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Determining Gaze Information from Steady-State Visually-Evoked Potentials

Durağan Durum Görsel Uyaran Potansiyellerinden Bakış Bilgilerini Çıkarma

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Abstract

Brain-Computer Interface (BCI) is a communication system that enables individuals who lack control and use of their existing muscular and nervous systems to interact with the outside world because of various reasons. A BCI enables its user to communicate with some electronic devices by processing signals generated during brain activities. This study attempts to detect and collect gaze data within Electroencephalogram (EEG) signals through classification. To this purpose, three datasets comprised of EEG signals recorded by researchers from the Autonomous University were adopted. The EEG signals in these datasets were collected in a setting where subjects' gaze into five boxes shown on a computer screen was recognized through Steady-State Visually Evoked Potential based BCI. The classification was performed using algorithms of Naive Bayes, Extreme Learning Machine, and Support Vector Machines. Three feature sets; Autoregressive, Hjorth, and Power Spectral Density, were extracted from EEG signals. As a result, using Autoregressive features, classifiers performed between 45.67% and 78.34%, whereas for Hjorth their classification performance was within 43.34-75.25%, and finally, by using Power Spectral Density their classification performance was between 57.36% and 83.42% Furthermore, classifier performances using Naive Bayes varied between 52.23% and 79.15% for Naive Bayes, 56.32-83.42% for Extreme Learning Machine, and 43.34-72.27% for Support Vector Machines by regarding classification algorithms. Among achieved accuracy performances, the best accuracy is 83.42%, achieved by the Power Spectral Density features and Extreme Learning Machine algorithm pair.

Keywords: Brain-computer interface, Classification, Electroencephalogram, Steady-state visual-evoked potential

Öz

Beyin-Bilgisayar Arayüzü (BBA), mevcut kas ve sinir sistemlerini çeşitli nedenlerle kontrol edemeyen bireylerin dış dünya ile etkileşime girmelerini sağlayan bir iletişim sistemidir. Temel olarak, bir BBA, kullanıcının beyin aktiviteleri sırasında üretilen sinyalleri işleyerek bazı elektronik cihazlarla iletişim kurmasını sağlar. Bu çalışma, sınıflandırma yoluyla Elektroensafalogram (EEG) sinyalleri içindeki sabit bakış verilerini belirlemeye ve toplamaya çalışmaktadır. Bu amaçla Autonomous Üniversitesi'ndeki araştırmacılar tarafından kaydedilen EEG sinyallerinden oluşan üç veri seti incelenmiştir. Bu veri kümelerindeki EEG sinyalleri, deneklerin bilgisayar ekranında gösterilen beş kutuya bakışlarının Durağan Durum Görsel Uyarılmış Potansiyel bazlı BBA ile tanındığı bir ortamda toplanmıştır. Naive Bayes, Aşırı Öğrenme Makinesi ve Destek Vektör Makineleri algoritmaları kullanılarak sınıflandırma yapıldı. EEG sinyallerinden Özbağlanımlı, Hjorth ve Güç Spektral Yoğunluğu olarak üç öznitelik seti çıkarılmıştır. Sonuç olarak, Özbağlanımlı özniteliklerin kullanıldığı durumda sınıflandırıcılar %45.67 ile %78.34 arasında performans gösterirken, Hjorth özniteliği kullanıldığında sınıflandırma performansları %43.34-75.25 ve son olarak Güç Spektral Yoğunluğu kullanılarak sınıflandırma performansları %57.36 ile %83.42 arasındadır. Ayrıca sınıflandırma performansları, sınıflandırma algoritmalarına göre Naive Bayes için %52.23 ile 79.15, Aşırı Öğrenme Makinesi için %56.32-83.42 ve Destek Vektör Makineleri için %43.34-72.27 arasında değişmektedir. Elde edilen doğruluk performansları arasında en iyi doğruluk değeri, Güç Spektral Yoğunluk özniteliği ve Aşırı Öğrenme Makinesi algoritması çifti ile elde edilen %83.42 olmuştur.

Anahtar Kelimeler: Beyin bilgisayar arayüzü, Sınıflandırma, Elektroensefalogram, Durağan-durum görsel-uyarılmış potansiyel

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1. Introduction

Brain-computer interfaces (BCI) translate brain activity into computer commands that provide direct communication between the brain and its environment, enabling users to interact within a predefined context without requiring muscle power (Wolpaw et al. 2000, Loo et al. 2011, Mason and Birch 2013). Today, the major focus of research on BCIs is on creating custom applications that enable individuals with severe motor disabilities to have effective control of devices such as computers, speech synthesizers, assistive devices and/or prostheses.

Electroencephalogram (EEG) signals are one of the most widely used types of biomedical signals for BCIs, owing to their portability, high time resolution, ease of acquisition and implementation, and cost-effectiveness (affordable) as compared to other brain activity monitoring techniques (Sayilgan et al. 2019, Sayilgan et al. 2020). There are four typical EEG-based BCI paradigms: steady-state visual-evoked potentials (SSVEP), slow cortical potentials (SCP), the P300 component of evoked potentials, and sensory-motor rhythms (SMR) (Pasqualotto et al. 2012). The SSVEP signal is a periodic response to a visual stimulator modulated at a frequency greater than 6 Hz (Wang et al. 2006) (or higher than 4 Hz (Regan 1990)). The amplitude and phase characteristics of the SSVEP depend on the stimulus intensity and frequency (Sayilgan et al. 2019b, Sayilgan et al. 2020).

SSVEP-based BCIs have become a popular research area utilizing many advantages over other types of BCIs, including higher signal-to-noise ratio (SNR) and faster information transfer rate (ITR), lesser training time. To improve SSVEP based BCIs performance, an effective frequency recognition algorithm plays an important role. In literature, various techniques for SSVEP based feature extraction and classification have been analyzed and developed by Carvalho et al. (2015), Oikonomou et al. (2016), Tello et al. (2014), Zerafa et al. (2018), and Zhang et al. (2018). The same features used in this study were previously investigated for different tasks (listening to music, mental task, motor task, etc.), and they reported high accuracies using the same features by Durmus et al. (2014), Ozmen et al. (2017), Sadreddini et al. (2014), Sayilgan et al. (2019a). Also, classification methods are proposed in Sayilgan et al. (2017), Sayilgan et al. (2019b). However, combinations of feature extraction and classification algorithms discussed in this study have not been studied for SSVEP signals.

In this study, various classification methods are used to classify SSVEP signals. The three well-known and popular classification algorithms, including Naive Bayes, Extreme Learning Machine (ELM), and Support Vector Machine (SVM) algorithms have a major impact on the performance of the entire systems, particularly on accuracy. Therefore, the achievements of these algorithms commonly used in SSVEP-based BCIs were compared in system performances.

This study was organized as follows: the second section introduces the materials. The characteristics of the raw signals recorded from the EEG device, details of the visual stimulation, basic information about the participants were provided and the visual task was described. Besides, detailed information on signal processing steps is presented in this section. In the next section, section 3, experimental results are shown that explain the performance of both classifiers and participants in successfully predicting tasks (through accuracy, sensitivity, and selectivity). Finally, the results of the classification and the performance differences among adopted classifiers are discussed and evaluated.

2. Materials and Methods

2.1 Collecting EEG Data: Experimental Setup and Protocol

2.1.1. The EEG signal dataset and participants

EEG signals recorded at the Autonomous University were downloaded from the Internet (http://archive.ics.uci.edu/ml/datasets/EEG+Steady-State+Visual+Evoked+Potential+Signals) and were used in this study. Dataset comprises of EEG signals acquired at experiments that were conducted on a total number of 29 healthy participants (17 males and 12 females) aged between 20-29 and 48-50. Seventeen of the participants had normal whereas twelve had corrected views (Fernandez-Fraga et al. 2018a).

2.1.2. The EEG device

EEG signals were obtained using a portable, high-resolution Emotive Epoc+ EEG model. The device has a total number of 16 electrodes (14 data channels, and 2 reference channels). The electrodes are positioned concerning the international standard called the International 10-20 System (Figure 1). The device was capable of measuring amplitude within a dynamic range of -4.17 mV and +4.17 mV for each channel. The device's sampling rate per channel was 128 Hz. However, by applying a band-pass filter, signals within a frequency response of 0.16 to 43 Hz was acquired and quantized using an Analog-to-Digital Converter with a quantization resolution of 16 bits per channel (Fernandez-Fraga et al. 2018a).

2.1.3. The setting and experimental protocol

During the experimental trials, participants were seated in a comfortable chair at a distance of 70 cm from the standard 15-inch LCD monitor (Fernandez-Fraga et al. 2018a). This experimental setup is developed by another group Makeig et al. (1999), for visual discrimination for the analysis of SSVEP-based BCI systems. The tests aimed to obtain data-related stimuli in brain signals during a simple attention exercise, and research was conducted to find the difference between carefully related and irrelevant stimuli. Test participants were expected to distinguish between different types of stimuli presented at high frequencies (Fernandez-Fraga et al. 2018a, Fernandez-Fraga et al. 2018b).

Before starting the test, the participant is asked to concentrate when a red cross appears in the green box (Makeig et al. 1999). The test begins with the configuration shown in Figure 2 (a). A total number of 100 stimuli were presented in each test: 20 attended (events) 80 unattended (Figure 2 (b) and 2 (c), respectively), the last 200 ms remain on the screen before the stimulus disappears (Courchesne et al. 1994).

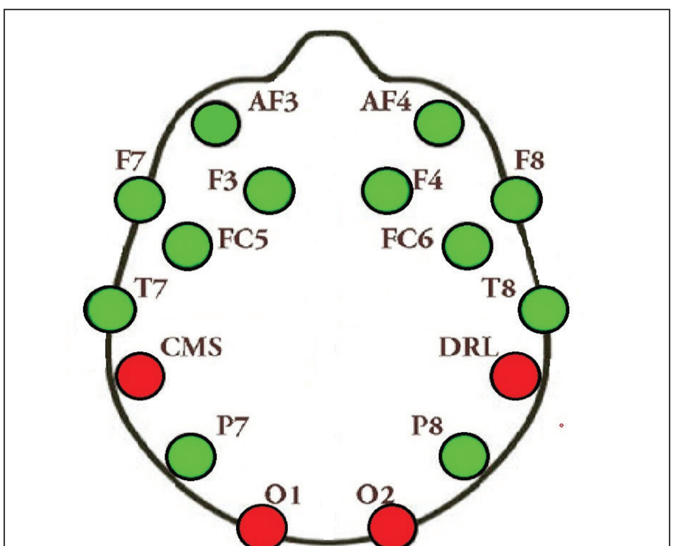

Figure 1. 10-20 international electrode topographic representation.

2.2. Analysis of Steady-State Visually-Evoked Potentials

2.2.1. Preprocessing

SSVEP signals, unfortunately, might easily get contaminated by other bio-signals or environmental noise. Therefore, the first step is to filter noisy data as much as possible (Diez et al. 2013). According to the literature, band-pass and notch filters are widely used as filters in the preprocessing step. The signals are digitized within a certain frequency range corresponding to the stimulus frequencies and their harmonics. Since the EEGs are in the narrow-band frequency range, a band-pass filter was used in the signal preprocessing step. Also, the notch filter is often used to filter the mains line interference. SSVEP is subdivided using stimulus points that indicate the beginning and end of the signal. The data were filtered by a band-pass filter with cutoff frequencies of 0.16 and 43 Hz to remove the DC component and high-frequency artifacts, including city mains interference (50 Hz). Since SSVEP signals are not sensitive to low-frequency structures such as eye or body movements, no extra artifact removal method has been used (Wu 2016, Oostenveld et al. 2011).

2.2.2. Feature extraction

Feature extraction and feature classification use distinctive features of SSVEP signals to define an individual's intention to control an external device. In other words, feature extraction consists of extracting important features from the recorded SSVEP data and obtaining the feature vector. In this way, the size of the feature vector is reduced while the most defining properties are selected for the classifier.

Feature extraction sometimes requires time-consuming signal analysis. Existing BCIs typically generate, frequency domain information such as mu (μ) (8-12 Hz) and/or

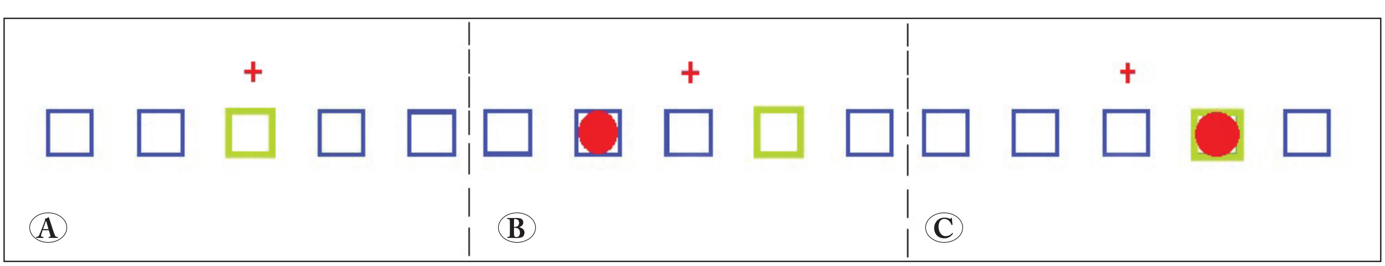

Figure 2. Five-box test **(A)** Initial state **(B)** Unattended stimulus **(C)** Attended stimulus (event).

high beta (18-26 Hz) rhythm amplitudes, or time-domain information such as P300 and slow cortical potentials (SCP) (Guger at al. 2009, Chiappa and Bengio 2004) or power spectral density (PSD) values (Millan and Mourino 2003, Penny et al. 2000), and autoregressive (AR), and Hjorth parameters (Pfurtscheller et al. 1998, Gunal 2001).

In this study, as the feature vectors, autoregressive parameters (AR), Hjorth parameters and power spectrum density (PSD) were tested. These three feature extraction methods were compared in terms of classification performances.

The autoregressive model (AR), whose order is p, is calculated by Eq. 1 equation. In this equation, x(n) indicates the output sequence, e(n) indicates the white noise sequence with the variance σ^2, a(k) indicates the relational parameters (AR) and/or feature. The AR(p) model is characterized by the AR model parameters {a [1], a [2], …, a [p], σ^2}.

$$[1],a[2],...,a[p],\sigma^2\}.$$
$$x[n]=-\sum\nolimits_{k=1}^{p} a[k]x[n-k]+e[n] \tag{1}$$

The Hjorth identifiers are constructed by combining three sub-parameters. These parameters are activity, mobility, and complexity. Activity is simply defined as the energy of the signal (σx). Mobility is the ratio of the standard deviation of the first derivative of the x signal to the standard deviation of the signal, expressed in the equation given in Eq. 2.

$$M=\frac{\sigma x'}{\sigma x} \tag{2}$$

Complexity, also known as form factor (FF), gives a computable value for the form of the signal.

$$FF=\frac{Mx'}{Mx}=\frac{\sigma x''/\sigma x'}{\sigma x'/\sigma x} \tag{3}$$

The power spectral density (PSD) can be considered as the power distribution on the frequency band of the signal. The strength of a signal is calculated by squaring it. PSD of a signal is calculated by taking the Fourier transform of the signal's autocorrelation function. PSD is widely used in the literature as a feature, was calculated by the Welch periodogram (Millan and Mourino 2003, Penny et al. 2000, Pfurtscheller et al. 1998, Gunal 2001, Oikonomou et al. 2016).

2.2.3. Classification methods

Naive Bayes is a clustering classification algorithm based on probability prediction which is widely used in pattern recognition studies. It is a successful classification model based on the principle of calculating the probability of membership in all data classes in a data set (Ibanez et al. 2014).

Extreme-learning machine (ELM) was developed based on a single-layer and feed-forward network model (Huang et al. 2006). ELM is preferred in many different areas of the literature due to its advantages such as short training time, high accuracy generalization (Altan and Kutlu 2018, Altan et al. 2016, Yayık 2017) over new samples in multi-class training clusters and no need for any training parameters (Huang and Chen 2007). ELM randomly assigns the input weights and hidden node values of the neural network, and the output layer weights are calculated by the least-squares method (Tang et al. 2015).

Support vector machine (SVM) has adopted the principle of large margins to formulate decision rules, using a solid foundation in statistical learning theory (Vapnik 1998). Depending on the selection of kernel functions, different classifiers, including linear and non-linear classifiers, can be created. For ease of evaluation, only linear classifiers were used and the penalty parameter was taken as 1 in SVM training.

2.2.4. Evaluation of classifiers

In order to evaluate the performance of the classification algorithms used in this study, *k*-fold cross-validation and confusion matrix evaluation criteria were used.

k-Fold Cross-Validation

One of the most commonly used methods to separate the data set as a training and test set is the k-fold cross-validation method. In this method, the data set is divided into random pieces. Each time k-1 is used for training the algorithm, while the remaining 1 is used for testing the algorithm. This process is repeated until all parts are used for testing purposes. Test errors are recorded each time and the average of the errors is calculated after the last piece (Narin et al. 2014). The performance of the classifier algorithm used is evaluated in this way. In this study, the data set is divided into 10 equal parts.

Confusion Matrix

To evaluate the classifier performance, the confusion matrix is first calculated. It is created by comparing the answers given by the classification algorithm to the test set with the real values in the data set. The confusion matrix criteria used for performance evaluation in this study are given below;

$$ACC=\frac{TP+TN}{TP+FN+FP+TN} \tag{4}$$

$$SEN = \frac{TP}{TP + FN} \tag{5}$$

$$SPE = \frac{TN}{TN + FP} \tag{6}$$

The above formulas are expressed as accuracy (ACC), sensitivity (SEN) and selectivity (SPE), respectively. All values in the equations are calculated in the Matlab environment using the "Confusion Matrix". TP belongs to a class and represents the number of data assigned to the same class by the classifier and FN represents the number of data assigned to a different class in error. The number of data belonging to a different class and assigned to a different class by the classifier is represented by TN, and the number of data assigned by mistake to the same class is represented by FP (Narin et al. 2014).

3. Results and Discussion

The performances of the classifier algorithms were calculated with the Matlab program and SSVEP data were classified by using Naive Bayes, ELM and SVM algorithms. For the SVM algorithm, the libSVM library was used with the library's default parameters (i.e. Linear Kernel and C = 1). In the remaining algorithms (Naive Bayes and ELM), we trusted MATLAB's Statistics and Machine Learning toolbox applications, using the default parameters for each classification scheme found in MATLAB's online manual. In order to obtain a correct solution in a reasonable time for each algorithm, the optimum number of iterations deemed appropriate in the literature was determined as convergence criteria. Performance values were determined by performing 10 iterations in total and averaging the results obtained. The performance of each classification algorithm was evaluated using 10-fold cross-validation. Nine combinations of different feature extraction and classifiers were tested for each person. Table 1 summarizes the average performance of all classification schemes.

The classification achievements of SSVEP data recorded from twenty-nine different individuals during visual tasks were given as percentages. According to these results, when the AR, Hjorth and PSD feature extraction methods were applied separately and tested with Naive Bayes, ELM and SVM classifiers, the success rates of the tasks were close to each other but the ACC rates were between 46.43-82.58% on average. When the classifiers are compared among themselves, the lowest and highest achievements of the Naive Bayes classifier are 52.23% and 79.15%, while the ELM classifier is 56.32-83.42% and the SVM classifier is the lowest 43.34% and the highest 72.27%. In terms of feature methods, the classification results of the AR and PSD features are 45.67-78.34%, and 57.36% and 83.42%, respectively, and for Hjorth 43.34-75.25%.

When the experimental results of the feature methods are examined, it is seen that the classification success of the AR and PSD feature parameters including the frequency domain properties is higher than the Hjorth descriptors. Also, the ELM algorithm gave the highest success among the classifiers that are investigated in this study while the SVM algorithm resulted in the worst performance among these classifiers.

Table 1. Classification results of SSVEP-based BCI data.

Trial set	Classifiers	Classifier Performances (%)								
		AR			Hjorth			PSD		
		SEN	SPE	ACC	SEN	SPE	ACC	SEN	SPE	ACC
Five Box Visual Task 1	Naive Bayes	59.85	55.33	57.93	52.23	56.81	54.30	68.96	75.43	71.03
	ELM	73.24	69.01	71.79	68.41	56.32	61.80	79.07	72.18	76.33
	SVM	45.67	52.84	50.11	47.22	43.34	46.43	60.33	57.36	59.20
Five Box Visual Task 2	Naive Bayes	58.02	62.76	60.94	52.58	59.05	54.90	70.40	66.65	68.41
	ELM	78.34	75.42	73.38	71.31	69.83	71.03	83.42	81.36	82.58
	SVM	49.92	58.33	57.45	54.20	51.10	53.17	64.88	61.39	63.44
Five Box Visual Task 3	Naive Bayes	62.43	68.98	66.68	60.38	66.41	64.31	79.15	73.59	77.26
	ELM	77.88	66.69	70.09	71.77	75.25	74.34	81.03	77.26	80.16
	SVM	65.14	58.03	63.32	53.43	54.42	52.75	72.27	69.40	71.39

In conclusion, since it is known that SSVEP data varies from person to person, a larger number of participants may be necessary to reach a general judgment. It is one of the drawbacks of our study. We used a general-purpose and freely-available dataset; hence, we were not able to use a larger dataset in this study. Besides, since it is difficult in many respects to experiment with people with neurophysiological disorders, trials have been conducted with healthy individuals in this study and many studies in the literature.

The experimental results show the potential of the proposed procedure in real-time applications to contribute to SSVEP based brain-computer interface applications.

4. References

Altan, G., Kutlu, Y., Allahverdi, N. 2016. Deep belief networks based brain activity classification using EEG from slow cortical potentials in stroke. *International Journal of Applied Mathematics, Electronics and Computers*, 4: 205-210. http://dx.doi.org/10.18100/ijamec.270307.

Altan, G., Kutlu, Y. 2018. Generative autoencoder kernels on deep learning for brain activity analysis. *Natural and Engineering Sciences*, 3(3): 311–322. https://doi.org/10.28978/nesciences.468978.

Carvalho, SN., Costa, TB., Uribe, LF., Soriano, DC., Yared, G. FG., Coradine, LC., Attux, R. 2015. Comparative analysis of strategies for feature extraction and classification in SSVEP BCIs. *Biomed. Signal Proces.*, 21: 34–42. https://doi.org/10.1016/j.bspc.2015.05.008.

Chiappa, S., Bengio, S. 2004. HMM and IOHMM modeling of EEG rhythms for asynchronous BCI Systems. *European Symposium on Artificial Neural Networks (ESANN)*, 199-204, Bruges, Belgium.

Courchesne, E., Townsend, J., Akshoomoff, NA., Saitoh, O., Yeung-Courchesne, R., Lincoln, AJ., James, HE., Haas, RH., Schreibman, L., Lau, L. 1994. Impairment in shifting attention in autistic and cerebellar patients. *Behav. Neurosci.*, 108(5): 848–865. https://doi.org/10.1037/0735-7044.108.5.848.

Diez, PF., Correa, AG., Leber, EL. 2013. SSVEP detection using adaptive filters. *5th Latin American Congress on Biomedical Engineering*, 33: 1154-1157.

Durmuş, E., Sadreddini, Z., Özmen, NG. 2014. Beyin bilgisayar arayüzü sistemleri için uygun öznitelik ve sınıflandırıcı seçimi. *Otomatik Kontrol Ulusal Toplantısı (TOK),* Kocaeli, 11-13 Eylül, 651-656.

Fernandez-Fraga, SM., Aceves-Fernandez, MA., Pedraza-Ortega, JC. 2018a. Feature extraction of EEG signal upon BCI systems based on steady-state visual evoked potentials using the ant colony optimization algorithm. *Discrete Dynamics in Nature and Society*, 2018: 1-19. https://doi.org/10.1155/2018/2143873.

Fernandez-Fraga, SM., Aceves-Fernandez, MA., Pedraza-Ortega, JC., Ramos-Arreguin, JM. 2018b. Screen task experiments for EEG signals based on SSVEP brain computer interface. *Int. J. Adv. Res. (Indore)*, 6(2): 1718-1732. http://dx.doi.org/10.21474/IJAR01/6612.

Guger, C., Ramoser, H., Pfurtscheller, G. 2009. Real-time EEG analysis with subject-specific spatial patterns for a brain-computer interface (BCI). *IEEE Trans. Rehabil. Eng.*, 8: 447–456. https://doi.org/10.1109/86.895947.

Gunal, S. 2001. *Örüntü tanıma uygulamalarında alt uzay analiziyle öznitelik seçimi ve sınıflandırma*. Doktora tezi, Osmangazi Üniversitesi, Fen Bilimleri Enstitüsü, Eskişehir.

Huang, G., Chen, L. 2007. Convex incremental extreme learning machine. *Neurocomputing*, 70(16-18): 3056-3062. https://doi.org/10.1016/j.neucom.2007.02.009.

Huang, G., Zhu, Q., Siew, C. 2006. Extreme learning machine: Theory and applications. *Neurocomputing*, 70: 489-501. https://doi.org/10.1016/j.neucom.2005.12.126.

Ibanez, A., Bielza, C., Larranaga, P. 2014. Cost-sensitive selective naive bayes classifiers for predicting the increase of the h-index for scientific journals. *Neurocomputing*, 135: 42-52. https://doi.org/10.1016/j.neucom.2013.08.042.

Loo, C. K., Samraj, A., Lee, G. C. 2011. Evaluation of methods for estimating fractal dimension in motor imagery-based brain computer interface. *Discrete Dynamics in Nature and Society,* 724697: 1-8. https://doi.org/10.1155/2011/724697.

Makeig, S., Westerfield, M., Jung, TP., Covington, J., Townsend, J., Sejnowski, TJ., Courchesne, E. 1999. Functionally independent components of the late positive event-related potential during visual spatial attention. *J. Neurosci.*, 19(7): 2665–2680. https://doi.org/10.1523/JNEUROSCI.19-07-02665.1999.

Mason, S. G., Birch, G. E. 2003. A general framework for brain-computer interface design. *IEEE Trans. Neural Syst. Rehabil. Eng.*, 11: 70-85. https://doi.org/10.1109/TNSRE.2003.810426.

Millan, JR., Mourino, J. 2003. Asynchronous BCI and local neural classifiers: An over view of the adaptive brain computer interface project. *IEEE Trans. Neural Syst. Rehabil. Eng.*, 11: 159–161. https://doi.org/10.1109/TNSRE.2003.814435

Narin, A., İşler, Y., Özer, M. 2014. Konjestif kalp yetmezliği teşhisinde kullanılan çapraz doğrulama yöntemlerinin sınıflandırıcı performanslarının belirlenmesine olan etkilerinin karşılaştırılması. *DEÜ Mühendislik Fakültesi Mühendislik Bilimleri Dergisi*, 16(48): 1-8. Retrieved from https://dergipark.org.tr/tr/pub/deumffmd/issue/40797/492155.

Oikonomou, VP., Liaros, G., Georgiadis, K., Chatzilari, E., Adam, K., Nikolopoulos, S., Kompatsiaris, I. 2016. Comparative evaluation of state-of-the-art algorithms for SSVEP-Based BCIs. *ArXiv*, 1-33. Retrieved from https://arxiv.org/abs/1602.00904v2.

Oostenveld, R., Fries, P., Maris, EJ., Schoffelen, M. 2011. Field trip: Open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. *Comput. Intel. Neurosc.*, 2011: 1-9. https://doi.org/10.1155/2011/156869.

Özmen, NG., Durmuş, E., Sadreddini, Z. 2017. Müzik sınıflandırması beyin bilgisayar arayüzü uygulamaları için bir alternatif olabilir mi?. *Uludağ University Journal of The Faculty of Engineering*, 22(2): 11-22. https://doi.org/10.17482/uumfd.335419.

Pasqualotto, E., Federici, S., Belardinelli, MO. 2012. Toward functioning and usable brain-computer interfaces (BCIs): A literature review. *Disabil. Rehabil. Assist. Technol.*, 7: 89-103. https://doi.org/10.3109/17483107.2011.589486.

Penny, WD., Roberts, SJ., Curran, EA., Stokes, MJ. 2000. EEG-Based Communication: a Pattern Recognition Approach. *IEEE Trans. Neural. Syst. Rehabil. Eng.*, 8: 214–215. https://doi.org/10.1109/86.847820.

Pfurtscheller, G., Neuper, C., Schlogl, A., Lugger, K. 1998. Separability of EEG signals recorded during right and left motor imagery using adaptive autoregressive parameters. *IEEE Trans. Neural Syst. Rehabil. Eng.*, 6: 316–325. https://doi.org/10.1109/86.712230.

Regan, D. 1990. Human brain electrophysiology: Evoked potentials and evoked magnetic fields in science and medicine. *Br. J. Ophthalmol.,* 7: 450-451. Retrieved from https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1042082/.

Sadreddini, Z., Durmuş, E., Özmen, N. G. 2014. EEG verilerinden farklı müzik türü ve zihinsel görevlerin ayırt edilmesi. *Akıllı sistemlerde Yenilik ve Uygulamaları (ASYU)*, İzmir, Türkiye, 9-10 Ekim, 44-48.

Sayilgan, E., Cura, O. K., Isler Y. 2017. Use of clustering algorithms and extreme learning machine in determining arrhythmia types. *IEEE 25th Signal Processing and Communications Applications Conference (SIU)*, 1–4. https://doi.org/10.1109/SIU.2017.7960236.

Sayilgan, E., Yuce YK., Isler Y. 2019a. Classification of hand movements from EEG signals using machine learning techniques. *2019 Innovations in Intelligent Systems and Applications Conference (ASYU)*, Izmir, Turkey, 1-4. https://doi.org/10.1109/ASYU48272.2019.8946334.

Sayilgan, E., Yuce YK., Isler Y. 2019b. Prediction of evoking frequency from steady-state visual evoked frequency. *Natural and Engineering Sciences*, 4(3): 91-99.

Sayilgan E., Yuce YK., Isler Y. 2020. Evaluation of wavelet features selected via statistical evidence from steady-state visually-evoked potentials to predict the stimulating frequency. *Gazi University Journal of Engineering and Architecture*, Accepted.

Tello, RG., Müller, S., Bastos, T., Ferreira A. 2014. A comparison of techniques and technologies for SSVEP Classification. *5th ISSNIP-IEEE Biosignals and Biorobotics Conference,* 1-6. https://doi.org/10.1109/BRC.2014.6880956.

Tang, J., Deng, C., Huang, G., Zhao, B. 2015. Compressed-domain ship detection on spaceborne optical image using deep neural network and extreme learning machine. *IEEE Geosci. Remote Sens. Lett.*, 53(3): 1174-1185. https://doi.org/10.1109/TGRS.2014.2335751.

Vapnik, V. 1998. Statistical learning theory. 978-0471030034, Wiley-Interscience, Canada.

Wang, Y., Wang, R., Gao, X., Hong, B., Gao, S. 2006. A practical VEP-based brain-computer interface. *IEEE Trans. Neural Syst. Rehabil. Eng.*, 14: 234-239. https://doi.org/10.1109/TNSRE.2006.875576.

Wolpaw, JR., Birbaumer, N., Heetderks, WJ., McFarland, DJ., Peckham, PH., Schalk, G., Donchin, E., Quatrano, LA., Robinson, CJ., Vaughan, TM. 2000. Brain-computer interface technology: A review of the first international meeting. *IEEE Trans. Rehabil. Eng.*, 8: 164-173. https://doi.org/10.1109/TRE.2000.847807.

Wu, Z. 2016. Physical connections between different SSVEP neural networks. *Scientific Reports – Nature*, 6: 22801. https://doi.org/10.1038/srep22801.

Yayık, Apdullah. 2017. Enhancing Extreme Learning Machine: Novel Extensions and Applications to Optimizing Visual Stimuli for Brain Computer Interface. PhD Thesis, *Mustafa Kemal University, Graduate School and Applied Sciences, Department of Informatics.* Hatay, Turkey.

Zerafa, R., Camilleri, T., Falzon, O., Camilleri, KP. 2018. To train or not to train? A survey on training of feature extraction methods for SSVEP-Based BCIs. *Journal of Neural Engineering,* 15(5). https://doi.org/10.1088/1741-2552/aaca6e.

Zhang, Y., Guo, D., Li, F., Yin, E., Zhang, Y., Li, P., Zhao, Q., Tanaka, T., Yao, D., Xu, P. 2018. Correlated component analysis for enhancing the performance of SSVEP-based brain-computer interface. *IEEE Trans. Neural Syst. Rehabil. Eng.,* 26(5): 948-956. https://doi.org/10.1109/TNSRE.2018.2826541.