The Third AFSS(1998), 417-422

Effective Design of Inference Rule for Shape Classification

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Abstract

This paper presents a method of object classification from dynamic image based on fuzzy inference. It concentrates on the design of fuzzy inference algorithm which is suitable for low speed such as, conveyor, uninhabited transportation. At first, by using feature parameters of moving object, fuzzy if - then rule that can be able to adapt the wide variety of surroundings is developed. Secondly, implication functions for fuzzy inference are compared with respect the proposed algorithm. Simulation results are presented to testify the performance and applicability of the proposed system.

Keywords: Fuzzy inference, If - then rule, Difference picture, Composition operation.

I. INTRODUCTION

Shape classification defined as a process of assigning an item or an observation to its proper place is one of the most fundamental of vision system-based industrial application as well as medical, sports. But, unfortunately, in the real field the common problems in shape or pattern classification is the lack of homogeneity among feature parameters or attributes. In spite of the short of a complete method of recognition and classification, extensive research of these problems has led to some satisfying treatments of the subject in the non-fuzzy way [1-4].

On the other hand, fuzzy logic has a great advantage in comparison with discrete formal logical systems: it can approximate very well, it is suitable for the construction of approximation models as well as computationally effective algorithms of reasoning and control.

In recent year several effective methods to approximate uncertain knowledge have been proposed such as neural network and a fuzzy inference. Especially, industrial applications of fuzzy logic have been more practical advanced, and produced many products ,such as plant, proportional integral(PI) controller, autonomous navigation of a mobile robot by using fuzzy inferencing chips [5-7] .

Even though fuzzy approximate reasoning provides a lots of concepts and techniques for representing and inferring from knowledge which is uncertain or lacking in reliability, what is used in practical applications is a relatively restricted and yet important part of fuzzy logic concentrating on the use of fuzzy if-then rules [6]. Indeed, the effective design and calculus of fuzzy if-then rules provide a good method for dealing with man-machine systems which can be regarded as a ultimate goal of fuzzy engineering.

This paper addressed the optimal design of fuzzy if - then rules, which can be adapted the wide variety of circumstance and analyzed a useful membership function to classify the moving object both from the experimental as well as methodological standpoint.

In the preprocessing, by using difference picture(DP) scheme, motion vectors are estimated and several feature parameters of moving object are calculated. Then, determined the tolerance range by using these feature parameters, which is due to the various conditions of surroundings of moving object. The essential role of the tolerance range is to generate a membership function. After the generation rule is made from the reference parameter, the fuzzy composition operation is performed. Furthermore, implication operators are compared by using proposed approach.

Ⅱ. STRUCTURE OF A FUZZY SYSTEM

Fuzzy logic formalize the idea that an object can belong to a class with a continuum of membership grade. It allows us to represent ambiguity or uncertainty about the membership of the object itself in a manner typical of human intuition.

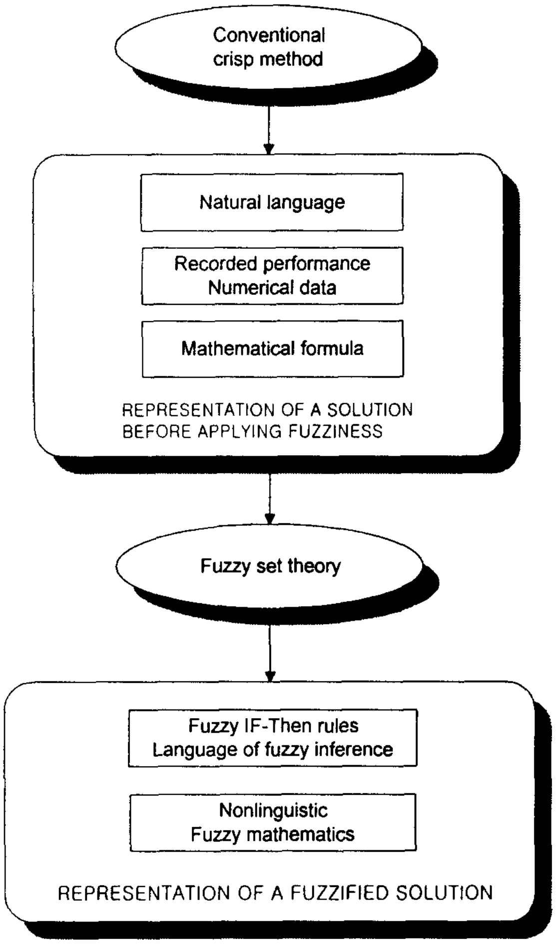

Fig. 1. Converting a conventional method into fuzzy method.

Consequently. in order to design a fuzzy inference system, a crisp data must be translate into if-then language of fuzzy inference. Fig.1 illustrate the conversion from conventional method to fuzzy method by application of fuzzy theory.

One of the most important step in fuzzy system design is the design of its membership function. It is also said the characteristic function, which can be expressed in a number of ways [8-10].

This function can take interval values between 1 and 0 and is often shown inside straight brackets[1,0]. Using the same notation as Eq.(1), the fuzzy set A can be expressed as

$$A = \{(x, \mu_A(x))\} \ , x \in X \qquad (1)$$

where μ denotes the membership function and $(x, \mu_A(x))$ is a singleton, precisely, a fuzzy set in universe of discourse U is characterized by membership function μ. Another common way of representing a fuzzy set is

$$A = \bigcup_{x_i \in X} \mu_A(x_i)/x_i \qquad (2)$$

where, the fuzzy set A is the collection or union of all singletons $\mu_A(x_i)/x_i$.

The shape of membership function can not be formed randomly because arbitrary design can produce unpredictable results in the basic fuzzy inference algorithm. In practice, many types of membership function have been proposed for analyzing pieces of patterns [11-12].

Ⅲ. INFERENCE ALGORITHM

In general, fuzzy algorithm can employ relational, compositional or implicational inference method. However the implication inference in the form of conditional if - then rules include theoretical features with all levels of complexity [13-14][17].

Fuzzy implication P → Q (P implies Q) is a mechanism for generalized modus pones inference. The implication relation is defined by

$$\begin{aligned} R(\chi, y) &= \bigcup_{xy} \mu(\chi, y)/(\chi, y) \\ \mu(\chi, y) &= \Phi[\mu_A(\chi), \mu_B(y)] \\ &\chi \in X, \quad y \in Y \end{aligned} \qquad (3)$$

where linguistic/fuzzy variable X and Y take the values of A and B, respectively, and $\mu(\chi, y)$ is the membership function of the implication relation. The widely used implication operators, such as Mamdani and Larsen are defined by :

$$\Phi[\mu_A(\chi), \mu_B(y)] = \mu_A(\chi) \wedge \mu_B(y)$$

$$\Phi[\mu_A(\chi), \mu_B(y)] = \mu_A(\chi) \cdot \mu_B(y) \quad (4)$$

Because the size of the inference rule is proportional with the number of various parameters, and thus, in order to generate a optimal inference rule, we mainly focused on following phases:

. Number of crisp and fuzzy in/outputs
. Number of rules
. Average of antecedents and consequents for each rules
. Shape of membership function per each input
. Methods chosen to perform the fuzzification, inference, and defuzzification step

In our approach, interpolative technique is utilized for the reduction of typical rules that is standard if-then inference based on the generalized modus ponens inference paradigm. Suppose that the following two rules are in the model:

If χ is L then y is JK
If χ is VL then y is JK $\in$ R

These two can be formulated by a single, combined rule

If χ is L or VL then y is JK

According to this, our inference rule can be formulated as follows:

$$R=\{ \text{If } \chi \text{ is } MA_1 \text{ then y is } MO_1 \\ \text{If } \chi \text{ is } MP_1 \text{ then y is } MO_1 \\ \text{If } \chi \text{ is } MR_1 \text{ then y is } MO_1 \\ \text{If } \chi \text{ is } MV_1 \text{ then y is } MO_1 \} \quad (5)$$

This rule can also be compressed into

$$R_M = \{ \text{ If } \chi \text{ is } MA_1 \text{ or } MP_1 \text{or } MR_1 \text{ or } MV_1 \text{ then y is } MO_1 \}$$

or

$$R_M = \{ \text{ If } \chi \text{ is } MA_1 \oplus MP_1 \oplus MR_1 \oplus MV_1 \text{ then y is } MO_1 \} \quad (6)$$

Here, the linguistic terms MA_1, MP_1, MR_1, MV_1, MO_1 are defined such feature parameters of moving object as area, perimeter, a/p ratio, and vertex, respectively.

Based on these conditions of both inference rule and practical considerations found in the industrial implication of automated classification , we devised new algorithm which can be adapted to the change of environments [16]. Proposed algorithm can be described informally as follows:

0. **Preprocessing.**
   Input is the image array.
   Extract the FPs (feature parameters) of RI(reference image).
   Set the max. tolerance range of movving object. Based on these range, **generation rule** is formulated.
   GRn(generation rule or seed for implication) is placed in S.
1. **While** the current image is not empty
   repeat step 2~9.
   Begin
2. **Find** the feature parameters for CI(current input) ;
   MA=area, MP=perimeter, MR=a/p ratio, MV=vertex
3. **If** input is new, **then** set S= S_1
   go to step 2
   Else If do:
   Begin
4. **Repeat** step 5~8
   Begin
5. **For** each value of FPs applying GRn from GRn_1 to GRn_4 **do:**
   Begin
6. **Find** the defuzzification value
7. **Find** the SI(similarity factor)
8. **If SI >** $\alpha-cut$ **then** SI equal RI
   else SI not equal RI.
   End if.
9. **Store** the number of similarity
   End.
   End.
   End.
10. **End of algorithm.**

IV. EXPERIMENTAL RESULTS

In this section, some experiments are conducted to testify the validity of proposed algorithm. The general architecture of the fuzzy inference system for inferencing the motion object is composed of three basic functional block as shown

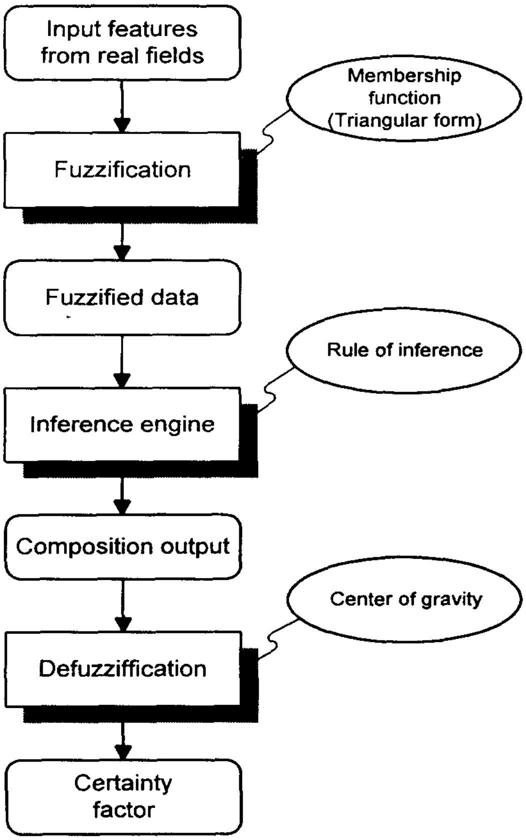

Fig. 2. Fuzzy functional structure for shape classification.

in Fig. 2. The two of them organize an information interface (the fuzzification and defuzzification) linking the fuzzy inference module.

Fuzzyfication step transforms an input crisp value into a fuzzy representing a degree of membership. Firstly, we obtained the maximum range of tolerance value of each parameters due to environmental condition such as variation of intensity, unpredicted noise. Then generate a fuzzy data by using these tolerance range.

Some geometric features such as area, perimeter, a/p ratio, and vertex are selected, which are very easy to calculate and useful to classify the moving object. The superior effect of these feature parameters is found the another literature.[15]

During the inference process, the system evaluates the contribution of each rule to the output computation based on the if-then rule given by (6). In this stage, fuzzy composition operation is performed by (6) with respect to the fuzzy relation between the reference and the currently acquired parameters of moving object. Here, the Mamdani and the Larsen operator are utilized to calculate the fuzzy relation operation.

Lastly, defuzzification phase, translates the fuzzy output into a crisp value, which is the similarity value of the classified object. Several defuzzification methods are reported in the literature, in the experiment, we used the center of gravity method, which is based on finding a balance point of a property that can be the total geometric figure of output. this is calculated by

$$x = \frac{\sum_{i=1}^{N} x_i \mu_0(x)}{\sum_{i=1}^{N} \mu_0(x)} \tag{7}$$

where $\mu_o(x)$ represents the fuzzy set of final output of fuzzy variable and x is the location of each singleton on the universe of discourse.

In order to evaluate the performance of proposed method some kinds of industrial assembly parts are chosen (Fig. 3). In the preprocessing operation, moving vectors are acquired, then geometric feature parameters are calculated based on difference picture method. Some extracted feature parameters of assembly part are listed in Table 1. This crisp values are transformed into a fuzzy degree based on proposed algorithm.

Table 1. Extracted feature parameters for each assembly parts.

	MA	MP	MR	MV
Assembly_1	540	210.5	2.56	34
Assembly_2	204	98.3	2.07	15
Assembly_3	430	154.4	2.78	25
Assembly_4	450	120.2	3.74	29

Figs. 4 and 5 show a classification results using the Larsen and the Mamdani operator with respect to the case of intensity variation as well as normal condition.

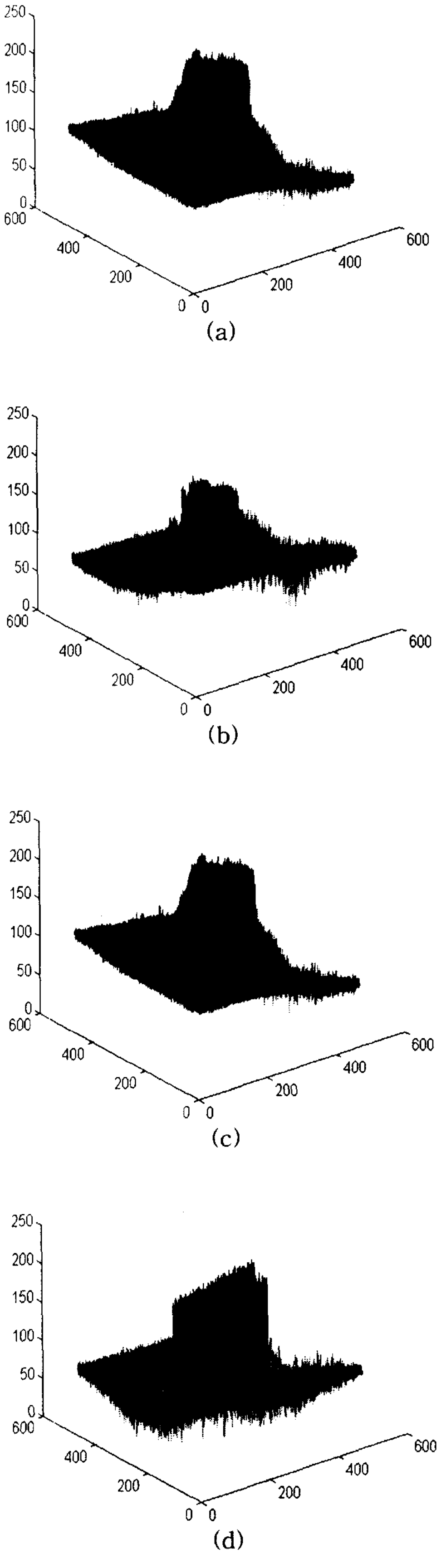

Fig. 3. An example of assembly parts.

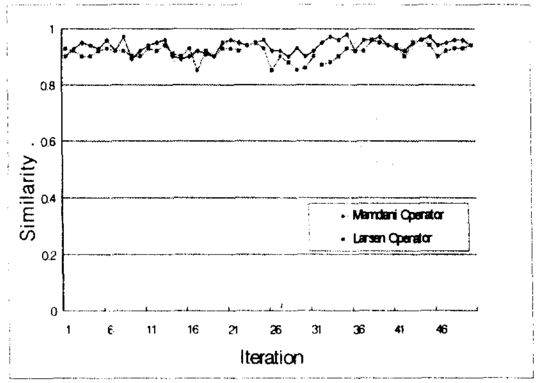

Fig. 4. Degree of similarity (Intensity invariation)

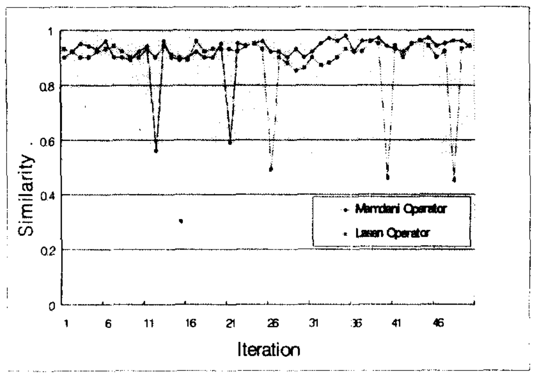

Fig. 5. Degree of similarity (Intensity variation)

For instance, shown in Fig. 4 is a case of stationary condition with respect to the intensity of illumination. Using the same training data, a case of non-stationary condition due to the change of illumination is shown in Fig. 5.

So as to find a classification rate, a threshold function or filter, which can be called α-cut is applied to each membership value in the output of similarity. Even for α-cut = 0.5, in Fig. 3, the proposed algorithm is still very effect and yields a 100% of classification rate. From Fig. 4, we can see that Mamdani operator is superior to that of Larsen's in degree of similarity. However, in this condition, applying an α-cut = 0.5 to similarity output correct solutions can not be obtained due to change of environments. To overcome this phenomenon, it is need to select a optimal value of α-cut.

V. CONCLUSION

In this paper, adaptive fuzzy inference algorithm for automatic classification of moving object is studied.

The performance has been evaluated with respect the different implication operator. All of the experimental results showed that proposed method can improve the performance for classifying the moving object under the such conditions as intensity varying, noisy circumstances.

Furthermore, It is also showed that similarity rate of proposed algorithm can be adjusted by tuning the α-cut. Under the same condition, mamdani implication operator is superior to that of Larsen's. This method can be applied to the automatic classification of objects in the industrial fields.

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