2014 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)
July 6-11, 2014, Beijing, China

Medical Diagnosis and Monotonicity Clarification using SIRMs Connected Fuzzy Inference Model with Functional Weights

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***Abstract*—This paper discusses the SIRMs (Single-Input Rule Modules) connected fuzzy inference model with functional weights (SIRMs model with FW). The SIRMs model with FW consists of a number of groups of simple fuzzy if-then rules with only a single attribute in the antecedent part. The final outputs of conventional SIRMs model are obtained by summarizing product of the functional weight and inference result from a rule module. In the SIRMs model of the paper, we firstly clarify its monotonicity. Secondly, we apply the SIRMs model with FW to medical diagnosis.**

***Index Terms*—Fuzzy inference, Single Input Rule Modules (SIRMs) connected fuzzy inference model, functional weight, monotonicity, medical data.**

I. Introduction

Single Input Rule Modules (SIRMs) connected fuzzy inference model proposed by Yubazaki et al. [1]–[7] consists of several groups of single-input fuzzy if-then rules. The advantage of the SIRMs models is computational efficiency. The number of involved fuzzy if-then rules is significantly less than the conventional model where each fuzzy if-then rule has as many inputs as the problem domain at hand. The SIRMs model has been applied to the automatic control of vehicles and the stability control of inverted pendulums. Seki et al. [7]–[9] analyzed the property of the SIRMs inference models and also proposed extended versions of SIRMs models.

In the standard formulation of SIRMs, the weight for each rule module is considered to be constant. However, it is often necessary to have variable weights for connecting rule modules in order to accommodate high-dimensional problem domains, which is the case in most of the practical cases. From this perspective, Yi et al. [5] proposed a new SIRMs model that introduces dynamic weights for rule modules and showed the effective ness of the model for control domains.

On the other hand, SIRMs connected fuzzy inference model with functional weights has been also proposed in [11], [12]. In this model, the weights for connecting rule modules are variable rather than constant. In order to realize this, funcional weights such as a linear expression, a square function, etc., are employed in the model. That is, the SIRMs model with FW is extended version of the dynamic weigt type SIRMs model.

In this paper, we firstly clarify the monotonicity of SIRMs model with FW from view of theoretical point. Moreover, the SIRMs model with FW is compared with the conventional SIRMs model by applying them to medical diagnosis.

II. A SIRMs Connected Fuzzy Inference Model with Functional Weights

In this section, we review the *SIRMs connected fuzzy inference model with functional weights* (SIRMs model with FW) [11], [12] in which the weight for the inference result of each rule module is generalized to a function, where the system has n inputs and a single output, and each rule module corresponds to one of the n input attributes and has only that input attribute in the antecedent part of fuzzy if-then rules in the rule module.

The rules of the SIRMs model with FW are given as follows:

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

where Rules-i stands for the "i-th single-input rule module," x_i corresponding to the i-th input item is the sole variable of the antecedent part of Rules-i, and y_i is the variable of its consequent part. A_j^i and y_j^i are, respectively, fuzzy set and real number of the jth rule of the Rules-i, where $i = 1, 2, \ldots, n$, $j = 1, 2, \ldots, m_i$, and m_i stands for the number of rules.

Given an input x_i^0 to Rules-i, the compatibility degree of the antecedent part in the j-th rule in Rules-i is given by (2), and the inference result y_i^0 of Rules-i is given as in (3).

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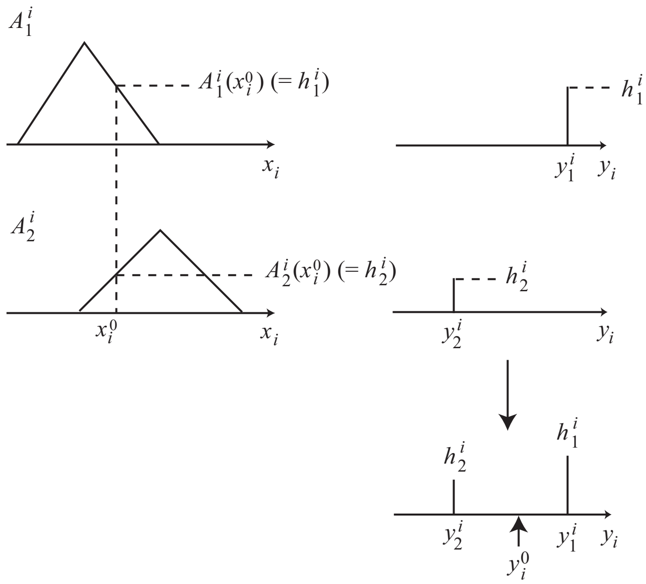

Fig. 1. Fuzzy inference method in Rules-i.

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

$$y_i^0 = \frac{\sum_{j=1}^{m_i} h_j^i y_j^i}{\sum_{j=1}^{m_i} h_j^i}. \tag{3}$$

Final inference result y^0 of the SIRMs model with FW is given by

$$y^0 = \sum_{i=1}^{n} w_i(x_i^0) y_i^0 \tag{4}$$

where functional weights $w_i(x_i^0)$'s stand for the importance degree for each input item x_i $(i = 1, 2, \ldots, n)$.

For example, the functional weight in case of using a square function is as follows [11], [12]:

$$w_i(x_i) = c_i x_i^2 \tag{5}$$

This SIRMs model is reduced to the conventional SIRMs model when functional weight $w_i(x_i)$ is replaced to a constant.

III. Properties of SIRMs Method with FW

In this section, we clarify the theoretical property of the SIRMs method with FW from the point of view of the monotonicity.

We have the following Theorem on the monotonicity in the SIRMs method with FW.

Theorem 1: In the SIRMs method with FW, the inference results have the property of monotonic increase if the antecedent parts, consequent parts and any functional weights are monotonically increasing. □

Proof: The proof of monotonicity will be enough to consider one of the rule modules, because the inference result of the SIRMs method with FW is obtained by linear combination as in (4).

We shall consider the following rule module consisting of m_i rules for input item x_i.

$$\text{Rules-}i = \{x_i = A_j^i \longrightarrow y_i = y_j^i\}_{i=1}^{m_i} \tag{6}$$

Let x_i be an input to the jth fuzzy set A_j^i, and x_i' larger than x_i be the input to the kth fuzzy set A_k^i, and the antecedent parts and consequent parts be monotonically increasing. Then the inference result y_i^0 for x_i becomes

$$y_i^0 = \frac{\sum_{p=1}^{M} A_{j_p}^i(x_i) y_{j_p}^i}{\sum_{p=1}^{M} A_{j_p}^i(x_i)} \tag{7}$$

M is the number of fired rules for input x_i. Similarly, the inference result ${y'}_i^0$ for input x_i' is obtained as

$${y'}_i^0 = \frac{\sum_{q=1}^{N} A_{k_q}^i(x_i') y_{k_q}^i}{\sum_{q=1}^{N} A_{k_q}^i(x_i')} \tag{8}$$

N is the number of fired rules for input x_i'. Then, ${y'}_i^0 - y_i^0$ will be the following equation [10].

$$\begin{aligned} {y'}_i^0 - y_i^0 &= \frac{\sum_{q=1}^{N} A_{k_q}^i(x_i') y_{k_q}^i}{\sum_{q=1}^{N} A_{k_q}^i(x_i')} - \frac{\sum_{p=1}^{M} A_{j_p}^i(x_i) y_{j_p}^i}{\sum_{p=1}^{M} A_{j_p}^i(x_i)} \\ &= \frac{\sum_{p=1}^{M}\sum_{q=1}^{N} A_{j_p}^i(x_i) A_{k_q}^i(x_i')(y_{k_q}^i - y_{j_p}^i)}{\left(\sum_{p=1}^{M} A_{j_p}^i(x_i)\right)\left(\sum_{q=1}^{N} A_{k_q}^i(x_i')\right)} \end{aligned} \tag{9}$$

From $y_{j_p}^i \le y_{k_q}^i$ for $j_p < k_q$ and $A_{j_p}^i(x_i), A_{k_q}^i(x_i') \ge 0$, we have ${y'}_i^0 - y_i^0 \ge 0$. Moreover, since functional weights are monotonically incrasesing, the following condition holds:

$$w_i(x_i) \le w_i(x_i') \tag{10}$$

Final outputs by the SIRMs method with FW are linear combination of weights $w_i(x_i^0)$ and inference results of rule modules as in (4), so that it is enough to show the monotonicity for a rule module. Therefore, Theorem 1 holds. □

IV. Learning Algorithm

This section presents the learning algorithm for the SIRMs model with FW. The learning algorithm is derived based on the gradient decent concept where the modification rules for the parameters of the SIRMs model is construct so that a predefined error is minimized [12]–[19].

In this paper, the functional weight in case of using a linear expression is used as follows [12]:

$$w_i(x_i) = c_i + d_i x_i \tag{11}$$

Let us assume that we use triangular-type membership functions for the antecedent parts of fuzzy if-then rules as follows:

$$A_j^i(x_i) = \begin{cases} 1 - |x_i - a_j^i|/b_j^i, & a_j^i - b_j^i \le x_i \le a_j^i + b_j^i, \\ 0, & \text{otherwise,} \end{cases} \tag{12}$$

where a_j^i and b_j^i are the center and the width of the fuzzy set $A_j^i(x_i)$, respectively, and x_i is an input value for the ith attribute. The modification rules for a_j^i, b_j^i, and y_j^i at the $(t+1)$th iteration are defined as follows:

$$\begin{aligned} a_j^i(t+1) &= a_j^i(t) + \alpha \cdot (y^T - y^0(t)) \cdot \{c_i(t) + d_i(t) \cdot x_i\} \\ &\quad \cdot \frac{y_j^i - y_i^0(t)}{\sum_{j=1}^{m_i} h_j^i(t)} \cdot \frac{\mathrm{sgn}(x_i - a_j^i(t))}{b_j^i(t)} \end{aligned} \tag{13}$$

$$\begin{aligned} b_j^i(t+1) &= b_j^i(t) + \beta \cdot (y^T - y^0(t)) \cdot \{c_i(t) + d_i(t) \cdot x_i\} \\ &\quad \cdot \frac{y_j^i - y_i^0(t)}{\sum_{j=1}^{m_i} h_j^i(t)} \cdot \frac{|x_i - a_j^i(t)|}{(b_j^i(t))^2} \end{aligned} \tag{14}$$

$$\begin{aligned} y_j^i(t+1) &= y_j^i(t) + \gamma \cdot (y^T - y^0(t)) \\ &\quad \cdot \{c_i(t) + d_i(t) \cdot x_i\} \cdot \frac{h_j^i(t)}{\sum_{j=1}^{m_i} h_j^i(t)} \end{aligned} \tag{15}$$

$$c_i(t+1) = c_i(t) + \delta \cdot (y^T - y^0(t)) \cdot y_i^0(t) \tag{16}$$

$$d_i(t+1) = d_i(t) + \epsilon \cdot (y^T - y^0(t)) \cdot y_i^0(t) \cdot x_i \tag{17}$$

where α, β, γ, δ and ϵ are learning rates, t represents the number of learning iterations, and sgn is a signum function that is defined as follows:

$$\mathrm{sgn} = \begin{cases} 1, & \text{if } x > 0, \\ 0, & \text{if } x = 0, \\ -1, & \text{otherwise.} \end{cases} \tag{18}$$

V. Formulation of a Medical Diagnosis System by SIRMs Method with FW

In this section, the SIRMs method with FW is applied to a medical diagnosis, and we compare the method with the conventional SIRMs method. 145 real diabetes data are used [20]. The data have 5 input items and 1 output, and the 5 input items are constituted as follows.

- Relative weight
- Fasting levels of plasma glucose concentrations
- Glucose value
- Insulin value
- SSPG (Steady State Plasma Glucose)

The inputs $x_1, x_2, \ldots, x_5$ are normalized as in [0, 1]. The data is classified Group 1 (Clinical Diabetes), Group 2 (Chemical Diabetes) or Group 3 (Soundness). The Group 1, Group 2 and Group 3 in a desired output which uses to inference are 1, 0.5 and 0, respectively. Moreover, inference result y^0 in fuzzy infernce is classified as follows.

$$\begin{cases} 1 \text{ (ClinicalDiabetes)} & : \quad y^0 \ge 0.75 \\ 0.5 \text{ (ChemicalDiabetes)} & : \quad 0.25 \le y^0 < 0.75 \\ 0 \text{ (Soundness)} & : \quad 0.25 < y^0 \end{cases}$$

In medical diagnosis, we use four membership functions for five inputs $x_1, x_2, \ldots, x_5$, where the centers of the membership functions $A_1^i, A_2^i, A_3^i, A_4^i$ for $i = 1, 2, \ldots, 5$ are $-0.5, 0, 0.5, 1$, and each width of the membership functions is 0.5. Moreover, all of the consequent parts and importance degree for each input item are set to be 0 and 0.5, respectively.

In our case, 72 training data are employed from 145 diabetes data in random order, and 73 checking data are used from the remaining diabetes data.

In the following, we apply the SIRMs method with FW to medical data in the case of using the triangular-type membership functions. Moreover, this method is also compared with the conventional SIRMs method.

For the above, learninig iterations are executed 1000 times, and 10 simulations are run. Table I shows the answer ratio using the checking data for medical diagnosis, where SIRMs-FW and SIRMs stand for the SIRMs method with FW and conventional SIRMs method, respectively, in the table.

TABLE I
Answer ratio(%) for medical data

Case	SIRMs-FW	SIRMs
1	86.3	84.9
2	86.3	84.9
3	91.8	89.0
4	89.0	89.0
5	89.0	89.0
6	91.8	89.0
7	91.8	89.0
8	87.7	86.3
9	95.6	95.6
10	93.2	93.2
Average	90.3	89.0

The SIRMs method with FW obtains good results compared with the conventional SIRMs method in all aspects, from Table I.

On the other hand, reference [19] has shown that the conventional SIRMs method is superior to the simplified fuzzy inference method in the same medical data. From the above reasons, the SIRMs method with FW will be usefull.

VI. Conclusions

In the conventional SIRMs model, the final inference result of the model for an input pattern is calculated as the weighted sum of the inference result from each rule module. Since the weight for each rule module is constant, the SIRMs model cannot be applied to highly dynamic problem domains.

On the other hand, the SIRMs model with FW employes functional weights instead of a constant value. Thus the weight for each rule module is no longer constant but variable according to input values.

We first crarify the monotonicity of the SIRMs model with FW. The monotonicity property is very important when the model is applied to various real systems. The SIRMs model with FW can easily satisfy the monotonicity condition. Therefore, the model is useful for monotonicity data.

The learning algorithm for the SIRMs model with FW is also derived using gradient decent method. The learning algorithm enables to automatically construct an appropriate input-output mapping by the SIRMs model with FW from a set of training patterns.

The inference results of the SIRMs model with square FW are strongly depended on input. Thus, input values should be normalized to apply the SIRMs model with FW to real systems.

Finally, as an example of data depended on input, the SIRMs model with FW is applied to medecal diagnosis. By grace of the functional weights for inputs, the model can obtain good results for medical data. In the well-known simplified fuzzy inference, $\Pi_{i=1}^{M}$ rules are involved in a single system while only $\sum_{i=1}^{M}$ rules in the SIRMs model. Therefore, the SIRMs model is more efficient and more effective approach than the other fuzzy inference models.

Future works include other data should be evaluated for functional weights of the SIRMs model with FW.

References

[1] N. Yubazaki, J. Yi and K. Hirota, "SIRMs (Single Input Rule Modules) connected fuzzy inference model," *Journal of Advanced Computational Intelligence and Intelligent Informatics*, vol. 1, no. 1, pp. 23–30, 1997.

[2] J. Yi, N. Yubazaki and K. Hirota, "Stabilization control of seriestype double inverted pendulum systems using the SIRMs dynamically connected fuzzy inference model," *Artificial Intelligence in Engineering*, vol. 15, no. 3, pp. 297–308, 2001.

[3] J. Yi, N. Yubazaki and K. Hirota, "Upswing and stabilization control of inverted pendulum system based on the SIRMs dynamically connected fuzzy inference model," *Fuzzy Sets and Systems*, vol. 122, no. 1, pp. 139–152, 2001.

[4] J. Yi, N. Yubazaki and K. Hirota, "A new fuzzy controller for stabilization of parallel-type double inverted pendulum system," *Fuzzy Sets and Systems*, vol. 126, no. 1, pp. 105–119, 2002.

[5] J. Yi, N. Yubazaki and K. Hirota, "A proposal of SIRMs dynamically connected fuzzy inference model for plural input fuzzy control," *Fuzzy Sets and Systems*, vol. 125, no. 1, pp. 79–92, 2002.

[6] J. Yi, N. Yubazaki and K. Hirota, "Anti-swing and positioning control of overhead traveling crane," *Inf. Sci.*, vol. 155, pp. 19–42, 2002.

[7] H. Seki and M. Mizumoto, "On the equivalence conditions of fuzzy inference methods—part 1: basic concept and definition" *IEEE Trans. on Fuzzy Sust.*, vol.19, no.6, pp.1097–1106, Dec. 2011.

[8] H. Seki, H. Ishii, and M. Mizumoto, "On the generalization of single input rule modules connected type fuzy reasoning method," *IEEE Trans. Fuzzy Systems*, vol.16, no.5, pp.1180–1187, 2008.

[9] H. Seki, H. Ishii, and M. Mizumoto, "On the monotonicity of fuzzy-inference methods related to T–S inference method," *IEEE Trans. Fuzzy Systems*, vol.18, no.3, pp.629–634, 2010.

[10] H. Seki and M. Mizumoto, "SIRMs connected fuzzy inference method adopting emphasis and suppression" *Fuzzy Sets and Systems*, vol.215, pp.112–126, March 2013.

[11] T. Nakashima and H. Seki, "A Study on SIRMs models with linear functional weights," Proc. 12th International Symposium on Advanced Intelligent Systems (ISIS2011), pp.224–226, Suwon, Korea, September 2011.

[12] H. Seki and T. Nakashima, "Some consideration of SIRMs connected fuzzy inference model with functional weights," *Proc. the 4th KES International Symposium on Intelligent Decision Technologies*, vol.2, pp.471–476, Gifu, Japan, May 2012.

[13] J. R. Jang, "Self-learning fuzzy controllers based on temporal back propagation," *IEEE Trans. Neural Networks*, vol.3, no.5, pp.714–723, 1992.

[14] H. Ichihashi, "Iterative fuzzy modeling and a hierarchical network," *Proc. 4th IFSA World Congress of Engineering*, Brussels, Belgium, pp.49–52, 1991.

[15] L. X. Wang and J. M. Mendel, "Back-Propagation fuzzy system as nonlinear dynamic system identifiers," *Proc. 1992 IEEE Int. Conf. Fuzzy Syst.*, San Diego, USA, pp.1409–1416, 1992.

[16] X. Cui and K. G. Shin, "Direct control and coordination using neural networks," *IEEE Trans. Syst. Man Cybern.*, vol.23, no.3, pp.686–697, 1993.

[17] C. F. Juang, "A TSK type recurrent fuzzy network for dynamic systems processing by neural network and genetic algorithms," *IEEE Trans. Fuzzy Syst.*, vol.10, no.2, pp.155–170, 2002.

[18] W. Yu and X. Li, "Fuzzy identification using fuzzy neural networks with stable learning algorithms," *IEEE Trans. Fuzzy Syst.*, vol.12, no.3, pp.411–420, 2004.

[19] H. Seki, H. Ishii, and M. Mizumoto, "Nonlinear identification and medical diagnosis system using functional-type SIRMs connected fuzzy inference method," *International Journal of Innovative Computing, Information and Control*, vol. 6, no.11, pp. 5275–5286, 2010.

[20] D. F. Andrews, A. M. Herzberg, Data:A collection of problems from many fields for the students and research worker, Springer, 1985.