An Efficient Classification of Motor Imagery ECOG Signals using Support Vector Machine for Brain Computer Interface

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Abstract--*Although brain–computer interface (BCI) methods have been evolving quickly in recent decades, there still a number of unsolved difficulties, such as enhancement of motor imagery (MI) classification. The most commonly used signals in BCI investigations is electroencephalography (EEG) recordings. EEG has restricted tenacity and needs extensive training and has restricted stability. Over the past ten years, an expanding number of studies has discovered the use of electrocorticography (ECoG) activity extracting signals from the surface of the mind. ECOG has attracted considerable and expanding interest, because its mechanical characteristics should readily support robust and chronic implementations of BCI systems in humans. In this paper, we suggest a hybrid algorithm to advance the classification achievement rate of MI based electrocorticography (ECoG) in BCIs. To verify the effectiveness of the suggested classifier, we restore the SVM classifier with the identical features extracted from the cross-correlation method for the classification. The performances of those procedures are assessed with classification correctness through a 10-fold cross-validation procedure. Then consider the performance of the suggested procedure by comparing it with existing system.*

Keywords**—***Brain–computer interface (BCI), cross-correlation technique, electrocorticography (ECoG), support vector machine (SVM), motor imagery (MI).*

I.INTRODUCTION

Over the past ten years, electric recordings from the exterior of the mind [i.e., electrocorticography (ECoG)] have become identified as an undertaking signal stage for brain computer interface (BCI) study and application. ECoG is acquired by placing electrodes below the skull, either overhead(epidural) or below (subdural) the dura mater, but not inside the mind parenchyma. These encompass high spatial tenacity and pointer fidelity, opposition to noise, and considerable robustness over long recording periods. Surface cortical potentials were first noted from animals and humans in the late 19th years[1]. More lately, in the past some decades there has been a improved technical interest in ECOG pointers in a kind of animal investigations (particularly in rats, rabbits, and cats) (e.g., [2]–[4]).

Lately, electro corticography (ECoG)-based brain–computer interfaces (BCIs) have become well liked in the study of mind research, neural technology and rehabilitation. A BCI presents a direct connection interface between a brain and an external apparatus. BCIs convert these pointers into yields that permit total lock-in patients suffering from brain or spinal cord wound to communicate without the participation of peripheral nerves and sinews via thoughts solely [5]. BCIs alter human aims or thoughts into command pointers to set up a direct communication between the human mind and yield devices, as presented in Fig. 1.

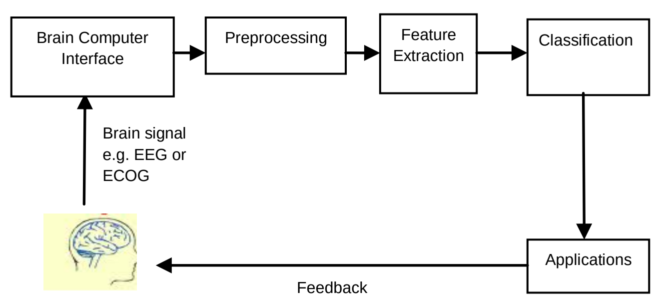

Fig.1. Fundamental structure of brain–computer interface (BCI).

A class of ECoG-based BCIs which rely on motor imagery (MI) of users are of particular interest to the BCI community since this type of BCI has a relatively robust connection performance and can help to understand the underlying mechanism of MI [6]. MI is a widespread mental task in which subjects are instructed to imagine themselves accomplishing a exact engine activity (such as a hand or foot movement). In most present MI founded BCIs, machine discovering algorithms are conveyed out in two stages: feature extraction and classification [7].

The aim of the study is to improve the classification correctness of MI facts and figures for

BCI schemes and furthermore to investigate if a cross-correlation technique is an befitting procedure for feature extraction in an ECOG-based MI facts and figures. For this reason, the present study proposes a innovative algorithm where a cross-correlation technique is evolved for feature extraction and a support vector machine (SVM) is employed for classifying the obtained characteristics. Cross-correlation is a very mighty method to recognize the connection between the ECOG pointers from two different electrodes and is furthermore to supply the discriminative data about those pointers. This method makes a new pointer called cross-correlogram (mathematically called cross correlation sequence) utilizing two pointers. If the two ECOG pointers have the identical rhythm, the peak of the cross-correlogram bend will appear in the centre. In supplement, the cross correlation can weaken noise from the ECOG pointers by means of correlation assessment because of the characteristics of signal periodicity. Therefore the cross-correlogram is a almost noise-free pointer that can supply more pointer information compared to the original pointer [8]. The method furthermore takes into consideration any potential phase dissimilarities between the two pointers via the addition of a lead or lag period [9]. Thus, a cross-correlation technique works better for the feature extraction from the MI EEG facts and figures.

The SVM is a robust smart method for classification in BCI submissions. The computation of the SVM is much quicker contrasted with other machine discovering techniques.

II.DATA AND METHOD

In this section, first the data acquisition used in this research is recounted. Next, the proposed method and its implementation on the untested data are presented. Finally, the presentation evaluation method is discussed for the suggested algorithm.

2.1 .Data Acquisition

ECoG notes apparatus are normally adjuncts to the clinical gear in an epilepsy supervising unit.The electrodes utilized for notes from the surface of the mind are normally benchmark. After a craniotomy (i.e., a method to eliminate a large window of bone), an electrode array is placed that wrappings a wide locality of cortex. The electrodes had a diameter of four millimetre (2.3mmexposed), one cm inter-electrode distance, and were embedded in silastic. Electrocorticographic (ECOG) signals (i.e., 62, 48, and sixty four channels from subjects one, 2, and 3, respectively) were non inheritable with relevancy a scalp reference and ground (Fig. 1), band pass filtered between 0.15 to two hundred cps, and sampled at a thousand cps.

As an alternate to a full craniotomy, little burr apertures are made and 1×4, 1×6, or 1×8 electrode narrow pieces are put bilaterally (this approach is normally utilized to lateralize the hemisphere of the seizure focus).With regard to quotation and grounding, the use of an intracranial quotation and non-cortical (skull opposite) grounding makes recordings less susceptible to noise compared to the use of scalp or cortical electrodes [10]. At present, most clinical (and even some study) ECOG amplification/digitization systems do not rendezvous these stringent obligations, and thus may not be capable of obtaining ECOG signals with adequate fidelity to arrest all the data required by a specific study.

2.2. Proposed Method

The present study evolves an algorithm that can mechanically classify the MI ECOG signals in BCI schemes. The proposed cross-correlation-based SVM design for the MI pointers classification is showed in Fig. 2. The approach uses a cross-correlation technique to extract features from the initial signals, and then the extracted characteristics are used as the inputs to the SVM classifier. The same characteristics extracted from the cross-correlation method as the inputs. The impede design drawing of the suggested method in Fig. 2 depicts the method for the MI ECOG signal classification as recounted in the following steps.

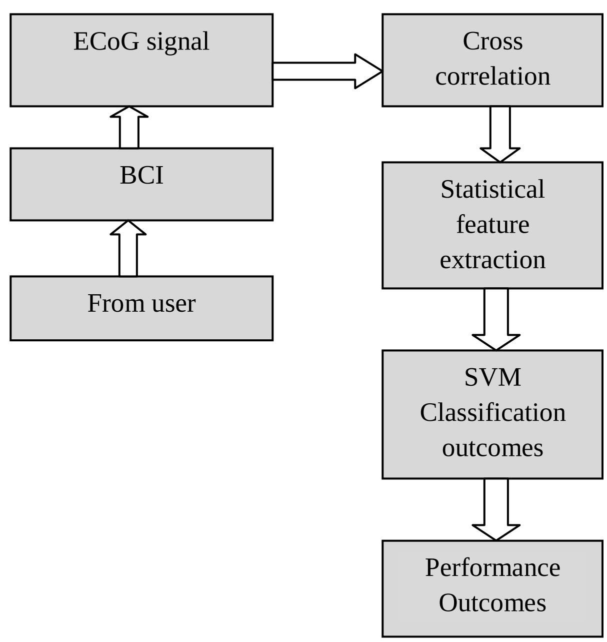

Fig.2. Block diagram of the proposed technique for the MI ECOG signal classification in BCIs development.

2.2.1 Computation of a Cross-Correlation Sequence: A cross-correlation sequence, denoted by " R_{xy}," is calculated recursively using a quotation signal and any one of other non reference pointers, utilizing the cross-correlation technique as shown in Fig. 2. In this study, the following (1) of the cross-correlation method [11], [12] is utilized to compute a cross-correlation sequence. Here x(i) is considered as the reference signal and y(i) is considered as any other non reference signal in one subject of the two-class MI EEG facts.

$$R_{xy}[m] = \sum_{i=0}^{N-|m|-1} x[i]\, y[i-m];$$

$$m = -(N-1), -(N-2), \quad 0,1,2,3\ldots(N-2),(N-1).. \qquad (1)$$

Here, N(N>1) is the number of experiment points, m represents time-shift parameters renowned as lag, and Rxy is the cross-correlated sequence. As each of the signals, x(i) and y(i), comprises of N finite number of trials, the resultant cross-correlation sequence has (2N-1)samples. The graphical presentation of a cross-correlation sequence is called a cross-correlogram. The quotation signal of a class is cross-correlated with the data of the residual signals of this class and the facts and figures of all pointers of another class. If we have two subjects of ECOG pointers, and class 1 has n pointers and class 2 has m pointers, and a quotation pointer is selected from class 1, then a total of (n-1) cross-correlation sequences are got from class 1 and a total of m cross-correlation sequences from class 2.

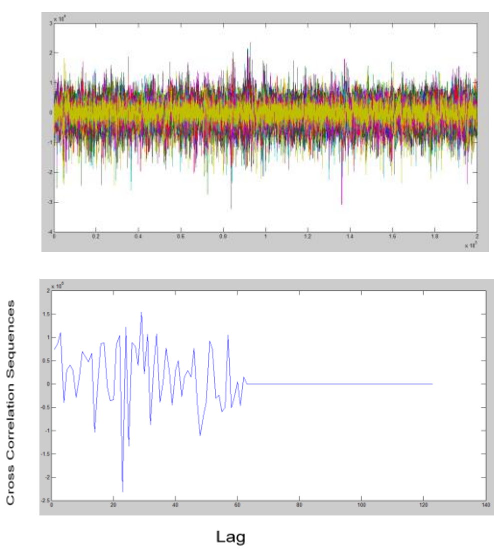

Fig. 3 Typical Finger movement and their respective cross correlograms for subject 1in dataset IVa.

Fig. 3 presents typical pointers of the finger movement for subject 1 of facts and figures set IVa. The typical cross correlograms for the finger movement of the same subject are furthermore shown. Fig. 4 displays usual pointers of dataset IVa for the finger movement for subject 2. This figure presents typical outcomes of the cross-correlogram.As shown in Fig. 4, the cross-correlogram of the subject 1and subject 2 is developed by the quotation pointer. It is known that if two curves have precisely the identical form, this means, they are highly cross-correlated with each other and cross-correlation is around 1. From Figs. 3 and 4, one can see that the shapes of the two bends are not exactly identical, which indicates the statistical independency. That means, there is more of a possibility to achieve better separation.

2.2.2 Stastical Feature Extraction: To decrease the dimensions of the cross-correlation sequences, this study considers six statistical features, mean, median, mode, benchmark deviation, greatest and smallest as the characteristic representatives ideally containing all significant information of the original signal patterns. These characteristics are calculated from each cross-correlation sequence or cross-correlogram to create characteristic vector groups. The six traits of the cross-correlation sequences are discovered to assist as significant indicators of the neurological state of the subjects [13].

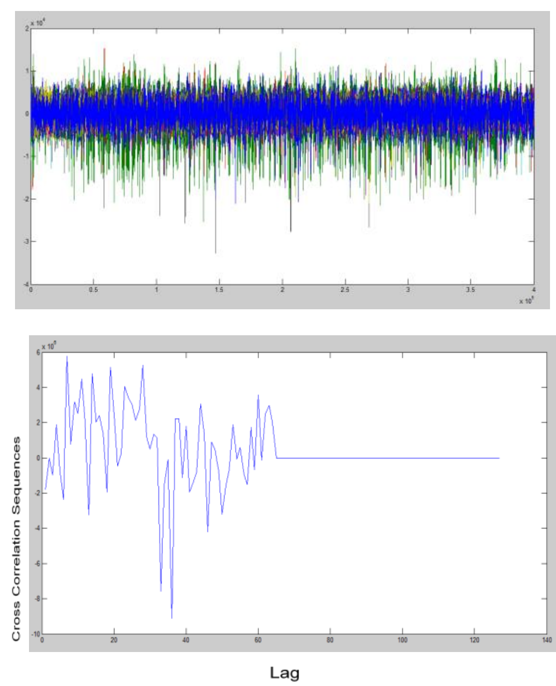

Fig:4 Typical Finger movement and their respective cross correlograms for subject 2 in dataset IVa.

2.2.3 Classification: This study employs the SVM with radial basis function (RBF) kernel as a classifier to differentiate the characteristics from the cross-correlation method. a 10-fold cross-validation procedure is used for assessing the presentation of the suggested procedure. This method divides the feature vector sets into 10 roughly equal-sized distinct partitions. One partition is then utilized for testing, whilst other partitions are utilized for training the model. The mean correctness over the ten sprints obtained from the test facts and figures is taken as the performance evaluation criteria in this study

III.CONCLUSION

The translation of brain undertakings into control signals in BCI systems needs a robust and classify of the various types of data. In this paper, we present a cross-correlation based SVM algorithm for advancing the classification correctness of the MI-based ECOG signals in BCI systems. The proposed design utilizes a cross-correlogram founded characteristic extraction procedure for the MI pointers, and evolves a SVM classifier for the classification of the extracted MI characteristics..ECOG has larger amplitude, higher topographical tenacity, and a much broader frequency variety than scalp-recorded EEG, and is also less susceptible to artifacts. At the identical time, ECOG is expected to have, greater long-term stability than do intra cortically noted signals. The major deductions of this study are summarized as follows.

1)The cross-correlation characteristic extraction method is productive for the classification presentation even when the data size is very large

2) The untested results utilizing the proposed algorithm are reliable because the parameter values of the SVM classifier are optimally chosen through the two-step grid search algorithm rather than by the manual assortment.

3)Its successful culmination, blended with resolution of the other matters summarized above, could lead to ECOG-based BCI schemes of large value to people with disabilities. Our outcomes suggest that an ECoG-based BCI could supply for persons with critical motor disabilities a non-muscular connection and control option that is mightier than EEG-based BCIs and is steadier and less traumatic than BCIs that use electrodes penetrating the brain. In the future, we will continue the suggested cross-correlation founded SVM algorithm to multiclass classification problems.

IV. ACKNOWLEDGMENT

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