Fuzzy Relaxation Based on the Theory of Possibility and FAM

Tae-Uk Uam, Yang-Woo Park, and Yeong-Ho Ha

Abstract

This paper presents a fuzzy relaxation algorithm, which is based on the possibility and FAM instead of the probability and compatibility coefficients used in most of existing probabilistic relaxation algorithms. Because of eliminating stages for estimating of compatibility coefficients and normalization of the probability estimates, the proposed fuzzy relaxation algorithm increases the parallelism and has a simple iteration scheme. The construction of fuzzy relaxation scheme consists of the following three tasks: (1) Definition of in/output linguistic variables, their term sets, and possibility. (2) Definition of FAM rule bases for relaxation using fuzzy compound relations. (3) Construction of the iteration scheme for calculating the new possibility estimates. Applications to region segmentation and edge detection algorithms show that the proposed method can be used for not only reducing the image ambiguity and segmentation errors, but also enhancing the raw edge iteratively.

I. Introduction

Image segmentation, the processing for subdividing an image into homogeneous and meaningful parts is important as the first step in image analysis and recognition processing. Most of segmentation algorithms were based on the theory of probability. The probabilistic relaxation algorithm, which is one of iterative segmentation methods has been used to reduce image ambiguity and segmentation errors, which may be occurred in the case of simply classifying pixels independently into one another[1, 2]. When the subpopulation of pixels is overlapped, these errors were severe in segmentation. Also, the relaxation algorithm can be used for enhancing the raw edge in the post-processing[3, 4]. The probabilistic relaxation algorithm has the iteration scheme for adjusting the probability for each pixel with respect to its neighbors. There are several modified methods of probabilistic relaxation algorithms which have different iteration schemes for removing segmentation errors and image degradation effect[5, 6].

Most of existing probabilistic relaxation algorithms have several difficulties. The first is the statistical estimation of compatibility coefficient, which is modification factor of probability by its neighbors. Most of definition methods are based on both priori and conditional probability[7]. The statistical estimation of these probability parameters has a bad effect on the parallelism which is the best point of relaxation algorithm. The second is the complex iteration scheme because of containing the stage for normalization of the new probability estimates. Finally, it is difficult to define initial probability which makes effect on the number of iteration and the image degradation[5].

To overcome these difficulties, we propose the new fuzzy relaxation algorithm which is based on the theory of both the possibility and FAM(fuzzy association memory). The theory of fuzzy set may provide a efficient algorithm for the segmentation and/or enhancement of the image which is characterized by fuzziness rather than "randomness". For example, there is no well defined boundary between object and background. The proposed fuzzy relaxation algorithm is constructed by the following three stages. The first is to define in/output linguistic variables, their fuzzy term sets and membership grade functions. The second is to construct FAM rule bases using compound relations of fuzzy term sets. The last is to construct the iteration scheme for calculating the new possibility estimate. The proposed fuzzy relaxation algorithm can be constructed by in/output linguistic variables and FAM rules, which have different definitions according to their application algorithms. FAM rules translate structured knowledge into numerical framework, and process in the manner of neural network processing. The theory of FAM rules is based on imprecision, which is similar to natural language, and human thinking method which is assumed to be possibilistic rather than probabilistic. By applying FAM rule to relaxation, we can obtain compound fuzzy relation of fuzzy term sets. We can express compound

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fuzzy relation to (A, B ; C), for simplicity. In the image segmentation which consists of object and background, A or B is object or background, and C is net in/decrement of the pixels possibility for fuzzy subsets(object, background). For using the fuzzy relation for relaxation algorithm, we construct different FAM rules according to the image processing algorithm. That is, according to the application area in the image processing algorithm, we must define a proper FAM rules. For example, in region segmentation algorithm of bimodal image, we can construct the following FAM rule. The FAM rule (object, object; positive small) for short means that "if both testing pixel and its neighbors are objects, then the net increment of pixel's possibility for the object is positive small". In the above statement, terms of "object" and "positive small" are fuzzy subset of input and output linguistic variables. Because of replacing compatibility coefficients with FAM rules, there is no need for estimating priori and conditional probabilities in fuzzy relaxation algorithm. Also, because of using a possibility, the proposed algorithm does not contain the stage of normalization which is necessary for most existing of probabilistic relaxation and removes the difficulty of defining initial probability.

This proposed paper is organized as follows : in section Ⅱ, we model an image into fuzzy set geometry, section Ⅲ describes the main idea and structure of the proposed fuzzy relaxation algorithm, section Ⅳ shows results for applying to region segmentation of the bimodal character image, section Ⅴ shows results for applying to edge detection of the natural image, and finally section Ⅵ gives the conclusions.

Ⅱ. Modeling an Image into Fuzzy Geometry

The theory of fuzzy set may provide an efficient algorithm for segmentation and/or enhancement of the image which is characterized by "fuzziness" rather than "randomness". For example, there is no well defined crisp boundary between object and background or edge and non-edge. There are several manuscripts for expending the concept of image geometry to fuzzy set[8]. To model an image into fuzzy set geometry, we can consider an image of size M*N as an array of fuzzy singletons, that is, the pixel is considered as fuzzy singleton. Also, a segmented region or detected edge of the image is equal to fuzzy subset or fuzzy term set. For example, in edge detection algorithm, the image can be divided into fuzzy subsets, "edge" or "non-edge". Using the membership grade function of fuzzy set, an image with M*N dimension can be expressed as the following equation.

$$X=\sum_{A}\sum_{i=1}^{M}\sum_{j=1}^{N}(\mu_A(x_{ij})) \tag{1}$$

where A is fuzzy subset in the image, μ_A is membership grade function of fuzzy set A, x_{ij} is the pixel, and M, N are dimension of an image. In Eq. (1), we can see that the image can be expressed as sum of fuzzy subsets which have their own membership grade of each pixel. For example, the image consisted of the object and background, can be expressed the sum of fuzzy subsets(object, background) which have their own membership grade of singleton array(pixels).

We consider the proposition "If x_{ij} is A", then x_{ij} will be the pixel (fuzzy singleton) and A is segmented region (fuzzy term set). The fuzzy subset, A is characterized by its membership function of $\mu_A(x_{ij})$. In the image segmentation, based on their level, x_{ij} is gray level of pixel (linguistic variable) in the appropriate universe of discourse. $\mu_A(x_{ij})$ is the membership grade of pixels for fuzzy subset, A. In singleton applications, a possibility distribution can be defined to be numerically equal to the membership function[9]. It means that if pixel x_{ij} has gray level "10" and membership grade function of fuzzy subset has the item (0.3/10), then the possibility of "pixel, x_{ij} with gray level "10" is fuzzy subset" is 0.3[9].

In summary, the image can be considered as array of singletons and the segmented region of image as fuzzy subset. Also, in the singleton application, the pixel's possibility for fuzzy set is the same as their membership grade.

Ⅲ. Fuzzy Relaxation Algorithm

Most of probabilistic relaxation algorithms have the iteration scheme for establishing the new probability using the weighted combination of estimate of probability at each iteration with initial probability and compatibility coefficients. At each iteration step, the net increment and new probability are calculated by the Eq. (2)[1].

$$q_{ij}^{(r)}=\frac{1}{n}\left(\sum_{h=1,h\neq i}^{n}\left(\sum_{k=1}^{m}c(i,j:h,k)P_{hk}^{(r)}\right)\right) \tag{2}$$

$$p_{ij}^{(r+1)}=\frac{P_{ij}^{(r)}(1+q_{ij}^{(r)})}{\sum_{j=1}^{m}(p_{ij}^{(r)}(1+q_{ij}^{(r)}))}$$

where net increment, $q_{ij}^{(r)}$ is the average, over all neighbors(h) of the *i*th pixel, of $\sum_{k=1}^{n}c(j,j:h,k)P_{hk}^{(r)}$, new probability estimate, $p_{ij}^{(r+1)}$ is the *(r+1)*th probability, that the *i*th pixel belongs to the *j*th class. and the n, m is the number of considering neighbors, classes. Using the Eq.(2), To calculate the new probability, we must estimate the *c(i, j: h, k)* statistically, which has bad effect on parallelism. Also, it has complex iteration scheme because of containing the normalization factor, $\sum_{j=1}^{m}p_{ij}^{(r)}(1+q_{ij}^{(r)})$. Because the $\sum_{j=1}^{m}p_{ij}^{(0)}$ must be one, there is some difficulty for defining the initial probability.

The main idea of the fuzzy relaxation is to adjust the possibility of fuzzy singletons iteratively by using initial possibility and the crisp output of FAM system. In section Ⅱ, we show that the initial pixel's possibility can be calculated by the membership grade function. To construct relaxation algorithm, we must define the compatibility coefficients needed in the iteration scheme. As stated in the above, one of the most difficult tasks in the conventional probabilistic relaxation is to estimate compatibility coefficients statistically, which have a bad effect on parallelism of relaxation scheme. The proposed fuzzy relaxation algorithm, which does not contain the stage of defining compatibility coefficients, is based on the theory of FAM. Because fuzzy set can be interpreted as a point in a hypercube, FAM system is considered as mapping between fuzzy sets. Comparing the proposed system with the AI(artificial intelligence) expert system which is symbolic and one-dimensional, FAM is numeric and multi-dimension.

In this paper, according to two different image processing algorithms (region segmentation, edge detection), we use FAM system encoded different FAM rule bases, which have two antecedents and one conclusion. The compound FAM rule is "IF X is A, and Y is B, then Z is C", (A, B; C) for short. Applying iterative relaxation segmentation to an image, input linguistic variables X and Y are defined by gray level of the pixel and its neighbors, also output linguistic variable, Z is variation of possibility of pixel and C is fuzzy term set of net increment. For example, in segmenting the bimodal image, we would divide each linguistic variable into two fuzzy term sets of object and background, and construct four FAM rules for fuzzy relaxation segmentation. In this case, FAM rules are encoded the knowledge of both homogeneity and consistence which are important characteristics in an image. That is, in the case of the possibility of "neighboring pixels is object" is high, the possibility of "testing pixel is object" is high.

The main idea of the proposed fuzzy relaxation algorithm is establishing the new possibility using the combination of both the old possibility and the output of FAM at each iteration. We construct the iteration scheme as shown in Fig. 1.

In Fig. 1, $\pi_A(x_{ij})^r$ is the *r-th* possibility of the pixel x_{ij} for fuzzy subset A and $\pi_A(x_{ij})^{r+1}$ is the new estimated possibility calculated by summing the *r-th* possibility and the net increment. In this paper, we proposed two different types of FAM rule which are applied to the bimodal image segmentation and the edge detection algorithm.

At each iteration step, the net increment of possibility is calculated by the following equation.

$$I_h = Deffuzificaton[\sum_l \sum_m \sum_n w_{lmn} \cdot FAM\ Rule(m, n; l)] \quad (3)$$

$$I_n = \frac{1}{p} \sum_{h=1}^{p} I_h$$

where l, m and n, are fuzzy subsets of in/output linguistic variables and p is the number of neighboring pixels to be considered. The increment, I_h is the contribution factor of the neighboring pixel "h" in the variation of testing pixels possibility and w_{lmn} is the weight factor for each FAM rule. In Eq.(3), the increment of pixel possibility with considering neighbor pixel, *Ih*

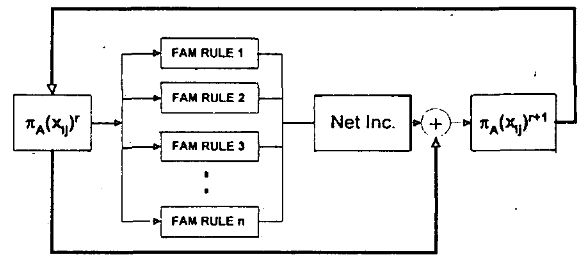


Fig. 1. The iteration scheme for fuzzy relaxation.

is the defuzzified number of inference procedure output of all activating FAM rules. The defuzzification process is designed to produce a crisp output. There is no optimal procedure for defuzzification strategy, in this paper, we used the center of area method. Also, net increment, *In* is the average value of increment contributed by all neighboring pixels. Using the net increment, we can estimate the new possibility using the Eq. (4).

$$\pi_A^{(r+1)}(x_{ij}) = \begin{bmatrix} \pi_A^{(r)}(x_{ij}) + I_n, & 0 < \pi_A^{(r+1)}(x_{ij}) < 1 \\ 0 & \pi_A^{(r+1)}(x_{ij}) < 0 \\ 1 & \pi_A^{(r+1)}(x_{ij}) > 1 \end{bmatrix} \quad (4)$$

In this case, the new estimated pixel's possibility is in [0,1]. Because of characteristic of possibility, there is no need that the sum of pixel's possibility for all fuzzy subsets, $(\sum_A \pi_A(x_{ij}))$ is one. Comparing with existing probabilistic relaxation expressed Eq.(2), the proposed fuzzy relaxation algorithm expressed Eq.(3) and Eq.(4) has simple iteration because of excluding the normalized stage of new probability estimate. Also, these equations do not contain the compatibility coefficient parameters.

Ⅳ. Application to Segmentation of Bimodal Image

To evaluate the proposed fuzzy relaxation algorithm, we applied it to the segmentation of the simple bimodal character image which consists of dark object and bright background. In this case, the image consists of two fuzzy subsets of *object* and *background*. Using fuzzy set geometry described in section Ⅱ, the image can be modeled by two membership grade functions of fuzzy singleton array. The M*N array image can be expressed as the Eq.(5).

$$X = \sum_{i=1}^{M} \sum_{j=1}^{N} \pi_A(x_{ij}) + \sum_{i=1}^{M} \sum_{j=1}^{N} \pi_B(x_{ij}) \quad (5)$$

where A is object and B is background fuzzy subset.

1. *Definition of Linguistic Variables, Fuzzy Term Set, and Their Membership Grade.*

For application, we used gray level of pixel as the input linguistic variable. Also, input linguistic variable is divided into

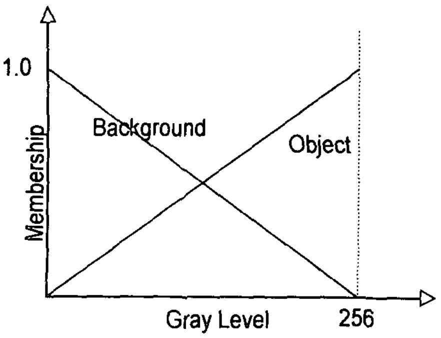


Fig. 2. The membership of pixel for fuzzy set(object, background).

two different fuzzy term sets(object, background) according to the their gray level and their membership grade can be defined by using standard triangular function in Fig. 2. In Fig. 2, the membership grade of pixel for fuzzy subset of object and background is estimated by their gray level. For example, pixel with 128 gray level has the membership grade 0.5 for object and 0.5 for background. This means that pixel's possibility of fuzzy set, object and background is 0.5 and 0.5, because the pixel is regarded as fuzzy singleton.

2. *Construction of FAM Rule for Image Segmentation*

The construction of FAM rule for image segmentation algorithm is the same task as defining compound relationship between input and output fuzzy term set. In applying to segmentation of bimodal image, we construct different four FAM rules using the fuzzy relation which has two antecedents and one conclusion. For example, if the testing pixel is object, and neighboring pixel is object, then the testing pixels possibility for object, $\pi_A(x_{ij})$ is incremented by positive small. For simplicity, we can express the above FAM rule as (object, object ; PS) for short. In segmentation of bimodal image which consists of two fuzzy subsets {object, background}, the input linguistic variable can be divided into fuzzy term sets {object, background}. The output linguistic variable, amount of variation of pixel's possibility, is divided into two fuzzy term sets {PS, NS}. In this case, fuzzy term set, PS is positive small and NS is negative small. Using definition described above, we can construct the following four FAM rules.

IF pixel is object AND N_pixel is object,
THEN $\nabla\pi_A(x_{ij})$ *is PS*
IF pixel is object AND N_pixel is background,
THEN $\nabla\pi_A(x_{ij})$ *is NS*
IF pixel is background AND N_pixel is object,
THEN $\nabla\pi_B(x_{ij})$ *NS*
IF pixel is background AND N_pixel is background,
THEN $\nabla\pi_B(x_{ij})$ *is PS*

In above reasoning statements, $\nabla\pi_A(x_{ij})$ and $\nabla\pi_B(x_{ij})$ are the variation of pixels possibility for fuzzy set A(object), B(background) and N-pixels are neighboring pixels to be considered in relaxation algorithm. The FAM rule, "*IF pixel is object AND N_pixel is background, THEN* $\nabla\pi_A(x_{ij})$ *is NS*" means that if the testing pixel is object and neighboring pixel is background, then the variation of testing pixels possibility for object is negative small. Four FAM rules are summarized in the Table 1.

Table 1. Four FAM rules for relaxation according to neighboring pixels.

	Object(A)	Background(B)
Object(A)	PS	NS
Background(B)	NS	PS

3. *Applying Results to Image Segmentation*

To evaluate the performance of fuzzy relaxation algorithm for image segmentation, we applied it to bimodal character image. Fig. 3 shows the results of applying the proposed algorithm to image segmentation. Fig. 3(a) shows the noisy original gray scale image and Fig. 3(f) is segmented image of Fig. 3(a). Fig. 3(b), (c), (d), and (e) show the gray scale images with iteration number of 1, 3, 5, and 10 and Fig. 3(g), (h), (i), (j) show segmented images of Fig. 3(b), (c), (d) and (e) with thresholded at 0.5. In these results, we can see that the relaxation approach based on possibilistic classification can make segmentation much easier by removing the image ambiguity and reducing classification errors which are appeared in segmentation of pixel independently. Also, there are no degradation effects of small priori possibility fuzzy subset, which is appeared in existing probabilistic relaxation. Fig. 4 shows the total variation of pixels possibility with increasing the number of iteration. In this figure, because the total variation of possibility decreases rapidly with increasing the number of iteration, we can guess the proposed relaxation algorithm be converged. To investigate the convergence performance quantitatively, we introduce the average variation rate of the pixel's possibility with iteration, $\nu(r)=\sum_{i=1}^{M}\sum_{j=1}^{N}(\pi_A^{(r-1)}(x_{ij})-\pi_A^{(r)}(x_{ij}))/M\cdot N$. In Fig. 5, the v(1) = 8(%), v(5) = 0.7(%), v(10) = 0.1(%) and v(15) = 0.01(%). There is a small variation after 10 iterations.

V. Application for Edge Detection of Natural Image

The main idea of fuzzy relaxation algorithm for edge detection is to in/decrease pixel's possibility of edge with considering both left and right vertex types. Fig. 5 shows various types of vertex. In this case, besides the central crack edge, the left vertex is one of four different types of vertexes (no crack edge, one directional crack edge, two directional crack edge, three directional crack edge). Types of right vertex are defined in the same way. Also,

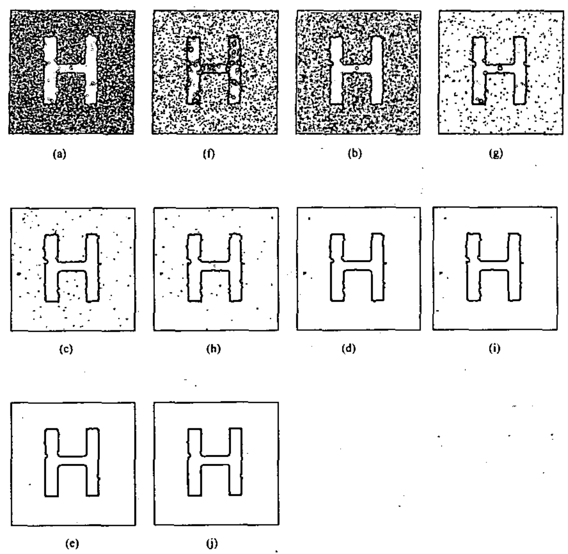


Fig. 3. Results of segmentation using the proposed fuzzy relaxation.
(a) Original Gray Scale Image
(b) Results after one iteration of proposed relaxation applied to (a)
(c) Results after three iterations of proposed relaxation applied to (a)
(d) Results after five iterations of proposed relaxation applied to (a)
(e) Results after ten iterations of proposed relaxation applied to (a)
(f) Segmented Image of (a) thresholded at 0.5
(g) Segmented Image of (b) thresholded at 0.5
(h) Segmented Image of (c) thresholded at 0.5
(i) Segmented Image of (d) thresholded at 0.5
(j) Segmented Image of (e) thresholded at 0.5

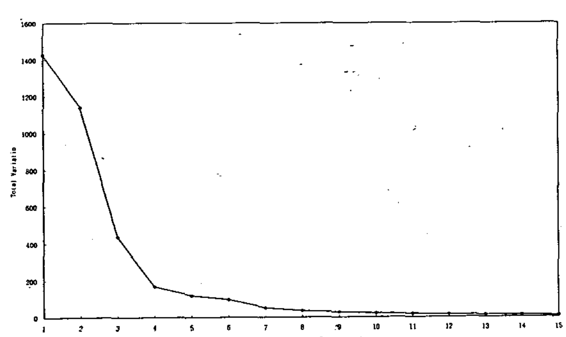


Fig. 4. The total variation of pixel's possibility ($\sum_{i=1}^{m}\sum_{j=1}^{n}\nabla\pi_A(x_{ij})$).

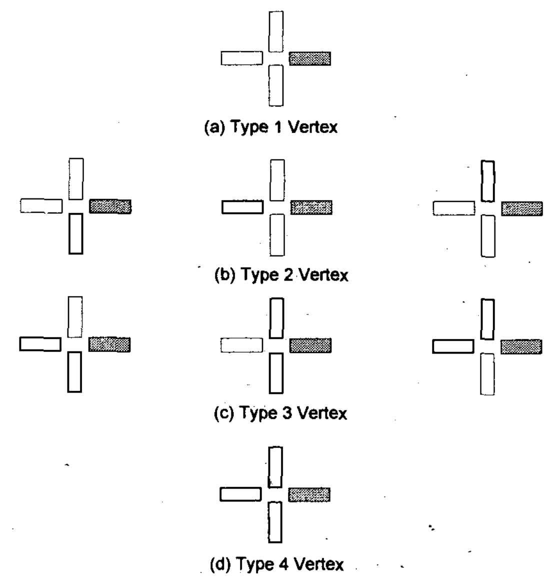
vertical edges are handled in the same way, exploiting the obvious symmetries with horizontal case.

1. Definition of Linguistic Variables, Fuzzy Term Set, and Their Membership Grade.

For application, we introduce the new input linguistic variable

$$M=a+b+c \tag{6}$$

Where a, b, and c are the normalized gradient for 3-directional crack edge of the testing pixel. In Fig. 5, we can see 3-directional



Four types of vertex (a) no crack edge (b) one directional crack edge (c) two directional crack edges (d) three directional crack edges

Fig. 5. Four types of vertex.

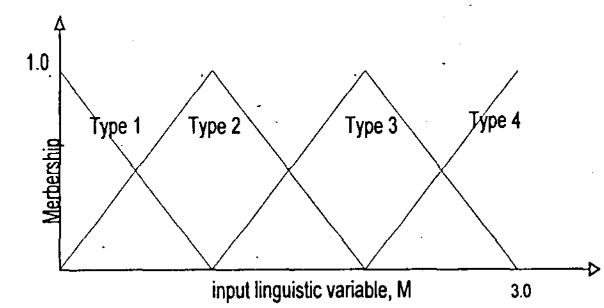


Fig. 6. The merbership of four vertex type fuzzy set.

crack edge in the left of testing pixel. Input linguistic variable, M has four different fuzzy term sets(type1, type2, type3, type 4) according to their levels and their membership grades can be defined by using standard triangular function in Fig. 6. For example, in the case of $M=0.5$, membership grade of each fuzzy subset is (0.5, 0.5, 0.0, 0.0). This means that if M is 0.5, the possibility for one of vertex type of 1, 2, 3 and 4 is 0.5, 0.5, 0.0 and 0.0. The output linguistic variable, the variation of possibility of testing edge, is divided into three fuzzy term sets, positive small (PS), negative small (NS), and almost zero (AZ).

2. Construction of FAM Rule for Edge Detection

The main idea of the proposed edge relaxation algorithm is to estimate iteratively the pixel's possibility for edge with considering both neighboring right and left vertex types. For example, if the left vertex is type 2 and right vertex is type 3, then the variation of pixel's possibility for edge is increased by positive small, (type 2, type 3 ; PS) for short. As the other example, if the left

Table 2. FAM rules for edge relaxation according to the left and right vertex types.

	Type 1	Type 2	Type 3	Type 4
Type1	NS	AZ	NS	NS
Type 2	AZ	PS	PS	PS
Type 3	NS	PS	AZ	AZ
Type 4	NS	PS	AZ	AZ

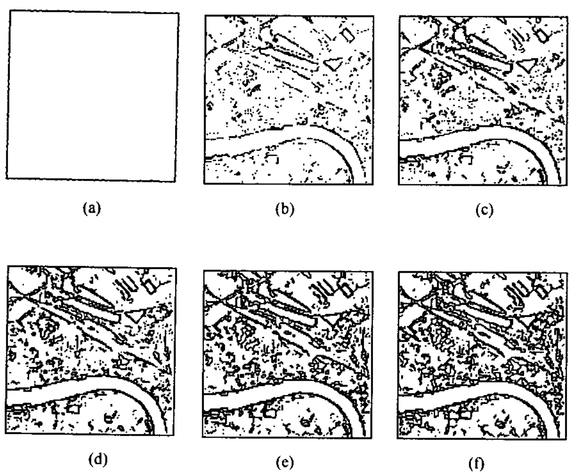


Fig. 7. Results of edge detection using the proposed fuzzy relaxation algorithm.
(a) Original gray scale image
(b) Raw edge image thresholded at 0.25 for display only
(c) Edge image after 5 iterations of the proposed relaxation to (a)
(d) Edge image after 10 iterations of the proposed relaxation to (a)
(e) Edge image after 15 iterations of the proposed relaxation to (a)
(f) Edge image after 20 iterations of the proposed relaxation to (a)

vertex is type 1 and right vertex is type 4, then the variation of pixel's possibility for edge is decreased by negative small, (type 1, type 4 ; NS) for short. Because the vertex has one of four different types, we can construct sixteen FAM rules for edge relaxation. Table 2 summarizes FAM rules for the proposed edge relaxation algorithm.

3. Application Results to Edge Detection

Fig. 7 shows the results of applying the proposed algorithm to edge detection of a natural image. Fig. 7(a) shows the original gray scale image. Fig. 7(b) shows the raw edge strength thresholded at 0.25 for display only, and Fig. 7 (c), (d), (e), and (f) show the results after 5, 10, 15 and 20 iterations of proposed fuzzy relaxation. In these results, we can see that the relaxation approach can be used for reinforcing weak and unconnected edges. It is not represented in this paper, we can get some different results with modification of FAM rule. More detail effects on the modification of FAM rules and membership grade functions will be the researching issue in our work. Also, to optimize FAM rule base, we will make effort to construct the adaptive FAM.

Ⅵ. Conclusion

Most of existing probabilistic relaxation algorithms have several difficulties: (1) statistical estimation of compatibility coefficients which have bad effects on the parallelism, (2) complex iteration scheme containing the normalization stage of probability estimate, (3) difficulty in defining initial probability.

In this paper, we proposed the fuzzy relaxation algorithm that is based on the theory of possibility and FAM instead of probability and compatibility coefficients. It has simple iteration scheme because of no need for normalization of probability and increases the parallelism of relaxation algorithm because of no need for statistical estimation of compatibility coefficients. Also, it removed the difficulty of definition of the initial probability. In applying for segmentation of bimodal image and edge detection of natural image, we can see that the proposed algorithm can be useful for removing the image ambiguity and reducing segmentation error in region segmentation and reinforcing the weak and unconnected edge in edge detection processing.

In future, we will make effort to apply the proposed algorithm to other image processing techniques contained the relaxation iteration scheme.

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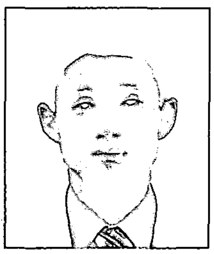

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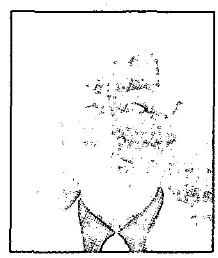

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