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Multiresolution analysis over graphs for a motor imagery based online BCI game

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ABSTRACT

Multiresolution analysis (MRA) over graph representation of EEG data has proved to be a promising method for offline brain–computer interfacing (BCI) data analysis. For the first time we aim to prove the feasibility of the graph lifting transform in an online BCI system. Instead of developing a pointer device or a wheel-chair controller as test bed for human–machine interaction, we have designed and developed an engaging game which can be controlled by means of imaginary limb movements. Some modifications to the existing MRA analysis over graphs for BCI have also been proposed, such as the use of common spatial patterns for feature extraction at the different levels of decomposition, and sequential floating forward search as a best basis selection technique. In the online game experiment we obtained for three classes an average classification rate of 63.0% for fourteen naive subjects. The application of a best basis selection method helps significantly decrease the computing resources needed. The present study allows us to further understand and assess the benefits of the use of tailored wavelet analysis for processing motor imagery data and contributes to the further development of BCI for gaming purposes.

1. Introduction

During the recent years many studies have focused on the use of electroencephalographic data (EEG) for human–machine interaction. This paradigm, known as brain–computer interfacing (BCI), is grounded on a diverse range of disciplines such as neuroscience, machine learning and digital signal processing among others.

The classification of imaginary limb movements has proven to be an adequate approach for augmenting motor functions for disabled and healthy subjects [1–4]. The physical basis of motor imagery (MI) BCIs comes from the changes on the μ rhythm during the performance of MI tasks, which is known as event-related desynchronisation (ERD) and event-related synchronisation (ERS) [5].

These changes on the EEG data occur in different locations on the scalp, at different time instants and on different frequencies. EEG data is also known to be highly noisy, and the patterns arisen during the MI process drastically change among different subjects. These characteristics make the analysis of MI data a remarkable complex task.

Wavelet analysis has been profusely applied for the analysis of EEG data [6–8]. The characteristics of this orthogonal system presents important benefits as it offers temporal-spectral analysis along different resolution levels. The introduction of the second generation wavelets has leveraged the design of new wavelet families that can adapt better to the domain of study [9].

In the present work we aim to explore the feasibility of applying multiresolution analysis over EEG data graph representation for an online real-time BCI system. The graph representation allows to embed the spatial information during the multiresolution analysis process covering the three dimensions involved in the ERS/ERD development (temporal, spectral and spatial dimensions). The method, fully described in [10], introduces the concept of tailored wavelet lifting for brain–computer interfaces.

The proposed online system is an *endless running game* where the subject has to control a character while it is constantly running forwards. During the game play the subject will have to decide which command to send to the game (either jump, stride left or stride right) depending on the game state at a given time. Video games have been recently used in the BCI field as they are easier to implement than other direct applications such as BCI controlled wheelchairs or robotic arms, and more engaging than spellers or pointing devices [11,12]. A detailed state of the art of the use of games in the BCI field is given in [13].

This paper is structured as follows. The data acquisition and preprocessing are detailed in Section 2.1.1. In Section 2.1.2 wavelet lifting on graphs is described. Section 2.1.3 describes the feature

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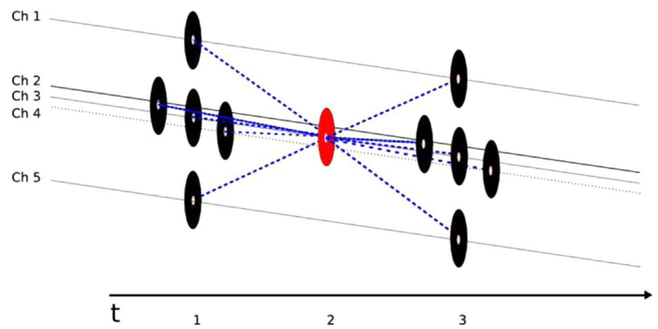

Fig. 1. Details of the graph after the even/odd split. Even nodes (black circles) are used to compute the detail coefficients, approximating the odd nodes (red circles). The number of channels depicted has been reduced for clarity, during the experiments 15 channels were used [10]. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

extraction technique applied and the classification method is detailed in Section 2.2. The game design along with the acquisition protocol are presented in Section 2.3. The results and discussions are detailed in Section 3 and conclusions are drawn in Section 4.

2. Methods

2.1. Data analysis and feature extraction

2.1.1. Data acquisition and preprocessing

Three different imaginary movements (right hand, left hand and feet) were recorded from fourteen healthy subjects, all of them naive on the use of online BCI. The subjects aged from 24 to 32 and 50% were female. All the participants, recruited from different schools and faculties at University of Essex, signed a consent form where the details of the experiment and the use of the acquired data were explained.

The data was recorded with a sampling frequency of 256 Hz. The monopolar electrodes covered the major part of the cortex area, specifically the following 15 locations: Fc3, Fc1, FcZ, Fc2, Fc4, C3, C1, CZ, C2, C4, Fp3, Fp1, FpZ, Fp2 and Fp4. Two reference electrodes were placed under the subjects' ears. The data from these two electrodes were averaged and subtracted from the rest of the electrodes at every sampling point.

Eight seconds of data were recorded for each trial and filtered using an elliptic band pass filter between 8 and 30 Hz. The signals were then cropped from $t=2$ s to the instant $t=7$ s as this period of the trial provides adequate information for motor imagery classification. Finally, a sliding window of one second with a sliding step of 50 was applied until the signal was divided into 20 segments. No extra preprocessing step was carried out in terms of artifact removal in order to assure a more dynamic feedback to the subject. In Section 2.3 a detailed explanation of the acquisition protocol is given.

The recording hardware used was the *BioSemi*'s *ActiveTwo* that reads the EEG signals using active electrodes.

2.1.2. Lifting transform over graphs

The data analysis is based on a graph lifting transform [14,15] over EEG data graph representation. Each MI segment of T samples and C channels $X^{T\times C}$ is embedded in a graph $G=(V,E)$, where V is the vertex set (a flattened version of X) and E represents the graph edges.

The edges of G are arranged such that they capture the temporal and spatial relationships present in the data segment X and they are represented by using an adjacency matrix Adj. As shown in Fig. 1, the node $v_{c_3,t}$, located on channel c_3 at instant t, is linked to $v_{c_3,t-1}$ and $v_{c_3,t+1}$ which are the closest temporal neighbours in the same channel. With the graph representation we also provide spatial information by including the four neighbouring electrodes of $v_{c_3,t-1}$: $v_{c_1,t-1}$, $v_{c_2,t-1}$, $v_{c_4,t-1}$ and $v_{c_5,t-1}$; and four more neighbours of $v_{c_3,t+1}$: $v_{c_1,t+1}$, $v_{c_2,t+1}$, $v_{c_4,t+1}$ and $v_{c_5,t+1}$. It is noteworthy that the proposed graph architecture makes the application of a graph lifting transform straight forward.

As in any lifting transform we need to define the *split, predict* and *update* steps.

The *split* step is defined over the node set by using the parity of t. The even vertex set V_e corresponds to the elements in segment X at even values of t, and analogously, the odd set V_o corresponds to the elements at odd values of t.

Prior to the definition of the *predict* and *update* functions the vertex set V of size $N=N_o+N_e$ has to be rearranged. The odd vertices V_o of size $N_o\times 1$ are relocated preceding the even vertices V_e of size $N_e\times 1$ obtaining the following graph definition:

$$\tilde{V}=\begin{pmatrix} V_o \\ V_e \end{pmatrix}$$
$$\tilde{Adj}=\begin{pmatrix} F^{N_o\times N_o} & J^{N_o\times N_e} \\ K^{N_e\times N_o} & L^{N_e\times N_e} \end{pmatrix} \quad (1)$$

The submatrices F and L in $\tilde{Adj}$ in Eq. (1) link the elements within the same node sets and are empty, so they are discarded. The block matrix J contains only edges linking odd elements to even elements and, analogously, K only links even elements to odd elements.

The lifting analysis function is then defined as

$$D=V_o-J^{\omega}\times V_e$$
$$A=V_e+K^{\omega}\times D \quad (2)$$

In Eq. (2) the prediction and update functions are defined as the matrix product $\mathcal{P}=J^{\omega}\times V_e$ and $\mathcal{U}=K^{\omega}\times D$, where J^{ω} and K^{ω} are the weighted adjacency block matrices. The predict matrix J is weighted row-wise applying the equation $J^{\omega}_{i,j}=1/(\sum_{j'}J_{i,j'})$ for each row i and column j, j' is the index used to iterate through the columns. The weighted version of K is analogously computed as $K^{\omega}_{i,j}=1/2*(\sum_{j'}J_{i,j'})$. The weighting is performed in order to maintain the spatio-temporal properties of the original graph and has been designed based on the linear wavelet lifting [10].

As a result of the lifting transform we obtain the detail coefficient set D and the approximation coefficient set A. The process described by Eq. (2) is repeated in each level. For level $l+1$, V is set as A obtained in level l. For the present study the transform was calculated for the first five levels of decomposition, obtaining ten coefficient sets $\{D^l,A^l\}, l\in 1,2,3,4,5$.

2.1.3. Common spatial patterns

The coefficient sets resulted from the transform in each level l, A^l and D^l, belong to $\mathbb{R}^{(T/2^l)\times C}$ with T=256 and C=15. Therefore, given the size of the data, a feature extraction step is needed before the classification process. For this task we chose to apply common spatial patterns (CSP) [16] as it has been successfully applied in other studies with a similar design [17,18].

For ease of understanding, we refer to the detail D^l and approximation A^l sets at different levels as $\overline{X}$. Each coefficient set is projected onto its own CSP space $\overline{Y}=W^T\times\overline{X}$ where W^T is the transposed CSP projection matrix.

CSP is a supervised spatial filtering technique which maximises the variance ratio between two different classes. It is computed as the generalised eigenvector decomposition of the estimated covariance matrix $\Sigma^{(+)}$ of the trials belonging to class $(+)$, and the estimated covariance matrix for the trials belonging to class (-), $\Sigma^{(-)}$:

$$\Sigma^{(+)}=W\Lambda^{(+)}W^T$$