**GENETATION OF SYNTHETIC EEG SIGNAL; EVALUATION OF MUTUAL INFORMATION AND CORRELATION COEFFICIENT**

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**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 often utilised 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 to test the characteristics of any such synthetic generated data. The characteristics proposed here are tested with standard data available on online repositories. 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].

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 $h_e(t)$ is given by:

$$h_e(t) = A \left[ e^{-a_1 t} - e^{-a_2 t} \right] \quad a_2 > a_1$$

The brainstem inhibitory transfer function $h_i(t)$ is given by:

$$h_i(t) = B \left[ e^{-b_1 t} - e^{-b_2 t} \right] \quad b_2 > b_1;$$

The spatial statistical function $f(V_e1)$ is given by:

$$f(V_e1) = \lambda_0 g \exp \left[ q (V - V_d) \right] \quad V > V_d$$

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 a number of other major advantages [7,8,9].

### 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 ($C_1$ or $C_2$) of the neuronal population model, the epileptic seizures can be simulated and studied.

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 hypersrrhythmia when the coherence parameters between brainstem and cortex, for example, C₁ and C₂ 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. CHARACTERIZATION 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].

![Typical Recording of CHB-MIT Scalp EEG Data (chb01_01)](image1)

![Typical Recording of CHB-MIT Scalp EEG Data (chb03_01)](image2)

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 \(y\),
- \(p(x)\) and \(p(y)\) are the marginal probability mass functions of \(x\) and \(y\) respectively.

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 data and 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. Events though the difference 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 coefficients | 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 |
|---------|--------------------------------------|
| 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 |
|---------|---------------------------------------------------------|
| Chb01_03| 0.3553 0.3395 0.3585                                   |
| 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.

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