Detection of Partial Seizure: An Application of Fuzzy Rule System for Wearable Ambulatory Systems.

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Abstract*— Electroencephalography (EEG) plays an intelligent role, especially EEG based health diagnosis of brain disorder, as well as brain-computer interface (BCI) applications. One such research field is related to epilepsy. The EEG based methods are not will designed for pre-occurrence recognition scheme to detect and predict partial seizure for epileptic patients. The system even becomes more complicated if the detection system is to be designed for ubiquitous operations, for the identification of people with seizure disabilities. In this case, the patients are not restricted to the clinical environment in which many devices are involved to the patient externally while he/she can continue daily activities. This paper demonstrates a classification method by using Fuzzy Logic System to identify, predict the Partial Seizure from Epileptic data. Here the paper shows preliminary results of the normal state, pre-seizure state and seizure state of the subject's brain signal data. This can be observed and the algorithm with the detection structure can produce cautioning signals for epileptic seizure.

***Index Terms*— Fuzzy systems, EEG, Seizure, Rule-based system, embedded systems.**

I. Introduction

Detection of disorders from EEG of people with disabilities is extremely important and useful since it can help them to achieve control over a number of aspects of things in their life such as better predictability and thereby, better cure for the seizure disorder. Most of the algorithms can only detect EEG seizure signal in a controlled environment. In this paper, different signal from different seizure case have been detected in various practical scenarios and have been used with Fuzzy classifiers in order to obtain a better classification/detection of a specific type of partial seizure. This will help in developing a more generalizable solution as a low cost wearable EEG monitoring and predicting system for the people with partial seizure disabilities. The alarm and notification system is a subset of such a system. A significant advantage of this system is that all the filtering and preprocessing is done by the main sensory unit, Emotiv headset and the SDK [1]. This helps in simplifying the process and reduces the cost in the initial stages of such study. From initial demonstrations of EEG single-neuron-based device for detection of partial seizure, researchers have gone on to use electroencephalographic, intracortical, electrocorticographic, and other brain signals. When it comes to more advanced prediction systems, tools like, Image processing-Virtual computing, multi-channel BCI were used. As a part of BCI, statistical pattern recognition, Type-2 Fuzzy Logic, spatial analysis, artificial intelligence was implemented and tested [2-6]. When it comes to T2-FLSs, it is recommended to be used for uncertain data and its modeling. Interpretability and transparency of models are attained by this technique. In some methods, wave signal features such as amplitude or frequency data from the EEG sensor EEG signal are stored to a database for comparison of the former vectors, which express the classification features. When it comes to any fuzzy logic technique, for each epoch, the functions of the membership functions are determined; and from which the score of membership (maximum degree) is calculated and further used to classify. Most of them have used language as C programing to implement this. Some system utilizes signals from a focused region of the brain in order to determine the possibility of having seizure; one such region is the parietal zone. Few systems followed the clinical environment, the EEG data (signals) are well optimized with external waveforms; using similar trigger related voltages. Spatial data is reduced in some algorithms whenever an EEG waveform is no notified by the system. Here while the spatial resolution is reduced, there is an increase in noise level of the input signal. Due to synchronous activation of thousands of neurons has low SNR (Signal to Noise Ratio), the accuracy of the BCI. In all the methodologies mentioned above require huge computational capabilities and would be very difficult to implement in near real-time ubiquitous system, moreover it will add cost especially if we intend to develop cost effective systems. Hence in this proposed system, we introduce low cost EEG partial seizure detection and prediction system by using Fuzzy logic interface to classify partial seizure.

II. Over All System

In order to detect and determine Normal state, Pre-seizure state and Seizure state of a patient data from a EEG data depository or real-time Epoch EEG sensors, a system is developed to overcome limitations such as simple processing which can be done in a simple microcontroller, communication with nearby clinics if case is critical and for appropriate control action. The work demonstrates a part of the whole work, in which here the detection of the partial seizure in EEG signal in different environments and cases. Specifically, less noisy environment, short thought of command, long command thought, command thought while in another action and command action while talking. This gives a very good data EEG sets to evaluate the responsiveness of the system for partial seizure.

Fig. 1. Overall System with all the blocks

The Figure 1 shows the general experimental setup. The aim of figure 1 is to acquire the EEG waveform either by commercially available cheap EEG headset or from EEG database to produce waveforms signal from the subject linked circumstances and investigating the EEG trying to predict the partial seizure. Even if research development kit headset from Emotiv provides data from 14 electrodes, the final version of the wearable prototype will only be equipped with most prominent two channels (F8 and FC6) for simplicity of computation for the microcontroller in experimentation.

Since the aim of the system is to predict seizure by EEG signal using fuzzy logic controller, in the first place we need to tap the EEG signal from the brain. For this purpose we are using Emotiv EPOC EEG research headset. This is used to identify a particular signature for a particular emotion, feelings or command in real-time to classify those brain patterns. The software development Kit provided by the manufacturer contains an analyzing software, an EEG sensor headset. This headset contains fourteen probe and CMS, DRL as references with P3, P4 positions. Another feature of this head set is that it is a wireless headset. The probe channel names follow International 10-20 probe location.

The data used here for the Seizure patients are from the CHB-MIT EEG scalp data depository. This database consists of EEG data of 22 patients from children's hospital at Boston. The database consists of 129 files with one or more seizure amounting to 129 cases with one or more pre-seizure. The file format is as '.edf'. Here the sampling rate of the signal per second is 256. And the resolution is 16 bit.

A local file of 24 patients which contains one or more pre-seizure and seizure have been saved in .txt extension file. And this file is accessed from MATLAB. We have found that from all the fourteen channels, the channel at the right fronto-temporal which is F8 and FC6 have shown good response. Hence we have taken data from this two channels and applied distribution techniques like Mean, Variance, and Sum of elements, Standard deviation, Skewness, Kurtosis and Entropy. For all the data sets, we got a resultant matrix of after applying all these filters.

III. The EEG Signals

The patient was asked to wear the EEG probe headset for tapping the signal from the brain and sending the signal wirelessly to the EEG SDK in the computer. This file is then saved as an excel sheet in real time. This this file is then accessed from the MATLAB. The physical situations of the patient was in a sitting posture waveform, has been used as the reference state of the subject in the presented work.

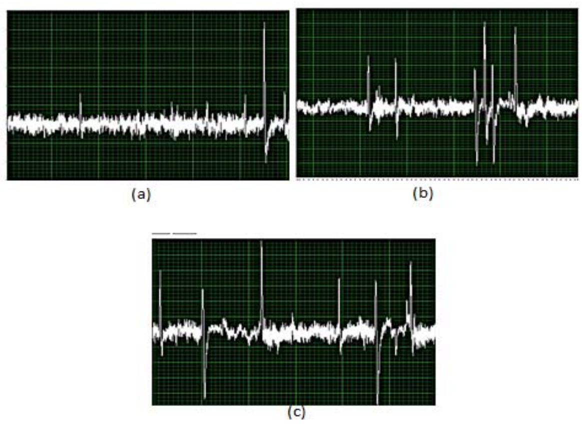

Fig. 2. EEG Signals of a patient: from probes F8 and FC6 (a) Normal, (b) Pre-seizure state and (c) Seizure.

The data from the Emotiv headset shows large noise. This shows that the sampling and the waveform data symbolize the raw dataset of the EEG excluding any preprocessing in it. Thus five different sets are nominated for classification and identification.

IV. Proposed Algorithm

The raw EEG data is taken from the data depository of each of the patient randomly; therefore we have each EEG data set from the 24 patients [7]. Here for all the patients, the first channel (FP1-F7) has been selected in the initial stage with the data value of 10 seconds each. This is done in order to reduce the load on the embedded processor later on. In order to test our algorithm's capability to clearly distinguish the signal even if the noise exists, will be one of the challenges for this paper. Figure 3 indicates different modules of the main algorithm used in this paper for this classification of thee EEG signals shown in Figure 2 (a)-(e).

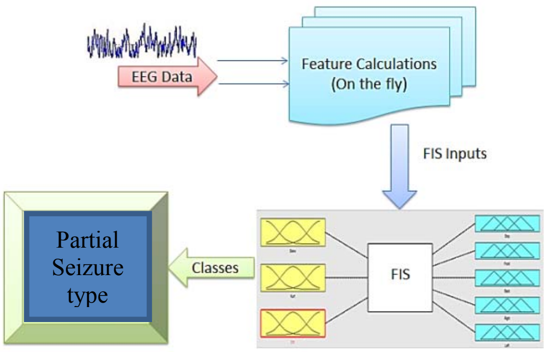

Fig. 3. Overall block diagram of the Fuzzy Classification System.

As a preprocessing, we design a low pas filter, into which the raw data will be passed into. The signals which falls in channel 1 (FP1-F7) from the database is selected and then passed into Delta low pass FIR Filter , from 0Hz to 4 Hz of order 31. This will be ideal for a low cost microcontroller in consideration with low computation power. This is followed as a standard procedure for all the 24 patients' iterations. This is done for the 10 seconds raw data window for normal, pre-seizure and seizure data set. Once the classification is solid, we have applied for the whole window of the raw data signal. This enables us to divide the signal into segments of frequency. This also enables us to suppress higher frequency components. Once the filtered signal is passed to the statistical tool box, we can make the classification possible for the Fuzzy Inference System.

V. Fuzzy Inference System

If we need to quantify perception of the human with respect to the 'common sense' information and its understanding by the perception of the surgeon, then Fuzzy Logic is the best tool for serving this purpose and to obtaining a better classification. The MATLAB is used for Fuzzy system is obtained by using Fuzzy Logic Tool; Fuzzy Inference System (FIS) is developed with this bundle. Crisp values are not considered unlike the binary logic distinctions. When considering structure and its functionality, it is an innovative application for clinical data research; and also influential because it has the ability to interpret human expert heuristics as an input data of quantitative in nature to the system and consequently into useful estimates.

Since the ultimate technique's usage is in an embedded wearable form, hence, there is a need for measures or Features that can be calculated quite quickly and recursively. Also, for the selected four classes of the outputs, it was found that only the EEG signal and the three feature selection technique output would be sufficient for the required classification. The proposed FIS system consists:

- Two descriptors-membership as input (feature space representation as SF0 & SF1). Here SF0 represent the Variance, SF1 represents Entropy of the original signal.
- Three descriptors-membership in lieu of cases and;
- A set of 5 rules that represents the heuristically combinational model of the membership functions with historical understanding of the human user in the domain under study.

The membership function of the input, in which the grouping is individual, is represented in Figure 5(a)-(c). Initially, the EEG data obtained from the database were categorized into feature set of three. For these groups, we need to find the data class boundaries between them, for this purpose, we have applied C-Mean Fuzzy clustering. For each class (data set) of the input-membership this value of the boundary is used in order to formulate the rule of the system. In the trapezoidal fuzzy function, the boundary value shows the midpoint of every distribution of the membership. For better distinction, a gradient of 20% altogether is induced on either side. A mathematical map can represent each degree that will point to input value with respect to functional degree to have a 'fuzzified' input data. Figure 6 shows output FIS variable, which indicates membership of degree three reflecting the three status of the brain (normal, pre-seizure and seizure). In each of the memberships, the triangular distributions are evenly distributed. These distributions are in degrees of: (a)'Un-likely', (b)'Likely', and (c) 'Highly-likely'. For all the curves, the horizontal axis shows value of the input for every function of the membership and the vertical axis represents Boolean range (0-1) of the probability.

Centered with respect to heuristics(visual), six 'rule' are developed by using degree of the membership and logic high or low (1-0) is performed for specific type of input bundle, which corresponds data linked from membership function a decision that is either normal, pre-seizure or seizure is generated in combination with other decision-rule. This produces a final decision surface. This rule is further taken into consideration with the decision of the physician's heuristics and a logical 'AND' operation is performed for the final decision; here mathematical model or statistical decision boundary is not used by any of the rules.

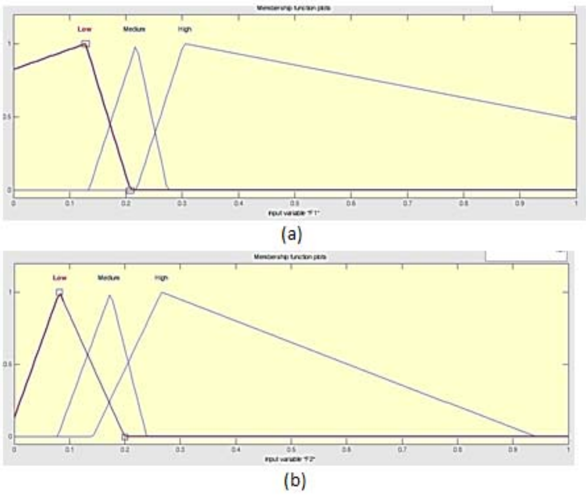

Fig. 4. Membership functions (Input); (a) SF0, (b) SF1.

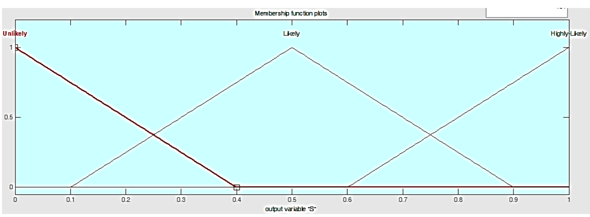

Fig. 5. Output Membership function.

TABLE I. RULE-BASE FOR OUTPUT CLASS INDICATION.

Variance(SF0)	Entropy(SF1)	Output
High	High	Pre-Seizure
Low	Low	Seizure
High	Medium	Normal
Medium	High	Normal

The decision surface is calculated after the instructions based on the rule are designed. Here the centroid is obtained for the each group of input variables, which is then used where ever decision rule overlaps with the decision surface for the memberships of the input. Centroid is a significant value which indicates the degree where the inputs points to the rule-base. Rule-Base for Output Class Indication This ultimately provides a value that represents output degree.

After the fuzzy classification is made, and when a clear differentiation is made, the data is passed from the laptop to the remote server or to a user mobile console for notification of the seizure disorders for monitoring and logging purpose.

VI. RESULTS AND CONCLUSION

Here about 93% exact recognition of normal, pre-seizure and partial seizure form the data set was obtained. Other data of patient can be included for classification and identification by using fuzzy system. In this work, a heuristic control is offered to achieve economically viable classification technique to distinguish real-time within the EEG data set of the signal. This system can be a classification engine or a predictor system for people with specific type of seizure disabilities. This algorithm is underway to be incorporated into an embedded microcontroller and develop in a wearable form so that the patient can be monitored wirelessly on the fly, 24/7 along with other day to day activates. By this system, we can expand even to detect other types of clinical signals.

Since overall methodology in this paper is unique, the results are useful and interesting since it can distinguish the important unique signature of data in signal , which can be used to predict the later state in the signal, then detect and then to notify. The actual function of the rule can be read from the matrix directly. For this case, other grouping for output characterization can also be obtained for these memberships, and there is room for scope.

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