Engineering Letters, 14:1, EL_14_1_17 (Advance online publication: 12 February 2007)

Diagnosis and Classification of Epilepsy Risk Levels from EEG Signals Using Fuzzy Aggregation Techniques

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Abstract— **This paper is intended to compare the performance of four different types of fuzzy aggregation methods in classification of epilepsy risk levels from EEG Signal parameters. The fuzzy technique is the first level classifier which works on the EEG Signal extracted features (patterns) such as energy, variance, peaks, events, duration and covariance. These features are obtained from an epoch of 2 seconds in all sixteen channels. Each epoch is sampled at 200Hz and digitized. The risk level patterns obtained by fuzzy techniques have low value of quality value and performance index. The aggregation operator based optimizations such as Ordered Weighted Average (OWA), Max-min method; Max product method and Sum-product method are applied on the fuzzy outputs. Comparison of these optimizations is studied and analyzed for a group of ten known epilepsy patients. Training and testing are performed using 480 EEG signal feature sets of 2 seconds epoch obtained from routine clinical trials. To evaluate the optimization performance, we also employed free response receiver operating characteristics method with mean number of false positive. High quality value as 23.78 is achieved in OWA method and Max-Product method.**

Index Terms— **EEG Signals, Epilepsy, Fuzzy Logic, Aggregation operators, Risk Levels**

I. Introduction

The Electroencephalogram (EEG) is a measure of the cumulative firing of neurons in various parts of the brain. It contains information regarding changes in the electrical potential of the brain obtained from a set of recording electrodes. EEG patterns have shown to be modified by a wide range of variables including biochemical, metabolic, circulatory, hormonal, Neuro-electric and behavioral factors [1]. In the past, the Encephalographer, by visual inspection was able to qualitatively distinguish normal EEG activity from localized or generalized abnormalities contained within relatively long EEG records. The most important activity possibly detected from the EEG record is the epilepsy [2]. Epilepsy is characterized by uncontrolled excessive activity or potential discharge by either a part or all of the central nervous system. The different types of epileptic seizures are characterized by different EEG waveform patterns. In this paper, we discuss the aggregation operators and fuzzy multicriteria evaluation with multiple objectives single level model to optimize the epileptic risk level of the patient classified by the fuzzy system. We also present a comparison of these methods based on their performance indices, quality value and Free Response Receiver Operating Characteristics (FROC) method.

Manuscript received on 16TH June 2006

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II. MATERIALS AND METHODS

EEG from 16 channels is recorded using the standard 10-20-electrode system. In this paper we use the recorded EEG to analyze for artifacts. Since the EEG records are over a continuous duration of about thirty seconds, they are divided into epochs of two second duration each by scanning into a bitmap image of size 400x100 pixels. A two second epoch is long enough to detect any significant changes in activity and presence of artifacts and also short enough to avoid any repetition or redundancy in the signal [1] [2] [3]. The EEG signal has a maximum frequency of 50Hz and so, each epoch is sampled at a frequency of 200Hz using graphics programming in C. Each sample corresponds to the instantaneous amplitude values of the signal, totaling 400 values for an epoch. The different parameters used for quantification of the EEG are computed using these amplitude values by suitable programming codes.

A. *Fuzzy System as a First Level Classifier*

The objective of this paper is to classify the epilepsy risk level of a patient from EEG signals. This is accomplished as:

1) Fuzzy classification for epilepsy risk level at each channel from EEG signals and its parameters.
2) Each channel results are optimized by four different optimizations procedures, since they are at different risk levels.
3) Performance of fuzzy classification before after the optimization is compared and analyzed.

The various parameters obtained by sampling are given as inputs to the fuzzy system [4], [6] as shown in figure 1.

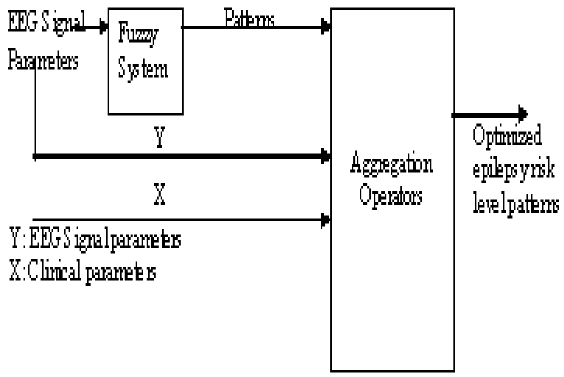

Fig.1. Fuzzy Aggregation Classification System

1. The energy in each two-second epoch is given by

$$E = \sum_{i=1}^{n} x_i^2 \tag{1}$$

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.

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

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

4. The total numbers of spike and sharp waves in an epoch are recorded as events.

5. The variance is computed as σ given by [14] [16]

$$\sigma^2 = \frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n} \tag{2}$$

Where $\mu = \frac{\sum_{i=1}^{n} x_i}{n}$ is the average amplitude of the epoch.

6. The average duration is given by

$$D = \frac{\sum_{i=1}^{p} t_i}{p} \tag{3}$$

Where t_i is one peak to peak duration and p is the number of such durations.

7. The variation of the average duration is defined by

$$CD = \frac{\sum_{i=1}^{p}\left(D - t_i\right)^2}{pD^2} \tag{4}$$

B. Fuzzy Membership functions

The energy is compared with the other six input features to give six outputs. Each input feature is classified into five fuzzy linguistic sets viz., *very low, low, medium, high* and *very high* [4]. The triangular membership functions are used for the linguistic sets of EEG Signal parameters. The output risk level is classified into five linguistic sets namely *normal, low, medium, high* and *very high.*

C. Fuzzy Rule Base

Rules are framed in the format

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

In this fuzzy system we have five linguistic sets of energy and five linguistic sets of other six features such as variance, peaks, events, spike and sharp waves, average duration and covariance of duration. We obtain a total rule base of 150 rules based on six sets of 25 rules each. This is a type of fuzzy rule based system [4], [8].Centre of Gravity method or Centroid method is selected for Defuzzification. The output epilepsy risk level is quantified as follows

Risk Level	Representation
Normal	U
Low	W
Medium	X
High	Y
Very High	Z

The results obtained from fuzzy systems for a data set 1 as given in sample output of the fuzzy system with actual patient readings is shown in figure 2, for eight channels over three epochs. It can be seen that the Channel 1 shows low risk levels while channel 7 shows high risk levels. Also, the risk level classification varies between adjacent epochs. Hence, we must go for optimization of the fuzzy results to arrive at a better risk level for each patient [6].

Epoch 1	**Epoch 2**	**Epoch 3**
WYYWYY	**WYYWYY**	**WZYYWW**
YZZYXX	**YYYYXX**	**YYYXYY**
YYZXYY	**YYYYYY**	**YYYYYY**
YZZYXY	**XZZXYY**	**YYYYYY**
ZZZYYY	**WYYYXX**	**YYYXYY**
YYZXXX	**WYZYYY**	**YZZYYY**
ZZZYYY	**YYYYYY**	**ZZZYYY**
YYYYXX	**YYYYXX**	**YYYXZY**

Fig. 2. Fuzzy Logic Output

The fuzzy method's classification efficiency is evaluated from the following parameter.

The Performance of the Fuzzy method is defined as follows [7]

$$PI = \frac{PC - MC - FA}{PC} \times 100 \quad (5)$$

Where, PC – Perfect Classification, MC – Missed Classification, and FA – False Alarm.

PI= [(0.5-0.2-0.1)/0.5] *100 =40%

Missed classification represents High level as Low level, False alarm represents low level as High level. The percentage of performance for Fuzzy systems is as low as 40%. Therefore optimization is necessary to improve the performance. The aggregation operators are selected for this purpose.

III. AGGREGATION OPERATORS IN FUZZY DECISION SUPPORT SYSTEMS

This section of the paper discusses how aggregation operators can be selected and adjusted to fit empirical data series of test case. Both parametric and non-parametric regressions are considered and compared. The problem of aggregating criteria functions to form overall decision functions is of considerable importance in many disciplines. A prime factor in the determination of the structure of such aggregation functions is the relationship between the criteria involved. In [10] Yager introduced the OWA operators, which is defined as follows. A fundamental aspect of the OWA operator is the reordering step, in particular an aggregate a_i is not associated with a particular weight w_i but a weight w_i is associated with a particular reordered position [5],[10]. The OWA operators can model the Max, Min and Arithmetic mean operators for certain vector of weights W. In order to obtain the better scores for aggregation, we have selected the weights as W= [0.4, 0.3, 0.3].

A. Aggregation Operators in Optimization of Epilepsy risk level

The optimization by aggregation operators in our case are given as, the variables x_1,x_2,x_3 from clinical parameters, and y_1,y_2,y_3,y_4 are derived from the EEG signals of epileptic cases. These variables are normalized in nonlinear fashion using Secant functions and Sigmoid functions over the range 0-1.Now consider the general aggregation operator f(x) used in our approach

$$f(x)= \alpha_1 (x_1+x_2+x_3)+\alpha_2 (y_1+y_2+y_3+y_4) \quad (6)$$

Where x_1,x_2,x_3 are defined as index of convulsions, seizure timing and total body fatigue. The variables y_1,y_2,y_3,y_4 are defined as Energy, Peaks, Events and Sharp waves of EEG features. The x factors are less relevant in well established in Random controlled trials (RCT's).They receive less importance of weight of α_1.The y factors are more relevant in(RCT's).They receive higher importance of weight of α_2 . Now consider the condition such that $\alpha_2 = 1-\alpha_1$ and α_1 is given different values, the following equations are generated.

$$f_1(x) =0.1(x_1+x_2+x_3)+0.9(y_1+y_2+y_3+y_4) \quad (7)$$

$$f_2(x) = 0.25(x_1+x_2+x_3) +0.75(y_1+y_2+y_3+y_4) \quad (8)$$

$$f_3(x)=0.15(x_1+x_2+x_3)+0.85(y_1+y_2+y_3+y_4) \quad (9)$$

Since we are using known patient so that the x variables are taken as constant in the above equations. The y variables are substituted with appropriate measured EEG parametric signal values in the above equations. Therefore each epoch will produce three values an average of these values is arrived. Like wise, three epochs in each channel will result in three average values. The operation of this module is shown in Table I.

Table I. Aggregation operators in optimizing channel outputs

Fuzzy classification level	**Aggregation Operators Output**			**Average**
	$f_1(x)$	**$f_2(x)$**	**$f_3(x)$**	
ZYYYYY	1.114	1.262	1.163	1.1796
ZZYZZZ	1.284	1.403	1.323	**1.336**
YYYXYY	1.206	1.3383	1.25	1.265

Maximum pattern **ZZYZZZ**

Now all the 16 channels are optimized based on the maximum average value of epoch in that bin. We have obtained 16 column values of patterns or codes corresponding to each bin at each channel. These channels are grouped into four via channels {I-IV}, {V-VIII}, {IX-XII} and {XIII- XVI} respectively. In order to optimize the fuzzy outputs in column wise we assign the following procedure

$$Fagg=0.4(Rmax) +0.3(Rmax-1) +0.2(Rmax-2)+0.1(Rmin) \quad (10)$$

And found min {Fagg –R} =R optimum. (11)

Where Rmax =maximum aggregated value of R pattern in that particular group. For-example in the patient set 4 the channels (I-IV) are aggregated as intermediate pattern of **ZYYYZZ**. This resultant value is matched with original maximum values of the patterns. The minimum difference between the resultant value and one of the four patterns is selected as the optimized pattern. Likewise we can proceed with other channels we obtained only four patterns in the intermediate stage the same procedure is repeated to obtain the single pattern epilepsy risk level. We have selected only one pattern which will be an optimum pattern from the 48 epilepsy risk level patterns of the fuzzy system outputs. In patient set 1 the obtained final epilepsy risk level pattern through aggregation method is **ZZYZZZ**. The performance is improved to 95.77% for patient data set 1 through the aggregation method.

B. *Fuzzy Multicriteria Evaluation with Multiple Objects*

We denote by U the set of objects for evaluation having a finite numbers of elements. U= $\{u_1, u_2, \ldots, u_q\}$ U will be the epilepsy patterns obtained from fuzzy classifier. The basic criteria of evaluation is the set C= $\{c_1, c_2, \ldots, c_m\}$; these criteria are supposed to be measurable that is ,every $c_j \in C$ has some values illustrated by a subset of real numbers. The purpose of the evaluation is to assign a mark for every object $u \in U$ or to place this object into a qualitative class. We denote the set of the qualitative classes by E: E= $\{e_1, e_2, \ldots, e_p\}$; For every $u \in U$ and the criterion $c_i \in C$ it is found the degree $c_i(u) \in [0,1]$. This degree illustrates the level of concordance between u and the criterion c_i. These $c_i(u)$ can be obtained by fuzzy statistical method. Thus we find the following fuzzy set: v(u)= $\{c_{1(u)}, c_{2(u)}, \ldots, c_{m(u)}\}$. The fuzzy set or the fuzzy vector v(u) is the whole criterion vector of the element $u \in U$

Related to the class $e_k \in E$ and the elements $u \in U$ there is a vectorial objectives function φ^k defined by;

$$\varphi^k(v(u)) = (\varphi_1^k(c_1(u)), \varphi_2^k(c_1(u)), \ldots \varphi_m^k(c_1(u))) \quad (12)$$

Taking the functions φ^k for all k=1,2,..,p we obtain the following matrix:

$$R(u)= \begin{matrix} r_{11}(u) & r_{12}(u) & .. & r_{1p}(u) \\ r_{21}(u) & r_{22}(u) & .. & r_{2p}(u) \\ .. & .. & .. & .. \\ r_{m1}(u) & r_{m2}(u) & .. & r_{mp}(u) \end{matrix}$$

The matrix R (u) is the single criterion evaluation of $u \in U$. This matrix may be viewed as a fuzzy relation between C and E. In the practical activity criteria have some relative importance. This fact may be fixed by a constant weight vector which is already defined. Let us consider in our case of epilepsy risk level optimization, the values arrived from the aggregation equations (7-9) are normalized. These values representing the relation matrix of the epilepsy risk level. The following three models are tested in the patient set 1 for the weight matrix W= [0.4, 0.3 0.2 0.1]. The resulted epilepsy risk levels are shown below,

a) The model $(\wedge, \vee)$ (that is the max-min model)

$W \overset{\vee}{\underset{\wedge}{o}} R(u)$ =**YZYZZZ**

b) The model $(\vee, \bullet)$(max–product model)

$W \overset{\vee}{\underset{\bullet}{o}} R(u)$ =**ZZYZZZ**

c) The model $(\sum, o)$(sum-product model)

$W \overset{\Sigma}{\underset{\bullet}{o}} R(u)$ =**ZYYZZZ**

The epilepsy risk level patterns obtained through Max-Product Model and OWA Model are one and the same.

IV. RESULTS AND DISCUSSIONS

The outputs are obtained for three epochs for every patient in classifying the epileptic risk level by the fuzzy and aggregation operators approach. The relative performances of these systems are evaluated on the basis of performance index, quality value and FROC of the classifier.

A. *Performance Index*

The Performance Index (PI) calculated for the aforesaid classification methods are illustrated in table 2 using (5). A missed classification occurs when a high level is represented as low level. False alarm occurs when low level is represented as high level. A sample of Performance Index for a known epilepsy data set at maximum value is shown in Table II.

Table II. Performance Index

Methods	**Perfect Classifi -cation**	**Missed Classifi -cation**	**False Alarm**	**Performance Index**
Fuzzy logic	50	20	10	40
OWA Optimization	97.9	1.3	1.0	97.01
Max-min	93.75	6.25	0	93.33
Max-product	97.92	2.08	0	97.8
Sum-product	93.75	6.25	0	93.3

It is evident that the optimizations give a better performance than the fuzzy techniques because of its lower false alarms and missed classifications. This model is evaluated in terms of its receiver operating characteristics (ROC) curve for test data sets. This enables the user to evaluate a model in terms of the trade -off between sensitivity and specificity. ROC matrices are used to show how changing detection threshold affects detection versus false alarms. If the threshold is set too high then the system will miss too much detection. Conversely, if the threshold is very low then there will be heavy false alarms. The percentage of detections classified correctly is plotted against the percentage of non -detections in correctly classified as detections (ie false alarms) as a function of the detection threshold. ROC is the best way to evaluate a detector.

The performance of classification for test data set is assessed by calculating the area under the ROC curve of A_Z. It is noticed that the values of A_Z from range of 0.5 to 1 for a

Perfect classifier [9]. A good trade-off is observed between detections and false alarms. ROC curve for the two types of classifiers are shown in figure 3a and 3b.

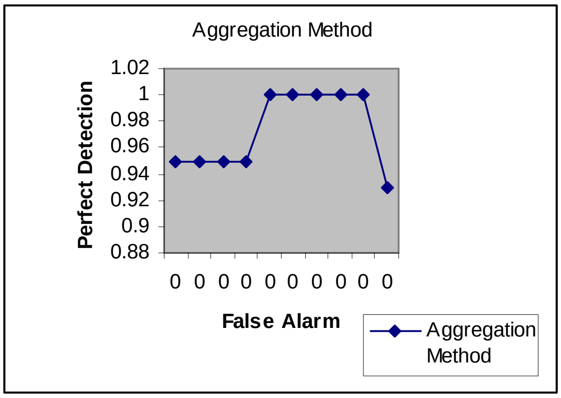

Fig 3a. ROC curve corresponding to Aggregation Method

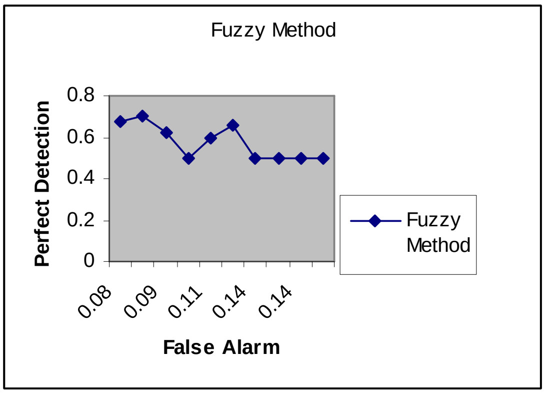

Fig 3b. ROC curve corresponding to Fuzzy Method

For fuzzy classifier we have max detection of 50% with false alarm of 14% .Similarly for combined classifier with fuzzy and aggregation optimization we obtained perfect detections of 97%with false alarms of 1.32%. This shows that the combined classifier is performing better than the single fuzzy classifier. Since other three aggregation models yields zero false alarms due to the higher threshold level of the classifiers. They suffer from high missed classification.

B. Quality Value

The goal of this project is to classify the epileptic risk level with as many perfect classifications and as few false alarms as possible. In Order to compare different classifier we need a measure that reflects the overall quality of the classifier. Their quality is determined by three factors.

1) Classification rate; 2) Classification delay; 3) False Alarm rate

The quality value Q_V is defined as [7]

$$Q_V = \frac{C}{(R_{fa} + 0.2)*(T_{dly} * P_{dct} + 6 * P_{msd})} \tag{13}$$

Where, C is the scaling constant

R_{fa} is the number of false alarm per set;

T_{dly} is the average delay of the on set classification in seconds;

P_{dct} is the percentage of perfect classification and P_{msd} is the percentage of perfect risk level missed. A constant C is empirically set to 10 because this scale is the value of Q_V to an easy reading range. The classifier with the highest Q_V should be the best. The quality value obtained by fuzzy system method is about 6.25.

C. Comparison of Optimization Results

The two different approaches give different results. Hence a comparative study is needed whereby the advantages of one over the other can be easily validated and the best method found out. A study of Fuzzy Logic without optimization and the aggregation operator based optimizations were studied and there results taken as the average of all ten known patients is tabulated in table III.

Table III. Results of Classifiers taken as Average of all ten Patients

Parameters	**Fuzzy method before Optimization**	**Aggregation operator Optimization**			
		OWA	**Max min**	**Max pro**	**Sum pro**
(%) Risk level classification rate	50	97.9	93.75	97.92	93.75
Weighted delay (s)	4	2.036	2.25	2.08	2.25
False-alarm rate/set	0.2	0.01	0	0	0
(%) P Index	40	97.01	93.33	97.87	93.75
Quality value	6.25	23.75	22.2	24	22.2

The fuzzy method followed by aggregation optimization yields good results and is a better performing system.

V. Conclusion

This paper aims at classifying the epilepsy risk level of epileptic patients from EEG signals. The parameters derived from the EEG signal are stored as data sets. Then the fuzzy technique is used to obtain the risk level from each epoch at every EEG channel. The goal was to classify perfect risk levels with high rate of classification, a short delay from onset, and a low false alarm rate. Though it is impossible to obtain a perfect performance in all these conditions, some compromises have been made. As a high false alarm rate ruins the effectiveness of the system, a low false-alarm rate is most important. Aggregation operator (four models) based optimization techniques are used to optimize the risk level by incorporating the above goals. High quality value as 23.78 is achieved in OWA method and Max-Product method. Therefore OWA method and Max-min method are better performing optimization methods than their counterparts. The spatial region of normal EEG is easily identified in this classification method. The major limitation of this method is that if one channel has a high-risk level, then the entire group will be maximized to that risk level. The number of cases from the present 10 patients has to be increased for better testing of the system. From this method we can infer the occurrence of High-risk level frequency and the possible medication to the patients.

VI. ACKNOWLEDGEMENT

The authors thank the Management and Principal of Bannari Amman Institute of Technology, Sathyamangalam, and the Management of Thiagarajar College of Engineering, Madurai for providing excellent computing facilities and encouragement. The authors are grateful to Dr.Asokan, Neurologist, Ramakrishna Hospital Coimbatore and Dr. B.Rajalakshmi, Diabetologist, Govt. Hospital Dindigul for providing the EEG signals.

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