Mental commands Recognition on Motor Imagery-Based Brain Computer Interface

Jzau-Sheng Lin and Che-Hao Lo

Abstract

In this thesis, we used the EEG signals of motor imagery (MI) to identify different imagery activities. The Emotiv EPOC was used to extract electroencephalogram (EEG) signals. Basically, the Emotiv EPOC can recognize several signals such as facial expressions, emotional metrics, and mental Commands. In the Emotiv EPOC, we used AF3, AF4, FC5 and FC6 to capture EEG signals. There are four voluntary actions i.e. no imaging, imagining tongue movement, imagining right hand movement, and imagining left hand to be recognized. Firstly, the received EEG signals from Emotiv EPOC were transmitted to computer by using wireless manner. Secondly, feature vector of EEG could be transferred by a Wavelet transform. And the four classified actions could be analyzed through SVM algorithm with the Gauss kernel function. Finally, the experimental results showed that high recognition rate can be obtained to identify the mental activities of motor imagery through the proposed Brain–Computer Interface (BCI) system.

Keyword: Electroencephalography (EEG), Brain–computer interface (BCI), Wavelet, Motor imagery (MI), Support vector machine (SVM)

1. Introduction

BCI systems provide one of the most important aspects, which is an alternative way of communication through brain signals. There are many applications of BCI in several fields [1-3]. One of those is to provide assistive devices for patients who are unable to perform physical movements. It is the primary aim of the BCI researchers to determine the right intention from the brain activities and reflect them into the desired movement accordingly [4, 5]. This particular area in BCI is known as Motor Imagery (MI) movement [6, 7]. Motor imagery refers to visualization of a limbic activity, or any other movement, without the actual execution of the motion imagined. It leads to various changes in the connectivity between the neurons present in the cortex. This results in either an event related desynchronization or event-related synchronization of mu rhythms. These effects are due to the changes in the chemical synapses of the neurons, the change in strength between the interconnections or the change of intrinsic membrane properties of local neurons.

In the research field of motor imagery-based BCI, an extraction approach with transform-based feature for MI tasks classification was proposed by Baali *et al.* [8]. They used a signal-dependent orthogonal transform, referred to as linear prediction singular value decomposition (LP-SVD), for feature extraction. A logistic tree-based model classifier is used; the extracted features are classified into one of four motor imagery movements. In 2015, Tomida et al. [9] presented an active data selection method for MI EEG classification. In the selection method, rejecting or selecting data from multiple trials of EEG recordings is crucial. To aim at brain machine interfaces (BMIs), they proposed a sparsity-aware method to select data from a set of multiple EEG recordings during motor-imagery tasks. Jois et al. [10] compared several classification techniques for Motor Imagery-Based BCI in 2015. They indicated that common features, e.g., band power values, present that the single EEG trials can be extracted by suitable methods for classification using support vector machines (SVM), neural networks or ensemble classifiers. The classifiers yield different efficiencies and are compared to find the optimal technique for same number of features. They believedt the neural net techniques proved to be the most efficient. The symmetric positive-definite (SPD) covariance matrices of EEG signals carry important discriminative information proposed by Xie et al. [11] for MI BCI system in 2016. In 2016,

Chatterjee and Bandyopadhyay [12] used SVM and Multi-layered Perceptron (MLP) for EEG based MI classification. They showed that both SVM and MLP were suitable for such MI classifications with the accuracy of 85% and 85.71%, respectively. Chatterjeel et al. [13] examined the quality of feature sets obtained from Wavelet-based Energy-entropy with variation of scale and wavelet type for MI classification in 2016. They have verified their study with three classifiers- Naive Bayes, Multi layered Perceptron and Support Vector Machine. In 2016, Wu et al. [14] used the fuzzy integral with particle swarm optimization (PSO), which can regulate subject-specific parameters for the assignment of optimal confidence levels for classifiers.

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A well-established tool in studying the neural-function correlates of cognitive processes for providing human brains with much-needed insight which can be created by EEG signals. A well-organized EEG headset has several advantages such as real-time data acquisition, wireless manner with Bluetooth or Wi-Fi, fast data refresh rate and exchange, and so on. Additionally, it is a low-cost system in diagnosis and health management. An EEG-based BCI system requires uncomplicated mechanisms and less time utilization for short-time development with low-cost manner. A low-cost headset named Emotiv EPOC neuro [15] was used to extract EEG signals to recognize the actions of MI in this paper. There are 14 electrodes with 2 reference channels in Emotiv EPOC to reveal facial actions, cognitive states, and affective intensity extracted from different EEG signals in a real-time manner. There have been some applications that successfully utilize this technology in several fields. Thobbi et al. [16] achieved the remote presence using the Emotiv Epoc headset to control a humanoid robot. Szarfir and Signorile [17] used an Emotiv system to extract the EEG signals from the headset to categorize them into one of several groups; that group was then translated to a robotic command, and finally controlled the robot. Ramirez and Vamvakousis [18] used an Emotive Epoc device to detect emotion from EEG signals. They extracted features from the EEG signals in order to characterize states of mind in the arousal-valence 2D emotion model. Using these features, they classified EEG signals into high/low arousal and positive/negative valence emotional states. In 2013, Duvinage et al. [19] proposal a BCI system to discuss the performance of the Emotiv Epoc headset for P300-based applications.

A wavelet is a mathematical transform model with a fast-decaying and finite-length oscillating waveform, which is used to divide a given function into different scale elements. The basic functions of wavelet transform (WT) [20] are small waves located in different times. WT generates a few significant coefficients around the discontinuity. In nonlinear approximation, a few significant coefficients of a signal are kept, and the rest are set to zero. WT produces a few significant coefficients for the signals with discontinuities to reconstruct the signal. Thus, better results for WT nonlinear approximation is obtained. WTs have several advantages over conventional Fourier transforms, as they can expose the nature of a function in the time and frequency domains simultaneously. In this paper, a wavelet transform is used to get the features from the captured EEG signals.

Support vector machines (SVMs) [21] are a machine learning method with a supervised rule used for classification and regression. The kernel learning function is probably the most widely used SVM. It achieves relatively a robust pattern recognition performance using well-established concepts in optimization strategies. Classifying data has been one of the major tasks in machine learning. The idea of SVM is to create a hyper plane between data sets to indicate which class a training sample belongs to. The challenge is to train the machine to understand structures from data and mapping with the right class label, and, for the best result, the hyper plane has the largest distance to the nearest training samples of any class. In this paper, SVM is also used to classify the reduced EEG data from WT into one of the four clusters of mental states.

This paper is organized as follows. The system architecture is introduced in Section 2. Section 3 shows the algorithms in the proposed system. Section 4 demonstrates the feature extraction and mental states prediction. Experimental results are displayed in Section 5, and finally, Section 6 is the conclusions.

2. System Architecture

The proposed EEG-based BCI system is shown as in Fig. 1. The architecture includes an EEG signal acquisition unit named as a nEmotive EPOC device with a 14-elctrode and 2-reference headset and a wireless communication interface to transmit EEG signals to a personal computer. The Emotiv EPOC headset, shown as in Fig. 2, is used to extract the EEG signals. It consists of 14-channel bio potential sensors with gold-plated electrodes to offer optimal positioning for an accurate spatial resolution. Additionally, CMS/DRL reference locations are also utilized. Based on the international 10-20 locations, these 14 EEG names are AF3, AF4, F7, F8, F3, F4, FC5, FC6, T7, T8, P7, P8, O1, and O2. In the Emotiv headset, the sampling rate is 128 Hz on the output, and the internal sampling rate is 2048 Hz with a 1.95-Least Significant Bit (LSB) voltage resolution. In this paper, we used AF3, AF4, FC5 and FC6 to capture EEG signals. There are four voluntary actions i.e. no imaging, imagining tongue movement, imagining right hand movement, and imagining left hand to be recognized. The brain activities were recorded in real time and compared with mental states by a cheap off-the-shelf EEG headset. First, EEG signals are sequentially and off line extracted from a headset and transmitted to a personal computer with a wireless manner. Large number of feature vectors of EEG can be reduced by a Wavelet transformation. Then the reduced EEG signals can be classified into four clusters by means of a SVM algorithm with a Gaussian kernel function.

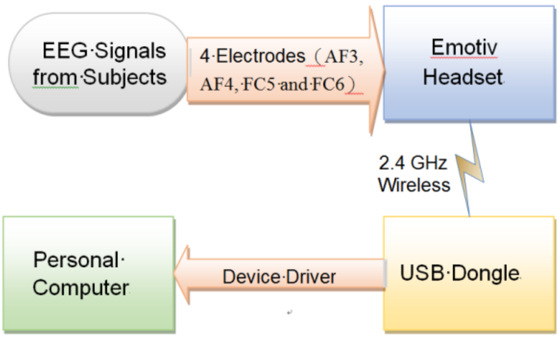


Figure 1: The proposed system diagram

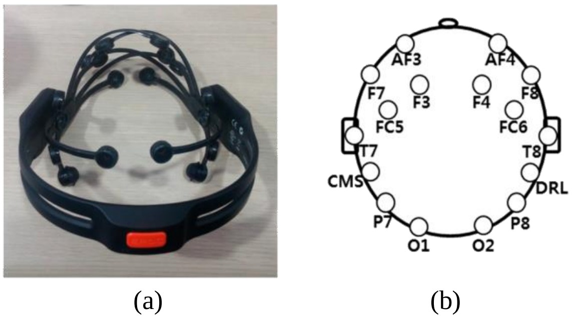


Figure 2: (a) Emotiv Epoc; (b) Locations of Emotiv electrodes

3. Algorithms in the Proposed System

In the proposed system, there are two phases named training phase and recognition phase to create a feature space and recognize the suitable facial action. In these two phases, we use a wavelet transform to reduce the size of extracted EEG data and the SVM algorithm to classify the acquired EEG data into a reasonable cluster in the feature space.

3.1 Wavelet Transformation

In this study, Daubechies [22] wavelet was used to extract the features from EEG signals. The Daubechies wavelet was proposed by Dr. Daubechies in 1988. Daubechies wavelet, being a discrete wavelet analysis, is often used in signal compression, digital signal analysis and noise filtering and so on. In Daubechies wavelet, several series db wavelets can get better performance in signal analysis. In this paper we use db4 wavelets to extract main features from EEG signals. Multi-resolution analysis in the WT algorithm was proposed by Mallat [23] in 1989. When a signal has a high-degree variation in a proper area, the single-resolution WT is difficult to get detailed features while the multi-resolution strategy can decompose the lower layer signal to get more information. Therefore, the decomposed low-frequency signal can be decomposed continuously to display more features. However, the decomposed iterations of the signal is so many to make the number of samples so few that results in less obvious characteristics of the signal. Therefore, the number of signal decomposition layer is limited. In the wavelet decomposition, the original signal is input to a low-pass filter and a high-pass filter, respectively. The low-pass filter retains the consistency of the original signal, and the high-pass filter reserves the variability of the original data. The decomposition for the low- and high-pass frequencies are defined as:

$$y_L[n] = \sum_{i=0}^{K-1} x[2n-i]g[i] \tag{1}$$

$$y_H[n] = \sum_{i=0}^{K-1} x[2n-i]h[i] \tag{2}$$

where $g[i]$ and $h[i]$ are the responses of low- and high-pass filters in layer i , respectively. In general, the features of a signal are contained in the high-frequency part. Therefore, Eq. (3) was used to calculate the energy distribution for high-frequency elements in WT, which were regarded as principal features for training feature spaces.

$$E_\ell = \frac{1}{N}\sum_{k=1}^{N} y_H[k]^2 \tag{3}$$

where ℓ is the electrode location while N indicates the number of samples.

3.2 Support Vector Machine (SVM)

A supervised learning model SVM is associated with learning algorithms to analyze data used for classification and regression analysis. In this paper, a subspace for EEG signals classification is produced by training a SVM classifier with the Gaussian kernel. A vector space is classified by training samples through a SVM system so that a clear and wide enough gap is obtained to divide training samples into separated clusters. The smallest distance between the decision boundaries is calculated to define margin or support vectors, and any of the samples are data points located on the margin line. In addition to perform linear classification, SVM can efficiently process a non-linear classification using the kernel trick, so their inputs are implicitly mapped into high-dimensional feature spaces. Many hyperplanes are used to classify the data. The largest margin between the two classes is selected as the best hyperplane. Therefore, the hyperplane is chosen so that the distance is maximized between it and the nearest data point on each side. It is named as the maximum-margin hyperplane, and the linear classifier can be defined as a maximum margin classifier if such a hyperplane exists.

Suppose class $z_i \in \{-1, +1\}$ can be linearly classified from training samples x_i. A hyper-plane $w \cdot x_i + b = 0$ can be determined by these training samples to make the distance from the support vectors separate margins maximum for each training sample

$$z_i(\mathrm{w} \cdot x_i + b) \geq 1, i = 1,2, \cdots p \tag{4}$$

When the distance from training sample to classification margin $1/\|w\|$ is maximum a maximum classification margin (separating hyper-plane) is obtained. The solution of the best separating hyper-plane is transformed into its dual problem by the Lagrange method. That is the maximal values calculated by the following function

$$max\left\{w(\beta) = \sum_{i=1}^{p} \beta_i - \frac{1}{2}\sum_{i=1}^{p}\sum_{j=1}^{p} \beta_i\beta_j z_i z_j (x_i \cdot y_j\right\} \tag{5}$$

s.t $\sum_{i=1}^{p} \beta_i z_i = 0, 0 \leq \alpha_i \leq C, i = 1,2, \cdots p$

where β_i is the Lagrange multiplier corresponding to the *i*-th sample. The corresponding sample x_i is called the support vector if β_i is not equal to 0. Constant C *(*C > *0)* is the penalty parameter for error classification. For a best value β_i^* and a suitable separating limit value b^*, the training sample x can be classified by the following decision function

$$f(x) = sgn\left[\sum_{i=1}^{p} \beta_i^* \, z_i(x_i \cdot x) + b^*\right] \tag{6}$$

For the nonlinear classification, training samples are mapped into a higher dimensional linear feature space $\mathbb{R}$ by a nonlinear function $\varphi(\cdot)$ with a kernel function $Ker(\cdot,\cdot)$. Then, the decision function can be defined as

$$f(x) = sgn\left[\sum_{i=1}^{p} \beta_i^* \, z_i Ker(x_i \cdot x) + b^*\right] \tag{7}$$

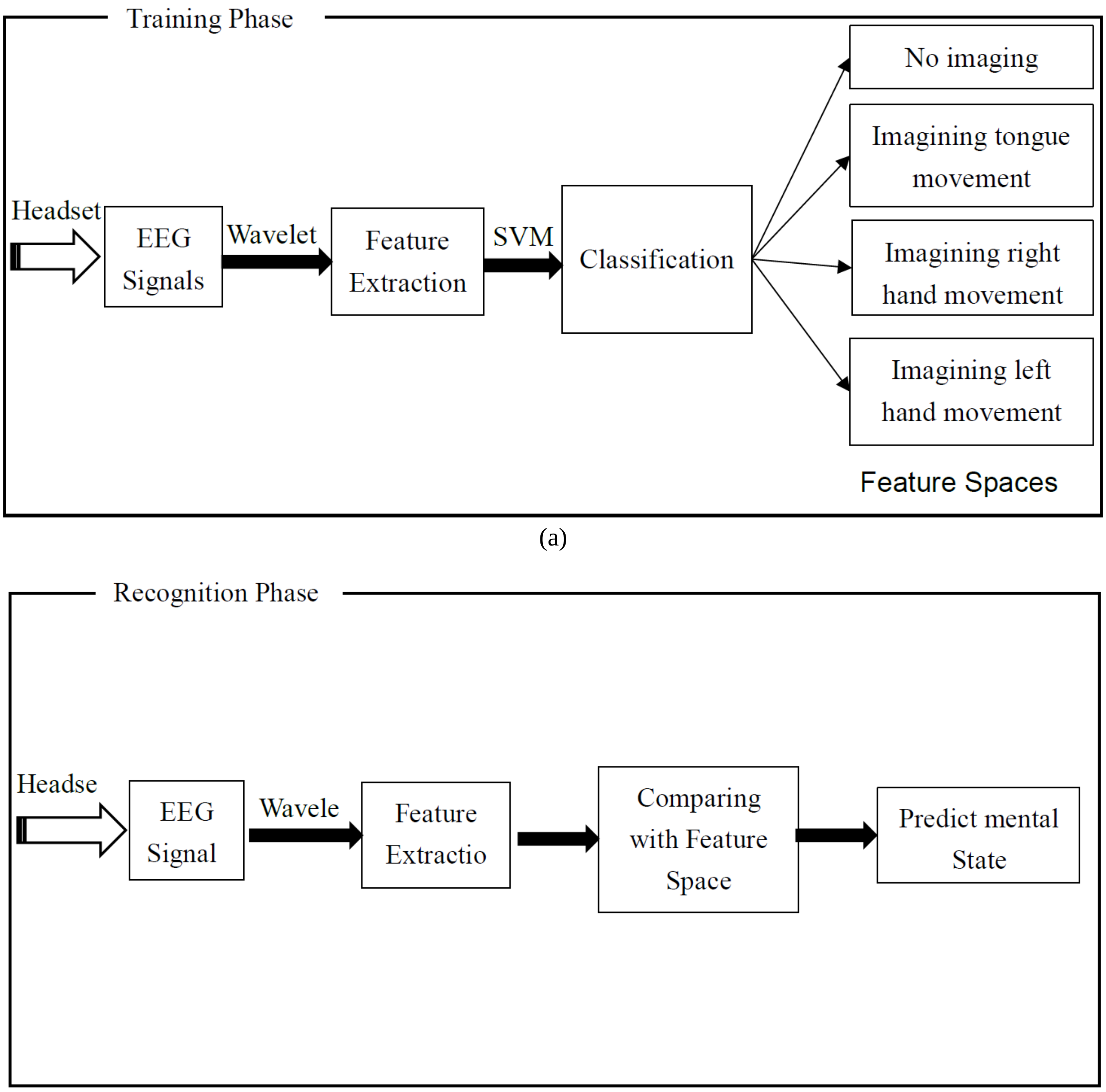
where kernel function $Ker(x_i \cdot x) = \varphi(x_i) \cdot \varphi(x)$ is the inner product of feature vectors. The Gaussian kernel is widely adopted in kernel methods, so we focus on the parameter selection of the Gaussian kernel in this paper. The Gaussian kernel function is defined as:

$$ke\,r(x_i, x) = \exp(\|\boldsymbol{x_i} - \boldsymbol{x}\|^2/s) \tag{8}$$

where s is the parameter to be selected.

4. Feature Extraction and Mental States Prediction

There are two phases to recognize four mental states in the proposed system. They are training phase and recognition phase as shown in Fig. 3, respectively. We extracted EEG signals reacted by mental states such as no imaging, imagining tongue movement, imagining right hand movement, and imagining left hand movement from 4 locations AF3, AF4, FC5 and FC6 at the headset in training phase. A cheap off-the-shelf EEG headset-Emotic Epoc device is used to record the brain activity in real time, which then is translated to mental states. First, EEG signals are sequentially and in real time extracted from a headset, which is then transmitted to a personal computer through a wireless interface. A Wavelet is used to transform large number of feature vectors of EEG in order to reduce the size of signals. Then four clusters can be obtained through classifying the reduced EEG signals by means of a SVM algorithm with the Gaussian kernel function. The subject's EEG signals are also extracted from the same four locations at the headset in recognition phase. And we obtain the energy distribution of EEG signals by a Wavelet transform. Then, the calculated energy distribution is compared with features in the feature space to select the closest one.



(b)

Figure 3: Two phases for recognizing the mental states from EEG, (a) Training Phase, and (b) Recognition Phase

5. Experimental Results

In this paper, six healthy subjects were separated into three groups to participate in experiments. For these six subjects, we extracted EEG signals from AF3, AF4, FC5 and FC6 locations to collect four mental states such as no imaging, imagining tongue movement, imagining right hand movement, and imagining left hand movement. In training phase, every subject wore a headset to image one of the four mental imaging actions each time, and the EEG was extracted 20 seconds to get 20 energy distributions. Every subject can get 80 energy distributions for four mental states. And every experiment was executed five times. Then the mental actions were recognized by the proposed system from the extracted EEG signals in line with recognition phase. The experiment is executed by comparing the energy distributions of two groups for every mental state with the feature vector of the other one on feature space. Therefore, we can get three comparison results as shown in Tables I, II, and III. In Table I, the accuracy rates for group 2 to recognize these four mental states form feature space of group 1 are over 85%. Additionally, the lower accuracy rates are 75% in experiments 1 and 7, and 70% in experiments 9 and 10 for imagining tongue movement in group 3 when the group 1 worked as the training sample. In Table II, the group 2 was as the training sample, and the lowest accuracy rate to recognize group 1 is 75% for imagining right hand movement in experiment 4, while the accuracy rates for recognizing these four mental states are over 85% in group 3. In Table III, the group 3 was the training samples, and all of the lowest accuracy rates are 75% for imagining left hand movement, imagining right hand movement, yet no imaging in experiments 3, 4, and 5 in group 1. The lowest accuracy rate is 75% for imagining left hand movement in experiment 7 in group 2. From the experimental results, we can find that group 2 as the training samples and group 3 as the test samples can obtain better results.

Table I: Group 1 as the training sample as well as Group 2 and Group 3 as testing samples

	G2-1	G2-2	G2-3	G2-4	G2-5	G2-6	G2-7	G2-8	G2-9	G2-10
T	20/20 100%	18/20 90%	18/20 90%	19/20 95%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	17/20 85%
R	20/20 100%	20/20 100%	20/20 100%	20/20 100%	18/20 90%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%
L	20/20 100%	20/20 100%	17/20 85%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%
N	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	19/20 95%	20/20 100%
	G3-1	G3-2	G3-3	G3-4	G3-5	G3-6	G3-7	G3-8	G3-9	G3-10
T	15/20 75%	18/20 90%	20/20 100%	19/20 95%	20/20 100%	20/20 100%	15/20 75%	20/20 100%	14/20 70%	14/20 70%
R	20/20 100%	18/20 90%	20/20 100%	20/20 95%	18/20 90%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%
L	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%
N	19/20 95%	20/20 100%	19/20 95%	20/20 100%	20/20 100%	19/20 95%	20/20 100%	19/20 95%	18/20 90%	20/20 100%

*T : imagining tongue movement, R: imagining right hand movement, L: imagining left hand movement, N: no imaging.

Table II: Group 2 as the training sample as well as Group 1 and Group 3 as testing samples

	G1-1	G1-2	G21-3	G1-4	G1-5	G1-6	G1-7	G1-8	G1-9	G1-10
T	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%
R	20/20 100%	20/20 100%	20/20 100%	15/20 75%	18/20 90%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	19/20 95%
L	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	19/20 95%	20/20 100%	20/20 100%	20/20 100%	20/20 100%
N	20/20 100%	20/20 100%	20/20 100%	19/20 95%	19/20 95%	17/20 85%	20/20 100%	20/20 100%	19/20 95%	20/20 100%
	G3-1	G3-2	G3-3	G3-4	G3-5	G3-6	G3-7	G3-8	G3-9	G3-0
T	20/20 100%	19/20 95%	20/20 100%	20/20 100%	19/20 95%	20/20 100%	19/20 95%	20/20 100%	19/20 95%	17/20 85%
R	18/20 90%	19/20 95%	20/20 100%	20/20 100%	19/20 95%	18/20 90%	19/20 95%	18/20 90%	20/20 100%	20/20 100%
L	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%
N	19/20 95%	20/20 100%	19/20 95%	19/20 95%	20/20 100%	18/20 90%	19/20 95%	19/20 95%	18/20 90%	18/20 90%

*T : imagining tongue movement, R: imagining right hand movement, L: imagining left hand movement, N: no imaging.

Table III: Group 3 as the training sample as well as Group 1 and Group 2 as testing samples

	G1-1	G1-2	G21-3	G1-4	G1-5	G1-6	G1-7	G1-8	G1-9	G1-10
T	20/20 100%	20/20 100%	20/20 100%	19/20 95%%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%
R	20/20 100%	20/20 100%	20/20 100%	15/20 75%	20/20 100%	20/20 100%	19/20 95%	20/20 100%	20/20 100%	20/20 100%
L	19/20 95%	20/20 100%	15/20 75%	20/20 100%	20/20 100%	19/20 95%	20/20 100%	20/20 100%	20/20 100%	20/20 100%
N	20/20 100%	20/20 100%	20/20 100%	18/20 90%	15/20 75%	17/20 85%	20/20 100%	18/20 90%	20/20 100%	18/20 90%

	G2-1	G2-2	G2-3	G2-4	G2-5	G2-6	G2-7	G2-8	G2-9	G2-10
T	20/20 100%	20/20 100%	20/20 100%	20/20 100%	20/20 100%	19/20 95%	20/20 100%	20/20 100%	20/20 100%	19/20 95%
R	20/20 100%	20/20 100%	20/20 100%	20/20 100%	18/20 90%	19/20 95%	20/20 100%	20/20 100%	20/20 100%	20/20 100%
L	20/20 100%	20/20 100%	17/20 85%	20/20 100%	20/20 100%	20/20 100%	15/20 75%	19/20 95%	20/20 100%	19/20 95%
N	18/20 90%	20/20 100%	19/20 95%	18/20 90%	20/20 100%	20/20 100%	20/20 100%	18/20 90%	18/20 90%	20/20 100%

*T : imagining tongue movement, R: imagining right hand movement, L: imagining left hand movement, N: no imaging.

6. Conclusion

In this paper, a wireless EEG-based BCI device was developed to extract EEG signals for recognizing the mental states with the motor imagery. The EEG signals were extracted from AF3, AF4, FC5 and FC6 locations with WT to reduce signal size and SVM to classify these reduced signals into 4-set features which were indicated as four mental states such as imagining tongue movement, imagining right hand movement, imagining left hand movement, no imaging. Six subjects were divided into three groups for every experiment. The experiments were executed by using one group as training samples, and the other two were used as testing samples to recognize one of four mental states. Form the experimental results, the proposed system can obtaining suitable results have accuracy rates with motor imagery.

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