfun(@rdivide, O, rowsum);
sum1=zeros(S,Z);


for E=1:2000
    BS=[1;zeros((S-1),1)]' ;
    PZ=zeros(S,Z);
    prevV1=Q1;
    prevV2=Q2;
    x=0;
    arr1=zeros(1,100);
    f=zeros(1,S);
    %learning phase
   for i=1:100
       [~,s]=max(BS);
       arr1(1,i)=s;
       [a,reward1,reward2]=SINRnew(power,A);

    %calculation of total observation probability
        if a==1
            Ta=T(1:S,:);
            Oa=O(1:S,:);
        else
            Ta=T((a-1)*S+1:(a-1)*S+9,:);
            Oa=O((a-1)*S+1:(a-1)*S+9,:);
        End



        %calculation of total observation probability PZ
        for i1=1:S
            for i3=1:S
                sum1=sum1+Ta(:,i3)*Oa(i3,:);
```

```
        end
        PZ=PZ+BS(:,i1)*sum1;
    end

    r1=BS(1,s)*reward1;
    r2=BS(1,s)*reward2;
    ab= Anti_Egalatarian( Q1,Q2,s);        %calculation of  Mixed strategy

    % calculation of Q values
    summ1=0;
    summ2=0;
    for j=1:A
        summ1=summ1+ab(1,j).*Q1(s,j);
        summ2=summ2+ab(1,j).*Q1(s,j);
    end
    Q1(s,a) = (1-.0009)*Q1 (s,a)+ 0.0009*(r1+ discount * summ1);
    Q2(s,a) = (1-.0009)*Q2(s,a)+ 0.0009*(r2+ discount * summ2);
    % calculation of updated BS(S)
    for i4=1:S
        sum3=Ta(:,i4)*Oa(i4,:);
        sum2=sum2+BS(:,i4)*sum3(i4,:);

    end
    BS=sum2/PZ;
    if max(max(abs(prevV1-Q1))) <=0.001 &&  max(max(abs(prevV2-Q2))) <=0.001
        x=x+1;
        if x>=20
            break
        end
    end
  end
  for i5 =1:S
     f(i5)=length(find(arr1==i5));
  end
  V1=max(Q1,[],2);
  V2=max(Q2,[],2);
  result1(1,E)=mean(mean(Q1));
  [~,index]=max(f);
  result2(1,E)=index;
end
 %plot(result2,'k','linewidth',2);
  hold on
 plot(result1,'g','linewidth',2);
end
```