The Eurasia Proceedings of Science, Technology, Engineering & Mathematics (EPSTEM)
ISSN: 2602-3199

The Eurasia Proceedings of Science, Technology, Engineering & Mathematics (EPSTEM), 2022

Volume 21, Pages 110-115

IConTES 2022: International Conference on Technology, Engineering and Science

Analysis of Eye Movements with 2D Images Obtained by EOG Signals

Yurdagul KARAGOZ-SAHIN
Turkcell Technology

Mehmet Recep BOZKURT
Sakarya University

Elcin KILIC
Erzincan Binali Yildirim University

Abstract: EOG signals are used for diagnosing of various eye diseases and dysfunctions and eye movement monitoring in neurological disorders. It has also been used as a source signal for various electronic systems and human-machine interfaces, especially in recent years, since the movements of the eye in the horizontal and vertical axis and blinking movements can be detected by EOG. In using EOG signals as source signals, it is necessary to analyze this signal and use various features extracted from the signal. In this study, EOG signals from one of the authors were used with the Biopac MP30 device within the scope of the Sakarya University Electrical and Electronics Engineering, Biomedical Laboratory course. EOG signs were used in four classes looking up, down, right and left. Scalogram matrices are extracted for each movement in the EOG signals with the continuous wavelet transform. As a result of the imaging of the scalogram matrices, it was seen that there were significant differences in the images of the four classes. It is predicted that the results of the analysis made on the images can improve the accuracy rates in classification systems according to one-dimensional analysis methods when used together with expert systems.

Keywords: Electro-oculography, Medical signal processing, Signal classification, Scalogram computation

Introduction

Electrooculogram (EOG) is an electrophysiological measurement method that measures the available resting electrical potential between the cornea and Bruch's membrane. The movements of the eyeball in the horizontal and vertical axes and the blinking movements can be distinguished on the EOG marks. This relationship between EOG signs and eyeball movements has been the source of many studies.

Electooculogram is a biological signal of electrical origin resulting from hyperpolarization and depolarization between eye movements and cornea-retina. Since eye movements act as dipole sources, they can be monitored and measured as vector moments. The amplitude of the raw EOG signal is 50-3500 µV, and the frequency band is between 0 -100Hz. EOG is measured with electrodes placed around the eyes. Electrodes are placed on the right and left of the eye as a horizontal channel, above and below the eye as a vertical channel, and on the forehead as a reference point. There is no potential difference between the electrodes when the eyes are at rest. Moving the eye to the right becomes more positive compared to the other electrode and more negative when moving to the left. An amplitude changes of 1 degree 14, 16µV in horizontal movement, and 14µV in vertical movement of the eye occurs. (Karagoz, Y., 2019)

In a study, they tried to detect four basic directional movements with the Neuro-Fuzzy model, an artificial intelligence technique; within this scope, a fuzzy neural controller with two inputs and one output is designed.

After the fuzzification process, the inputs are trained with artificial neural networks. Finally, they made a performance analysis and achieved 98% success (Erkaymaz et al., 2015). In another example, EOG signals are depurated of noise with the pre-threshold filtering algorithm, and horizontal and vertical movements are used as input to the classifier. In the system developed with artificial neural networks, statistical accuracy and confusion matrix analyzes were made, and a performance of 94% levels was obtained (Erkaymaz et al., 2015). In another study, a system for estimating gaze direction was designed using EOG signals. In this system, after applying a Butterworth filter and Bessel filter to the EOG signals, framing and normalization are to make the signals easier to classify. After the features were determined, they were classified with the Back Propagation Neural Network, and 96% success was achieved at the point of detection of different directions (Bei et al., 2016). Another study proposes a system to detect eye dystonia by eye movement analysis. The designed system is aimed at counting the number of blinks for a specific time interval and to determining the risk of eye dystonia. After EOG signals are acquired, blinks are classified using the combination of the Radial Fundamental Function (RBF) kernel, the Support Vector Machine (SVM) classifier, and the Feedforward Neural Network classifier, Wavelet coefficients, Autoregressive (AR) parameters, and Power Spectral Density and Hjorth parameters. A maximum average accuracy of 95.33% over all classes and participants is obtained using the RBF-SVM classifier with a feature field of AR parameters of order 5 and PSD taken together (Banerjee et al., 20). In another study, wavelet filtering and normalization are performed after EOG signals are obtained, and then the signals are separated by discrete wavelet transform. After the signals were processed, they were classified with the Support Vector Machine to detect four main directions as right, left, up, and down, and 93.8% accuracy in horizontal eye movements and 86.3% accuracy in vertical eye movements was obtained (Li et al., 2018). In another study, the max and min peaks of the signals obtained with right, left and two blinks were determined. After the peaks were detected, they were classified with the k-NN algorithm, and the highest accuracy rate has been obtained when k=3 (Vahdani-Manaf & Pournamdar, 2017). Feature extraction is an essential step of signal processing. Extraction from the EOG signals in the time domain was done, and classification performances have been tested with feature reduction methods. In one study, the number of features was reduced with f-score and, 97% accuracy of classification was achieved using selected features (Zengin et al., 2019).

In this study, using EOG signals as source signals, 2-dimensional scalogram graphics were created to be input to the deep learning system in a study that will be designed as a brain-computer interface for paralyzed patients. The EOG data on the horizontal and vertical axes were first filtered, then split into windows that would contain only one eye movement. Continuous wavelet transform scalogram matrices were obtained from these single motion data. By showing the scalogram matrices as two-dimensional graphs, distinctive differences were observed in the graphs of looking right and left on the horizontal axis and looking up and down on the vertical axis. It has been seen that scalogram graphs are suitable for use in deep learning by generating source signals for BCI from EOG signals.

Method

Data Collection

In this study, EOG signals from one of the authors were used with the Biopac MP30 device within the scope of Sakarya University Electrical and Electronics Engineering, Biomedical Laboratory course. The Biopac MP30 is an electrically isolated 4-channel data acquisition unit designed for physiological measurements. It has different presets customized for different physiological measurements and filters suitable for the sign to be measured. This data collection device is used by connecting to a computer and the data is saved to the computer. EOG marks are recorded on the horizontal and vertical axis. There are 2 classes on each axis, a total of 4 classes. Right and left gaze on the horizontal axis and up and down gaze on the vertical axis are considered separate classes. The data obtained with the Biopac MP30 device were properly recorded and the data processing steps were performed in the Matlab program.

Data Processing

All data processing steps were performed using Matlab 2021a program licensed by Sakarya University. The obtained data were first preprocessed, then continuous wavelet transform was performed and as a result scalogram matrices were obtained. Data processing is completed by displaying the scalogram matrices as two-dimensional graphics. Since the Biopac MP30 device has preset filters for the EOG mark, extensive filtering was not required. An average moving filter was used to make the sign smoother. Data files containing more than one motion sign were divided into parts to contain a single motion. This process was performed manually as the data were not very large. With these processes, the preprocessing step was completed.

Continuous Wavelet Transform

The natural state of signals is often non-stationary. In this respect, it is important to examine non-stationary signals in many different disciplines. Wavelet analysis has found broad scope in the study of non-stationary signals (Newland, 2012). It is widely used in fields such as data compression (Vetterli & Jelena, 1998) and biomedical engineering (Akay, 1998 and Carmona et. al.,1995).

Similar to the Fourier transform, in the wavelet transform, a function called the main wavelet is the window, but this main wavelet is scaled and translated during the transform process. Scaling corresponds to the expansion and contraction of the wave, and translation corresponds to the displacement of the wave in the time axis (Ari et al., 2008). Since the width of window function, which remains constant throughout the Fourier transform, changes continuously in the wavelet transform, the resolution of both the time and frequency domains increases. In this respect, the wavelet transform is superior to the Fourier transform.

The most important parameter of the wavelet transform is the wavelet. The function of the window function in the Fourier transform is performed by the main wavelet functions in the wavelet transform. For a function to be a wavelet depends on the condition that its duration is limited and its mean value is zero. Therefore, the wavelet function should oscillate in the positive and negative directions of the amplitude axis and this oscillation should end by sitting at zero on the amplitude axis as it progresses in the time axis. A normal wavefunction such as sine and cosine oscillate along the amplitude axis but has infinite duration. Therefore, wave and wavelet are different concepts. There are many main wavelets with different properties and uses. The term wavelet is expressed in the sense of a small wave. The smallness here can be defined as the window function of a certain length. The main wavelet is a prototype, and when considered qualitatively, it should have a real-valued function that satisfies the following two conditions.

$$\int_{-\infty}^{+\infty} \psi(x)^2 dx = 1 \tag{1}$$

$$\int_{-\infty}^{+\infty} \psi(x) dx = 0 \tag{2}$$

Some main wavelet functions used in wavelet transform are given in Figure 1. As can be seen in the figure, the main wavelets oscillate in the amplitude axis and settle to zero.

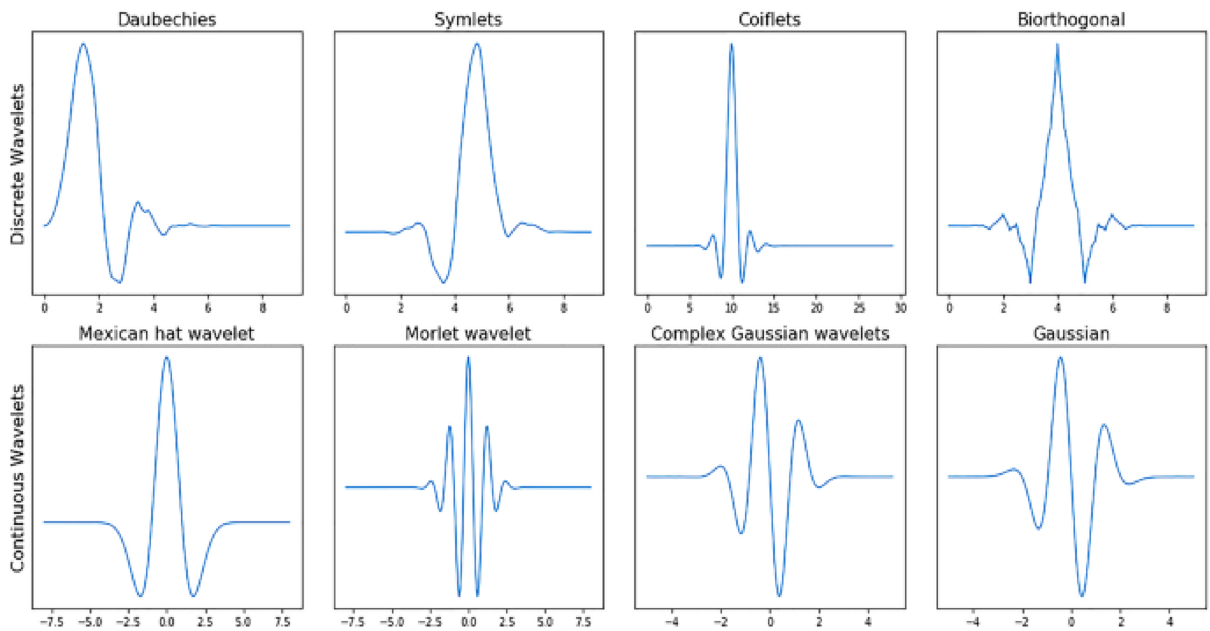

Figure 1. Sample wavelet functions.

The continuous wavelet transform (CWT) is obtained by shifting the wavelet function and multiplying it by a scale, then summing over the time domain and is calculated as follows (Ari et al., 2008).

$$SDD_{(s,\tau)} = \int_{-\infty}^{+\infty} g(t)\psi(x)^{*}_{(s,\tau)}(t)dt$$

*: Kompleks eslenik
$g(t)$: donusumu yapilacak fonksiyon
$\psi(x)^{*}_{(s,\tau)}(t)dt$: Dalgacik ya da ana dalgacik fonksiyonu
τ : Kaydirma Parametresi
τ >0: zaman ekseninde saga dogru kayma,
τ <0: zaman ekseninde sola dogru kayma
s: Olcek Parametresi
(s>1: zaman ekseninde fonksiyon genisler ve genligi duser)
(s<1: zaman ekseninde fonksiyon daralir ve genlik buyur)
(s<0: t=0 noktasina gore simetri alinir)

Wavelet analysis, which eliminates the problem of time information loss in the Fourier transform, can detect the times and the amplitudes of all frequency components in a signal. Because of these advantages, wavelet analysis is widely used. In this study, scalogram matrices obtained by continuous wavelet transform were used. Since the continuous wavelet transform has the ability to represent a signal in the time-frequency domain, a 1-dimensional signal can be represented in 2-dimensional at various scales. As a result of this process, the signal is obtained in an expanded and scaled form (Acharya et al., 2017).

With the help of continuous wavelet transform, 2-dimensional Scalogram image matrices for 4 different classes of EOG signals were obtained. These images have been resized to 128x128 pixels. In the resulting Scalogram matrices, the x-axis represents the translational shift along the time-axis and the y-axis represents the scaling factor of the wavelet. For this study, different wavelet functions were tried and when the images obtained for the "Coiflet 1" wavelet were examined, it was seen that there was a significant difference between the classes. With this study, Scalogram images obtained from EOG signs can be used to distinguish classes.

Results and Discussion

This study was carried out as a preliminary study of a deep learning-based classification design. In the study, EOG sign was recorded for a total of 4 movements from 2 movements in the horizontal and vertical axes. These signs were filtered with the Moving Average filter and windowed manually. Scalogram matrices were created and plotted by using different wavelet functions on the windowed signals. Among the different wavelet functions, the most distinctive graphs are obtained with the Coiflet-1 wavelet. In Figure.2, scalogram graphs created with Coiflet-1 wavelet are given for 4 different classes. In this way, the distinctiveness of scalogram graphs is shown by obtaining different graphs between different classes.After this stage, the classification process can be done by using the scalogram matrices obtained as input to various classification algorithms. The advanced phase of this study is planned as deep learning. In deep learning, high-performance results are obtained against two-dimensional graphics inputs.

A large number of EOG samples should be taken for classification processes and the system should be trained with a large number of inputs. The use of more professional devices in the acquisition of EOG data and the base correction and filtering of the received signals will increase the success rate. EOG signs taken from different people can be evaluated in a pool and a system that will give accurate results when applied to different people can be created. The next step after the classification is to establish a BCI that the person can manage with eye movements using these classes.

Conclusion

Within the scope of this study, EOG data were recorded in 4 different classes (class 1, class 2, class 3 and class 4) against the movements of the eyeball in the horizontal and vertical axis. These data were filtered by the Moving Average filter and windowed manually. Then, continuous wavelet transforms with different wavelet functions is applied to these windows. As a result of these processes, scalogram matrices and related graphics were obtained. When the results of different wavelet functions were compared, it was seen that the discrimination of the scalogram matrices obtained as a result of the transformation performed with the Coiflet -1 wavelet was higher. The scalogram graphs obtained by using the Coiflet -1 wavelet are given in Figure.2. The results show that the scalogram graphs obtained from the EOG signs are distinctive for the classes. The system can be made more successful with the suggestions given in the discussion section. This system, which was designed as a preliminary study of a classifier design based on deep learning, has achieved the desired success.

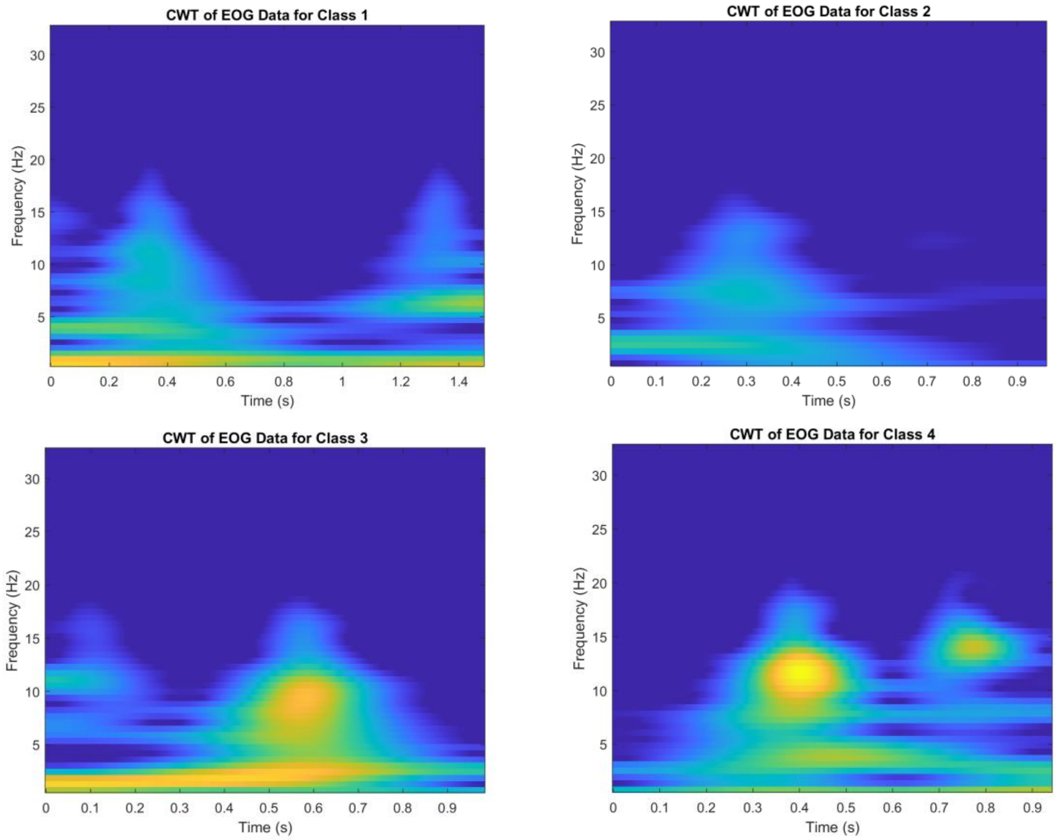

Figure. 2. The scalogram graphs obtained by using the Coiflet -1 wavelet

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

Acknowledgements or Notes

* This article was presented as an oral presentation at the International Conference on Technology, Engineering and Science (www.icontes.net) held in Antalya/Turkey on November 16-19, 2022.

*We thank Turkcell corporation for financing the presentation of this study. We also thank Sebahattin Babur, a lecturer in Turk-Alman University, for his contributions.

References

Acharya, U. R., M., Fujita, H., Sudarshan, K. V., … Chua, C. K., (2017). Automated characterization of coronary artery disease, myocardial infarction, and congestive heart failure using contourlet and shearlet transforms of electrocardiogram signal. *Knowledge-Based Systems.* 156–166.

Akay, M. (1998). *Time frequency and wavelets in biomedical signal processing*. IEEE press series in Biomedical Engineering.

Ari, N., Ozen, S. & Colak, O. H. (2008). *Dalgacik teorisi.* Palme Yayincilik, Ankara.

Banerjee, A., Pal, M., Tibarewala, D. N., & Konar, A. (2015). Electrooculogram based blink detection to limit the risk of eye dystonia. *Eighth International Conference on Advances in Pattern Recognition*, C

Bei, Y., Sichun, Y., Mengke, L., & Xiangkun, L., (2016). Gaze estimation method based on EOG signals. *Sixth International Conference on Instrumentation & Measurement, Computer, Communication and Control*, 443-446.

Carmona, R. A., Hwang W. L. & Frostig, R. D., (1995). Wavelet analysis for brain-function imaging. *Transactions on Medical Imaging*. 556-564.

Erkaymaz, H., Ozer M., & Kaysa, C., (2015). EOG controlled direction detect system with neuro-fuzzy approach. *19th National Biomedical Engineering Meeting, 1-4*

Erkaymaz, H., Ozer M., Kaya, C., & Orak. M., (2015). EOG based intelligent direction detect system with pre-filtering algorithm. *23nd Signal Processing and Communications Applications Conference*, 1228 - 1231

Fidan, H. (2006). *Dalgacik donusumu teknigi ile motor ariza tespiti*. Diss. SDU Fen Bilimleri Enstitusu.

Hanteh, M., Rezaifar, O. & Gholhaki, M., (2021). Selecting the appropriate wavelet function in the damage detection of precast full panel building based on experimental results and wavelet analysis. *Journal of Civil Structural Health Monitoring volume*. 1013–1036. https://www.biopac.com/wp-content/uploads/MP30-35-spec.pdf Accessed: November 6, 2022

Karagoz, Y., (2019). *Electrooculogram based human-machine interface application*. Sakarya University – 591126.

Li, T., Yang, J., Bai, D. & Yang, Y. (2018). A new directional intention identification approach for intelligent wheelchair based on fusion of EOG signal and eye movement signal. *International Conference on Intelligence and Safety for Robotics*, 470-474.

Newland, D. E. (2012). *An introduction to random vibrations, spectral & wavelet analysis*. Dover Publications.

Vahdani-Manaf, N. & Pournamdar, V., (2017). Classification of eye movement signals using electrooculography in order to device controlling. *4th International Conference on Knowledge-Based Engineering and Innovation*. 0339 – 0342.

Vetterli, M. & Jelena, K. (1998). *Wavelets and subband coding.* Vol. 995. Englewood Cliffs: Prentice Hall.

Zengin, I., Bozkurt, M. R. & Ucar, M. K., (2019). Determining effective features to use the EOG sign as a source sign. *Sakarya University Journal of Computer and Information Sciences.* 134-144.

Author Information

Yurdagul Karagoz Sahin
Turkcell Technology
Maltepe, Istanbul, Turkey
Contact e-mail: *yurdagul.sahin@turkcelll.com.tr*

Mehmet Recep Bozkurt
Sakarya University
Serdivan, Sakarya, Turkey

Elcin Kilic
Erzincan Binali Yildirim University
Erzincan, Turkey

To cite this article:

Karagoz-Sahin, Y., Bozkurt, M. R., Kilic, E. (2022). Analysis of eye movements with 2D images obtained by EOG signals. *The Eurasia Proceedings of Science, Technology, Engineering & Mathematics (EPSTEM), 21,* 110-115.