International Journal of
Science and Engineering Investigations vol. 8, issue 91, August 2019
Received on August 22, 2019 ISSN: 2251-8843

Time-Series Analysis and Feature Extraction of EEG Signals

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Abstract- EEG signals contain valuable properties that could be linked to brain activity. However, some common techniques might not be always suitable to extract such properties. This paper presents the results of a comparative study aimed at evaluation of the efficacy of multiple time and frequency domain analysis techniques used for EEG signal classification and feature extraction. Several time and frequency domain techniques including: the higher order moments, the Shannon entropy, the log-energy entropy, and spectral analysis methods such as : the Welch power spectrum density have been tested. Results were compared and presented in this paper. Sampled, artifact-free data obtained from visual evoked potential recordings from multiple subjects and EEG signals of epileptic patients and control subjects waere used to test and assess the efficacy of the investigated techniques. Results show a significant distinction in the efficacy of these techniques in revealing properties carried by the tested signals.

Keywords- *EEG Signals, Higher Order Moments, Welch Power Spectrum, Entropy*

I. Introduction

Brain cells communicate by producing tiny electrical impulses. In an electroencephalogram (EEG), electrodes are placed on the scalp over multiple areas of the brain to detect and record patterns of electrical activity to check for abnormalities. The EEG signal is then amplified, artifacts would be removed, and the EEG signal would be displayed either by itself or its clinically relevant features using suitable monitors. The EEG signal is a waveform that varies with time. Characteristics and properties of this waveform such as amplitude and frequency vary with the change of the brain activity [1-2]. The EEG signal contains frequency components that can be measured and analyzed. These frequency components have meaning, and valuable properties that could be linked to the brain activity.

Information theory particularly as applied to the field of biomedical signal analysis and feature extraction, provides a mode of processing, classifying, and visualizing electrical signal outputs corresponding with various physiological variables. Some of the most common physiological variables are those associated with the evoked potential in electroencephalograms (EEGs), electrocardiograms (ECGs), and electromyograms (EMGs) [3]. A common application of signal processing is observed in the diagnostic classification of EEG signals using time-series and frequency domain methods, providing insights into medical conditions such as epilepsy by allowing for the automatic detection of epileptic episodes through the characterization of abnormal pre-ictal (pre-seizure), ictal (seizure) and inter-ictal (inter-seizure) signal features (relative to a state of 'normality') in place of traditional seizure detection [4]. Such methods include the measurement of statistical parameters such as higher-order moments, Shannon entropy, the log energy entropy, and the Welch power spectrum (Appendix A).

In the time-domain methods, the use of statistical moments (including the higher order moments) in signal classification and feature extraction entails the comparison of extracted statistical features such as mean, variance, skewness, and kurtosis (Appendix A) between signals corresponding with normal and abnormal physical states using neural networks and linear classifiers [2].

Shannon entropy is a useful criterion in the classification of any distribution, that provide a measurement of intrinsic 'disorder' or 'uncertainty,' especially in the case of nonlinear, non-stationary, and complex EEG signals [6]. The log energy entropy with statistical features, like those of the Shannon entropy, also representing 'uncertainty' in the time-series signal [3,6].

In the frequency domain methods for signal classification and feature extraction, the aim of spectral analysis is to decompose the data into a sum of weighted sinusoids. This decomposition allows one to assess the frequency content of the phenomena or signal under study. The phenomenon under study may be concentrated in some narrow frequency bands or might be spread across a broad range of frequencies. To study the signal and extract the the desired features, some sort of averaging or smoothing is employed. The Welch power spectrum method is also called the weighted overlapped segment averaging method and periodogram averaging method. Welch power spectrum as a frequency domain method could reveal discrepancies between physical states on the basis power densities within the frequency domain [8].

This paper presents the results and conclusions of a comparative study aimed at the investigation and evaluation of the efficacy of multiple time and frequency domain techniques used for time-series analysis and EEG signal classification and feature extraction. Several time and frequency domain techniques including the higher order moments, the Shannon entropy, the log-energy entropy, and spectral analysis methods including the Welch power spectrum density have been tested and the results were compared and presented in this paper. Sampled, artifact-free data obtained from visual evoked potential recordings from multiple subjects and EEG signals of epileptic patients and control subjects was used to assess the efficacy of the investigated techniques. In this comparative study, the fidelity of the signal classification and feature extraction methods is determined based on qualitative and quantitative analysis in testing pre- and post-stimulus EEG data displaying the efficacy of these signal classification and feature extraction methods in an applied scenario.

II. EEG DATA SETS AND METHODOLOGY

Sampled, artifact-free data obtained from visual evoked potential recordings that were taken from multiple subjects was used to assess the efficacy of the investigated techniques. Multiple data files were used, where each file corresponds to the recording on a different subject in the left occipital electrode, with linked earlobes reference. Each file contains several artifact-free trials, with each trial containing 512 data points (256 pre- and 256 post-stimulation) stored with a sampling frequency of 250 Hz [9]. Data was pre-filtered in the range 0.1-70Hz. All trials correspond to target stimulation with an odd ball paradigm [9].

The EEG signals from epileptic patients and control subjects were taken from an available dataset [10]. In the original data set, each file is a recording of brain activity for 23.6 seconds with the corresponding time-series sampled into 4097 data points. Each data point is the value of the EEG recording at a different point in time [10]. The EEG data from different epileptic subjects and controls are each labeled with a reference number from 1 to 5 with 1 for example represents recording of seizure activity and 5 represents “eyes open” which means the recording of the EEG signal of the brain while the subject had their eyes open. All subjects falling in classes 2, 3, 4, and 5 are subjects who did not have epileptic seizure. Only subjects in class 1 have epileptic seizure. Although there are 5 classes most authors have done binary classification, namely class 1 (Epileptic seizure) against the rest [10].

Techniques deemed effective for the present case-study of EEG signal analysis and feature extraction would be those that provided the greatest objective discrimination of characteristics of the pre- and post-stimulus evoked potential signals as well as clearly discriminated epileptic patients from control subjects. Appendix A provides more details on the basic definitions of the EEG processing techniques investigated in this study.

III. RESULTS AND DISCUSSION

All EEG signal processing and feature extraction and presentation of the results in this study were done in a MATLAB® environment. Various figures and tables were produced to provide a means of visualization or qualitative characterization for each of the respective method.

Additionally, a measure of the average power spectral density was obtained for ease of visualization of the Welch power spectra. To allow for automated classification in the most effective of these methods, machine learning could be utilized (e.g. neural networks). Moreover, a paired t-test was performed on pre- and post-stimulus EEG signals for all five statistical features, providing an objective means of determining efficacy in classification.

A plot of the sampled and artifact-free evoked potential signal for two trials with both pre- and post-stimulus of the same subject is displayed in Fig. 1. Aside from a seemingly higher signal amplitude within the post-stimulus part of the trials, the simple visualization shows the signals posing minimal features regarding signal classification and desirable feature extraction, Fig. 1. However, using autocorrelation features on the EEG signals, it was shown that post-stimulus signals do possess a greater degree of consistency, posing another potential method of signal classification as shown in Figures 6 and 7.

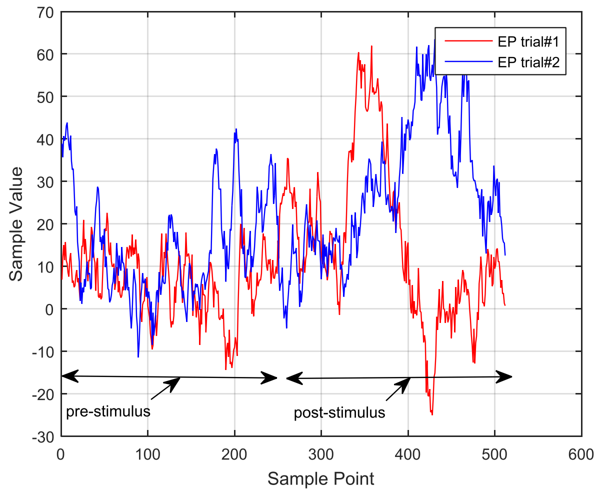
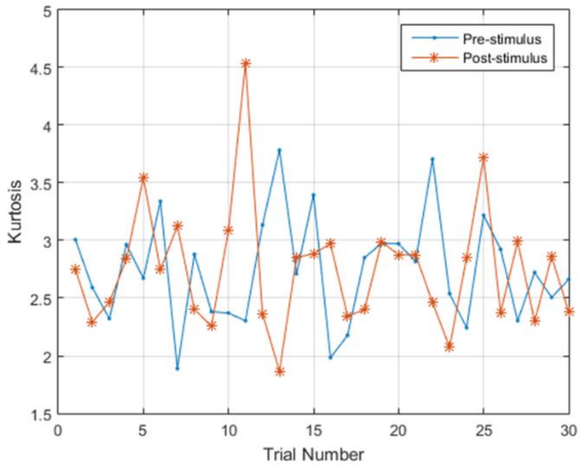
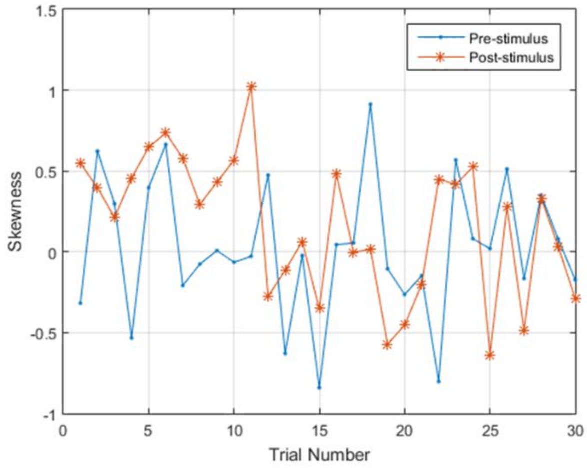


Figure 1. Plot of the sampled visual evoked potential trials showing pre- and post-stimulus

Using higher order moments, more specifically, skewness and higher moments, as statistical features in the characterization and classification of EEG signals in this study proved rather inconclusive, presenting no clear qualitative means of discrimination between pre- and post-stimulus signals. Kurtosis shows no definite trend or pattern each trial signal distributions. It’s apparent that this method fails to discriminate between states in its characterization of the pre- and post-stimulus signals. Skewness, from a subjective standpoint, provided a more discernable degree of differentiation than kurtosis, Figure 2a and b.



(a)

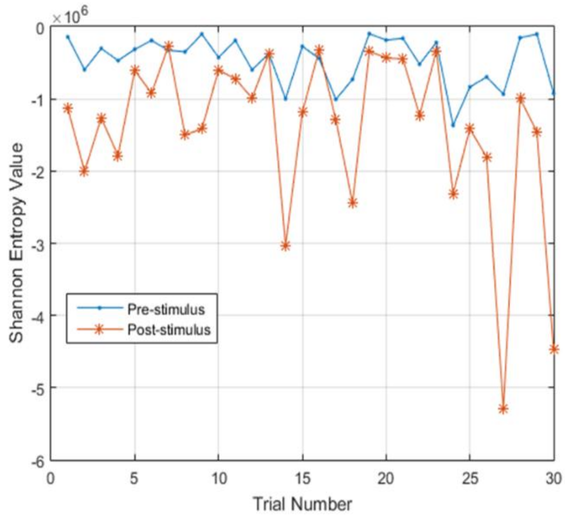


(b)

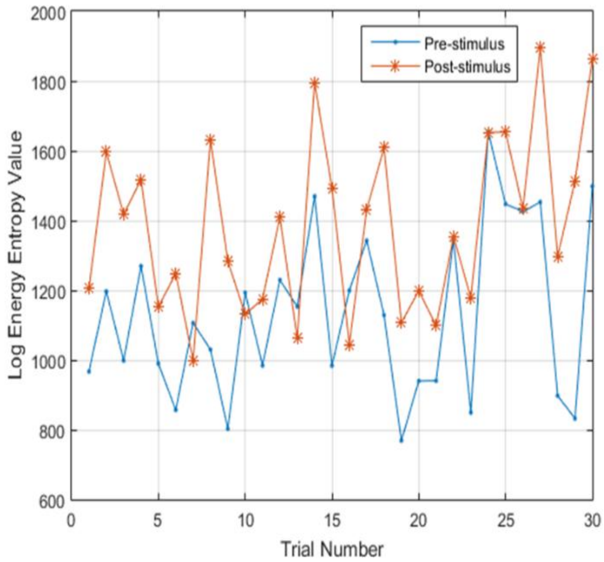
Figure 2. (a) Kurtosis and (b) Skewness of pre- and post-stimulus trials of evoked potential signals

This study thus presents the extraction and use of higher-order moments as less viable means of classification of visual evoked potential type signals relative to methods using other statistical features. This qualitative assessment corroborated quantitatively using a paired t-test as a statistically insignificant difference in the pre- and post-stimulus kurtosis and skewness mean values was displayed, Table 1.

Testing two entropy-concerned statistical features for efficacy of signal classification using Shannon entropy and the log energy entropy, it was found that both produced a qualitatively discernable degree of discrimination between pre- and post-stimulus trials in the evoked potential EEG signals, Figure 3a&b. Additionally, as displayed by a paired t-test, both methods produced a quantitative indication of discrimination between the pre-and post-stimulus EEG signals (with both parameters presenting p-values of ~0 in their respective tests), Table 1.



(a)

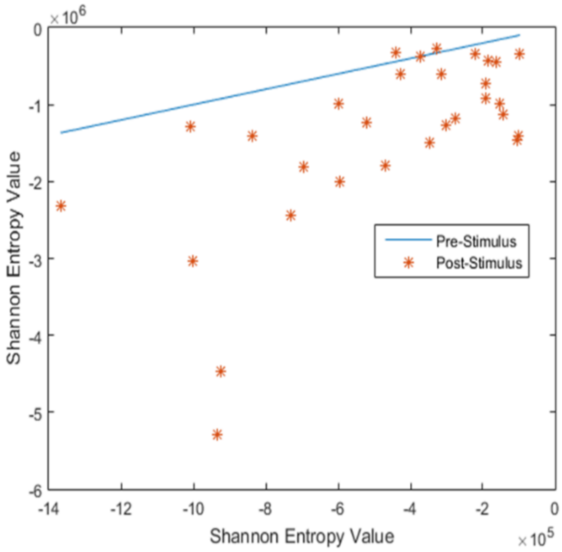


(b)

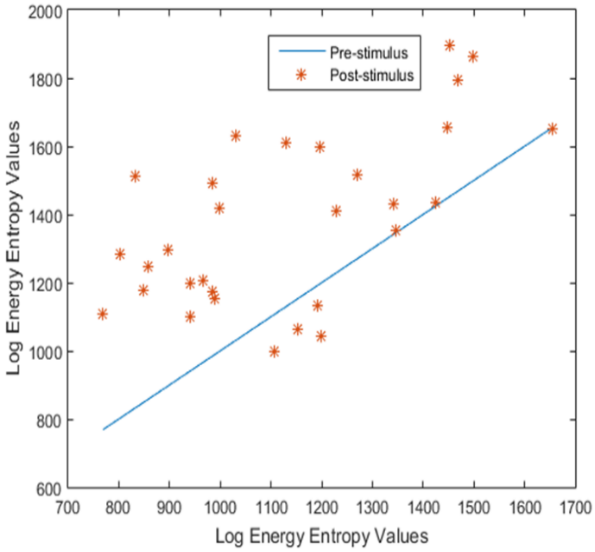
Figure 3. (a) Shannon entropy and (b) Log energy entropy of pre- and post-stimulus trials of evoked potential signal

Figure 4(a) and (b) shows clustering of the Shannon and log-energy entropy values of the post-stimulus trials over the pre-stimulus entropies.

There is a significant and discernable difference in the characterization of the pre- and post-stimulus trials of evoked potential signals using both the Shannon and log energy entropy method of classification, qualitatively serving as an improvement upon the characterization produced using higher-order moments. Observation of near identical level of efficacy of feature extraction using Shannon and log energy entropy would expected due to the similarity of the statistical features or quantities extracted for both methods (i.e. entropy or uncertainty).



(a)



(b)

Figure 4. Clustering of entropy values of post-stimulus trials over pre-stimulus entropy of evoked potential signal, (a) Shannon entropy and (b) Log-energy entropy

Figure 5 shows the averaged Welch power spectral density for pre- and post-stimulus trials of visual evoked potential signal. Additionally, a paired t-test produced an objective indication of a statistically significant discrimination in pre- and post-stimulus trials of evoked potential EEG signals using Welch power spectrum characterization with a p-value of ~0 obtained, Table 1. The use of Welch power spectrum as a statistical feature for signal classification yielded significant qualitative discrimination in pre- and post-stimulus trials of visual evoked potential EEG signals, Figures 6 and 7.

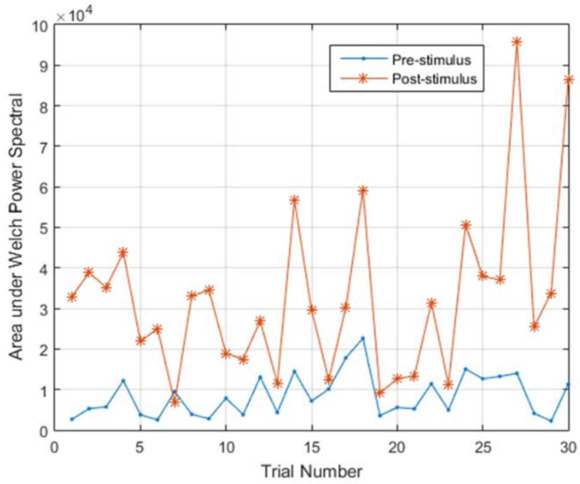


Figure 5. Averaged Welch power spectral density for pre- and post-stimulus trials of visual evoked potential signal.

TABLE I. PAIRED T-TEST PRE- AND POST-STIMULUS GROUPS

Variable (Pre- vs. Post- Pair)	Mean Diff	Std. Mean Difference	t-test	D of Frdm	Sig. (2tailed)
Kurtosis	0.00434	0.785	-0.0303	29	0.976
Skewness	0.146	0.537	-1.49	29	0.145
Shannon Entropy	9.46E+5	9.86E+5	5.25	29	~0
Energy Entropy	2.50E+2	2.18E+2	-6.26	29	~0
Welch PSD	2.42E+4	1.87E+4	-7.08	29	~0

The level of autocorrelation was calculated for the time-series with both the pre- and post-stimulus of evoked potential signals for a given case. It can be observed that the post-stimulus signal displays a greater degree of signal consistency, given that it displays a response to a determined stimulus.

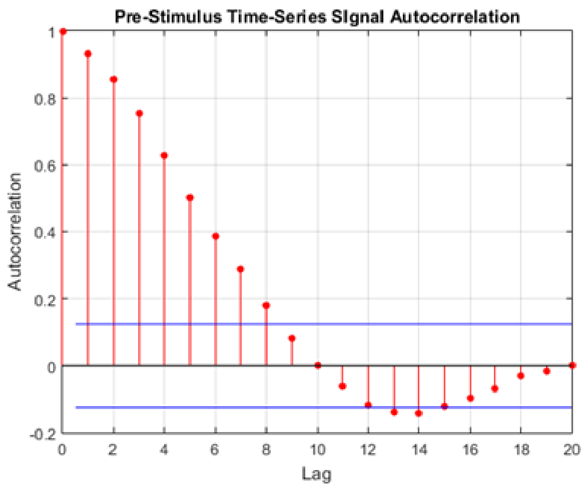


Figure 6. Autocorrelation of pre-stimulus trials of evoked potential signals.

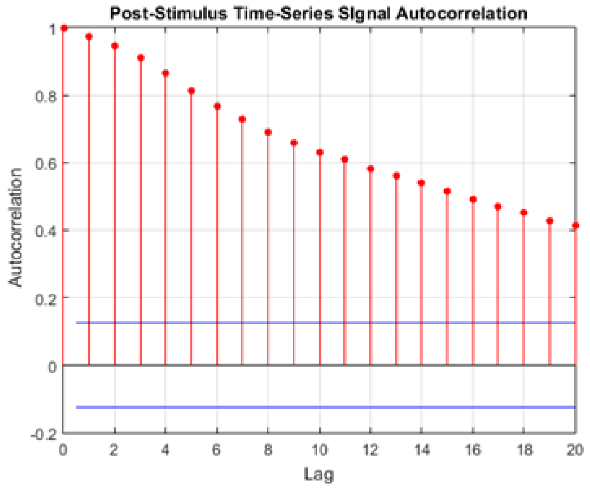


Figure 7. Autocorrelation of post-stimulus trials of evoked potential signals.

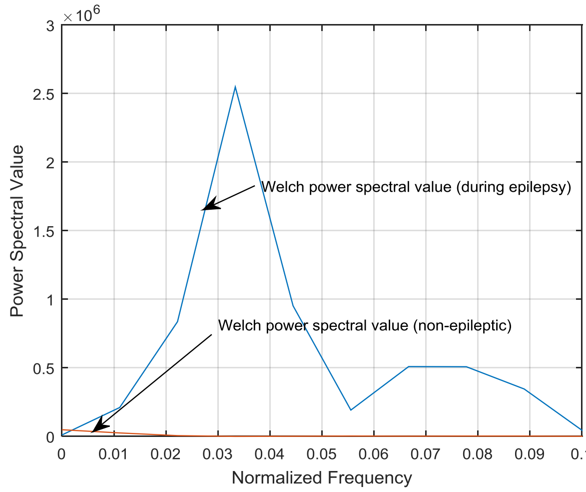


Figure 9. Welch power spectrum of an EEG signal recorded during epilepsy over an EEG signal from a non-epileptic subject

Assessment of the investigated techniques was extended to EEG signals from epileptic patients and control subjects. Figure 8 shows the apparent features of an EEG signal recorded during an epilepsy compared to the signal recorded from a non-epileptic subject. Figure 9 shows an example of Welch power spectrum for an EEG signal recorded from an epileptic patient during an epilepsy episode. Visual inspection of Fig. 9 shows that the level of efficacy of Welch power spectrum method regarding feature extraction of EEG signals from epileptic patients is significant. This in turn shows that the Welch power spectrum along with the Shannon and log energy entropy generally enjoy an overall higher level of success in EEG signal classification and feature extraction.

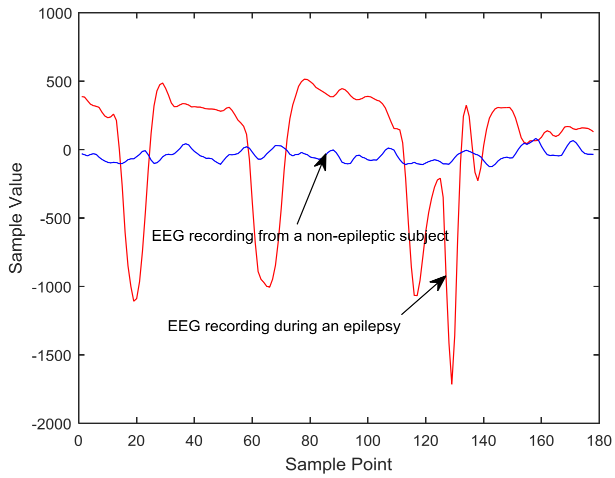


Figure 8. Visualization of a sampled EEG signal recorded during epilepsy over an EEG signal from a non-epileptic subject

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IV. CONCLUSIONS

In this comparative study, five separate methods, falling into three general categories, were tested for their efficacy in EEG signal classification, most specifically in the differentiation between pre- and post-stimulus trials of evoked potential signals and EEG signals from epileptic subjects. To this end, the use of higher-order moments as a statistical feature basis for signal classification and feature extraction proved relatively ineffective from both a qualitative and quantitative standpoint. As for the other methods tested: Shannon entropy, energy entropy, and Welch power spectra, all revealed a higher degree of differentiation in the classification of evoked potential EEG signals. Observation of near identical level of efficacy of feature extraction using Shannon and log energy entropy would be expected due to the similarity of the statistical features or quantities extracted for both methods, i.e. entropy or uncertainty. As an extension study, machine learning in the form of neural networks could be used to provide an automated means of classification, with applications in fields such as the detection of epileptic events and personal identification.

REFERENCES

[1] Tzallas, A., Tsipouras, M., & Fotiadis, D. (2009). Epileptic Seizure Detection in EEGs Using Time–Frequency Analysis. *IEEE Transactions on Information Technology in Biomedicine,13*(5), 703-710. doi:10.1109/titb.2009.2017939

[2] Reena, R & Raj, Rose & Subhashini, Kumaran. (2011). EPILEPTIC SEIZURE DETECTION USING HIGHER ORDER MOMENTS ON EEG SIGNALS. 2. 21-25.

[3] P. Li, C. Yan, C. Karmakar and C. Liu, "Distribution entropy analysis of epileptic EEG signals," 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Milan, 2015, pp. 4170-4173. doi: 10.1109/EMBC.2015.7319313

[4] Aydın, S., Saraoğlu, H. M., & Kara, S. (2009). Log Energy Entropy-Based EEG Classification with Multilayer Neural Networks in Seizure. Annals of Biomedical Engineering,37(12), 2626-2630. doi:10.1007/s10439-009-9795-x

[5] Wang, R., Wang, J., Yu, H., Wei, X., Yang, C., & Deng, B. (2015). Power spectral density and coherence analysis of Alzheimer's EEG. Cognitive neurodynamics, 9(3), 291–304. doi:10.1007/s11571-014-9325-x

[6] Shannon, C. E. (1948), A Mathematical Theory of Communication. Bell System Technical Journal, 27: 379-423. doi:10.1002/j.1538-7305.1948.tb01338.x

[7] Puthankattil, Subha Dharmapalan & Joseph, Paul & Acharya, U Rajendra & Lim, Choo. (2010). EEG signal analysis: a survey. Journal of medical systems. 34. 195-212. 10.1007/s10916-008-9231-z.

[8] Xu Huang, S. Altahat, D. Tran and D. Sharma, "Human identification with electroencephalogram (EEG) signal processing," 2012 International Symposium on Communications and Information Technologies (ISCIT), Gold Coast, QLD, 2012, pp. 1021-1026. doi: 10.1109/ISCIT.2012.6380841

[9] R. Quian Quiroga and M Schermann , Functions and sources of evoked EEG alpha oscillations studied with the Wavelet Transform. Clin. Neurophysiol., 1999; 110: 643-654.

[10] Andrzejak RG, Lehnertz K, Rieke C, Mormann F, David P, Elger CE (2001) Indications of nonlinear deterministic and finite dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state, Phys. Rev. E, 64, 061907

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APPENDIX A

A. *Processing techniques*

Skewness is a measure of the asymmetry of a probabilistic distribution and is derived from the third moment about the distribution mean. Skewness can be calculated using the equation [2];

$$\beta = \frac{1}{N}\sum_{i=1}^{N}\frac{(x_i - \mu)^3}{\sigma^3} \quad (1)$$

where β is skewness, σ is the standard deviation of the distribution, μ is the mean of the distribution, and the distribution is represented by the N–point data set $x \in X\{x_{1,}, x_2 \ldots x_N\}$.

Kurtosis is a measure of the degree to which the distribution possesses peaks or 'peakedness'. Kurtosis can be calculated using the equation [2];

$$\gamma = \frac{1}{N}\sum_{i=1}^{N}\frac{(x_i - \mu)^4}{\sigma^4} \quad (2)$$

where γ is skewness, σ is the standard deviation of the distribution, μ is the mean of the distribution, and the distribution is represented by the N–point data set $x \in X\{x_{1,}, x_2 \ldots x_N\}$.

Shannon entropy measures the complexity of a time-series by assigning degrees of 'uncertainty' to the values associated with data points, can be quantitatively described using the equation [3,6];

$$H_{Sh}(s) = -\sum_i s_i^2 \log(s_i^2), H(0) = 0 \quad (3)$$

where s is the signal, s_i is a unit vector contained within s and H_{Sh} is Shannon entropy.

Similar to Shannon entropy, the **log Energy entropy** can be obtained using the equation [4];

$$H_{Log}(s) = \sum_i \log(s_i^2) \quad (4)$$

where s is the signal, s_i is a unit vector contained within s, and H_{Log} is energy entropy.

Power spectral density refers to the power spectrum of a given time series, calculated using a fast Fourier Transform (FFT), creating a frequency-domain representation of the original time-domain signal. Power spectrum density can be found using the power spectral density (PSD).

$$\hat{P}_d(f) = \frac{1}{MU}\left|\sum_{n=0}^{M-1} x_d(n)w(n)e^{-j2\pi fn}\right|^2 \quad (5)$$

Where the signal interval length is M, U is a window normalization factor, and $\{x_d(n)\}$ is the signal sequence (where d=1, 2, 3,.. L is the signal intervals).

$$\hat{P}_{welch} = \frac{1}{L}\sum_{i=0}^{L-1} \hat{P}_d(f) \quad (6)$$

The Welch power spectrum, as given in equation (6), is an average of the prior transforms over the signal intervals [7].

How to Cite this Article:

El-Kishky, O. & Barakat N. (2019) Time-Series Analysis and Feature Extraction of EEG Signals. International Journal of Science and Engineering Investigations (IJSEI), 8(91), 181-186. http://www.ijsei.com/papers/ijsei-89119-24.pdf