Durağan Durum Görsel Uyarılmış Potansiyellerin Uyarı Frekansını Kestirmek için Wigner-Ville Dağılım Özniteliklerinin Değerlendirilmesi
Evaluation of Wigner-Ville Distribution Features to Estimate Steady-State Visual Evoked Potentials' Stimulation Frequency

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Özetçe— ***Beyin Bilgisayar Arayüzü (BBA), insanların sadece beyin aktivitesini (motor hareket hayal gücü, duygusal durum, herhangi bir odaklanmış görsel veya işitsel uyartı vb.) yorumlayarak dış dünya ile iletişim kurmasını ve çeşitli elektronik cihazları kontrol etmesini sağlayan bir sistemdir. Görsel uyarıma dayalı kayıt, çeşitli elektroensefalografi (EEG) kayıt yöntemleri arasında en popüler yöntemlerden biridir. Görsel nesnelerin sabit bir frekansta yanıp söndüğü durağan durum görsel uyarılmış potansiyeller (DDGUP), BBA uygulamalarında yüksek sinyal-gürültü oranı ve daha yüksek bilgi aktarım hızı nedeniyle önemli bir rol oynar. Ancak, DDGUP tabanlı BBA sistemlerinde çoklu (3'ten fazla) komut sisteminin tasarımı sınırlıdır. Bu sorunların üstesinden gelmek için farklı yaklaşımlar önerilmektedir. Bu çalışmada, DDGUP sinyallerindeki uyarıcı frekansı belirlemek için makine öğrenmesine dayalı bir yaklaşım önerilmektedir. Veri seti (AVI SSVEP Veri Seti) simülasyonlar için internetten açık erişim yoluyla elde edildi. Veri seti, denekler yedi farklı frekansta (6-6.5-7-7.5-8.2-9.3-10Hz) yanıp sönen bir frekansa baktıklarında kaydedilen EEG sinyallerini içerir. Makine öğrenimine dayalı yaklaşımda Wigner-Ville Dağılımı (WVD) kullanılır ve EEG sinyallerinin Zaman-Frekans (ZF) gösterimleri kullanılarak öznitelikler çıkarılır. Bu öznitelikler, Karar Ağacı, Doğrusal Ayırım Analizi (DAA), k-En Yakın Komşu (k-NN), Destek Vektör Makinesi (DVM), Naive Bayes, Topluluk Öğrenme sınıflandırıcılarıyla sınıflandırılır. Simülasyon sonuçları, önerilen yaklaşımın 7 komutlu DDGUP sistemler için umut verici doğruluk oranlarına ulaştığını göstermektedir. Sonuç olarak, Topluluk Öğrenmesi sınıflandırıcısında %47,60 ile maksimum doğruluk elde edilir.***

Anahtar Kelimeler—beyin-bilgisayar arayüzü (BBA); durağan-durum görsel-uyaran potansiyelleri (DDGUP); elektroensefalogram (EEG); zaman-frekans gösterimi; Wigner-Ville dağılımı.

Abstract— Brain Computer Interface (BCI) is a system that enables people to communicate with the outside world and control various electronic devices by interpreting only brain activity (motor movement imagination, emotional state, any focused visual or auditory stimulus, etc.). The visual stimulation based recording is one of the most popular methods among various electroencephalography (EEG) recording methods. Steady-state visual-evoked potentials (SSVEPs) where visual objects are blinking at a fixed frequency play an important role due to their high signal-to-noise ratio and higher information transfer rate in BCI applications. However, the design of multiple (more than 3) command systems in SSVEPs based BCI systems is limited. The different approaches are recommended to overcome these problems. In this study, an approach based on machine learning is proposed to determine stimulating frequency in SSVEP signals. The data set (AVI SSVEP Dataset) is obtained through open access from the internet for simulations. The dataset includes EEG signals that was recorded when subjects looked at a flickering frequency at seven different frequencies (6-6.5-7-7.5-8.2-9.3-10Hz). In the machine learning-based approach Wigner-Ville Distribution (WVD) is used and features are extracted using Time-Frequency (TF) representations of EEG signals. These features are classified by Decision Tree, Linear Discriminant Analysis (LDA), k-Nearest Neighbor (k-NN), Support Vector Machine (SVM), Naive Bayes, Ensemble Learning classifiers. Simulation results demonstrate that the proposed approach achieved promising accuracy rates for 7 command SSVEP systems. As a consequence, the maximum accuracy is achieved in the Ensemble Learning classifier with 47.60%.

Keywords—brain-computer interface (BCI); electroencephalography (EEG); steady-state visually-evoked potentials (SSVEPs); time-frequency (TF) representation; Wigner-Ville distribution.

I. INTRODUCTION

Brain Computer Interfaces (BCIs) are a system or set of systems that enable people to communicate with their environment by controlling various electronic devices and / or prostheses, orthoses by interpreting and interpreting only brain activity [1, 2]. The basic building blocks of BCI systems based on the detection of some neurophysiological interactions in the brain consist of biological signal measurements, software and hardware for signals, various signal processing methods and machine learning algorithms.

Electroencephalography (EEG) is a method that provides measurement of the brain activity of the subject. In recent years, BCIs based on noninvasive scalp EEG have become an increasingly popular study field. The visual evoked potentials (VEP) are a type of commonly used signals in EEG-based BCIs with owing to higher signal-to-noise ratio (SNR), a high information transfer rate (ITR), convenient system preparation, and little user training. EEG signals recorded during the application of some visual stimuli (image, video, light) to the subject are called visual potentials. VEPs are obtained from the brain's response to visual stimulation. If the visual stimulus itself is applied by modulating at a frequency higher than 6 Hz, the resulting visual evoked potentials are called steady-state visual-evoked potentials (SSVEPs). Photic driving response, that is qualified by an increase in amplitude at the stimulus frequency, cause occurrence of the significant fundamental and second harmonics [3]. Hence, it is possible to estimate the evoking frequency based on measurement of SSVEP.

In the literature about SSVEP-based BCI system design, there are studies conducted with various methods that examine the differences between visual stimulus types (shape, size, light source, color, etc.) and the state of careful focusing on the stimulus shown, usually using up to four different frequencies. In these studies, the commands mostly associated with only two stimulation frequencies were tried to be classified. Zhang et al. [4] proposed Continous Wavelet Trasform (CWT)-based SSVEP feature extraction and features are classified by Support Vector Machine (SVM) achieving nearly 95% success for detection of four commands in SSVEP signals. In another study [5], the four-class SSVEP signals are detected with a classification method based on the maximum and minimum values of the features extracted by the Fast Fourier Transform (FFT) and they achieved success in the range of 44-88%. Diez et al. [6] used FFT based features to detect stimulating frequency into three ranges with success between 65-100%. Another study [7], applied Discrete Wavelet Transform for feature extraction of SSVEP signals and feature selection process is applied using t test. Decision Tree, SVM and Bayesian classifier based detection is proposed and the highest accuracy was about 83.32% which is obtained through Bayes classification. Yeh et al. [8] presented a multiclass support vector machine (SVM)-based classification approach for four class gaze-target detections using the amplitude and phase features of SSVEP signals with accuracy of 89.88%.

In addition to studies where only two different frequencies are used, there are quite a few studies studying to predict higher number of simulating frequency from SSVEP signals at the same time. In a recent study, Sayılgan et al. [9] used Naive Bayes, Extreme Learning Machine (ELM) and SVM algorithms to predict which of the five different boxes among the SSVEP signals were selected, using three different feature sets that are obtained features of Autoregressive (AR) parameters, Hjorth and Power Spectral Density (PSD) from EEG signals. The best accuracy is 83.42%, achieved by integration of the PSD features and Extreme Learning Machine algorithm among achieved accuracy performances. However, in this study, the evoking frequency was constant and it was tried to predict which box was selected from the SSVEP signal according to the five box colors and positions. In another study [10], conducted by the same team, extracted twenty-five features containing only time-domain based features from SSVEP signals to predict the eight different stimulating frequency in the data set (AVI SSVEP Dataset). These features were applied to classifiers of six different classifiers and they obtained the maximum accuracy of 42.9% for each subject separately. In the same study, when all subjects were evaluated together, an average performance of 20.00% was achieved. Accordingly, it is clear that there is a need for methods that can simultaneously estimate a greater number of stimulating frequencies with higher performance in SSVEP-based BCI research area.

In this paper, Wigner-Ville Distribution based classification approach for detection of the seven different stimulating frequency is introduced. The Time-Frequency (TF) representations of SSVEP signals are provided using WVD for each EEG signal seperately and six different features are extracted from the magnitudes of TF matrices. The six classifier algorithms are utilized to predict stimulating frequency in SSVEP signals and their performances are compared with each other.

II. MATERIALS AND METHODS

In this study, WVD method is applied to predict stimulating frequency in SSVEP signals. The simulations were performed on the data set (AVI SSVEP Dataset) obtained from the internet via open access. EEG signals that the flickering frequency at seven different frequencies (6-6.5-7-7.5-8.2-9.3-10Hz) are selected and features are extracted using WVD based TF representation. These features classified into six classification algorithms. The flowchart of the proposed approach is represented in Fig. 1

A. Dataset

Adnan Vilic's steady-state visually-evoked potential data set (AVI SSVEP) is used for the simulations [11]. The data set includes EEG recordings of healthy subjects looking at the flashing target to trigger SSVEP responses. All recording obtained utilizing three electrodes which are the signal electrode (Oz), the ground electrode (Fpz) and the reference electrode (Fz) and these electrodes are positioned

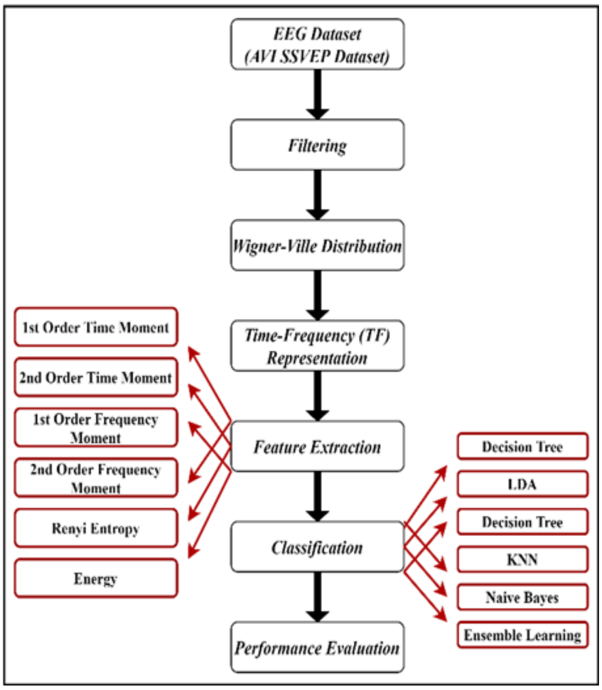

Figure 1. *The block diagram of the WVD-based approach.*

based on the standart 10-20 system for electrode placement. Impedances and the sampling rate are setted as 5kΩ or less and 512 Hz respectively. The subjects were seated in front of an LCD computer screen with a 120 Hz refresh rate and a resolution of 1680x1050 pixels for experiment. The contrast and brightness were set to maximum and the screen brightness of 350 cd / m2 was kept. The visual stimulus application is designed in Microsoft Silverlight and runs on Windows 8 based PC. In filtering step, the anologue notch filter with mains frequency (50 Hz) is processed for the data. A single flashing target whose color changed rapidly from black to white is represented subjects. As an stimulus, a flickering box at 7 different frequencies (6, 6.5, 7, 7.5, 8.2, 9.3, 10Hz) is used. The data set includes four sessions with four different participants. The rcording designed as each trial in a session take 30 seconds and take a short break between trials. In each frequency, experiments were repeated at least 3 times. The gender and age information of participants is given with Table 1.

Tablo I. List of the participants for single target flickering

Participant	1	2	3	4
Gender	Male	Male	Male	Female
Age	32	27	27	31

B. *Wigner-Ville Distribution*

The proposed approach based on analyzing the TF domain of EEG signals for detection of the stimulating frequency in SSVEP signals. For this reason traditional WVD method is applied to extract feature vectors of the recommended method. In each EEG signal, WVD based 2D TF representations are obtained. Then, the machine learning algorithms are used to extract features and classify these features on estimation of the stimulating frequency. The WVD is a significant method for TF signal analysis. It was found in quantum mechanics by Wigner [12], and also implemented in signal analysis by Ville [13].

A detailed proccessing of frequency component of the signal during time is defined as TF representation. The advanced frequency distrubution aproaches are necessary for non-stationary signal analysis. The high resolution TF representations of a signals are obtained by WVD. The Wigner distribution (WD) based on real time $x(t)$ signal processing, while WVD used analytic version, $z(t)$ to provide $W(t,\omega)$. WVD suppress the cross term with equation of

$$W(t,\omega) = \int_{-\infty}^{\infty} z\left(t+\frac{\tau}{2}\right) z^*\left(t-\frac{\tau}{2}\right) exp^{-j\omega\tau} \qquad (1)$$

Hilbert transform $H(.)$ is used to provide $z(t)$ by

$$z(t) = a(t)e^{j\phi(t)} = x(t) + jH\{x(t)\} \qquad (2)$$

where $a(t)$ and $\phi(t)$ are assigned instantaneous amplitude and phase respectively. An example of WVD magnitude spectra is represented in Fig. 2.

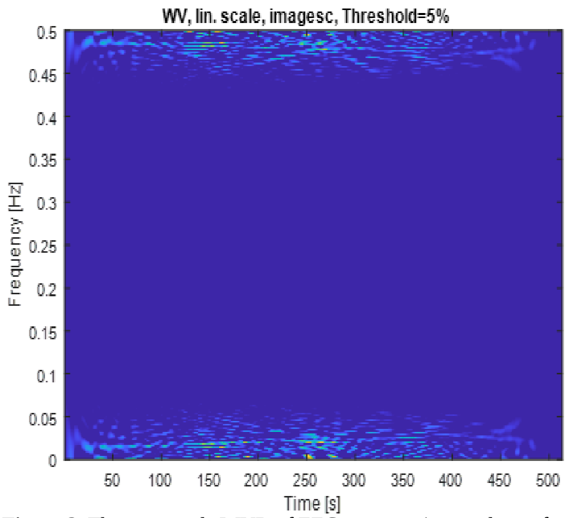

Figure 2. The magnitude WVD of EEG segment (at simulating frequency 7 Hz).

C. *Machine Learning based Approach*

In the proposed machine learning-based approach, 1st order time moment, 2nd order time moment, 1st order frequency moment, 2nd order frequency moment, Renyi entropy, and energy were determined as features using the magnitude of WVD and machine learning algorithms like Decision Tree, LDA, k-NN, SVM, Naïve Bayes, and Ensemble Learning classifiers were processed for classification [14]. Classification algorithms are applied similar to studies with Ref. [14, 15, 16]. 1x6 feature vector is provided for each EEG signals. The 5-fold crossvalidation process was applied for performance evaluation. The accuracy metric-based performance evaluation is computed.

III. Results and Discussion

In this paper, using the WVD algorithm machine learning-based approach is proposed to predict stimulating frequency in SSVEP signals. The feature set that includes 1st order time moment, 2nd order time moment, 1st order frequency moment, 2nd order frequency moment, Renyi entropy, energy features from TF representations was applied to six different classifier. The accuracy metric based performance comparison of all machine learning-based approaches are presented in Table 2. The performance evaluations revealed that the proposed WVD-based approach achieved high performance rates in the prediction of seven different stimulating frequency in SSVEP signals. As a consequence, the highest performance was achieved in the Ensemble Learning classifier with 47.60%. Also, the subject-dependent performance evaluation is investigated in this study. The best results achieved on subject 3 using the SVM and Ensemle Learning classifiers.

Tablo II. Performance evaluations (%) for the estimation of stimulating frequency in SSVEP signals

Classifier/ Subject	S1	S2	S3	S4
Decision Tree	22,20	19,20	33,30	19,00
Naive Bayes	14,80	***34,60***	33,30	28,60
SVM	22,20	26,90	***47,60***	***38,10***
KNN	22,20	26,90	33,30	33,30
Ensemble Learning	***40,70***	30,80	***47,60***	***38,10***
LDA	0	0	0	0

IV. Conclusion

In the proposed approach EEG signals that belongs to the seven different stimulating frequency are used. TF representations are obtained applying WVD for each EEG signal. The feature set which contains 1st order time moment, 2nd order time moment, 1st order frequency moment, 2nd order frequency moment, Renyi entropy, energy features are obtained using WVD-based TF matrices. Classification algorithms such as Decision Tree, LDA, k-NN, SVM, Naïve Bayes, Ensemble Learning classifiers were applied to classify for feature set. The proposed methods demostrated that a high performance rates are achieved in prediction of stimulating frequency in SSVEP signals.

We aim to evaluate different high-resolution TF representation methods and compare them with the proposed WVD-based approach as future studies. Also different feature extraction techniques with various classification algorithms for machine learning-based approach can be used. The deep learnig-based approach may be used with recording of the WVD matrix as an image.

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