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Using a New Hybrid Method for Characteristics Classifying of Limb Movements in Brain-Computer Interface Applications

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Abstract

The interface between brain and computer has received increasing attention in the last decade of scientific progress. The most common use of this type of technology is the direct control of a computer cursor by a person or animal using brain computer interfaces (BCIs) based on electrophysiological signals. brain computer interface systems can benefit the elderly in many ways, such as: teaching motor/cognitive abilities, controlling household appliances, communicating with others, and controlling the exoskeleton. Exchange can be done between software, computer hardware, peripherals, humans and a combination of them. This paper presents a limb movement classification system based on the electroencephalogram signal. The system contains five parts: preprocessing using wavelet transform, feature extraction, feature reduction and classification. The experimental results are shown that the support vector machine classifier with non-linear kernel and nearest neighbor classifier has an efficiency higher than 80%. The best indicators for support vector machine classification with nonlinear kernel and nearest neighbor are shown by the simulation results.

Keywords: Brain and computer interface, electroencephalogram, Mu rhythm, beta rhythm, wavelet transform
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1. Introduction

Nowadays, technologies based on computer knowledge have widely penetrated the field of biomedical knowledge, in such a way that the border between human knowledge and software and hard-ware technologies has been minimized [1,2]. This issue can be seen in the field of medical diagnostic and treatment processes in the application of proces-sing methods and in the quantification of expert and human knowledge in the form of software and hardware [3,4].

The design and control of electric wheelchairs has received increasing attention from researchers in recent years [5,6]. However, most of the proposed control methods are based on the use of control levers that must be controlled by wheelchair users, which may be inconvenient for those users who suffer from physical disabilities [7,8]. Therefore, several methods based on physiological parameters extracted from the body and without the need for control levers have been proposed [9,10]. For this purpose, the use of sound detection methods [11], eye movement direction [12], head position [13] and biological signals [14] recorded from different areas have been proposed in several studies during the research process to control electric wheelchairs.

The electrical signals or bio-potentials recor-ded in most of these studies can be divided into three categories: The first category is the signals that are the result of the electrical activity of brain neurons, which is called the electroencephalogram signal. The electroencephalogram electrical signal, which has been proposed in several studies to control electric wheelchairs, can be recorded in two ways: invasive recording (using needle electrodes) and non-invasive recording (using surface electrodes) [15,16]. It should be noted that recording the electrical activity of the brain in the thinking mode or in the mode of sending a movement command or receiving a sensory response can be a control command for controlling electric wheelchairs [17,18].

The brain is a very complex part of the human body [19,20]. So far, various brain signals that are easily visible and controllable have been suggested for brain computer interface (BCI) [21,22]. General architecture of an online brain-computer interface is shown in Fig. 1 [23,24].

Fig. 1. Basic BCI system

The second category are the signals that are the result of the electrical activity of the muscles in the state of contraction and rest, which can be recorded superficially or in the form of a needle, and the recorded signal is called an electromyogram. Several studies of electromyogram signal processing and feature extraction have been presented, which have made it possible to send a control command to a wheelchair with the help of a structure classifying the type of muscle activity.

The third category is the signals that are the result of the electrical activity of the muscles around the eyeball, and through the processing of this signal, the direction of eye movement to the right or left can be recognized and a control order can be issued to control the wheelchair. This signal is called electro-oculogram.

Brain-computer interface (BCI) (which may be referred to as brain-machine interface) [25,26], is a hardware or software communication [27,28], which enables human interaction with the surrounding environment without the intervention of peripheral nerves or muscles and by using control signals resulting from electroencephalographic activities [29,30].

The processing method adopted in the brain-computer interface system proposed in the studies can be analysed in three parts: (1) the algorithm adopted for data pre-processing and processing; (2) the characteristics that are extracted from the signal and (3) the classification structure used and the accuracy of each technique that will be referred to in the following [31].

In order to examine this point of view, studies are predicted in two general categories in terms of the purpose of the research: the first category of studies whose aim was to classify several classes of mental images of movements and the second category of studies whose aim was to classify two classes of mental images.

In [32], the frequency band power feature was used to classify the perception of left, right and leg movements, in which a neural network was used for classification and an accuracy of 60% was obtained. In [33], to increase the reliability of the brain-computer user interface based on moving images, a research has been carried out that considers subject optimization and subject-based classification, and specifically, wavelet-based feature extraction in different ratio bands. To the available selections from the wavelet family, length and number of decomposition levels have been optimized. In the same way, the classification stage of three general families of classifications, whose parameters are optimized in a similar way, is considered. In [34], the same features have been used for the classification of the movement perception class similar to the research done in [30], but by using the hidden Markov model for classification, the accuracy of the method has been improved to 77.5%. In [35], the coefficients of the adaptive autoregressive model have been used to classify the perception of left, right hand, foot and tongue movements, and the accuracy of the linear support vector machine classifier is 63%, for the linear discriminant analysis classifier (LDA) is equal to 54.46%, for the nearest neighbor classifier it is equal to 41.74% and for the Mahalanobis distance (MD) classification technique, the accuracy is 53.5%. In [36], an accuracy of 52.6% was obtained for the classification of the perception of left and right hand movements, foot and tongue movements, and relaxed state by using band power features and hidden Markov model.

In [37], a single-channel bipolar electroencephalogram-based spelling system has been developed with sufficient accuracy. The proposed system includes a custom-designed headset, a new virtual keyboard with 58 characters, special symbols and digits, and a visual evoked potential based on Steady-state (SSVEP) is a five-objective brain-computer interface. Also, to validate the proposed model, the training data set with numerous experimental conditions has been determined. The experimental results of eight people show that, on average, the proposed model can classify five-class SSVEP data with a high accuracy of 99.2%.

In [38] to visualize left and right hand movements in asynchronous mode by using features extracted from power spectrum density analysis by Welch method for MD classification technique, Gaussian classifier and hidden Markov model (HMM) respectively accuracy 90, 80 and 65 percent have been reported. In [39], the feature of power frequency band and LDA classifier have been used to classify the perception of left, right hand and leg movements, and an accuracy of 95% has been reported.

In the following, we refer to the second category of studies.

In [40], the visualization of left and right hand movements has been made use of the correlation and correlation characteristics as well as the time-frequency characteristics, and by using the Gaussian vector machine classifier and LDA, the accuracy of 86 and 61% has been reported, respectively.

For the same database, in [41], by using the band power features and multilayer neural network classifier, an accuracy of 76.4 was obtained, which by using fractal dimension features and LDA classifier and multilayer neural network to The order of accuracy is 80.6 and 80.4 percent.

In [42], a classification method for EEG signals using support vector machines (SVM) with time-frequency kernels is presented. Due to the non-stationary nature, EEG signals do not show unique characteristics in the frequency domain. Therefore, time-frequency transformations are proposed to extract common features for a specific mental task performed by different people. Experimental results show that SVM classification using such feature vectors is very effective for EEG signal classification.

In [43], using the database used in this article, after pre-processing the data using a 4-45 Hz low-pass filter, features based on power spectrum density analysis have been used. For the four Gaussian, LDA, Bayes10 and MD classifiers, the accuracy is 65.4, 65.6, 63.4 and 63.1%, respectively. Data pre-processing methods in most studies are filtering in an intermediate frequency band (0.5-45 Hz) which is the operating frequency of electroencephalography and it has been avoided to mention it to avoid repetition.

According to the records raised for research in this study, a five-step algorithm is presented.

Fig. 1 shows the flowchart of the proposed method, which are briefly explained below.

In the first step, the surface electroencephalogram signal is collected. For this purpose, the BCI competition II database and data set number three (registered by the Department of Medical Informatics, Institute of Medical Engineering, Graz University of Technology) are used.

In the second step, the proposed pre-processing algorithm of the recorded data is implemented. For this purpose, appropriate filtering is used in the frequency domain.

In the third step, the processing of electroencephalogram data with reduced noise is done. Mio and beta rhythm of the electroencephalogram signal, which originates in the range of 8-12 Hz and 13-30 Hz, respectively, in the sensorimotor cortex area, to achieve this goal of the signal by applying a suitable mother wavelet transform (such as the mother wavelet transform of the Daubichiz family) and Electroencephalogram analysis is extracted by passing through the multi-resolution bank filter in the time-frequency domain, removing undesirable details and reconstructing the Mio and Beta rhythm signals.

In the fourth step, from the signal obtained by the wavelet transform reconstruction, appropriate statistical and time-domain characteristics of frequency and entropy are extracted.

In the fifth step, classification of the resulting features is done using linear and non-linear classification structures. The classification method is implemented with the supervisor and the output of the classification structure will be the class label of right hand movement perception or left hand movement perception. To validate the proposed method, the confusion analysis of the output matrix of the classifier is used. All simulation steps are executed and implemented under Matlab software.

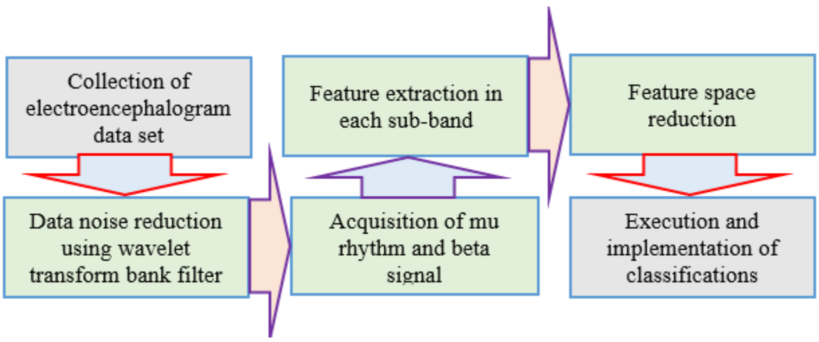

Fig. 2. Process of the proposed method

2. Research Method

A) Data collection and pre-processing

BCI competition database and data set number three (registered by the Department of Medical Informatics, Institute of Medical Engineering, Graz University of Technology) are used for data collection.

This database contains 288 electroencephalog-ram signal data. These data were recorded from an adult and healthy human sample with female gender and age of 25 years as three channels and with bipolar technique (anterior positive and posterior negative) in the area of placement of C3, CZ and C4 electrodes in standard electroencephalography 10-20. The electrodes used were made of silver-silver chloride and the sampling frequency of the recording device was 128 Hz. A low-pass filter of 0.5-30 Hz (operating frequency of electroen-cephalography) was used to filter the recorded data. The subject is asked to sit comfortably in a chair and control a tape during a feedback session. For this, the sign is controlled by the mental images of the movement of the right hand and the movement of the left hand, the tongue and the feet. The symbols are chosen completely randomly. The labels of left hand movement imagination and right hand movement imagination are considered one and two, respect-ively. The length of each recording is 9 seconds and the user is given a break between recordings.

B) Data processing

Discrete wavelet transform has been used to extract mu and beta rhythms from the electroenc-ephalogram signal [44,45].. The discrete version of the wavelet transform is a series of wavelets sampled from the continuous wavelet transform [46,47]. Therefore, the information contained in it is very redundant and extra, which leads to an unreasonable increase in the computational load. Therefore, discrete wavelet transform is used, which is much simpler and more optimal in terms of implementation.

The main idea of this method is similar to the continuous wavelet transform, in which a kind of time-scale description of the discrete signal is presented using digital filters. Wavelet transform is the result of similarity measurement (correlation) between the frequency (scalar) content of the signal and the wavelet function in different scales. In order to calculate the continuous wavelet transform, the desired window is contracted/expanded and shifted, and in each situation, the time integral is taken from its product in the signal. In the discrete mode, filters with different cut-off frequencies are used to analyse the signal at different scales. By passing the signal through high-pass and low-pass filters, its different frequencies are analysed. In the discrete mode, the signal resolution is controlled by the functions of the filters, and the scale is changed through Down-sampling and Up-sampling. Normally, this process of changing the rate of samples is done on a network.

The process of processing starts with the discrete wavelet transform as follows: First, the signal passes through a digital low-pass half-band filter with the impulse response h[n], and therefore the output of the filter is equal to the input convolution and the impulse response of the filter. As a result of this filtering process, all frequency components that are more than half of the largest frequency in the signal are removed. Since the highest frequency in the output signal of the filter is equal to π/2 radians, half of the samples can be removed. Therefore, by removing one of the samples, the length of the signal will be halved. A similar process is performed using a half-band high-pass digital filter with the impulse response g[n].

As a result, in the output of the first stage of the wavelet transformation, two versions, one high-pass and the other low-pass, with reduced length (halved) are obtained from the original signal in the following form:

$$y_{high}[k] = \sum_n x[n], g[2k-n] \tag{1}$$

$$y_{low}[k] = \sum_n x[n], h[2k-n] \tag{2}$$

With this action, the time resolution is halved and the frequency resolution is doubled. This process can be applied again on the downgraded version and in each step, by reducing the time resolution to half of the previous step, the frequency resolution is doubled. This idea for calculating the discrete wavelet transform is known as the filter bank method. It can be seen that the output coefficients of the low-pass filter follow the original form of the signal, for this reason, these coefficients are called approximations. Also, the output coefficients of the high-pass filter include the details of the high frequency of the signal, for this reason, these coefficients are called details, as the number of conversion steps increases, the amount of details also decreases.

It should be noted that the number of steps needed to transform the discrete wavelet depends on the frequency characteristics of the analysed signal. Finally, the discrete wavelet transformation of the signal is obtained by placing the outputs of the filters next to each other, from the first stage of applying filtering. Thus, the number of wavelet transform coefficients will be equal to the number of input discrete signal samples.

In this study, in order to reduce the noise, the 4th type of Dabychiz wavelet transform (which is suitable for vital signals) is used. The considered analysis level is 4 levels and the details of the first level are known as noise. The details of the second and third levels are respectively considered as mu and beta rhythms, which originate in the range of 8-12 Hz and 13-30 Hz in the sensorimotor cortex. Also, the default coefficients of MATLAB software have been used to achieve the goal.

C) Extraction of features

Since extracting a frequency band from an electroencephalogram signal limits the frequency range, but it does not change the volume and length of the data (of course, it should be noted that due to the sparse representation of the wavelet transform, the data volume decreases (of course (Not significant) is in front.) Therefore, it is necessary to extract a set of characteristics from each frequency sub-band as a representative. These features should be chosen in such a way that firstly their calculation is appropriate in terms of computational volume and secondly they make a significant difference for a two-class problem (like the one in this article). In this article, features based on signal spectral analysis, auto-regressive model and high-order statistics were used.

A) Analysis of the main components

Since a system for classifying images of upper limb movements must perform the act of classifying features with high classification speed and accuracy, it is necessary to achieve speed in classification and improve its sensitivity and accuracy. Reduce feature space. For this purpose, in this research, the method of principal components analysis was used in the composition of the feature space. One of the most common statistical methods in order to reduce data dimensions is principal component analysis. In this method, the total variance of the existing characteristics is analysed. The components are estimated in such a way that they show the variance of the characteristics in the smallest dimensions. In fact, the main components are the weighted sum of special attributes. This method can be useful in applications related to pattern recognition and image compression. Also, this method is considered a technique to find a pattern in high-dimensional data. This method uses eigenvalues and eigenvectors of the data covariance matrix.

3. Results and Discussion

In order to obtain a stable and reliable model, cross-validation is adopted to evaluate the performance of the classifier. Cross-validation, also known as loop estimation, captures as much information as possible when the training set is not large enough, and to some extent, can avoid the model from overfitting. In this paper, the K-fold cross-validation is employed. K is set to be 5, and the average of these 5 models' results are calculated as the final result.

In order to evaluate the performance of the presented method, three evaluation criteria of accuracy, sensitivity and specificity are defined according to relations 3 to 5. In which TP, TN, FP and FN express true positive, true negative, false positive and false negative, respectively.

$$Accuracy = \frac{TP}{TP + TN + FP + FN} \tag{3}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{4}$$

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

The classification results are reported in tables (1) to (4). As seen in table (1), support vector machine with nonlinear kernel and nearest neighbor with the features presented in this study has brought better results. The feature index for evaluating the performance of the nearest neighbor classifier before and after applying principal component analysis is shown in fig 2. Fig. 3 shows the feature index for the evaluation of the performance of the support vector machine classifier before and after applying principal component analysis. The first column is the results after applying principal components analysis.Fig. 4 shows the performance evaluation of the nearest neighbor classifier after principal components analysis.

Table 1.
Evaluation of the nearest neighbor classifier performance

Classifier type	*Specificity index (%)*	*Accuracy (%)*	*Specificity (%)*
The closest neighbor is weighted	88.2	87.3	89.7
Nearest neighbour cosine kernel	71.4	75.4	76.2
Nearest neighbour quadratic kernel	79.3	77.1	78.3
Large scale nearest neighbor	88.7	88.0	90.0
The nearest neighbour middle scale	72.7	75.3	76.4
Microscale nearest neighbor	91.2	89.9	90.0

Table 2.
Evaluation of support vector machine classifier performance

Classifier type	*Specificity index (%)*	*Accuracy (%)*	*Specificity (%)*
Linear support vector machine	78.2	79.3	80.4
Vector machine-quadratic kernel	89.5	90.7	91.3
Vector machine-third degree kernel	90.2	92.5	93.2
Large-scale Gaussian support vector machine	73.4	75.3	77.8
Medium-scale Gaussian support vector machine	89.2	87.9	83.2
Small-scale Gaussian support vector machine	92.8	93.3	93.7

Table 3.
Evaluation of the nearest neighbor classifier performance after principal component analysis

Classifier type	*Specificity index (%)*	*Accuracy (%)*	*Specificity (%)*
The closest neighbor is weighted	94.8	96.1	96.2
Nearest neighbor with cosine kernel	92.2	93.3	93.9
Nearest neighbor with quadratic kernel	91.1	91.2	91.7
Large scale nearest neighbor	91.2	92.5	93.7
The nearest neighbor of the middle scale	93.2	94.1	94.2
Microscale nearest neighbor	94.3	95.6	95.9

Table 4.
Evaluation of the performance of the support vector machine classifier after applying principal component analysis

Classifier type	*Specificity index (%)*	*Accuracy (%)*	*Specificity (%)*
Linear support vector machine	94.7	95.2	96.3
Vector machine with quadratic kernel	93.9	94.7	96.6
Vector machine with third degree kernel	95.2	96.3	96.5
Large-scale Gaussian support vector machine	85.9	86.7	88.6
Medium-scale Gaussian support vector machine	84.6	86.3	87.8
Small-scale Gaussian support vector machine	95.6	95.3	95.2

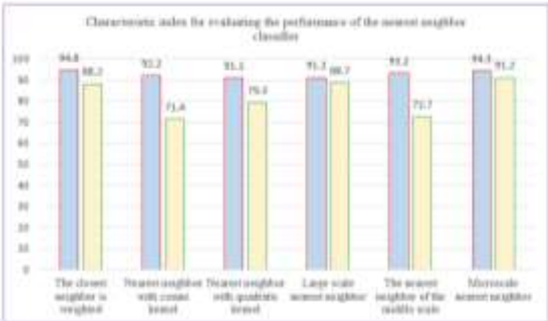

Fig. 3. Characteristic index for evaluating the performance of the nearest neighbor classifier before and after principal component analysis, specificity index (%)

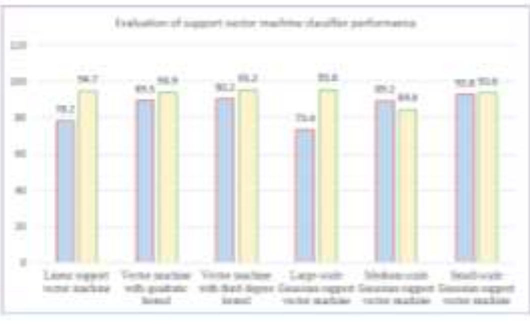

Fig. 4. Evaluating the performance of the support vector machine classifier before and after applying principal component analysis, specificity index (%)

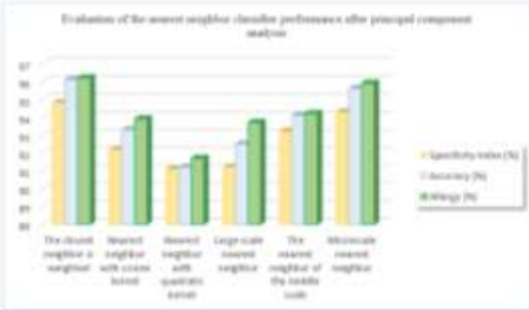

Fig. 5. Performance evaluation of the nearest neighbor classifier after principal components analysis

4. Conclusion

In this study, a technique was presented in classifying the characteristics of the electroencephalogram signal to classify the perception of right and left hand movements. The time-frequency analysis of the wavelet transformation was used to extract the Mio and Alpha rhythms. Next, a set of statistical and entropy-based features were extracted. The results of the simulation have reported the best indicators for the support vector machine classification with nonlinear kernel and nearest neighbor.

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