Investigation of Hunger and Satiety Status During Eyes Open and Closed Using EEG Signals Gözler Açık ve Kapalı iken Alınan EEG Sinyallerinden Açlık Tokluk Durumunun Tespiti

Egehan Çetin [1], Gürkan Bilgin [2], Süleyman Bilgin [3], Yasemin Biçer Gömceli [4], Alparslan Melik Kayıkçi[4]
[1] Department of Electrical & Electronics Engineering, Institute of Natural Sciences, Akdeniz University, Antalya, Turkey
[2] Department of Electrical and Electronics Engineering, Mehmet Akif Ersoy University, Burdur, Turkey
[3] Department of Electrical & Electronics Engineering, Faculty of Engineering, Akdeniz University, Antalya, Turkey
[4] Department of Neurology, Antalya Research and Training Hospital, Antalya, Turkey
suleymanbilgin@akdeniz.edu.tr

Abstract*—Surface EEG measurements that can be performed in hospitals and laboratories have reached a wearable and portable level with the development of today's technologies. Artificial intelligence-assisted brain-computer interface (BCI) systems play an important role in individuals with disabilities to process EEG signals and interact with the outside world. In particular, the research is becoming widespread to meet the basic needs of individuals in need of home care with an increasing population. In this study, it is aimed to design the BCI system that will detect the hunger and satiety status of the people on the computer platform through EEG measurements. In this context, a database was created by recording EEG signals with eyes open and eyes closed by 20 healthy participants in the first stage of the study. The noise of the EEG signal is eliminated by using a low pass, high pass, and notch filters. In the classification, using Wavelet Packet Transform (WPT) with Coiflet 1 and Daubechies 4 wavelets, 77.50% accuracy was achieved in eyes closed measurement, and 81% in eyes open measurement.

***Keywords*—EEG; wavelet packet transform; linear discriminant analysis.**

Özet*—Hastanelerde ve laboratuvarlarda gerçekleştirilebilen yüzeysel EEG ölçümleri günümüz teknolojilerinin gelişmesiyle giyilebilir ve taşınabilir düzeye ulaşmıştır. Yapay zeka destekli beyin bilgisayar arayüzü (BCI) sistemleri engeli olan bireylerin EEG sinyallerinin işlenmesi ile dış dünyayla etkileşimde bulunmasında önemli rol oynamaktadır. Özellikle artan nüfusla evde bakım ihtiyacı olan bireylerin temel ihtiyaçlarının karşılanmasına yönelik araştırmalar yaygınlaşmaktadır. Bu çalışmada, EEG ölçümleri üzerinden kişilerin açlık ve tokluk durumunu bilgisayar ortamında tespit edecek BCI sisteminin tasarlanması amaçlanmıştır. Bu kapsamda, çalışmanın ilk aşamasında 20 sağlıklı katılımcının gözler açık, gözler kapalı EEG sinyalleri kaydedilerek veri tabanı oluşturulmuştur. Alçak geçiren, yüksek geçiren ve çentik filtreler kullanılarak EEG sinyalleri gürültüden arındırılmıştır. Sınıflandırma aşamasında, Coiflet 1 ve Daubechies 4 dalgacıklarıyla Dalgacık Paket Dönüşümü (WPT) kullanılarak gözler kapalı ölçümde %77,50, gözler açık ölçümde %81 doğruluğa erişilmiştir.

***Anahtar Kelimeler*—EEG; dalgacık paket dönüşümü; doğrusal ayraç analizi.**

I. INTRODUCTİON

One of the most basic tools to interact with the external environment is speech. It is difficult to express their basic needs, especially when the person cannot speak. Studies show that brain activity expressing emotions can be detected and classified by electroencephalography (EEG) measurements [1].

The brain-computer interface (BCI) is a system that analyzes EEG signals measured from the person and predicts the person's cognitive status in real-time. It produces helpful technological solutions for individuals with speech anomalies. EEG measurements, which can be performed in hospitals and laboratory environments until today, have become wearable and portable with the development of today's technologies and have reached the level that can be used easily at home. As a result, studies on EEG have focused on wearable devices [2]. Today, a BCI system is needed for individuals in need of home care. In this context, the main subject of the study is to detect the feeling of hunger, which is one of the basic needs, with the EEG signal.

By the study of Hoffman and Polich (1998), the participants were given auditory stimulation in open and closed conditions, hungry and satiated conditions of the participants, and ERP measurement and analysis of resting status without stimulation were performed. In EEG analysis, the spectral power density of the delta (1-4 Hz), theta (4-8 Hz) and alpha 2 (9.5-12.5 Hz) frequency bands decreased after alpha intake, alpha 1 (7.5-9, 5 Hz) and the spectral power density of the frequency bands increased. In the ERP analysis, it was stated that the P300 amplitude did not change in the fasted and saturated states, but the latency increased in the saturated state [3]. An et al. (2015), in order to determine the effect of the change in blood glucose level on EEG, 11 male, and 13 female participants had resting and attention test EEG measurements after at least 8 hours of fasting and after drinking a high glucose level drink. After the blood glucose level increased, the power spectral density of the low alpha (8-10 Hz) and theta (4-8 Hz) frequency bands increased especially in the left frontal (FP1, F7, F3) and parietooccipital lobe (P3, P7, O1). More successful results were found in attention tests after food intake and produced electrophysiological and neuropsychological results supporting the increase of attention performance according to fasting status [4]. Al-Zubaidi et al. (2019) examined the effect of fasting and satiety on resting-state fMRI using three connection models (local connection, general connection, and amplitude resting state) using fMRI. After extracting the connection parameters of 90 brain regions for each model, linear DVM classifier and permutation tests were used to reveal which connection model differs best between fasting and satiety. As a result of the study, 81% classification accuracy was obtained in determining brain changes in resting-state fMRI images amplitude, hunger, and satiety [5].

Analysis of food intake, eating behaviors and brain responses of different stimuli were analyzed by EEG and other brain imaging systems. In previous studies, fasting and satiety fMRI-based classification, EEG based frequency, and channel analyzes were performed. Within the scope of the study, 20 healthy male participants were blindfolded, eyes closed (resting state), eyes open EEG measurements were performed with Emotiv Epoc + Mobile EEG device. EEG signals were recorded simultaneously with the program of the Opensesame and Emotiv Pro program. Detailed time-frequency analyzes of EEG signals in the database were realized. During the analysis phase, the signals were cleared from noise by eliminating the erroneous data in the pretreatment section and applying digital filters. In feature extraction, as a result of Wavelet Packet Transformation (WPT), the most successful channels and features were determined by using the energy density ratios of 120 wavelet packets as properties input to the Linear Discriminant Analysis (LDA) classifier.

II. Material and Methods

A. Database

Twenty volunteer male subjects were attended to the study, their age was 26.60 ± 3.54, height was 177.7 ± 6.54 cm, weight was 78.45 ± 11.74 kg, and BMI was between 24.61 ± 2.90. Before the measurement started, 14 channel EEG signals were recorded in the Emotiv Pro software by writing the participant's name and measurement type. The recordings have 256 Hz sampling frequency, internal 50 Hz notch filter, 16-bit resolution for each channel. A total of 4 data-files were created for each participant, eyes open-hungry, eyes closed-hungry, eyes open-satiated, eyes closed-satiated. The raw data were extracted from Emotiv Pro software with the extension ".csv" and transferred to the data processing program for analysis.

Emotiv Epoc+ EEG device has the International 10-20 electrode placement system. The electrodes of the EEG device with 14 channels are located in the positions AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4, reference electrodes P3, P4 (CMS / DRL references) on the cortex [6].

B. Experimental Task

Before the day of the experiment, participants were advised not to take food for at least 8 hours. When the participants came to the laboratory where the measurements will be taken, after resting for 15 minutes, the measurement process started. In this process, the “Minimum Informed Volunteer Consent Form” was read and signed by giving information about the experiment. Then, while the people were hungry, eyes were open, eyes were closed and ERP tests were performed respectively. Participants were offered a menu of at least 400 calories with cheddar cheese and juice between two 2 slices of toast bread. It was waited for 45 minutes for the blood sugar level to increase and physiological stimuli to occur. The measurement sequence, which was performed while hungry, was repeated in the same way when full. Measurements were taken sitting, keeping the room temperature in the range of 20-24 ° C during the measurement, and ensuring that the light level of the room was as dark as possible (Figure 1).

Opensesame is an open-access software that supports Python commands with a comprehensive interface that enables the development and implementation of behavioral experiments such as psychology, neuroscience, and economics [7]. Experiments are designed and applied according to the desired branch, scenario, and flow. Within the scope of the study, markers, open-closed times, and warning notifications were used through the Opensesame program.

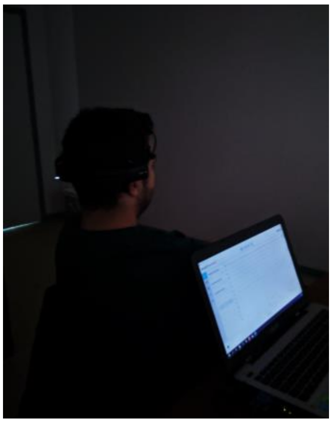

Figure 1. Eyes open measurement

Eyes open and closed test was performed with a cycle of 2 min eyes open, 2 min eyes closed. In each cycle, the eyes start with a beeping sound, and with a beeping sound coming every 2 minutes, the eyes are closed if they are open, and if they are closed, they are opened. By making a

$$\psi_{m,n}(t) = \frac{1}{\sqrt{a_0^m}}\psi\left(\frac{t - nb_0 a_0^m}{a_0^m}\right) \tag{1}$$

total of 3 cycles, the total open time was 6 minutes, and the closed time was 6 minutes. In the eyes-open test, the participants were asked to look at a point marked on the wall at 3 feet ahead of the head. People remained stationary

$$W_{2j} = \sqrt{2}\sum_k h(k)W_j(2t - k) \tag{2}$$

$$W_{2j+1} = \sqrt{2}\sum_k g(k)W_j(2t - k) \tag{3}$$

without any external stimulation.

C. Signal Preprocessing

EEG signals include basically three types of the physiological noise signal. (Figure 2). Ocular artifacts are signals propagating over the scalp consisting of blinking and eye movements. Eye movement artifacts are produced by changes in the orientation of the retina and cornea dipole. Blinking artifacts, on the other hand, are noises caused by ocular conductivity as the cornea's contact with the eyelid changes. EMG artifacts are caused by the stretching and contraction of the muscles in the measurement recording area for reasons such as speech, swallowing, sniffing of the person being measured. Cardiac movements are pulse artifacts around 1.2 Hz that can occur when the electrodes are placed on or near the expanding and shrinking blood vessels. ECG, which is one of the cardiac activities, can be cleaned more easily than the EEG signal by having a certain waveform [8].

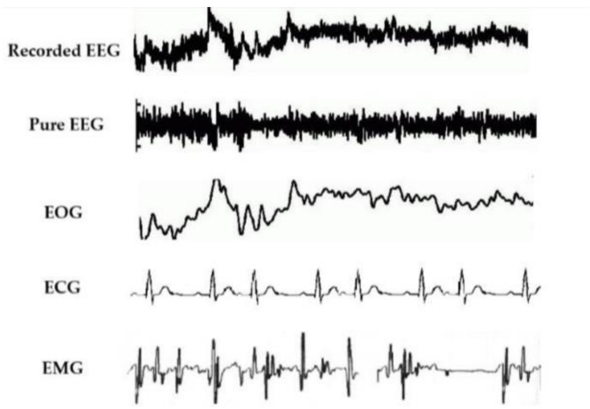

Figure 2. Noises affecting the EEG signal

In the study, the signals recorded in the database were applied with a cut frequency of 0.49 Hz and a 12th Degree High Pass IIR Filter, a 12 Hz Low Pass IIR Filter with 60 Hz cut frequency, and a 50 Hz Notch IIR Filter to prevent network noise

D. Wavelet Packet Transform

Wavelet Transform Analysis (WTA) provides high-resolution results with time-frequency analysis of signals in low-frequency ranges, high-dimensional searches in high-frequency ranges, and small-size windowing. WTA is obtained by integrating the signal with the selected wavelet function. The selected wavelet is analyzed by adding scaling and translation parameters. $\psi_{\mathrm{m,n}}(\mathrm{t})$ wavelet function (1) is the expansion factor "α" in the equation $\alpha = \alpha_0^m$ (scaling parameter). It is obtained by using the translation parameters "b" in the equation $b = nb_0\alpha_0^m$.

Low-pass filter coefficients $g(k)$, high-pass filter coefficients $h(k)$, filter coefficients, W_{2j} high-pass filters for WPT, W_{2j+1} low-pass filters, the number of k filter coefficients in relation (2), and (3) It is stated in the relation [9].

The total energy of a signal decomposed at n level in WPT is calculated as E_n in relation (4).

$$E_n = \sum_{j=0}^{2^n-1} \left|W_{RMS,n,j}\right|^2 \tag{4}$$

The energy ratio of a package is calculated by the formula in the $E_p$relation (5), which is the ratio of the energy of all packages [10].

$$E_p = \frac{E_n}{E_{TOTAL}} \times 100 \tag{5}$$

Within the scope of the study, 8 levels were realized with WPT Coiflet 1 and Daubechies 4 wavelets. The package energy ratio of the 256 packages obtained as a result of decomposition was used as a feature.

E. Linear Discriminant Analysis

LDA is formulated on two-class problems by R.A Fisher, who is known for his research in mathematics and statistics. It was developed by Rao for problems involving more than two classes. LDA is a method used to distinguish linear combinations of data with at least two classes. This method has an algorithm that tries to distinguish the classes in the data set at the highest level, to maximize the variance value between the classes, and creates a decision area between the classes. It is also important in making the data more understandable. In the study, a 5-fold cross-validation value was used to calculate the LDA accuracy rate.

In a two-class problem (p1, p2) the linear discriminant function $y(x)$; The x, n-dimensional input vector is defined in its correlation as w weight vector (6).

$$y(x) = w^T x \tag{6}$$

S_1 and S_2 are in-class distribution matrices of two examples. S_b is the class distribution matrix of class instances. When expressed as $S_w = S_1 + S_2$, LDA function (7) can be written as in its relation [10].

$$f_{LDA}(w) = \frac{w^T S_b w}{w^T S_w w} \tag{7}$$

The best w weight vector that maximizes the f_{LDA} function to relation (8) can be determined by the following equation.

When $y(x) = 0$, the region boundary will be calculated by the formula in relation (9) [11].

$$\frac{w^T x}{|w|} = -\frac{w_0}{|w|} \tag{9}$$

III. RESULTS

Within the scope of the research, in order to suppress low and high frequencies and mains noise on the raw EEG signals in the preprocessing stage, filtering was performed to create delta, theta, alpha, beta, and gamma frequency bands. Besides, the artifacts caused by the movement of the electrodes during the measurement and the loss of data transmission were detected by scanning the signals and clipped over the signal (Figure 3).

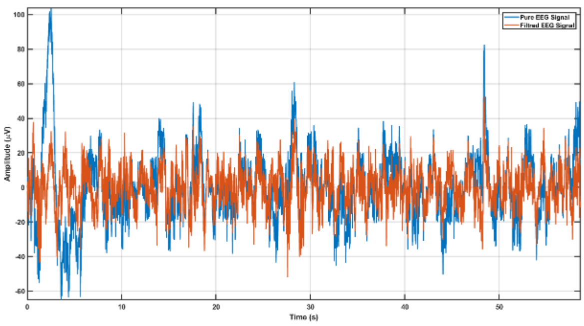

Figure 3. Filtering process applied to EEG signal

WPT was used in 8 levels with Coiflet 1 and Daubechies 4 wavelets at the feature extraction stage over the filtered signal. The classification was carried out with the percentage energy ratio of 120 packets that make up the frequency bands of the signals whose frequency range is 0-60 Hz. It is aimed to increase the classification success by normalizing the values between -1 and 1. The energy ratios of two different packages were used as input to the LDA classifier and the results were compared. 5-fold cross-validation value was used.

In the classification of eyes open measurements, 5 packages and channels that give the highest accuracy using Coiflet 1 wavelet are shown in Table 2, and 5 packages and channels that give the highest accuracy using Daubechies 4 wavelets are shown in Table 3.

$$C = \begin{cases} < 0, x \in p_1 \\ > 0, x \in p_2 \\ 0, undefined \end{cases} \tag{8}$$

Table 2. The most successful packets, channels and accuracy rates detected by the Coiflet 1 wavelet of eyes open measurement signals

1st Packet	2nd Packet	Channel	Accuracy (%)
18	53	P8	81.00
50	84	F4	77.50
50	117	F4	77.50
50	76	F4	76.50
47	50	F4	76.50

Table 3. The most successful packages, channels and accuracy rates detected by the Daubechies 4 wavelet of eyes open measurement signals

1st Packet	2nd Packet	Channel	Accuracy (%)
31	98	FC5	76.50
86	111	P7	75.50
39	82	O1	75.50
52	69	T7	75.50
60	69	T7	75.50

In the classification of eyes closed measurements, 5 packages and channels each giving the highest accuracy using Coiflet 1 wavelet are shown in Table 4, and 5 packages and channels that give the highest accuracy using Daubechies 4 wavelength are shown in Table 5.

Table 4. The most successful packets, channels and accuracy rates detected by the Coiflet 1 wavelet of eyes close measurement signals

1st Packet	2nd Packet	Channel	Accuracy (%)
48	87	T7	75.50
48	81	FC5	75.00
48	86	FC5	75.00
48	61	T7	74.50
48	86	T7	74.50

The channels with the highest accuracy are shown in Figure 4.

Table 5. The most successful packets, channels and accuracy rates detected by the Coiflet 1 wavelet of eyes close measurement signals

1st Packet	2nd Packet	Channel	Accuracy (%)
64	95	F3	77.50
64	93	F3	77.00
67	81	T7	76.00
84	120	F4	76.00
101	117	FC5	76.00

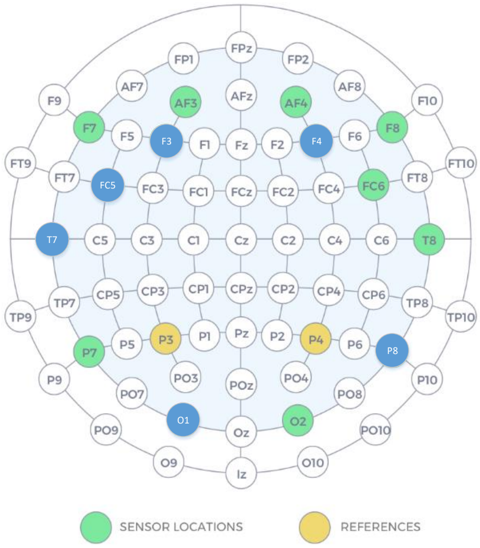

Figure 4. The most successful channels according to the measurement results

IV. Discussion and Conclusion

A database created by EEG records in hungry and full cases was used from 20 healthy male participants under appropriate environmental conditions. The low pass, high pass, and notch filters were applied to the EEG signals and the pretreatment stage was completed by removing noise. In the classification phase of WPT package energy rates, 120 packages and 14 different channels were used as LDA inputs, and 5 channels and packages with the highest accuracy were determined. When we examine the eyes, the Coiflet 1 wavelength is 18 (8.5-9 Hz) and 53. (26-26.5 Hz) Packages and P8 channel in classification based on open measurement; Daubechies 4 wavelengths and 64th (31.5-32 Hz) and 95th (47-47.5 Hz) packages distinguished with the highest accuracy in classification based on eyes closed measurement. When analyzed by channel, it was observed that the most effective channels were P8, F3, F4, FC5, T7, O1.

Acknowledge

This study was supported by the Research Project Department of Akdeniz University, Antalya, Turkey (Project Number: FBA-2018-4270). We acknowledge the volunteers for their contribution to this study. All experiments were approved by the local Ethics Committees of the University of Akdeniz (Date/number: 10.10.2018/713). Prior to the experiments, all subjects read and signed and informed consent participation form.

References

[1] Chu, N. N. (2015). Brain-Computer Interface Technology and Development: The emergence of imprecise brainwave headsets in the commercial world. IEEE Consumer Electronics Magazine, 4(3), 34-41.

[2] Lin, B. S., Pan, J. S., Chu, T. Y., & Lin, B. S. (2016). Development of a wearable motor-imagery-based brain–computer interface. Journal of medical systems, 40(3), 71.

[3] Hoffman, L. D., & Polich, J. (1998). EEG, ERPs and food consumption. Biological psychology, 48(2), 139-151.

[4] An, Y. J., Jung, K. Y., Kim, S. M., Lee, C., & Kim, D. W. (2015). Effects of blood glucose levels on resting-state EEG and attention in healthy volunteers. Journal of Clinical Neurophysiology, 32(1), 51-56.

[5] Al-Zubaidi, A., Mertins, A., Heldmann, M., Jauch-Chara, and K., Münte, T. F. 2019. Machine learning based classification of resting-state fMRI features exemplified by metabolic state (hunger/satiety). Frontiers in Human Neuroscience, 13, 164.

[6] https://emotiv.gitbook.io/epoc-user-Manual/introduction-1/ technical_ specifications

[7] Mathôt, S., Schreij, D., & Theeuwes, J. (2012). OpenSesame: An open source, graphical experiment builder for the social sciences. Behavior research methods, 44(2), 314-324.

[8] Jiang, X., Bian, G. B., & Tian, Z. (2019). Removal of artifacts from EEG signals: a review. Sensors, 19(5), 987.

[9] Amin, H. U., Malik, A. S., Ahmad, R. F., Badruddin, N., Kamel, N., Hussain, M., & Chooi, W. T. (2015). Feature extraction and classification for EEG signals using wavelet transform and machine learning techniques. Australasian physical & engineering sciences in medicine, 38(1), 139-149.

[10] Bilgin, S. (2017). The impact of feature extraction for the classification of amyotrophic lateral sclerosis among neurodegenerative diseases and healthy subjects. Biomedical Signal Processing and Control, 31, 288-294.

[11] Mohammed, M., Khan, M. B., & Bashier, E. B. M. (2016). Machine learning: algorithms and applications. Crc Press