Available at
www.ComputerScienceWeb.com
POWERED BY SCIENCE @ DIRECT®

ELSEVIER

Pattern Recognition Letters 24 (2003) 81–87

Pattern Recognition Letters

www.elsevier.com/locate/patrec

Color image enhancement by fuzzy intensification

M. Hanmandlu [a,*], Devendra Jha [a], Rochak Sharma [b]

[a] *Department of Electrical Engineering, Indian Institute of Technology, Hauz Khas, New Delhi 110016, India*
[b] *Department of Electrical Engineering, Delhi College of Engineering, New Delhi 110042, India*

Received 8 June 2000; received in revised form 27 January 2001

Abstract

A Gaussian membership function to model image information in spatial domain has been proposed in this paper. We introduce a new contrast intensification operator, which involves a parameter t for enhancement of color images. By minimizing the fuzzy entropy of the image information, the parameter t is calculated globally. A visible improvement in the image quality for human contrast perception is observed, also demonstrated here by the reduction in 'index of fuzziness' and 'entropy' of the output image.

Keywords: Image processing; Color enhancement; Fuzzy logic; Fuzzy contrast; Entropy; Index of fuzziness; Fuzzifier; Intensification operator

1. Introduction

The main objective of image enhancement is to process the image so that the result is more suitable than the original image for a specific application. Image enhancement methods (Gonzalez and Woods, 1992) may be categorized into two broad classes: Transform domain methods and spatial domain methods. The techniques in the first category are based on modifying the frequency transform of an image. However, computing a two dimensional transform for a large array (an image) is a very time consuming task even with fast transformation techniques (Lee, 1980) and are not suitable for real time processing.

The techniques in the second category directly operate on the pixels. Contrast enhancement is one of the important image enhancement techniques in spatial domain. Besides two popular methods: histogram equalization and histogram specifications (Gonzalez and Woods, 1992), we may mention a few important spatial domain methods such as an iterative histogram modification of gray images (Gauch, 1992), an efficient adaptive neighborhood histogram equalization (Mukherjee and Chatterji, 1995) and Gabor's technique (Lindenbaum et al., 1994). Adaptive neighborhood histogram method achieves better identification of different gray level regions by an analysis of

* Corresponding author.
E-mail addresses: mhmandlu@hotmail.com (M. Hanmandlu), devendrajha@hotmail.com (D. Jha), rochak@mailandnews.com (R. Sharma).

0167-8655/03/$ - see front matter
PII: S0167-8655(02)00191-5

histogram in the locality of every pixel. Lindenbaum et al. (1994) have used Gabor's technique for image enhancement, edge detection and segmentation. They have suggested a method for image deblurring based on directional sensitive filters.

Because of poor and non-uniform lighting conditions of the object and non-linearity of the imaging system, vagueness is introduced in the acquired image. This vagueness in an image appears in the form of imprecise boundaries and color values. Fuzzy sets (Zadeh, 1973) offer a problem-solving tool between the precision of classical mathematics and the inherent imprecision of the real world. The imprecision in an image contained within color value can be handled using fuzzy sets (Jimmermann, 1991). The notations like "good contrast" or "sharp boundaries", "light red", "dark green" etc. used in image enhancement by fuzzy logic are termed as linguistic hedges. These hedges can be perceived qualitatively by the human reasoning. As they lack in crisp and exhaustive quantification, they may not be understood by a machine. To overcome this limitation to a large extent, fuzzy logic tools empower a machine to mimic human reasoning.

In the fuzzy framework of image enhancement and smoothing, two contributions merit an elaboration. The first one deals with 'IF..THEN.. ELSE' fuzzy rules (Russo and Ramponi, 1995) for image enhancement. Here, a set of neighborhood pixels forms the antecedent part of the rule and the pixel to be enhanced is changed by the consequent part of the rule. These fuzzy rules give directives much similar to humane-like reasoning. The second one proposes a rule based filtering (Choi and Krishnapuram, 1997) in which different filter classes are devised on the basis of compatibility with the neighborhood.

We now discuss another kind of approaches where some pixel property like, gray tone, or color intensity is modeled into a fuzzy set using a membership function. In these approaches, an image can be considered as an array of fuzzy singletons (Pal and King, 1981) having a membership value that denotes the degree of some image property in the range [0,1]. Applying an intensification operator globally modifies the membership function. The approach by Hauli and Yang (1989) describes an efficient enhancement based on fuzzy relaxation technique. Different orders of fuzzy membership functions and different statistics are attempted to improve the enhancement speed and quality respectively. Hanmandlu et al. (1997) have proposed a Gaussian type of fuzzification function that contains a single fuzzifier and a new intensification operator called NINT that contains an intensification parameter. Fuzzifier is obtained by maximizing the fuzzy contrast and the parameter is obtained by minimizing the entropy. Note that the above works have been confined to the enhancement of gray images only.

In this paper, we have extended the approach in (Hanmandlu et al., 1997) for the enhancement of color images. We use histogram as the basis for fuzzy modeling of color images. The main emphasis has been laid on the fuzzy entropy measure. The 'index of fuzziness' and 'entropy' (Pal and King, 1981) are used to represent the quantitative measures of image quality in the fuzzy domain, though the image quality remains subjective in nature.

It has been found that RGB color model is not suitable for enhancement because the color components are not decoupled. On the other hand, in HSV color model, hue (H), the color content, is separate from saturation (S), which can be used to dilute the color content and V, the intensity of the color content. By preserving H, and changing only S and V, it is possible to enhance color image. Therefore, we need to convert RGB into HSV for the purpose. A Gaussian type membership function is used to model S and V property of the image. This membership function uses only one fuzzifier and is evaluated by maximizing fuzzy contrast, which is cumulative fuzzy variance about the crossover point. The contrast of S and V is stretched globally using NINT operator. The entropy is minimized to find the intensification parameter involved in NINT operator. The intensification operation leads to enhancement by improving the fuzzy homogeneity of the pixel about the crossover point. Since our intention is to use fuzzy based approaches for automatic image enhancement, we will find the fuzzifier and the intensification parameter by optimizing relevant functions as mentioned above.

2. Fuzzification and intensification

An image I of size $M \times N$ and intensity level in the range (0, $L-1$) can be considered as collection of fuzzy singletons in the fuzzy set notation,

$$I = \cup\{\mu_X(x_{mn})\} = \{\mu_{mn}/x_{mn}\};$$
$$m = 1,2\ldots,M; \quad n = 1,2\ldots,N \tag{1}$$

where $\mu_X(x_{mn})$ or μ_{mn}/x_{mn} represents the membership or grade of some property μ_{mn} of x_{mn}. x_{mn} is the color intensity at (m,n)th pixel. For a color image, the membership functions are taken for the unions of all colors X, $X \in \{\mathrm{R,G,B}\}$ or $X \in \{\mathrm{H,S,V}\}$. For the transformation of the color X in the range (0, 255) to the fuzzy property plane in the interval (0,1), a membership function of the Gaussian type:

$$\mu_X(x_{mn}) = \exp[-(x_{\max} - x_{mn})^2/2f_{\mathrm{h}}^2] \tag{2}$$

was suggested by Hanmandlu et al. (1997) as it involves a single fuzzifier, f_{h}. Here, $x_{\max} \leqslant L-1$, is the maximum color value and L is the number of intensity values present in the image. The membership values are restricted to the range $[\alpha, 1]$, with $\alpha = \exp(-x_{\max}^2/2f_{\mathrm{h}}^2)$. For computational efficiency, histogram of color X is considered for fuzzification. So, $\mu_X(k)$ represents the membership function of color X for intensity k, $k = 0,1,2,\ldots L-1$,

$$\mu_X(k) = \exp[-(x_{\max} - k)^2/2f_{\mathrm{h}}^2] \tag{3}$$

This function is the same as in (2), with x_{mn} replaced by an index k, the intensity at the (m,n)th spatial location. For a test image 'timber yard', Fig. 1(a) shows the Gaussian membership functions of S and V with typical $f_{\mathrm{h}} = 163$ for S and $f_{\mathrm{h}} = 138$ for V. It is observed that higher values of f_{h} are obtained for a brighter image.

The membership values are transformed back to the spatial domain after the intensification operator is applied in the fuzzy domain. The inverse operation that converts fuzzy domain quantities to the spatial domain is given by:

$$k' = x_{\max} - \{-2\ln[\mu'_X(k)]f_{\mathrm{h}}^2\}^{1/2} \tag{4}$$

where, $\mu'_X(k)$ and k' are the modified membership function and intensity value respectively.

We restrict ourselves to image enhancement using a contrast intensification operator. The original contrast intensification operator, INT (Zadeh, 1973) depends on the membership function only. It needs to be applied successively on an image for obtaining the desired enhancement. This limitation is removed in the new intensification (NINT) operator proposed by Hanmandlu et al. (1997). This is in the form of a sigmoid function given by:

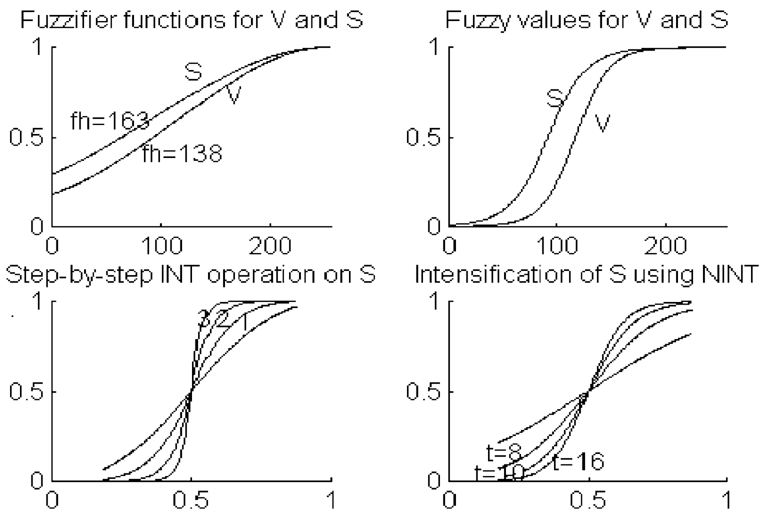

Fig. 1. Membership function and intensification operators (a)–(d) from top left clockwise.

Table 1
Test images

Images	Saturation (S)			Intensity (V)			t
	E	γ	f_h	E	γ	f_h	
Face							
Original	0.8952	0.9324	156	0.8732	0.9311	143	17
Enhanced	0.7320	0.8451	0.7531	0.8322	*Trees*		
Original	0.8104	0.9692	78	0.8360	0.9545	77	15
Enhanced	0.7521	0.8819	0.7503	0.8952	*Timber yard*		
Original	0.8853	0.8995	163	0.9012	0.8825	138	16
Enhanced	0.6983	0.8563	0.7489	0.8698	*Meeting*		
Original	0.7985	0.9357	159	0.7752	0.9448	166	16
Enhanced	0.7545	0.8778	0.7332	0.9190	*Lab*		
Original	0.8195	0.9331	161	0.7929	0.9417	168	17
Enhanced	0.7675	0.8786	0.7218	0.8867			

$$\mu'_X(k) = \frac{1}{1 + e^{-t(\mu_X(k)-0.5)}} \tag{5}$$

A plot of $\mu_X(k)$ vs $\mu'_X(k)$ for different values of parameter t is shown in Fig. 1. It is observed that except for values of $t < 5$, the NINT operator, shown in Fig. 1(d) has a similar response as that of INT operator, shown in Fig. 1(c). For $t < 5$, NINT operator has no appreciable influence on the membership function. In the case of enhancement using INT operator, the operator is applied repetitively on the membership values. This leaves wide gaps between successive intensified curves. If the parameter t were incremented by one in the NINT operator, the gap between successive curves would be much less than that due to INT operator applied repetitively. Thus minute changes in the level of enhancement are possible with the new operator. This behavior of changes in the membership values using both INT and NINT operators is shown in Fig. 1(d) and (c) respectively. Unlike INT operator, NINT operator does not change uniformly. At the extremes, the change in the membership function is marginal, but in the middle range it is almost linear.

3. Determination of Fuzzifier

We now introduce the concept of fuzzy contrast that depends on how far the membership functions, are stretched by an operator with respect to the crossover point, i.e., and 0.5. The crossover point need not be a constant as will be realized later. We take it as the cumulative variance of difference between the membership function and 0.5 over all pixels. Then the fuzzy contrast is written as:

$$C = \sum_{k=0}^{L-1} [\mu'_X(k) - 0.5]^2 p(k) \tag{6}$$

$$\sum_{k=0}^{L-1} p(k) = 1 \tag{7}$$

where, $p(k)$ stands for the frequency of occurrence of intensity k. After substituting for the membership function in (6) from (3) and (5) and maximizing C with respect to f_h, we can derive an approximate formula by taking the first two terms in the expansion of (6) as follows:

$$f_h^2 = \frac{1}{2} \frac{\sum_{k=0}^{L-1} (x_{\max} - k)^4 p(k)}{\sum_{k=0}^{L-1} (x_{\max} - k)^2 p(k)} \tag{8}$$

It may be noted that the intensification operator does not change the frequency of occurrence of a membership function. However, after transforming back to the spatial plane, the distribution might change due to enhancement.

4. Derivation for intensification parameter

The 'index of fuzziness' $\gamma(X)$ that gives the amount of fuzziness present in an image determines the amount of vagueness by measuring the distance between its fuzzy property plane and the nearest ordinary plane. Accordingly, 'entropy', $E(X)$, which makes use of Shanon's function, is regarded as a measure of quality of information in an image in the fuzzy domain. It gives the value of indefiniteness of an image. These quantities are defined by the following equations:

$$E(X) = \frac{1}{\ln 2} \sum_{k=0}^{L-1} -[\mu_X(k)\ln(\mu_X(k)) + (1-\mu_X(k))\ln(1-\mu_X(k))]p(k) \tag{9}$$

$$\gamma(X) = \sum_{k=0}^{L-1} \min[\mu_X(k), 1-\mu_X(k)]p(k) \tag{10}$$

Since $E(X)$ provides useful information about the extent to which the information can be retrieved from the image, this should serve as a guide for finding a suitable value for t by global minimization. Considering $E'(X)$ as a function of $\mu'_X(k)$ which in turn is a function of t, $\mu_X(k)$ and f_h, the derivative of $E'(X)$ with respect to t is obtained as,

$$\frac{\partial E'(X)}{\partial t} = \frac{1}{\ln 2} \times \sum_{k=0}^{L-1} \left[\frac{-t(\mu_X(k)-0.5)^2 e^{-t(\mu_X(k)-0.5)}}{(1+e^{-t(\mu_X(k)-0.5)})^2} \right] p(k) \tag{11}$$

This equation indicates that t needs to be computed numerically.

5. Results and discussion

The color image is first converted from RGB to HSV domain to preserve the hue of the image. We find the maximum values, $x_{\max}$ and $p(k)$ for S and V components of the given image, the fuzzifier, f_h and the intensification parameter, t for both components are calculated separately. After intensification, V and S are defuzzified. In the fuzzy domain, 'index of fuzziness' and 'entropy' are calculated before and after the intensification in order to see changes in these measures. Then H, S and V components of the enhanced image are transformed into RGB. We have also found the histograms for RGB for the original and enhanced images for comparison and to see the effect of enhancement.

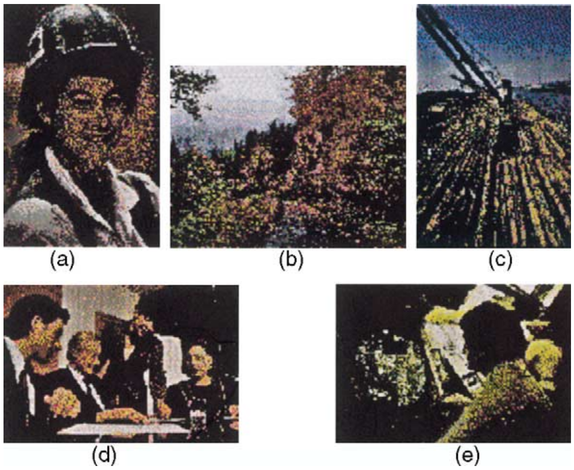

Fig. 2. Set of original images.

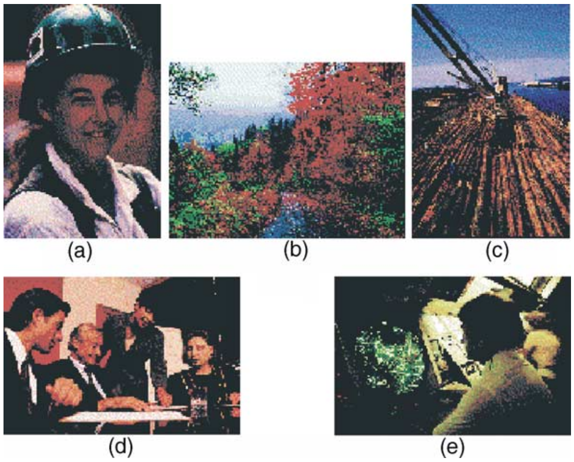

Fig. 3. Set of enhanced images.

While carrying out experiments, the following observations are made. Though, in general, the cross-over point is 0.5, which we have used for evaluating f_h and t, but during intensification using (5) we have used a value of 0.6 instead of 0.5.

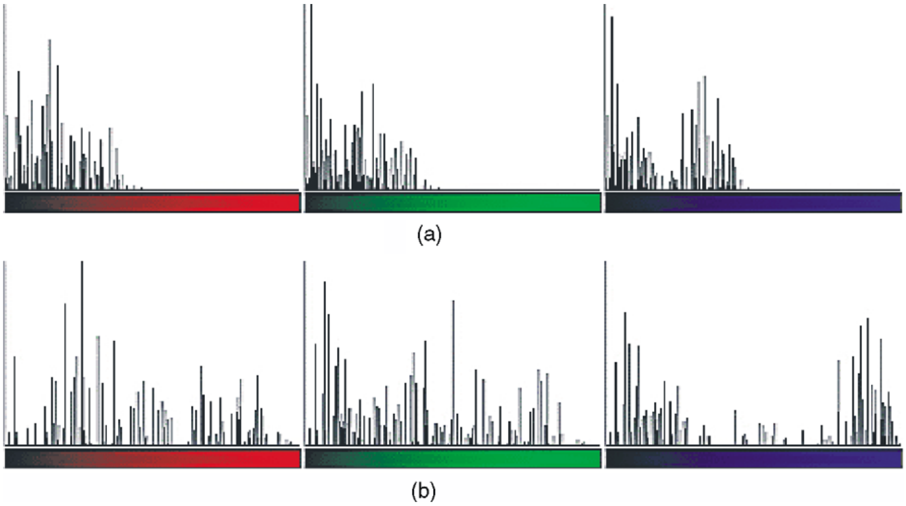

Fig. 4. (a) Histograms for original image of Fig. 2(c) timber. (b) Histograms for enhanced image of Fig. 3(c) timber.

This gives an improvement in image quality determined through visual assessment. For two test images (timber yard and trees), the crossover point of 0.5 gives the best results but for all the test images 0.6 has been found to be the optimum choice. This observation suggests that the intensification operator should treat the crossover point, which is presently a constant, as another parameter in addition to t. The values of t for S and V components are found to be almost the same. Accordingly, there exists only one entry of t for each image in the Table 1.

The index of fuzziness and entropy of V and S for the original and enhanced images are also calculated as shown in Table 1. These quantities decrease as the enhancement proceeds. This indicates that as a result of decrease in fuzziness, enhancement in an image takes place but at the cost of reduction in information content. This is because the higher the fuzziness, the higher the entropy and hence the information content. Thus, there is a need for a compromise between enhancement and information.

We have considered five images, viz., human face, trees, a timber yard, a meeting and a lab for the demonstration. These images and their enhanced versions are shown in Fig. 2(a–e) and Fig. 3(a–e) respectively. The original images have poor brightness and the details are not discernable. Also colors are not perceivable to the eye. A clear improvement is seen as far as the details and restoration of colors are concerned. The histograms for both the original and enhanced 'timber yard' images are shown in Fig. 4. The results of this technique have been compared with those obtained using MATLAB functions for histogram equalization and histogram stretching in Fig. 5(a–e) and Fig. 6(a–e) respectively. The superiority of the proposed technique is demonstrated by visual comparison.

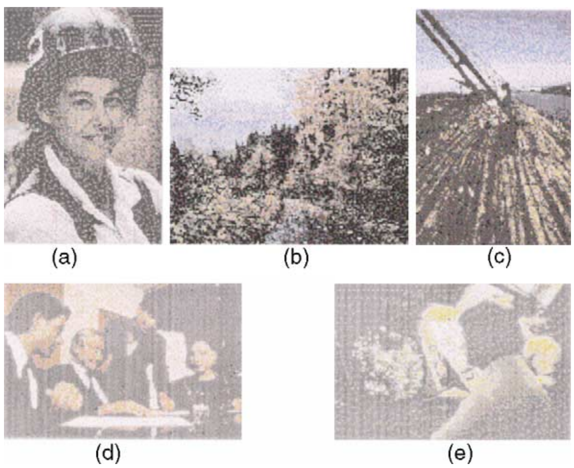

Fig. 5. Enhanced images using histogram equalization.

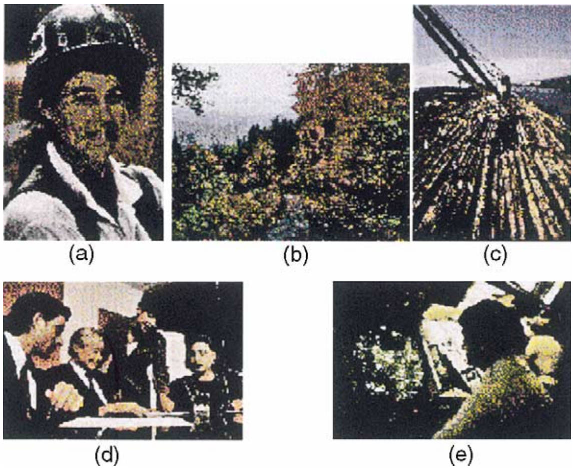

Fig. 6. Enhanced images using histogram stretching.

In the proposed technique, fuzzy intensification is suggested on the basis of optimization of fuzzy contrast and entropy globally. Optimizing f_h, t, and the crossover point iteratively can accomplish the possible improvement.

6. Conclusions

This paper presents a Gaussian membership function that transforms the saturation and intensity histograms of HSV color model into the fuzzy domain. A new intensification operator named NINT is used for global contrast enhancement. The fuzzifier and intensification parameters are evaluated automatically for the input color image, by optimizing the contrast and entropy in the fuzzy domain. The method has been applied to various test images and found suitable for enhancement of low contrast and low intensity color images. It is observed that the 'index of fuzziness' and the 'entropy' decrease with enhancement. There is a further scope for improvement of an image, if the crossover point is treated as another parameter in addition to the proposed intensification parameter. This would make the new intensification operator more general as the enhancement can be made bereft of visual assessment.

References

Choi, Y.S., Krishnapuram, R., 1997. A robust approach to image enhancement based on fuzzy logic. IEEE Trans. Image Process. 6 (6), 808–825.

Gauch, J.M., 1992. Investigation of Image contrast space defined by variation of histogram equalization. Graph. Models Image Process. 54 (4), 269–280.

Gonzalez, R.C., Woods, R.E., 1992. Digital Image Processing. Addison-Wesley, Reading, MA.

Hanmandlu, M., Tandon, S.N., Mir, A.H., 1997. A new fuzzy logic based image enhancement, 34th Rocky Mountain Symposium on bioengineering, Dayton, Ohio, USA, pp. 590–595.

Hauli, Yang, H.S., 1989. Fast and Reliable Image Enhancement using Fuzzy Relaxation Technique. IEEE Trans. Sys. Man. Cybern. SMC 19 (5), 1276–1281.

Jimmermann, H.J., 1991. Fuzzy Set Theory and its Applications, second ed. Kluwer Academic Publishers, Dordrecht.

Lee, J.-S., 1980. Digital Image Enhancement and noise filtering. IEEE Trans. Pattern Anal. Machine Intell. 2, 165–168.

Lindenbaum, M., Fischer, M., Bruckestein, A., 1994. On Gabor's Contribution to Image Enhancement. Pattern Recogn. 7, 1–8.

Mukherjee, P., Chatterji, B.N., 1995. Note: Adaptive Neighbourhood Extended Contrast Enhancement and its Modifications. Graph. Models Image Process. 57 (3), 254–265.

Pal, S.K., King, R.A., 1981. Image enhancement using smoothing with Fuzzy Sets. IEEE Trans. Sys. Man Cybern. SMC-11, 494–501.

Russo, M., Ramponi, G., 1995. A fuzzy operator for the enhancement of blurred and noisy images. IEEE Trans. Image Process. 4 (8), 1169–1174.

Zadeh, L.A., 1973. Outline of a new approach to the analysis of complex systems and decision processes. IEEE Trans. Sys. Man Cybern. SMC-3, 29–44.