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A Study of EEG Based MI-BCI for Imaginary Vowels and Words

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ABSTRACT

Some people may have congenital or acquired biological or physical disabilities. For individuals in this situation, some positive developments are experienced with the advancement of technology. One of these developments can be considered today as BCI (Brain Computer Interface).BCI systems can be divided into invasive and non-invasive. Different techniques are used to obtain brain activities in non-invasive BCI systems. Some of these techniques are; EEG, ECoG, fNIRS, MEG, PET, MRI. Among these techniques, EEG and fNIRS are often preferred because of their easy applicability compared to other techniques. In this study, EEG-based motor imagery BCI system is used. In this study, an experimental BCI system has been developed in which Turkish vowels that individuals say imaginatively are perceived over the EEG signal. In the methods section of this article, information is given about the experimental environment and techniques used in the study. The results obtained with the designed system are included in the results section. In the conclusion part, a general evaluation of the study is made and improvements that can be made to improve it are emphasized.

KEYWORD: *EEG, BCI, Classification, Imaginary, vowel, CSP*

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I. INTRODUCTION

Some people may have congenital or acquired biological or physical disabilities. For individuals in this situation, some positive developments are experienced with the advancement of technology. One of these developments can be considered today as BCI (Brain Computer Interface). In the most basic sense, BCI; It can be defined as a system that enables an individual to use some virtual, such as games, apps etc., or physical tools, such as wheelchairs, by processing their brain activity [1][2].

BCI systems can be divided into invasive and non-invasive. Different techniques are used to obtain brain activities in non-invasive BCI systems. Some of these techniques are; EEG, ECoG, fNIRS, MEG, PET, MRI. Among these techniques, EEG and fNIRS are often preferred because of their easy applicability compared to other techniques [3][4].

EEG is a technique in which the changes in electrical potentials occurring in the nerves in the cortex are recorded. In BCI systems, when examining the signals obtained with EEG, different properties of the signals can be focused. Frequently used observed properties; Visual evoked potentials (P300, SSVEP etc), slow cortical potentials and motor imagery. In this study, EEG-based motor imagery BCI system is used [5][6][7][8].

The basic steps of a BCI system can be listed as signal registration, preprocessing, feature extraction, classification and command sending.

In the pre-processing phase, operations such as removing the noise existing in the obtained signals and increasing the power are performed. Then, in feature extraction, the features that are thought to represent the signals during classification are determined. Feature extraction is an important step that affects classification. In the classification stage, signals are divided into classes based on the properties obtained and the final decision is made about the output command of the system [9][2][5].

It is possible to find many BCI systems designed for different purposes in the literature. In this study, an experimental BCI system has been developed in which Turkish vowels that individuals say imaginatively are perceived over the EEG signal. In the Methods section of this article, information is given about the experimental environment and techniques used in the study. The results obtained with the designed system are included in the Results section. In the Conclusion part, a general evaluation of the study is made.

II. METHODS

A. Experimental Design

Participants in the experiment were made ten motor movements in random order, with ten repetitions. Then they were asked to do ten same motor movements, again randomly, in their minds mentally.

The motor movements the participants are asked to do are as follows; Clenching the right fist, clenching the left fist, forward movement of the right foot, forward movement of the left foot, saying the word "No", saying the word "Yes", saying the word "OK", saying the letter "A", saying the letter "E", "İ Saying the letter ". The letters "A", "E" and "İ" were chosen because they are the 3 vowels with the highest frequency of use in Turkish. The words "Tamam", "Evet" and "Hayır" were chosen because they are frequently used in daily life and express certainty.

Participants were asked to prepare for a new command when the notification screen in Figure 1 came. The screen in Figure 1 appears for 1 second. Then, the information screen appears in Figure 2, informing the content of the command. The participant reads on the screen what the motor movement he has to do. This information screen appears for 2 seconds. In addition, when the screen in Figure 2 appears, the place of the next motor movement in the EEG signal recording is marked. When the screen in Figure 3 comes, the participant has 3 seconds to make the command that was reported on the previous screen.

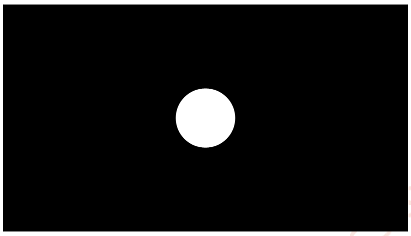

Fig 1Command preparation notification screen

Fig 2Command content notification screen

Fig 3Command execution notification screen

In this study, EEG signals were recorded using a mobile eeg recorder named EPOC+ from Emotiv. The technical features of the device named EPOC + are as follows;

- Electrode array has been prepared according to the internationally accepted 10-20 sequence.
- Recorded electrode points; AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, AF4.
- The frequency sampling rate can be set to 128 and 256 Hz.
- Signal measurement sensitivity is 0.51μV.

B. Pre-processing Stage

It is the necessary first step in making EEG signals available in BCI systems. In this step, it is mainly used for the removal of artefacts by using the aimed filtering processes and for the separation of the signal belonging to the frequency studied. At this stage, after determining the signal frequency to be examined in the developed system, frequency normalization or special filters are generally used. For example, there are many applications where band-pass filters filtering 8-30 Hz range for μ and β rhythms are used in EEG based MI-BCI systems. The μ and β rhythms are known as EEG frequencies that are frequently studied in motor imagery BCI systems. The techniques frequently used in the preprocessing stage; PCA, ICA, spatial filters (such as common reference or surface laplacian), frequency normalization (band pass filters, etc.), CSP. In addition to these techniques, it can be observed in the literature that many more techniques are applied in the pre-processing phase of the system.

In this study, the average of each channel is subtracted from the channel signal value for DC offset removal in the filtering process.

A 5th order Butterworth IIR filter with a frequency range of 8-30 Hz is used to filter the frequency bands. In the results section, the results obtained by changing the filtering parameters are stated. The reason for choosing the frequency bands between 8-30Hz is to focus on μ and β rhythms [10].

In the study, the duration of an event was taken as 4 seconds. The incident start offset is determined as 0.5 sec. The results obtained by changing the mentioned values are shown in the next sections.

C. Feature Extraction

Due to the multi-dimensional EEG records, calculation costs are quite high. Therefore, before starting the classification process, various techniques are applied on the data set to determine the features to be considered in the classification process and / or to reduce the size of the EEG data.The techniques frequently used in the literature for the said procedure; It can be expressed as PCA, CSP, GA, and DSLVQ. As can be seen, both pre-processing and feature extraction stages of the PCA and CSP system are used. Especially, CSP classes are frequently used because of its competence in clarifying the difference between signal clusters that are thought to represent.PCA is mainly used to represent multidimensional data with smaller data sets[10].

The basis of the CSP algorithm;

$$J(w) = \frac{w^T C_1 w}{w^T C_2 w} \qquad [10](1)$$

constitute the objective function. In **Error! Reference source not found.**, *T* matrix transpose, C_i is the spatial covariance matrix of X_i belonging to class *i*, and X_i is the raw data matrix for class *i*. The matrix was created as [number of EEG channels X time sample]. From this relation, we come across the generalized standard eigenvalue and eigenvector problem as follows;

$$C_1 \omega = \lambda C_2 \omega \qquad [10](2)$$

With the solution of **Error! Reference source not found.**, spatial filters of EEG signals are obtained. In projects where CSP is used in the feature extraction stage, bandpass filters are generally used in the preprocessing stage to process signals at certain frequencies.

In this study, CSP algorithm is used for feature extraction. First of all, feature matrices of each event are calculated. These matrices consist of "eigenvalue" vectors, which are summary vectors of signal values. After the root vectors of the matrices (eigenvalues) are found, the number of filters is determined to select the vectors that will make it easier to reveal the class difference of the matrices. In this study, the basic filter number is set to 2. In addition, different results were obtained by changing the number of filters. The values obtained are shown in the results section.

D. Classification

Motion or motion simulations of EEG signals emerge as a result of the classification process in MI-based BCI systems. These can be hand gestures, language gestures or even word outputs. The classification algorithms used in MI-BCI systems vary according to the system designer's preference. This means that there is no standard algorithm used in MI-BCI systems [11][12][6][9][13].

Classification algorithms such as SVM, LDA, kNN, ANN etc. are frequently used in MI-BCI systems. In addition to these algorithms, CNN and hybrid algorithms have also been used in the recent past. The efficiency of the classification algorithm used varies according to the study [13][14][6].

Linear Discriminant Analysis (LDA); In many studies, it appears in the category of Linear classification algorithms. It has been used in many studies mainly because of its relatively low computational costs and its ease of application[7][4].Basically, by gathering the input size into a narrower area, it increases the existing separation between classes and decreases the intra-class distribution. Its most important disadvantage is that it generally does not yield good results in complex EEG data. However, it provides an important advantage that small changes in learning data do not affect LDA performance [10].

In this study, LDA is used as the classification algorithm. As mentioned before, the values obtained by changing the learning and test data numbers are specified in the results section. A basic parameter that will affect the classification success in the structure of the LDA algorithm has not been changed.

III. RESULTS

The system designed in the study has been tested by creating a basic test environment. Then, different test environments were created by changing some parameters of the system. The results of these test environments are given in the relevant tables.

Environment variables of the basic test environment (Test Environment 1) can be listed as follows;

- Event offset set to 0.5 sec, event duration set to 4 sec.
- All available data (real motor movements and imaginary movements) of the subject were combined in a pool. Then divided into test and learning data according to the selected ratio.
- Learning data rate set to 60%, test data rate to 40%
- Filtering: DC offset removal was performed and a 5th order 8-30 Hz band-pass Butterworth IIR filter was used [4].
- From among the feature vectors obtained in feature extraction, the best and the worst representative two root vectors were selected [10].

Each test environment was run 5 times and the best 3 results obtained were noted.

Test environment 1 (basic test environment); the classes used are saying "No" and "Yes".

TABLE 1shows the data of the best 3 results obtained from 5 runs of the environment.

TABLE 1 Results data for Test Environment 1.

	Subject 1	Subject 2
Accuracy (%)	58.8235	68.75
	47.0588	50
	58.8235	56.25

Test environment 2; Movements classified as different from Test Environment 1 are the discourse of the letters "A" and "E".TABLE 2shows the data of the best 3 results obtained from 5 runs belonging to the environment.

TABLE 2 Results data for Test Environment 2

	Subject 1	Subject 2
Accuracy (%)	62.5	50
	25	56.25
	56.25	56.25

Test environment 3; Unlike Test Environment 2, the 8th Order Butterworth IIR filter was used. TABLE 3shows the data of the best 3 results obtained from 5 runs belonging to the environment.

TABLE 3 Results data for Test Environment 3

	Subject 1	Subject 2
Accuracy (%)	50	68.75
	68.75	62.5
	50	50

Test environment 4; Unlike Test Environment 1, learning and test data rates were set to 50%. Table 4shows the data of the best 3 results obtained from 5 runs belonging to the environment.

Table 4 Results data for Test Environment 4

	Subject 1	Subject 2
Accuracy (%)	52.381	47.3684
	66.6667	68.4211
	57.1429	68.4211

IV. CONCLUSION

The results of the EEG-based MI-BCI system, which is designed to try to classify the discourses of the words "Yes" and "No" in Turkish and the letters "A" and "E", which are also frequently used vowels in Turkish, appear in the results section. It can be said that the results obtained by the researchers are positive in order to further the study. However, there are certain points that need improvement.

As can be seen from the results, the basic test environment gave positive results for the "Yes" and "No" classes at the beginning level. On the contrary, the basic test environment was not sufficient for the classification of the vowels "A" and "E". However, changing the order of the IIR filter in the filtering process used in the test environment has been promising for the following steps of the study. On the other hand, with the change made over the learning data and test data rates, it gave better results in labeling the "No" and "Yes" classes compared to the basic test environment.

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