Data Mining for extraction of fuzzy IF-THEN rules using Mamdani and Takagi-Sugeno-Kang FIS

Juan E. Moreno, Oscar Castillo, Juan R. Castro, Luis G. Martínez, Patricia Melin

***Abstract*— This paper presents clustering techniques (K-means, Fuzzy K-means, Subtractive) applied on specific databases (Flower Classification and Mackey-Glass time series) , to automatically process large volumes of raw data, to identify the most relevant and significative patterns in pattern recognition, to extract production rules using Mamdani and Takagi-Sugeno-Kang fuzzy logic inference system types.**

***Index terms*— Clustering, Extraction, Fuzzy K-means, Fuzzy Logic, Identification, Inference Systems. K-means, Subtractive Clustering.**

I. Introduction

In the past years we have seen a growth in the capacity of storage and generation of information, product of an increment in automatization processes and progress in the capacity of storage of information.

Unfortunately, we have not seen an equal development on the information analysis techniques, thus the need of a new kind of technique and generating computer tool with the capacity to support users on automatic and intelligent analysis of great volumes of data to find useful knowledge and satisfy the users goals.

Data mining can be define as the process of automatically searching large volumes of data for patterns [3] [14] [15]. Data mining employs a searching process through a large volume of data, using clustering techniques (K-means, Fuzzy K-means, Subtractive) to acquire relevant and significant data in pattern recognition; and fuzzy logic from inference system (Mamdani and Takagi-Sugeno-Kang Type) based techniques to extract production rules (IF-THEN).

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This paper has been organized in sections. Section II tackles the subject of clustering and rule extraction using Mamdani Fuzzy Inference System (FIS). Section III presents clustering and rule extraction using Takagi-Sugeno-Kang Inference System (TSK). Section IV shows this work's results of the techniques employed. Section V displays the graphics and charts of the flower identification (Iris data) case study. Section VI presents the graphics and charts of the Mackey-Glass (Mg data) time series case study.

II. Clustering and Rule Extraction Using Mamdani Fuzzy Inference System

A. Algorithm to obtain rule antecedent and consequent with Mamdani Fuzzy Inference System

Detailed next is the algorithm to obtain the rule antecedents using clustering techniques (K-means, Fuzzy K-means, Subtractive) and the rule consequents with the Mamdani Fuzzy Inference System.

Inputs:

$$X = \lfloor x_{p,i} \rfloor \quad \forall\, i = 1,\ldots n$$

$$y = \lfloor y_p \rfloor \qquad \forall\, p = 1,\ldots q$$

Output:

$\hat{y} = \lfloor y_p \rfloor$, rules and parameters for gaussian membership functions of antecedents and consequents.

Step 1: Group input values using clustering techniques (K-means, Fuzzy K-means, Subtractive) to calculate centroid $c^a_{i,j}$ and standard deviation $\sigma^a_{i,j}$ formulated in equation (1) giving the antecedents membership function values $\mu^i_j(x_j)$ from equation (2).

$$\sigma^a_{i,j} = \left(\frac{(r_a * (\max(X) - \min(X)))}{\sqrt{8}} \right) \tag{1}$$

where X is a matrix.

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Step 2: Calculate the consequents with Mamdani fuzzy reasoning.

$$\mu_j^i\left(\hat{x}_j\right) = e^{-\frac{1}{2}\left(\frac{\left\|x_{p,j}-c_{i,j}^a\right\|}{\left(\sigma_{i,j}^a\right)^2}\right)} \quad (2)$$

$$\alpha_i = \mu_1^i\left(\hat{x}_1\right) * \ldots * \mu_j^i\left(\hat{x}_j\right) * \ldots * \mu_n^i\left(\hat{x}_n\right) \quad \forall i = 1,2,\ldots,r \quad (3)$$

$$\beta_i = \frac{\alpha_i}{\sum_{i=1}^{r} \alpha_i} \quad \forall i = 1,2,\ldots,r \quad (4)$$

$$\hat{y} = \left[\beta_1 \ldots \beta_i \ldots \beta_r\right] \begin{bmatrix} \overline{y}^1 \\ \vdots \\ \overline{y}^i \\ \vdots \\ \overline{y}^r \end{bmatrix} = \beta \cdot \overline{y} \quad (5)$$

$$e = y - \beta \cdot \overline{y} \quad (6)$$

To find the consequent membership function values $\overline{y}^i$, we can use the approximation method or minimum square method, resulting a centroid matrix of the rule consequents $\left(\overline{y} = c^c\right)$.

Step 3: Extract the rules based on antecedents $\mu_j^i\left(x_j\right)$ membership function values and Mamdani FIS rules consequents $\rho^i\left(y\right)$, denoted in equation (7).

$$\begin{aligned} \Re^i = & \; IF \; x_1 \; is \; \mu_1^i \; and \ldots and \; x_j \; is \; \mu_j^i \; and \ldots and \; x_n \; is \; \mu_n^i \\ & THEN \; y \; is \; \rho^i \end{aligned} \quad (7)$$

Step 4: Evaluate Mamdani FIS with input values (x) to get outputs $\left(\hat{y}\right)$ and calculate root mean square error $rmse = \sqrt{mse(e)}$

III. CLUSTERING AND RULE EXTRACTION USING TAKAGI-SUGENO-KANG INFERENCE SYSTEM

A. Algorithm to obtain rule antecedent and consequent using Takagi-Sugeno-Kang Inference System (TSK)

Detailed next is the algorithm to obtain the rule antecedents using clustering techniques (K-means, Fuzzy K-means, Subtractive) and rule consequents with Takagi-Sugeno-Kang Inference System.

Inputs:

$$X = \left\lfloor x_{p,i} \right\rfloor \quad \forall i = 1,\ldots n$$
$$y = \left\lfloor y_p \right\rfloor \quad \forall p = 1,\ldots q$$

Output:

$\hat{y} = \left[y_p\right]$,rules and parameters for gaussian membership functions of antecedents and consequents.

Step 1: Group input values using clustering techniques (K-means, Fuzzy K-means, Subtractive) to calculate centroid $c_{i,j}^a$ and standard deviation $\sigma_{i,j}^a$ formulated in equation (7) giving the antecedents membership function values $\mu_j^i\left(x_j\right)$ from equation (8).

$$\sigma_{i,j}^a = \left(\frac{\left(r_a * \left(\max(X) - \min(X)\right)\right)}{\sqrt{8}}\right) \quad (7)$$

where X is a matrix.

Step 2: Calculate the consequents with Takagi-Sugeno-Kang fuzzy reasoning.

$$\mu_j^i\left(\hat{x}_j\right) = e^{-\frac{1}{2}\left(\frac{\left\|x_{p,j}-c_{i,j}^a\right\|}{\left(\sigma_{i,j}^a\right)^2}\right)} \quad (8)$$

$$\alpha_i = \mu_1^i\left(\hat{x}_1\right) * \ldots * \mu_j^i\left(\hat{x}_j\right) * \ldots * \mu_n^i\left(\hat{x}_n\right) \quad \forall i = 1,2,\ldots,r \quad (9)$$

$$\Phi_i = \frac{\alpha_i}{\sum_{i=1}^{r} \alpha_i} \quad \forall i = 1,2,\ldots,r \quad (10)$$

$$\hat{y} = \sum_{i=1}^{r} \Phi_i \cdot f_i \quad (11)$$

$$M = \left[\Phi_1 x_1 \ldots \Phi_1 x_j \ldots \Phi_1 x_n \, \Phi_1 \ldots \Phi_i x_1 \ldots \Phi_i x_j \ldots \Phi_i x_n \, \Phi_i \ldots \Phi_r x_1 \ldots \Phi_r x_j \ldots \Phi_r x_n \, \Phi_r\right] \quad (12)$$

$$P = \left[a_{11} \ldots a_{ij} \ldots a_{1n} \, a_{10} \left| a_{i1} \ldots a_{ij} \ldots a_{in} \, a_{i0} \right| a_{r1} \ldots a_{rj} \ldots a_{rn} \, a_{n0}\right]^T \quad (13)$$

$$\hat{y} = M \cdot P \quad (14)$$

$$e = y - M \cdot P \quad (15)$$

To find the consequent membership function values P, we can use the approximation method or minimum square method, obtaining the rule consequent values.

$\left(P = \left[M^{-1}\right]^{T} \cdot y\right).$

Step 3: Extract the rules based on antecedents membership function values $\mu_j^i(x_j)$, and Takagi-Sugeno-Kang fuzzy inference system rules consequents $f_i(x)$, denoted in equation (16).

$$\begin{aligned} \Re^i &= IF\ x_1\ is\ \mu_1^i\ and \ldots and\ x_j\ is\ \mu_j^i\ and \ldots and\ x_n\ is\ \mu_n^i \\ &THEN\ y\ is\ f_1 = a_{i1}x_1 + \ldots + a_{ij}x_j + \ldots + a_{in}x_n + a_{i0} \end{aligned} \quad (16)$$

Paso 4: Evaluate Takagi-Sugeno-Kang FIS with input values (x) to get outputs $\left(\hat{y}\right)$ and calculate the root mean square error $rmse = \sqrt{mse(e)}$

IV. RESULTS

A. *Flower Identification Case Study (Iris data)*

The main idea is to group the flower attributes and generate IF-THEN production rules that can tell us what type of flowers the attributes belongs to. The database we are using consists of 150 tuples with 5 attributes, where 4 of them describe the characteristics of the flowers and the fifth one corresponds to the type of flower as shown in Table I. Every 50 tuples represent one type of flower as shown in Table II.

Table I. Flower Value Metrics

Flower Characteristic	Meaning
Attribute 1	Sepal Length
Attribute 2	Sepal Width
Attribute 3	Petal Length
Attribute 4	Petal Width
Attribute 5	Type of flower

Table II. Types of flower

Attribute 5	Meaning
1	Iris setosa
2	Iris versicolor
3	Iris virginica

Table III presents a test sample of identification values of flowers (Iris data) using clustering techniques (K-mean, Fuzzy K-mean, Subtractive) and the two fuzzy inference system (Mamdani, Takagi-Sugeno-Kang) rule extraction techniques. As we can see the Subtractive technique with a Mamdani fuzzy inference system had the minimum error, testing it with 20 clusters and a 0.15 radius in each technique except in the Subtractive where there isn't need for a pre-establish number of clusters to group; generating 27 rules (presented in Tables V and VI), more than in the other techniques, thus the error value shows it is the closest solution for the flower identification problem. We show in Fig. 1 and Fig. 3 the input variables cluster for each clustering technique with the Mamdani FIS method, and we show in Fig. 2 and Fig. 4 the output variables cluster for each technique respectively, observing that the subtractive technique has the best performance. Using the Takagi-Sugeno-Kang FIS method we tested the first two clustering techniques with 20 clusters and the subtractive that requires no specific number of clusters, and again the subtractive technique throws the minimum error. Therefore the subtractive technique presents to be the better clustering technique with the Takagi-Sugeno-Kang FIS method, furthermore the error (RMSE) is the lesser one compared to the others and the one that best identifies the problem to solve. Although in terms of handling linguistic variables Mamdani is a better choice and as we can see its respective error values are very good too.

The time results presented in Table III were obtained on a PC-Computer with an Intel Centrino 1.73 GHz processor and 512 megabytes of RAM.

Table III. Identification Flowers Case Study Results

IRIS	MAMDANI		
	RMSE	Number of rules	Time (sec)
HKM	0.0348	20	0.8810
FKM	0.0336	20	1.0020
SUBTRACTIVE	0.0310	27	0.3100
IRIS	TAKAGI-SUGENO-KANG		
	RMSE	Number of rules	Time (sec)
HKM	0.0025	20	0.4610
FKM	0.0053	20	0.4710
SUBTRACTIVE	8.0835e-007	27	0.3910

B. *Mackey-Glass Time Series Case Study (MG)*

The primordial idea is to cluster the attributes of the Mackey-Glass time series and then generate the IF-THEN product rules with Mamdani and Takagi-Sugeno-Kang FIS algorithms.

The Mackey-Glass time series is a differential equation of time delays [16] [17] as shown in equation (17). Well known and used in neural network forecasting and fuzzy logic models.

$$x(t) = \frac{0.2x(t-\tau)}{1 + x^{10}} - 0.1x(t) \quad (17)$$

Equation (17) is a chaotic time series where its trajectory is highly sensitive as its initial conditions.

The Runge-Kutta method order 4 is used for finding numeric solutions of equation (17) and is described as

MACKEY GLASS	MAMDANI		
	RMSE	Number of rules	Time (sec)
HKM	0.0016	20	0.5910
FKM	0.0015	20	1.7200
SUBTRACTIVE	8.8760e-004	47	0.5410
MACKEY GLASS	TAKAGI-SUGENO-KANG		
	RMSE	Number of rules	Time (sec)
HKM	3.6259e-005	20	0.5010
FKM	2.6131e-005	20	0.7710
SUBTRACTIVE	2.2897e-006	47	0.5410

Table IV. Mackey-Glass Time Series Case Study Results

follows, assuming that x(0)= 1.2, $\tau = 17$, and x(t)= 0 for all t<0.

Inputs: X= $\{x(t-18)\, x(t-12)\, x(t-6)\, x(t)\}$

Outputs: $x(t+6)$

We take the sample values from $t = 118 \ldots 1117$, where the first 500 are used for the time series training and the other 500 left are the test values.

Table IV presents the sample test made with the Mackey-Glass time series data (mg data) using the clustering techniques (K-mean, Fuzzy K-mean, Subtractive) and the rule extraction methods with the 2 inference systems fore mentioned (Mamdani, Takagi-Sugeno-Kang) with their respective evaluations. As we can see the subtractive technique for the Mamdani FIS resulted with the minimum error, tested with 20 clusters and a 0.15 radius in each technique except on the subtractive where there isn't need for a pre-establish number of clusters to group; generating 47 rules (presented in Tables VII and VIII), although they were more than in any other technique, the error shows it was the closest solution for the Mackey-Glass time series problem. We show in Fig. 5 and Fig. 7 the input variables cluster for each clustering technique with the Mamdani FIS method, and we show in Fig. 6 and Fig. 8 the output variables respectively, observing that the subtractive technique once again has the best performance. In the case of Takagi-Sugeno-Kang FIS method we tested the first two clustering techniques with 20 clusters and the subtractive that not requires specific number of clusters; once again the subtractive technique throws the minimum error. Therefore the subtractive technique presents to be the better clustering technique with the Takagi-Sugeno-Kang FIS method, furthermore the error (RMSE) is the lesser one compared to the others and best identifies the problem to solve. Although in terms of handling linguistic variables Mamdani is a better choice and as we can see its respective error values are very good too.

The time results presented in Table IV were also made on a PC-Computer with an Intel Centrino 1.73 Ghz processor and 512 megabytes of RAM.

V. FLOWER IDENTIFICATION (IRIS DATA) CASE STUDY CHARTS

We show in Fig. 1 and Fig. 3 the clustering techniques (K-means, Fuzzy K-means, Subtractive) focused in the 2 FIS methods used (Mamdani, Takagi-Sugeno-Kang) for rule extraction, the original values of the flower classification are represented by circles and the cluster values by small crosses, each chart shows how each flower attribute clusters (Sepal Length, Sepal Width, Petal Length, Petal Width) for each respective flower type. We show in Fig. 2 and Fig. 4 the output cluster from all attributes before mentioned with the flower type (Iris setosa, Iris versicolor, Iris virginica), once clustered the values are sent to the Mamdani and Takagi-Sugeno-Kang FIS methods to extract IF-THEN production rules. Tables V and VI show some of the rules obtained in the FIS methods mentioned, classifying each flower (consequents) by their attributes respectively (antecedents).

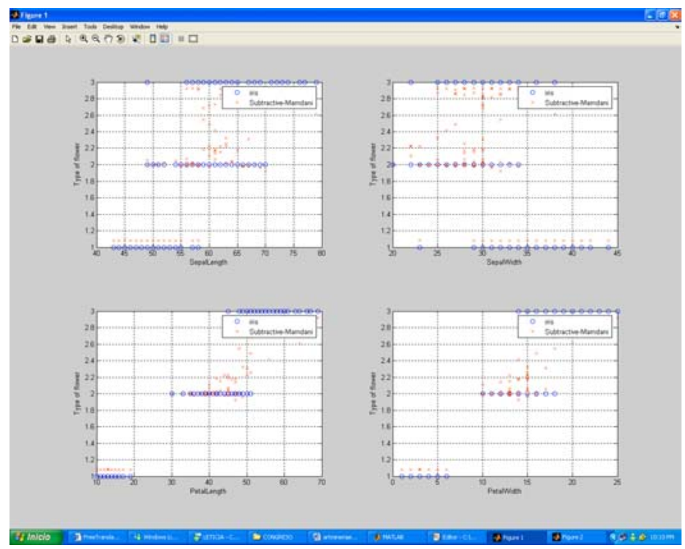

Fig. 1. Flower Attributes Clustering (Subtractive-Mamdani).

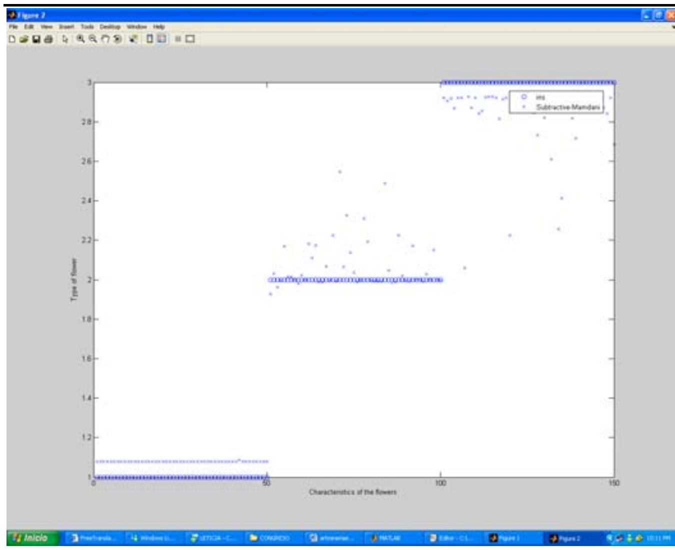

Fig. 2. Attribute Based Flower Type Identification (Subtractive-Mamdani).

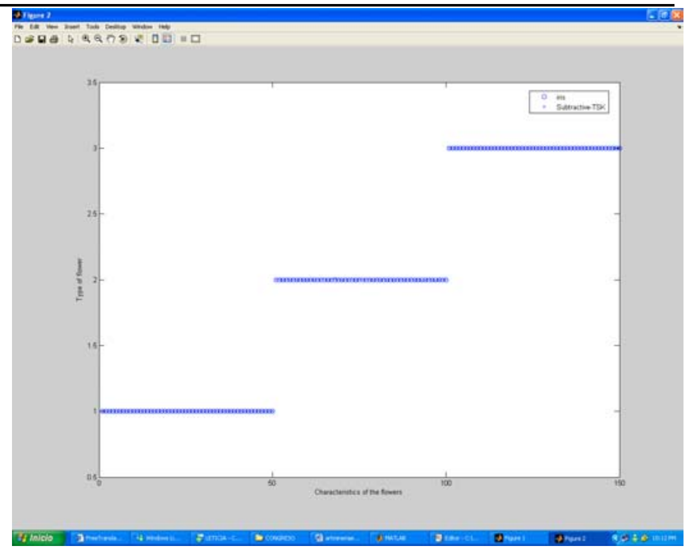

Fig. 4. Attribute Based Flower Type Identification (Subtractive-TSK).

Table V. IF-THEN Rule Extraction Mamdani FIS (Subtractive-Mamdani)

Rule Number	Rule
1	If (in1 is in1cluster1) and (in2 is in2cluster1) and (in3 is in3cluster1) and (in4 is in4cluster1) THEN (out1 is out1cluster1) (1)
2	If (in1 is in1cluster2) and (in2 is in2cluster2) and (in3 is in3cluster2) and (in4 is in4cluster2) THEN (out1 is out1cluster2) (1)

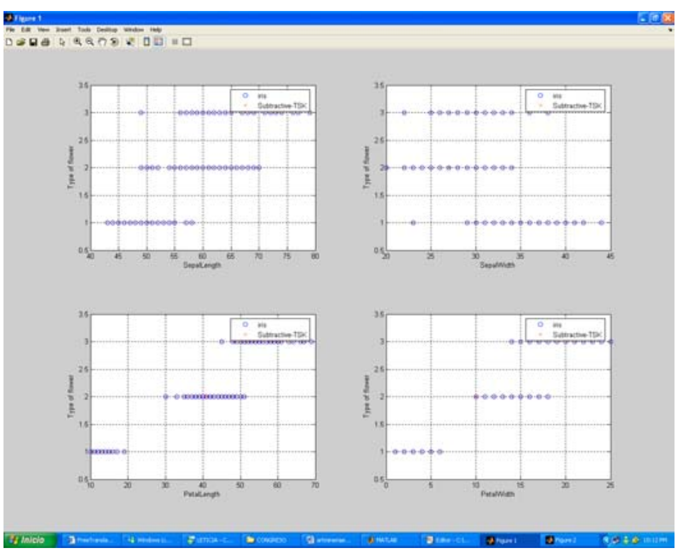

Fig. 3. Flower Attributes Clustering (Subtractive-TSK).

Table VI. IF-THEN Rule Extraction Takagi-Sugeno-Kang FIS (Subtractive-TSK)

Rule Number	Rule
1	If (in1 is in1cluster1) and (in2 is in2cluster1) and (in3 is in3cluster1) and (in4 is in4cluster1) THEN (out1 is out1cluster1) (1)
2	If (in1 is in1cluster2) and (in2 is in2cluster2) and (in3 is in3cluster2) and (in4 is in4cluster2) THEN (out1 is out1cluster2) (1)

VI. MACKEY-GLASS (MG DATA) TIME SERIES CASE STUDY CHARTS

We shown in Fig. 5 and Fig. 7 the clustering techniques (K-means, Fuzzy K-means, Subtractive) focused in the 2 FIS methods used (Mamdani, Takagi-Sugeno-Kang) for rule extraction, the original values for the Mackey-Glass time series are represented by circles and the cluster values by small crosses, each chart shows how the input attributes (x(t), x(t-6), x(t-12), x(t-18)) cluster to the output x(t+6) respectively, once clustered the values are sent to the Mamdani and Takagi-Sugeno-Kang FIS methods to extract IF-THEN production rules. Tables VII and VIII show some of the rules generated with the FIS methods mentioned, obtaining the Mackey-Glass time series delays (consequents) from the Mackey-Glass time series input attributes respectively (antecedents).

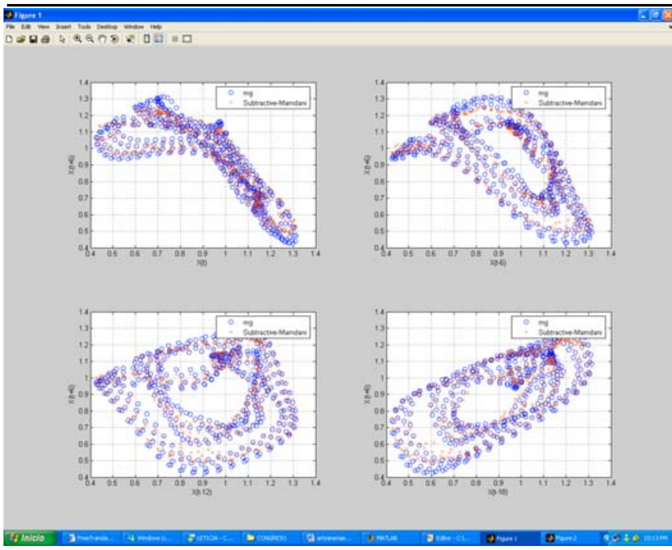

Fig. 5. Mackey-Glass Time Series Time Delays Clustering (Subtractive-Mamdani).

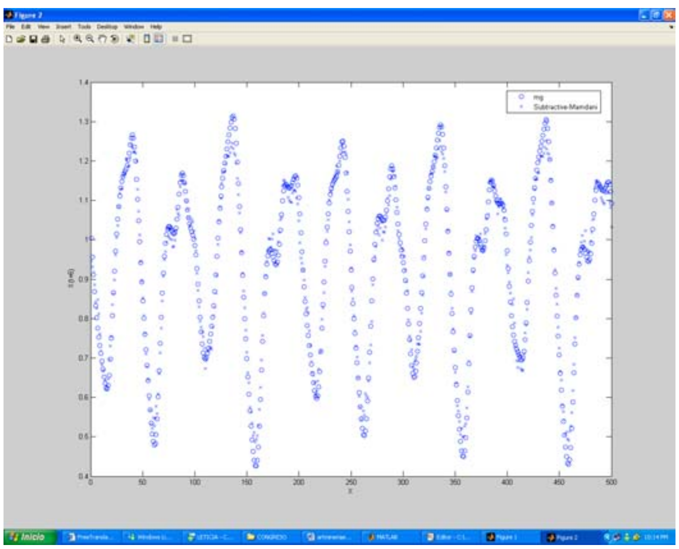

Fig. 6. Mackey Glass Time Series Clustering Output (Subtractive-Mamdani).

Table VII. IF-THEN Rule Extraction Mamdani FIS (Subtractive-Mamdani).

Rule Number	Rule
1	If (in1 is in1cluster1) and (in2 is in2cluster1) and (in3 is in3cluster1) and (in4 is in4cluster1) THEN (out1 is out1cluster1) (1)
2	If (in1 is in1cluster2) and (in2 is in2cluster2) and (in3 is in3cluster2) and (in4 is in4cluster2) THEN (out1 is out1cluster2) (1)

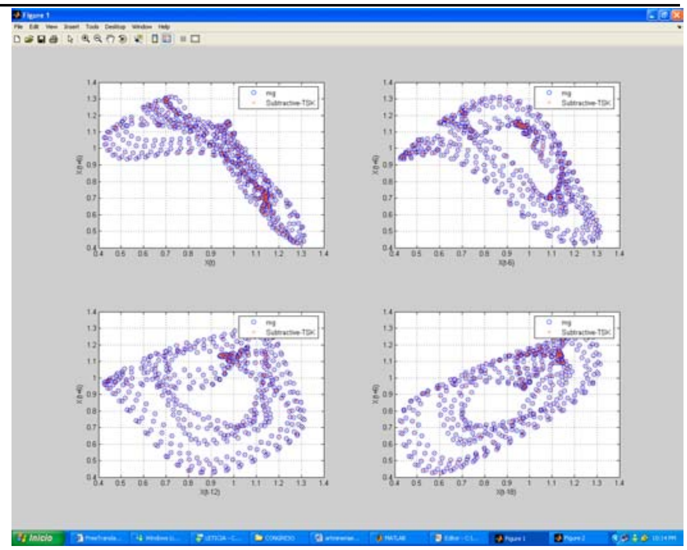

Fig. 7. Mackey-Glass Time Series Time Delay Clustering (Subtractive-TSK).

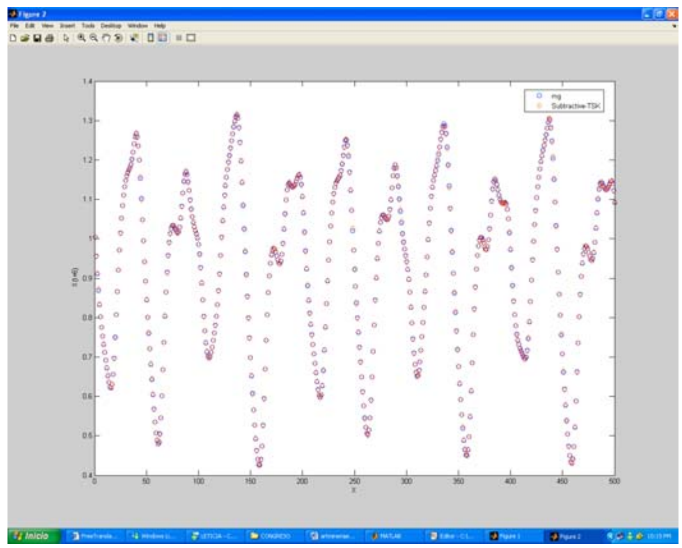

Fig. 8. Mackey-Glass Time Series Clustering Output (Subtractive-TSK).

Table VIII. IF-THEN Rule Extraction Takagi-Sugeno-Kang FIS (Subtractive-TSK).

Rule Number	Rule
1	If (in1 is in1cluster1) and (in2 is in2cluster1) and (in3 is in3cluster1) and (in4 is in4cluster1) THEN (out1 is out1cluster1) (1)
2	If (in1 is in1cluster2) and (in2 is in2cluster2) and (in3 is in3cluster2) and (in4 is in4cluster2) THEN (out1 is out1cluster2) (1)

VII. Conclusion

One of the goals of data mining is data pattern recognition, goal met with satisfaction through clustering techniques (K-means, Fuzzy K-means, Subtractive) used, techniques of great help in pattern recognition for the flower classification problem (Iris setosa, Iris versicolor, Iris virginica); and with Mackey-Glass time series values for further IF-THEN product rule extraction using fuzzy logic reasoning with FIS methods (Mamdani and Takagi-Sugeno-Kang). The subtractive clustering technique in conjunction with the FIS methods (Takagi-Sugeno-Kang and Mamdani) in all sample tests showed a better performance than any other technique because it best optimizes the objective function and the value of the root mean square error (RMSE) minimizes enormously, presenting the best results as seen on Tables III and IV.

References

[1] W. J. Frawley, G. Piatetsky-Shapiro and C. J. Matheus, " Knowledge Discovery in Databases: An Overview .", in G. Piatetsky-Shapiro and W. J. Frawley (eds), "Knowledge Discovery in Databases", AAAI/MIT Press, 1991, 1-27.

[2] Fayyad, U., Pietetsky-Shapiro, G., Smyth, P., Uthurusamy, R., "Advances in Knowledge Discovery and Data Mining.", McGraw-Hill, 1997.

[3] Y. Cai, N. Cercone and J. Han, "Attribute-Oriented Induction in Relational Databases.", in G. Pietetsky-Shapiro and W. J. Frawley (eds.), "Knowledge Discovery in Databases", AAAI/MIT Press, 1991, 231-228.

[4] Magazine Articles: "Data Mining and Knowledge Discovery", Kluwer Academic Publisher.

[5] R. Agrawal, T. Imielinski, and A. Swawi. "Mining association rules between sets of items in large databases." in Proc. ACM-SIGMOD Int. Conf. Management of Data (SIGMOD'93), 1993 , pp. 207-216, Washington, D.C.

[6] Dorian Pyle, "Data preparation for data mining.", Morgan Kaufmann publishers, 1999.

[7] Jim C. Bezdek. "Fuzzy Mathematics in Pattern Classification." Cornell University, Ithaca, 1973.

[8] Zadeh, Lotfi, "The Calculus of Fuzzy Restrictions in fuzzy Sets and Applications to Cognitive and Decision Making Processes", edited by L.A. Zadeh et. al., Academic Press, New York, 1975, 1-39.

[9] R. R. Yager and D. P. Filev. "Generation of fuzzy rules by mountain clustering.", Journal of Intelligent and Fuzzy Systems, 1994.

[10] S. L. Chiu. "Fuzzy model identification based on cluster estimation.", Journal of Intelligent and Fuzzy Systems, 1994.

[11] E.H. Mamdani and S. Assilian. "An experiment in linguistic synthesis with a fuzzy logic controller.", International Journal of Man-Machine Studies, 1975.

[12] Takagi, T., Sugeno, M., "Fuzzy identification of systems and its applications to modeling and control.", IEEE Trans. On Systems, Man, and Cybern, 15, No. 1, 1985, 116-132.

[13] Y. Cai, N. Cercone and J. Han, "Attribute-Oriented Induction in Relational Databases", in G. Pietetsky-Shapiro and W. J. Frawley (eds.), "Knowledge Discovery in Databases", AAAI/MIT Press, 1991, 231-228.

[14] E.Simous, B. livezey and R. Kerber. "Integrating Inductive and Deductive Reasoning for Data Mining.", in U. M. Fayyad, G. Pietetsky-Shapiro, P. Smith, and R. Uthurusamy, editors, "Advances in knowledge Discovery and Data Mining", Cambridge, MA:AAAI/MIT Press, 1996, pp. 353-373.

[15] P. Cabena, P. Hadjinian, r. Stadler, J. Verhees, A. Zanasi, "Discovering Data Mining From concept to implementation", Prentice Hall, 1997.

[16] Wang Li-Xing "Adaptative Fuzzy Systems And Control: Design and Stability Analysis", Englewood, cliffs, Prentice Hall. 1994.

[17] Bezdek, J. "Pattern recognition with fuzzy objective function algorithms", Plenum, New York. 1981.

[18] Moreno P. Juan E., Master Thesis: "Minería de datos para la extracción del conocimiento a partir de bases de datos", Tijuana Institute of Technology, 2006.

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