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Decision tree structure based classification of EEG signals recorded during two dimensional cursor movement imagery

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HIGHLIGHTS

- We developed a method for classification of 2-D cursor movement imagery EEG data.
- EEG data were acquired from three subjects on different days in two sessions.
- The method achieved 65.35% average classification accuracy rate on the test data.
- The proposed method provided 12.25% improvement over the most related studies.
- The results proved that SVM is a more successful classifier than k-NN and LDA.

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ABSTRACT

Background: Input signals of an EEG based brain computer interface (BCI) system are naturally non-stationary, have poor signal to noise ratio, depend on physical or mental tasks and are contaminated with various artifacts such as external electromagnetic waves, electromyogram and electrooculogram. All these disadvantages have motivated researchers to substantially improve speed and accuracy of all components of the communication system between brain and a BCI output device.
New method: In this study, a fast and accurate decision tree structure based classification method was proposed for classifying EEG data to up/down/right/left computer cursor movement imagery EEG data. The data sets were acquired from three healthy human subjects in age group of between 24 and 29 years old in two sessions on different days.
Results: The proposed decision tree structure based method was successfully applied to the present data sets and achieved 55.92%, 57.90% and 82.24% classification accuracy rate on the test data of three subjects.
Comparison with existing method(s): The results indicated that the proposed method provided 12.25% improvement over the best results of the most closely related studies although the EEG signals were collected on two different sessions with about 1 week interval.
Conclusions: The proposed method required only a training set of the subject and automatically generated specific DTS for each new subject by determining the most appropriate feature set and classifier for each node. Additionally, with further developments of feature extraction and/or classification algorithms, any existing node can be easily replaced with new one without breaking the whole DTS. This attribute makes the proposed method flexible.

1. Introduction

Brain computer interface (BCI) technology is a system which makes it possible for paralyzed people to use an electronic device such as a computer cursor, a robotic arm or even a mobile phone by their thoughts. To execute it, a BCI system measures specific features of brain activity and translates them into device control signals. Input signal of such a system may be magnetoencephalography (Mellinger et al., 2007), near infrared spectroscopy (Adhika et al., 2012; Power et al., 2011), functional magnetic resonance imaging (Weiskopf et al., 2004; Lee et al., 2009), positron emission tomography (Deiber et al., 1998), electrocorticography (Aydemir and Kayikcioglu, 2011) or EEG (Siuly and Li, 2012; Nicolas-Alonso and Gomez-Gil, 2012; Aydemir and Kayikcioglu, 2013). Among these techniques, EEG is the most widely studied potential, mainly

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owing to its affordable and easy recording equipment which facilitates real-time operation and fine temporal resolution with its low set-up costs and noninvasive nature.

One of the most useful applications of a BCI is in controlling a computer cursor. The first EEG based cursor control studies focused on 1-D cursor control (Pfurtscheller et al., 1995; Kostov and Polak, 2000; Blankertz et al., 2004; Kayikcioglu and Aydemir, 2010). After satisfactory results were obtained, in order to enable considerably enhanced interfacing between the user and machine and utilize a much wider range of applications, researchers have focused on multi-dimensional cursor control. These studies have shown that multi-dimensional cursor control can be implemented using various brain signals, e.g. P300 potentials (Piccione et al., 2006), event-related desynchronization/synchronization (McFarland et al., 2010; Royer et al., 2010; Bai et al., 2008) and steady-state visual evoked potentials (Trejo et al., 2006; Bakardjian et al., 2009).

It is well-known that input signals of an EEG-based brain computer interface (BCI) system are naturally non-stationary, have poor signal to noise ratio, depend on physical or mental tasks and are contaminated with various artifacts such as external electromagnetic waves, electromyogram and electrooculogram. All these disadvantages have motivated researchers to substantially improve key performance characteristics of BCI systems, which are speed (i.e. how long it takes to translate input signal to device control signal) and classification accuracy (i.e. how often the translated device control signal is the one the user intends). Current motor imagery (MI) EEG-based BCI systems allow for one device control signal within several seconds (Lei et al., 2009; Kayagil et al., 2009) and have average classification accuracy (ACA) rate of 83% in a binary task (Hazrati and Erfanian, 2010). It is worth mentioning that an increase in the number of mental tasks decreases ACA (Obermaier et al., 2001).

Besides improving key performance characteristics, making EEG-based BCI system practical and more realistic is another important challenge. To do so, classifiers should be able to discriminate EEG signals which are recorded in different sessions on different days and mental tasks should be directly related to BCI application (Schalk et al., 2008; Aydemir and Kayikcioglu, 2011). In literature, many works dealing with EEG-based BCI have been based on classification of EEG signals recorded in only one session or on the same day (Hwang et al., 2009; Galan et al., 2007; Ting et al., 2008). There are also some works in which researchers have chosen separable mental tasks that are not directly related to BCI application but are easily detected. In an EEG-Based cursor movement study, Kus et al. (2012) navigated a cursor along a computer rendered 2-D maze into three directions of left, right and up. To do so, the five participants of the experiment were given the instruction to imagine the continuous opening and closing of left/right hand for left/right cursor movement and to imagine gripping an object with both feet for up cursor movement. In this 3-class MI classification problem, they achieved ACA rate of 74.84%. In another approach, Huang et al. (2011) proposed a two-dimensional MI-based BCI using event-related desynchronization (ERD) and event-related synchronization (ERS) and acquired EEG recordings from three subjects in one session on the same day. For a two-dimensional control, they detected left-hand ERD to command movement to the left, left-hand ERS to command movement up, right-hand ERD to command movement to the right and right-hand ERS to command movement down. In this 4-class MI classification problem, they achieved ACA rate of 48.5%. These studies are relatively successful and accurate; however, they are not practical and realistic.

In this study, fast and accurate classification methods were proposed for classifying EEG data of up/down/right/left computer cursor movement imagery. The proposed structure combined k-nearest neighbor (k-NN), linear discriminant analysis (LDA) and support vector machine (SVM) algorithms into a decision tree structure (DTS).

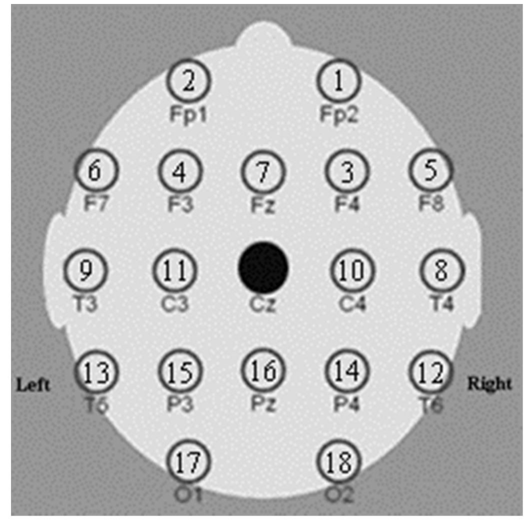

Fig. 1. Montage of EEG electrodes as International 10–20 System.

Following in the paper, in Section 2, first, the EEG-based BCI data set is introduced and then feature extraction methods are mathematically explained. In the last parts of this section, the three classifiers used in this study are briefly defined and the proposed decision tree structure is explained. The EEG-based BCI data sets are classified by these classifiers and the results are provided in tables and figures in Section 3. Finally, Sections 4 and 5 present the performance comparison and conclude the paper, respectively.

2. Materials and methods

2.1. Data set description

In this study the Brain Quick EEG System (Micromed, Italy) was used to acquire EEG signals. The brain activity was sampled by 256 Hz and filtered between 0.1 and 120 Hz. Additionally, a 50 Hz notch filter was used to eliminate line noise. 18 EEG electrodes were located according to the International 10–20 System as shown in Fig. 1 and they were referenced to the electrode Cz. All the electrode impedances were kept below 5 kΩ. Because EOG and EMG artifacts were strong on the Fp1, Fp2, O1 and O2 electrodes, they were not selected for the analysis.

EEG signals were collected from three healthy male adults (subjects A, B and C aging 24, 24 and 29 years old, respectively) on two different offline sessions with about 1 week interval. All the subjects signed an informed consent for the experiment, which was reviewed and approved by Ethics Committee of Trabzon Clinical Researches.

Each session consisted of four runs and each run had 40 trials with 10 trials per class (up, left, down and right). Each run lasted for about 10 min and the whole session of data collection lasted for about 65 min. Each session yielded 160 trials (40 trials per class). However, because the subjects were incorrectly motivated (when an unexpected noise came from outside the laboratory) in relatively few trials, those trials were omitted from further analysis.

Each subject sat on an armchair facing a video screen and was asked to remain motionless during the trial. The subjects looked at a screen which had 19 × 19 white grids on a black background. Each trial lasted for 10 s and began with a 2 s delay. Then, the target appeared in one of the four possible positions (up, left, down and right) on the middle edge. After the target entered on the screen, a cursor appeared in its center and the subject had to perform a