DOI: http://dx.doi.org/10.26483/ijarcs.v12i5.6773

Volume 12, No. 5, September-October 2021

ISSN No. 0976-5697

International Journal of Advanced Research in Computer Science

RESEARCH PAPER

Available Online at www.ijarcs.info

GENERTATION OF SYNTHETIC EEG SIGNAL; EVALUATION OF MUTUAL INFORMATION AND CORRELATION COEFFICIENT

Saneesh Cleatus T
Department of Electronics and Communication Engineering
BMS Institute of Technology and Management
Affiliated to Visvesvaraya Technological University
Bangalore, India

Dr. Thungamani M
Department of Computer Science
College of Horticulture, University of Horticulture Sciences,
Bangalore, India

Abstract: When it comes to the diagnosis and treatment of epilepsy, as well as the general quality of life of the patient, the electroencephalogram (EEG) is an oftenutilisedas auxiliary test to aid in the process. It is the primary diagnostic test for epilepsy because it gives a continuous assessment of brain function with great temporal resolution over a long period of time, making it an excellent tool for early detection of epilepsy. Specifically, in this paper, we propose the creation of two Simulink models that can generate synthetic EEG data while maintaining the statistical characteristics of the EEG. In addition, we present the evaluation of two characteristics such as mutual information and correlation coefficient, in order totest the characteristics of any such synthetic generated data. The characteristics proposed here are tested with standard data available on online repository. Apart from using these characteristics for testing the validity of synthetic data, we may use these characteristics as features for machine learning applications.

Keywords: Electro Encephalogram, Mutual Information, Correlation.

I. INTRODUCTION

EEG is a regularly used auxiliary test to aid in the diagnosis of epilepsy, as well as to treat the condition and enhance the patient's quality of life. In epilepsy, electroencephalography (EEG), which offers a continuous assessment of brain function with great temporal resolution, is the major diagnostic test used. It is nothing more than a "snapshot" of the brain at the time of the capture. Despite the advent of numerous alternative technologies such as Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI), EEG signals continue to be widely employed because they provide a wealth of information about the functioning of the brain and are inexpensive. The interpretation of EEG data for clinical purposes necessitates a significant amount of time and effort. Visual inspection and manual annotation are still the gold standard for interpreting EEG in modern clinical practice, even though it is time-consuming and ultimately subjective. In addition, there is a scarcity of qualified electroencephalography technicians. As a result, there is a significant demand for EEG interpretation systems that are automated [1].

II. MODELING OF EEG SIGNALS

Beyond being an effective tool for simulating the dynamics of brain networks involved in epileptic seizures, computational EEG models can serve as a trustworthy test platform for investigating new treatment options. These studies are being carried out in order to get a better knowledge of the mechanisms that are involved in the dynamics of brain signals, as well as to design stimulation paradigms that can be utilized to regulate epileptic seizures as well as to recognize them.

Established by Veronika, Svozilova, and Martin Mezl, three models for generating EEG activity are described, together with their structural and analytic descriptions, as well as the parameters that can be used to control them [2].

Dennis Immanuel T and Chaitanya Srinivas L V A suggested a Simulink model for the generation of epileptic seizures and the treatment of epileptic seizures using neurotherapy. Models of theirs The nonlinear model between the brainstem, cortex, and thalamus circuits that has been created at the neural population level on Matlab/Simulink is discussed [3].

According to Shujuan Geng and Weidong Zhou, a Bifurcation Phenomenon of Wendling's EEG Model has been proposed, in which the mathematical analysis of an EEG model proposed by Wendling is explored [4].

The simulation and control of epileptic EEG using a nonlinear model using Simulink was proposed by X. Tian and Z.G. Xiao. An interactive dynamic neural population model between brainstem, cortex, and thalamus circuits was developed using Matlab/Simulink in this work [5].

Ben H. Jansen and Vincent G. Rit used a mathematical model of connected cortical columns to create electroencephalograms and visual evoked potentials in their theoretical work, which was published in Psychological Science. This work is concerned with the development of neurophysiological based models for modelling electrical activity in the brain [6].

In this work, models such as the Jansen and Wendling models are used to illustrate this type of model, and they are both implemented in this work.

The models produced by Jansen were based on earlier mathematical models developed by Lopes da Silva and Van Rotterdam in 1982, which served as a motivation for their work. It is based on the concept of cortical columns reflecting either the excitatory or the inhibitory neuronal populations that Jansen described in his single-column model. In order to reproduce the spontaneous electrical activity of neurons recorded by EEG equipment, a mathematical model has been constructed with a special emphasis on the simulation of alpha waves in the brain. The interaction between neuronal populations is mediated by excitation and inhibition, which culminates in the creation of alpha waves as a result of the interaction between neuronal populations. As a side note, the single-column model devised by Jansen is capable of replicating EEG activity, in which spikes associated with epilepsy can be seen.

The brainstem excitatory transfer function he(t) is given by;

$he(t)= A\ [exp\ (-a1t) – exp\ (-a2t)] \quad a2 > a1$

The brainstem inhibitory transfer function hi(t) is given by

$hi(t) = B\ [exp\ (-b1t) – exp\ (-b2t)] \quad b2 > b1;$

The spatial statistical function f (Ve1) is given by

$f\ (Ve1) = \lambda g0\ exp\ [q\ (V - Vd)] \qquad V >Vd$

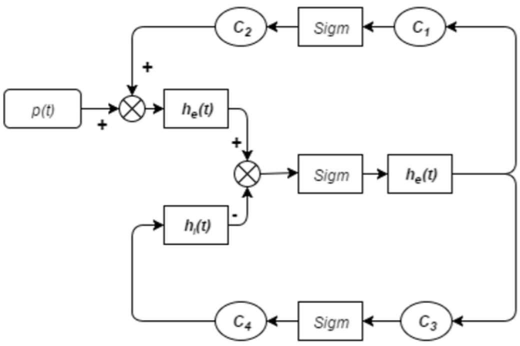

Figure 1 Structureof Jansen's single-column model

In his model, Wendling draws on the work of Jansen and Rit as a foundation. To represent a subgroup of interneurons that provide somatic inhibition to pyramidal cells, an inhibitory feedback loop has been included to the model, which can be seen in the figure below. As a result of Wendling's model, six various types of EEG activity can be observed, including seizure activity suggestive of an epileptic attack, which is the model's final outcome. The model developed by Wendling not only has the advantage of replicating actual epileptiform activity that should be caused by an imbalance between excitatory and inhibitory synaptic gains, but it also has anumber of other major advantages [7,8,9].

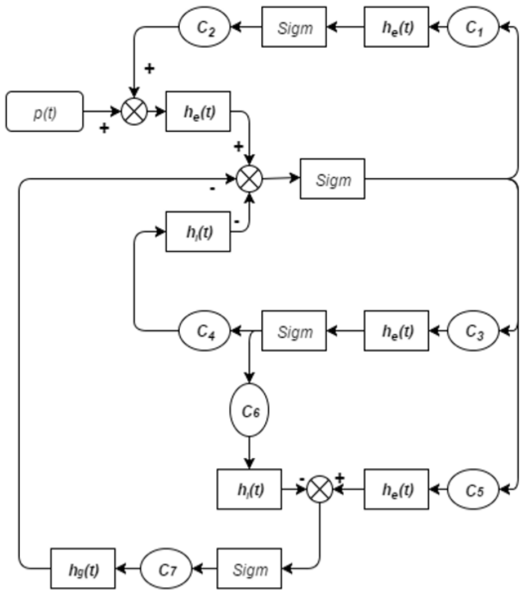

Figure 2 Structure of Wendling's model

III. SIMULINK MODELS

Simulink is used to simulate the Jansen single column model as well as Wendling's model, both of which are presented here. Among Simulink's many simulation parameters are the following: The simulation time is 10 seconds, the step resolver is fixed (each step is 0.004 seconds), and the Runge – Kutta Algorithm is selected in four orders. By varying the coupling constants (C1 or C2) of the neuronal population model, the epileptic seizures can be simulated and studied.

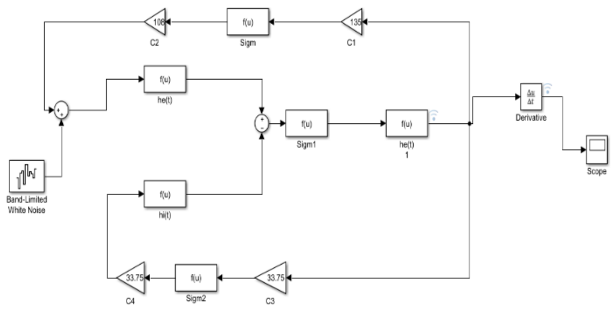

Figure 3Jansen's single column model as established on Simulink

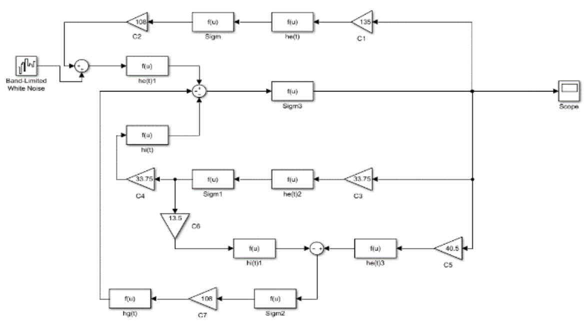

Figure 4 Wendling's model established on Simulink

In this model, both normal and seizure-like EEGs are simulated with altering coherence parameters between the brainstem and cortical neuronal populations, and the results are compared to the experimental results. The model output exhibits seizure-like EEG and can be detected hypsarrhythmia when the coherence parameters between brainstem and cortex, for example, C_1 and C_2 are lower than normal values. To test the characterization of seizure EEG, the mutual information between multiple output data is proposed. The proposed techniques are implemented in the simulated data and data obtained from standard seizure data base available in online repository [10,11].

IV. CHARECTERIZATION OF SEIZURE EEG

Obtaining mutual information and correlation coefficient from data from several EEG recordings is a strategy we propose to test the characterization of seizure-induced EEG in order to understand study the properties of EEG. Two features were used in this study. The mutual information content between two EEG signal and the correlation coefficient value between two EEG signal [12,13]. The EEG recordings used in this study were taken from the CHB-MIT Scalp EEG Database.

The CHB-MIT Scalp EEG database, which was compiled at the Children's Hospital Boston, contains EEG recordings from pediatric patients who have been diagnosed with intractable epilepsy.22 people (5 men, ages 3–22; and 17 girls, ages 1.5–19) participated in the study, and their recordings were organized into 23 instances. It is possible that between 9 and 42 continuous‘.edf’ files from a single subject are contained within each instance (chb01, etc.). In the majority of cases, the‘.edf’ files contain exactly one hour's worth of digitized electroencephalogram signals. All the signals were sampled at a rate of 256 samples per second with a resolution of 16 bits. In this application, we have gathered the sets chb01 and chb03 that were previously mentioned [14,15].

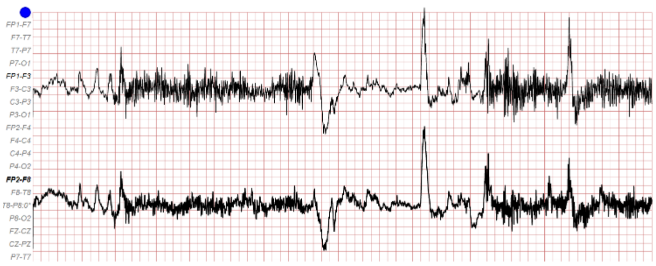

Figure 5 Typical Recording of CHB-MIT Scalp EEG Data (chb01_01)

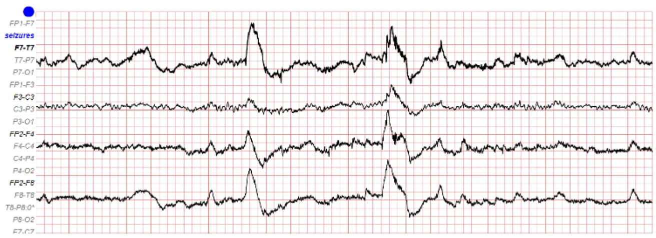

Figure 6 Typical Recording of CHB-MIT Scalp EEG Data (chb03_01)

A. *Mutual Information and Correlation Coefficient*

The study proposed extracted two features which are the mutual information content two EEG recordings and the correlation coefficient value between two EEG signals. Mutual information of two signals is a measure of the mutual dependence between the two signals. It quantifies the "amount of information" which can be obtained about one signal just by observing the other signal [16,17].

Mutual Information between two signals x and y are defined as

$$I(x,y) = \sum_{x,y} p(x,y) log \frac{p(x,y)}{p(x)p(y)}$$

where

p(x,y) is the joint probability mass function of x and x , and p (x) and p (y) are the marginal probability mass functions of x and y respectively. In this work, x and y are the two EEG signal obtained from two channels. This value will give an insight about how the EEG signals are connected when it comes to certain medical ailments. The results obtained after calculating the mutual information values for selected EEG channels are available in Table 3 and Table 4.

Correlation between two signals is another feature which is of equal important that can characterize the relationship between two signals. Correlation coefficients are used to find how strong a relationship is between two given data. They return a value between -1 and 1 where: a coefficient of 1 means that for every positive increase in one variable there is a positive increase of a fixed proportion in the other whereas a coefficient of -1 suggests that for every positive increase in one variable, there is a negative decrease of a fixed proportion in the other.
The general equation for obtaining the correlation coefficient between two signals is

$$r(x,y) = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2(y_i - \bar{y})^2}}$$

Where x and y are two input signals which are represented in discrete time.

Correlation coefficient is obtained between two channel data. This gives a good indication about how two EEG signals acts together when there is an abnormality. This is a useful feature one can use for studying the effects of seizures. The results obtained after calculating the correlation coefficients for selected EEG channels are available in Table 1 and Table 2 and Table 5.

V. RESULTS AND DISCUSSIONS

The mutual information and correlation coefficient values are evaluated between different selected EEG channels. Two methodology is adopted to evaluated both the features. In the first methodology the characteristics are obtained between two distinct EEG signals; first set being normal EEG and second set being EEG signal during seizure event. Table 1 shows the results of average value of correlation coefficient. Five data set corresponds to seizure dataand non seizure data are shown in the results. It may be observed that the average value of correlation coefficient is slightly higher for seizure data in comparison with non seizure data. Eventhough the dofference is not significant. Authors feel this can lead to a good starting point while obtaining the distinct feature when classifying the signals.

Table 1 Correlation coefficients for sets with Seizure and Non Seizure

Dataset (with Seizure)	Average value of correlation coefficients	Dataset (without Seizure)	Average value of correlation coefficients
Chb01_04	0.8040	Chb01_10	0.7978
Chb01_15	0.8087	Chb01_14	0.7008
Chb01_21	0.6285	Chb01_22	0.5708
Chb01_18	0.6110	Chb01_23	0.5303
Chb01_16	0.5267	Chb01_17	0.4996

In the second method the characteristics are obtained between two distinct time window of same EEG signal. In this process we will be able to obtain the effect of seizure on the signal before the seizure occurs and after the seizure event. Table 2 shows the results of average value of correlation coefficient of the same EEG signal before, during and after seizure event. Four data set corresponds to seizure signal are shown in the results. It may be observed that the average value of correlation coefficient is slightly higher during seizure event in comparison the pre-ictal event.

Table 2 Correlation coefficients of Seizure, Pre Seizure and Post seizure states for the set chb03

Dataset (with Seizure)	Average value of correlation coefficientss		
	Before Seizure	During Seizure	After Seizure
Chb03_01	0.5298	0.5302	0.5298
Chb03_03	0.4794	0.5218	0.5172
Chb03_04	0.4820	0.5255	0.5188
Chb03_34	0.5062	0.5417	0.5058

The results if mutual information are shown in the Table 3. It may be observed that the mutual information values are very close during the seizure event. The reason could be the synchronous behavior of electrical signals from parts of brain during the seizure event. In order to obtain more useful information, we have obtained the variance of the mutual information and could see the variance is more during pre-ictal event. These results are shown in Table 4.

Table 3 Mutual Information average values of Seizure, Pre Seizure and Post seizure states for the set

Dataset	Average values of Mutual Information		
	Before Seizure	During Seizure	After Seizure
Chb01_03	6.9368	6.9296	7.0532
Chb01_04	5.5667	5.5628	5.5740
Chb01_15	6.8975	6.7917	6.9444
Chb01_18	37.4172	37.6207	37.7506
Chb01_21	16.6511	16.7606	16.7651

Table 4 Variance values of Mutual Information of Seizure, Pre Seizure and Post seizure states for the set chb01

Dataset	Average Standard Deviation values of Mutual Information		
	Before Seizure	During Seizure	After Seizure
Chb01_03	0.3553	0.3395	0.3858
Chb01_04	0.3218	0.3187	0.3264
Chb01_15	0.3544	0.3535	0.3379
Chb01_18	0.9180	0.9338	0.9461
Chb01_21	0.5191	0.4981	0.5336

VI. CONCLUSION

The seizure recordings resulted in greater correlation values than the baseline recordings. When the same channel data was examined over time, the correlation coefficient values for seizure state were higher than the correlation coefficient values for pre seizure and post seizure states. When comparing the same channel data for seizure state to pre seizure and post seizure states, the mutual information values were lower for seizure state than for pre seizure and post seizure states. The variance and standard deviation values of mutual information for seizure state were also lower when compared to the values for pre seizure and post seizure states, indicating that the seizure state was showing more synchrony.

VII. REFERENCES

[1] S. Sanei and J. A. Chambers, EEG Signal Processing, vol. 1. 2013.

[2] V. Svozilova, M. Mezl, V. Svozilova, and M. Mezl, “Modeling of the EEG signal Modeling of the EEG signal,” 2016.

[3] Dennis Immanuel, T., and Chaitanya Srinivas LV. "A Simulink Model for Generating Epileptic Seizures and its Neurotherapy Treatment." International Journal of Bio Sciences and Engineering, Vol. 1, no. August, pp. 13–21, 2014.

[4] Geng, S., Zhou, W., Yuan, Q. & Ma, Z. Bifurcation phenomenon of wendling’s EEG model. in International Symposium on Bioelectronics and Bioinformations 2011 111–114 (2011). doi:10.1109/ISBB.2011.6107658.

[5] Tian, X., and Z. G. Xiao. "Simulation and control of epileptic EEG via a nonlinear model on Simulink." Proceedings. 2005 First International Conference on Neural Interface and Control, IEEE, 2005.

[6] E. Dong, A. Jansen, and R. Model, “The Multi-frequency EEG Rhythms modeling based on two-parameter bifurcation of neural mass model,” no. 1, pp. 1564–1569, 2014.

[7] 1. Wendling, F., Hernandez, A., Bellanger, J.-J., Chauvel, P. & Bartolomei, F. Interictal to ictal transition in human temporal lobe epilepsy: insights from a computational model of intracerebral EEG. J. Clin. Neurophysiol.**22**, 343 (2005).

[8] C. Bernard, M. Guye, P. Chauvel, and F. Bartolomei, “The Virtual Epileptic Patient: Individualized whole-brain models of epilepsy spread,” Neuroimage, 2016.

[9] S. Geng, W. Zhou, and Q. Yuan, “Bifurcation Phenomenon of Wendling’s EEG Model,” vol. 4, no. 1, pp. 3–6.

[10] B. B. Kemp, A. K. H. Zwinderman, B. Tuk, H. A. C. Kamphuisen, and J. J. L. J. Oberyé, “Analysis of a Sleep-Dependent Neuronal Feedback Loop : The Slow-Wave Microcontinuity of the EEG,” vol. 47, no. 9, pp. 1185–1194, 2000.

[11] M. Koppert, Computational modelling of epileptic seizure dynamics and control.

[12] T. N. De Silva, X. Zhibo, Z. Rui, and M. Kezhi, “Causal Relation Identification Using Convolutional Neural Networks and Knowledge Based Features,” vol. 11, no. 6, pp. 696–701, 2017.

[13] S. Srinivasa, “A review on multivariate mutual information,” no. 2, pp. 1–6.

[14] Ali Shoeb. Application of Machine Learning to Epileptic Seizure Onset Detection and Treatment. PhD Thesis, Massachusetts Institute of Technology, September 2009.

[15] Goldberger, A., Amaral, L., Glass, L., Hausdorff, J., Ivanov, P. C., Mark, R., ... & Stanley, H. E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation [Online]. 101 (23), pp. e215–e220.

[16] Astolfi, L. et al. Estimation of the cortical connectivity by high-resolution EEG and structural equation modeling: Simulations and application to finger tapping data. IEEE Trans. Biomed. Eng.**52**, 757–768 (2005).

[17] Cejnar, P., Vysata, O., Valis, M. & Prochazka, A. The Complex Behaviour of a Simple Neural Oscillator Model in the Human Cortex. IEEE Trans. Neural Syst. Rehabil. Eng.**27**, 337–347 (2019).