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Full Length Article

Classification of motor imagery movements using multivariate empirical mode decomposition and short time Fourier transform based hybrid method

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ABSTRACT

Effective online processing of electroencephalogram (EEG) signals is a prerequisite of brain computer interfacing (BCI). In this paper, we propose a hybrid method consisting of multivariate empirical mode decomposition (MEMD) and short time Fourier transform (STFT) to identify left and right hand imaginary movements from EEG signals. Experiments are carried out using the publicly available benchmark BCI competition II Graz motor imagery data base. The EEG epochs are decomposed into multiple intrinsic mode functions (IMFs) by applying MEMD. The most significant mode is subjected to the short time Fourier transform; the peak of the magnitude spectrum is used as feature representing the corresponding epoch. The efficacy of the proposed feature extraction scheme is demonstrated by intuitive, statistical and graphical analyses. The performance of the proposed feature extraction scheme is investigated for various choices of classifiers. Our findings suggest that k-Nearest Neighbor (kNN) emerges as the best classification model yielding 90.71% accuracy. The performance of our method is also compared to that of existing works in the literature. Experimental outcomes backed by statistical validation manifest that the performance of the proposed method is comparable or better than many of the state-of-the-art algorithms.

1. Introduction

Brain computer interfacing allows to control and operate computer aided systems by intent alone. The major objective of BCI is to assist disable people for their rehabilitation. BCI involves detection, analysis and classification of different types of motor imagery movements to implement real time control and communication. Electroencephalogram (EEG) signals are often used for BCI purpose since it can be implemented as a non-invasive system [1].

There are several categories of EEG-based BCI such as limb motor imagery classification [2], continuous arm movements direction detection [3], individual finger movement decoding [4], forward–backward hand movement prediction [5], P300 evoked potential based character recognition [6] etc. One major category of BCI is the detection of motor imagery movements such as left and right hand movements [7]. Various methods have been developed in the literature for classifying different types of arm movements. A wavelet-based common spatial pattern (CSP) algorithm using low frequency features and Fisher linear discriminant classifier is developed to classify fast and slow hand movements in [8]. In [9], filter bank common spatial pattern (FBCSP) is implemented with mutual information based feature selection and for the identification task, Naive Bayesian Parzen Window (NBPW) classifier is used. Wrist movement classification has been done by extracting gamma band features from wavelet packet transform and employing radial basis function (RBF) classifier in [10]. Separability of EEG signals using adaptive auto regressive parameters is proposed in [11]. Time–frequency optimization and linear discriminant analysis is performed to classify left and right hand movements with reduced electrodes in [12].

Since EEG data for research purpose can be acquired with varying experimental setup and conditions, BCI competition was held providing standard data sets to evaluate and compare different algorithms. The standard data sets are proved to be representative in motor imagery and are suitable for BCI research. Different approaches have been studied to classify motor imagery movements in BCI competition II Graz motor imagery data set. Band passed EEG signals and power spectral density based linear discriminant analysis (LDA) is proposed in [13]. A Hidden Markov Model (HMM) based method is presented in [14] by the same author. Adaptive Auto Regressive (AAR) model based features are

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used with Bayesian Graphical Network (BGN) and Multi Layer Perceptron classifiers in [15,16]. Morlet wavelet is used to extract features from mu rhythms that are used in Bayes quadratic classifiers in [17]. Wavelet coefficient based statistical features and fuzzy support vector machine (FSVM) classifier is described in [18]. Discrete wavelet transform (DWT) along with autoregressive (AR) model is used to classify hand movements in [19]. In [20], higher order statistical features based on bi-spectrum of EEG signals are extracted to classify mental tasks. Multiple auto-correlation based feature extraction method along with learning vector quantization (LVQ) is proposed in [21]. Most recently, discriminative area selection (DAS) method is implemented with fuzzy Hopfield neural network (FHNN) classifier in [22].

To the best of authors' knowledge, a hybrid of multivariate EMD and short time Fourier transform is applied for the first time in EEG signal processing. The objective of this work is to identify imagery hand movements by extracting suitable features from EEG signals. Since EEG signal is invariably nonlinear and non-stationary [23], fixed linear orthogonal basis functions are not suitable for real life EEG data. The underlying dynamics of EEG signals is spread over various sub-bands in the frequency domain and particularly for motor imagery analysis, mu (8–12 Hz) and beta (18–25 Hz) rhythms have significant importance in neurophysiological context [24]. Empirical mode decomposition (EMD) has been successfully utilized in the processing of EEG signals [25,26]. It requires no pre-defined basis functions as in Fourier or traditional time–frequency transforms. However, EEG signals are usually multi-channel type whereas the EMD is applied on a single-channel basis; thus it ignores cross-channel dependence. Recently, the multivariate EMD (MEMD) has been introduced which can capture the cross-channel dependency and can be applied directly to all the EEG channels. Thus, in this paper the multi-channel EEG signal is decomposed into various intrinsic mode functions (IMFs) using MEMD. In addition, the 3rd IMF is shown to be most significant in terms of energy. Furthermore, in order to obtain localized information, the most significant intrinsic mode function is subjected to STFT and the peaks of the magnitude spectrum are used as features. The justification of the extracted features by this hybrid method is provided through statistical analysis (ANOVA and Kruskal–Wallis test) and graphical representations such as scatter plots, box plots and histograms. The features are then employed in the kNN classifier to discriminate left and right hand imagery movements. The performance of the proposed method is extensively studied for different classifiers and compared with that of other existing techniques.

2. Description of the EEG database

BCI competition II data set (GRAZ motor imagery III) provided by Technical University of Graz is used in this paper. The data is acquired from a normal subject while the subject is sitting in a chair with armrests. The subject is trying to control a feedback bar by making imagery movements of left or right hands. Left and right cues are in random order [27]. 7 runs are used with 40 trials for each run. During each trial at 2 s, an acoustic stimulus indicates the beginning of the trial and a cross '+' is displayed for 1 s. After this an arrow (left or right) is displayed at 3 s as the cue. At the same time the subject is asked to move a bar into the direction of the cue which is controlled by adaptive auto-regressive parameters of channel C3 and C4. The EEG signal is filtered between 0.5 and 30 Hz while the sampling rate is 128 Hz. The data set has both training and testing trial sets (containing 140 trials in each set) which are randomly selected to prevent any systematic effect due to feedback. The 140 train trials are provided with labels using which the test labels are to be determined. Fig. 1(a) shows the timing scheme of the experimental procedure while Fig. 1(b) presents the electrodes position of the EEG signal acquisition system. A detail description of the data set can be found in [28].

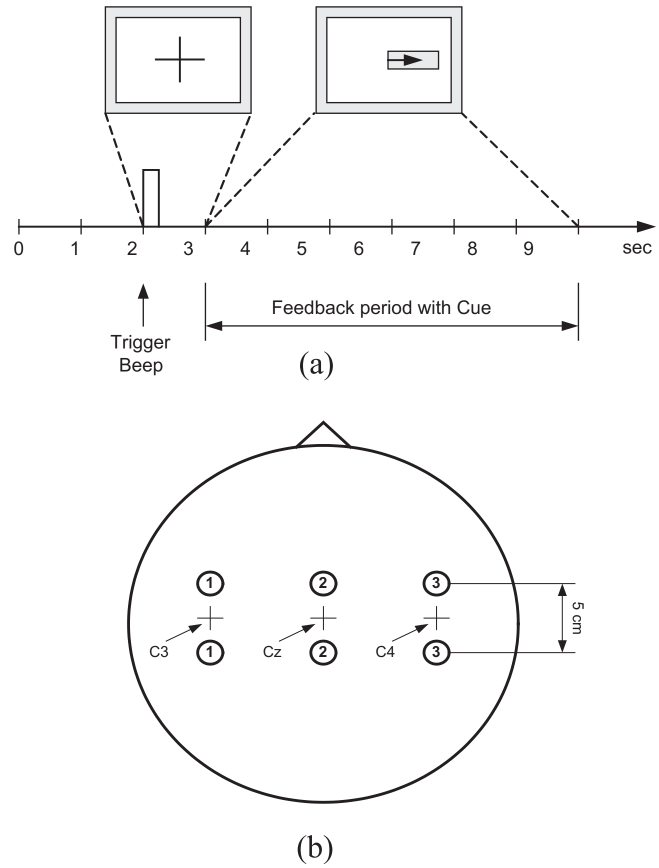

Fig. 1. (a) Timing scheme of the experiment; (b) electrode positions.

3. Multivariate empirical mode decomposition

Empirical mode decomposition (EMD) is a data driven technique to decompose a signal into a finite set of band limited basis functions called intrinsic mode functions (IMFs) [29]. The multivariate empirical mode decomposition (MEMD) is recently developed, where instead of computing the local mean using the average of upper and lower envelopes like conventional EMD, the multiple n dimensional envelopes are generated by projecting the signal along every directions in n variate spaces in MEMD. These projections are averaged to obtain the local mean.

Let a multivariate signal with n components is denoted by n dimensional vectors $\{\mathbf{v}(t)\}_{t=1}^{T} = \{v_1(t), v_2(t), \ldots, v_n(t)\}$ where $\mathbf{x}^{\theta_k} = x_1^k, x_2^k, \ldots, x_n^k$ denotes a set of direction vectors along the directions given by angles $\theta^k = \{\theta_1^k, \theta_2^k, \ldots, \theta_{(n-1)}^k\}$ on an $(n-1)$ sphere. The steps to compute MEMD is given below [30]:

1. Select suitable points for sampling on an $(n-1)$ sphere.
2. Calculate projection $\{p^{\theta_k(t)}\}_{t=1}^{T}$ along the direction vector $\mathbf{x}^{\theta_k}$ of the input signal $\{\mathbf{v}(t)\}_{t=1}^{T}$ for all k resulting $\{p^{\theta_k(t)}\}_{k=1}^{K}$ as the projection set.
3. Find the time instants $\{t_i^{\theta_k}\}$ corresponding to the maxima of $\{p^{\theta_k(t)}\}_{k=1}^{K}$.
4. Interpolate $[t_i^{\theta_k}, \mathbf{v}(t_i^{\theta_k})]$ to obtain multivariate envelope curves $\{\mathbf{e}^{\theta_k}(t)\}_{k=1}^{K}$.