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Multivariate EEG Signal Processing Techniques for the Aid of Severely Disabled People

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Abstract — Electroencephalography (EEG) has been used for several years as a trace of signals for facilitating subjects with serious infirmities to communicate with computers and other devices. Many studies have revealed the correlation of mental tasks with the EEG signals for actual or fictional movements. However, the performance of Brain Computer Interface (BCI) using EEG signal is still below enough to assist any disabled people. One reason could be that the researchers in this field (motor imagery based BCI) normally use two to three channels of EEG signal. This might limit the performance of BCI, as an extra source of information generally helps in detecting a person's motor movement intentions. Therefore, the proposed research work is involved with three or more channels of EEG signal for online BCI. Two fundamental objectives for BCI based on motor movement imagery from multichannel signals are aimed at in this research work: i) to develop a technique of multivariate feature extraction for motor imagery related to multichannel EEG signals; and ii) to develop an appropriate machine learning based feature classification algorithm for Brain Computer Interface. Nevertheless, all other problems like interfacing and real-time operations with current BCIs are also addressed and attempts are made to reduce the problems. The methodology can be described by following steps as follows: i) at least 3 channels of EEG signal are recorded; ii) a few features are extracted from preprocessed EEG signal; iii) all extracted features are classified to generate commands for BCI; iv) finally evaluate the performance of the proposed algorithm for BCI. The challenge of this research work is to investigate and find an appropriate model for online (real-time) BCI with a realistic performance to be made in achieving better lives for people with severe disabilities in Malaysia and abroad.

Keywords: *Electroencephalography, Brain Computer Interface, Motor Imagery EEG, and Cohen's Kappa*

1. INTRODUCTION

Many studies have revealed the correlation of mental tasks with the EEG signals for actual or fictional movements. Current BCIs mostly concentrate on signals from extends of the cortex that is likely to demonstrate activity that is directly linked to a particular type of intention (e.g., movement intention). Though, the well-off interconnectivity between different cortical extends may permit events in one area to be preceded or accompanied by detectable patterns in other distinct areas. This fact has only been narrowly explored in relation to BCIs. Hence, the main objective of this research work is to investigate the functional time-related cortical interconnectivity both as an alternative and as an additional source of information for detecting a person's motor intentions within EEG signals.

An additional source of information generally helps in detecting a person's motor movement intentions; thus, the proposed research work is aimed to involve three or more channels of EEGs for online BCI. Though with a higher number of EEG channels and a higher degree of signal processing technique may yield a quicker latency than what is available currently, the challenge of this research work is to investigate and find an appropriate model for online (real-time) BCI.

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2. MOTIVATION

A person with disabilities is being given protection under the law of Persons with Disabilities Act 2008 in Malaysia. This act includes habilitation and rehabilitation as well as the development of the quality of life and well-being of individuals with serious disabilities.

Brain Computer Interface (BCI) is a system that establishes a direct interaction path between the brain and an outside device. It is often designed to aid, intensify or restore human cognitive or sensory-motor functions. The conception of BCI is not very new but still in its earliest research stages and has vast scope to explore. US, Europe, Japan and even neighbor country Singapore is doing research on BCI and neuro-informatics, but Malaysia is far behind in doing so. Few groups in Malaysia have started work in BCI, but no group is working in motor imagery related BCI so far. On the other hand, very few research groups are available in Malaysia that work on EEG signal analysis. Therefore, this research is to be made to achieve better lives for individuals with serious disabilities for fulfilling the needs and rights of disabled people, especially in Malaysia.

3. REVIEWS

A Brain Computer Interface (BCI) creates a direct interaction channel between a human brain and a control or interaction device without involving neuro-muscular paths [1]. Such user interfaces can be extremely beneficial to individuals with complete dysfunction of the neuromuscular system. To effective use of a BCI, the user should generate various brain activities that will be recognized by the system and translated into commands to control outside devices such as computers, wheelchairs etc. The development of a BCI implies three functions: (i) recording of the cerebral (brain) signal, e.g., EEG; (ii) extraction of mental task related features or information from the recorded signal; and (iii) translation (classification) of the extracted information to a control command [2].

Research on Human Brain Map explains the association of brain segments with every physiological or mental action. Sensory and motor homunculus are the representation of the body parts to every segment of the brainpower. Hence, for every key EEG rhythm and for a collection of induced capabilities, the sites and mechanisms of initiating EEG and their relations with particular aspects of brain work are no longer entirely obscure [3]. The imagery of motor progress could be identified from non-invasive EEGs by arranging electrodes (with a brain cap) around the motor and sensory cortex fields of the subject's scalp [4]. It is notable that a variety of Gaussian and linear signal processing methods have been applied frequently for spotting the Motor Imagery (MI) based EEG signals. Though, by nature, the MI linked EEG signals are not extremely Gaussian, motionless, or linear dynamical [5]. It has become essential to find a leading method that can classify specifically non-linear signals and reach the best possible output. Different kinds of artifacts cancel data recording. Thus, some preprocessing tasks are performed prior to the feature extraction to lessen the Electrooculogram (EOG) artifacts [6, 7]. It becomes more complicated to settle the multichannel or multiclass feature extraction difficulties.

The feature extraction is a vital job in a BCI as its intention is to extract mental chore related information (features) from the brain signal irrespective of the quality of the EEG signal. The likelihood of proper brain state recognition can be improved if the feature extraction unit converts the EEG signal in such a way that the signal to noise ratio (SNR) can be increased as much as possible. Since the last decade, a countless variability of features has been extracted from EEG signals and tried to design BCI, such as, band powers (BP), power spectral density (PSD) standards, autoregressive (AR) and adaptive autoregressive (AAR) parameters, Wavelet, Kalman filtering, principal component analysis, independent component analysis, common spatial pattern, and multivariate autoregressive model [8]. Among the variety of features, the frequency domain and common spatial patterns (CSP) features are popular in designing BCI. The frequency feature is based on the ERD/ERS (Event-related synchronization and desynchronization) phenomenon that is an authentic movement or motor imagery of left- or right-hand results in desynchronization of μ-band (e.g., 8-13 Hz) oscillations in the contralateral EEG along with simultaneous synchronization of central β-bands (e.g., 18-26 Hz) oscillations in the ipsilateral EEG signal [9]. The CSP feature illustrates the topographic pattern of brain rhythm modulations which is different in different motor movement imagination. Regarding the design of a BCI system, some critical aspects of these features must be considered: EEG signals have a poor signal-to-noise ratio, feature vectors are often of high dimensionality and the EEG features are not motionless since the EEG signals may promptly fluctuate over time and particularly over sessions. To deal with these factors, the proposed research work will use CSP, and higher order statistics-based features, and investigate the possibilities of adaptive CSP filter for multichannel signal processing.

Another important question in designing a BCI is interpreting the extracted features from multichannel EEG signals [10]. To achieve this goal, classification algorithms (supervised or unsupervised) are mostly used. In BCI development, the machine learning technique is used to obtain an effective classifier that can accommodate many parameters (features) to the characteristics of the user's brain signals. Till now, several classification algorithms have been used to design the BCI systems, e.g., linear classifiers (Linear Discriminant Analysis (LDA), Fisher's LDA Support Vector Machine), neural networks (Multilayer Perception-NN], Learning Vector Quantization-NN), nonlinear Bayesian classifiers (Hidden Markov Model, Bayes quadratic), nearest neighbor classifiers (k-NN, Mahalanobis distance), and combinations of classifiers [11, 12]. These algorithms are applied to detect 'patterns' of EEG features and develop a rule to identify the feature characteristic to separate into intended labels. The performance of pattern identification depends on both the extracted features and the classification technique employed [13]. In connection with feature interpretation, the primary consideration of this research work is to use the linear classification method, but other available classification techniques will also be investigated.

4. TECHNIQUES

The proposed research work is to develop an algorithm (interface) that will be consumed a human's intention of motor progress in the shape of multichannel EEG signals; and, in return, will manage (translate) the input signal to provide a control signal for an outside device. The line of the art of the proposed research work is shown in Fig. 2, and it can be described in the following steps below.

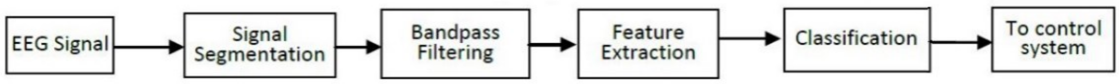

Fig. 2. Flow Diagram for Feature Extraction and Classification in a BCI

4.1 Data Acquisition and Paradigm

One of the objectives of this research work is to apply multichannel EEG signal and, hence, at least 3 channels of EEG signal will be recorded from the motor cortex area: usually C3, C4 and Cz location of EEG electrode montage. BIOPAC-MP160 amplifier with EEG (Electroencephalography) data acquisition and analysis platform with AcqKnowledge software, permitting advanced research for BCI applications and establishing acquisition of a broad range of signals and measurements. A computer-controlled thinking technique (paradigm) will be applied to record EEG signals. The paradigm will regulate up to 4 types of imagery (left, right, up and down). For any subject, multiple numbers of EEG sessions will be arranged, where some of these sessions will be used for training and validation of the interface, and the rest will be used for testing the interface with unknown EEG signals. For the online interface, the EEG signal will be acquired and processed without any paradigm.

4.2 Feature Extraction Technique

To differentiate the EEG signals in terms of any event of paradigm, several features will be extracted from the preprocessed EEG signal (usually after artifact removal and bandpass filtering). The primary aim of this research work is to extract and characterize the features related to ERD/ERS phenomenon (power spectral density due to event related desynchronization and synchronization) and the feature due to common spatial filtering [14]. In addition, the research work will look at the feature by adaptive autoregressive parameters and independent component analysis.

4.3 Classification Algorithm

Each extracted feature will be transformed and generates commands at this time of signal processing. In the training phase, feature characteristics will be assessed, and a thought identification rule will be established. The same rule will be applied in the online (evaluation) phase. The LDA classifier (Fisher's LDA) will be the primary aim to implement into BCI [15]. Besides this, Support Vector Machine and nonlinear Bayesian classifiers will be explored to achieve higher performance of the interfacing system.

4.4 Performance Measures

A microcontroller-based interfacing circuit and its code will be established, which will lead to the steps toward an evaluation of the classification algorithm based on multichannel EEG signals. The interfacing performance will be assessed by two standard statistical measures: detection accuracy and Kohen's kappa [15]. A confusion matrix will be computed for performance measurement when compared with actual and interface assessed events in all training instances. The performance of the proposed algorithm will be compared with the same of the contemporary algorithm for the Brain Computer Interface with the subject's intention.

4.4.1. Detection Accuracy

Using the confusion matrix (CM), the left and right accuracies for each instant of the paradigm are computed by the following formulae:

$$\text{Left accuracy} = \frac{(\text{finally obtained negative in CM} \times 100)}{(\text{total number of input as left})} \tag{1}$$

$$\text{Right accuracy} = \frac{(\text{finally obtained positive in CM} \times 100)}{(\text{total number of input as right})} \tag{2}$$

The mean of left and right hand MI accuracy are called here as the overall accuracy.

4.4.2. Cohen's Kappa

Cohen's kappa is a statistical measurement that provides an index of interrater reliability. The computation of kappa at each instance begins from the CM ready by comparing the appearance of two raters: the actual events and the estimated events (observed at the classifier's output). From the definition, Cohen's kappa can be written as,

$$k = \frac{(P_0 - \mathrm{P_c})}{(1-P_c)} \tag{3}$$

Where, Po means the relative observed agreement between raters and Pc for the hypothetical likelihood of chance agreement. The maximum possible value of Cohen's kappa is limited to 1 and then the raters are in complete agreement if there is no agreement among the raters, k = 0.

5. BENEFIT AND FINANCIAL IMPACT

As stated earlier, the proposed research work will deal with multichannel EEG signals processing that is related to the development of the BCI, e.g., acquisition of event-related EEG signals and feature interpretation (clustering/classification techniques) and the protocols to send messages to output devices. Since this research work will involve all issues related to signal processing which will enrich Malaysian expertise in signal processing (especially EEG processing), neuro-informatics, and rehabilitation using BCI. Disability involves hundreds of millions of families in developing countries. While the population ages, this figure is expected to rise. According to the UN Development Program (UNDP), eighty percent of people with disabilities live in developing countries. Therefore, the development of an efficient BCI for the total dysfunction of the neuromuscular system can contribute to wealth creation, enhance the quality of life and create new industries.

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