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Epileptic Electroencephalogram Classification using Relative Wavelet Sub-band Energy and Wavelet Entropy

S. Hadiyoso*[a], I. D. Irawati[a], A. Rizal[b]

[a] School of Applied Science, Telkom University, Bandung, Indonesia
[b] School of Electrical Engineering, Telkom University, Bandung, Indonesia

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ABSTRACT

Epilepsy is one of the common neurological disorders which can cause unprovoked seizures. Currently, diagnosis and evaluation are carried out using electroencephalogram (EEG) signal analysis, which is performed visually by clinicians. Since EEG signals tend to be random and non-stationary, the visual inspection often provides misrepresentation of results. Numerous studies have been proposed computer-based analysis for epileptic EEG classification; however, there is still a gap to improve detection accuracy with a small number of features. Therefore, in this study, we proposed an automatic detection protocol for epileptic EEG classification. The proposed methods are relative wavelet energy and wavelet entropy for feature extraction and combined with the classifier method for automatic detection. In this study, three classes of EEG consisted of pre-ictal, ictal, and interictal were used as test data and also evaluate the proposed method. EEG signals were decomposed using wavelet transform into five conventional sub-bands, including gamma, beta, alpha, theta, and delta. The relative energy and entropy were then calculated in each of these bands as a feature set. These methods are chosen with consider of low-cost computing. We tested the performance of our feature extraction method using Support Vector Machine (SVM), both linear and non-linear kernels. From the simulation, the highest accuracy was 80-96.7% for ictal vs. pre-ictal, ictal vs. inter-ictal, pre-ictal vs. inter-ictal, and ictal vs. non-ictal. Finally, this work was expected to help clinicians in the detection of epilepsy onset based on EEG signals.

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NOMENCLATURE

Ψ	Basis wavelet	w	Normal vector length
a	Scale	T	Trade-off parameter
b	Shift	ε_i	Set of slack variables
t	Time	a_i, b_i	Training set

1. INTRODUCTION[1]

Epilepsy is one of the most common neurological disorders. Patients may suffer seizures due to abnormal or excessive of electrical brain activity [1]. Currently, neurologists conduct the diagnosis and evaluation of epilepsy patients based on analysis of EEG signals by visual inspection [2]. This process takes a long time and allows many error detections [3]. EEG signals show dynamic changes in nerve activity concerning seizures in the brain [4]. Nowadays, computer based-methods have been developed to detect and analyze epilepsy based on EEG signal so that it is more effective and accurate.

EEG signals are processed to obtain features that can represent information characteristics to be classified [5, 6]. According to literature [7], EEG signal classification can be performed by processing the signals in the time domain, frequency domain, time-frequency domain, and many others using nonlinear techniques. Researchers developed a wavelet method for extracting features on EEG signals based on energy and entropy of the signal [8]. Faust et al. [4] stated that wavelet transforms produce

*Corresponding Author Institutional Email: sugondo@telkomuniversity.ac.id (S. Hadiyoso)

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detailed information of EEG signal to detect and predict seizures. Wavelet transform has better representation than other signal processing methods. Wavelet energy describes energy information at different frequencies in the EEG signal that is adjusted to the needs of the analysis [9]. Entropy shows an index that illustrates brain wave disorder. Wavelet entropy can analyze EEG signals with very dynamic features [10]. Daubechies discrete wavelet transform and wavelet harmonic used to characterize and analyze epileptiform [11]. Wavelet analysis of EEG signals may produced accurate features to analyze different brain rhythm, even on a low scale. The other study by Lee et al. [12] combined wavelet transforms, phase-space reconstruction, and Euclidean distance to classify the normal EEG and epileptic seizures on the EEG signal. This method produced 24 features, and a minimum of four features with the highest accuracy was selected for classification using fuzzy logic. Guo et al. [9] explored relative wavelet energy for representing the EEG signal and classifying it using artificial neural networks. In our previous work, we examined the classification of seizure patterns on the EEG signal using SVM. We divided four classifications scenarios, which are three based on seizure and normal conditions from feature extractions combination consisting of Hjorth Descriptor, Independent Component Analysis (ICA), and Mel Frequency Cepstral Coefficients (MFCC) [13].

Based on previous research, we proposed a new method for seizure detection in epilepsy patients based on the relative wavelet energy and wavelet entropy from the EEG signal. In this study, a combination of wavelet methods for feature extraction and SVM for classification were conducted. Wavelet transform segmented the EEG signals into five bands consisting of gamma, beta, alpha, theta, and delta. Relative wavelet energy and entropy are then calculated for these bands as feature sets. Finally, we evaluate the performance of the proposed feature extraction method using support vector machine.

The rest of this paper is organized as follows. Section 2 illustrates the EEG dataset collection and methods that support the findings of this study. The performance evaluation and discussion are shown in section 3. The conclusion and future works are drawn in section 4.

2. MATERIAL and METHOD

2. 1. EEG Dataset In this study, the epilepsy EEG dataset, which was used for simulations, was taken from the Hauz Khas Neurology and Sleep Center, India. It is available on the https://www.researchgate.net/publication/308719109_EEG_Epilepsy_Datasets. The EEG was taken from 10 epilepsy patients in the department and recorded using Grass Telefactor Comet AS40 with 200 Hz sampling frequency. The 10-20 system placement standard was applied to 16 scalp electrodes. The EEG signal was pre-processed with a band-pass filter (0.5 Hz and 70 Hz) to reject large amounts of noise.

Furthermore, the EEG dataset was segmented into pre-ictal, ictal, and inter-ictal. Each stage contained 50 segments of the EEG signal with a duration of 5.12 seconds. Our proposed method was tested in several classification schemes included: ictal vs. pre-ictal, ictal vs. inter-ictal, pre-ictal vs. inter-ictal, and ictal vs. non-ictal.

2. 2. Proposed Method Figure 1 presents a proposed method for epileptic EEG classification. First, the EEG signal which consists of ictal, pre-ictal, and inter-ictal is segmented into delta, theta, alpha, beta, and gamma bands using Wavelet transform. The relative energy and entropy are then measured for each band. Finally, a performance evaluation was carried out using a support vector machine with various kernels. The following sub-sections describe the details of the proposed method.

2. 2. 1 Band Segmentation Using Wavelet Transform Wavelet transform (WT), or then called wavelet decomposition, is generally a frequency decomposition of sub-band signals where the components are produced by decreasing the hierarchical decomposition. Wavelet-based transformation methods has been widely used over the past decades [14]. Implementation of wavelet transform can be done by passing the high-frequency signal or high pass filter and low frequency or lowpass filter [15, 16]. This method is suitable for representing EEG signals that have characteristics, high frequency in a short period, and low frequency in a long period. Wavelet extracts features that can be used for analyzing the diverse transient case in the signal, as in the EEG signal. Wavelet transform has been commonly used for EEG analysis, as reported in studies [17-19], where WT produces high performance in signal characterization.

In the family of wavelet, the mother wavelet is the set of basis functions which is expressed in Equation (1) below.

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\,\Psi\left(\frac{t-b}{a}\right) \quad (1)$$

where Ψ is basis or mother wavelet, $a, b \epsilon \Re, a \neq 0$ is the scale parameter, and b is the shift parameter, while t is the time.

In its function for signal segmentation or decomposition, WT is often used as a filter bank (consists of low pass and high pass filter) [20]. In this research, we use wavelet decomposition to obtain the delta, theta, alpha, beta, and gamma bands. Since the sampling frequency is 200 Hz, 5-level decomposition was applied to obtain these bands with Daubechies-2 (DB2) as the

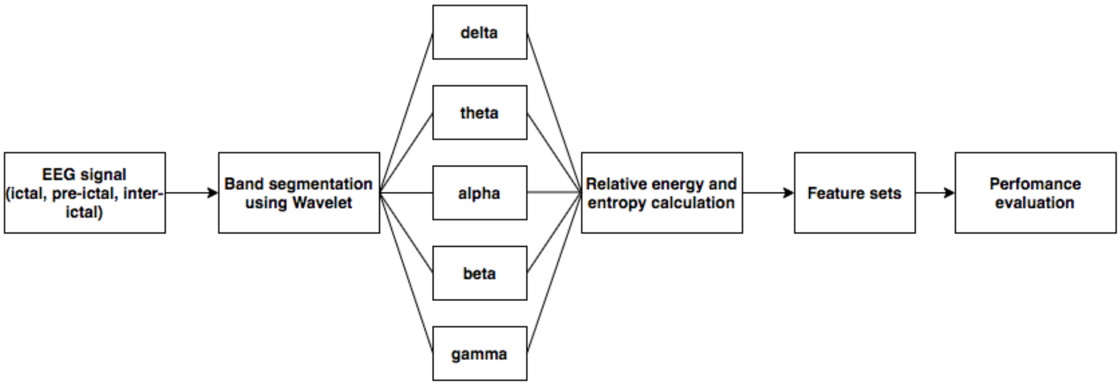

Figure 1. Proposed method for epileptic EEG classification

basis wavelet function. Sub-band D2 correspondence with gamma, D3 correspondence with beta, D4 correspondence with alpha, D5 correspondence with theta, and A5 correspondence with delta. The relative energy in each band is then measured as a function of normalization with the total energy of all bands. Shannon entropy is also calculated on all bands as a representation of the randomness or uncertainty of the signal. The scheme of the WT method can be seen in Figure 2.

2. 2. 2 Classification with Support Vector Machine (SVM)

Support vector machine (SVM) is one method that is commonly used for classification problems in biomedical signal processing [21-24]. SVM is a supervised learning method. Initially, SVM was used to classify two groups and then developed to solve multi-class classification problems. In addition, SVM is also able to overcome the problem of linear and non-linear classification. SVM is used to find optimal hyperplane functions by maximizing the distance between classes [25]. Hyperplane can be determined by calculating the hyperplane's margin and measuring its maximum point. The closest pattern is called a support vector. The hyperplane in SVM is illustrated, as shown in Figure 3.

In this study, linear SVM and non-linear SVM are used to validate the proposed method. The function of linear SVM is expressed in Equation (2).

$$\min {}^{1}\!/_{2}\,\|\vec{w}\|^2 + T\sum_{i=1}^{k}\varepsilon_i \tag{2}$$

Where w is normal vector length, T is the trade-off parameter between training set errors and class separation. Whereas ε_i is the set of slack variables. The aim of this function is to find the minimum distance between two hyperplanes ($2\|\vec{w}\|$) by minimizing $\|\vec{w}\|$.

Since the boundary line have variations by applying other kernels, therefore non-linear SVM kernels including quadratic and cubic SVM also simulated to find the best performance in classification. This function is obtained by Equation (3).

$$k(a_i, b_i) = (a_i, b_i + 1)^d \tag{3}$$

where (a_i, b_i) is training set, meanwhile for quadratic function the $d = 2$, and for cubic function, the $d = 3$.

3. RESULTS AND DISCUSSION

Figure 4 shows the results of the Wavelet transform which generates the five conventional EEG bands,

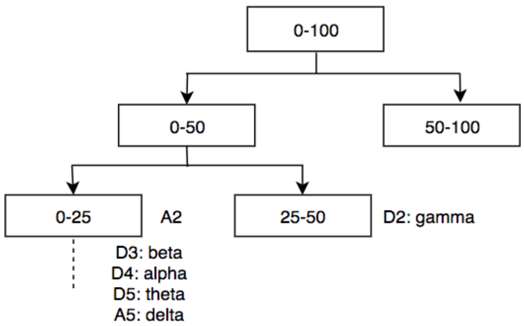

Figure 2. Wavelet decomposition and correspondence with the EEG sub-band

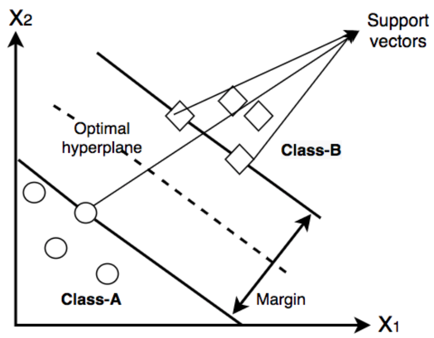

Figure 3. Hyperplane as a separator between classes [26]

including delta, theta, alpha, beta, and gamma. Then the relative energy and entropy are measured for each band. The average values of the relative energy and entropy of each EEG stage are shown in Figures 5 and 6. The relative energy in the delta and theta bands in the ictal stage tends to be higher compared to the non-ictal stage. This indicates a slowing of the EEG wave in the ictal stage. Pre-ictal and inter-ictal stages show that the relative energy in the alpha, beta, and gamma bands is higher than the ictal stage. Meanwhile, the entropy value in the ictal stage is the lowest in all EEG bands compared to the non-ictal stage.

Since entropy is related to the degree of complexity of the dynamic system, the ictal stage has the lowest signal complexity compared with other conditions. These results were confirmed by Weng et al. [27], that the ictal EEG decreased the complexity of the signal with the entropy value of the pre-ictal stage higher than the ictal stage. The parameters which are measured in this study provide discriminant features between groups of epileptic EEG signals. We also confirmed by conducting a significance test using the analysis of variance (ANOVA). In this study, features with statistically significant differences if they have a p-value <0.05 and if it generates a p-value <0.01, it has a higher degree of significant difference. The results of the significance tests for each classification problem are presented in Table 1. From these results, we highlight that in all ictal vs. non-ictal stage scenarios, there are differences with high significance (p <0.01), which is almost generated by all features. Meanwhile, in the case of inter-ictal vs. pre-ictal, there were six features that did not have high significance, two of which had p <0.05. This indicates that these two stages have several similar signal properties, which may be more difficult to classify. Next is the performance validation of the proposed method using SVM. In this study, the number of features which is used as a predictor is 10 features from the measurement of the relative energy and entropy of each EEG band.

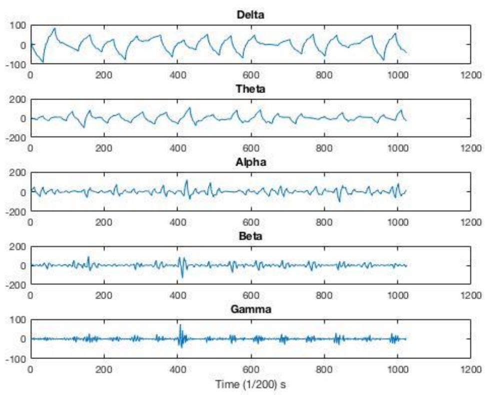

Figure 4. The results of decomposition using wavelet transform in the ictal stage

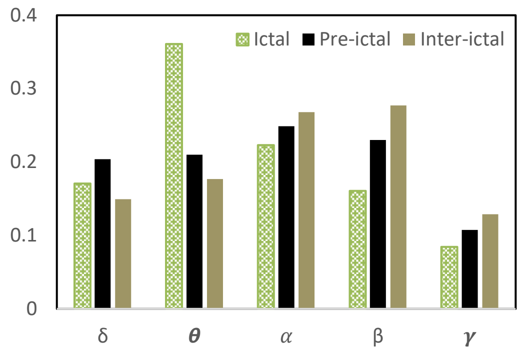

Figure 5. The average of the relative energy of the ictal, inter-ictal, and pre-ictal stages

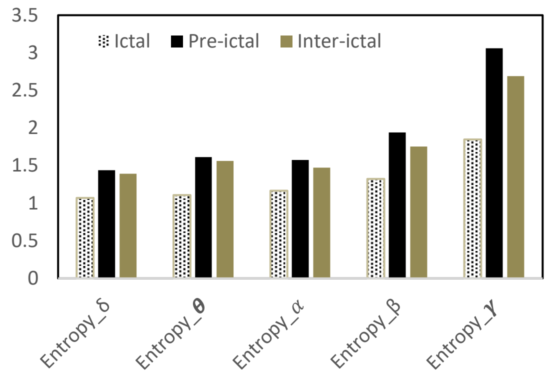

Figure 6. The average of entropy of the ictal, inter-ictal, and pre-ictal stage

TABLE 1. p-value for each classification scenarios

Feature	Ictal vs inter-ictal	Ictal vs pre-ictal	Inter-ictal vs pre-ictal	Ictal vs Inter-ictal vs pre-ictal
RGP	5.15E-09**	6.97E-03**	3.89E-03**	1.65E-07**
RBP	9.00E-18**	3.09E-05**	1.66E-03**	3.55E-13**
RAP	1.05E-05**	2.45E-02*	O.0971	2.76E-04**
RTP	1.14E-23**	4.95E-12**	0.0649	3.70E-21**
RDP	0.0812	0.117	1.08E-02*	1.37E-02*
EG	1.42E-26**	2.02E-24**	1.43E-04**	5.87E-31**
EB	2.88E-18**	2.38E-17**	6.35E-03**	4.89E-20**
EA	4.02E-18**	1.57E-16**	2.93E-02*	7.81E-20**
ET	2.88E-19**	2.33E-14**	0.435	4.80E-18**
ED	1.18E-14**	5.20E-11**	0.358	3.81E-14**

RGP = Relative gamma power; RBP = Relative beta power; RAP = Relative alpha power; RTP = Relative theta power; RDP = Relative delta power; EG = Entropy gamma; EB = Entropy beta; EA = Entropy alpha; ET = Entropy theta; ED = Entropy delta
* p-value < 0.05
** p-value < 0.01

Since SVM is a supervised learning method, a cross-validation algorithm is needed to split the training and test data. The use of this algorithm also aims to avoid overfitting. 10-fold cross-validation with SVM is used to evaluate the performance of the proposed method in the four classification problems, as explained in the sub-section above. The test results for each scenario are presented in Table 2. In the case of classification between ictal and pre-ictal the highest accuracy is 95%, with sensitivity and specificity of 94 and 96%, respectively. For ictal vs. inter-ictal cases, the highest accuracy, which is achieved, is 96%. In this case, 100% specificity was obtained, which means that the system is able to detect all inter-ictal stages without miss classification. Meanwhile, in the ictal vs non-ictal (pre-ictal and inter-ictal) stage classification, the proposed method generates an accuracy of 96.7 with 99% specificity in detecting non-ictal onset. This scenario shows that the proposed method is able to detect ictal and non-ictal onset with high accuracy and has a consistent performance when applied to ictal vs. pre-ictal or ictal vs. inter-ictal classification problems. The simulation results in this scenario are expected to be used to predict the onset of seizures. In the pre-ictal vs. inter-ictal classification problem, the system is able to produce the highest accuracy of 80% and a sensitivity of 90%. This result is quite good, considering both of the onsets have similar characteristics. Where the two conditions are the onset before the occurrence of seizures at different intervals, from the simulations conducted using different SVM kernels, it can be concluded that the quadratic kernel has the best performance, providing the highest accuracy for the three test scenarios.

The evaluation of the proposed method was also carried out by comparing it with previous studies that used the same dataset. In the ictal vs. pre-ictal scenario,

TABLE 2. The classification results for each scenario

Scenario	SVM	Accuracy (%)	Sensitivity	Specificity
Ictal vs Pre-ictal	Linear	94	92	96
	Quadratic	95	92	96
	Qubic	95	94	96
Ictal vs Inter-ictal	Linear	94	88	100
	Quadratic	95	90	100
	Qubic	96	92	100
Pre-ictal vs Inter-ictal	Linear	78	88	68
	Quadratic	80	90	70
	Qubic	76	86	66
Ictal vs Non-ictal	Linear	96.7	92	99
	Quadratic	96.7	92	99
	Qubic	95.3	90	98

TABLE 3. The system performance comparison

Study by	Method	Class	Acc. (%)
Sharma, et. al [28]	minimally mean squared frequency localized (MMSFL)-optimal orthogonal wavelet filter bank (OWFB)	ictal vs. pre-ictal	90
		pre-ictal vs. inter-ictal	NA
		inter-ictal vs. ictal	100
Gupta, et. al [29]	Discrete cosine transform (DCT), Hurst Exponent	ictal vs. pre-ictal	79.7
		pre-ictal vs. inter-ictal	74.6
		inter-ictal vs. ictal	96.5
Proposed study	**Relative Wavelet Energy (RWE) and Wavelet Entropy**	ictal vs. pre-ictal	**95**
		pre-ictal vs. inter-ictal	**80**
		inter-ictal vs. ictal	96

the proposed method outperforms the study by Sharma et al. [28] and Gupta et al. [29] where the accuracy was 90 and 79.7%, respectively. In the pre-ictal vs. inter-ictal scenario, the proposed method also outperforms the study by Gupta et al. [29], yielding an accuracy of 74.6%. This is a good result and should notably since the two stages have similar characteristics. Meanwhile, the ictal vs. inter-ictal scenario has lower performance than the study by Sharma et al. [28] and Gupta et al. [29]; however, the gap is relatively low. A brief summary of the comparisons with previous studies is presented in Table 3.

4. CONCLUSION

This paper presents a method for epileptic EEG detection using relative wavelet energy and wavelet entropy. Wavelet transform was used to generate conventional EEG bands consisting of the delta, theta, alpha, beta, and gamma. Then relative energy and entropy were measured as a feature set. From the measurement of relative power, it was known that the delta and theta band in the ictal stage was higher than in the non-ictal stage. Entropy measurements showed that the value of entropy in ictal tended to be lower than the non-ictal stage. The entropy value in pre-ictal was highest compared to other stages. This measurement was considered to be able to provide discriminant features between epileptic EEG groups. Therefore, performance evaluations were performed with SVM and cross-validation to the feature vectors, which were generated by the proposed method. Performance evaluation was done in the four classification problems, including ictal vs. pre-ictal, ictal vs. inter-ictal, pre-ictal vs. inter-ictal, and ictal vs. non-ictal. Each scenario generates the highest accuracy of 95%, 96%, 80%, and 96.7%, respectively. In ictal vs. pre-ictal and inter-ictal vs. pre-ictal scenario, the proposed method outperformed previous studies. We notably highlighted the cases of ictal vs. non-ictal, where the proposed method produced high accuracy. It means that the proposed method was expected to be used for the prediction of onset seizures.

In future works, the results of this study will be simulated to a larger EEG epilepsy dataset. Moreover, various feature extraction and classification methods will be explored so that it becomes an opportunity to solve the more complicated case of EEG signal classification. Other classification parameters are also meaningful so that research is more challenging to be addressed.

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Persian Abstract

چکیده

صرع یکی از اختلالات عصبی رایج است که می تواند باعث تشنج بدون برانگیختگی شود. در حال حاضر ، تشخیص و ارزیابی با استفاده از آنالیز سیگنال الکتروانسفالوگرام (EEG)انجام می شود که توسط پزشکان بصری انجام می شود. از آنجا که سیگنالهای EEG تصادفی و غیر ثابت هستند ، بازرسی بصری اغلب بیان نادرست نتایج است. مطالعات متعددی تجزیه و تحلیل مبتنی بر رایانه برای طبقه بندی EEG صرعی پیشنهاد شده است. با این حال ، هنوز فاصله ای برای بهبود دقت تشخیص با تعداد کمی از ویژگی ها وجود دارد. بنابراین ، در این مطالعه ، ما یک پروتکل تشخیص خودکار برای طبقه بندی EEG صرعی پیشنهاد کردیم. روش های پیشنهادی انرژی موجک نسبی و آنتروپی موجک برای استخراج ویژگی و ترکیب شده با روش طبقه بندی برای تشخیص خودکار است. در این مطالعه ، سه کلاس EEG شامل پیش اکتال ، ictal و interictal به عنوان داده های آزمون استفاده شد و همچنین روش پیشنهادی را ارزیابی کرد. سیگنال های EEG با استفاده از تبدیل موجک به پنج زیر گروه معمولی ، از جمله گاما ، بتا ، آلفا ، تتا و دلتا تجزیه شدند. سپس انرژی نسبی و آنتروپی در هر یک از این باند ها به عنوان یک مجموعه ویژگی محاسبه شد. این روش ها با در نظر گرفتن محاسبات کم هزینه انتخاب می شوند. ما عملکرد روش استخراج ویژگی خود را با استفاده از هسته های خطی و غیر خطی با استفاده از ماشین بردار پشتیبانی (SVM) آزمایش کردیم. از طریق شبیه سازی ، بالاترین دقت ۸۰-۹۶,۷٪ برای ictal در مقابل pre-ictal، ictal در مقابل inter ictal، pre ictal در مقابل inter ictal ، و ictal در مقابل غیر ictal بود. سرانجام انتظار می رفت که این کار به پزشکان در تشخیص شروع صرع بر اساس سیگنال های EEG کمک کند.