Embedded Fuzzy Classifier for Detection and Classification of Preseizure state using Real EEG data.

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***Abstract*— This paper presents a classification technique using Fuzzy Logic Inference System to identify and predict the partial seizure from the epileptic EEG data. The presented work covers the initial findings related to some of the brain conditions in different scenarios so that the detection system can produce warning signals for epileptic seizure. Electroencephalography (EEG) plays an important role, especially EEG based health diagnosis of brain disorder. However, the common clinical approaches fall short when attempting to design an automated system to detect and predict partial seizure for epileptic patients. The situation becomes even more difficult when the detection system is being designed for a ubiquitous application in which the patient is not confined to the hospital and the device is attached to him/her externally while the person is involved in daily chores. Therefore, the work presented here includes embedded hardware system that works with classification algorithm on real EEG signals, in a ubiquitous setting. The performance of the system is shown under various conditions of daily activities. In order to make all this in a ubiquitous form factor, the algorithm for classification and detection of the pre-seizure conditions should be tremendously simple for processing the signal in a low cost ubiquitous microcontroller. This has been achieved in this work through the use of Fuzzy Classifiers based on the lookup table to empower system simplicity. The algorithm also utilizes certain statistical features from the EEG signal that are used as features to the classifier logic. While the clinical testing of the device is still awaited, various scenarios have been implemented using a custom-built hardware simulator based on empirical modeling of the real EEG signals. This shown various performance modes of the system and confirms the detection of pre-seizure state for a number of parameters related to the patients such as age, gender, etc… By using this type of fuzzy logic classifier, we were able to get over 90% accurate classifications for the partial seizure.**

***Index Terms*— Fuzzy Classifier, Partial Seizure, Wearable Devices, Electroencephalography (EEG), Ubiquitous computing, , Brain Computer Interface(BCI).**

I. Introduction

The EEG Embedded bio-signal Fuzzy Classifier is proposed for deploying disorder detection algorithms and signal processing in a portable system [1], by utilizing the power of LabVIEW for testing and to implement it into an embedded Data Acquisition System (DAQ). Patient module can assess the signal and communicate the EEG data sets to a remote system for data processing and identification. Since the bio signal are very complex, and vary from patient to patient, it is important to develop a validating system for the epileptic EEG signal before implementing it into a wearable monitoring system before applying the algorithm into the actual epilepsy detection system, and can be used for fine tuning the and rehearse the product (wearable system). Testing approach is obtained using the dataflow graphical form, with the combination of signal generation from the hardware for simulation of the Partial Pre-seizure EEG signal. This as a platform enables us to focus on the system design, system testing and rapid prototyping, even if lots of other languages for programming are accessible for constructing or generating the analog EEG signals and the specific part of the signal. The control of a rapid transition from a one psycho-physical state to another [4] is easily attainable with an EEG simulator using a Data Acquisition System (DAQ). In LabVIEW, basically the biomedical tool kit provides applications which are Ready-to-run. They in cooperate File Format Converter Player, Bio signal Data logger , Bio signal Generator ,File Viewer, Blood Pressure (BP) Analyzer, Image Reconstruction of image in 3D , Feature Extractor for ECG, Variability Analyzer for the heartbeat rate. All the common file types' conversions are possible like the TDMS extension (National Instruments Technical Data Management Streaming), including ACQ, iWorx, Biopac, .edf, .mat, .txt and HL7. This tool kit is also capable of implementing algorithms for the signal processing on EEG bio signals. It also enables signal simulation of the signal, analysis of coherence and bi-spectral EEG, extraction of specific feature of the ECG, and power analysis of the EMG waveform, predefined virtual simulators for electroencephalography (EEG) and electrocardiogram (ECG). This system helps for the system which can be implemented and for the investigations of tiny, one-channel electroencephalogram systems in an ambulatory setting [5]. We will be using a part of this tool kit only just to validate the LabVIEW program build specifically to test the program data flow and its functionality to generate the pre-seizure signal from the real patient database via a DAQ and to transmit to a in range UN032 microcontroller from Digilent. This microcontroller reads the analog data from the inline analog to digital convertor port.

II. Method and Design

When designing algorithms for low power platforms, with memory constrains and computational limitations [6], graphical FPGA design software play an important role in optimization. First, a dedicated system for this intension is built to improve with respect to the current system limitations, associated to approach of substantial processing, real-time healthcare facility accessibility and proper analysis. In the EEG DAQ simulator, the peak positions are not invariable, but may change from one region to another [7] from patient to patient. Here the procedure to simulate the EEG signal in LabVIEW environment and to detect the presence of healthy EEG and Pre-seizure signal which is to be detected by the cost effective microcontroller is achieved. The selection of EEG zones is simulated with respect to the alarm priority and two states which are also selected for the testing and execution in the initial prototype of the whole system. The LabVIEW program is used to simulate the abnormal EEG morphology [8], in three steps: (i) read the existing files recordings from a database or from the patient in real-time which may or may not contain normal, pre-seizure and seizure signals and (ii) simulate and transmit the EEG signal wired or wirelessly to the microcontroller (iii) the microcontroller will do all the fuzzy computation and generate a notification/alarm when pre-seizure signal is detected by using the algorithm.

Fig. 1. Functional System

In Figure 1, the system demonstrates a general setup for the experimentation and functioning flow. Here, the EEG signal waveform is fed from the LabVIEW to a NI-DAQ, which is available from commercially or for freely available data base which contains normal, pre-seizure and seizure datasets. Any irregular pattern in the data, it reflects that there are abnormal activities in the EEG signal [9] which could be seizure; and the program should be set to activate an alarm with respect to a set point in the program.

III. EXPERIMENTAL SETUP

The simulation of real patient data in real time is obtained using NI X Series or NI-USB from National Instruments, which is a USB compatible device for acquisition and generation of data signals. This multifunctional device have high performance digital I/O, control channels, counter/timers and analog measurement onto the portable wired or a wireless microcontroller (UNO32 in this test bench case). By using this device, we can extend the applications from multiple microcontroller data-logging applications, measurement and portable test. This device has four analog outputs, thirty two analog inputs, four counters and forty eight I/O digital lines. It also has Analog input which is multiplexed simultaneous sampling up to 2 Mega Samples per second per channel. Whereas USB 6008 8 analog inputs (12-bit, 10 kS/s), 2 analog outputs (12-bit, 150 S/s), 12 digital I/O and 32-bit counter. This device supported with flowchart type graphical programming with LabVIEW. In case of real time EEG acquisition of data, we can directly wire the channel signal to the analog input for post processing including classification and identification of seizure types. This device also supports more accurate triggering, advanced timing, synchronization and high speed bidirectional real time streaming of signal and data by using NI-STC3 protocol technology. This protocol supports dedicated digital Input-Output and analog subsystems with independent timing engines for parallel digital I/O and analog to execution at different frequency synchronization with the help of 32-bit counters. This counter can also be used for encoders pulse width modulation (PWM). This device can also be used for recording and analyzing transient time.

The only disadvantage with this DAQ is that if we want to record and analyze more than 4 channels of EEG signals of the real time patients, then we have to use Analog-Digital MUX. So an additional 16 channels can be added. If we wanted to transmit more than four channels by reading from the EEG database to the microcontroller via NI-DAQ, then we have to use parallel 8/16/32 bit Digital to Analog Convertor (DAC). This depends on the number of available digital I/O pins. In this workbench, we have 32 I/O pins; therefore we can create an additional four more ADC ports with a resolution of 8/10/12 bits per channel (in case of 8-bit parallel DAC we use AD5330 from analog devices).

In the subset of the program, the abnormal EEG dataset indicates central nervous system abnormality [11], cognitive states such as alertness and arousal [12]. This system also have the option to acquire in real time via EEG headsets like 128 channel headset or 16 channel head set like the Emotiv, and then transmit to the microcontroller for validation of the algorithm developed in order to identify by classification the state of pre-seizure in order to eliminate false prediction as much as possible. Once the algorithms have identified the pre-seizure, immediately the alarm is invoked in order to take precautionary acts to save the patient/user from more injury or accidents. By using a simulator we can optimize the electrode position in the patient when it comes to implementation of standalone microcontroller system to sense the EEG signal directly from the patient. The lesser number of ADCs input to the microcontroller, the faster the response to invoke the alarm. This also helps in simplify the computational algorithms, moreover frees temporary memory inside the microcontroller.

Fig. 2. NI-DAQ –X Series and NI-USB 6008 Signal Genration Unit for EEG Simulation.

The data from the DAQ is transferred to the microcontroller from the analog output port A01 of the USB-6008 DAQ. The microcontroller used in this setup is the mainboard ChipKIT UN032. This board is based on the popular Arduino™ open-source hardware prototyping platform and adds the performance of the Microchip PIC32 microcontroller. The Uno32 is the same form factor as the Arduino Uno board and is compatible with Arduino shields. It features a USB serial port interface for connection to the IDE and can be powered via USB or an external power supply. The Uno32 board takes advantage of the powerful

PIC32MX320F128 microcontroller. This microcontroller features a 32-bit MIPS processor core running at 80 MHz, 128K of flash program memory and 16K of SRAM data memory. The Uno32 can be programmed using the Multi-Platform Integrated Development Environment (MPIDE), an environment based on the original Arduino IDE modified to support PIC32. It contains everything needed to start developing embedded applications.

Fig. 3. ChipKIT UNO32 Microcontroller.

In mode one (to simulate and experiment external EEG database), the EEG signal with pre-seizure and seizure patients, into the hardware DAQ, the EEG scalp data is used from CHB-MIT database. This EEG depository consists of dataset of twenty three patients (129 datasets with more than one seizure in .edf file format). The database of the EEG signal is provided by Boston children-hospital. The signals are sampled at the rate of 256 samples per second, with sixteen bits of resolution. Since the hardware simulator emulates the patient for the microcontroller, we can specifically select the channel to be transmitted to implement the algorithm on the individual channel to find out the individual response of the channel when processed by the microcontroller. In the microcontroller part, the statistical parameters like the energy, variance, kurtosis, Skewness etc. will be calculated on individual channel depending upon the user. This enables selectivity by the microcontroller.

IV. GENERATION OF EEG SIGNAL

The generation of signal from the EEG dataset is dependent of a number of variables [13]. This dataset changes from subject to subject and this simulator can generate any type of EEG signal. The seizure start points and end points have been clearly described in the database given by the CHB-MIT database. Before sending the test signal to the NI-DAQ hardware, the signal should be checked in the graph to select the start point of the seizure occurrence, manually by entering the values or parsing from a text file which contains an array of the file name, time (ms) and the waveform data. With respect to this, we calculate pre-seizure, seizure and normal EEG. We have arbitrary selected pre-seizure as ten seconds before the incidence of seizure, as per defined from the database. Twenty seconds before the seizure, is the start point of the normal EEG.

In figure 5, the ADC of the UNO32 microcontroller connected to the National Instruments DAQ ADC, the advantage is that it provides flexibility to the user to design our with EEG signal by using the Signal Simulator from the signal processing toolbox or toolkit.

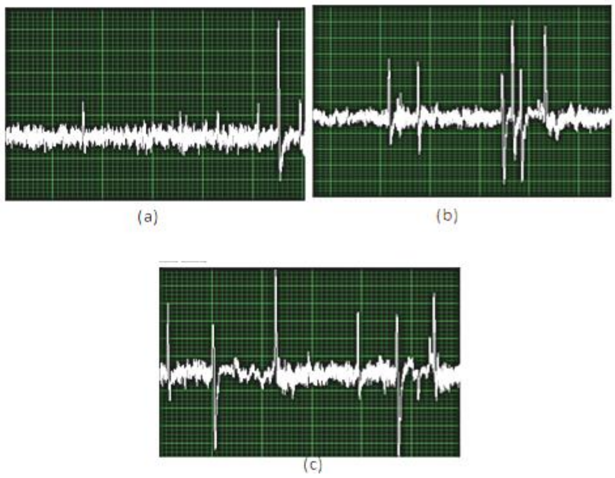

Fig. 4. Sample signal from the EEG data base in labVIEW graph: (a)Non-Seizure, (b) preseizure and ,(c) paritial Seizure.

We can change the frequency, and design filter if needed before transmitting to the microcontroller for classification. In this mode we can also create customized signal equations with respect the approximation model of EEG signal and generate the signal in the LabVIEW user interface program.

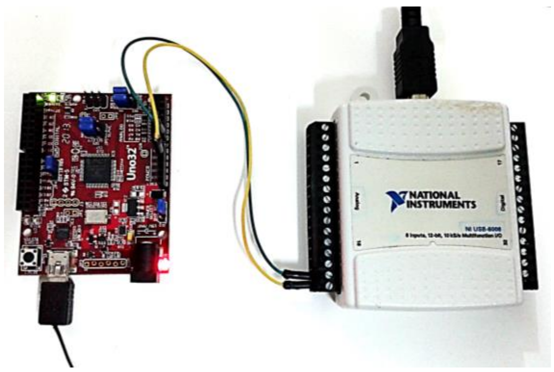

Fig. 5. EEG Simulator system with UNO32 microcontroller for testing.

Here in the figure 7, to Read the EEG signal from the database then normalize pass it to Alpha and Beta filter and calculate the statistical variables of the particular waveform and save it in .txt file for reference.

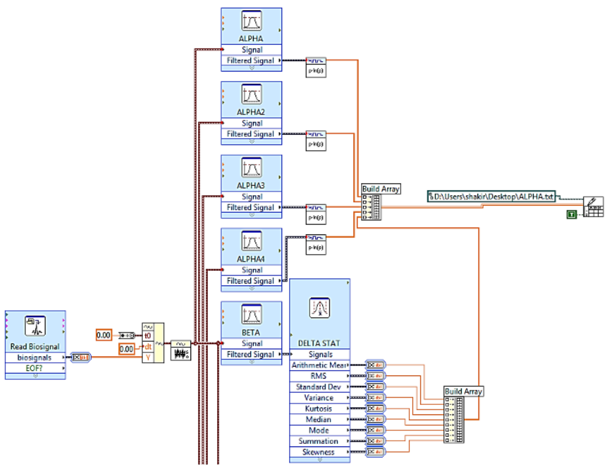

Fig. 6. A functional Blockdiagram of the program in LabVIEW for filtering and saving.

Once the algorithm is finalized in the microcontroller by using the signals from the EEG simulator workbench, it can replaced with the real patient EEG data probe in real time on the fly. In this mode of operation, the UNO32 microcontroller will pre-process the input EEG signal from the human subject and look for a pre-seizure state. After analysis and classification, if a pre-seizure state occurs, the microcontroller will alert locally and with the Bluetooth link to the mobile device. In future, we can add additional connectivity to the hospital database to transfer the time stamp of the occurrence of seizure/pre-seizure, location of occurrence and the EEG signal waveform itself at that time. This will help the medical doctor to look into more details about the EEG characteristics of the signal and the subject itself for further analysis by heuristics data. This software and the hardware provide support for the education and research of electrophysiology [14].

V. 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 patient. The selected data sets are: chb01_03.edf, chb02_16+.edf, chb03_04.edf, chb04_05.edf, chb05_17.edf, chb06_13.edf, chb07_13.edf, chb08_02.edf, chb09_19.edf, chb10_30.edf, chb11_92.edf, chb12_11.edf, chb13_59.edf, chb14_04.edf, chb15_17.edf, chb16_10.edf, chb17a_04.edf, chb18_31.edf, chb19_30.edf, chb20_16.edf, chb21_22.edf, chb22_25.edf, chb23_06.edf and chb24_13.edf [14]. 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).

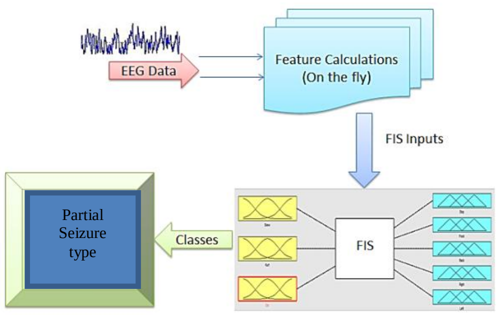

Fig. 7. Overall block diagram of the classification system.

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.

VI. 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 sergeon, 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 distictions. When considering strucuture 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. This led to the decision to use the statistical measures only instead of geometrical measures as used by most of the automated detection algorithms. As mentioned before, a set of 7 different features were tried out with various waveforms obtained from the filter banks. The features used are: (a). Mean,(b).Standard Deviation, (c).Variance, (d).Energy (sum squared values), (e).Skewness, (f). Kurtosis & (g).Entropy. Figure 4(a)-(c) shows the values of various waveforms from the filter bank. Based on the selectivity of various measures, it can be seen from Figure 4 (a)-(c) that certain measures are good in classifying the five control command signal from the EEG. After applying all the features to the EEG signals which defines all the control command on F8 and FC6 signal, we have found that features 5, 6 and 7 showed better dynamic variation for all the 25 cases. This helped the system to further simplify the algorithm.

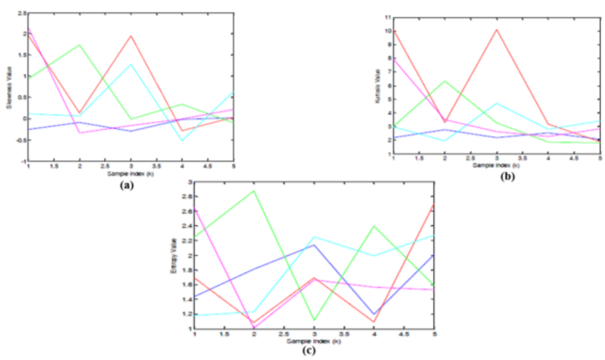

Fig. 8. Feature selection strategy: Plot of the feature values for filtered outputs from by using (a) Skewness feature (b) Kurtosis feature & (c) Entropy, for all the EEG cases.

As can be seen that the features 5, 6, and 7 occur most frequently and hence were used for the feature space. 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 representition as SF0 & SF1). Here SF0 represent the Variance , SF1 represents Enropy of the original signal.
- three descriptors-membership in lieu of cases and
- A set of 5 rules that represents the heuristical combination 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 these values of the boundary are 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 model can represent each degree, which 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). Each of the memberships the triangular distributions is 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.

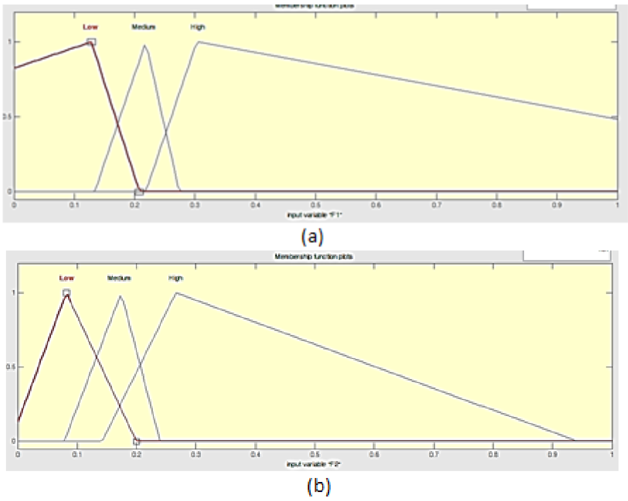

Fig. 9. Membership functions (Input); (a) SF0, (b) SF1.

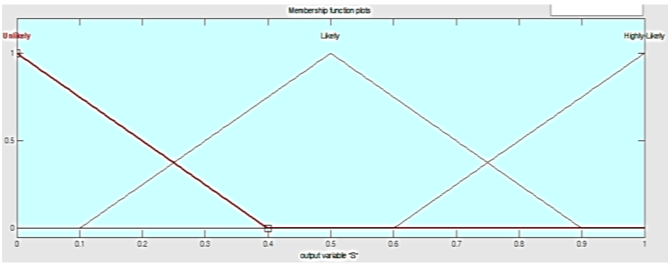

Fig. 10. Output Membership function.

6.2. Decision Based Rule

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 is also followed for rest of them. This produces a final decision surface. This rule is further taken into consideration with the decision of the physicians' 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 rule.

Table 1: Rule- based on output for 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. This ultimately provides a value that represents output degree. In figure 7, subset of the surface of decision are only shown because of the multi-dimensional nature of the subsequent decision

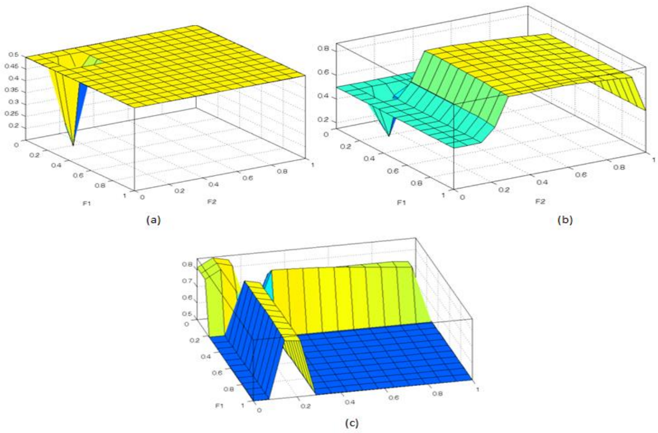

Fig. 11. Decision surface: (a) Normal, (b)Pre-seizure (c)Seizure.

VII. ALERT SYSTEM

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.

VIII. CONCLUSION

In this paper, a strategy is presented in order to modify an existing Data Acquisition/Generation module to function as an EEG simulator and to validate the identification of pre-seizure signal using statistical methods and fuzzy logic. Such a system will be very helpful in EEG related research since all the initial algorithms can be tuned to the controlled data first before going to the actual human subjects. Unlike the commercial EEG simulators, to the best of our knowledge, there is no such commercially available system that can be used for such research tasks. The use of NI device and LabVIEW environment makes it very user friendly for anyone to develop a device tailored to their requirements. The data we have used is from actual patients and the system converts the text files for the data values into electrical voltages similar to what would be measured by the EEG probes. Further work is being done in producing more simulated data based on empirical models of the real waveforms. With controlled data types, Healthy/Normal, Seizure, and Pre-Seizure classes, the user can select the type and work on tuning their algorithms for detection and classification applications.

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