



AN ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM FOR THE PHYSIOLOGICAL PRESENTATION OF SEIZURE DISORDER

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ABSTRACT

Seizure is the clinical manifestation of an excessive, hypersynchronous discharge of a population of cortical neurons accompanied by indescribable "pins- and needles-like" bodily sensations, smells or sounds, fear or depression, hallucinations, momentary jerks or head nods, staring with loss of awareness, and convulsive movements (i.e., involuntary muscle contractions) lasting for some seconds to a few minutes. In this work, an attempt is made to promote a better understanding of seizure disorder by proposing an adaptive neuro-fuzzy simulation model as a tool for capturing the physiological presentation of the disorder. Decision making was performed in two stages, namely the feature extractions using Microsoft Excel for corresponding digital value of the waveform of the EEG recordings of a seizure and those of a non-seizure patient directly from the EEG machine, and the transient features are accurately captured and localized in both time and amplitude. This extracted data were used for our Adaptive Neuro-Fuzzy Inference System (ANFIS) training and the ANFIS was trained with the backpropagation gradient descent method in combination with the least squares method to establish the validity of our ANFIS. The result shows an accuracy of 90.7% of predictions as the number of epochs increase.

Keywords: Adaptive Neuro-Fuzzy Inference System, Electroencephalogram, Seizure Disorder.

1. INTRODUCTION

Derived from a Latin word *sacire* which literally translate to "take possession of", seizure is a discrete, time-limited alterations in the brain functions which involves interruption of motor activity and autonomic function (lack of consciousness). It is the second most common neurological disorder next to stroke, affecting about 50 million people worldwide. According to [1 & 2], 25 % of seizure patient do not respond to available therapies. In the official release of [3], at least 50 % of seizure cases begin at childhood or adolescence, and globally, there are about 2.4 million new cases every year. Sudden onset may also arise in geriatric population (people above the age of 65) [4]. According to the aforementioned world health organization (WHO) source, seizure patients are two or three times more likely to die prematurely as a result of the traumatic manifestations of the disease. Nevertheless, up to 10 % of the population of the world will experience a seizure during their lifetime. Epilepsy is a disorder of the central nervous system characterized by recurrence of seizures, unprovoked by an acute systemic or neurologic insult and is also "an occasional,

an excessive and a disorderly discharge of nervous tissue" induced by any process involving the cerebral cortex that pathologically increases the likelihood of depolarization and synchronized firing of groups of neurons [5].

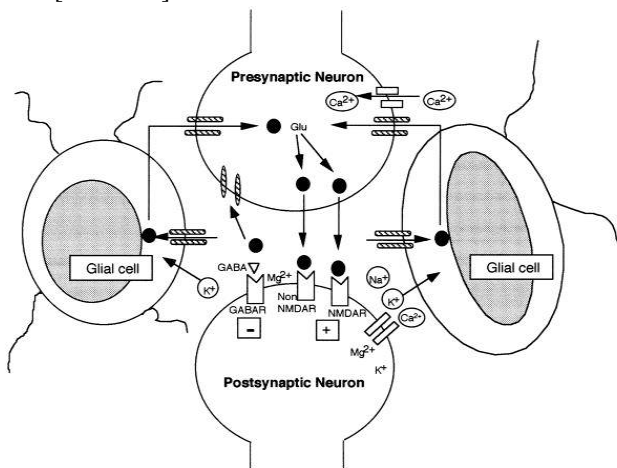
1.1 Neurophysiological Analysis of Seizure

A seizure is produced when neurons within an area of the brain are activated in an unusually synchronous manner. The focal activation of a group of neurons may subsequently spread to involve nearby or distant neurons in an abnormal activation pattern. Thus, any event or combination of events that disturbs the delicate balance between neuronal excitation and inhibition can produce a seizure. According to literature, neurons are interconnected with one another to form circuits and many neural circuits together form a neural system [6]. Neural circuits present information in the form of a pattern of action potentials (discovered by Emil du Bois-Reymond in 1848), and this is the means by which information is transmitted from one point to the next in the nervous system [7 & 8]. However, the basic mechanism of

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neuronal excitability is the action potential and the excitable state can be caused by: increased excitatory synaptic neurotransmission, a decrease in inhibitory synaptic neurotransmission and an alteration in voltage-gated ion channels, or an alteration of intra- or extra-cellular ion concentrations in favor of membrane depolarization. Nonetheless, a faulty circuitry network system can cause excessive firing in a particular neighbourhood of the central nervous system [9].

In general, depolarization is mediated by synaptic currents generated by the excitatory neurotransmitters glutamate and aspartate [10]. Moreover, neuronal synchronization occurs through local enhancement of excitatory circuits and an increase in synaptic efficacy is thought to be due to recruitment of N-methyl-D-aspartate (NMDA) receptors [11]. Furthermore, as more NMDA receptors are activated, further depolarization occurs, additional calcium enters the cell, and excitability is enhanced. However, as these excitatory processes increase, there may be a simultaneous reduction in the activity of inhibitory circuits that are down-regulated during high-frequency activation. Neurons can also be synchronized by extracellular currents that may reflect changes in the perineuronal environment, such as local edema, or changes in the extracellular potassium, calcium, or magnesium concentration [12]. Finally, neurons may also be synchronized by local ephaptic (nonsynaptic) contacts, which facilitate the development of excitatory circuits [13 – 145].



Source: www.pinterest.com/art

Figure 1: Neuro-excitability at synaptic cleft

Excitatory amino acids are released from the presynaptic terminal and act on postsynaptic NMDA and non-NMDA receptors (NMDAR) to cause excitation. Gamma-aminobutyric acid (GABA) is an inhibitory neurotransmitter and acts on postsynaptic GABA receptors (GABAR). However, the glial cells play a central homeostatic role in the control of neuro-

excitation by controlling extra-neuronal potassium concentration and by removing excitatory neurotransmitters such as glutamate (Glu). Neuronal excitability may also be influenced by ions such as magnesium. However, the onset of seizure appears to occur when a small group of abnormal neurons undergo a prolonged depolarization that is associated with the rapid firing of repeated action potentials. These abnormally discharging epileptic neurons recruit adjacent neurons with which they are connected into the process. On the other hand, a clinical seizure occurs when the electrical discharge of a large number of neurons become abnormally linked together, it thus create a storm of electrical activity in the brain. In spite of that, seizure may then spread to involve adjacent areas of the brain or through established anatomic pathways to other distant areas.

1.2 Adaptive Neuro-Fuzzy Inference System

In machine learning and cognitive science, artificial neural networks (ANN) refers to an information processing paradigm that is inspired by the way biological nervous systems, such as the brain, process information (i.e. an eclectic simulation of biological neuron, and it consists of its own dendrites, synapses, cell body and axon terminals), [15]. Nonetheless, it receives stimulation from nearby cells, or from its environment, and generates a modified action potential or nerve signal. It's a system of interconnected neurons working in unison to solve specific problems through a learning process and usually configured for a specific application. Because it has greater predictive power than signal analysis technique, ANN have been used as computational tools for pattern classification including diagnosis of diseases [16 – 19]. Wilson and Emerson [20] used ANN for automatic seizure detection. Xu, *et al* [21], used ANN to classify seizures using radial basis function. On the other hand, [22 & 23] detected epileptogenic transient waveforms by using wavelet coefficients as an input to a feed-forward neural network. In their studies, Guler and Ubeyli [24] and Yaunanghi, *et al* [25] both deployed extracted EEG to identify normal and abnormal EEG using back propagation algorithm.

Fuzzy set theory introduced by [26] plays a vital role in dealing with uncertainty when making decisions in biomedical applications. However, Fuzzy logic and fuzzy set theory are employed to describe human thinking and reasoning in a mathematical framework. According to [27], fuzzy-rule based modeling is a qualitative modeling scheme where the system behavior is described using a natural language. Nevertheless, fuzzy sets have attracted the growing

attention and interest in modern information technology, production technique, decision making, pattern recognition, diagnostics and data analysis to mention but a few [28 & 29]. However, when the underlying physical relationships are not fully understood, the intelligent computational method of fuzzy logic comes to real advantage than conventional crisp modeling.

Neural network and fuzzy logic can be incorporated into a single framework, thereby capturing the prowess of both fields. This however has given birth to a Neuro-Fuzzy system which actually eliminates the basic problem in fuzzy system design (i.e. obtaining a set of fuzzy if-then rules) by effectively using the learning capability of an ANN for automatic fuzzy if-then rule generation and parameter optimization. Neuro-Fuzzy utilizes linguistic information from the human expert as well as measured data during modeling. However, this system can be used for signal processing, automatic control, information retrieval, database management, computer vision and data classification. Another approach in neuro-fuzzy development is the Adaptive Neuro-Fuzzy Inference System (ANFIS), which produced remarkable results in modeling nonlinear functions [30]. In ANFIS, the membership function parameters are extracted from a data set that describes the system behavior. The ANFIS learns features in the data set and adjusts the system parameters according to a given error criterion. However, in the field of Biomedical Engineering, ANFIS has been successfully implemented for: classification [19, 24, 30 - 32], modeling and controlling real systems, [33] and also in data analysis [34].

2 MATERIALS AND METHOD

This study used electroencephalography (EEG): a recording of the electrical activity of the cerebral cortex

through electrodes placed on the scalp. EEG measures the electrical potentials of cortical neuronal dendrites near the brain's surface [35, 36]. Its recordings reveals the epileptiform discharge of a patient with generalized tonic clonic seizure. Conventionally, the electrodes are labeled and each electrode is attached to an individual connector for the onward transmission of signal to the machine. Basically, electrode locations and names are specified by the international 10 - 20 system (Figure 2) for most clinical and research applications except when high-density arrays are necessary. This system ensures that the naming of electrodes is consistent across laboratories, [37].

2.1 Basis for formulating the Model

The EEG data used in this study is a recording of a patient with generalized tonic clonic seizure and the outcome is compare with that of a non-seizure Patient. During the course of the study, the following bipolar channel were selected for analysis: F4-C4, C4-P4, P4-O2, FP1-F3, F3-C3, C3-P3, P3 -O1, FP2-F8, F8 -T4, T4 -T6, T6 -O2, P1-F7, F7 -T3, T3 -T5, T5 -O1. In order to access the performance of the classifier, we selected 129*15 EEG segments of the pages that show epileptiform discharges for the patient with seizure disorder. Both the longitudinal (R) and the transverse (R) montages were considered during the course of this study, and the selected pages include the recording in which the hyperventilation simulation and Photic simulation were done.

Furthermore, two pages were selected from the recordings and each page contains sixteen channels but some portion of the EEG contains Electrocardiogram (ECG) artifacts.

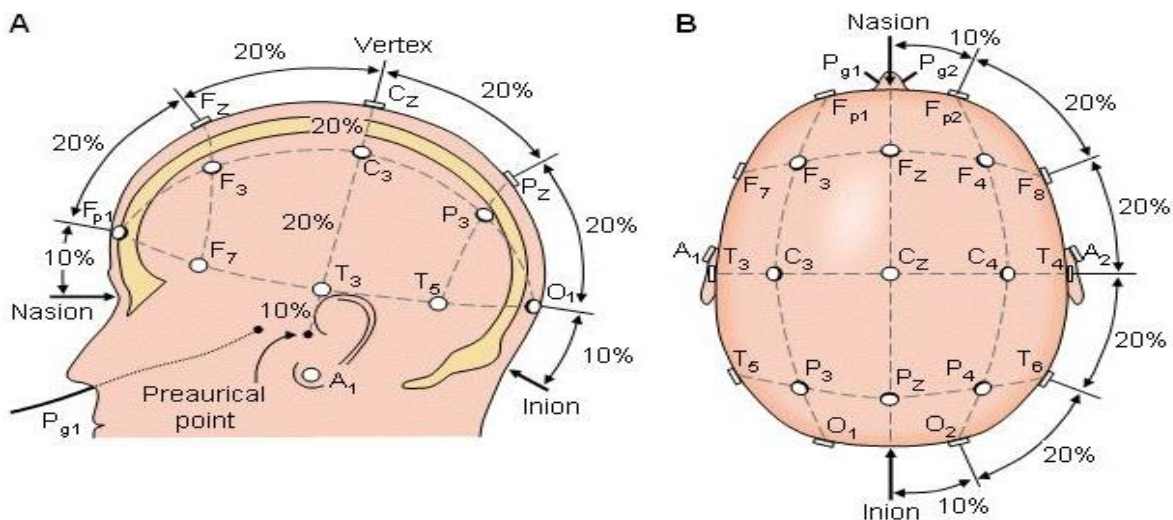


Figure 2: The international 10-20 system of electrode placement. Source: International 10 - 20 system

Therefore, the channel containing the ECG artifacts (i.e. the ECG-REF) channels are not included in our selected channels for analysis. So, a set of fifteen bipolar channels each were selected as inputs from the EEG recordings of a seizure and a non-seizure patients. The abnormal subject is diagnosed of a generalized tonic-clonic seizure with no other accompanying disorders. Recordings were done during interictal stage and the different stages of EEG signals were determined by two physicians. However, EEG data were acquired with Ag/AgCl disk electrodes placed using the 10-20 international electrode placement system. The recordings are band-pass filtered (1-70Hz) EEG, speed of 30mm/s while sensitivity of 7.5 and 10µV/mm for seizure and Non-seizure patient respectively. Every recording was individually inspected by two neurologists together with two technologists with many years of experience in clinical analysis of the EEG signals and they scored the recordings into Seizure or non-seizure. However, the judgments of the four analysts were evaluated and compared twice in order to check if there were disparities in their scoring of the EEG signals. When revising this unified event sets, the human experts by mutual consent marked each state as seizure or normal. Therefore, this validated set provided the reference evaluation to estimate the sensitivity and specificity of computer scorings. Afterwards, the EEG waveform are converted to a digital EEG data (i.e. the digital data corresponding to the analogue data of the selected waveform of the channels of each page is analyzed and are extracted to Microsoft Excel sheet). Each page has 10seconds recording for each channel. Basically, the EEG waveforms are generally classified according to their frequency, amplitude, waveform/morphology and the sites on the scalp at which they were recorded. The digital EEG data used in this study were measured in Amplitude. Amplitude is expressed in terms of voltage in microvolts based on a peak-to-peak measurement and one needs to know the sensitivity at which a recording was made. The amplitude varies with the technique of the recording: the bipolar montages with short inter-electrode distance will give a smaller amplitude than the referential montages with large inter-electrode distance. Ideally, amplitude should be described in terms of the actual voltage; however, the term low, medium, and high amplitude are often used and the same has been adopted in this study: it is low when it is lesser than 20 µV, Medium when it falls between 20 µV and 50 µV and it is considered as High when the amplitude is higher than 50 µV. These digital values are supplied to the Adaptive Neuro-Fuzzy

Inference System as input data set for training. The digital input of patient with seizure has '1' as its output while the patient without Seizure has '0' as its data output.

The sufficiency in the functioning of ANFIS depends on the size of the training set and test set. In this study, we used 258 * 15 features in training and 129 *15 features were used for testing in order to verify the accuracy and the effectiveness of the trained ANFIS for the detection of epileptic seizure in patient with generalized tonic-clonic seizure. And the training data set is different from the test data set in order to improve the general capabilities of our ANFIS.

2.2 Adapting ANFIS to Seizure phenomena

The ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation [38]. In 1993, Jang introduced ANFIS as a model that maps inputs through input membership functions (MF) and associated parameters, and then through output MF to crisp output [39]. However, the initial membership functions and the rule base for fuzzy inference system can be designed by employing human expertise about the target system to be modelled. Such framework makes the ANFIS modelling more systematic and less reliant on expert knowledge. Thus, to present the ANFIS architecture, two fuzzy if-then rules based on a first order Sugeno model are considered:

Rule 1:

$$\text{If } x \in A_1 \text{ and } y \in B_1 \text{ then } (f_1 = p_1x + q_1y + r_1)$$

Rule 2:

$$\text{If } x \in A_2 \text{ and } y \in B_2 \text{ then } (f_2 = p_2x + q_2y + r_2)$$

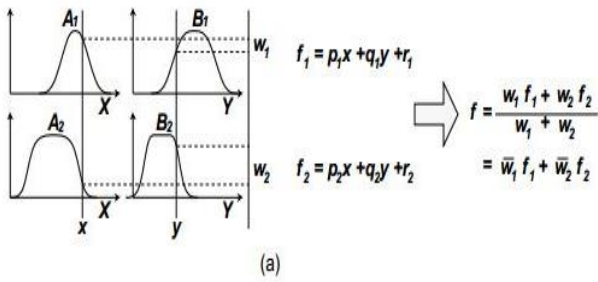
where x and y are the inputs; A_1 and B_1 are the fuzzy sets; f_1 are the outputs within the fuzzy region specified by the fuzzy rule; p_1, q_1 and r_1 are the design parameters that are determined during the training process. Moreover, the ANFIS architecture to implement these two rules is shown in Figure 4, in which a circle indicates a fixed node, whereas a square indicates an adaptive node.

In the first layer, all the nodes are adaptive nodes. Thus, the outputs of layer 1 are the fuzzy membership grade of the inputs, which are given by equations (1) and (2) respectively:

$$O_i^1 = \mu_{A_i}(x); \quad i = 1, 2 \tag{1}$$

$$O_i^1 = \mu_{B_{i-2}}(y); \quad i = 3, 4 \tag{2}$$

where $\mu_{A_i}(x), \mu_{B_{i-2}}(y)$ can adopt any fuzzy membership function.



Source: Xiaomi · Press & Media
 Figure 3: First Order Sugeno Fuzzy Model

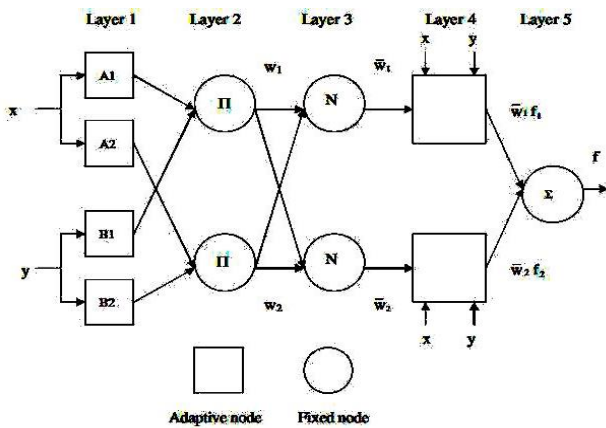


Figure 4: ANFIS Architecture

For example, if the bell-shaped membership function is employed, $\mu_{A_i}(x)$ is given by:

$$\mu_{A_i}(x) = \frac{1}{1 + \left\{ \left(\frac{x - c_i}{a_i} \right)^2 \right\}^{b_i}} \quad (3)$$

where a_i , b_i and c_i are the parameters of the membership function, governing the bell-shaped functions accordingly. However, each node in this layer generates a membership grade of a linguistic label, where 'X' is the input to node. In the second layer, the nodes are fixed nodes. Thus, they are labeled with Π indicating that they perform as simple multipliers. The outputs of this layer can be represented as:

$$O_i^2 = w_i \mu_{A_i}(x) \mu_{B_i}(y) ; i = 1, 2 \quad (4)$$

They are the so-called firing strengths of the rules. However, each node in this layer calculates the strength of the rule via multiplication. In the third layer, the nodes are also fixed nodes. Thus, they are labeled with N indicating that they play a normalization role to the firing strengths from the previous layer. However, the outputs of this layer can be represented as:

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2} ; i = 1, 2 \quad (5)$$

They are the so-called normalized firing strengths. And in the fourth layer, the nodes are adaptive nodes. Thus,

the output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial (for a first order Sugeno model). The outputs of this layer are given by:

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) ; 1, 2 \quad (6)$$

In the fifth layer, there is only one single fixed node labeled with Σ . Thus, this node performs the summation of all incoming signals. Hence, the overall output of the model is given by:

$$O_i^5 = \sum_{i=1}^2 \bar{w}_i f_i = \frac{\left(\sum_{i=1}^2 \bar{w}_i f_i \right)}{w_1 + w_2} \quad (7)$$

However, it can be observed that there are two adaptive layers in this ANFIS architecture namely; the first layer and the fourth layer. In the first layer, there are three modifiable parameters $\{a_i; b_i; c_i\}$; which are related to the input membership functions. These parameters are the premise parameters. In the fourth layer, there are also three modifiable parameters $\{p_i; q_i; r_i\}$; pertaining to the first order polynomial which represent the consequent parameters.

2.3 Learning algorithm of ANFIS

The task of the learning algorithm for this architecture is to tune all the modifiable parameters, namely $\{a_i; b_i; c_i\}$ and $\{p_i; q_i; r_i\}$; to make the ANFIS output match the training data. However, for any premise parameters $a_i; b_i$ and c_i of the membership function, the output of the ANFIS model can be written as:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \quad (8)$$

Substituting Eq. (6) into Eq. (8) yields:

$$f = \bar{w}_1 f_1 + \bar{w}_2 f_2 \quad (9)$$

Insert the fuzzy if-then rules into Eq. (9), it becomes:

$$f = \bar{w}_1 (p_1 x + q_1 y + r_1) + \bar{w}_2 (p_2 x + q_2 y + r_2) \quad (10)$$

After rearrangement, the output can be expressed as:

$$f = (\bar{w}_1 x) p_1 + (\bar{w}_1 y) q_1 + (\bar{w}_1 y) r_1 + (\bar{w}_2 x) p_2 + (\bar{w}_2 y) q_2 + (\bar{w}_2 y) r_2 \quad (11)$$

Equation (11) is a linear combination of the modifiable consequent parameters p_1, q_1, r_1, p_2, q_2 and r_2 .

However, the least squares method can be used to identify the optimal values of these parameters easily. When the premise parameters are not fixed, the search space becomes larger and the convergence of the training becomes slower. Thus, a hybrid algorithm combining the least squares method and the gradient descent method is adopted to solve this problem. Furthermore, the hybrid algorithm is composed of a

forward pass and a backward pass, the least squares method (forward pass) is used to optimize the consequent parameters with the premise parameters fixed. Once the optimal consequent parameters are found, the backward pass starts immediately, the gradient descent method (backward pass) is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. And the output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. Nevertheless, the output error is used to adapt the premise parameters by means of a standard backpropagation algorithm. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS [38 & 39]. Therefore, in the present study the proposed ANFIS model was trained with the backpropagation gradient descent method in combination with the least squares method when 15 channels of EEG waveforms were used as inputs. Finally, the coding of this algorithm is carried out in the MATLAB (R2013a) environment. The program written in the MATLAB editor was based on the source data from the digital extraction of the EEG recordings of patient with seizure and the non-seizure.

3. RESULTS AND DISCUSSION

In this study, the ANFIS architecture consists of five layers, the first layer which is an adaptive node generates the membership grade of a linguistic label, where 'x' in Equation (3) is the input parameter.

However, the Linguistic label (A_i) is classified based on the range of the amplitude namely Low, Medium and High. Thus, we have three input membership variables described by (A_i) viz: low, medium and high for each input channel with the range between 0 and 1. The following graphs were obtained from the data used in training the ANFIS model.

Figure 5 shows the outputs of all the 15 inputs in layer 1 of the ANFIS architecture (i.e. the fuzzy membership grade of all the fifteen inputs), this shows their strength and spread. It maps non-fuzzy input values to fuzzy linguistic terms and vice versa. In Equation (3), a_i, b_i, c_i are the parameter set that determine the shape of the membership function (MF) with maximum of 1 and minimum of 0. However, the red color is for the low amplitude, the green color is for the medium amplitude, while the blue color is for the high amplitude.

Figure 6 represents the ANFIS test result after the first training for a seizure patient. However, the data sets are still far away from the expected output of 1. In Figure 7 shows the ANFIS test result after the first training for a non-seizure patient. However, the data sets were far away from the expected output of 0. Figure 8 is the ANFIS test result after the second training for a seizure patient. The figure reveals that there is converging trend towards the expected output of 1.

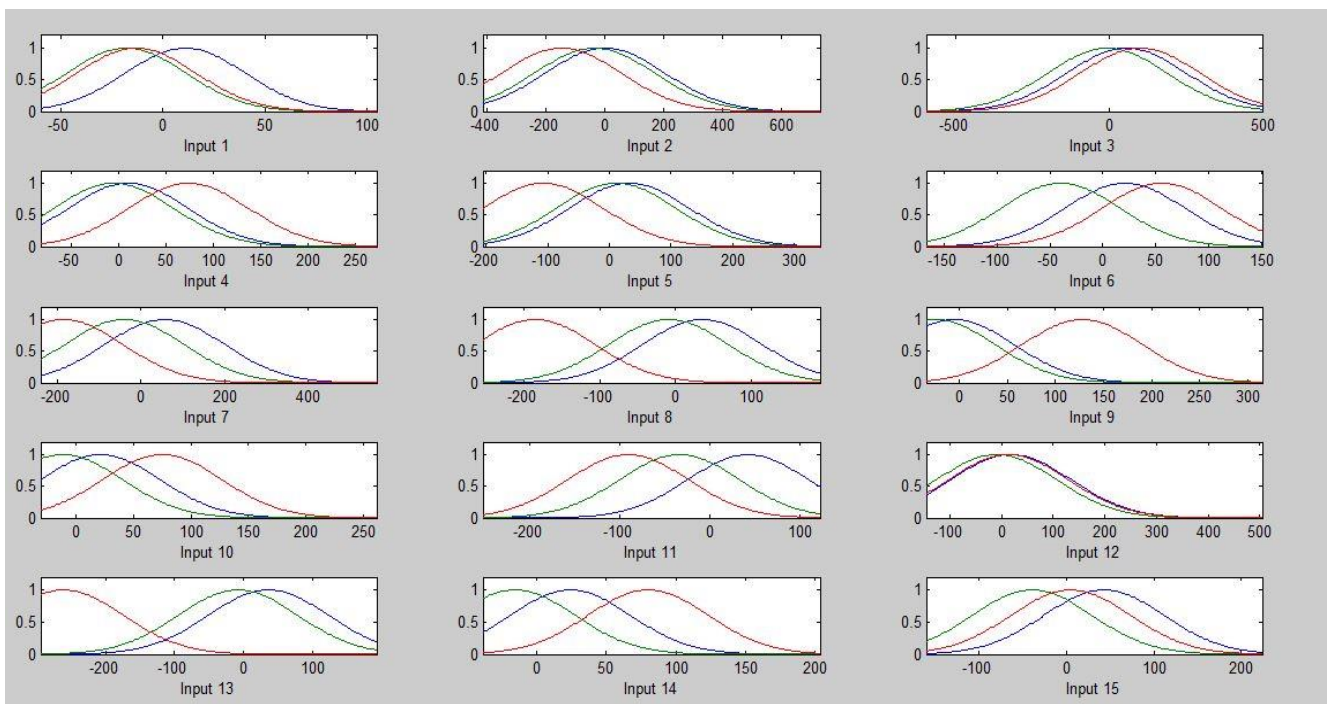


Figure 5: Membership Function for all the Fifteen Inputs

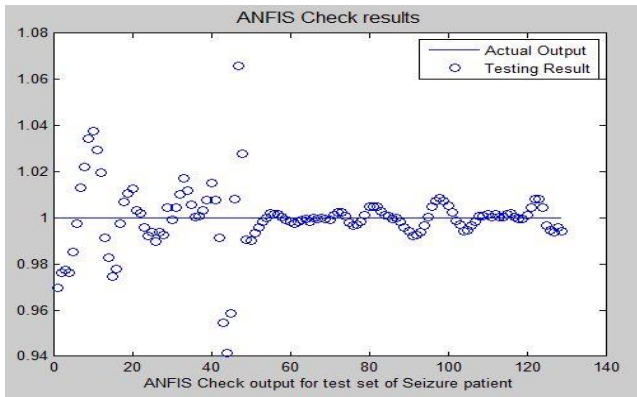


Figure 6: Training test results after the first ANFIS for a Seizure Patient

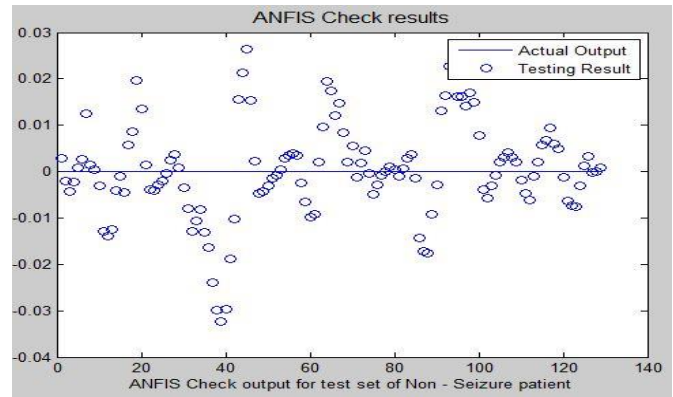


Figure 7: Training test results after the first ANFIS for a Non-Seizure Patient

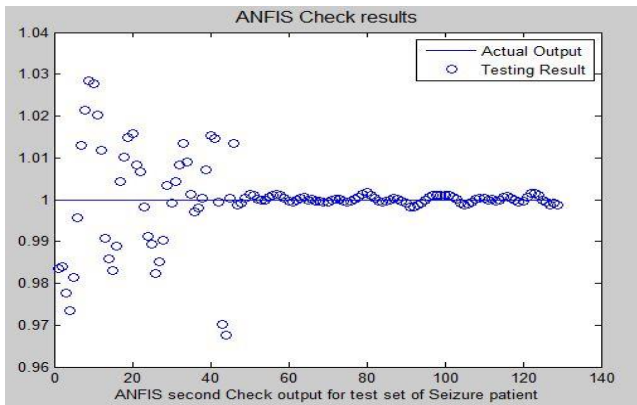


Figure 8: Training test results after the second ANFIS for a Seizure Patient

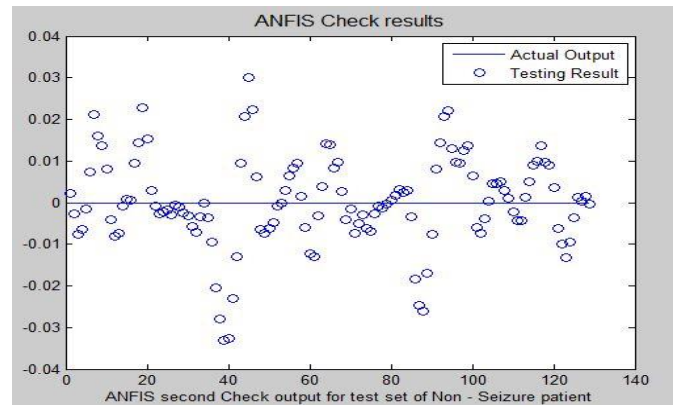


Figure 9: Training test results after the second ANFIS for a Non-Seizure Patient

Figure 9 shows the ANFIS test result after the second training for a Non-seizure patient. The figure reveals that there is converging trend towards the expected output of 0. Figure 10 shows the comparison between the training data and the test data for a Non-seizure patient. Figure 11 shows the comparison between the training data and the test data for a seizure patient. Figure 12 shows the graphical representation of the RMSE for the ANFIS model against the Epoch.

The test performance of the ANFIS model was determined by the computation of the statistical parameters such as sensitivity, specificity and total classification accuracy. The sensitivity, specificity and total classification accuracy are defined as follows:

Sensitivity: The ratio of the number of True Positives (TP) to the sum of true positives and False Negatives (FN).

Specificity: The ratio of the number of True Negatives (TN) to the sum of true negatives and False Positives (FP)

Accuracy: It is the number of patterns detected by the total number of patterns.

Out of the 129 feature vectors of seizure 129 patterns were detected (TP) leaving 0 FN. Also, out of 108 feature vectors of non-seizure 86 patterns were

detected (TN) implying that 22 were not detected. Therefore, the performance of the classifier for normal and seizure conditions are shown in Table 1 and success rate in Table 2 respectively.

Diagnosing epileptic seizure on EEG rely on the detection of a particular signal which requires the observation of the patient, EEG recordings, and gathering of additional clinical information.

Table 1: The performance of the classifier for Normal and Seizure Conditions.

Class	Total Feature	Correctly Detected	Incorrectly Detected
Normal	108	86	22
Seizure	129	129	0

Table 2: Accuracy of the Network.

Test Outcome	Total Feature	Correctly Detected	Accuracy (%)
Specificity	129	129	100
Sensitivity	108	86	79.6
Accuracy	237	215	90.7

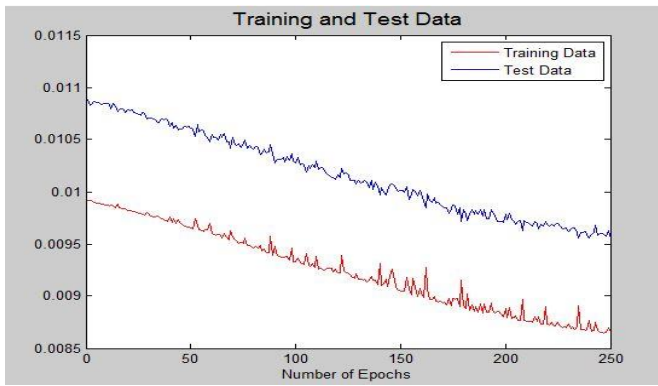


Figure 10: Training Vs. Test data for a Non-Seizure Patient

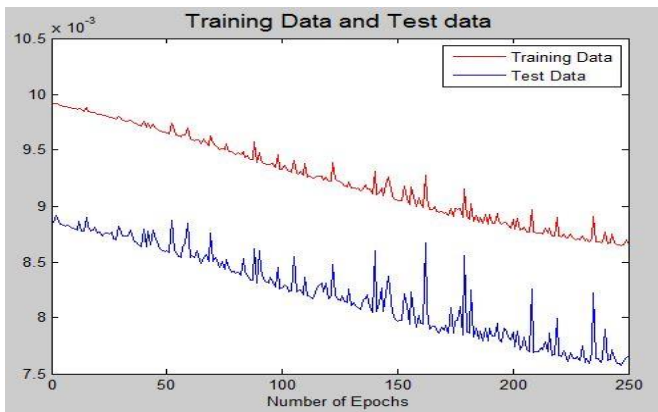


Figure 11: Training Vs. Test data for a Seizure Patient

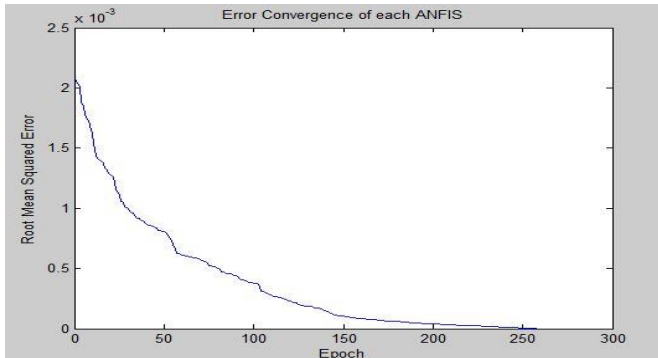


Figure 12: Root Mean Squared Error (RMSE) Vs. Epoch

However, conventional analysis of EEG recordings by a trained professional are very tedious and time consuming especially a long term recordings obtained from an ambulatory recording systems of a patient which includes EEG recordings of up to 1 week period and this can cause errors which may frustrate the outcomes of clinical analyses. Therefore, the advantages of using an automatic detection system cannot be overemphasized. In this study, we described the detection of epileptic seizures from EEG signals using statistical features in amplitude extracted directly from the EEG machine and a diagnostic ANFIS to assist an expert to draw inference from EEG without going through a process of analyzing cumbersome

recordings in real time. This will provide a valuable diagnostic decision support tool for physician treating epileptic seizure. The ANFIS used 258 *15 training data set in 300 training periods and the step size for parameter adaptation had an initial value of 0.0075 with the Root Mean Square Error (RMSE) of 0.0122, the curve of network error convergence of the ANFIS as shown in Figure 12 is 9.1645×10^{-6} . However, the error decreases exponentially as the system epoch increases. The ANFIS performance as displayed in Table 2 shows the classification of normal subject and seizure patient using ANFIS model which were done with the accuracy of 79.6 and 100% respectively while total accuracy of 90.7% is achieved. The classification results, the values of statistical parameters and performance evaluation parameters indicated that testing of the ANFIS was successful.

The phenomenon captured in Figure 11 is the EEG manifestation of the aberrant hyper-excitable state and these delineates the clinical syndrome of Seizure disorder (i.e. paroxysmal depolarization shifts, or interictal spikes) which is an abrupt, all-or-none depolarization which occurred during interictal discharges lasting a few hundred milliseconds [40]. However, it consist of giant Excitatory Postsynaptic Potentials (EPSPs) and these potentials are the excitation and the manifestation of synchronous burst firing of many neurons, and the EPSP builds up from the resting potential to the point of threshold [41]. According to literature, the all-or-none depolarization (i.e. an action potential) propagates down to induce neurotransmitter release at the axon terminal [42 – 44]. However, there exists no such thing as a weak or partial action potential. Either the threshold potential is reached and an action potential occurs, or action potential does not occur [45 – 47]. Therefore, if IPSP fails to match the EPSP, the excessive precipitation of excitatory physiological information (EPI) that could attain threshold level occurs, and this pathologically increases the likelihood of depolarization and synchronized firing of groups of neurons, then a frank seizure activity is initiated.

4. CONCLUSIONS

In this work, a major headway has been made in medical practice by formulating an ANFIS that captures the physiological presentation of seizure disorder for the purpose of analysing its clinical symptoms. Efforts targeted at management of seizure through Electroconvulsive Therapy (ECT) has not yielded any encouraging result due to the fact that the point of trigger of a seizure is not necessarily the same for successive presentation of seizure even for the same

patient. However, it should be possible to deploy an expert system that would be able to manage the Clinical Symptoms of Seizure. To achieve this aim, we have made an efforts to analyze the physiological attributes of Seizure disorder by using an Adaptive Neuro-Fuzzy Inference system so that we could proffer a workable model for the Clinical Symptoms of Seizure. In the nearest future, we hope to develop a management model based on the same paradigm as a pedestal for the development of an Expert system for the management of seizure disorder.

5. ACKNOWLEDGMENT

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7. APPENDIX

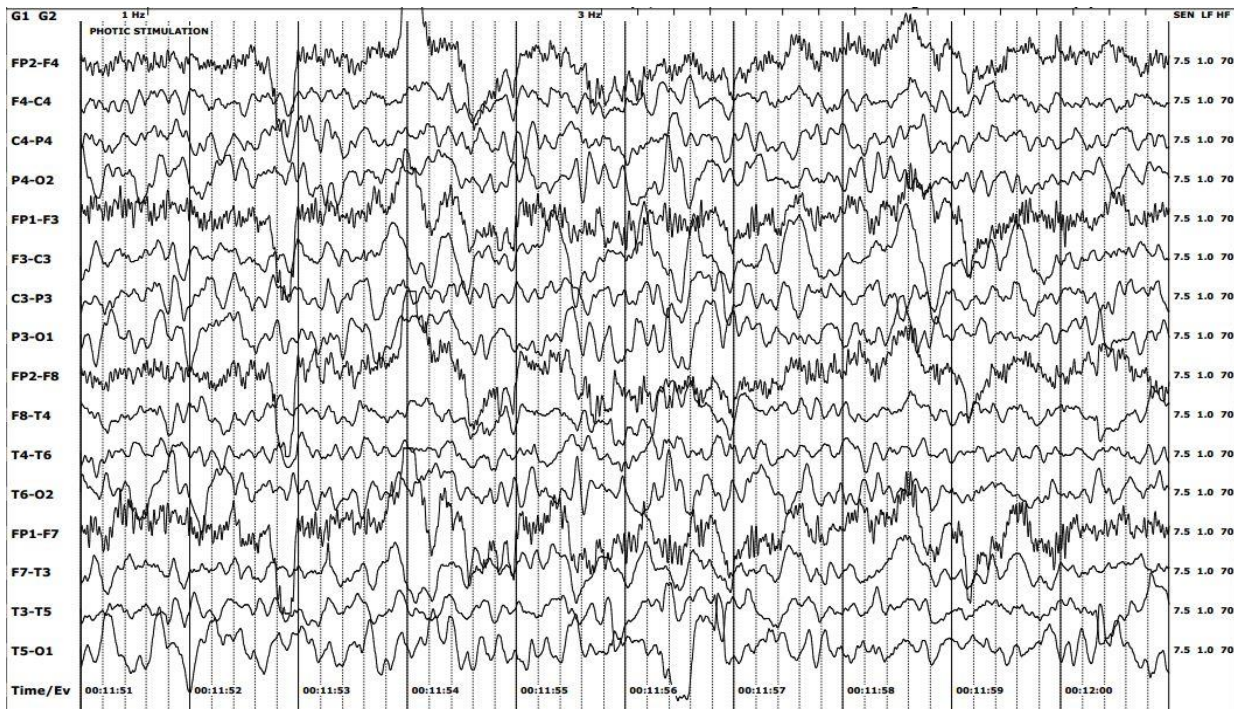


Figure 13: EEG recording of a Seizure patient



Figure 14: EEG recording of a Non-seizure patient

F4 -C4	C4 -P4	P4 -O2	FP1-F3	F3 -C3	C3 -P3	P3 -O1	FP2-F8	F8 -T4	T4 -T6	T6 -O2	FP1-F7	F7 -T3	T3 -T5	T5 -O1
-121	14	-31	-4	-204	-105	52	-416	1	63	-81	-225	22	-26	-31
-191	-53	-75	544	-335	-131	153	-486	-61	256	-177	174	139	-137	55
-313	-173	-136	1429	-557	-177	318	-582	-166	571	-342	820	316	-322	200
-474	-327	-211	2540	-841	-230	523	-683	-300	967	-553	1630	534	-559	387
-661	-495	-297	3773	-1158	-284	743	-777	-449	1401	-788	2529	780	-831	595
-828	-639	-374	4850	-1434	-326	927	-847	-580	1777	-992	3317	1001	-1075	774
-931	-724	-422	5499	-1598	-347	1032	-880	-659	2000	-1113	3795	1137	-1226	880
-961	-745	-437	5685	-1640	-348	1056	-878	-681	2059	-1145	3936	1180	-1272	909
-944	-728	-431	5578	-1606	-339	1031	-859	-668	2017	-1122	3864	1161	-1252	889
-910	-702	-416	5372	-1549	-329	992	-835	-643	1943	-1081	3720	1120	-1207	854
-876	-678	-400	5176	-1495	-320	959	-811	-620	1874	-1043	3582	1078	-1163	823
-850	-659	-387	5022	-1453	-312	933	-789	-602	1820	-1013	3473	1043	-1126	800
-831	-643	-378	4904	-1419	-303	912	-768	-588	1778	-989	3392	1018	-1099	782
-814	-627	-371	4799	-1387	-295	890	-749	-575	1738	-967	3320	999	-1076	765
-794	-612	-363	4683	-1353	-288	867	-729	-561	1695	-943	3240	976	-1052	745
-772	-596	-352	4554	-1316	-282	844	-707	-546	1649	-918	3150	948	-1023	724
-750	-581	-342	4431	-1282	-275	823	-681	-531	1606	-894	3064	921	-994	705
-734	-568	-334	4331	-1253	-268	805	-655	-519	1570	-874	2995	900	-971	690
-719	-555	-328	4245	-1227	-261	787	-630	-509	1538	-856	2936	883	-952	677
-703	-543	-321	4149	-1199	-255	768	-609	-497	1502	-836	2871	864	-931	660
-684	-529	-312	4037	-1167	-250	748	-589	-484	1462	-814	2793	840	-907	642
-665	-515	-303	3926	-1136	-243	729	-573	-471	1423	-792	2716	816	-881	625
-649	-502	-296	3832	-1108	-237	712	-560	-459	1389	-773	2650	797	-859	610
-636	-491	-290	3750	-1084	-231	696	-550	-450	1359	-756	2594	780	-841	597
-621	-480	-283	3666	-1059	-226	679	-541	-439	1327	-739	2536	763	-823	583
-605	-468	-276	3571	-1032	-221	662	-531	-428	1293	-720	2470	743	-802	568
-589	-455	-269	3476	-1005	-215	645	-521	-417	1259	-701	2404	723	-780	553
-575	-444	-262	3392	-981	-210	629	-511	-407	1229	-684	2346	705	-761	540

Figure 15: Data Extraction from the corresponding EEG recordings of a Seizure patient

F4 -C4	C4 -P4	P4 -O2	FP1-F3	F3 -C3	C3 -P3	P3 -O1	FP2-F8	F8 -T4	T4 -T6	T6 -O2	FP1-F7	F7 -T3	T3 -T5	T5 -O1
-58	-16	-39	39	-54	-55	4	-62	-42	22	-69	21	-20	-61	-7
-118	-68	-116	164	-179	-109	113	-261	-119	204	-176	-40	96	-201	134
-214	-143	-235	374	-377	-193	296	-584	-245	502	-337	-133	287	-427	372
-338	-229	-384	646	-631	-300	523	-995	-404	869	-524	-245	532	-716	667
-480	-320	-547	953	-922	-422	770	-1456	-577	1267	-719	-369	807	-1044	985
-604	-398	-687	1225	-1182	-532	983	-1861	-727	1607	-883	-478	1050	-1336	1257
-679	-444	-769	1391	-1343	-601	1108	-2106	-816	1806	-975	-544	1199	-1515	1415
-700	-455	-791	1438	-1392	-622	1140	-2177	-839	1857	-995	-564	1243	-1569	1454
-687	-446	-775	1411	-1369	-612	1117	-2137	-821	1819	-973	-555	1220	-1541	1422
-660	-431	-747	1358	-1318	-590	1078	-2058	-792	1755	-941	-535	1174	-1484	1372
-636	-417	-721	1308	-1268	-568	1042	-1982	-765	1697	-912	-514	1130	-1428	1327
-618	-404	-700	1270	-1229	-550	1012	-1923	-743	1647	-886	-498	1096	-1384	1289
-604	-394	-683	1241	-1201	-537	985	-1879	-725	1605	-862	-486	1071	-1353	1256
-592	-385	-668	1214	-1178	-527	962	-1840	-708	1567	-841	-477	1049	-1326	1226
-577	-376	-652	1184	-1149	-515	940	-1795	-691	1531	-822	-466	1023	-1294	1196
-560	-367	-634	1151	-1116	-500	916	-1745	-673	1491	-802	-453	994	-1257	1166
-545	-357	-617	1120	-1085	-486	892	-1698	-655	1452	-781	-440	967	-1222	1137
-534	-348	-604	1096	-1061	-475	871	-1660	-640	1418	-762	-430	946	-1195	1110
-523	-341	-591	1074	-1041	-466	852	-1627	-627	1388	-745	-422	927	-1172	1085
-511	-333	-578	1049	-1018	-456	833	-1590	-612	1356	-729	-413	906	-1146	1061
-497	-325	-562	1021	-990	-443	811	-1547	-596	1321	-710	-401	882	-1115	1034
-483	-316	-547	993	-962	-431	790	-1505	-580	1286	-691	-390	857	-1083	1006
-472	-308	-534	969	-939	-420	770	-1469	-566	1254	-674	-381	837	-1058	981
-462	-301	-523	949	-919	-412	753	-1438	-554	1227	-659	-373	819	-1036	960
-451	-295	-511	927	-899	-402	736	-1405	-541	1199	-644	-364	801	-1012	938
-440	-287	-497	903	-875	-392	717	-1369	-527	1168	-628	-355	780	-986	914
-428	-280	-484	879	-852	-382	699	-1332	-514	1138	-612	-345	759	-960	890
-418	-273	-473	858	-831	-372	681	-1300	-501	1110	-597	-337	741	-936	868

Figure 16: Data Extraction from the corresponding EEG recordings of a Non-seizure Patient