Application to a Medical Diagnosis System by Extended Functional-type SIRMs Connected Fuzzy Inference Method

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***Abstract*—This paper proposes the learning algorithm for the extended-functional SIRMs (Single-Input Rule Modules) fuzzy inference model. The consequent part of an extended-functional SIRMs is a non-linear function. Moreover, this paper shows the results of applying this method to a medical dataset and compare this to the conventional SIRMs and functional SIRMs.**

***Index Terms*—Approximate reasoning, fuzzy inference systems, SIRMs connected fuzzy inference model.**

I. Introduction

Single input rule modules connected fuzzy inference methods (SIRMs method) [1] is a fuzzy inference method that unifies the inference outputs from fuzzy rule modules of one input type. These modules, of the type '`IF-THEN`' drastically increase the computational efficiency, since the number of rules are equal to the amount of input.

SIRMs has effectively been used in many applications [2]. Most popular are controlling and medical data analysis [3], [4].

An extension of the conventional SIRMs is the functional type SIRMs [5]. Since the number of rules of the SIRMs method is limited as compared tot the traditional fuzzy reasoning method, inference results gained by the SIRMs method are simple in general. In a functional type SIRMs the consequent part is generalized to a linear function, instead of the real number obtained by the conventional SIRMs. This functional type SIRMs is superior in the analysis of medical data and non-linear functions [6].

These functional type SIRMs can be expended to the extended-functional type SIRMs [7]. Although the extended-functional type SIRMs has a broad range for inference compared with conventional SIRMs model, the result shown in [7] was theoretical results only. In this paper, the extended-functional type SIRMs is applied it to real medical deta.

II. SIRM

In a conventional SIRMs, there are n inputs and 1 output. Each rule module corresponds to one of the n input items, and has only the input item as antecedent.

The rules are given as follows:

$$\begin{aligned} &\text{Rules-1} : \{x_1 = A_j^1 \to y_1 = y_j^1\}_{j=1}^{m_1} \\ &\vdots \\ &\text{Rules-}i : \{x_i = A_j^i \to y_i = y_j^i\}_{j=1}^{m_i} \\ &\vdots \\ &\text{Rules-}n : \{x_n = A_j^n \to y_n = y_j^n\}_{j=1}^{m_n} \end{aligned} \tag{1}$$

Where Rules-i stands for the ith SIRM, the ith input x_i is the sole variable of the antecedent part of the Rules-i, and y_i stands for the variable of its consequent part. A_j^i means the fuzzy set of the jth rule of the Rules-i, y_j^i is the real value of the consequent part, $i = 1, 2, ..., n$, $j = 1, 2, ..., m_i$ and m_i is the number of rules in Rules-i.

The degree of the antecedent part in the jth rule of Rules-i is obtained for input x_i^0. The inference result y_i^0 from Rules-i depends on the SIRMs method. These will be discussed in the next sections.

$$h_j^i = A_j^i(x_j^0) \tag{2}$$

Triangular-type fuzzy set $A_j^i(x_i)$

$$A_j^i(x_i) = \begin{cases} 1 - \frac{x_i - a_j^i}{b_j^i} & a_j^i - b_j^i \le x_i \le a_j^i + b_j^i \\ 0 & else \end{cases} \tag{3}$$

The final inference result y_0 of the SIRMs method is given, with the weight for the Rules-i ($i = 1, 2, ..., n$) is set as w_i.

$$y^0 = \sum_{i=1}^{n} w_i y_j^0 \tag{4}$$

A. Conventional SIRM

The inference result y_i^0 from Rules-i for the conventional SIRMs is calculated as follows:

$$y_i^0 = \frac{\sum_{j=1}^{m_i} h_j^i y_j^i(x_j^0)}{\sum_{j=1}^{m_i} h_j^i}$$

B. Functional SIRM

The Rules-i for Functional SIRMs differ in the sense that the consequent parts are functional types.

$$\begin{aligned}
\text{Rules-1} &: \{x_1 = A_j^1 \rightarrow y_1 = f_j^1(x_1)\}_{j=1}^{m_1} \\
&\vdots \\
\text{Rules-}i &: \{x_i = A_j^i \rightarrow y_i = f_j^i(x_i)\}_{j=1}^{m_i} \qquad (5) \\
&\vdots \\
\text{Rules-}n &: \{x_n = A_j^n \rightarrow y_n = f_j^n(x_n)\}_{j=1}^{m_n}
\end{aligned}$$

Where the function is:

$$f(x) = d_j^i x + c_j^i$$

The final inference result y_0 of the functional SIRMs method is

$$y_i^0 = \frac{\sum_{j=1}^{m_i} h_j^i f_j^i(x_j^0)}{\sum_{j=1}^{m_i} h_j^i}$$

C. Extended-functional SIRMs

The rules and inference results are the same as the functional type, but the function is different:

Extended-Functional example with 2 inputs:

$$f(x_1, x_2) = d_j^i x_1 + e_j^i x_2 + c_j^i$$

Our medical data has 5 inputs, and this results in the following function.

$$f(x_1, x_2, x_3, x_4, x_5) = d_j^i x_1 + e_j^i x_2 + f_j^i x_3 + g_j^i x_4 + k_j^i x_5 + c_j^i$$

III. Learning Algorithms

Since the setup of the membership functions and fuzzy rules is difficult, we expect to automatically optimize these based on input-output. In this section the different learning algorithms for the different methods are shown. In the table below the parameters learned are shown.

Each learning algorithm will use steepest descent method to optimize the values of the SIRM. This is based on the objective function equation 6. This calculates the error between the desired output(y^T) and the corresponding fuzzy inference result(y^0).

$$E = \frac{1}{2}(y^T - y^0)^2 \qquad (6)$$

8 learning rates are used:

symbol	variable	explanation	value
α	a_j^i	center of A_j^i	0.001
β	b_j^i	spread of A_j^i	0.001
γ	y_j^i	consequent value	0.001
δ	w^i	importance degree	0.001
ϵ	c^i	constant of the consequent	0.001
ζ	d^i	x_1 multiplier	0.0001
η	e^i	x_2 multiplier	0.0001
θ	f^i	x_3 multiplier	0.0001
ι	g^i	x_4 multiplier	0.0001
κ	k^i	x_5 multiplier	0.0001

A. Conventional SIRM

The learning method for the conventional SIRMs is calculated using the partial derivative using the steepest decent method. The conventional SIRMs has 4 variables to learn. The center and spread of A_j^i, consequent value and importance degree or weight. The learning algorithms for the conventional SIRMs was proposed in [8].

B. Functional SIRM

The functional SIRMs method is calculated in the same was as described in the conventional SIRMs method. However due to the difference in the methods, the actual learning formulae are different. Also due to the change from a constant consequent to functional, the consequent learning function is replaced by the functional learning in a few equations. These were proposed by [6].

C. Extended-Functional SIRM

The learning algorithm for the extended-functional SIRMs are proposed in this subsection. The learning functions 11 - 13 are shown as the medical learning case as follows:

$$\begin{aligned} a_j^i(t+1) &= a_j^i(t) - \alpha(y^0 - y^T)w_i \times \\ &\frac{d_j^i x_1^i + e_j^i x_2^i + c_j^i - y_i^0}{\sum_{j=1}^m h_j^i} \frac{sgn(x_i - a_j^i(t))}{b_j^i(t)} \end{aligned} \qquad (7)$$

$$\begin{aligned} b_j^i(t+1) &= b_j^i(t) - \beta(y^0 - y^T)w_i \times \\ &\frac{d_j^i x_1^i + e_j^i x_2^i + c_j^i - y_i^0}{\sum_{j=1}^m h_j^i} \frac{|x_i - a_j^i(t)|}{b_j^i(t)^2} \end{aligned} \qquad (8)$$

$$d_j^i(t+1) = d_j^i(t) - \zeta(y^0 - y^T)w_i \frac{h_j^i x_i}{\sum_{j=1}^m h_j^i} \qquad (9)$$

$$e_j^i(t+1) = e_j^i(t) - \eta(y^0 - y^T)w_i \frac{h_j^i x_i}{\sum_{j=1}^m h_j^i} \qquad (10)$$

$$f_j^i(t+1) = f_j^i(t) - \theta(y^0 - y^T)w_i \frac{h_j^i x_i}{\sum_{j=1}^m h_j^i} \qquad (11)$$

$$g_j^i(t+1) = g_j^i(t) - \iota(y^0 - y^T)w_i \frac{h_j^i x_i}{\sum_{j=1}^m h_j^i} \qquad (12)$$

$$k_j^i(t+1) = k_j^i(t) - \kappa(y^0 - y^T)w_i \frac{h_j^i x_i}{\sum_{j=1}^m h_j^i} \qquad (13)$$

$$c_j^i(t+1) = c_j^i(t) - \epsilon(y^0 - y^T)w_i \frac{h_j^i}{\sum_{j=1}^m h_j^i} \qquad (14)$$

$$w_j^i(t+1) = w_j^i(t) - \delta(y^0 - y^T)y_j^i(t) \qquad (15)$$

where there are 5 inputs.

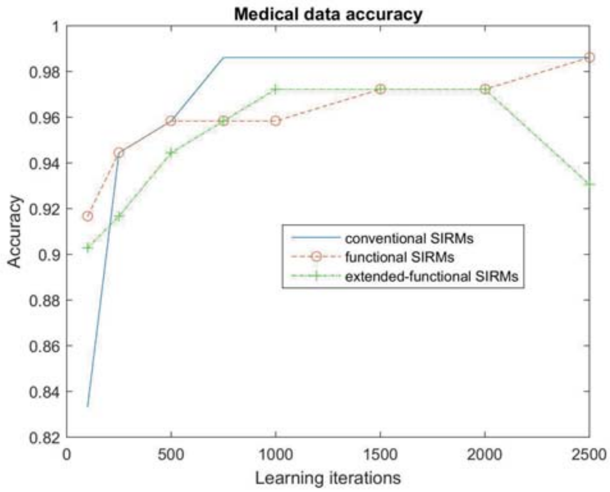

Fig. 1. Accuracy plot of the medical data for the 3 different SIRMs methods.

IV. Application to real medical data

The data set tested is the real medical diagnosis dataset. 145 real data are used, which consist of 5 input items and 1 output. The input items $(x_1, ..., x_5)$ are normalised $[-1, 1]$. The data is classified in 3 groups, Clinical Diabetes, Chemical Diabetis, and Soundness. The desired output for these groups are respectively 1, 0.5, and 0.

The same membership functions as in the non-linear section are used, expect that there are 5 for the 5 input items. 72 training data are used, with 73 testing data.

For the medical data no real difference can be seen between the three different SIRMs methods. This is contrary to expectations and previous research. Unknown is the cause of this. The results can be seen in figure 1.

V. Conclusion

In this paper we have proposed the learning algorithm of the extended-functional SIRMs. Unfortunately we were unable to improve the accuracy using these new SIRMs methods.

The problem probably lies in the amount of possible variables that needed to be updated. Many iterations, learning rates, and functions were tried. Still a very large part of the possible variable values were lacking in our experiments.

A solution would be to use a Multi-objective optimization technique to find the optimal learning coefficients.

The most import learning coefficient we assumed in this paper was that of the extended-functional learning function (variable e^i through k^i). This was set on 0.0001 in this paper. This of course may not be the optimal value. In order to obtain good results, we have to try various coefficients for e, f, g and k.

The extended-functional SIRMs were not obtain good results compared with conventional SIRMs models because selection of consequent functions and optimization for the parameter of the extended-functional SIRMs are difficult. However, since the accuracy by the extended-functional SIRMs can obtain over 90%. So, it will be useful by selecting optimal consequent functions.

So possible further research can be applied on the optimal variables and the optimal functions. As explained, the extended-functional consequent can be used for non-linear functions. This allows for extensive further research.

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