Intelligent Fuzzy Classifier for Pre-Seizure Detection from Real Epileptic Data*

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Abstract— **In this paper, a classification method is presented using an Fuzzy Inference Engine to detect the incidences of pre-seizures in real/raw Epilepsy data. The system distinguishes between 'Normal', 'Pre-Seizure' and 'Seizure' states using on-the-fly calculated features representing the statistical measures for specifically filtered signals from the raw data. It was noticed that for a large number of cases, the seizure waveforms manifest higher energy components during the seizure episodes as compared to the normal brain activity in specific bands of frequencies. Same is also true for a separate band of frequency where the energy levels change from higher to lower when a patient goes from Normal to a Seizure state. This fact has been exploited in this paper and specific filter has been developed to isolate the seizure band. The Fuzzy inference system (FIS) has been developed on the calculated measures for the filtered signal from this band and classification is performed on the basis of certain experimental thresholds. The complexity of calculations has been kept quite low which makes the algorithm highly suitable for implementation in a small micro-controller environment with near-real-time operation. This gives a more practical functionality for such a system to be used in a wearable fashion over the existing Electroencephalogram (EEG) based seizure detection systems due to their complex pattern classification methodologies. Based on the presented technique, a wearable ubiquitous system can be easily developed with applications in personal healthcare and clinical usage. In this case, the users are not necessarily restricted to the clinical environment in which many devices are connected to the patient externally. The wearable devices allow the user to continue daily activities while being monitored for seizure incidents. This will provide them with a window of 30 seconds before a seizure would occur. Although, a small amount of time, but can be very useful for the patient to change his/her position in order to avoid additional harm that could be inflicted on them while they are seizing. For example, a person is driving or handling power tools can stop, a person carrying a baby can lie-down, etc…**

Keywords—Fuzzy Classifier; Partial Seizure; Wearable; Embedded system; Seizure; Wearable system; classification; filters

I. Introduction

Epilepsy can be described as a brain disorder, in which the brain cells starts malfunctioning, leading to the generation of sudden burst of abnormal electrical signal impulse activity, which ultimately results in changes or complete loss of awareness. Over the past two decades, Seizure detection using signal processing techniques and its categorization remained a vital issue for researchers. Researchers from various institutions have tried to identify signal characteristics of different types and features of different domains and to categorize the segments of the signal based on the identified features. Therefore various automated spike detection approaches have been developed. The physiological aspects of seizure generation, the cure and monitoring of a seizure are important issues that need to be considered.

The advantage of wearable monitoring systems is that it will facilitate and enable ubiquitous monitoring and active personalized health management of the health conditions of a seizure patient [1]. This will lead to the development of a more generalizable, fast processing solution as a low cost wearable EEG monitoring and predicting system for the people with partial seizure disabilities [2]. Wearable healthcare gadgets, such as heartbeat monitoring, elderly monitoring, etc… will definitely play an important role in shaping the future of personalized healthcare. For the prediction of seizure, brain signal decrypting devices are used to search for the pointers to seizure [3]. When it comes to real-time monitoring of the EEG signals, simpler probes such as commercially available Brain Computer interface (BCI) headsets can also be used [4] due to the nature of processing and application involved. In ambulatory setting, the commercially available EEG recording systems are not optimized when it comes to initiating rehabilitations or alarm activation and to prevent seizure spreading [5]. Hence in this proposed system, a low cost EEG partial seizure detection and prediction system has been introduced by using Fuzzy system to classify and detect pre-seizure state and to notify, the user and/or healthcare giver, on the fly.

II. Proposed System

The main issue in EEG based implementation is quantifying and evaluating the waves from the EEG data depository to classify normal, pre-seizure and seizure signals individually [6]. Fuzzy classification algorithms can be implemented in an embedded system setting [7], to carry out intelligent task such as detection of pre-seizure state while maintaining ubiquitous/wearable form factor. This allows for the notification to the hospital or nearby clinic for immediate response and the EEG signal acquired during the seizure episode since the seizure EEG signals at the time of occurrence are very critical to make an evaluation by the neurologists.

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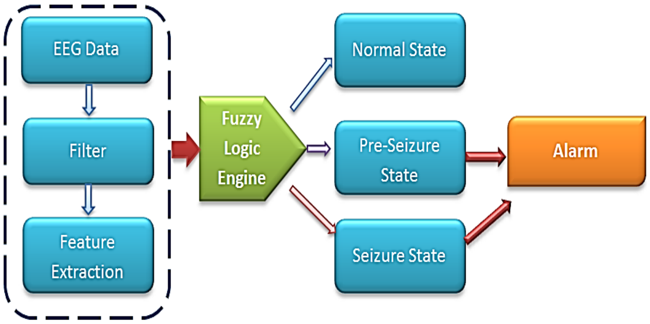

Fig. 1. Overall System with all the functional blocks.

In Figure 1, a generalized system is shown in which the raw EEG data is first passed to a specific filter. After the filtering, the data is passed to the Feature extraction module that uses statistical classifier. Once the features are obtained, they are passed on to the Fuzzy inference engine to distinguish/detect the pre-seizure, seizure and normal state EEG signal. If the signal falls in pre-seizure or seizure zone, then an alarm is triggered to notify.

For the initial test of the system, the data used here for the seizure patients are from the CHB-MIT EEG scalp data depository [8]. This database consists of EEG Seizure signals of 24 patients from Children's Hospital in Boston, Massachusetts, USA. This database consists of 129 files with one or more seizure amounting to 129 cases with one or more seizures. The sampling rate of the signal is 256 Hz, and the resolution is 16 bits. This raw EEG data is selected from the data depository of each of the patient randomly. From all the patients, the channels that have been selected in the initial stage are (FP1-F7), (T7-FT9), (P7-T7), (FP2-F8), (F4-C4), (FP2-F4), (C3-P3), (PF-01), (T7-P7) and (F7-T7) and are referred as P1, P2, P3, P4, P5, P6, P7, P8, P9 and P10 respectively. The signal durations were experimentally selected to be 60 seconds for pre-seizure and normal state and 90 seconds for seizure state as shown in Figure 2. These channels were selected because they showed most prominent seizure characteristics amongst the multichannel EEG signal data set.

The actual positions of the seizures are indicated in the data set by the doctors and are used as truth class for developing the algorithms. For example for the dataset 'chb01_03.edf' of patient-1, it is stated that the seizure point in the dataset of that particular patient is at 2996 seconds after the data has been acquired, until 3086 seconds and returns to normal state there on; therefore in our system, the normal signal is until 2936 seconds time line of the dataset and the pre-seizure is in between 2966 and 2996 seconds interval reference in order keep the seizure signal clean from the normal signal and to divide the signal pre-processing stages. These signals are passed to a digital band pass filter, with a lower cut-off frequency of 25 Hz and a higher cut-off frequency of 35 Hz; generally seizure activity is testified to be prominent within this range [9], so the pre-seizure can also be observed in between 25Hz and 35Hz. A typical Infinite Impulse Response (IIR) Filter with Elliptic topology of order 10 was designed for this purpose and was built into the embedded settings as multiplier coefficients.

III. FEATURE SELECTION

The proposed technique has been designed in mind to be implemented within an embedded or wearable form factor with lower computational complexities. Hence, there is a need for measures or Features that can be calculated quite quickly and recursively as well as the whole algorithm to be as simple as possible. Several statistical measures were calculated and compared between the filtered signal and the frequencies corresponding to the non-seizure region, i.e. the band from 0 to 25 Hz. These measures include: Skewness, Arithmetic Mean, Kurtosis, Mode, Root Mean Square, Median, Standard Deviation, Sum of Values and Variance.

A threshold-based decision on certain statistical measures was made the classification possible using a simple look up table. Two features were isolated from the above list since they showed maximum differentiation of the two output classes and were found sufficient for the required classification. These are: Kurtosis (K) and Summation (S).

From the EEG data set, after passing through the statistical tools, both the Kurtosis and Summation property of the signal showed some distinguishable dynamics when it reached the point of pre-seizure and seizure. The low frequency components of the EEG signal vanished or significantly reduced.

At the same point, the Kurtosis of the EEG signal showed a spontaneous average rise in threshold from 5 to 15 in their value whereas the Summation showed a sudden average drop in threshold from 0.8 to 0.2 in their value, as shown in Figure 3.

IV. THE FUZZY INFERENCE SYSTEM

In order to quantify perception of the human with respect to the 'common sense' information and its understanding by the perception of the surgeon, the Fuzzy Logic serves to fulfill this purpose and to obtaining a better classification.

After undergoing the above process of pre-processing the signal, the calculated features are given to the fuzzy inference engine. By using fuzzy system, one can eliminate the issue of set-point setback within the embedded system due to noise.

Figure 4 indicates different modules of the main fuzzy algorithm. When considering structure and its functionality, it is an innovative application for clinical data research. The algorithm is sophisticated enough since it has the ability to interpret human expert heuristics as Rules of decisions. Initially, the EEG data obtained from the database were categorized into feature set of two. For each class (data set) of the input-membership this value of the boundary is used in order to formulate with the rule-base of the system.

In this fuzzy inference system, a triangular fuzzy set is used, where the number of points is closer to the center or the peak (middle) with a taper towards the sides.

The cloud of points around the center has maximum density with the cloud density thinning towards the sides of the set. The distribution of points on the support of the fuzzy set is taken as a means to evaluate the fitness of the set as shown in figure 5.

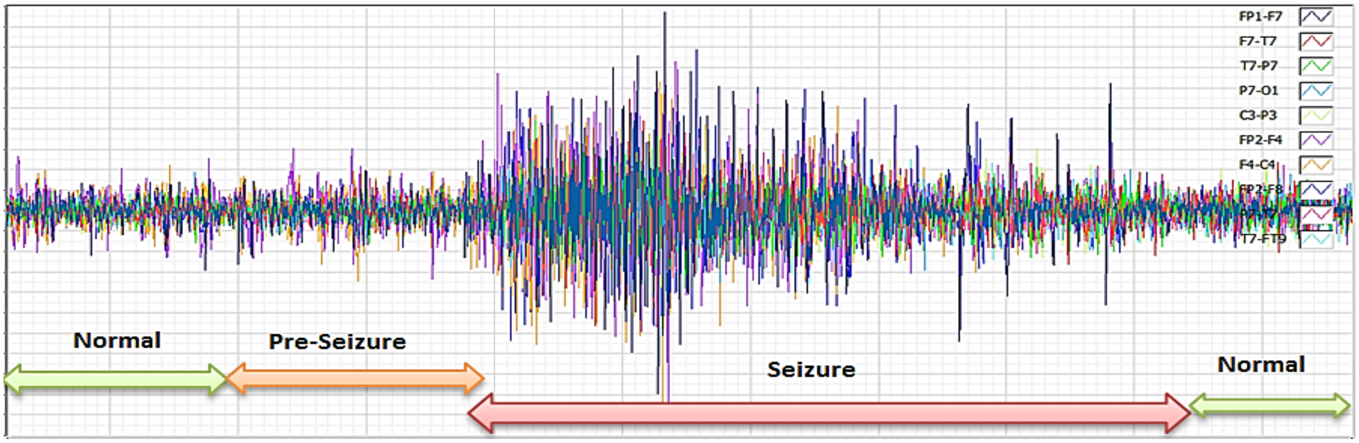

Fig. 2. EEG signal which consist of Normal, Seizure and Pre-Seizure Signals from the channels (FP1-F7), (T7-FT9), (P7-T7), (FP2-F8), (F4-C4), (FP2-F4),(C3-P3),(PF-01), (T7-P7) and (F7-T7) for classification.

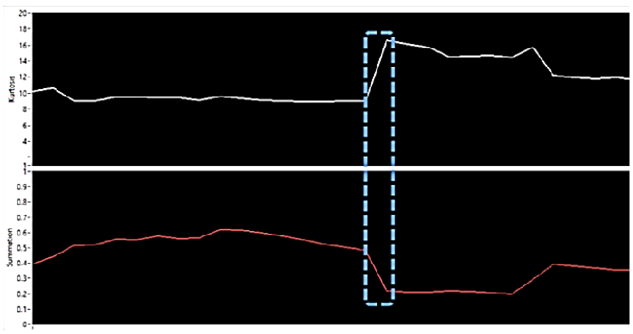

Fig. 3. The dotted region shows the place where Seizure class discrimination is seen quite obviously of the Kurtosis and Summation respectively.

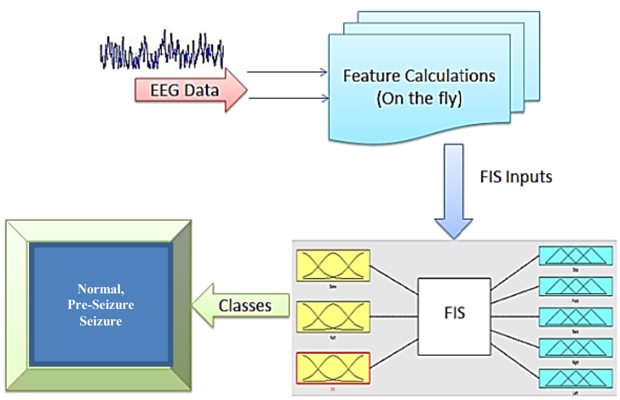

Fig. 4. Block Diagram of the Fuzzy Engine System.

A mathematical map can represent each degree that will point to input value with respect to functional degree to have a 'fuzzified' input data. In the output FIS variable indicates membership of degree three (three membership functions) reflecting the three states of the brain (normal, seizure and pre-seizure). For each of the Output memberships, the triangular functions were arranged such that the output classes are evenly distributed. These distributions are in degrees of: (a)'Un-likely', (b)'Likely', and (c) 'Highly-likely' as in Figure 6.

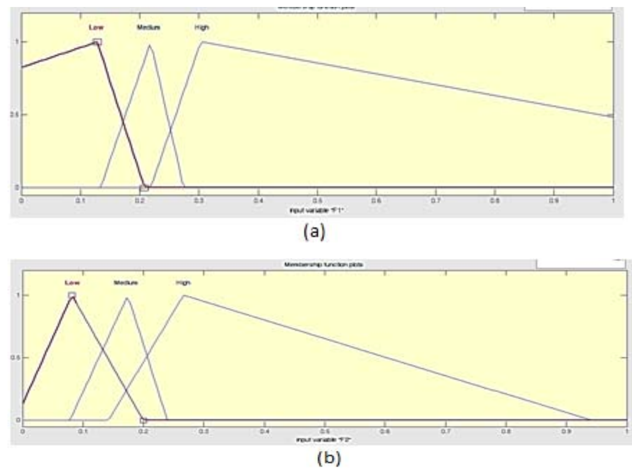

Fig. 5. Membership functions (Input); (a) Kurtosis, (b) Summation.

For all the curves, the horizontal axes show values of the input for every function of the membership and the vertical axes represent Boolean range (0-1) of the probability of belonging to that particular membership function. The decision surface is calculated after the overlaps of various membership functions are mapped through the rule-base. At this point, the centroid is obtained for the overlapped region, which is then considered as the de-fuzzified value of the output. Centroid is a significant value which indicates the degree where the inputs points to the rules. This ultimately provides a value that represents output degree.

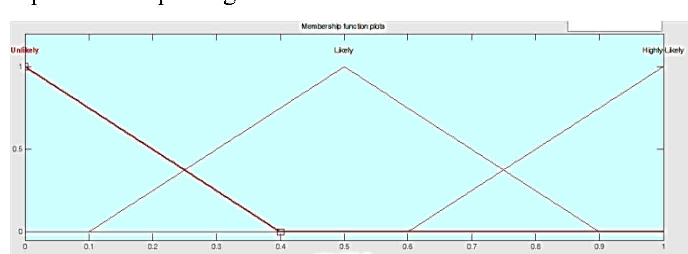

Fig. 6. Output Membership function.

Following the Rule-base used for these features:

*1) If (**K** of P1, P3, P5, P7, P8 is High) and (**S** of P1, P3, P4, P6, P9, P10 is Low) then (Pre-Seizure is Highly-Likely)(Seizure is Highly-Unlikely)(Normal is Highly Un-likely)*

*2) If (**K** of P1 is only High) and (**S** of P1 is only Low) then (Seizure is Highly-Likely)(Pre-seizure is Highly-Unlikely)(Normal is Highly-Unlikely)*

*3) If (**K** of P1 is only Low) and (**S** of P1 is only High) then (Normal is Highly-Likely)(Pre-seizure is Highly-Unlikely)(Seizure is Highly-Unlikely)*

*4) If (**K** of P1, P3, P5, P7, P8 is Low) and (**S** of P1, P3, P4, P6, P9, P10 is High) then (Normal is Highly-Likely) (Pre-Seizure is Highly-Unlikely) (Seizure is Highly-Unlikely).*

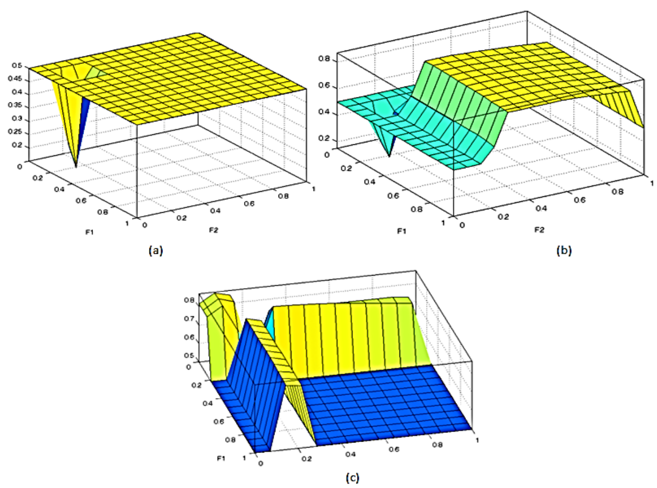

Fig. 7. Decision surface: (a) Normal, (b)Pre-seizure (c)Seizure.

Figure 7 shows typical decision curves that can be pre-calculated for a range of values of input data stream and hence can be stored in the microcontroller system as look-up table which makes it simple and fast.

V. RESULTS AND CONCLUSION

In this work, a Fuzzy Classifier has been developed, with overall 93.47% accuracy of correct recognition of pre-seizure state from the EEG data set with a pre-seizure detection latency of 3 seconds in duration and less than 5% false prediction rate, Specificity of 93%, sensitivity of 93.97% and False Detection rate of 6.98% , derived from in Table1.

In this work, Fuzzy Inference System based classification is offered as an extension to achieve economically viable classification technique to distinguish normal, seizure and pre-seizure signal.

TABLE I. DETECTION RESULTS

Type	Positive	Negative
Pre-Seizure	(TP)109	(FN)9
Normal	(FP)7	(TN)120

This method can be used to design algorithms for wearable device to detect pre-seizure, which will be achieved by making the classification method simpler and helps in enhancing ambulatory EEG monitoring system. This system can be a classification engine or a prediction system for people with specific type of seizure disabilities. This algorithm is being incorporated into a wearable form so that the patient can be monitored wirelessly on the fly, 24/7 while being involved with other day to day activates.

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