Automatic User Preference Service in EPG System using rough fuzzy MLP

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ABSTRACT

One of the various functions in EPG (Electronic Program Guide) applications, user preference service including channel and program preference, is mostly required in Digital TV field these days to provide User useful information in convenience [1]. In this paper, we investigate RFMLP (Rough Fuzzy Multi-Layer Perceptron) as a base model for user preference system.

The proposed is a hybrid system that combines Rough set theory, Fuzzy and MLP to provide viewers more dynamic and interactive service efficiently [2].

Experimental results show that a system with RFMLP can properly provide the channel/program preference service. In addition, we could find out the error conversion in RFMLP system can be achieved faster than conventional MLP, which boosts system's performance.

1. INTRODUCTION

There have been many researches on EPG in broadcasting fields to provide interactivity to User. The integration of rough, fuzzy set theory and artificial neural networks, knowledge-based network, provides more intelligent functionality to handle real-time recognition/decision making problems such as automatic channel/program preference service that is one of the most important and required function in broadcasting area.

In this paper, we describe how automatic decision-making, viewers' channel preference service, can be achieved and how much it can be efficient with respect to training and testing time comparing to conventional MLP.

2. ROUGH FUZZY MLP DESIGN

Fig. 1 shows the block diagram of RFMLP. It shows the entire process to build the initial hybrid system [2].

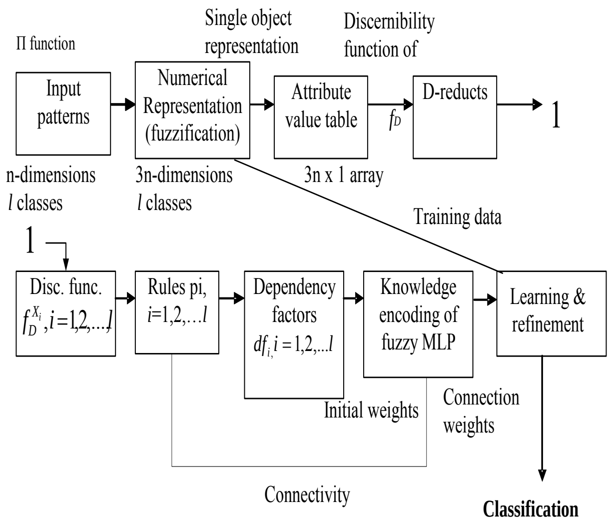

Figure 1. Structure of Rough Fuzzy MLP

The n-dimension input patterns become 3n-dimension using π function that produces membership values (Fig. 1).

In case of an input pattern in class A, {2, 4, 9} is applied to the membership functions – Low, Medium, High, the membership functions result in {0.6, 0.05, 0, 0.92, 0.6, 0.05, 0.6, 0.05, 0} where 3-dimension is expanded to 9. And, according to a threshold value, they become 0 or 1. When the threshold value of 0.8 is applied, the result would be the P1 in Table 1.

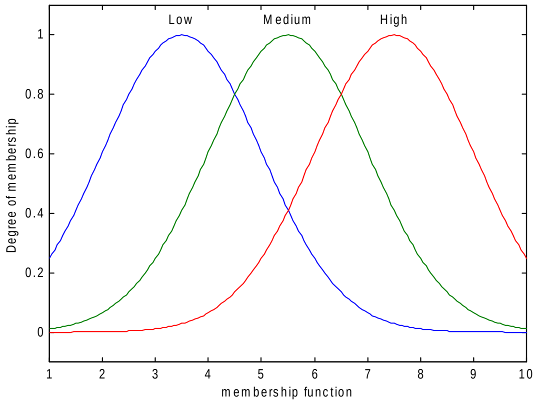

Figure 2. Membership Function

In other words, the result becomes the elements of the attribute table and then reduced attribute tables as shown in Table 1 and 2.

The attribute table includes all patterns with respect to their frequencies (Table 1). The number of patterns shall be determined to construct reduced attribute table. In this example are selected 4 most frequent patterns, P1, P2, P3, and P4. And, the level leads to the reduced attribute tables (Table 2).

Table 1. Attribute table for class A

Pattern	Class 1(attribute table)	Freqeuncy
P1	000 100 000	10
P2	000 000 000	9
P3	000 000 100	8
P4	000 110 000	6
Other patterns	xxx xxx xxx	17

Table 2 Reduced Attribute table for class A

Level / Pattern	L1	M1	H 1	L2	M2	H 2	L3	M3	H 3
P1	0	0	0	1	1	1	0	0	0
P2	0	0	0	1	1	0	0	0	0
P3	0	0	0	1	0	0	0	0	0
P4	0	0	0	1	1	0	0	0	

With the reduced attribute table, the discernibility matrix is produced as Fig. 3. It describes the distinguishable levels among other patterns, which will be used as the base information to separate one from other patterns.

Table 3. Discernibility Matrix for class A

	P1	P2	P3	P4
P1	0			
P2	{H2}	0		
P3	{M2,H2 }	{M2}	0	
P4	{L2}	{L2,H2 }	{L2,M2,H2 }	0

In order to find the essential information; that is, disjunctive normal form to differentiate each pattern using the discernibility matrix, the discernibility function shall be applied as *(1)* that represents uniquely class A.

$$H2 \wedge M2 \wedge L2 \wedge (M2 \vee H2) \wedge (L2 \vee H2) \wedge (L2 \vee M2 \vee H2) \qquad (1)$$

By simplifying *(2)*, disjunctive normal form is defined as following.

$$(L2 \wedge M2 \wedge H2) \qquad (2)$$

It is the essential information to help class A to be uniquely identified from others [2]. It also leads to build the initial structure of MLP. In other words, all the connection between nodes and the initial weight of the nodes in MLP structure can be easily calculated based upon the information. The entire process shall apply to all classes provided in any experiments. In this paper the process for only one class is described.

The initial structure of MLP using the disjunctive normal form is shown below in Fig. 4. In case of 3 classes, there are an input layer with 3 input nodes, a hidden layer with 3 nodes and an output layer with 3n dimension nodes. For instance, the elements of disjunctive normal form for class 1 are L2, M2 and H2 that are levels and essential information to help classifying class A from another. Therefore, the connections between hidden and output layer are L2, M2 and H2, and the initial weights are 1 over the number of output nodes, that is, 1/3 for class A.

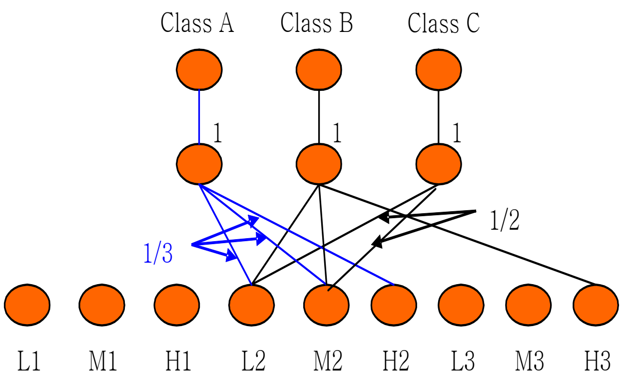

Figure 3. The Structure of RFMLP with initial weight values

Comparing to conventional MLP, the number of connection nodes used in this system is much smaller and simpler, and the initial weight values can be appropriately calculated that it is easily error-converged since essential information to represent each class is efficiently used.

3. EXPERIMENT

For the experiment we used a test data model for user preference system as shown in Table 4. The dimension and number of input patterns are 6 and 50 respectively. As described in the Table 4, each dimension represents channel, genre, actors, scheduled time, viewed time, and day information provided in broadcasting environment presumably via PSIP [3]. And, each pattern stands for types for above 6 categories. The first 30 data samples are used as training data, and the rest for testing in this experiment.

Table 4. Test data set model for user preference system with RFMLP

	Channel	Genre	Actors	Scheduled Time	Viewed time	Day
1	SBS	Drama	Heasoo Kim	1:00	Within 10 min	Mon
2	KBS1	Sports	Namjoo Kim	2:00	Within 30 min	Tues
3	KBS2	News	SeokKyu Han	3:00	Within 1 hour	Wed
4	MBC	Special Document	Lim Choi .	…	Within 2 hrs	Thurs
5	EBS	Music	…	.	Within 3 hrs	Fri
6		Comedy	.	.	Within 4 hrs	Sat
7			.			Sun
…			…	…		
24				24:00		
…			…			
50			Soyoung Koh			

As depicted in section 2, the input data set with 6x50 expands to 18x50 after membership function applied. There are 3 membership functions used: low, medium, and high. Those are Gaussian functions with centers at 2, 4 and 18 respectively, and with variances of 2, 2, and 2. The numbers were chosen from experiments. The membership values were calculated according to the membership functions. They are then determined to be 1 or 0 according to threshold applied. The threshold point used in this experiment is 0.8. The essential information, disjunctive normal form, is derived from the procedure described in section 2.

We construct the structure of neural network for classification with the essential information. For the neural network, we selected one input, output and hidden layer, respectively. The number of nodes is 3, 18 and 3 in sequence. Tangent sigmoid is used as transfer functions, and as mean square error for performance function.

The initial neural network is trained with 30 data samples. Next, we choose the values of 0.13, 100, 0.05, 0.7, 1.05, 0.7, and 5 for error goal, number of iterations, initial learning rate, decrease learning rate, increase learning rate, and momentum constant, respectively.

The initial network is then trained with expanded patterns from the membership function. During the training, the weight vectors of the neural network were properly refined, and with the refined weight vectors a classification is achieved [4].

4. RESULTS

From the experiment, result shows that the automatic channel/program preference service in EPG application can be efficiently provided with the proposed system. The correction ratio of the experiment is almost same as conventional MLP. However, the faster error conversion can be achieved comparing to conventional MLP. This is well shown in Fig. 6. The system with RFMLP can converge to the error goal in 60 echoes while conventional MLP is still in calculation. According to rough set theory, the neural network constructed by the rough set theory produces an optimal classification performance since it can always find the global minimum with a small amount of running time. And that is proven throughout this experiment.

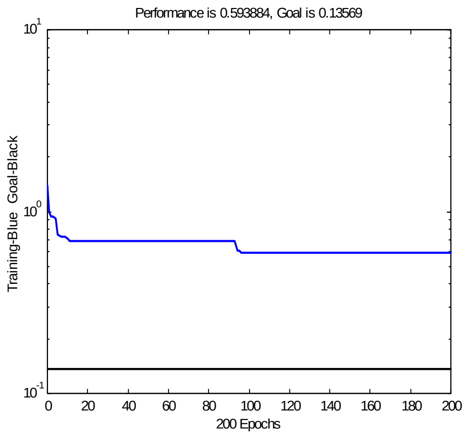

Figure 4. Convergence performance with conventional MLP

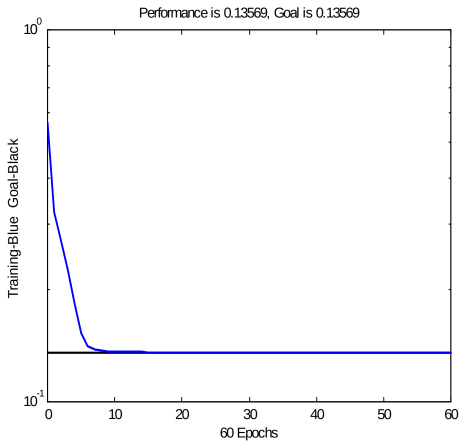

Figure 5. Convergence performance with RFMLP

Moreover, the experiment indicates that automatic user preference system can be implemented with RFMLP mechanism. An example of program preference service in digital TV is well shown in Figure 6.

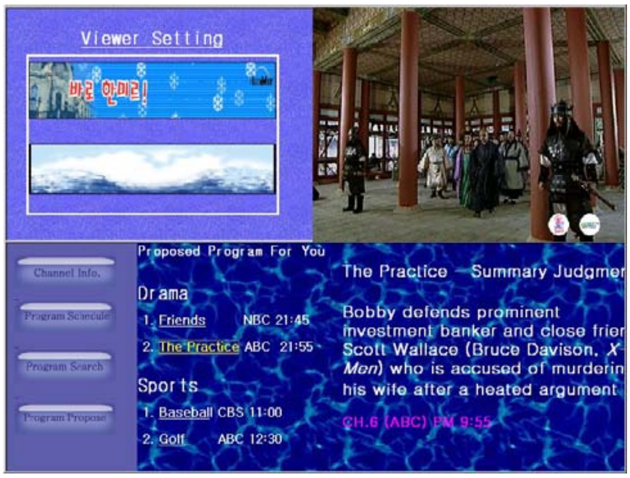

Figure 6. Example of program preference service in TV terminal

5. CONCLUSION

Consequently, automatic user preference service such as channel/program preference service in EPG application using RFMLP can provide interactivity to viewers efficiently in broadcasting systems.

In addition, the hybrid system can accelerate the performance of the system, which helps overall STB performance with proper algorithm as proven in result.

9. REFERENCES

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