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Brain–computer interface: The next frontier of telemedicine in human–computer interaction

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A B S T R A C T

The study proposes a novel brain–computer interface scheme for the next frontier of telemedicine in human–computer interaction, where the goal is to improve the interactions between users and computers in telemedicine. The system consists of discriminative area selection, feature extraction and classification. Discriminative area selection is proposed to obtain the optimal discriminative area, which can decrease the time length of event-related area to achieve more efficient computation and higher accuracy. A fuzzy Hopfield neural network is used to classify the features extracted by means of wavelet-fractal approach. Experimental results show that the proposed system is robust and performs better than several previous methods. It is also suggested being suitable for the applications of telemedicine in human–computer interaction.

1. Introduction

Since beginning of computer use, input devices have been limited to a few well-understood instruments, such as punch cards, the joystick, keyboard, and mouse. In the past decade, however, the potential of unconventional input devices has become increasingly apparent, and a wide variety of sensors and mechanisms are in the process of development (Williamson et al., 2009). Currently, the touch panel, somatosensory, and voice control are the most popular new input devices for human–computer interaction (HCI). Though commercial applications of the brain–computer interface (BCI) are still problematic, researchers currently involved in HCI have recognized the importance of emotional assessment using electroencephalographic (EEG) methods (Channel et al., 2009).

2. Objective

BCI is a new communication system that provides an alternative channel for directly transmitting messages from the human brain to computers by analyzing the brain's mental activities (Williamson et al., 2009). Further, BCI might be a highly feasible method to assist limb-disabled users. BCI systems based on the single-trial analysis of EEG signals associated with finger lifting (FL) or motor imagery (MI) have grown rapidly in the last decade. EEG analysis is based on discriminating the left and right FL/MI using event-related brain potentials (ERP). For this, the raw EEG data are continuous signals in the time-domain that can be transformed by means of filters. These include, spatial filters, and an effective selection of the most appropriate frequency-bands in the frequency domain is known to improve the classification accuracy (Aler et al., 2012).

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However, the EEG data are non-stationary and their characteristics vary with time. This suggests that there are special characteristics of event-related desynchronization and synchronization in μ and β rhythms over the sensorimotor cortices during the tasks (Williamson et al., 2009).

3. State of the art

Generally, BCI systems consist of two main processes, feature extraction and classification. Feature extraction is an important process since it greatly affects the effectiveness of EEG classification accuracy. Feature extraction is based on band power and usually computes the powers at the α and β bands, whose frequency components are in mental tasks (Obermaier et al., 2001). A great many feature extraction approaches have been proposed, among which, band power (Obermaier et al., 2001) and autoregressive (AR) parameters (Burke et al., 2005) are the most commonly used. The EEG time series is fitted with an AR model to produce the parameters.

Fractal geometry provides a proper mathematical model to describe complex and irregular shapes that exist in nature by using fractal features (Mandelbrot, 1982). Fractal dimensions are one of the most commonly used fractal features and they have been applied to various fields. In the present study, we decompose selected discriminative area into multi-scale signals by means of discrete wavelet transform (DWT). The wavelet-fractal features (WFFs) are then extracted via the proposed modified fractal dimensions. In addition to multi-scale characteristics, WFFs also contain important fractal information in the time-scale space.

For the classification process, supervised classifiers are usually adopted to recognize single-trial FL/MI EEG data. Some of these classifiers, such as linear discriminant analysis (Saprikis, 2013), multilayer perceptron (Telfer et al., 1993), support vector machines (Doukas et al., 2011), and artificial neural networks (ANN) (Sim et al., 2014), are quite popular and generally used for this type of classification. However, they are supervised, and their parameters need to be trained in advance before being applied to on-line applications. The fuzzy Hopfield neural network (FHNN) is an unsupervised approach that combines with the fuzzy clustering method (FCM) (Dunn, 1973) and the Hopfield neural network (HNN) (Hopfield, 1982), and then partitions a collection of feature vectors into a number of subgroups based on minimizing the trace of a within-cluster scatter matrix (Hsu, 2012). Hsu (2012) also indicated that the classification of FL/MI EEG data with an unsupervised FHNN may lead to better classification accuracy than can be obtained with conventional supervised classifiers. Therefore, the present study employed ANN, HNN, and FHNN for the single-trial classification.

4. Materials and methods

4.1. Data acquisition and description

Three datasets were used to evaluate the performance of the proposed scheme.

In the first dataset, EEG signals associated with FL signals were recorded from four untrained subjects (three males and one female, two left-handed and two right-handed) in a shielded room. As illustrated in Fig. 1 there were 13 silver/silver chloride electrodes, including ten scalp EEG channels (*C3*, *C5*, *FC3*, *C1*, *CP3*, *C4*, *C2*, *C6*, *FC4*, and *CP4*), two EMG channels

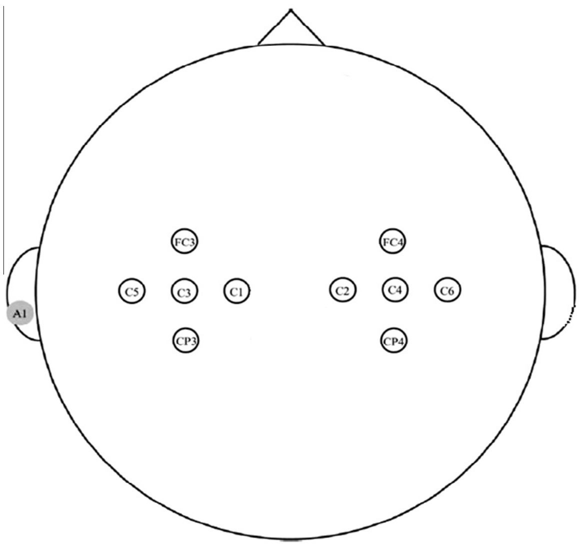

Fig. 1. Location of EEG electrodes for the first data set.