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BCI APPLICATION: AN EEG BASED SIGNAL ANALYSIS AND CLASSIFICATION FOR NEURO DEGENERATIVE DISORDER PATIENTS – A SURVEY

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Abstract- Today the neurodegenerative disorder is one of the major concerns in the Healthcare industry. There are several types of neurodegenerative disorder and it directly affects the driving force of the body, Brain. As a result, the involuntary movement occurs such as tremor and this causes disability, which leads the person to depend on others neurodegenerative diseases represent a major threat to human health. These age-dependent disorders are becoming increasingly prevalent, in part because the elderly population has increased in recent years. To support the disabled person as well as the care taker a communication channel is vital. The system bridges the gap between the patient and the care taker. The EEG of the Neuro Degenerative patients is Recorded, Preprocessed, Feature Extracted and Classified with the help of neural network to trigger the alert system. The system also focuses on the fall detection system with the help of three axis accelerometer. The system will play a vital role in assisting the Neuro Degenerative Disorder patients for their betterment of life.

Keywords: Neuro Degenerative disorder, EEG(Electroencephalography) ,Preprocessing , Feature Extraction , Classification

1. INTRODUCTION

Neurodegeneration is the progressive loss of structure or function of neurons, which may ultimately involve cell death. Many neurodegenerative diseases such as amyotrophic lateral sclerosis, multiple sclerosis, Parkinson's disease, Alzheimer's disease, Huntington's disease, and prion diseases occur as a result of neurodegenerative processes. These similarities suggest that therapeutic advances against one neurodegenerative disease might ameliorate other diseases as well. Neurodegenerative diseases affect millions of people worldwide. Although there isn’t a complete cure for most of these complex neurological diseases, Southwestern offers comprehensive, individualized treatment to help patients manage them. Motor Neuron Disease (MND) is the name given to the group of diseases in which the motor neurons undergo degeneration and die. This group includes diseases such as amyotrophic lateral sclerosis, progressive bulbar palsy, primary lateral sclerosis, progressive muscular atrophy, spinal muscular atrophy, Kennedy’s disease, and post-polio syndrome. Normally, messages or signals from nerve cells in the brain (upper motor neurons) are transmitted to nerve cells in the brain stem and spinal cord (lower motor neurons) and from them to muscles in the body. Currently, no neurodegenerative disease is curable, and the treatments available only manage the symptoms or halt the progression of the disease. Therefore, there is an urgent need for new treatments for this kind of disease, since the World Health Organization has predicted that neurodegenerative diseases affecting motor function will become the second-most prevalent cause of death in the next 20 years. There have been several studies on the potential of old drugs for the most relevant neurodegenerative diseases, including Alzheimer's disease, Parkinson's disease, Huntington's disease, Multiple Sclerosis and Amyotrophic Lateral Sclerosis. Neurodegenerative disorders encompass a wide range of conditions that result from progressive damage to cells and nervous system connections that are essential for mobility, coordination, strength, sensation, and cognition. Normally, messages or signals from nerve cells in the brain (upper motor neurons) are transmitted to nerve cells in the brain stem and spinal cord (lower motor neurons) and from them to muscles in the body. Upper motor neurons direct the lower motor neurons to produce muscle movements. When the muscles cannot receive signals from the lower motor neurons, they begin to weaken and shrink in size (muscle atrophy or wasting). The muscles may also start to spontaneously twitch. These twitches (fasciculations) can be seen and felt below the surface of the skin. When the lower motor neurons cannot receive signals from the upper motor neurons, it can cause muscle stiffness (spasticity) and overactive reflexes. This can make voluntary movements slow and difficult. Over time, individuals with MNDs may lose the ability to walk or control other movements. MNDs are classified according to whether they are inherited or sporadic, and to whether degeneration affects upper motor neurons, lower motor neurons, or both. Neurodegenerative diseases are increasing in number, given that the general global population is becoming older.

2. EEG BASED ASSISTIVE TOOL FOR MND PATIENTS

A. EEG Based BCI for ALS Using complex wavelets and multi layered neural network

In EEG signal processing in particular for ALS EEG signal analysis the EEG signals captured are non-stationary. ALS patients may need proper assistance and response from both gadgets and care takers. EEG signals captured at different intervals of time need to provide the same information and any changes in signal features will lead to false response [1]. One of the primary aim of this work is to use the complex wavelet sub bands that provide information on both magnitude and phase to identify the signal entropy every time accurately. The complex wavelets will generate. Large number of sub bands and hence will have redundant information that will improve complexity in feature classification. The neural network algorithm needs to be designed to process the nonredundant features and perform classification accurately. The Data Flow Diagram is depicted in Figure 2.1

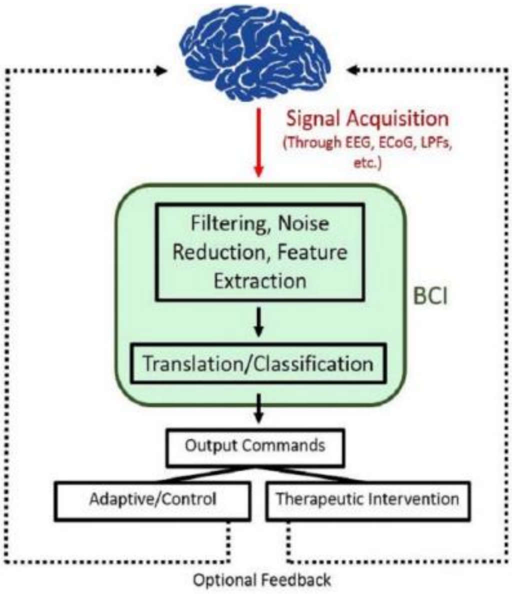

Figure 2.1 Data Flow Diagram In BCI Assistive Devices

B. EEG Based BCI for ALS Using complex wavelets and multi layered neural network

A novel deep neural network is for emotion classification using EEG systems, which combines the Convolutional Neural Network (CNN), Sparse Auto encoder (SAE), and Deep Neural Network (DNN) together. In the network, the features extracted by the CNN are first sent to SAE for encoding and decoding. Then the data with reduced redundancy are used as the input features of a DNN for classification task. The public datasets of DEAP and SEED are used for testing. Experimental results show that the network is more effective than conventional CNN methods on the emotion recognitions. For the DEAP dataset, the highest recognition accuracies of 89.49% and 92.86% are achieved for valence and arousal, respectively. For the SEED dataset, however, the best recognition accuracy reaches 96.77%. By combining the CNN, SAE, and DNN and training them separately, the network is shown as an efficient method with a faster convergence than the conventional CNN. The features extracted from original EEG data are sent to the CNN first. The CNN model includes several convolution-pooling layer pairs and one output layer. Before sending to the CNN, features are concatenated into image form which is then convolved with several one-dimensional filters in convolution layers. After the pooling layer, the data are further subsampled to images with smaller size. Network weights and filters in the convolution layers are learned through back-propagation algorithm. Length of data in the DEAP dataset is 63 s, and the first 3 s are removed in the experiments. Then band pass filtering is then applied. Among 40 channels, EEG data are contained in 32 channels, which are chosen for experiments. After that, EEG signals are decomposed into α (1–7 Hz), β (8–13 Hz), θ (14–30 Hz), and γ bands (30–45 Hz). After band pass filtering, signal windowing on four frequency bands is applied. EEG signals are divided into short time frames in order to facilitate signal processing, thus time windows with different overlaps are applied to EEG data in order to increase samples for training. Two window sizes, 8 and 12 s, are used for evaluating the network. The configuration of the network is depicted in Figure 2.2

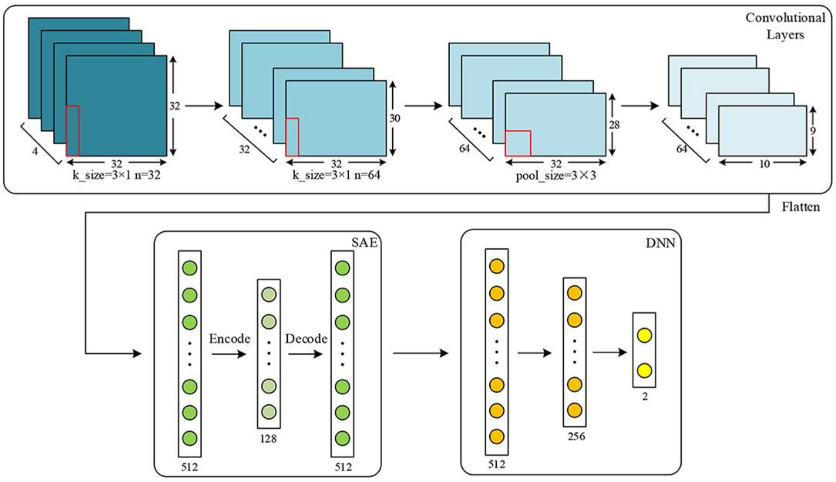

Figure 2.2 Configuration of the network for the DEAP dataset.

C. EEG signals classification using the k-means clustering and a multilayer perceptron neural network model

A multilayer perceptron neural network (MLPNN) based classification model as a diagnostic decision support mechanism in the epilepsy treatment has been. EEG signals were decomposed into frequency sub-bands using discrete wavelet transform (DWT) [11]. The Sub-band decomposition of a signal by using DWT is depicted in Figure 2.3. The wavelet coefficients were clustered using the K-means algorithm for each frequency sub-band. The probability distributions were computed according to distribution of wavelet coefficients to the clusters, and then used as inputs to the MLPNN model. We conducted five different experiments to evaluate the performance of the model in the classifications of different mixtures of healthy segments, epileptic seizure free segments and epileptic seizure segments. The model resulted in satisfactory classification accuracy results.

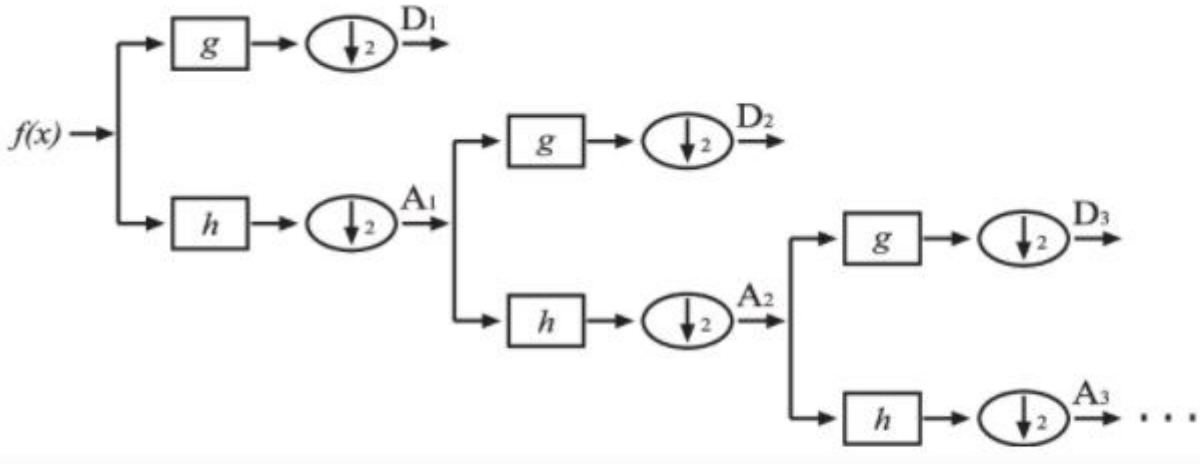

Figure 2.3 Sub-band decomposition of a signal by using DWT.

D. The PREP pipeline: standardized preprocessing for large-scale EEG analysis

The technology to collect brain imaging and physiological measures has become portable and ubiquitous, opening the possibility of large-scale analysis of real-world human imaging. By its nature, such data is large and complex, making automated processing essential. This paper shows how lack of attention to the very early stages of an EEG preprocessing pipeline can reduce the signal-to-noise ratio and introduce unwanted artifacts into the data, particularly for computations done in single precision. We demonstrate that ordinary average referencing improves the signal-to-noise ratio, but that noisy channels can contaminate the results. We also show that identification of noisy channels depends on the reference and examine the complex interaction of filtering, noisy channel identification, and referencing. We introduce a multi-stage robust referencing scheme to deal with the noisy channel-reference interaction. We propose a standardized early-stage EEG processing pipeline (PREP) and discuss the application of the pipeline to more than 600 EEG datasets. The pipeline includes an automatically generated report for each dataset processed. The scalp visualization of the results from PREP is depicted in Figure 2.4

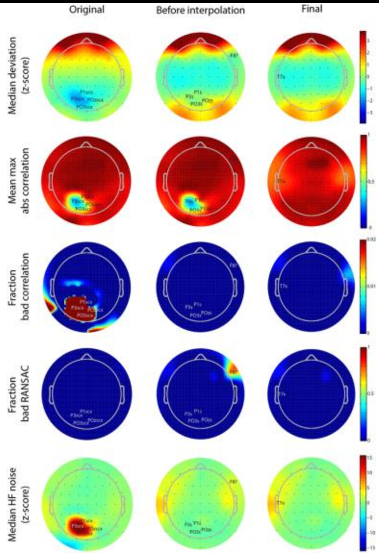

Figure 2.3 Scalp map visualizations of noisy channel produced by the PREP reporting facility

D. EEG-Based Brain–Computer Interfaces for Communication and Rehabilitation of People with Motor Impairment

People with severe neurological impairments face many challenges in sensorimotor functions and communication with the environment; therefore they have increased demand for advanced, adaptive and personalized rehabilitation. During the last several decades, numerous studies have developed brain–computer interfaces (BCIs) with the goals ranging from providing means of communication to functional rehabilitation. Here we review the research on non-invasive, electroencephalography (EEG)-based BCI systems for communication and rehabilitation. We focus on the approaches intended to help severely paralyzed and locked-in patients regain communication using three different BCI modalities: slow cortical potentials, sensorimotor rhythms and P300 potentials, as operational mechanisms. We also review BCI systems for restoration of motor function in patients with spinal cord injury and chronic stroke. The Overview of the framework is depicted in Figure 2.4

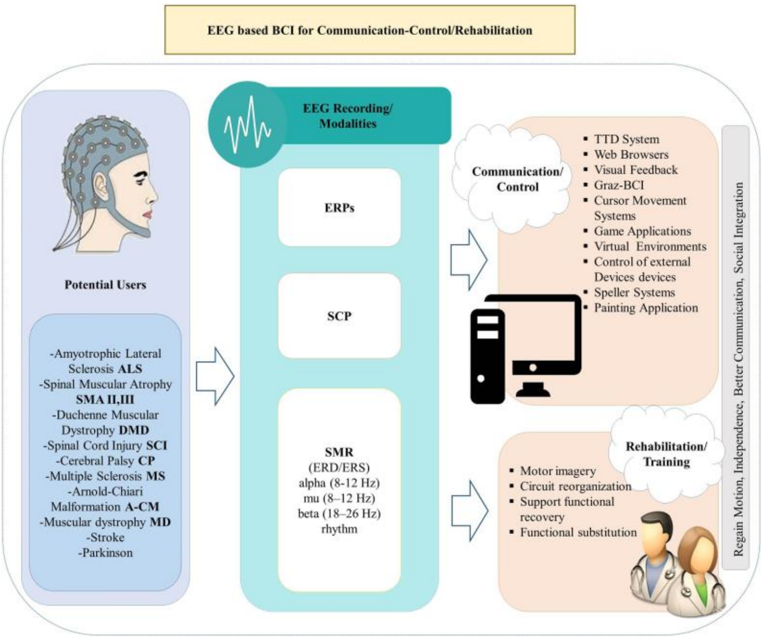

Figure 2.4 Overview of the review framework.

3. CONCLUSION

Motor neuron disease is an uncommon condition that affects the brain and nerves. There is a vital necessary of the presence of care taker. The communication could not be made effective as the patient have the inability of speech so the system bridges this gap between the patient and care taker. Various methods and pipelines used for Signal Preprocessing and Classification have been presented and the importance of EEG signals in assisting the MND patients have been discussed elaborately.

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