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SEEM: A Structural Enhancement of evolving method for fuzzy system

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***Abstract*— Abstract – Determining the optimal fuzzy terms, which lead to the minimum global error, remains a challenge in the fuzzy methods. Another challenge is that the parameters of the consequent section are usually selected individually thus resulting insufficient fuzzy systems. In this paper, A Structural Enhancement of evolving method (SEEM) has been proposed to solve such problems. SEEM has been developed evolutionarily based on incremental partitioning learning. SEEM begins with an initial fuzzy system that has double fuzzy terms for the antecedent part. Then, to create a more accurate fuzzy system, it keeps improving by identifying the ideal input fuzzy term and ideal consequent parameter. There are two steps involved in determining the antecedent component and the consequent parameters. By detecting the distinction points (extremum and inflection points) using the gradient descent approach, it first identifies fuzzy terms and the consequent parameters. This continues until all of the fuzzy terms and consequent parameters are obtained. The second step is identifying the ideal new fuzzy terms that produce the global best result. This model utilizes the gradient descent estimator to obtain the optimum consequent parameters. As a result, SEEM produces sufficient fuzzy systems that have fewer number of fuzzy rules with high accuracy.**

Keywords— Evolving methods, incremental learning, and function approximation.

I. INTRODUCTION

Recently, a variety of application domains, including medical applications and system control applications, have become more interesting in fuzzy modeling [1-3]. One of the most popular fuzzy modelling techniques, based on an error reduction approach, is the fixed grid partitioning [4-6]. This technique, however, has a number of shortcomings that make it unsuitable for use, including: It first leads to an exponential expansion in the rule base and the antecedents' parameters. Second, the antecedent part's fuzzy terms are frequently not the right ones. Thirdly, it makes use of input partitioning that is fixed and predefined. To get around these issues, a number of strategies, such [7-10] are suggested. These techniques are regarded as evolving methods that use incremental learning to enhance performance. The evolving approaches based on input-output clustering [11-16],[21] are another kind.

The problem of finding the best fuzzy terms, which results in the best global error, still concerns the approaches outlined above. Additionally, the parameters of the consequent part significantly contribute to improving the precision of the fuzzy system. In order to create the most accurate fuzzy system possible, it is necessary to get the consequent parameters that are compatible with the generated fuzzy terms. Our previous works [17,18] suggest a solution for the medium and large dataset but not the small one which will be proposed in this paper.

In this study, a structural enhancement of evolving method (SEEM) is suggested. The evolving-construction scheme for fuzzy systems (ECSF) is a major driving force behind SEEM [9]. Unlike ECSF, SEEM selects the best fuzzy word that results in the overall best outcome. Additionally, SEEM employs gradient descent to identify the ideal consequent parameters.

II. METHODOLOGY

In this section, the methodology of how the proposed SEEM is evolved is demonstrated and divided into four sub-sections. It starts with the general mathematical formulations for the fuzzy rules of the SEEM then Splitting Techniques, adding and updating Membership function are presented to find the fuzzy terms. After that, finding the intersection of adjacent subranges to locate the optimal consequent parameters is presented. Finally, A summary of the algorithm is discussed and illustrated. Evolving system

A. *Formulations*

Similarly to our pervious works [17, 18], the proposed work uses mamdani type due to the high interpretability as compared to Takagi-Suqeno(T-S) type [19]. SEEM begins with a closed range that covers the whole training data (initial domain). The membership function that is used in this paper is the triangular function. The initial domain (closed range) starts with [c, c'] where c and c' are the minimal and maximal value of the input variable x, respectively. c_n and c'_n represent the edges of nth range. Therefore, the first fuzzy rule is as follow

$$\text{IF } x \text{ is } A^k \text{ THEN } y \text{ is } y^k, \; k = 0,1$$

where $A^0 = c,$ when k =0, $A^1 = c',$ when k = 1. k is used to represents the edges of the closed range. y^k are singleton parameters.

In this section, the formulation of the membership functions for the closed range is demonstrated. From now on, the index n refers to the closed range that will be split. First, the membership function for the fuzzy term of the antecedent part $A^0(k = 0)$. is

$$\hat{\mu}_n^0(x) = \frac{c'_n - x}{c'_n - c_n} \tag{1}$$

Second, for the fuzzy term $A^1(k = 1)$

$$\hat{\mu}_n^1(x) = \frac{x - c_n}{c'_n - c_n} \tag{2}$$

Based on the centroid defuzzifier [20], and the characteristics of the triangular membership function, the model output can be computed as the following equations.

$$O = \frac{A^0 * y^0 + A^1 * y^1}{A^0 + A^1} \tag{3}$$

$$A^0 + A^1 = 1 \tag{4}$$

$$O = A^0 * y^0 + A^1 * y^1 \tag{5}$$

B. *Splitting Techniques, adding and updating Membership function*

The proposed fuzzy system begins with very simple domain (closed range) as illustrated earlier. Then, based on the maximal average error, the closed range is selected for splitting. The selected range will be divided into two subranges at the training sample point (x_{sp} = splitting sample point) which has the maximal error. This splitting technique is implemented in the first stage of locating the optimum fuzzy terms with the optimum consequent parameters. It is similar to the ECSF. The following formulas represent how a new membership function is created and how the old ones are updated for the splitted subrange as follow.

The new membership function (MF) is

$$\hat{\mu}_{sp} = \begin{cases} \dfrac{x - c_n}{x_{sp} - c_n}, & if \;\; x \in [c_n, x_{sp}) \\ \dfrac{c'_n - x}{c'_n - x_{sp}}, & if \;\; x \in [x_{sp}, c'_n) \end{cases} \tag{6}$$

Here is how the old MFs is updated for the closed range as follow

$$\hat{\mu}_n^0(x) = \frac{x_{sp} - x}{x_{sp} - c_n} \tag{7}$$

$$\hat{\mu}_n^1(x) = \frac{x - x_{sp}}{c'_n - x_{sp}} \tag{8}$$

C. *Finding the intersection of adjacent subranges*

In SEEM, singleton membership functions are used for the consequent parameters and obtained using gradient descent estimator. One membership function is required for each splitting point, although two singleton membership functions are employed for each splitting point (the distinction point). Therefore, the intersection's value (x, y) of each adjacent subrange is used to represent the new splitting point ($x_{sp} = x$) and consequent parameter (y) as in Figure 1. Consider a fuzzy system with three fuzzy terms as an example. When applying the gradient descent estimator for the two subranges, the splitting point's consequent parameter (x_{sp} = 15) has two values: one is taken from the left subrange, and the other is obtained from the right subrange, as illustrated in

Figure 2. The optimum consequent parameters between the two values [9, 11] were found using the ECSF while preserving the same splitting point as a solution to this problem. As a result of this refinement having an impact on both subranges of the training data, the error will grow. However, using the intersection point demonstrates that there are only a small number of training samples that are affected. As a result, this method will be used as the next step for discovering the best fuzzy terms and the best resulting parameters because the accuracy will be improved more than ECSF refining.

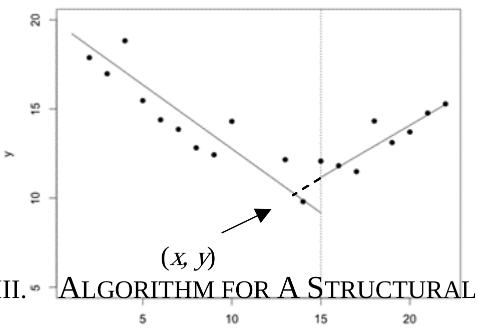

Fig 1: Adjusting the split point using the intersection to find the best consequent parameters and split point

III. ALGORITHM FOR A STRUCTURAL ENHANCEMENT OF EVOLVING METHOD

Parameters: Predefined threshold = β, number of subrange = η, desired number of subrange = ή and global average error = GAE.

Stage 1:- Locating the primary splitting points and consequents parameters

Step 1: Define the initial domain as a closed range [c, c'], where c and c' are the minimal and maximal values of the input variable, respectively.

Step 2: Locate the consequent parameters using gradient descent. As a result, the initial system is created.

Step 3: Select the subrange with the maximal average error to be divided into two subranges.

Step 4: Find the training sample with maximal error for the selected subrange to be the splitting point (x_{sp}).

TABLE I. COMPARISON OF SEEM IN RMSE WITH FGP AND ECSF FOR DATASET 1

Number of fuzzy rules	Accuracy in RMSE		
	The proposed SEEM	*ECSF*	*FGP*
2	**0.99905**	1.007251	1.007251
3	**0.93188**	0.964071	1.001439
4	**0.41535**	0.428396	0.484671
5	**0.32015**	0.398373	0.494885
6	**0.30854**	0.358614	0.618366
7	**0.23247**	0.283207	0.474807
8	**0.12524**	0.163423	0.137907
9	**0.09950**	0.140443	0.299793
10	**0.07624**	0.135001	0.203244

Step 5: Split the selected subrange at x_{sp}

Step 6: Retrain the consequent parameters y^k for the whole system after the splitting using gradient descent.

Step 7: If (GAE < β) & (η < ή) go to step 3.

Stage 2:- Locating the best splitting points and consequents parameters

Step 8: Find the new consequent parameters y^k (locally) for each subranges using gradient descent.

Step 9: Find the new split-points by finding the intersection of the new consequent parameters y^k (found in step 8) for each adjacent subrange.

Step 10: For each split point select either the old split point or the new split point from step 9 that produces minimal average error.

Step 11: After finding the best split points at step 10, apply gradient descent to the whole y^k to get the final optimal consequent parameters y^k.

IV. RESULT AND DISCUSSION

Dataset: Consider the one-dimensional function-approximation issue presented by::

$$f(x)=\begin{cases} x, & x\in(0,2) \\ 6-(x-4)^2, & x\in[2,5) \\ x, & x\in[5,7) \\ 6-(x-8)^2, & x\in[7,10) \\ x, & x\in[10,12) \end{cases} \quad (9)$$

In this dataset, 200 data samples are created at random from the range of $x \in (0, 12)$. Table 1 compares the SEEM, ECSF, and Fixed-grid-partitioning approaches (FGP) that have been presented. Root mean square error (RMSE) is used to evaluate accuracy.

The comparison demonstrates unequivocally that SEEM generates greater accuracy with regard to fewer fuzzy rules. As an illustration, the RMSE of the SEEM model with eight fuzzy rules is 0.125, while the RMSE of the FGP and ECSF models with ten fuzzy rules is 0.203 and 0.135, respectively. Furthemore, SEEM produces RMSE of 0.07624 for ten fuzzy rules. On the other hand, for the same number of fuzzy rules, ECSF and FGP produces 0.135001, and 0.203244 respectively. which indicates lower performance than the proposed SEEM. Two factors account for the proposed approach's great performance: First, choose the best split points, and then use gradient descent to fine-tune the parameters of the consequents.

V. Conclusion

This paper proposes A Structural Enhancement of evolving method for fuzzy systems. The primary contribution of SEEM is to identify the antecedent part's best global fuzzy terms that result in the smallest global average error. Moreover, it finds the best consequent parameters using gradient descent estimator. The examination of SEEM showed significant results among the other methods.

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