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Optimization of Fuzzy Output through Gaussian Mixture Model for Epilepsy Detection.

Harikumar Rajaguru, and Sunil Kumar Prabhakar*

Department of ECE, Bannari Amman Institute of Technology, India.

ABSTRACT

The primary aim of the paper is to optimize the fuzzy output with the help of Gaussian Mixture Model (GMM) for Epilepsy Classification and Detection from EEG Signals. Initially, the fuzzy techniques are incorporated in order to classify the epilepsy risk levels based on extracted parameters like energy, peaks, sharp and spike waves, variance, duration, covariance and events which are obtained from the EEG of the patient. The Gaussian Mixture Model is then implemented on the classified data in order to obtain the risk level optimization which helps us to characterize the risk level of the epilepsy in the patient. The bench mark parameters considered here are Performance Index (PI), Specificity, Sensitivity, Quality Values, Accuracy and Time Delay.
Keywords: Fuzzy, GMM, EEG, Epilepsy

***Corresponding author**

INTRODUCTION

The cumulative firing of neurons in various regions of the brain can be measured easily with the help of EEG [1]. The vital information regarding the electrical potential of the brain can be obtained easily with the help of EEG. The EEG patterns can be varied by a lot of internal and external factors like biochemical reasons, metabolic reasons, hormonal and behavioral reasons [2]. One of the important activities detected from the EEG is the epilepsy. Epilepsy is determined by the uncontrolled excessive activity of potential discharge in the Central Nervous System (CNS) [3]. The various EEG waveform patterns characterize the different types of epileptic seizures. With the advent of automatic classification and detection algorithms, it has become easier for the clinicians to understand and diagnose the problems related to epilepsy in a better manner [4]. Fuzzy Techniques are one such methods used to understand the problems related to epilepsy [5]. In this paper, Gaussian Mixture Model is used to optimize the risk level of the epilepsy patient classified by the fuzzy system.

A few important works in EEG signal processing for epilepsy classification are reviewed here. A non linear view point of the epileptic seizure detection was done by Paivinen et.al [6]. The high-frequency EEG activity at the start of seizures was analyzed by Fischer et.al [7]. The application of periodogram and AR spectral analysis to EEG signals was done by Akin and Kiymik [8]. The non negative matrix factorization for motor imagery EEG classification was done by Lee et.al [9]. The analysis of EEG records in an epileptic patient using wavelet transform was done by Adeli et.al [10]. The AR spectral analysis of EEG signals by using maximum likelihood estimation was performed by Inan Guler et al [11]. The entropies of the EEG was computed by Sleigh et.al [12] .The dynamical analysis of EEG signals at various sleep stages was done by Acharya et.al [13]. Adeli used improved spiking neural networks for EEG classification and epilepsy and seizure detection in [14]. A radial basis function neural network model for classification of epilepsy using EEG signals was done by Aslan et.al.[15]. The automatic identification of epileptic EEG signals using higher order spectra was done by Chua et.al [16]. The automatic identification of epileptic EEG Signals using non linear parameters was done by Acharya et.al [17]. The neuromodulation of epileptic foci in patients with non-lesional refractory motor epilepsy was done by Velasco et.al [18].

In this paper as a level one classifier, Fuzzy techniques are incorporated and as level two classifier for further optimization Gaussian Mixture Model is used for the classification of epilepsy risk levels from EEG Signals. The organization of the paper is as follows: In section 2, the materials and methods are discussed followed by the usage of fuzzy techniques in section 3. In section 4, the usage of Gaussian Mixture Model is used as a post classifier for the classification of epilepsy from EEG signals. Section 5 gives the results and discussion followed by the conclusion in section 6.

MATERIALS AND METHODS

The EEG data is recorded from 16 channels in the standard 10-20 electrode system. The EEG recordings are continuos for a period of thirty minutes and they are divided into epochs of 2 second duration [19]. It is done by scanning into a specific bitmap image of size 400 x 100 pixels. To identify the important changes in the activities of the EEG signal, a 2 second epoch is pretty long enough. Since the maximum frequency of EEG is 50 Hz, it is sampled at a frequency of 200 Hz with the aid of graphic programming. Totally 400 values are present in an epoch where each value corresponds to each and every sample. For the quantification of the EEG, the amplitude values are generated with the help of good programming. In order to identify the variations in the epileptic activities, the parameters are obtained for three different epochs at discrete times.

Basic Fuzzy System:

Fuzzy set theory gives the useful tools in order to manipulate the noisy and imprecise data and make decisions based on such data. Also a linguistic approach is offered with the help of fuzzy set theory and so it offers a good approximation to medical contexts. Adlassing et.al [20] performed a full diagnosis system on the basis of fuzzy theory by managing and constructing the fuzzy relations from the frequency of occurrence of diseases and its respective symptoms. One such system is determined as follows:

Step 1: The Fuzzy Classification for epilepsy risk level optimization at each and every channel from EEG signals along with all its parameters [21]

Step 2: Each of the channel results are optimized because they are at different risk levels
Step 3: Even if the optimization is delayed, the performance of the fuzzy classification is noted.

The parameters obtained by sampling process are given as inputs to the fuzzy system as shown in figure 1. The figure 1 shows the Fuzzy Classification system with Gaussian Mixture Model as a Post Classifier for the Classification of epilepsy from EEG Signals.

The important parameters derived from EEG signals are as follows:

Energy of the epoch

The energy in each two-second epoch is given by $E = \sum_{i=1}^{n} x_i^2$

where x_i is signal sample value and n is number of samples. The normalized energy is taken by dividing the energy term by 1000.

Peaks

The total number of positive and negative peaks exceeding a threshold is found.

Spikes and Sharps

Spikes are detected when the zero crossing duration of predominantly high amplitude peaks in the EEG waveform lies between 20 and 70 ms and sharp waves are detected when the duration lies between 70 and 200ms.

Events

The total number of spike and sharp waves in an epoch is recorded as events.

Variance

The variance is computed as σ given by $\sigma^2 = \frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n}$ where $\mu = \frac{\sum_{i=1}^{n} x_i}{n}$ is the average amplitude of the epoch.

Average Duration

The average duration is given by $D = \frac{\sum_{i=1}^{p} t_i}{p}$ where t_i is one peak to peak duration and p is the number of such durations.

Covariance of Duration

The variation of the average duration is defined by $CD = \frac{\sum_{i=1}^{p}(D - t_i)^2}{pD^2}$

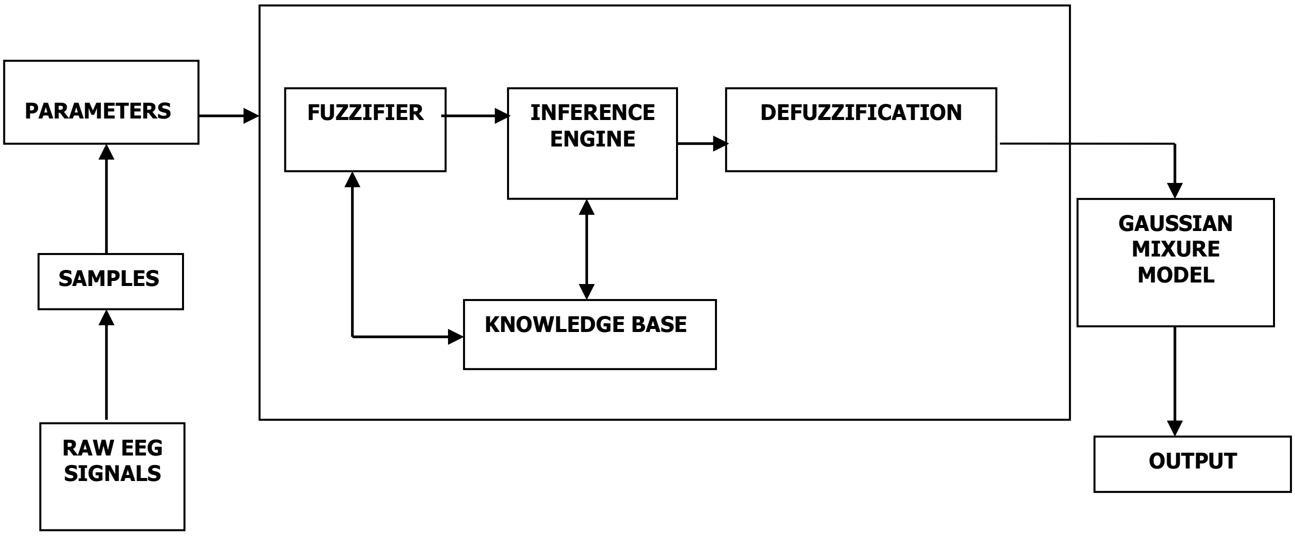
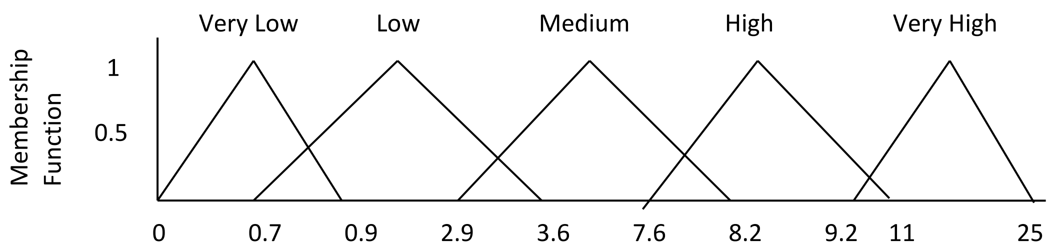


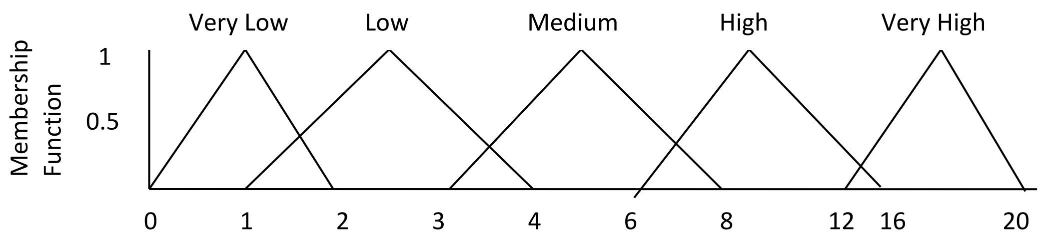
Figure 1: Fuzzy Classification System

Fuzzy Membership Functions:

The energy here is compared with the other 6 input features in order to get six outputs. Each and every input feature is classified into five different fuzzy linguistic levels like, very low, low, medium, high and very high [22]. The membership functions used here is triangular and it is utilized for the determination of linguistic levels of energy, peak and variance. More or less similar functions for other input variables like events, spike and sharp waves, covariance of duration and average duration are defined. The output risk levels is classified mainly into five linguistic levels as normal, low, medium, high and very high. The input and output membership functions are shown in Figure 2.



Energy Input Function



Positive and Negative Peaks

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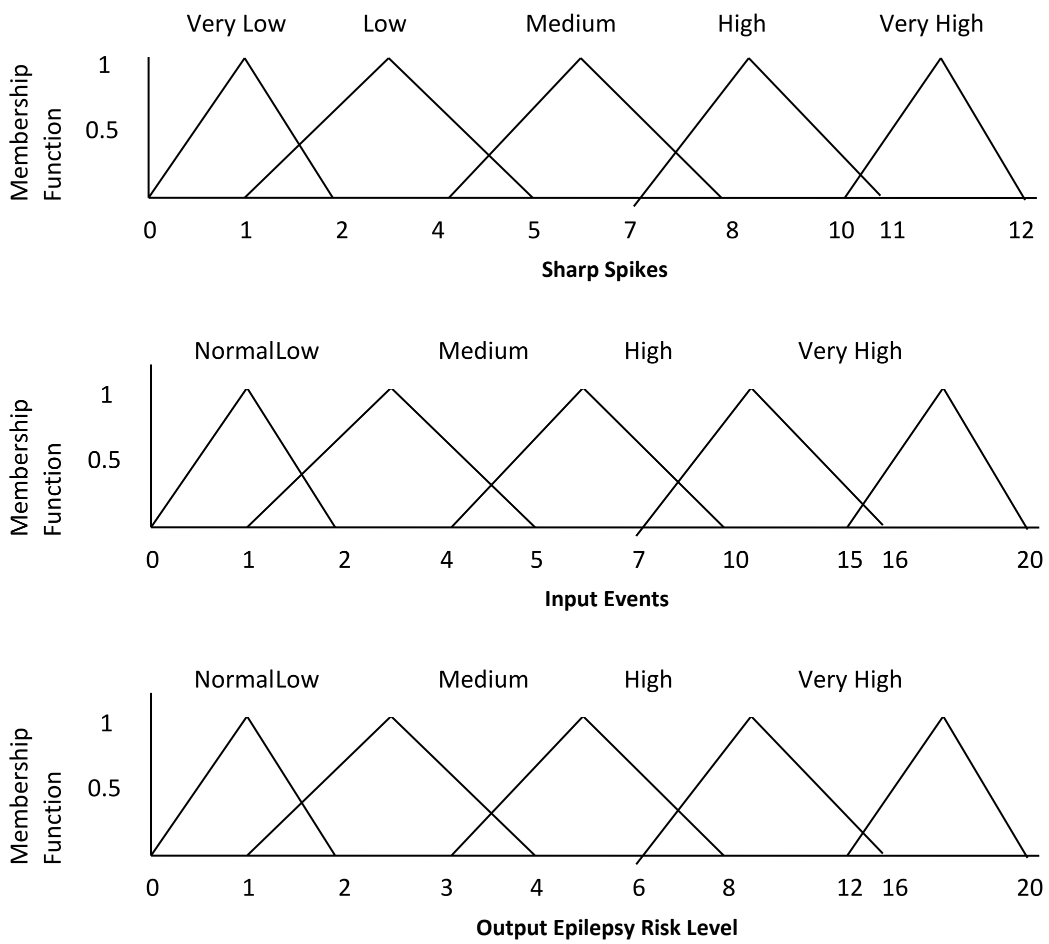

Figure 2: Input and Output Fuzzy Membership Functions

Fuzzy Rule Set

The rules are obtained and framed in the format as follows

IF Energy is low AND Variance is low THEN Output Risk Level is low

Here, a kind of exhaustive fuzzy rule based system is utilized. Totally, there are five linguistic levels of energy and five linguistic levels of other six features such as variance, peaks, spike and sharp waves, events of duration, covariance duration and average duration. A total rule base of 150 rules is obtained based on six sets consisting of 25 rules [23].

The proposed fuzzy system which is trained with both the simulation of input and output variables are studied thoroughly. All the fuzzy set variable are having nine input values grouped under one category. There are totally five sets such as very low, low, medium, high and very high. Totally 45 test inputs are considered for simulation for each and every input like energy, variance, sharp waves etc… The output analysis is done and the corresponding error matrix shows the deviations in the output risk level classification [24]. The error matrix of energy is always determined with respect to the input function. The fuzzy logic output is shown in Figure 3.

Epoch 1	Epoch 2	Epoch 3
WYYWYY	WYYWYY	WZYYWW
YZZYXX	YYYYXX	YYYXYY
YYZXYY	YYYYYY	YYYYYY
YZZYXY	XYYXYY	YYYYYY
ZZZYYY	WYYYXX	YYYXYY

YYZXXX	WYZYYY	YZZYYY
ZZZYYY	YYYYYY	ZZZYYY
YYYYXX	YYYYXX	YYYXZY

Figure 3: Fuzzy Logic Output

Gaussian Mixture Model as Post Classifier

The Probability Density Function (PDF) of a particular random variable can be represented with the help of GMM. For a particular random variable [25], $y \in Z^c$, in the presence of total weighted sum of q Gaussian distributions, it is expressed as follows

$$P(y|\theta) = \sum_{l=1}^{k} \alpha_l P(y|\theta_l)$$

where the mixture model is represented as θ

The weight of each component l is represented by α_l and the density of each component is represented by the probability function which is normal is nature as

$$P(y|\theta_l) = \frac{|\Sigma_l|^{-1/2}}{[2\pi]^{l/2}} \exp\left\{-\frac{1}{2}(y-\mu_l)^T \Sigma_l^{-1}(y-\mu_l)\right\}$$

During the training phase occurrence, the parameters α, μ, and Σ are optimized iteratively through the EM algorithm just for the sake of minimizing the log-likelihood function of the model [26]. If there are totally 'n' independent and identically distributed samples, $X = \{x^1, x^2, ..., x^n\}$, the log-likelihood concept corresponding to a mixture model θ is given as follows

$$S(X;\theta) = \log \prod_{i=1}^{n} P(y_i;\theta) = \sum_{i=1}^{n} \log \sum_{l=1}^{k} \alpha_l^P (y_i;\theta_l)$$

In this particular study, the investigations is done on both the diagonal and symmetrical matrices for the given covariance matrix Σ in the Gaussian distribution function. Less data and computational time is required during the training phase if the GMM is used with diagonal covariance matrix. However, the diagonal covariance matrix is incapable of performing the modeling of correlations for the feature dimensions. In the training stage, the GMM is trained for each and every class like seizure and non seizure. To represent the seizure class, a maximum of 2 minutes of seizure data for each patient is extracted from EEG signals for all the channel annotations. In the testing stage of the GMM classifier, a likelihood estimate is assumed for the seizure class which is defined by the model θ_s and for the non-seizures class, it is defined by the model θ_n. The combination of the likelihood estimates are done to obtain the seizure's posterior probability using the standard Bayesian formula [26].

RESULTS AND DISCUSSION

For the optimization of fuzzy outputs and implementing it with GMM as a Post Classifier, based on the Perfect Classification, Missed Classification, False Alarm, Performance Index, Quality values, Time Delay and Accuracy the results are computed in Tables 1 and 2 respectively. The formulae for the Performance Index (PI), Sensitivity, Specificity and Accuracy are given as follows

$$PI = \frac{PC - MC - FA}{PC} \times 100$$

where PC – Perfect Classification, MC – Missed Classification, FA – False Alarm,
The Sensitivity, Specificity and Accuracy measures are stated by the following

$$Sensitivity = \frac{PC}{PC + FA} \times 100$$

$$Specificity = \frac{PC}{PC + MC} \times 100$$

$$Accuracy = \frac{Sensitivity + Specificity}{2} \times 100$$

The Quality Value Q_V is defined as

$$Q_V = \frac{C}{(R_{fa} + 0.2) * (T_{dly} * P_{dct} + 6 * P_{msd})}$$

where C is the scaling constant,
R_{fa} denotes the total number of false alarm per set,
T_{dly} indicates the average delay of the onset classification in seconds
P_{dct} means the percentage of perfect classification
P_{msd} tells the percentage of perfect risk level missed
The time delay is given as follows

$$\text{Time Delay} = \left[2 \times \frac{PC}{100} + 6 \times \frac{MC}{100} \right]$$

Table 1: Performance Analysis Average Classification Values for 20 patients

Patient No	PC	MC	FA	PI
1	95.84	0	4.16	95.65
2	95.84	0	4.16	95.65
3	91.6	8.33	0	91.58
4	100	0	0	100
5	95.84	0	4.16	95.65
6	83.34	16.66	0	80.01
7	95.84	4.16	0	95.65
8	95.84	0	4.16	95.65
9	100	0	0	100
10	95.84	0	4.16	95.65
11	91.67	0	8.33	91.58
12	91.6	8.33	0	91.58
13	100	0	0	100
14	95.84	0	4.16	95.65
15	100	0	0	100
16	95.84	4.16	0	95.65
17	95.84	4.16	0	95.65
18	100	0	0	100
19	95.84	0	4.16	95.65
20	95.84	4.16	0	95.65

Table 2: Performance Analysis Average Classification Values for 20 patients

Patient No	Sensitivity	Specificity	Time Delay	Quality Values	Accuracy
1	93.84	100	1.92	21.55	96.92
2	93.84	100	1.92	21.55	96.92

3	100	91.67	2.33	24.46	95.835
4	100	100	2	25	100
5	93.84	100	1.92	21.55	96.92
6	100	83.34	2.67	18.73	91.67
7	100	95.84	2.17	23.04	97.92
8	93.84	100	1.92	21.55	96.92
9	100	100	2	25	100
10	93.84	100	1.92	21.55	96.92
11	91.67	100	1.83	19.31	95.835
12	100	91.67	2.33	24.46	95.835
13	100	100	2	25	100
14	93.84	100	1.92	21.55	96.92
15	100	100	2	25	100
16	100	95.84	2.17	23.04	97.92
17	100	95.84	2.17	23.04	97.92
18	100	100	2	25	100
19	93.84	100	1.92	21.55	96.92
20	100	95.84	2.17	23.04	97.92

CONCLUSION

Thus in this paper, the optimization of the fuzzy output with the help of Gaussian Mixture Model (GMM) for Epilepsy Classification and Detection from EEG Signals was carried out successfully. Initially, the fuzzy techniques were incorporated in order to classify the epilepsy risk levels based on extracted parameters like energy, peaks, sharp and spike waves, variance, duration, covariance and events which are obtained from the EEG of the patient. The Gaussian Mixture Model is then implemented on the classified data in order to obtain the risk level optimization which helps us to characterize the risk level of the epilepsy in the patient. The bench mark parameters considered here are Performance Index (PI), Quality Values (QV), Accuracy and Time Delay. It is observed on the analysis that an average Perfect Classification of about 95.62% is obtained, average performance index of about 95.34% is obtained, average sensitivity of about 97.42%, average specificity of about 97.50%, average quality value of about 22.74 and an average accuracy of 97.46% was obtained. Future work plans to implement other types of classifiers for the optimization of the fuzzy outputs.

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