Adaptive Fuzzy Inference Algorithm for Shape Classification

Yoon-Ho Kim*, Kwang-Ryol RYU**

Abstract

This paper presents a shape classification method of dynamic image based on adaptive fuzzy inference. It describes the design scheme of fuzzy inference algorithm which makes it suitable for low speed systems such as conveyor, uninhabited transportation. In the first Discrete Wavelet Transform(DWT) is utilized to extract the motion vector in a sequential images. This approach provides a mechanism to simple but robust information which is desirable when dealing with an unknown environment. By using feature parameters of moving object, fuzzy if - then rule which can be able to adapt the variation of circumstances is devised. Then applying the implication function, shape classification processes are performed. Experimental results are presented to testify the performance and applicability of the proposed algorithm

Ⅰ. Introduction

The basic frame of a traditional pattern recognition system is consist of sensor(input stage), a feature extraction mechanism(algorithm stage), and a classification or description algorithm(application stage). Shape classification or description is the process of assigning an item or an observation to its resonable place. It is a fundamental scheme of pattern recognition system-based industrial applications, as well as biomedical, sports science. Basically, the idea in classification is to recognize object by using features. many types of features are used for object recognition, and also most of all features are based on either regions or boundaries in an images. 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 insufficient of a complete method of recognition and classification, an extensive research of these problems has led to some satisfying treatments of the subject in the non-fuzzy way [1][2][3]. On the other hand, fuzzy logic has a great advantage in comparison with discrete formal logical systems: it can approximate very well, it is

* 목원대학교 컴퓨터공학과
** 목원대학교 전자정보통신공학부
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suitable for the construction of approximation models as well as computationally effective algorithms of reasoning and control [4][5]. 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 controller, autonomous navigation of a mobile robot by using fuzzy inferencing chips [6][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 [8].

In this paper, an optimal design scheme of fuzzy if - then rules is addressed, 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. Globally, the proposed approach can be divided into two steps; the first is a process for extracting feature parameters so-called segmentation, the second is a shape classification process which is based on knowledge of feature parameter that gives the necessary information for shape classification. Especially, our concern in this research is focused on the later step. In the first, DWT with two level coefficient matrix was employed to extract the feature parameter. Then determined the tolerance range by using these feature parameters, which is due to the various conditions in the 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.

Ⅱ. Extraction of Feature Parameters Based on DWT

At first, we shall determine the meaningful coefficients according to the specification of two level DWT, Since our generalized preprocessing of extracting feature parameter is based on this coding scheme. Wavelet theory has been developed as a unifying framework only recently, even though similar ideas and constructions took place in the early of the century. It has been successfully applied in such areas of signal processing as image, speech and multi-resolution analysis. A wavelet decomposition of a function is a decomposition in a special basis of functions, so called wavelets. An important property of wavelet transform is that they preserve the spatial localization of image features [9]. And so, we invoke the idea that taking the DWT as a preprocessor, feature parameters are directly obtained by transformed coefficients matrix. Since the extracting operation computes for each group of pixels a list of its properties, the coefficients matrix guarantees that the output of the DWT have some properties might include its centroid, its area, its circumscribing portion, its orientation, its spatial moments, and so on. The continuous wavelet transform can be defined as

$$CWT_f(a,b)=\frac{1}{\sqrt{a}}\int_R \psi\left(\frac{t-b}{a}\right)f(t)dt \quad \cdots\cdots\cdots (1)$$

where $a \in R^+$, $b \in R$ with $a \neq 0$ and ψ is admissible. and then function $\psi^{a,b}$ are called "wavelets"; the function ψ is sometimes called "mother wavelet". From Eq. (1), we choose $a=a_0^m$, where m∈Z, and the dilation step is fixed. For convenience, we will assume $a_0 > 1$, and thus we choose $a=a_0^m$, $b=nb_0a_0^m$, where m, n range over Z, and $a_0 > 1$, $b_0 > 0$ are fixed; the appropriate choices for a_0, b_0 depend on the wavelet ψ. And so the discretized family of wavelet is given by

$$\psi_{m,n}(x) = a_0^{-m/2}\psi\left(\frac{x - nb_0 a_0^m}{a_0^m}\right) = a_0^{-m/2}\psi(a_0^{-m}x - nb_0) \quad \cdots\cdots (2)$$

Finally, discrete wavelet transform can be expressed as Eq.(4). In both case, of course, from Eq. (1) and Eq.(4) we assume that ψ satisfies Eq.(5).

$$DWT_{m,n(f)} = a_0^{-m/2}\int dt\, f(t)\ \psi\ (a_0^{-m}t - nb_0) \quad \cdots\cdots (3)$$

$$\int dt\ \psi(t) = 0 \quad \cdots\cdots (4)$$

Consider a two-channel orthogonal filter bank, the usual wavelet decomposition for 2-D images can be expressed as

$$\begin{aligned} A_{2^{j+1}}f &= \sum_k\sum_l h(2m-k)\, h(2n-l) A_{2^j}f \\ H_{2^{j+1}}f &= \sum_k\sum_l h(2m-k)\, g(2n-l) A_{2^j}f \\ V_{2^{j+1}}f &= \sum_k\sum_l g(2m-k)\, h(2n-l) A_{2^j}f \\ D_{2^{j+1}}f &= \sum_k\sum_l g(2m-k)\, g(2n-l) A_{2^j}f \end{aligned} \quad \cdots\cdots (5)$$

There exist many different types of wavelet functions, all starting from the basic formulas (1),(5). Among these functions orthogonal wavelet filter banks have lots of good features. In order to good design a fuzzy inference system, we need to not only extract the position information of wavelet coefficients along with the magnitude information but also calculate the distinct feature parameters of motion vectors. In brief, proposed feature extraction scheme proceeds as follows:

Step 0. Acquire the 1'st frame from sequence images.
Step 1. Perform the 2-level DWT.
Step 2. Extract a set of motion features by using DWT coefficients.
Step 3. Set a reference value as feature parameters result from step 3.
Step 4. Using reference features, compare the disparity with 2-level based parameters.
Step 5. If the disparity is less than threshold value
then calculate a geometric features and repeat the step 3 - step 4.
else go to step 1.

Ⅲ. Formulation of Inference Algorithm

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 [10][11]. This function can take interval values between 1 and 0 and is often shown inside straight brackets[1,0]. Namely the fuzzy set A can be expressed as

$$A = \{(x, \mu_A(x))\}\ , x \in X \quad \cdots\cdots (6)$$

where μ denotes the membership function and $(x, \mu_A(x))$ is a singleton. 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 [12][13].

Here, so as to regulate the disparity of feature parameters, a typical S-shaped function is used. This sigmoidal (S) shape can be expressed in a number of ways in calculus. we define S-shape function $S(x;\alpha,\beta,\gamma)$ as

$$\begin{aligned} S(x;\alpha,\beta,\gamma) &= 2\left(\frac{x-\alpha}{\gamma-\alpha}\right)^2 & \alpha \le x \le \beta \\ S(x;\alpha,\beta,\gamma) &= 1 - 2\left(\frac{x-\gamma}{\gamma-\alpha}\right)^2 & \beta \le x \le \gamma \\ S(x;\alpha,\beta,\gamma) &= 1 & x \ge \gamma \end{aligned} \quad \cdots\cdots (7)$$

Here α, β, γ are the points on the universe where possibility is 0, 1, 0.5, respectively.

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

$$R(\chi, y) = \bigcup_{xy} \mu(\chi, y)/(\chi, y)$$
$$\mu(\chi, y) = \Phi[\mu_A(\chi), \mu_B(y)] \qquad \chi \in X,\ y \in Y \qquad \cdots (8)$$

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 :

$$\Phi[\mu_A(\chi), \mu_B(y)] = \mu_A(\chi) \wedge \mu_B(y)$$
$$\Phi[\mu_A(\chi), \mu_B(y)] = \mu_A(\chi) \cdot \mu_B(y) \qquad \cdots (9)$$

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
. 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 S then y is JM
If χ is VS then y is JM $\in$ R

These two can be formulated by a single, combined rule

If χ is S or VS then y is JM

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

R={ If χ is MA_1 then y is MO_1
If χ is MP_1 then y is MO_1
If χ is MV_1 then y is MO_1 }

This rule can also be compressed into

R_{base} = { If χ is MA_1 or MP_1 or MV_1 then y is MO_1 }

or

R_{base}={If χ is $MA_1 \oplus MP_1 \oplus MV_1$ then y is MO_1 } ……(10)

Here, the linguistic terms MA_1, MP_1, MV_1, MO_1 are defined such feature parameters of moving object as area, perimeter, 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. Proposed algorithm can be described as follows:

Step 0. Preprocessing:
Input is a time varying images. Extract the motion vector based on DWT.

Step 1. Calculation:
Calculate a set of PoF(parameter of feature). Determine the maximum tolerance range of object.

Step 2. Fuzzification:
Fuzzify the data obtained from max. tolerance range

Step 3. Generation:
Generate the fuzzy inference rule.

Step 4. Inference:
Perform the fuzzy reasoning to evaluate a similarity. Repeat this step until no more components can be compared.

Step 6. Defuzzification:
Set the $\alpha-cut$. Find the Defuzzification

value.

Ⅳ. Experimental Considerations

We have performed some experiments to testify the validity of proposed algorithm. The principle architecture of the proposed inference system for classifying the object shape is composed of four basic functional block as shown in Fig. 1.

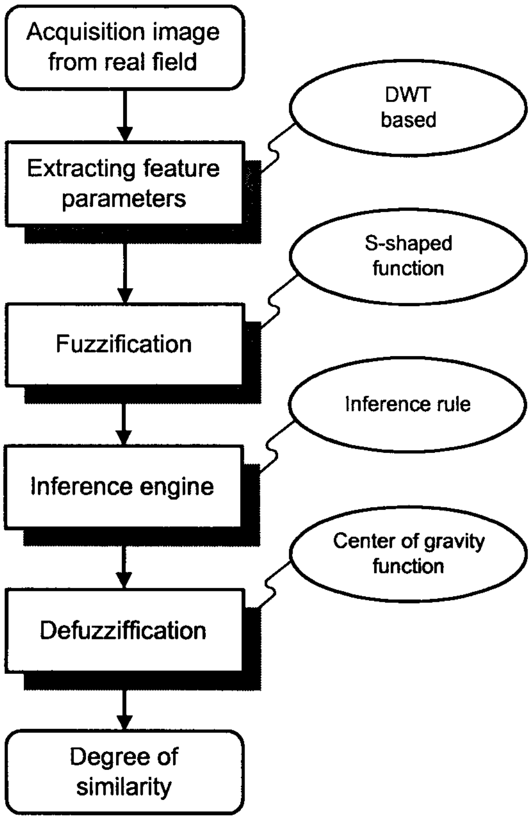


Fig. 1. Functional structure of proposed algorithm

The main goal of the first functional block is to extract feature parameters based on DWT so-called, preprocessing stage. The two of them construct an information interface (the fuzzification and defuzzification) linking the fuzzy inference module. Fuzzyfication step converts an input crisp value into a fuzzy representing a degree of membership.

In the first 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. Relatively simple geometric features such as area, perimeter, and vertex are selected, which are very easy to calculate and useful to classify the moving object. During the inference process, the system evaluates the contribution of each rule to the output computation based on the if-then rule given by (10). In this stage, fuzzy composition operation is performed by (9) 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, transforms 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 Eq. (11).

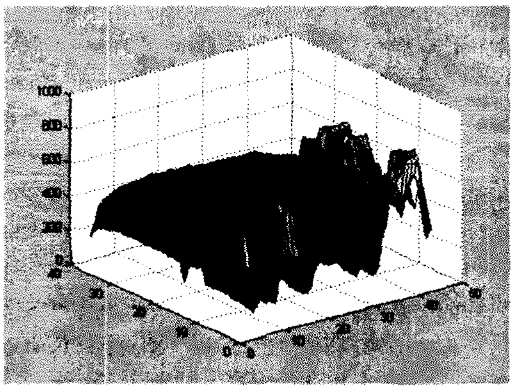
$$\chi = \frac{\sum_{i=1}^{N} \chi_i \mu_0(\chi)}{\sum_{i=1}^{N} \mu_0(\chi)} \qquad \cdots\cdots (11)$$

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.

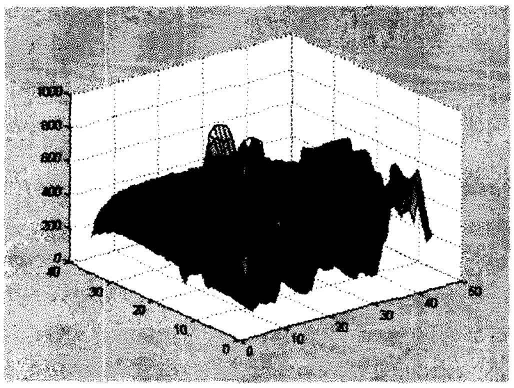
In this point of view, the need for threshold arises from the fact that low possibilities are undesirable because they are caused by failure of classification. The simplest form of a threshold is the α-cut that limits the spread of a membership function on the universe of discourse. This α-cut threshold as expressed by Eq. (12) creates a sudden drop in the evaluation of membership function.

$$\begin{aligned} \mu(x) &= 0 && \text{if } \mu(x)\mid_{x_i}^{x_j} \le \alpha \\ \mu(x) &= f(\mu(x)) && \text{if } \mu(x)\mid_{x_i}^{x_j} \le \alpha \end{aligned} \qquad \cdots\cdots\cdots\cdots (12)$$

In here, this factor is used for Degree of Certainty(DoC) which is basis of judgement weather it is properly classify or not. In order to evaluate the performance of proposed method some kinds of industrial assembly parts are chosen Fig. 2. Simulation results were obtained and are shown in Figs. 3 and 4. We have applied Mamdani operator and the Larsen's to evaluate the shape classification in terms of both case intensity variation and normal condition. In all case the number of experiment N = 60 is sufficient for estimating the DoC.



(a)



(b)

Fig. 2. Spectrum output of the tested images.

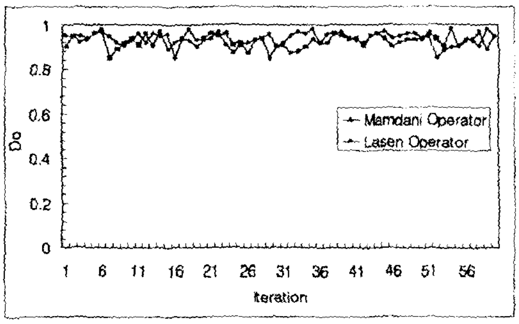


Fig. 3. Degree of certainty
(In case of brightness unchangeability)

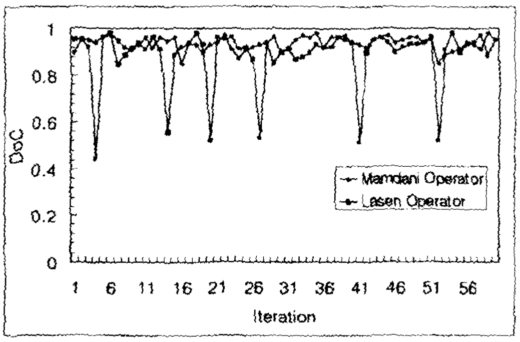


Fig. 4. Degree of certainty
(In case of brightness variation)

For instance, shown in Fig. 3 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. 4. So as to find a classification rate, a threshold function as described above, which can be called α-cut is applied to each membership value in the output of similarity. Even for α-cut = 0.8, 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 DoC.

V. Conclusion

We have presented a fuzzy reasoning approach for classifying a object based on adaptive inference algorithm. In order to confirm the validity of proposed scheme, two main procedures are involved in our simulation. The first procedure is DWT based preprocessing for extracting feature informations. The second is a classification procedure by using devised inference system. Experimental results have been evaluated with respect the different implication operator. All of the experimental results showed that proposed method can improve the performance for classifying the object adaptively under the such conditions as intensity varying, noisy circumstances. Furthermore, It is also showed that out put of DoC can be adjusted by tuning the α -cut. This system can be applied to the automatic classification of objects in the industrial fields.

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Yoon-Ho Kim
received the B. S. degree in electronic engineering from Cheong Ju University 1983, and the M. S. degree in electronic engineering from Kyung Hee University in 1986, and the Ph. D. degree in electronic engineering in 1992 from the Cheong Ju University, respectively. In 1992, He joined the

faculty of the MokWon University, where he is currently an Associate Professor in the Department of Computer Engineering. His research interests focus on image processing, including pattern recognition, computer vision, fuzzy inference technologies, and neural network applications.

Kwang-Ryol RYU

received the B.S. degree in radio communication engineering from Kwangwoon University in 1975, the M.S. and Ph.D. degree in electronic engineering from Kyunghee University in 1980 and 1988, respectively.

From 1996 to 1997 he was a professor in the University of Pittsburgh. He is currently professor in Mokwon University. He is a chair of computer vision sectional committee of the KIMICS. His research interests are in digital medical image processing and computer vision system, and digital speech recognition.