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A Framework of Modified Adaptive Fuzzy Inference Engine (MAFIE) and Its Application

J. Hossen[1], S. Sayeed[2], I. Yusof[2] and S.M.A. Kalaiarasi[2]

[1]Faculty of Engineering and Technology (FET)
Multimedia University, Melaka, Malaysia.
jakir.hossen@mmu.edu.my

[2]Faculty of Information Science and Technology (FIST)
Multimedia University, Melaka, Malaysia
{shohel.sayeed, ibrahim.yusof, kalaiarasi}@mmu.edu.my

Abstract*: This paper introduces a complete framework of Modified Adaptive Fuzzy Inference Engine (MAFIE) and its application. The fuzzy with hybridization schemes has become of research interest in versatile applications over the past decade. The fuzzy hybridizations models are quite popular among practitioners or researchers in various advanced promising fields to help solve problems with a small number of inputs. However, there are limitations faced by all popular fuzzy systems when they are applied to systems with a large number of inputs. A modified apriori algorithm technique is utilized to reduce a minimal set of decision rules based on input-output dataset. A TSK type fuzzy inference system is constructed by the automatic generation of membership functions and fuzzy rules by the hybrid fuzzy clustering (Fuzzy C-Means and Subtractive Clustering) and apriori algorithms techniques, respectively. The generated adaptive fuzzy inference engine is adjusted by the least-square estimator and a conjugate gradient descent algorithm towards better performance with a minimal set of fuzzy rules. The proposed MAFIE is able to reduce the number of fuzzy rules which increases exponentially when large input dimensions are involved. The performance of the proposed MAFIE is compared with other existing models when applied to pattern classification schemes using Fisher's Iris and Wisconsin Breast Cancer benchmark datasets. The results are shown to be very competitive and MAFIE is ready for high dimension practical applications.

Keywords: Apriori algorithm, Hybrid fuzzy clustering algorithm, MAFIE, TSK

I. Introduction

In past decades, fuzzy systems have been combined with neural networks (learning algorithms) and/or hybridization for performing versatile applications [1]-[3]. Many approaches have been proposed to address the issue of automatic generation of fuzzy membership functions and a fuzzy rule base from an input-output dataset and also subsequent adjustment of them towards more satisfactory performance [4], [5]. Most of these schemes that incorporate the learning property of neural networks within a fuzzy system framework provide encouraging results. However, most of these techniques also have difficulties associated with the number of resulting fuzzy rules, which increase exponentially when high numbers of input attributes are employed [30]. The computational load required to search for a corresponding rule becomes very heavy as the number of fuzzy rules in a complicated situation is increased.

Apriori algorithm (a shortened form of *a priori* algorithm) from data mining field has been used with fuzzy inference system to obtain more compact information from a dataset [6]. This is a popular algorithm used in data mining using associative rules [7]. *Apriori* algorithm techniques provides a methodology to do this in data analysis based on empirical data and it has been applied to a variety of areas including web text mining, data mining, medical data analysis, and so on [8].

It is known that the *apriori* algorithm approach [7] is able to find a minimal set of decision rules that map input-output (I/O) variables. The TSK type of fuzzy model has an ability to exactly approximate non-linear systems with a combination of linear systems [8]. A minimal set of fuzzy rules are obtained by the hybrid fuzzy clustering (Fuzzy C-Means and Subtractive Clustering) and the modified *apriori* approaches are able to be used to carry out the TSK type fuzzy inference system. The advantages of both the modified hybrid fuzzy clustering and *apriori algorithms* approaches with the TSK fuzzy model are combined in order to introduce a hybrid modified adaptive fuzzy pattern classifier (MAFIE). After this initial construction of the adaptive fuzzy inference system (MAFIE), the membership functions (MFs) are adjusted to achieve better performance.

This paper is organized as follows: Section II provides a design approach of a modified adaptive fuzzy inference engine followed with the TSK type fuzzy inference system, hybrid fuzzy clustering algorithm and *apriori* algorithm. Section III presents the proposed modified adaptive fuzzy inference engine (MAFIE) block diagram and flowchart algorithm of developed model. The tuning process of membership functions are shown in section IV. Experimental results based on Fisher's Iris and Wisconsin Breast Cancer benchmark datasets for the MAFIE are compared the results with other existing pattern classification algorithms in Section V, and final conclusions are drawn in Section VI.

II. Design of a Modified Adaptive Fuzzy Inference Engine (MAFIE)

The design of the MAFIE is discussed in this section. The MAFIE consists of TSK type fuzzy inference systems (including fuzzification, knowledge-base, inference and defuzzification functions) with modified algorithms such as hybrid fuzzy clustering (combination of FCM and SC) and modified a*priori* algorithms. These algorithms were implemented and they constructed a novel fuzzy inference system which is called MAFIE. The MAFIE has been designed and developed in a step by step process as follows.

A. Fuzzy Inference System (FIS)

The TSK type fuzzy inference system suggested by Takagi Sugeno and Kang [9] is capable of defining a general type of nonlinear systems. It can be represented as a linear arrangement of input variables and a constant term as described by equation (1).

$Rule_i$: *If* x_{k1} *is* F_{i1} *AND* x_{k2} *is* F_{i2} ... *AND* x_{km} *is* F_{im} *THEN* $y_i = c_{i0} + c_{i1}x_{k1} + \ldots + c_{im}x_{km}$

$$y = \frac{\sum_{i=1}^{N} w_i y_i}{\sum_{i=1}^{N} w_i}, \quad w_i = \prod_{j=1}^{m} F_{ij}(x_{kj}) \tag{1}$$

Where $Rule_i$ $(i=1, 2, \ldots N)$ is the i^{th} fuzzy rule, x_{kj} $(j=1, 2, \ldots, m)$ is the j^{th} input variable of the k^{th} pattern vector, and F_{ij} is a fuzzy variable of the j^{th} input variable in the i^{th} rule. Also Π is a fuzzy *T-norm* operator and w_i is a rule firing-strength of the i^{th} rule, and y_i is the i^{th} rule output and y is the overall output.

A TSK type fuzzy inference system of Multi-Input-Single-Output (MISO) has been taken for granted because it is known that the Multi-Input-Multi-Output (MIMO) system can be molded into a number of MISO systems with no loss of generality [10]. The TSK type fuzzy inference system approximates a nonlinear system with an arrangement of many linear systems by molding the whole input space into many partial spaces and expressing each input/output (I/O) domain with a linear system function. In order to obtain the coefficients of the linear systems, the least-square estimator has been commonly employed. It is essential to entirely inspect the minimal number of high strength rules in the process of a fuzzy rule generation. If the minimal number of rules found from *apriori* and hybrid fuzzy clustering algorithm is appropriate to be employed as a set of fuzzy inference rules in the TSK type fuzzy inference system, the numbers of fuzzy membership functions and fuzzy rules in the knowledge-base of fuzzy inference system are capable of being decreased successfully.

B. Hybrid Fuzzy Clustering Algorithm for Automatic Generation of Membership Functions

The clustering algorithms are a method which is usually employed to discover a cluster center and inform the position of heart (center) of each cluster [31]. Fuzzy C-means algorithm [11] is good for clustering accuracy but depends on telling a priori the number of clusters. At this stage, the fuzzy c-mean clustering algorithm strives to categorize the data into the specified quantity of clusters. The capability of the fuzzy c-means clustering is robustly reliant on the selection of a priori center of cluster and tends to join to a close by regional optimum. A number of researchers are attempting to build up universal optimizers for fuzzy C-means clustering [12]-[14].

In this study, subtractive clustering [15] was employed to identify the preliminary number of centers and clusters. The subtractive clustering begins to discover the centers and clusters automatically by finding the largest cluster, then the second large cluster, followed by the third. The subtractive cluster is a faster method, but the issue is, the accuracy is reliant on the exact preference of four parameters, for instance, r_a, r_b, ε_l and ε_h [15]. Considering the advantages of both clustering algorithms in terms of accuracy and speed, in this study, it has been proposed hybrid fuzzy clustering techniques.

The Hybrid Fuzzy clustering algorithm is represented as follows:

Step 1: From the following equation, the r_a indicate the local radius for each cluster, n is the number of data points and $|.|$ is Euclidean distance of the dataset x where $i, j = 1, .., n$, compute the potential D_i using the equation (2).

$$D_i = \sum_{j=i}^{n} \exp\left[\frac{|x_i - x_j|^2}{\left(\frac{r_a}{2}\right)^2}\right] \tag{2}$$

Step 2: Assume the maximum potential of sample point is D_{c1} and the position of that sample point is x_{c1} as first cluster center when set $n_c = 1$.

Step 3: In this step, updating each and every data point of potential using the equation (3).

$$D_i = D_i - D_{c1} \exp\left(\frac{|x_i - x_{c1}|^2}{\left(\frac{r_b}{2}\right)^2}\right) \tag{3}$$

Step 4: If max $D_i \geq \varepsilon_h D_{c1}$ is true, admit x_{ci} is the next cluster center, continue until getting the final (all) cluster center from the whole set of data.

Step 5: If max $D_i < \varepsilon_h D_{c1}$ is true, go to Step 4, or check to see if the data point provides the best exchange between getting sufficient potential and having a satisfactory distance from obtainable cluster centers. If the situation is that, this data point will be chosen for the next center of cluster.

Step 6: Calculate u_{ij} (membership matrix) where *d* is the Euclidean distance using equation (4).

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}} \right)^{\frac{2}{m-1}}} \quad (4)$$

Step 7: Updating fuzzy cluster center using equation (5).

$$c_i = \frac{\sum_{j=1}^{N} u_{ij}^m x_j}{\sum_{i=j}^{N} u_{ij}^m} \quad (5)$$

Step 8: Calculate the cost function (Objective function) using the following equation (6).

$$J(U,c) = \sum_{i=1}^{c} \sum_{j=1}^{n} (u_{ij})^m (d_{ij})^2 \quad (6)$$

Where $d_{ij} = (x_j - c_i)$

Step 9: compute the standard deviation (width) of each and every membership function using the following equation (7).

$$\sigma_{ik} = \sqrt{Diag(FC_i)}, \quad (7)$$

Step 10: If the algorithm is not assigned a small noise as a same membership value to each cluster centre then go to step 9, otherwise overcome the problem using equation (8).

$$\mu_{ij} = \mu_{ij1} \times \mu_{ij2} \quad (8)$$

$$\mu_{ij1} = e^{-\left(\frac{x_{kj} - c_{ij1}}{\sigma_{ij1}}\right)^2} \times Index_{v_{ij1}} + (1 - Index_{v_{ij1}})$$

$$\mu_{ij2} = e^{-\left(\frac{x_{kj} - c_{ij2}}{\sigma_{ij2}}\right)^2} \times Index_{v_{ij2}} + (1 - Index_{v_{ij2}})$$

$$if\ x_{kj} \le c_{ij1}, Index_{vij1} = 1,\ otherwise\ 0$$

$$if\ x_{kj} \ge c_{ij2}, Index_{vij2} = 1,\ otherwise\ 0$$

Stop the program if it is lower a specific tolerance value or if its improvement is less than a certain threshold. Else, go to Step 4.

C. A Modified Apriori Algorithm for Rule Formation

In this section, the proposed modified *apriori* algorithm for rule formation is shown in Figure 1. This algorithm was inspired by the ways of finding the maximum itemset in the *apriori* algorithm. However, the proposed algorithm is different from the one used in the *apriori* algorithm. In a way, the proposed algorithm is like running the maximum itemset determination algorithm backwards. Instead of considering each item by itself, here it begins with the clusters identified in the hybrid fuzzy clustering method.

This is a simple example to illustrate the proposed rule formation method. First consider the D_1 column. There are three clusters: {1, 2, 3}, {4, 5, 6} and {6, 7, 8} respectively. This is shown in the table called "Clustered Data" in Figure 1. For convenience, {1, 2, 3} is labeled as cluster 1, {4, 5, 6} as cluster 2 and {6, 7, 8} as cluster 3. Each cluster consists of three data labels. This information is displayed in the Table called L_1 in Figure 1. Assume that the threshold is 1. The first column of "Cluster Data" has three cluster sets each denotes the cluster {1, 2, 3}, cluster {4, 5, 6} and cluster {6, 7, 8} respectively. The column "Combination of clusters" denotes the label provided for these three clusters, i.e., cluster 1, cluster 2 and cluster 3 respectively. The column "Count of common elements" denotes the number of elements in the cluster. In these three cases, there are three elements in a cluster.

Concatenate the clusters from dimension D_1 with those from dimension D_2 using a join operation. As there are three clusters in the D_2 dimension: {1, 2}, {3, 4, 5, 6}, {9, 8, 9}, concatenate the clusters of the dimension D_1 with those in dimension D_2 to find the common elements. Thus, in the Table called C_2 in Figure 3.1, the first element in the column "Compare clusters" shows the concatenation of the first cluster {1, 2, 3} in dimension D_1 with the first cluster {1, 2} in dimension D_2. This is denoted by {1, 2, 3}∩{1,2}. This is denoted by (1),1 in column "Combination of clusters" in Table C_2 (Indicating Cluster1 in D_1 and Cluster1 in D_2). In this case, there are two common elements 1 and 2, and thus the entry of 2 in the column "Counts of common elements" in Table C_2.

In a similar manner, find the values of all the columns in Table C_2. Since the threshold is 1, remove the entry (Zero) corresponding to {1, 2, 3,}∩{9, 8,9}, as there are no common elements in this concatenation. Then transfer this information into Table L_2. The entries in the column "Clusters" are the concatenation of the clusters and the common elements. For example, the first entry of column "Clusters" is obtained by the concatenation of cluster 1 {1, 2, 3} in D_1 dimension, cluster 1 {1, 2} in dimension D_2. The common elements in these two clusters are {1, 2}. The entry in the column "Combination of clusters" in Table L_2 denoted by (1),1 signifies the result obtained by the concatenation of cluster 1 in D_1 dimension with that of cluster 1 in the D_2 dimension. There are only two common elements, and therefore the entry in the column "Counts of common elements" is 2. The entries in the Table called C_3 denote the join operation of the results of Table L_2 with those clusters on the D_3 dimension. In the Table C_3, it is denoted by {1, 2} ∩ {1, 2, 3, 4} in the column of "Compare cluster". The meaning of the first entry in the column "Combination of clusters" (1,1)1 is indicating that the common data (1,2) is cluster 1 in D_1, cluster 1 in D_2 and cluster 1 in D_3 . There are two common elements, {1 2}. Hence the first entry in the column "Counts of common elements" is 2. This process is repeated for the other clusters until Table C_3 is fully populated. Since the threshold is 1, eliminate entries {1,2}∩{5, 6}, and {4, 5, 6}∩{1,2,3,4} and others which are threshold and below threshold value. The remaining information is transferred to the table called L_3. There are only two values which are above the threshold {1,2}∩{1, 2, 3, 4}, and {4, 5, 6}∩{5, 6}. Therefore the entries in the final column of Table L_3 are both 2 denoting that there are only two common elements. The entries in the column "Combination of clusters" denote the way in which the clusters are formed. For example, the first element is formed by the concatenation of cluster 1 in D_1 dimension, cluster 1 in D_2 dimension and cluster 1 in D_3 dimension. The "Clusters" column denotes the common elements as a result of the concatenation process. Since there are only three input dimensions, the process will stop.

In this example, finally conclude that there are two fuzzy rules (as in Figure 1, there are only two remaining entries) and the minimal rules are formed as follows from the column of "Combination of clusters" are shown in Figure 1.

*Rule1: **If** cluster1 in D_1 dimension **AND** cluster1 in D_2 dimension **AND** cluster1 in D_3 dimension **THEN** Consequence1.*

*Rule2: **If** cluster2 in D_1 dimension **AND** cluster2 in D_2 dimension **AND** cluster2 in D_3 dimension **THEN** Consequence2.*

Clustered Data	D_1	D_2	D_3
$Clust_3$	{6,7,8}	{9,8,9}	{3,4,3}
$Clust_2$	{4,5,6}	{3,4,5,6}	{5,6}
$Clust_1$	{1,2,3}	{1,2}	{1,2,3,4}

L_1		
Clusters in D_1	Combination of cluster in D_1	Counts of common elements in the cluster
{1,2,3}	1	3
{4,5,6}	2	3
{6,7,8}	3	3

C_2		
Compare clusters in L_1 with D_2	Combination of clusters	Counts of common element in the clusters
{{1,2,3}∩{1,2}}	(1),1	2
{{1,2,3}∩{3,4,5,6}}	(1),2	1
{{1,2,3}∩{9,8,9}}	(1),3	0
{{4,5,6}∩{1,2}}	(2),1	0
{{4,5,6}∩{3,4,5,6}}	(2),2	3
{{4,5,6}∩{9,8,9}}	(2),3	0
{{6,7,8}∩{1,2}}	(3),1	0
{{6,7,8}∩{3,4,5,6}}	(3),2	0
{{6,7,8}∩{9,8,9}}	(3),3	1

L_2		
Clusters after pruning	Combination of clusters	Counts of common element in the clusters
{1,2}	(1),1	2
{4,5,6}	(2),2	3

C_3		
Compare clusters in L_2 with D_3	Combination of clusters	Counts of common element in the clusters
{{1,2}∩{1,2,3,4}}	(1,1),1	2
{{1,2}∩{5,6}}	(1,1),2	0
{{1,2}∩{3,4,3}}	(1,1),3	0
{{4,5,6}∩{1,2,3,4}}	(2,2),1	1
{{4,5,6}∩{5,6}}	(2,2),2	2
{{4,5,6}∩{3,4,3}}	(2,2),3	1

L_3		
Clusters after pruning	Combination of clusters	Counts of common element in the clusters
{1,2}	(1,1),1	2
{5,6}	(2,2),2	2

Figure 1. An Example of Proposed Modified *Apriori* Algorithm

From this description it can be observed that the proposed procedure is quite different from the maximum itemset determination in the *apriori* algorithm. It seeks to find the combination of clusters such that there are common elements in the clusters. Note that these common elements are represented by the data labels stored in the clusters. The proposed algorithm is inspired by the maximum itemset determination algorithm in the *apriori* algorithm. It is possible to simulate the *apriori* algorithm to compute the *support* and the *confidence* of the rules formed.

III. Modified Adaptive Fuzzy Inference Engine (MAFIE)

When the parameters of antecedent membership functions and consequent linear equations are obtained via the hybrid fuzzy clustering algorithm, and the minimal number of rules is found through the *apriori* algorithm approach with TSK type fuzzy inference system (FIS), the modified adaptive fuzzy inference engine (MAFIE) can be constructed. A functional block diagram of the proposed framework of MAFIE is shown in Figure 2. As a brief overview, a pre-processing was applied to the given input and output data to generate two major components of the proposed system; first, adaptive fuzzy clusters for the inputs using the hybrid fuzzy clustering algorithm, and second, minimal decision rules of the given information using the rules generation algorithm using modified *apriori* algorithm. The obtained fuzzy clusters and minimal rules were used to model membership functions and TSK type fuzzy rules in the knowledge-base. Once the TSK type MAFIE fuzzy inference engine was constructed with input/output dataset, a system evaluation process was carried out as a post-processing.

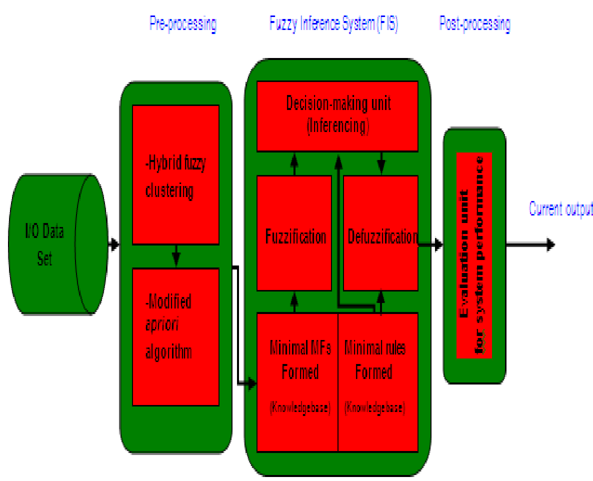

Figure 2. Functional Block Diagram of Modified Adaptive Fuzzy Inference Engine (MAFIE)

The developed architecture was designed as a MISO type fuzzy inference system called MAFIE. The adaptive cluster information are getting from corresponding inputs as an antecedent variables (Fuzzy terms) using the hybrid fuzzy clustering algorithm. A type of compositional fuzzy rules was employed to produce a minimal number of fuzzy rules in the knowledge-base using modified *apriori* algorithm if needed, and the logical operator was conducted to compute fuzzy *T-norm* (*AND*) process among the antecedent variables. The coefficients of the consequent variable are found and incorporated with a constant term to form a linear output using the least squares estimation algorithm.

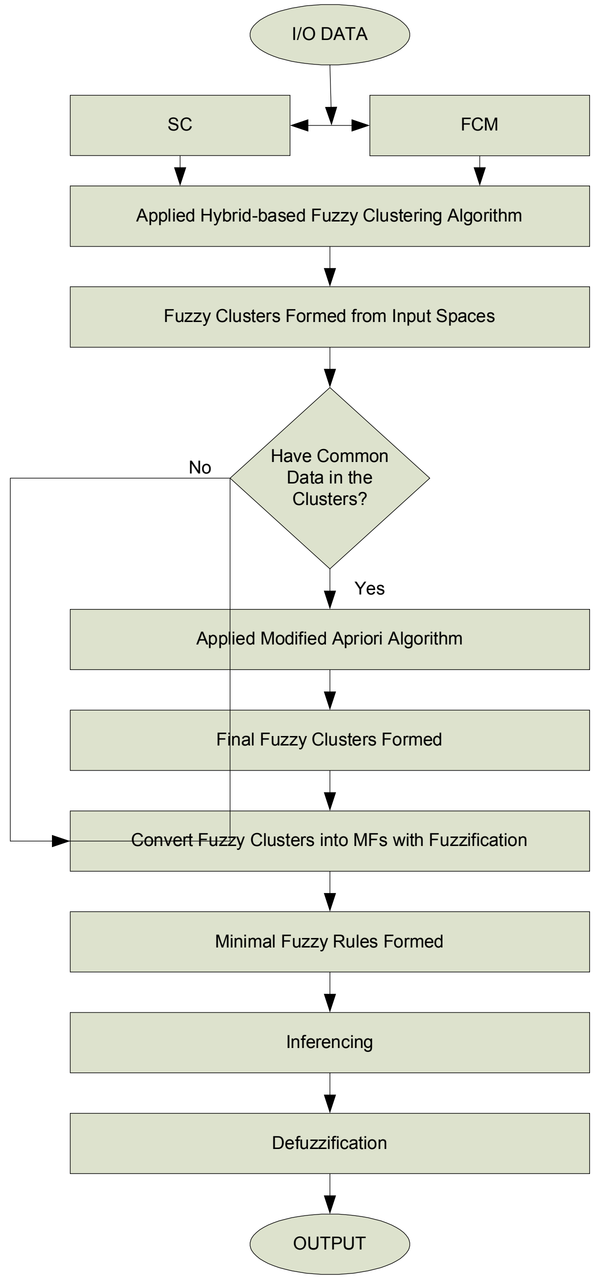

Figure 3. Flowchart of MAFIE Algorithm (Developed Model)

In order to develop the modified adaptive fuzzy inference engine (MAFIE), software programming language is required where the MAFIE is written in MATLAB programming language which can be compiled and simulated with the help of fuzzy logic toolbox in MATLAB version R2010b. The flowchart of MAFIE model (A completed developed algorithm) is shown in Figure 3.

II. Tuning Process of Membership Functions

The performance of the system needs to be evaluated and enhanced towards a higher accuracy after the construction stage. If the RMSE error measure in (9) is not satisfactory when compared to an arbitrary error criterion, the parameters of antecedent membership functions are adjusted using the Polak-Ribiere conjugate gradient algorithm based on the difference between the desired and the actual output.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(err_i)^2}{n}}, err_i = y^d - y^o \qquad (9)$$

where, err_i is the error between the desired output, y^d, and the current output, y^o, from the fuzzy inference system at one epoch.

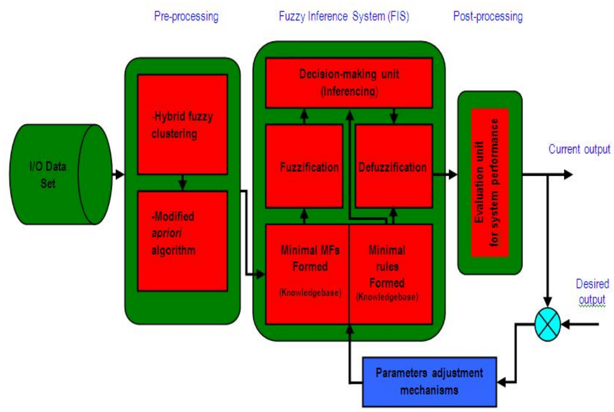

Figure 4. Modified Adaptive Fuzzy Inference Engine (MAFIE) with Parameters Adjustment Mechanisms

The modified adaptive fuzzy inference engine with parameter adjustment mechanism block diagram is shown in Figure 4. Once the coefficients of the TSK type consequent variable are fitted with the training data, the performance evaluation is done first with the training data to compare its RMSE with a user-defined error criterion. If the RMSE is not satisfactory, the adjustment of antecedent membership functions is carried out with the training dataset.

III. Experimental Results

In the past, many different approaches have been suggested to achieve a higher accuracy on a variety of datasets in the pattern classification scheme. For example, as reported in [16], conventional methods [17], [18] and fuzzy-based classifiers; Adaptive Fuzzy Leader Clustering (AFLC) [19], Wu and Chen's algorithm [20], Fuzzy Entropy-Based Fuzzy Classifier (FEBFC) [21], Influential Rule Search Scheme (IRSS) [22], Adaptive Rough-Fuzzy Inference System (ARFIS) [23] and Rough Adaptive Neuro Fuzzy Inference System (RANFIS) [24] have been applied on Iris data set and Wisconsin breast cancer data set to achieve better performance. However, some of these approaches still have difficulties with the number of fuzzy rules when a higher dimensional data set is applied, because in fuzzy inference systems the size of their knowledge base is directly associated with the computational complexity and the system performance. The proposed MAFIE has been developed to overcome this problem by reducing the number of fuzzy rules effectively through the knowledge-reduction process and by adjusting the antecedent MFs after the performance evaluation.

A. The Fisher's Iris Dataset

In this experiment, the Fisher's Iris dataset [25] contained 150 pattern vectors with four input attributes of flower plant as sepal length (in1), sepal width (in2), petal length (in3), and petal width (in4) and one output of three classes (Setosa, Versicolor, and Virginica) contain 50 samples each, where each class refers to a type of Iris plant. The MAFIE model selected the first 50 percent of the data for the training dataset and the last 50 percent of the data for the checking dataset for each output class. The training and the checking datasets were swapped once the experiment was implemented and tested using those datasets.

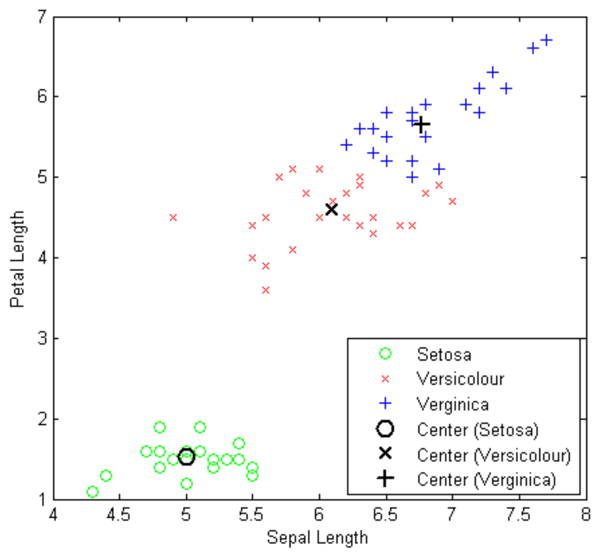

Figure 5. The Clustering Data (Sepal length Vs Petal length) using MANFIE for Iris Training Dataset

The data classification plots for the Fisher's Iris training dataset are shown in Figure 5 (Sepal length Vs Petal length). The final adjusted antecedent membership functions were automatically generated as patterns for the Iris dataset and all attributes are shown in Figure 6. It can be seen that each membership function was fitted to different shapes of the asymmetric Gaussian membership function.

The best (high strength) final number of reduced fuzzy rules was three (3) on averages after 10 independent runs using the proposed method (MAFIE). In contrast, the number of the generated fuzzy rules in the IRSS [22] and ANFIS models [27] are increased exponentially as 3^4 (81 rules, where 4 inputs and 3 membership functions of each input). The proposed system model achieved a massive amount of reduction rules of 96.3% for the same Iris training dataset. Accordingly, the computational complexity was reduced effectively by the proposed method approach. The result of the classification accuracy and other parameters are shown in Table I for comparison results indicated as system performance. It can be seen that the classification accuracy produced by the proposed framework of MAFIE was favorable and competitive when compared to the results of other classification approaches.

Table 1. Comparison results with other classification schemes on Iris training dataset

Models	Average Accuracy (%)	Rules	Fitting Parameters	Process Time (sec)
ANFIS [27]	96.00	81	441	0.50
AFLC [19]	95.33	81	441	0.60
IRSS [22]	96.00	81	441	0.50
ARFIS [23]	96.28	23	65	0.07
MAFIE with hybrid Method [28]	**97.84**	**16**	**208**	**0.20**
MAFIE	**96.50**	**3**	**39**	**0.027**

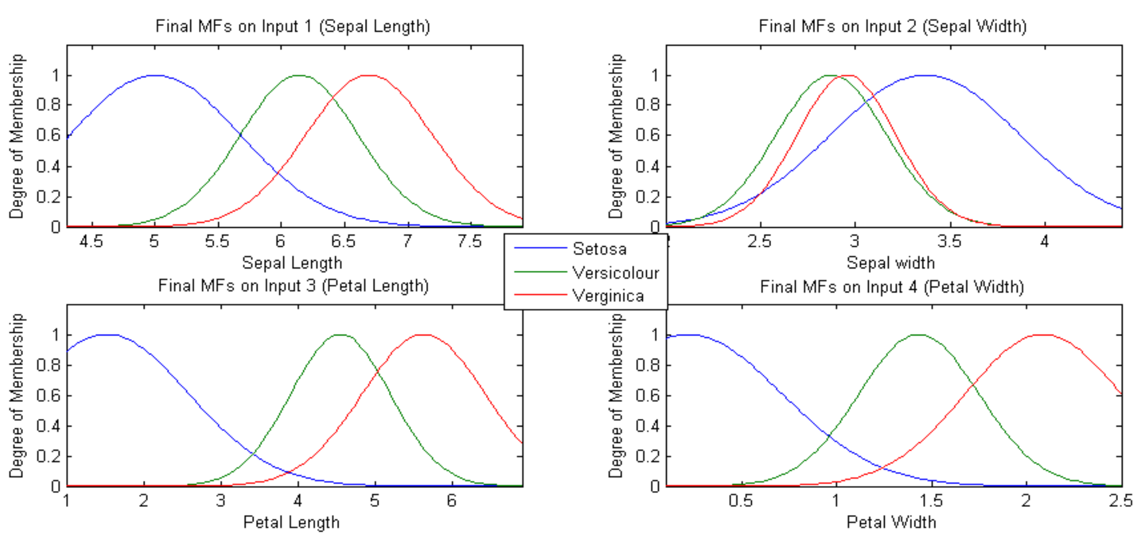

Figure 6. The Final Antecedent Membership Functions (MFs) for Four Inputs

B. Wisconsin Breast Cancer Dataset

This experiment was performed in the same manner (conditions) utilized for the Fisher's Iris dataset. The proposed MAFIE model was also applied using the Wisconsin breast cancer dataset [25] to determine whether the classification methods are efficient enough to handle such a large number of input dataset. This dataset has 699 vectors with nine input attributes as Clump thickness (in1), Cell size (in2), Cell shape (in3), Marginal Adhesion (in4), Single epithelial cell size (in5), Bare Nuclei (in6), Bland chromatin (in7), Normal Nucleoli (in8), Mitoses (in9) and one output of two classes as "benign" and "malignant" samples. In order to generate the training and the checking datasets, the following steps were taken. To begin with, about 17 data pairs from the 699 pattern vectors from the original dataset that included missing attributes were first removed. One hundred data pairs of vectors were randomly assigned as the training dataset and 100 data pairs of vectors were randomly selected for the checking dataset.

The data classification plots for the Wisconsin breast cancer dataset are shown in Figure 7 (Cell size Vs Marginal adhesion). In contrast, the number of the generated fuzzy rules in the MSC [26] and ANFIS models [27] is increased exponentially to 2^9 (512 rules, where 9 inputs and 2 membership functions of each input).

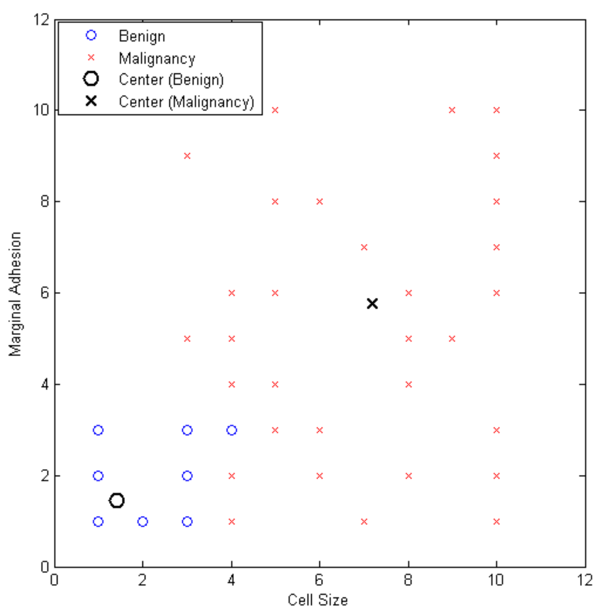

Figure 7. The Clustering Data (Cell size Vs Marginal adhesion) using MANFIE Architecture

The proposed system (MAFIE) achieved a massive amount of reduction rules (2 rules) of 99.6% for the same training dataset. Accordingly, the computational complexity was reduced effectively by the proposed method approach.

The final adjusted antecedent membership functions were automatically generated for Wisconsin dataset and four inputs attributes are shown in Figure 8. It is shown that each membership function was fitted to different shapes of asymmetric Gaussian membership function as a pattern.

Table II. Comparison results with other classification schemes for Wisconsin training dataset

Models	Average Accuracy (%)	Rules	Fitting Parameters (Total)	Processing Time (sec)
ANFIS [27]	96.20	512	5210	49.23
MSC [26]	94.90	512	5210	50.23
IRSS [22]	95.89	512	5210	51.20
ARFIS [23]	96.35	128	140	1.35
MAFIE With FCM [29]	**97.24**	**12**	**336**	**5.6**
MAFIE	**96.35**	**2**	**56**	**0.95**

As shown in Table II, the proposed algorithm MAFIE provided encouraging results for classification on the Wisconsin breast cancer training dataset when compared with other classification techniques. The results demonstrate that the proposed method is a much better performance using only two rules when a large number of inputs are applied. This was achieved by combining the effective reduction process of the hybrid fuzzy clustering and *apriori* algorithm together with the parameters tuning procedure.

The Fisher's Iris and the Wisconsin Breast Cancer training datasets results are discussed and are shown in Table I and Table II. The different types of models are indicated and the results are compared in terms of pattern accuracy, reduction rules, fitting parameters, and processing time in these tables. It can be clearly seen that the number of rules are significantly reduced (96.3% for the Iris and 99.6% for the Wisconsin) with fitting parameters. The processing time needed was only 0.027 of a second for the Iris and 0.95 of a second for the Wisconsin which is a significant reduction. The average accuracy (96.50% for the Iris and 96.35% for the Wisconsin) of pattern classifications of the proposed method MAFIE was found to be the best and the most competitive when compared to other models.

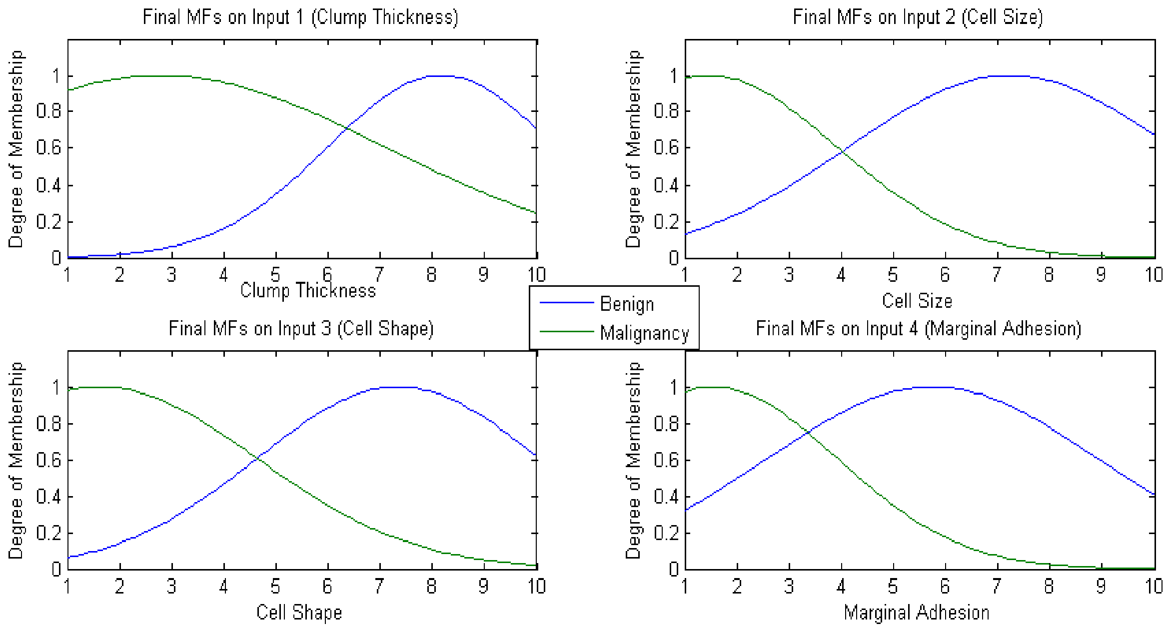

Figure 8. The Final Antecedent Membership Functions (MFs) Adjusted for Four Inputs

IV. Conclusion

A novel modified adaptive fuzzy inference engine (MAFIE) has been proposed which automatically generates fuzzy membership functions via the hybrid fuzzy clustering algorithm. The minimal fuzzy rules are generated from the modified *apriori* algorithm based on input-output datasets. The performance evaluation was done to achieve better performance through the adjustment of antecedent membership functions using learning algorithms. It is significant that the number of rules generated by MAFIE were reduced effectively by the *apriori* approach towards better performance. The comparisons with other pattern classifiers indicated that the performances of MAFIE were found to be encouraging and satisfactory results using benchmark datasets. Research is continuing on the refinement process of the fuzzy rules to achieve better accuracy in a pattern classification scheme.

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Author Biographies

Jakir Hossen is graduated in Mechanical Engineering from the Dhaka University of Engineering and Technology (1997), Masters in Communication and Network Engineering from Universiti Putra Malaysia (2003) and PhD in Smart Technology and Robotic Engineering at Universiti Putra Malaysia (2012). He is currently a Lecturer at the Faculty of Engineering and Technology, Multimedia University, Malaysia. His research interests are in the area of Artificial intelligence (fuzzy logic, neural network), Inference systems, pattern classification, mobile robot navigation and control.

Shohel Sayeed is graduated in Agriculture from Bangladesh Agricultural University (1989), Masters in Information Technology from National University of Malaysia (2000) and PhD in Engineering from Multimedia University, Malaysia (2010). Dr. Shohel has been a member of Multimedia University since 2001 and now he serves as an Associate Professor at Faculty of Information Science and Technology. Dr. Shohel's core research interest is in the area of Biometrics, information security, image and signal processing, pattern recognition and classification.

Ibrahim Yusof is graduated in Marketing from Universiti Teknologi Mara (1992), Masters in Information Technology from Universiti Utara Malaysia (2002) and currently he is pursuing his PhD in Inforamtion Security at Asean E University. He has been a member of Multimedia University since 2004 and now he serves as a Lecturer at Faculty of Information Science and Technology. His core research interest is in the area of Biometrics, information security, network security, image processing, pattern recognition and classification.

Kalaiarasi Sonai Muthu Anbananthen is graduated in Economics from University Science Malaysia (1996), Masters in Information Technology from University Science Malaysia (2000) and Ph D in Artificial Intelligence from University Malaysia Sabah (2008). Dr. Kalaiarasi's core research interest in the area of artificial neural network, rule extraction, data mining, opinion mining, neural network, mobile technology and knowledge management..