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Discrimination of four class simple limb motor imagery movements for brain–computer interface

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ABSTRACT

The discrimination of four simple limb motor imagery movements for brain-computer interface (BCI) applications is still challenging. This is because most of the movement imaginations have close spatial representations on the motor cortex area. Nevertheless, due to its potential applications in significant areas including BCI, solutions need to be formulated to overcome the task discrimination issues faced when a motor imagery movement approach is utilized. Feature extraction is one of the most important steps in any BCI system; as such, enhancement to the existing methods has been incorporated in this work. For this, we propose four-class movement imaginations of the right hand, left hand, right foot, and left foot, and develop feature extraction methods utilizing discrete wavelet transform (DWT) and empirical mode decomposition (EMD); in both methods, artificial neural network (ANN) was used as a classifier. Based on the processed electroencephalography (EEG) data recorded from eleven subjects, it can be seen that EMD features outperform DWT features; the average accuracy achieved by the EMD features is 90.02%, and 84.77% using the DWT features. EMD even performs better than DWT in discriminating the most challenging tasks involving the right foot and left foot imageries, whose EEG data were derived from the same Cz node of the motor cortex.

1. Introduction

A brain computer interface (BCI) system provides a link between the human brain and a computer. Among its numerous potential uses, it can provide a substitute form of communication for people with limited motor functions, like those with locked-in syndrome, to reduce their healthcare costs and improve quality of life [1,2]. Over the past two decades, many studies have shown that BCI systems can allow disabled people to send messages or commands from their brains to external devices by using only brain activities instead of using muscle activities, providing an alternative non-muscle-based channel for communication and control [1–4]. Fortunately, the brains of these people can normally generate different mental states; in other words, they have the ability to perform motor imagery. These mental tasks can be detected through electroencephalography (EEG) when they are modulated, and these can be adopted as a control signals to drive an assistive device such as a wheelchair [1].

EEG is a common physiological method used to observe the dynamics of the human brain [5]. EEG and functional magnetic resonance imaging (fMRI) studies have shown strong evidences that the motor execution and imaginary movement of the same action can affect neuronal activities in the primary sensorimotor and related areas [5,6]. The tasks associated with motor imagery, known as event-related de-synchronization/synchronization (ERD/ERS), can produce variations in the rhythmic activities of the brain's electrophysiological signals. De-synchronization yields a decrease in the power of the EEG rhythm during or before an event occurs; conversely, synchronization causes an increase in the amplitude of an EEG pattern corresponding to the event [7–11]. The changes in the amplitude of particular cortical rhythms, mu and beta, during motor imagery movements have been used as important features in BCI systems [12–15]. Motor imagery using single movements, such as imagining moving a hand (left or right) or moving a foot (left or right), has been previously investigated [7,11,13,16–18], and brain oscillatory patterns induced by the simple motor imagery of the left hand, right hand, tongue or foot have also been studied

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[12,19–22]. Fewer studies have been reported on analyzing EEG rhythm-induced imagery utilizing compound limb movements [23].

Besides using different input signals for BCI control, researchers have proposed different methods for decoding EEG signals [6–8]. These methods generally involve signal preprocessing techniques to enhance the inputted signals and change them into suitable forms for further processing: feature extraction techniques to identify brain signals that have been recorded; classification methods to make classification decisions; and finally methods to translate the classified signals into meaningful commands for a connected output device, such as a wheelchair. Different standard techniques have been attempted to detect and classify mental tasks' motor imagery using various domain measures, such as power spectral density (PSD) [24], the autoregressive filter [25], the adaptive autoregressive filter (AAR) [12], Common Spatial Patterns (CSP) [23], and band power (BP) [7]. However, these techniques do not provide a precise representation of the information. Furthermore, most of them are based on the Fourier analysis; therefore, they suffer from poor time-frequency localization [26]. Additionally, they mainly use fixed linear orthogonal basis functions; hence, they are not suitable for processing real-world data such as EEG, which are almost invariably non-linear and non-stationary [27]. To overcome this problem, various techniques such as the empirical mode decomposition (EMD) [18,26,28] and wavelet transform [19,29] have been introduced to transform non-stationary signals into stationary ones.

In this paper, the following questions have been addressed: (1) Is it possible to discriminate between four classes of motor imagery movements involving the right hand, left hand, right foot, or left foot, in a healthy naive participant without any motor imagery experience? (2) Which method is more suited for the classification of a four-class motor imagery based BCI? Table 1 below summarizes the related literature on brain–computer interfaces based on motor imagery movements using different feature extraction and classification methods. As shown in row #1 of the table, when discrete wavelet transformation (DWT) and a naive Bayesian classifier (BSC) were used for the detection of ERD/ERS of EEG signals of eight subjects, they gave an accuracy of 65% for the imagery, and approximately 78% for the actual movement [19]. In row #2, band power features were used for the classification of two classes using linear discriminant analysis (LDA), giving an accuracy of nearly 77% [7]. In row #3–with multi-class common spatial patterns (MCSP) features, the EEG data from three simple and three compound limb motor imagery tasks were classified using support vector machine (SVM), giving an accuracy of 70% [23]. The parameterization of EEG using a spatial filter, power spectrum estimation and its integration with logistic regression, produced a classification accuracy of 74.84% for the three classes [16], as shown in row #4. The continuous wavelet transform (CWT) was used as a feature extraction for four motor imagery tasks, and k-Nearest Neighbors (KNN), LDA, and SVM were used for the classification of the four classes [30], as presented in row #5, generating 65.35% discrimination accuracy. Next, CSP features and a SVM classifier, three tasks namely right hand, left hand, and feet motor imagery signals were classified by reference [4], obtaining a mean accuracy of 82.56%.

Table 1
Summary of the related literature of BCI based on motor imagery movements.

No.	Activity	Brain signal type	Electrode placement	Feature extraction method	Classification method	Number of classes	Number of participants	Classification accuracy
1	Movement/imagery planning [19]	ERD/ERS	29 channels	DWT	BSC	Four task movements/motor imageries: right hand, left hand, tongue, or right foot	8	65% (≈78% for actual movement)
2	Grasping of hand [7]	Motor imagery	C3, Cz, and C4	Band power features	LDA	Two task movements/motor imageries: right or left hand	23	≈77%
3	Limb motor imagery [23]	Motor imagery	C3, Cz, and C4	MCSP	SVM	Three tasks of simple limb: right hand, left hand, or feet; and three tasks of compound limb motor imagery: both hands, left hand combined with right foot, right hand combined with left foot	10	70%
4	Modulation of sensorimotor oscillation by motor imagery [16]	Motor imagery	16 channels	Parameterization of EEG using spatial filter, power spectrum estimation and integration	Logistic regression	Three tasks: right hand, left hand, or both feet	8	74.84%
5	Controlled cursor movement [30]	Motor imagery	18 channels	CWT	KNN, LDA, SVM	Four tasks: up, down, right, or left computer cursor movement imageries	3	65.35%
6	Wheelchair controls [4]	Motor imagery	14 channels using only C3, Cz, and C4	CSP	SVM	Three tasks of motor imagery tasks: right hand, left hand or both feet	3	82.56%
7	Proposed work	Motor imagery	8 channels using only C3, Cz, and C4	DWT	ANN	Four tasks: right hand, left hand, right foot, or left foot movement imageries	11	84.77%
8	Proposed work	Motor imagery	8 channels using only C3, Cz, and C4	EMD	ANN	Four tasks: right hand, left hand, right foot, or left foot movement imageries	11	90.02%

2. Materials and methods

2.1. Participants and experimental tasks

Eleven healthy right handed volunteers (9 males and 2 females, aged 20–38 years) participated in this study. Participants were not affected by any medication that could influence imagination responses. A consent form signed by each participant which