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Extracting Phase Space Morphological Features for Electroencephalogram-Based Brain-Computer Interface

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In this paper, we introduce new features that quantitatively characterize the shape of the *m*-dimensional phase space trajectory reconstructed for the electroencephalogram (EEG) signals which reflects the brain electrical activity at different motor imagery tasks. The proposed features consist of the distances between the two extreme points along each embedding dimension of the reconstructed phase space (RPS) as well as the length of the line segment representing the projection of the trajectory points on every embedding dimension separately. The new features were extracted for dataset III from BCI competition II while the K-nearest neighbor (KNN) classifier was used to evaluate the effectiveness of the proposed set of features. The maximum classification accuracy was 89.29% while the maximum mutual information (MI) obtained-the competition criterion- was 0.70 which outperform the state of the art algorithms proposed for the same dataset.

Keywords: Brain-Computer Interface, Motor Imagery, Nonlinear Dynamical Modeling, Phase Space.

1. INTRODUCTION

Brain-computer interface (BCI) is considered as a communication channel between the human brain and the external world.[1] BCI systems were developed to make it is easier for the disabled people to communicate with their environment through measuring the brain activity at different mental states.[2] Different techniques may be used to measure the brain activity but the electroencephalogram (EEG) offers EEG-based BCI systems with high temporal resolution, relatively low cost, and more convenient for patients to use.[3]

The EEG signals are measurements of the brain electrical activity at different mental states through scalp electrodes. These signals contain multiple frequency bands which can be used to characterize each mental state. The analysis of the EEG signals measured when awake subject does not produce any sensory or motor actions shows brain activity over the sensorimotor cortex at mu (8–13 Hz) and beta (14–25 Hz) bands which is termed as "event-related synchronization (ERS)" while these activities at mu and beta frequency bands are attenuated when the human subject starts to process sensory stimuli or motor commands and this phenomenon is called "event-related desynchronization (ERD)."[4] The ERS/ERD activities could be occurred also during the imagination of movements and hence the changes of these activities could be used to build a BCI system which depends on the motor imagery tasks.[5]

Different classification algorithms were introduced to differentiate between the EEG signals recorded at different mental states proposing extracting different features. The winner of BCI competition II who addressed dataset III extracted features based on Morlet-wavelets with the Bayesian classifier to classify two different motor imagery tasks; imagination of left and right hand movements.[6] Xu et al. extracted statistical features for the set of wavelet coefficients and used fuzzy support vector machine (FSVM) classifier.[7] Zhou et al. introduced bispectrum-based features to characterize the non-Gaussian information embedded in the EEG signals with different classifiers.[8]

In addition, different algorithms addressed the nonlinear information contained in the EEG measurements through the nonlinear dynamical modeling of the EEG signals.[9] Hosseinifard et al. extracted nonlinear features such as Lyapunov exponent, correlation dimension, Higuchi fractal, and detrended fluctuation analysis (DFA) with the KNN classifier to differentiate between normal and depression patients.[10] Banitalebi et al. extracted features such as mutual information, correlation dimension, Lyapunov exponents, and minimum embedding dimension to classify between different motor imagery tasks.[11]

In this work, we introduce extracting nonlinear dynamical modeling features based on the characterization of the shape of

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the reconstructed phase space (RPS) which transform the 1D EEG signal into an m-dimensional trajectory. The new features represent simple phase space morphological descriptors that can be used to differentiate between the imagination of left and right hand movements.

2. DATASET DESCRIPTION

Dataset III from BCI competition II[12] which was recorded during motor imagery tasks at the Laboratory of Brain-Computer Interface, Graz University of Technology[13] was used to examine the effectiveness of the new set of features. The EEG signals in this dataset were measured using channels C3, Cz, and C4 for one normal female subject who was required to control a feedback bar by the imagination of left or right hand movements. The dataset contains 140 trials for training and 140 trials for testing. In addition, the trials were divided equally between the imagination of right and left hand movements. The sampling rate of the measured EEG signals was 128 Hz and these signals were filtered using band-pass filter with corner frequencies 0.5 and 30 Hz. The duration of each trial is 9 seconds and the imagination starts at $t = 3$ when an arrow appears on the screen in random order to indicate the direction at which the subject should imagine the movement.

3. METHODOLOGY

The EEG-based BCI systems consist of different stages namely; preprocessing, feature extraction, feature selection or dimensionality reduction, and finally the classification stage.

3.1. Preprocessing

The EEG signals were filtered using third-order Butterworth band-pass filter with corner frequencies 0.5–30 Hz. In addition, the spectral subtraction denoising (SSD) methodology[14] was utilized with $\alpha = 5$ for further removal of the undesired noise in the filtered EEG signals.

3.2. Feature Extraction

3.2.1. Phase Space Reconstruction

The time-delay embedding methodology[15] has been widely employed to reconstruct an m-dimensional phase space trajectory or attractor using one or more time series measured from a dynamical system. Takens[16] proved that the reconstructed phase space (RPS) for a measured time series will has the same dynamical properties as the true attractor of the system that produced this time series, and hence the characterization of the RPS will reflect the system's behavior at different states.

Two parameters should be identified for the time series modeled by phase space which are the embedding dimension and the delay-time. Let $\{x_k : k = 1, 2, \ldots, N\}$ be the measured time series. Then, the reconstructed phase space $Y(m)$ can be represented as the following:

$$Y_i(m) = \begin{bmatrix} Y_1 \\ Y_2 \\ \cdots \\ Y_M \end{bmatrix} = \begin{bmatrix} x_1 & x_{1+\tau} & \cdots & x_{1+(m-1)\tau} \\ x_2 & x_{2+\tau} & \cdots & x_{2+(m-1)\tau} \\ \cdots & \cdots & \cdots & \cdots \\ x_M & x_{N-m\tau} & \cdots & x_{N+(m-1)\tau} \end{bmatrix} \quad (1)$$

where $M = N - (m-1)\tau$, N is the length of the time series, m is the embedding dimension, and τ is the delay-time.

Here, we dealt with the EEG signals as measurements obtained from a nonlinear dynamical system that can be modeled by phase space. The delay-time τ was selected to be the time lag at which the first local minimum of the mutual information between the EEG time series x_k and its delayed version $x_{k+\tau}$ occurs.[17] Furthermore, Cao's algorithm[18] was used to calculate the embedding dimension m for each time series. The average of the delay-time τ as well as the average of the embedding dimension m calculated for the whole training dataset were selected to be the optimal delay-time and the optimal embedding dimension respectively.

3.2.2. Morphological Features

The RPS is considered as an m-dimensional object which could be characterized by some quantitative measures describing its shape. Two morphological descriptors are introduced here;

(a) The Euclidian distance between the two extreme points along each embedding dimension and

(b) The length of the line segment representing the projection of the trajectory points over each dimension.

Figure 1 shows a simplified 2D phase space trajectory where each point is represented by two values $(X1, X2)$ and the morphological features that can be extracted to characterize its shape. As shown in Figure 1(a); $D1$ and $D2$ represent the distance between the farthest and nearest points along embedding

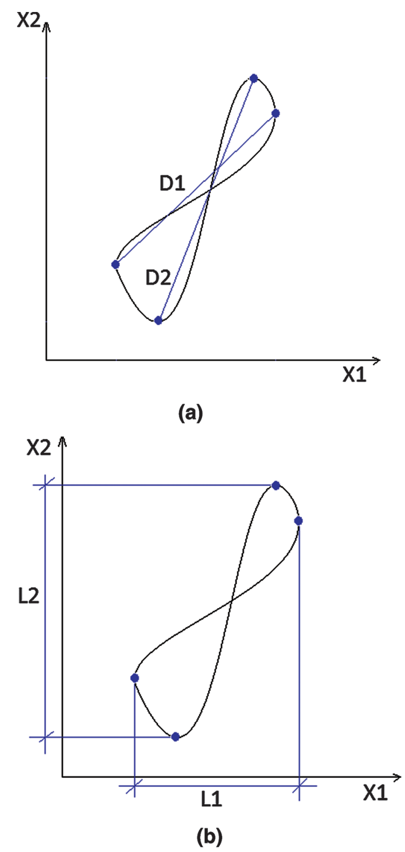

Fig. 1. Simplified phase space trajectory. (a) Distance between two extreme points, (b) length of the projection regions.

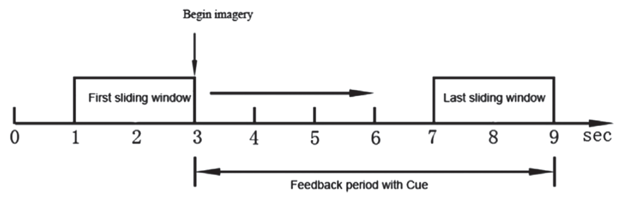

Fig. 2. EEG data segmentation using sliding window procedure.

dimensions $X1$ and $X2$ respectively. The farthest point along embedding dimension $X1$ is considered as the point which has the maximum value of $X1$ with its corresponding value of $X2$, while the farthest point along embedding dimension $X2$ is considered as the point that has the maximum value of $X2$ with its corresponding value for $X1$. The nearest points are determined in the same way but they are characterized by the minimum value along each dimension.

On the other hand, if the trajectory points projected over $X1$ or $X2$, they would occupy a region of length $L1$ or $L2$ respectively as shown in Figure 1(b). $L1$ and $L2$ are calculated by subtracting the minimum value of each embedding dimension from the maximum value of the same dimension as follows:

$$L1 = \max(X1) - \min(X1) \quad (2)$$

$$L2 = \max(X2) - \min(X2) \quad (3)$$

3.3. Dimensionality Reduction and Classification

The principal component analysis (PCA) with 99% of variances was used here for the dimensionality reduction purposes while the K-nearest neighbor (KNN) classifier at different values of K was used for classification. The classification procedure used in this work is similar to the procedure used by Fang et al.[19] who extracted features from an EEG segment inside a sliding window of 2 sec length which starts at $t = 3$ sec and moves by one time step until $t = 9$ sec as shown in Figure 2. The classification is performed at every time step and the maximum performance measures over the whole classification period are reported.

4. RESULTS AND DISCUSSION

To extract the morphological features for the RPS, the embedding parameters should be identified first. The optimal delay-time τ and the optimal embedding dimension m calculated for the training dataset using the first minimum of mutual information and Cao's algorithm were 3 and 9 respectively.

Using the aforementioned parameters, the phase space was reconstructed for each EEG segment inside the sliding window for channels C3 and C4 and the proposed features were extracted from the RPS and fed to the classifier as three feature sets;

(a) the features based on distance between the two extreme points (e.g., $D1$ and $D2$),

(b) the features based on the length of the line segment representing the projection region (e.g., $L1$ and $L2$) and

(c) the combined feature vector using the first and second sets.

The length of the feature vector in sets 1 and 2 is 2 m while the length of the feature vector is 4 m for the third set. Furthermore, the mutual information (MI) which represents the information transfer between the human brain and the external devices[20] was used as an evaluation criterion to evaluate the effectiveness of each feature set.

Table I presents the minimum error rate (ERR) as well as the maximum MI obtained using only the first set of features while Table II shows the performance measures obtained using the second set of features. Furthermore, Table III shows the minimum error rate (ERR) as well as the maximum MI obtained over the whole classification period in addition to the time at which the maximum MI occurred. In addition, Figure 3 shows the time course of the MI and the error rate (ERR) from $t = 3$ sec to $t = 9$ sec that was calculated using feature set 3 with the KNN classifier at $K = 5$ which produced the maximum MI.

Different methods were introduced to boost the MI for the dataset addressed in this paper to enhance the performance of the BCI systems developed for the motor imagery tasks. Table IV shows the comparison between the proposed system using the phase space morphological features and the other studies which addressed the same dataset.

The proposed set of features outperformed the methods in comparison based on the competition criterion (i.e., MI). Table IV shows that the first winner of the competition[6] obtained MI equals to 0.61 using Morlet-Wavelets at frequencies between 10 and 22 Hz for channels C3 and C4. Zhou et al.[8] proposed autoregressive (AR) based features combined with higher-order statistical features extracted from the bi-spectrum of channels C3 and C4 in addition to the power spectral density. Furthermore, they employed different classifiers to evaluate the performance of their system such as the linear discriminant analysis (LDA) and neural networks (NN). Using the NN classifier, they obtained MI equals to 0.64 bit. In addition, Xu et. al.[7] utilized fuzzy support vector machine (FSVM) to classify the two different motor imagery tasks using statistical features calculated for the set of the wavelet coefficients extracted from the EEG segments. Fang et al.[19] extracted features based on the phase

Table I. Maximum performance measures using set 1.

Classifier	Min ERR (%)	Max MI (bit)	Time of max MI (sec)
$K = 1$	17.86	0.38	5.95
$K = 3$	15.71	0.45	6.01
$K = 5$	**12.14**	0.62	5.94
$K = 7$	**12.14**	0.62	5.95
$K = 9$	14.29	0.52	6.37
$K = 11$	14.29	0.51	5.77

Table II. Maximum performance measures using set 2.

Classifier	Min ERR (%)	Max MI (bit)	Time of max MI (sec)
$K = 1$	16.43	0.46	6.07
$K = 3$	15.00	0.49	6.05
$K = 5$	13.57	0.54	5.90
$K = 7$	12.86	0.60	5.91
$K = 9$	**11.43**	**0.64**	5.91
$K = 11$	12.86	0.54	5.90

Table III. Maximum performance measures using set 3.

Classifier	Min ERR (%)	Max MI (bit)	Time of max MI (sec)
$K = 1$	15.00	0.47	5.65
$K = 3$	14.29	0.54	5.72
$K = 5$	**10.71**	**0.70**	5.86
$K = 7$	12.14	0.61	5.93
$K = 9$	12.86	0.55	5.91
$K = 11$	14.29	0.46	5.91

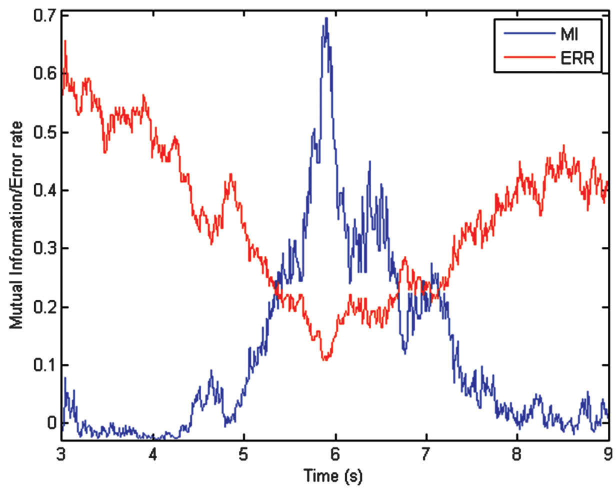

Fig. 3. Time Course of MI and ERR using KNN with $K = 5$.

Table IV. Comparison between the proposed method and other studies for the same dataset.

Method	Features	Classifier	Max MI (bits)	Min ERR (%)	Time of max MI (sec)
Proposed	Features set 3	KNN, $K = 5$	**0.70**	10.71	5.86
Fang et al.[19]	AFAPS + ARPS	LDA	0.67	9.29	5.76
Xu et al.[7]	Wavelet based features	FSVM	0.66	12.14	5.92
Zhou et al.[8]	Higher order statistics	NN	0.64	10	–
Zhou et al.[8]	Higher order statistics	LDA	0.63	10.71	–
Winner[6]	Morlet Wavelets	Bayesian classifier	0.61	10.71	7.59

space reconstruction of the EEG signals. They assumed that the embedding dimension value is $m = 2$. In addition, the delay-time τ was selected as the delay-time that produce the maximum performance measures using cross validation over the training data. No optimization procedures were used in their procedure to select the optimal embedding dimension and the delay-time. Fang et al. extracted two sets of features which were: the AR model coefficients of the RPS (ARPS) and the maximum amplitude of the discrete Fourier transform of the RPS in μ and β bands (AFAPS). The features were extracted from each embedding dimension for channels C3 and C4 and the feature vector was fed to LDA classifier.

The delay-time and the embedding dimension used in this work were selected using selection algorithms such as the first minimum of the mutual information and Cao's algorithm to avoid any assumptions. In addition, The MI obtained using the combined feature vector with simple classifier such as the KNN at $K = 5$ was 0.70 bits which outperform the studies in comparison and suggest that these new features can be used in differentiating between the imagination of left and right hand movements.

5. CONCLUSIONS

In this paper, we introduced new descriptors that characterize the shape of the reconstructed phase space trajectory for the EEG signals at different motor imagery tasks. These descriptors are based on calculating the distances between the two extreme points for each embedding dimension as well as the lengths of the line segment representing the projection region of the trajectory points over each embedding dimension. The KNN classifier was used to evaluate the performance of the proposed system and the maximum MI obtained was 0.70 which outperform the state of the art algorithms which addressed dataset III from BCI competition II.

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