Fractal Dimension Methods for Feature Extraction in Optimized Harmony Search-based Hidden Markov Model during Motor Imagery

Prajwali P. Korde
ME IInd year
PG dept of Computer Science
SGBAU Amravati

V. M. Thakare, PhD
HOD
PG dept of Computer Science
SGBAU Amravati

ABSTRACT
Brain Computer Interface (BCI) has become a hot spot in recent years. The goal of proposed method is the development of a fractal dimension method that can be used to increase accuracy and computation time in harmony search model (HMM) during motor imagery tasks. The HMMs were originally applied to speech recognition; they have proven to be highly successful in the modeling of dynamic data sequences. However, the success of HMMs is highly related to their ability to encode electroencephalography (EEG) in their parameters while allowing many unknown quantities to be learned through the optimization of their emission and transition probabilities. The optimized approach for the HMM in the training phase of time series electroencephalography data during motor imagery-related mental tasks is used.

In this paper Differential Signal method (DS) and Time Dependent Fractal Dimension (TDFD) are used to achieve more computation time and accuracy. TDFD method gives better result than other two methods. In this method Optimized HMM method and Fractal dimension method are combined to achieve better performance.

General Terms
Algoritham, Hidden markov model

Keywords
Brain computer Interface, Motor Imagery, EEG

1. INTRODUCTION
A brain–computer interface (BCI) is a communication path between the brain and an external device [1]. BCIs are often intended for augmenting, assisting, or fixing human cognitive or sensory-motor functions. BCI systems permit people to send commands to electronic devices from brain activity instead of muscular activity [1]. EEG is the tracing of electric potentials produced in cortical neuropile by the local collective partial synchrony of electrical field activity. Now a day's most commonly determined by electrode array which are attached to the scalp with water based gel [2]. EEG is the mostly studied portable noninvasive brain imaging modality; functional near-infrared spectroscopy (fNIR) is less developed technology [3]. Practical EEGs are dynamic with regard to nonlinear changes in signal patterns over time. To resolve this problem, new method proposed is dynamic EEG classification for hidden Markov models. While the HMMs were initially applied to speech recognition, this is proven to be highly successful in the modeling of dynamic data sequences [3].

Motor imagery tasks are realized by detecting the desynchronization and synchronization of SMRs. The frequently used motor imagery tasks are imagery hand, tongue and foot movements. Once obtained, SMRs are analyzed using classification operations preprocessing, and feature extraction [4]. Feature extraction is the process of precisely make simpler, the representation of data by diminishing its dimensionality while extracting its relevant characteristics for the required task. HS algorithm is a capable meta-heuristic optimization method which is effectively applied to dissimilar engineering and scientific problems.

2. BACKGROUND
EEG-based research is most widely performed in clinical and neuro engineering areas because of its convenient measurement and non-invasiveness system. The authors review a variety of classification algorithms, like, support vector machines, independent component analysis and so on. Most of the electroencephalogram (EEG)-based MI BCI studies deal with healthy subjects [2]. BCI training has been performed with patients with cerebral palsy, spinal cord injury (SCI), or with amyotrophic lateral sclerosis. Motor imagery can obtain brain oscillations in central beta rhythm and Rolandic mu rhythm, both are initiating in the sensorimotor cortex. Lesser work was reported in compound limb motor imagery, involves several parts of limbs than simple limb motor imagery [3, 4].

Feature extraction is the procedure of correctly simplifying the representation of data by diminishing its dimensionality while taking out its relevant characteristics for the required task [1]. Fractal dimension is a statistical measure that specifies the complexity of objects or a quantity that is self-similar over several region of time interval or space [1]. It has been successfully used in various areas to characterize such quantities and objects but its usage in motor imagery based BCI has been more up to date. There are numerous fractal dimension estimation methods; some of them are not applicable to every type of data revealing fractal properties. In order to accomplish a higher speed and classification accuracy, the fractal dimension method that is most useful to the data at hand should be chosen [6]. Electrophysiological differences between healthy users and patient groups are measured in sensorimotor rhythm deflections from baseline at some stage in motor imagery[10]. Additionally, using a linear discriminant analysis classifier and common spatial pattern algorithm, the classification accuracy was compared and calculated between groups. It seems to be a good advice to apply a more general mental screening procedure [10].

3. PREVIOUS WORK DONE

Kwang-Eun Ko et.al [1] has proposed an adaptive learning method is based on an optimization process of the hidden Markov model (HMM) that is based on meta-heuristic algorithms. This method has some issues of model interpretation and complexity control. This method advances performance in regards of robustness and accuracy. Optimized HMM classifier is further capable of classifying EEG datasets over ordinary HMM during motor imagery. One of the major problems of BCI research has been using event-related potentials from mental tasks that are applicable to real-world situations. Scott Makeig et.al [2] provides discussion on the current neuro scientific questions and data processing challenges. These challenges are facing by BCI designers and outline promising some present and future directions to address these issues. Bayesian approaches are particularly well suited to hypothesis refinement and thus may represent a particularly appropriate framework. Appropriate functional links to dissimilar types of physiological and behavioral data make it possible to mix and develop information from a diversity of source modalities within an ordinary computational framework. G R M¨uller-Putz et.al [3] has proposed electrophysiological differences between healthy users and patient groups are measured in terms of sensorimotor rhythm deflections from baseline in motor imagery, electroencephalogram microstate scalp maps and strengths of inter-channel phase synchronization. Furthermore, using a common spatial pattern algorithm and a linear discriminant analysis classifier, the classification accuracy was calculated and compared between groups. It seems to be a good advice to apply a more general mental screening procedure. Author highlights the difficulty in unswervingly translating consequences from healthy subjects to participants with SCI. Weibo Yi, Shuang Qiu et.al [4] has proposed the differences between 3 EEG patterns of simple limb motor imagery and three kinds of compound limb motor imagery proposed by spatial distribution coefficient and power spectral entropy event-related spectral perturbation. In addition, three modified multi-class CSP algorithms were used for taking out feature of 7 mental tasks. The work implies that tthe separable differences between simple compound limb motor imagery and limb motor imagery are exits. These can be utilized to assemble a multimodal classification paradigm in motor imagery based BCI systems. Yan Bian, Hongwei Li et.al [5] has proposed the Steady State Visual Evoked Potential (SSVEP) is a very appropriate input for the signal of BCI system because of its high information transfer rate and short training time. The outcomes were mainly originated by individual difference. Some subjects did not do well because he/she was not sensitive to several frequency or did not get adjust to the BCI system or did not observe the target earnestly. Furthermore, some stimuli frequencies were the double frequency of a further stimuli frequency in this system and the classification results may be affected. Min Chen et,al [6] has proposed new man-machine interactive mode, brain computer interface to construct brain-controlled spelling devices, single recognition of communication carrier signals must be recognized. Support vector machine (SVM) is a non-linear classifier, as its optimization procedure is completed only by its support vectors. Furthermore, it has good generalization ability, fast and is especially applicable for classifying EEG signals with some non-linear behaviors. This algorithm is very sensitive to parameters ν and γ; thus, it must be carefully determined. These results create a good foundation for increasing the overall communication speed of the brain computer interface. Gerwin Schalk et.al [7] has proposed clinical implementation of ECOG-based BCIs. A chronically implanted ECoG-based BCI system would consist of either a subdural or epidural array that includes amplification/ digitization/ wireless electronics, is powered by a battery at a remote site and is permanently implanted through a small (e.g., 19-mm) burr hole in the skull. This ECoG based system is implemented by 4 simple steps that are functional Localization, coregistration, implementation, integration. ECoG based system are appropriate for chronic use must be wholly implanted and capable of performing reliability for many years. Gamma activity at higher frequencies shows much greater anatomical and functional specificity than signals in the mu and beta bands, and can also not readily be detected by EEG. These ECoG based BCI systems are not yet developed. The individual component that comprises them is under development. Various perspectives of BCI using ECoG are explored, by using these methods many advance techniques can be developed in future for better single acquisition. F Schettini et.al [8] has proposed whether a repeated (automatic) update of the classifier's parameters across BCI sessions increased the system's performance in terms of accuracy and communication efficiency and also evaluated a self-calibration algorithm to label data that were acquired in the unsupervised modality. The algorithm will be used to update the classifier parameters without the need for an explicit calibration session. Continuous recalibration of classifier parameters can enhance the system's performance over several sessions in a single day, and the proposed algorithm can recalibrate the system using unlabeled data from online sessions and ensure performance stability. BCIs should implicitly withhold control when the user is not attending to the interface, even without an explicit mechanism to enter a pause mode. Further online tests that involve end users for multiple sessions over several days should be performed to determine the efficacy and reliability of the proposed algorithm in non-experimental conditions. Gang Luo et.al [9] has proposed certain distance constraint specified in orthogonal latin square pairs can be used to increase both the communication speed and classification accuracy of the P300 BCI system. This paper shows that for every matrix size commonly used in P300 BCI, thousands to millions of such orthogonal Latin square pairs and distance-constrained can be systematically and efficiently constructed. It takes 2 days to enumerate all possible, simultaneous row or column permutations to obtain the complete set of 13,716,864 orthogonal Latin square pairs satisfying the minimal distance constraint. A direction for future work is to investigate quantitatively the benefits that these distance-constrained, orthogonal Latin square pairs can bring to P300 BCI, mostly on ALS patients.

In this method Time Dependent Fractal Dimension (TDFD) and Differential Signal method (DS) are used to achieve more computation time and accuracy. TDFD method gives better result than other two methods. In this method Fractal dimension method and Optimized HMM method are combined to achieve better performance.

4. EXISTING METHODOLOGY

4.1 Harmony Search Algorithm

The harmony search (HS) algorithm [1] is promising meta-heuristic optimization method that has been effectively applied to dissimilar engineering and scientific problems. Other meta-heuristic algorithms, like simulated annealing, particle swarm optimization, and GA, have a major drawback in that a complex technique for setting the novel model parameters is required.

In the online classification process, the incoming EEG signals are processed as follows:

1) The spatial features of the EEG signals are filtered via the CSP analysis. The signals in every spatial feature are transformed using an STFT to extract the time-varying spectra.

2) From the feature vectors at time t, the initial parameter set of the three states of HMM are estimated by the selective BW algorithm.

3) The initially trained parameters are applied to the HS algorithm to optimize the HMM parameter set.

4) The HMM with optimized parameters performs the online classification, which uses posterior probability estimation for each motor imagery task every t/100.

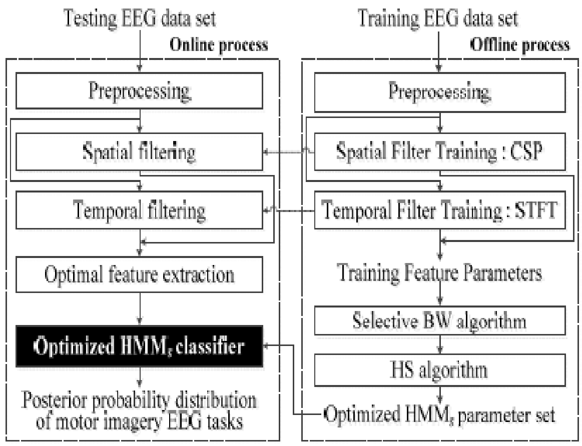

Figure 1:- Architecture of online classification of motor imagery EEG signals [1]

4.2 Motor Imagery-Induced EEG Patterns in Individual with SCI

Electrophysiological differences between healthy users and patient groups are measured in terms of SMR deflections from baseline during motor imagery, electroencephalogram microstate scalp maps and strengths of inter-channel phase synchronization. Furthermore, using a common spatial pattern algorithm and linear discriminant analysis classifier, the classification accuracy was compared and calculated between groups [3].

4.3 Spatial Distribution Coefficient and Power Spectral Entropy

Entropy provides a physical measurement to evaluate the order of a system [4]. Power spectral entropy (PSE) estimates modification in the amplitude component of the power spectrum of the EEG is modified from Shannon's definition of entropy, with the amplitude components at each frequency of the power spectrum as the probabilities in the entropy estimations.

4.4 The Steady State Visual Evoked Potential (SSVEP)

The Steady State Visual Evoked Potential (SSVEP) [5] is a very appropriate input signal of BCI system. It provides short training time and high information transfer rate. A four direction motion control system of ball moving on the computer screen was set up to test the performance of the proposed method. The system used wavelet packet technology to discover the normalized powers of extraordinary sub wavebands as feature vector for the linear classifier and then translated them to the control commands. The results after experiment have proved comparing with conventional Finite Fourier Transform method, the wavelet packet technology method obtains and the control accuracy can reach more than 83 percent and the feature vector faster.

5. ANALYSIS AND DISCUSSION

5.1 Harmony Search Algorithm

For the offline and online processes of the proposed classification routine, the raw EEGs were obtained using a previously permitted EEG electrode layout. The training data set was recorded from 11 multinational subjects (ten males, one female). The brain activities were recorded by a multichannel (64CH) measurement system (Synamp 2, NeuroScan Corp.) with a feedback session, sampling at 1,000 Hz and band-pass filtering between 0.05 and 200 Hz [1].

5.2 Characteristics of Compound Limb MI

A contralateral dominance is not observed in left hand imagery. The parallel spatial distribution and ERD pattern in left hand motor imagery were also disclosed by examining four different MI tasks, which are probably due to the right handedness [4].

5.3 Spatial Patterns in CSP

The spatial patterns of 7 kinds of mental tasks obtained with dissimilar multi-class CSP algorithms are visualized, which can be used to verify the neurophysiologic plausibility of ERD/ERS for different types of motor imagery. The figure 2 shows the spatial patterns obtained by different multi-class CSP algorithms for single subject. Topographical distributions are made based on the spatial patterns.

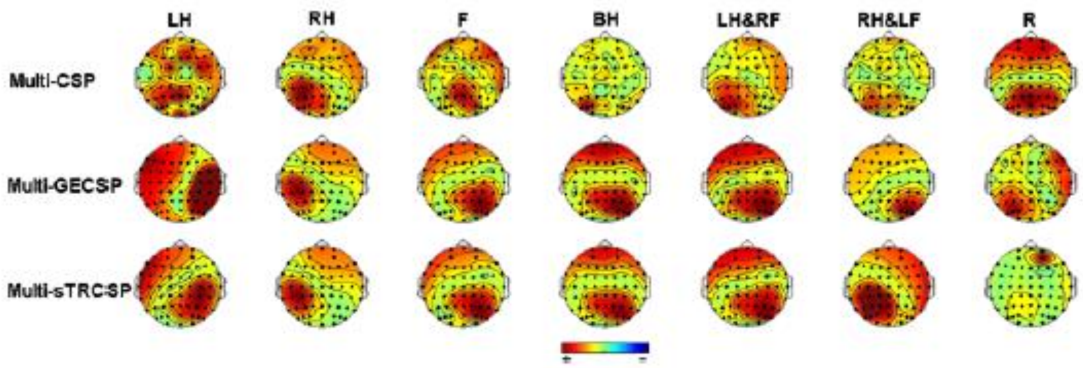

Figure 2: The spatial patterns obtained by different multi-class CSP algorithms for single subject. Topographical distributions are made based on the spatial patterns [4].

6. PROPOSED METHODOLOGY

The proposed method is Fractal dimension methods for feature extraction in Optimized Harmony Search-based Hidden Markov Model during motor imagery. In this method feature extraction part of model is expanded to fractal dimension method for HMM model. The optimized HMM technique and fractal dimension methods are combined in this paper. Here, TDFD method DFD and DS method are added in feature extraction for motor impairment.

6.1 TDFD Method

In TDFD method, a sliding window (with size *s*) is over a sample by a time step and the fractal dimension of the part of the sample within the window is estimated. The fractal dimensions were merged into feature vectors. Dissimilar window sizes were tested using a time step of one second.

6.2 DFD and DS Methods

The DFD method is a variation of the DS method. Firstly in the DFD method, the fractal dimensions of the samples from chosen electrodes are estimated and later on the pairwise differences of the fractal dimensions are calculated. On the other hand, in the DS method, the pairwise differences of the samples from chosen electrodes are estimated and later, the fractal dimensions of the pairwise differences are calculated. In both methods, the resulting values were concatenated into feature vectors. Just the three electrode configuration was tested while the two electrode configuration results in one dimensional feature vectors. Advance improvements in the classification accuracy were achieved by implementing TDFD method.

Following Figure 3 shows architecture of optimized HMM method with fractal dimension method TDFD, DS and DFD methods.

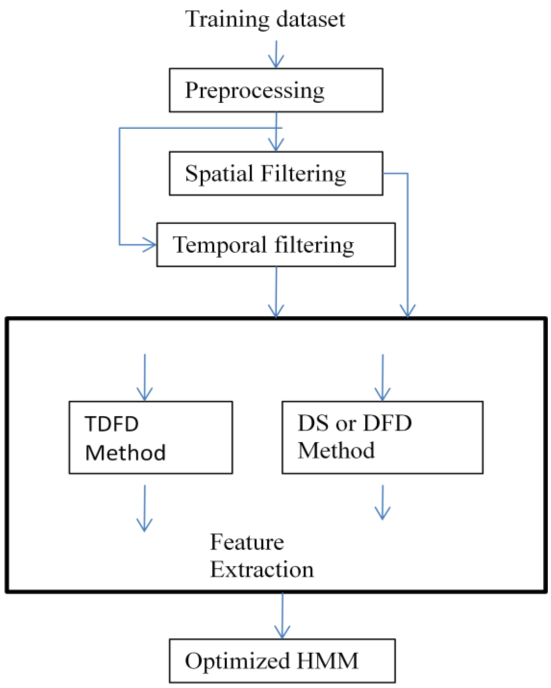

Figure 3- Advanced architecture of HMM

7. POSSIBLE OUTCOME AND RESULTS

Classification accuracies and computation times obtained by modifying the best performing methodology. Even though all the modifications increased the computation time, more improvements in the classification accuracy (by 3 %) were achieved only by implementing TDFD method. Conversely, implementing the DFD and DS methods resulted in lesser classification accuracies.

8. CONCLUSION

Fractal dimension methods provide much more classification accuracy and increase computation time. Advance enhancements in the classification accuracy were achieved by implementing TDFD method. Nevertheless, implementing the DFD and DS methods gives lower classification accuracies. All these methods provide better performance in comparison. Mainly TDFD method gives much better result than DFD and DS method. The advancements in the classification accuracy increased the computation time (by 3 %) were achieved only by implementing TDFD method. On the contrary, implementing the DFD and DS methods resulted in lesser classification accuracies. Motor imagery does not involve any muscular activity, motor imagery normalized SMRs are commonly utilized in BCI. This is beneficial for people with neurological disorders since their voluntary muscular activities might be impaired. One more advantage of the utilization of MI regulated sensory motor rhythms in BCI is the short training period required.

9. FUTURE SCOPE

Results can be improved by using other methods for fractal dimension for feature extraction. In future more robust method can be developed. Improvements also needed for actual implementation of this model.

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