Design of Steady-State Visually-Evoked Potential Based Brain-Computer Interface System
Durağan-Durum Görsel-Uyarılmış Potansiyel Tabanlı Beyin-Bilgisayar Arayüzü Tasarımı

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***Abstract*—In this study, Steady-State Visual Evoked Potential (SSVEP)-based Brain-Computer Interface (BCI) system, which is popular in many sectors (game, defense, sports, etc.), especially in medicine, was composed. In addition, a robot hand was designed to be integrated into the BCI system, especially to help partially or completely disabled individuals. For this purpose, feature extraction was performed using discrete wavelet transform (Db6) from SSVEP signals recorded from seven different frequencies (6, 6.5, 7, 7.5, 8.2, 9.3, 10 Hz) and four different individuals. Extracted features were classified by support vector machine (SVM) and k-nearest neighbor (k-NN) algorithms. According to the classification results, the highest performance was obtained in the SVM algorithm with an accuracy of 84%.**

***Keywords*—steady-state visually-evoked potentials; brain-computer interfaces; wavelet transform; machine learning**

***Özetçe*—Bu çalışmada, günümüzde medikal başta olmak üzere bir çok sektörde (oyun, savunma, spor vb.) popüler olan Durağan Durum Görsel Uyarılmış Potansiyel (SSVEP) tabanlı Beyin Bilgisayar Arayüzü (BCI) sistemi oluşturulmuştur. Ayrıca BCI sistemine entegre edilecek, özellikle kısmen veya tamamen engelli bireylere yardımcı olması için robot el tasarımı gerçekleştirilmiştir. Bu amaçla, öncelikle yedi farklı frekanstan (6, 6.5, 7, 7.5, 8.2, 9.3, 10 Hz) ve dört farklı bireyden kaydedilen SSVEP sinyallerinden, ayrık dalgacık dönüşümü (Db6) kullanılarak öznitelik çıkarımı gerçekleştirilmiş. Çıkarılan öznitelikler destek vektör makinesi (SVM) ve k-en yakın komşuluk (k-NN) algoritmaları ile sınıflandırılmıştır. Sınıflandırma sonuçlarına göre en yüksek başarım %84 doğruluk değeri ile SVM algoritmasında elde edilmiştir.**

***Anahtar Kelimeler*—durağan durum görsel uyarılmış potansiyeller; beyin bilgisayar arayüzü; dalgacık dönüşümü; makine öğrenimi**

I. Introduction

A brain-computer interface (BCI) is a computer-based system that collects, analyzes, and converts brain signals into commands that are sent to an output device for execution. The BCI and the user are in sync. The user creates brain signals that encode purpose after a period of training, and the BCI decodes the signals and converts them into commands to an output device that carries out the user's goal after training as well. BCI's major purpose is to help persons with neuromuscular illnesses such as amyotrophic lateral sclerosis, cerebral palsy, stroke, or spinal cord damage replace or recover functional function. Brain-computer interfaces could also help with stroke recovery and other conditions. They might improve it in the future [1], [2].

Electroencephalography (EEG) is a noninvasive technique for recording brain electrical activity. The electroencephalogram (EEG) is a scalp-based recording of cerebral electrical potentials. Brief action potentials that produce restricted electrical fields and slower, more broad postsynaptic potentials are examples of cerebral electrical activity. The solid angle subtended at the electrode determines the size of the signal recorded from a neural generator. As a result, an adjacent microelectrode can record the activity of a single neuron, but not a distant scalp electrode. Synchronous activity in a horizontal laminar aggregate of neurons with parallel orientation, on the other hand, could be a large enough generator to be detected on the scalp. Over the cerebral convexity, the EEG is a spatiotemporal average of synchronous postsynaptic potentials occurring in radially oriented pyramidal cells in cortical gyri [2], [3].

SSVEP-based BCI systems give a robust performance from different laboratories. It has attracted many researchers due to its high information transfer rate (ITR), high signal-to-noise ratio (SNR), simplicity in configuration, and users' shorter training time [3]–[6].

In this study, we wanted to create a BCI system that works with SSVEP EEG signals. For this purpose, we first provided SSVEP signals as ready dataset and passed them through signal processing procedures. We designed a robot arm and assigned functions to the robot arm with the processed signals. As a result, we aimed to make an assistive robot arm that can make opening and closing movements that work with SSVEP signals.

II. Materials & Methods

A. Dataset Description

In this study, the dataset (AVI SSVEP Dataset) consisting of SSVEP signals acquired by Adnan Vilic was used [7]. The AVI SSVEP Dataset is public. The data set consists of SSVEP signals, which is the control signal of the EEG, measurements of the triggered responses of SSVEP signals from four healthy individuals. In this experiment, individuals have seated 60 cm away from a monitor staring at a single flashing target whose color changed rapidly from black to white. The test stimulus is a flashing box at 7 different frequencies (6 - 6.5 - 7 - 7.5 - 8.2 - 9.3 - 10 Hz) presented on the monitor. All EEG data were recorded using three electrodes (Oz, Fpz, and Fz) from the standard international 10-20 system for electrode placement. The sampling frequency of the EEG signal is 512 Hz. The reference electrode was positioned in Fz with the signal electrode in Oz and Fpz in the ground electrode. The dataset was acquired through four sessions, i.e. one session for each participant. Each session was conducted with three identical experiments. Each experiment yielded EEG data for seven frequencies with short breaks among them and took 30 seconds.

In addition, an analog notch filter was applied to the data obtained at interference frequency (50Hz) [8].

B. Signal Processing

Feature extraction is the process of obtaining the information hiding in EEG signals. Time-domain, frequency-domain, and time-frequency features have been used in EEG- and SSVEP-based systems. One of the most popular signal processing methods of these signals is wavelet transform (WT). There are two major reasons to use WT. First, WT is an effective method yield the signal in the both time and frequency domains. Second, WT is a robust transformation method in non-stationarity signals like all biomedical signals.

In this study, feature vectors have been calculated by using discrete wavelet transform method. Using one Discrete Wavelet Transform function (Db6), SSVEP signals are subdivided into frequency subbands (delta, theta, alpha, beta, gamma) and the energy, entropy and variance values of each band calculated. Thus, a number of features represented in the frequency bands were obtained.

In order to control SSVEP based BCI system, individuals must produce different brain activity patterns that will be recognized and identified by the system and translated into commands. In the literature and most existing applications of BCI, this identification process relies on a machine learning (classification) algorithm [9]. These algorithms aim at automatically estimating the class of the data as represented by feature vectors [10]. In this paper, SSVEP based BCI system is considered as a pattern recognition system and focuses on the classification algorithms used to design them. The performance of the pattern recognition system depends on both features and classification algorithms [11]. For that reason, in this study, feature vectors extracted from the SSVEP signal have been tested with two different methods. These classifiers are Support Vector Machine (SVM) and k Nearest Neighbour Classifier (k-NN).

The *k*-fold cross-validation and confusion matrix evaluation criteria were used to evaluate the performance of the classification algorithms used in this study. *k* value selected as optimum value which gives the best performance according to the trial, it is equal five.

C. Mechanical Design of Robotic Hand

The mechanical design preferred in this study mimics the anatomical structure of the human hand and arm as possible. This property is important because more closer the system designed to the natural anatomy, more functional the robotic hand will be. There are many design suggestions about the mechanical design in the literature [12], [13]. After the literature survey performed, InMoov company's open source robotic hand prototype was selected as the base design for the project [14]. The design suggested includes a simplified human hand model, a human-like forearm, two servo motors and Arduino Mega as main components. For controlling the opening and closing functions, fishing lines will be used as non-elastic cables and placed to the inner part of the palm and fingers inside which canals were put for the lines to pass [15]. There will be a force sensor on each fingertip and palm. Different from other four fingers the thumb has only two cylinders inside therefore will be controlled independently. The motion of the servo motor was planned to be controlled by a simple PID controller design and an Arduino Mega providing only the required amount of force to hold the object without slippage [16]. For a more aesthetic and objective oriented result a human-like forearm was designed to both hold the hand in a fixed position and components such as Arduino Mega and servo motors was planned to be positioned inside the handstand providing a clean final product image. The design of the hand was made using the 3D Computer-Aided Design program SolidWorks.

III. Results

A. Signal Processing Results

In the signal processing performed in the MATLAB environment, the signal accuracy values obtained by training the feature extraction kNN and SVM machine learning algorithm.

As can be seen in Table I, an accuracy of 84% was obtained as a result of training the 8.2 & 10 Hz dual frequency group using the SVM classification method. The accuracy rate of 84% is sufficient for the commands of the robotic arm. With the help of these two frequencies, two command can be generated with high accuracy. In addition, an accuracy of 82.1% was observed when the 6.5 & 7 Hz frequencies were trained using the kNN algorithm. If problems occur after assigning commands to other frequencies, frequencies of 6.5 & 7 Hz can also be used.

B. Final Design And Application

For the final design, the prototype of both robotic hand and handstand was completed. The static calculations for the motor sizing and maximum load that can be lifted was calculated and design was verified. Even though the lines that will enable the movement of the fingers are not added yet, the cylinders in which the lines will be wrapped and controlled were drawn successfully. The mechanical design and operation procedure is still open to developments and optimization for the upcoming study. But until now, the brain controlled assistive robot's mechanical design was adapted for holding an object and arrange the load applied as necessary. The handstand works for both holding the hand stable and covering cables, actuators to present an aesthetic image. For the application part, the robotic hand was expected to grasp an object with unknown geometry and dimensions (dimensions of the object limited to hand dimensions). To do so, three different sensors being temperature, proximity, and force, will get reading and the data received will be used as input by the control algorithm. Movement of the hand will either start grasping action, stop grasping action or never start grasping due to high temperature reading obtained and give a warning as output. Fig. 1 and 2 show both front and back views of the designed prototype.

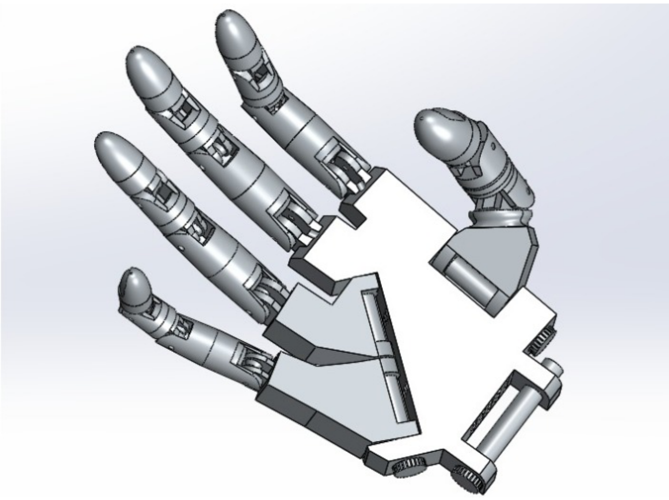

Figure 1: Prototype Design Front View

C. Manufacturing Method

The decided manufacturing method for robotic hand is 3D printing. The printing operation will be performed after the prototype mechanical design reaches final form after required developments. The material for both the hand and handstand part was ABS due to easy printing, elasticity properties and suitability for the application aimed.

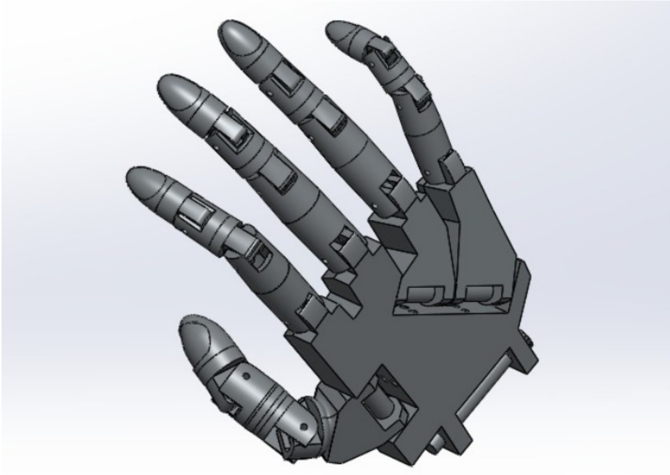

Figure 2: Prototype Design Back View

IV. Conclusion and Future Works

The designed project will not function as a rehabilitation device rather robotic hand will assist the person in holding and moving an object around as the name also suggests. The planned work packages regarding the study were completed successfully. The mechanical design and signal processing steps were both completed. The action which will be performed by the robotic hand could be adapted to many other areas which includes robotics. Additionally, the assistive robot will not only aim to help the patient physically but also provide some independency for the mean to other people. Doing so, psychological help is hoped to be also provided. At the future studies, the control algorithm design and 3D printing of the prototype will be performed. Adding the completion of the mechanical design and signal processing steps, the project will be assembled and hopefully work without any errors.

The brain controlled assistive robot requires a free movement ability for holding and transporting an object. Therefore, first limitation comes from the weight of the hand. Considering an object will be grasped and lifted for transportation, total weight of the system should not exceed a certain value. The design obtained until now will be developed further in next study. Another validation for using ABS material was also shown. Besides weight of the object the dimension including the fingers, palm and wrist was designed based on average human hand geometry. Another limitation is caused by the sensors because of the implementation position. The robotic hand requires specific and precise readings from the sensors to function as planned. As a result, the position selection of the sensors causes some minor problems. When placed at fingertips the direct contact of sensors with the object held will cause friction loss and this can cause slippage.

Frequencies	KNN-1 (%)	KNN-2 (%)	KNN-3 (%)	KNN-4 (%)	KNN-5 (%)	SVM-1 (%)	SVM-2 (%)	SVM-3 (%)	SVM-4 (%)	SVM-5 (%)
6.0-6.5	53.6	53.6	53.6	53.6	53.6	53.6	53.6	53.6	53.6	53.6
6.0-7.0	80.0	80.0	80.0	80.0	80.0	66.7	73.3	73.3	70.0	70.0
6.0-7.5	55.6	55.6	55.6	55.6	55.6	66.7	66.7	66.7	66.7	66.7
6.0-8.2	71.4	64.3	64.3	57.1	67.9	60.7	71.4	57.1	60.7	57.1
6.0-9.3	55.6	55.6	55.6	55.6	55.6	55.6	55.6	55.6	55.6	55.6
6.0-10.0	59.3	51.9	55.6	51.9	59.3	59.3	55.6	55.6	55.6	55.6
6.5-7.0	75.0	75.0	82.1	75.0	78.6	75.0	75.0	75.0	75.0	75.0
6.5-7.5	56.0	60.0	72.0	60.0	64.0	60.0	60.0	60.0	68.0	64.0
6.5-8.2	53.8	50.0	61.5	61.5	61.5	53.8	50.0	61.5	53.8	50.0
6.5-9.3	52.0	56.0	40.0	52.0	48.0	44.0	40.0	56.0	52.0	56.0
6.5-10.0	52.0	52.0	52.0	52.0	52.0	60.0	60.0	60.0	60.0	60.0
7.0-7.5	55.6	55.6	55.6	55.6	55.6	55.6	55.6	55.6	55.6	55.6
7.0-8.2	64.3	53.6	64.3	67.9	64.3	60.7	57.1	60.7	64.3	60.7
7.0-9.3	55.6	51.9	59.3	55.6	61.9	59.3	59.3	51.9	63.0	59.3
7.0-10.0	74.1	63.0	55.6	70.4	66.7	55.6	51.0	51.9	55.6	59.3
7.5-8.2	56.0	48.0	60.0	60.0	56.0	44.0	40.0	52.0	48.0	54.0
7.5-9.3	60.0	52.0	56.0	52.0	60.0	60.0	40.0	56.0	44.0	44.0
7.5-10.0	70.8	54.2	58.3	54.0	58.3	66.7	62.0	58.3	50.0	66.7
8.2-9.3	52.0	44.0	52.0	36.0	64.0	52.0	48.0	48.0	44.0	60.0
8.2-10.0	72.0	52.0	72.0	76.0	76.0	68.0	68.0	84.0	84.0	84.0
9.3-10.0	41.7	33.3	54.8	37.5	45.8	41.7	33.3	54.2	50.0	54.2

Table I: Classifier performances SVM and KNN classifiers in the discrimination of frequency pairs

Additionally, inaccurate force measurements will be taken since slippage will cause less force read. On the other hand, sensors positioned at palm will have no effect on measuring the force applied. As a solution to this, thin silicon or rubber caps can be used at fingertips to prevent slippage. Another constraint was caused by the design. Human hand drawing is complex because of the anatomical structure and aimed motion being complicated to mimic. This constraint resulted in some simplifications on the final product design limiting the usage of the hand only optimized only for holding an object. Since the main objective was achieved, result was found to be satisfying. Finally, the most important limitation is budget. Budget puts some limits on the selection of parts to be used and materials preferred. ABS material, aside being easy to 3D print, is relatively high cost therefore limiting the dimensions and geometry of the robotic hand. Other than material, the cost of electronic components and EMOTIV EEG headset put some limitations on the final product.

Author Contributions

This paper is a part of *Meryem Beyza Avci, Rabia Hamurcu, Ozge Ada Bozbas, Ege Gurman*'s capstone project. *Ebru Sayilgan* is the advisor of the project. All authors equally contributed on writing the paper.

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