Durağan-Durum Görsel Uyarılmış Potansiyellere Dayalı Beyin-Bilgisayar Arayüzünün Zamansal ve Frekanssal Derinliğinden Frekans Tanıma

Frequency Recognition from Temporal and Frequency Depth of the Brain-Computer Interface based on Steady-State Visual Evoked Potentials

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***Özetçe*—Durağan-durum görsel-uyarılmış potansiyellere (DDGUP) dayalı beyin-bilgisayar arayüzü (BBA) sistemi, klinik nörobilim, bilişsel ve mühendislik araştırmalarının kullanımı gibi eğlenceden rehabilitasyona kadar farklı uygulama alanlarında hızla kullanılmaktadır. Çeşitli elektroensefalografi paradigmalarından DDGUP tabanlı BBA sistemleri, apoplektik kişilerin basit sistem yapıları, kısa veya hiç eğitim süreleri, yüksek zamansal çözünürlükleri, yüksek bilgi aktarım hızları ve diğer yöntemlere göre ekonomik olması nedeniyle dış dünya ile kolayca iletişim kurmasını sağlar. DDGUP tabanlı BBA'lar, farklı komutlar oluşturmak için farklı frekanslarda titreşen birden çok görsel uyarıcı kullanır. Bu yazıda, zamansal ve spektral yöntemleri kullanarak hangi frekans çiftinin en yüksek performansı verdiğini belirlemek için yedi farklı frekansta titreşen ikili komut kombinasyonlarının sınıflandırıcı performanslarını karşılaştırdık. DDGUP'tan frekans tanıma için, DDGUP sinyalinden toplam 25 zamansal değişim özniteliği ve 15 frekans tabanlı öznitelik vektörü çıkarıldı. Bu öznitelik vektörleri, iyi bilinen yedi makine öğrenme algoritmasının (Karar Ağacı, Ayırıcı Analiz, Lojistik Regresyon, Naive Bayes, Destek Vektör Makineleri, En Yakın Komşuluk ve Topluluk Öğrenmesi) girdisine uygulandı. Sonuç olarak, 2,520 farklı koşturma arasında 7.5 - 10 frekans çiftinde %100 doğruluk elde ettik ve en başarılı sınıflandırıcının Topluluk Öğrenmesi sınıflandırıcısı olduğunu gördük. Bu yöntemlerin kombinasyonu, klasik yaklaşımların sağlamlığını ve etkinliğini temsil eden uygun, ayrıntılı ve karşılaştırmalı bir analize götürmektedir.**

Anahtar Kelimeler*—beyin-bilgisayar arayüzü; durağan-durum görsel-uyarılmış potansiyel; EEG; makine öğrenmesi.

***Abstract*—Brain-computer interface (BCI) system based on steady-state visual evoked potentials (SSVEP) have been acceleratingly used in different application areas from entertainment to rehabilitation, like clinical neuroscience, cognitive, and use of engineering researches. Of various electroencephalography paradigms, SSVEP-based BCI systems enable apoplectic people to communicate with outside world easily, due to their simple system structure, short or no training time, high temporal resolution, high information transfer rate, and affordable by comparing to other methods. SSVEP-based BCIs use multiple visual stimuli flickering at different frequencies to generate distinct commands. In this paper, we compared the classifier performances of combinations of binary commands flickering at seven different frequencies to determine which frequency pair gives the highest performance using temporal and spectral methods. For SSVEP frequency recognition, in total 25 temporal change characteristics of the signals and 15 frequency-based feature vectors extracted from the SSVEP signal. These feature vectors were applied to the input of seven well-known machine learning algorithms (Decision Tree, Discriminant Analysis, Logistic Regression, Naive Bayes, Support Vector Machines, Nearest Neighbour, and Ensemble Learning). In conclusion, we achieved 100% accuracy in 7.5 - 10 frequency pairs among these 2,520 distinct runs and we found that the most successful classifier is the Ensemble Learning classifier. The combination of these methods leads to an appropriate detailed and comparative analysis that represents the robustness and effectiveness of classical approaches.**

Keywords*—brain-computer interface; steady-state visual-evoked potential; EEG; machine learning.

I. INTRODUCTION

Various methods are available to monitor brain activity [1, 2]. These include electrocorticography (ECoG), intra-cortical, EEG, functional magnetic resonance imaging (fMRI), magnetoencephalography (MEG), positron emission tomography (PET), and optical imaging. However, intra-cortical, ECoG, fMRI, PET, MEG, and optical imaging are not preferred because they are technically challenging, more invasive, and expensive [2]. Among these monitoring methods, only EEG methods offer a practical BCI possibility. It is relatively non-invasive to other methods, requires a short time, is workable in most environments, and has the advantages of more straightforward and cheaper equipment [3].

Commonly used control signal in EEG-based BCIs is SSVEP [3, 4]. SSVEP is a resonance phenomenon that occurs mainly in the visual cortex when an individual's visual attention focuses on a light source that flickers with a frequency above 6 Hz [5, 6, 7]. Also, SSVEP consists of a periodic component of the same frequency as the flickering light source, likewise of many harmonic frequencies [5]. Since SSVEP is an intrinsic neuronal response relatively independent of higher-level cognitive processes, it is widely used to study low-level processing in the brain and perform clinical assessments of visual pathways [6]. SSVEP could be recorded on the visual cortex from the scalp with maximum amplitude in the occipital region [8]. The interest in SSVEP based BCI studies is mainly owing to the robustness of the SSVEP phenomenon. Besides, it has advantages such as high information transfer rate (ITR), simple system structure, short user training, and short time requirement [5-9].

Generally four main steps are applied in the design of the SSVEP-based BCI system [8]. These are (1) SSVEP signal acquisition, (2) pre-processing, (3) feature extraction and, (4) classification. In many recent studies, feature extraction methods for detecting SSVEP frequencies, respectively: Autoregressive [8], Discrete Fourier Transform (DFT) [9], Canonical Correlation Analysis (CCA) [10], Empirical Mode Decomposition (EMD) [11], Fuzzy Ensemble System [12, 13], Discrete Wavelet Transform (DWT) [14, 15, 16], Minimum energy combination (MEC) [17], Common Spatial Pattern (CSP) [18], etc. multivariate analysis methods were used.

In this study, the success of two approaches, which are basic perception approaches for a simplest structured SSVEP-based BCI system, is proved by different machine learning techniques. Time domain characteristics of raw SSVEP signals and Power Spectral Density Analysis (PSDA) based on Fast Fourier Transform (FFT) by transforming SSVEP signals into frequency domain, temporal and frequency characteristic information of each stimulation frequency was obtained for further target (flickering frequency) identification procedure. These fundamental and effective features were classified using seven different machine learning (ML) algorithms that are well known in the literature but have not been compared with each other before. In addition, ML algorithms were evaluated using the k-fold cross validation method.

II. MATERIALS AND METHODS

A. Data Recording Process and Users

In this study, the dataset (AVI SSVEP Dataset) containing steady-state visual evoked potential signals designed and recorded by Adnan Vilic was used [19]. The data set contains data that include EEG measurements of healthy individuals (three men and one woman, and their ages range from 27 to 32) looking at the flickering target to trigger responses of SSVEP signals at different frequencies, and the data set used for this study is publicly available. Using the standard international 10-20 system for electrode placement, the reference electrode is positioned in Fz with the signal electrode in Oz and Fpz in the ground electrode. In this experiment, individuals have seated 60 cm away from a monitor staring at a single flashing target whose colour changed rapidly from black to white. The test stimulus is a flashing box at seven different frequencies (6 - 6.5 - 7 - 7.5 - 8.2 - 9.3 - 10 Hz) presented on the monitor. The data set comprises of four sessions with four different participants. Each session in a session lasts 30 seconds and participants take a short break between trials. Experiments were repeated at least three times for each frequency.

B. Feature Extraction

1) Time-domain based feature extraction: The SSVEP time-domain features are extracted from information in the original field of the EEG signal. The relevant and distinctive SSVEP time-domain features we identified. These features are based on the amplitude (e.g. Average amplitude change value, root mean square, interquartile ranges, etc.) and statistical changes of the EEG signal (e.g., mean, variance, skewness, and kurtosis, etc.) [20, 21, 22].

2) Frequency-domain based feature extraction: EEG signals consist of a series of specific oscillations known as rhythms, as mentioned earlier. Performing a specific mental, sensory or visual task changes the amplitude of these rhythms [3, 4]. Moreover, signals such as SSVEP are identified by oscillations with frequencies synchronized with the stimulus frequency [23]. For this reason, many EEG-based BCI systems use frequency information embedded in the signal in the feature extraction process. In the literature, spectral estimation methods are generally used [24, 25, 26] due to their high precision and simplicity. Within the scope of this study, EEG frequency features were extracted from the frequency domain representation of the EEG signal using a Fast Fourier Transform (FFT). The relevant and distinctive EEG frequency characteristics we detected are based on the spectral information of EEG signals for each EEG rhythm, such as energy, variance and spectral entropy.

These features explain how power, variance, and irregularity (entropy) change in some related frequency bands. In practice, this means that these features will use their power in certain frequency bands.

Features based on power spectrum, energy of each frequency band,

$$F_1^{(f)} = Energy_f = \sum_{k=1}^{M} y(k)^2 \qquad (1)$$

Here is the Fourier transform of the analytic signal y of a real discrete time EEG signal x.

$F_1^{(f)} = E_f$ stands for the EEG features computed from y, and M corresponds to the maximum frequency.

Features based on variance of each EEG frequency band

$$F_2^{(f)} = Variance_f = \frac{1}{M-1} \sum_{k=1}^{M} (y_k - \bar{y})^2 \qquad (2)$$

"$\bar{y}$" in the formula gives the average of the "y" signal.

Fetaure based on entropy of each EEG frequency band: Spectral entropy measures the regularity of the power spectrum of EEG signal

$$F_3^{(f)} = Entropy_f = \frac{1}{\log(M)} \sum_{k=1}^{M} P(y(k)) \log P(y(k)) \quad (3)$$

C. *Machine Learning Classification Algorithms*

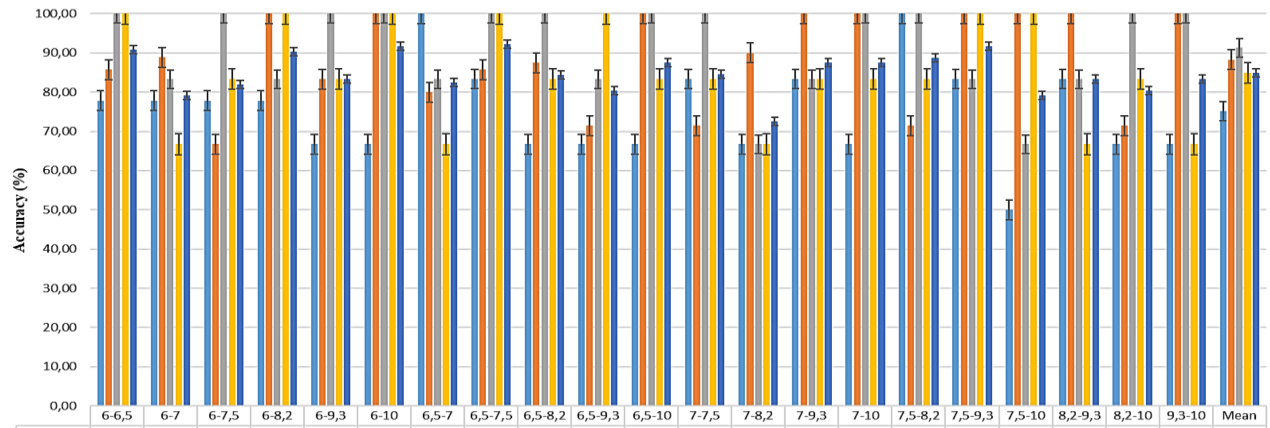
In the classification phase, a single classifier was used in many EEG-based BCI systems [7, 8, 21, 22]. On the other hand, combinations of classifiers are very useful in synchronous experiments [13-17, 26, 27]. In other words, measuring the performance of the system designed by looking at the performance of a single classifier may not always be the right way. Therefore, in this study, feature vectors extracted from the SSVEP signal have been tested with seven basic classifiers. The "Classifier Learner" application in the MATLAB software was used for the classification process, and the performances of all classifiers were examined (used in default mode). These classifiers consist of the following algorithms: Decision Trees, Discriminant Analysis, Logistic Regression, Naive Bayes, Support Vector Machines, k-Nearest Neighbor and Ensemble Learning Classifiers.

D. *Evaluation of Machine Learning Algorithms Performance*

While training ML algorithm to classify SSVEP signals is an important step, it is essential to consider how the algorithm is generalized on unprecedented data (test set) [28]. We need to know if the algorithm works correctly and whether we can trust its predictions. The machine learning algorithm can only memorize the training set. Therefore, it can make reasonable predictions about future examples or examples that it has not seen before. Thus, it is one of the essential steps for BCI systems to know and apply the techniques used to evaluate how well a ML model generalizes to new, unprecedented data [28, 29]. For this goal the "k-fold cross-validation" [30, 31] and "confusion matrix" [32] evaluation criteria were used to evaluate the performance of the ML algorithms used in this study.

III. RESULTS AND DISCUSSION

The SSVEP data used in this study were obtained through open access from "https://www.setzner.com/avi-ssvep-dataset/." [19] with the permission of the dataset owner. All signal processing and performance analyses were implemented using MATLAB software. The performance of each ML algorithm was evaluated by the accuracy (ACC) criterion using the confusion matrix.
Characterized as an increase in the amplitude of the stimulating frequency, the photic driver response results in significant baseline and harmonics [23]. Thus, it is possible to determine the stimulus frequency based on the SSVEP measurement. For this purpose, 40 feature vectors were extracted from the SSVEP signals recorded using seven different frequencies: the time domain, and the frequency domain. The extracted feature vectors were run with 25



	6-6,5	6-7	6-7,5	6-8,2	6-9,3	6-10	6,5-7	6,5-7,5	6,5-8,2	6,5-9,3	6,5-10	7-7,5	7-8,2	7-9,3	7-10	7,5-8,2	7,5-9,3	7,5-10	8,2-9,3	8,2-10	9,3-10	Mean
Subject1	77,80	77,80	77,80	77,80	66,70	66,70	100,00	83,30	66,70	66,70	66,70	83,30	66,70	83,30	66,70	100,00	83,30	50,00	83,30	66,70	66,70	75,14
Subject2	85,70	88,90	66,70	100,00	83,30	100,00	80,00	85,70	87,50	71,40	100,00	71,40	90,00	100,00	100,00	71,40	100,00	100,00	100,00	71,40	100,00	88,26
Subject3	100,00	83,30	100,00	83,30	100,00	100,00	83,30	100,00	100,00	83,30	100,00	100,00	66,70	83,30	100,00	100,00	83,30	66,70	83,30	100,00	100,00	91,26
Subject4	100,00	66,70	83,30	100,00	83,30	100,00	66,70	100,00	83,30	100,00	83,30	83,30	66,70	83,30	83,30	83,30	100,00	100,00	66,70	83,30	66,70	84,91
Mean	90,88	79,18	81,95	90,28	83,33	91,68	82,50	92,25	84,38	80,35	87,50	84,50	72,53	87,48	87,50	88,68	91,65	79,18	83,33	80,35	83,35	84,89

Target Frequencies

Figure 1. Binary classification performance of the time-domain features.

machine learning algorithms due to 7 basic classifiers and sub-parameters. Also, the effect of the increase in the difference between frequencies on the accuracy criterion was investigated.

A. Time-Domain Features Results

Binary classification results of 25 feature vectors extracted from SSVEP signals using time domain properties are given below, respectively. According to the results shown in Figure 1, the best performance was obtained with an accuracy value of 91.68% in 6-10 frequency pairs based on the average of the subjects. Simultaneously, when the subjects are considered separately, up to 100% results were obtained. In addition, there is no definitive finding related to the increase in the accuracy value parallel to the difference between frequencies for the time domain. When the results are evaluated in terms of classifiers, it is seen in Figure 2 that the best performance is in the Ensemble Learning classifier.

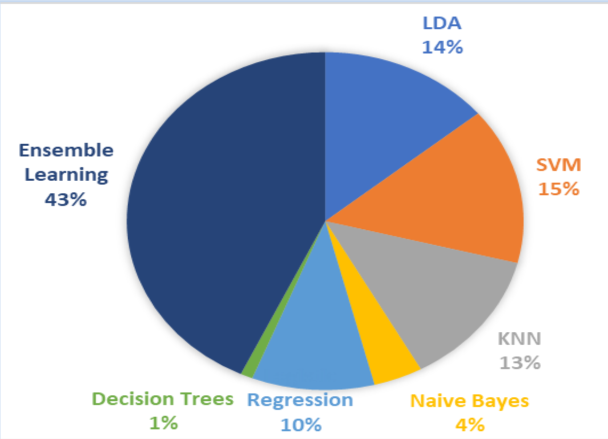
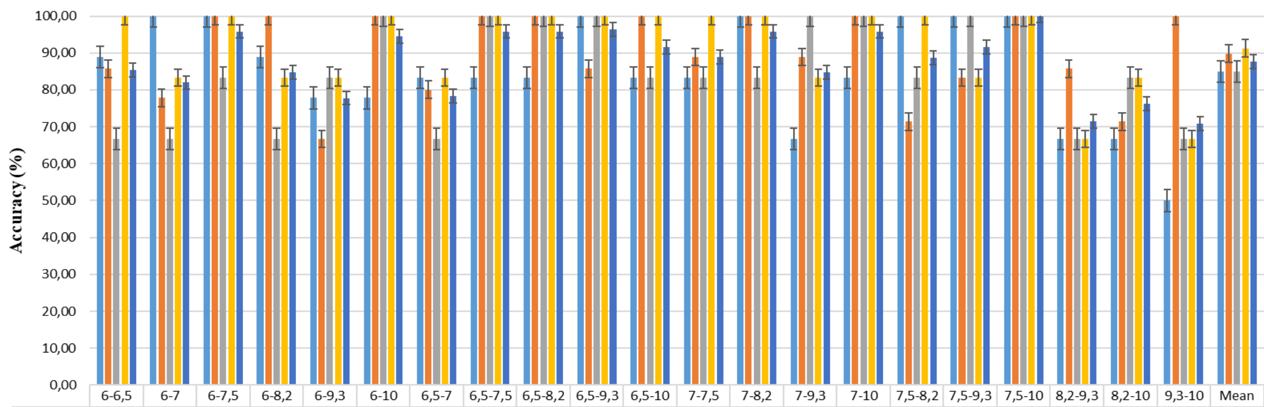


Figure 2. Percentage of classifier where the best result is the most often obtained as a result of running the algorithms 2,520 times in total (for time-domain features).

B. Frequency-Domain Features Results

For the frequency domain characteristics used in the problem of determining seven different frequencies, firstly, spectrum analysis was performed to detect the stimulus frequencies more clearly than the signal. This analysis is often used to obtain frequency information in evoked SSVEP responses. The basic idea is always the same: a flashing or moving visual stimulus at a constant frequency (stimulus frequency) reveals a response or even harmonics at the same frequency in the brain. At the same time, the power spectrum of EEG signals was determined by FFT using MATLAB software to calculate its power, entropy, and variance for each band in the frequency range corresponding to the frequencies. For this purpose, the signal received FFT is divided into EEG sub-bands (delta, theta, alpha, beta, gamma), and energy, entropy, and variance values of each band are calculated. A total of 15 feature vectors are generated. The results of evaluating the generated features with ML algorithms are presented in Figure 3 with accuracy.

Considering the averages of the binary classification results of frequency features for four participants, the performances obtained vary between the lowest 70.85% and the highest 100%. Accordingly, the highest performance was determined with 100% accuracy value in 7.5 - 10 frequency pairs. The following six highest performances are 96.43% accuracy in the 6.5 - 9.3 frequency pairs, 95.83% in the 6 - 7.5 frequency pairs, 95.83% in the 6.5 - 7.5 frequency pairs, 95.83% in the 6.5 - 8.2 frequency pairs, 95.83% in the frequency pairs 7 - 8.2, and the last it was obtained with the accuracy values of 95.83% in 7 - 10 frequency pairs. The lowest performance was found in the frequency pair 9.3-10 with an accuracy of 70.85%. It is noteworthy that the highest performance obtained is determined in the frequency pair where the difference between them is relatively high.



	6-6,5	6-7	6-7,5	6-8,2	6-9,3	6-10	6,5-7	6,5-7,5	6,5-8,2	6,5-9,3	6,5-10	7-7,5	7-8,2	7-9,3	7-10	7,5-8,2	7,5-9,3	7,5-10	8,2-9,3	8,2-10	9,3-10	Mean
Subject 1	88,90	100,00	100,00	88,90	77,80	77,80	83,30	83,30	83,30	100,00	83,30	83,30	100,00	66,70	83,30	100,00	100,00	100,00	66,70	66,70	50,00	84,92
Subject 2	85,70	77,80	100,00	100,00	66,70	100,00	80,00	100,00	100,00	85,70	100,00	88,90	100,00	88,90	100,00	71,40	83,30	100,00	85,70	71,40	100,00	89,79
Subject 3	66,70	66,70	83,30	66,70	83,30	100,00	66,70	100,00	100,00	100,00	83,30	83,30	83,30	100,00	100,00	83,30	100,00	100,00	66,70	83,30	66,70	84,92
Subject 4	100,00	83,30	100,00	83,30	83,30	100,00	83,30	100,00	100,00	100,00	100,00	100,00	100,00	83,30	100,00	100,00	83,30	100,00	66,70	83,30	66,70	91,26
Mean	85,33	81,95	95,83	84,73	77,78	94,45	78,33	95,83	95,83	96,43	91,65	88,88	95,83	84,73	95,83	88,68	91,65	100,00	71,45	76,18	70,85	87,72

Target Frequencies

Figure 3. Binary classification performance of the frequency-domain features.

When the results are evaluated in terms of classifiers, it is clearly seen in Figure 4 that the classifier that performs with the highest rate is the Ensemble Learning classifier. Another classifier that follows the Ensemble learning classifier and has obvious success has been the SVM classifier. Other classifiers following Ensemble Learning and SVM were identified as KNN, Logistic Regression and Naive Bayes classifiers, respectively. It is also seen that no successful results have been obtained in the LDA and Decision Tree classifiers.

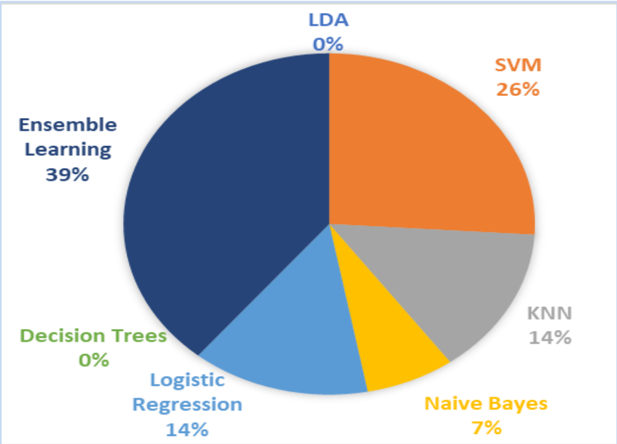


Figure 4. Percentage of classifier where the best result is the most often obtained as a result of running the algorithms 2,520 times in total (for frequency-domain features).

IV. Conclusion

This study aimed to achieve significant optimization of cortical visual responses, signal processing methods, and ML algorithms, as well as the accuracy and reliability of the superior two-command SSVEP-based BCI system. Two basic approaches have been explored using existing methods to develop an accurate, reliable, comfortable SSVEP-based BCI that can offer people with severe motor neuron diseases a communication alternative using attention modulation without requiring neuromuscular activities or eye movements.

As a result, the following research objectives were achieved in this study: (i) When the results of the time domain features are evaluated first, it can be seen that these features give usable (noteworthy) results in the classification of SSVEP signals. However, given the natural structure of the SSVEP signal, it is a fact that the results obtained are not sufficient for a real-time SSVEP-based BCI design, since the time domain properties do not reflect the characteristics of the signal alone. (ii) When the classification results of the frequency domain features, another feature group, were evaluated alone, satisfactory results were obtained. Higher accuracy values were obtained in binary classification compared to time domain.

Contributions

The subject of this paper is the part of E. Sayilgan's Ph.D. thesis. Y. Isler is the supervisor and Y. K. Yuce is the cosupervisor of the thesis. All authors equally contribute on writing this article.

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