The Use of Interval Type-2 Fuzzy Logic as a General Method for Edge Detection

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Abstract—*We describe a method for edge detection in digital images based on the morphological gradient and fuzzy logic. The goal is to improve one of the basic methods for edge detection in order to obtain a better result even without applying any filter to the image. The tests were made with a type-1 fuzzy inference system (T1FIS) and with an interval type-2 fuzzy inference system (IT2FIS). We show that the images obtained with fuzzy logic are better than the ones obtained with only the morphological gradient method. In particular the IT2FIS achieved the best results, because of the flexibility to model the uncertainty in the gradient values and the gray ranges for the edge images. In both TIFIS and IT2FIS the membership function parameters were obtained directly from the images; this allows application of the proposed method to images with different gray scales.*

Keywords— digital images, edge detection, image processing, interval type-2 fuzzy logic.

1 Introduction

Edge detection is an intermediate step in image pattern recognition in digital images and has the opposite effect of noise elimination; it consists on emphasizing pixels with gray tones that are different than their neighbours [1]. Some of the existing methods for edge detection have been enhanced with type-1 fuzzy logic [2][3], fractal theory [4][5], neural networks [6][7][8] and recently with interval-valued fuzzy operators [9].

In previous works proposed by the authors, the improvement of the Sobel edge detector using an IT2FIS was achieved [10][11]. The images resulting from these experiments were used as training data for image recognition with modular neural networks, obtaining good results [12][13].

In this paper, an improvement of a traditional edge detection method based on the morphological gradient is presented. This method does not need any filter to obtain the edges, but it is necessary to perform calculations in order to find the relation of each pixel of the image with the eight neighbours pixels around it.

In section two we present a brief description of an edge detection method based in morphological gradient, in section three we explain our contribution consisting on the development and tests with a type-1 fuzzy inference system and an interval type-2 fuzzy inference system; in both cases we apply the same criteria and conditions, for a valid comparison of the results. Section four shows the obtained results with the three methods. The main topic in this paper is the comparison of the results obtained with the IT2FIS, applying different footprint of uncertainty (FOU).

2 Edge detection using morphological gradient

The morphological gradient of a grayscale image can be viewed as the greatest absolute intensity difference between any two pixels within the structuring element, and can be defined with Equation (1) [14].

$$\left| \nabla(f) = \delta_g(f) - \varepsilon_g(f) \right| \tag{1}$$

For the discrete case, we use D_i instead $\nabla(f)$, then if we apply (1) to a 3x3 sample matrix as shown in Fig. 1, we can to obtain coefficients z_i with Equation (2), the possible edge directions D_i with (3). An approximation of (3) can be calculated without the root square using the absolute values of the differences instead the square values (4). The edges E can be calculated with Equation (5) [15][16].

$$\begin{aligned}
z_1 &= f(x-1, y-1) & z_2 &= f(x, y-1) \\
z_3 &= f(x+1, y-1) & z_4 &= f(x-1, y) \\
z_5 &= f(x, y) & z_6 &= f(x+1, y) \\
z_7 &= f(x-1, y+1) & z_8 &= f(x, y+1) \\
z_9 &= f(x+1, y+1) & &
\end{aligned} \tag{2}$$

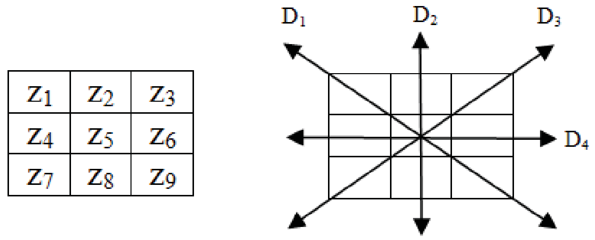

Figure 1: A 3x3 sample matrix with coefficients and edge directions.

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$$D_1 = \sqrt{(z_5 - z_1)^2 + (z_9 - z_5)^2}$$
$$D_2 = \sqrt{(z_5 - z_2)^2 + (z_8 - z_5)^2}$$
$$D_3 = \sqrt{(z_5 - z_3)^2 + (z_7 - z_5)^2}$$
$$D_4 = \sqrt{(z_5 - z_4)^2 + (z_6 - z_5)^2} \quad (3)$$

$$D_1 = | z_5 - z_1 | + | z_9 - z_5 |$$
$$D_2 = | z_5 - z_2 | + | z_8 - z_5 |$$
$$D_3 = | z_5 - z_3 | + | z_7 - z_5 |$$
$$D_4 = | z_5 - z_4 | + | z_6 - z_5 | \quad (4)$$

$$E = D_1 + D_2 + D_3 + D_4 \quad (5)$$

The edge image obtained with Equation (5) does not consider any parameters to prevent noise or regions with very low or high contrast. Then some very dark or bright images could be a problem for this edge detector.

3 Edge detection using a fuzzy inference system

The fuzzy approach for edge detection using morphological gradient consists of using Equation (3) or (4) to obtain the gradient in the four directions, and use them as inputs for a fuzzy inference system (FIS) instead the Equation (5). This approach allows us to analyze the gray tones range of any particular image and use them as parameters to the membership functions in the FIS.

3.1 *Type-1 fuzzy linguistic variables*

The inputs to consider for the T1FIS are the morphological gradients D_i for each pixel with respect to a 3x3 neighbourhood matrix. The membership functions must represent the magnitude of the gradient. In order to adapt the membership functions to the range of gray tones depending on the image, we obtain the maximum, minimum and middle values of D_i, and we use these values for the centre of the membership functions, as shown in the example of Fig. 3.

The σ value for the particular example plotted in Fig. 3 is 20, the Gaussian membership functions for each D input were obtained with (9)(10) and (11), and the center of each function were obtained with (6)(7) and (8). This is the method that we propose to adapt the parameters of the membership functions depending on the contrast level of each image.

$$dlow_i = \min(D_i) \quad (6)$$
$$dhigh_i = \max(D_i) \quad (7)$$
$$dmiddle_i = dlow_i + (dhigh_i - dlow_i)/2 \quad (8)$$

$$\mu(dlow_i) = e^{\frac{-(x-dlow_i)^2}{2(\sigma_i)^2}} \quad (9)$$

$$\mu(dhigh_i) = e^{\frac{-(x-dhigh_i)^2}{2(\sigma_i)^2}} \quad (10)$$

$$\mu(dmiddle_i) = e^{\frac{-(x-dmiddle_i)^2}{2(\sigma_i)^2}} \quad (11)$$

where $\sigma_i = dhigh_i / 8$

For the outputs E (the edges), we select the range [0,255] as the gray tones scale, then we can obtain these membership functions directly with (12)(13) and (14). If some application needs a different gray tones scale, is necessary to adjust the values of *black*, *gray* and *white* of (12), (13) and (14) to the desire scale.

$$\mu_{black} = e^{\frac{-(x-black)^2}{2\sigma^2}} \quad (12)$$

where black=0

$$\mu_{gray} = e^{\frac{-(x-gray)^2}{2\sigma^2}} \quad (13)$$

where gray=255/2

$$\mu_{white} = e^{\frac{-(x-white)^2}{2\sigma^2}} \quad (14)$$

where white=255

where $\sigma = white/8$

In order to plot the membership functions for the inputs D_i of the FIS, as particular example we used the image in Fig. 2. First the image was converted to gray scale, then the following values were calculated, for each variable D.

$dlow_1=0$, $dmiddle_1=94.7$, $dhigh_1=189.4$, $\sigma_1=23.6$
$dlow_1=0$, $dmiddle_2=87.9$, $dhigh_2=175.8$, $\sigma_2=21.9$
$dlow_1=0$, $dmiddle_3=89.8$, $dhigh_3=179.6$, $\sigma_3=22.4$
$dlow_1=0$, $dmiddle_4=75.6$, $dhigh_4=151.3$, $\sigma_4=18.9$

Figure 2. Particular image to explain the parameters for the FIS variables.

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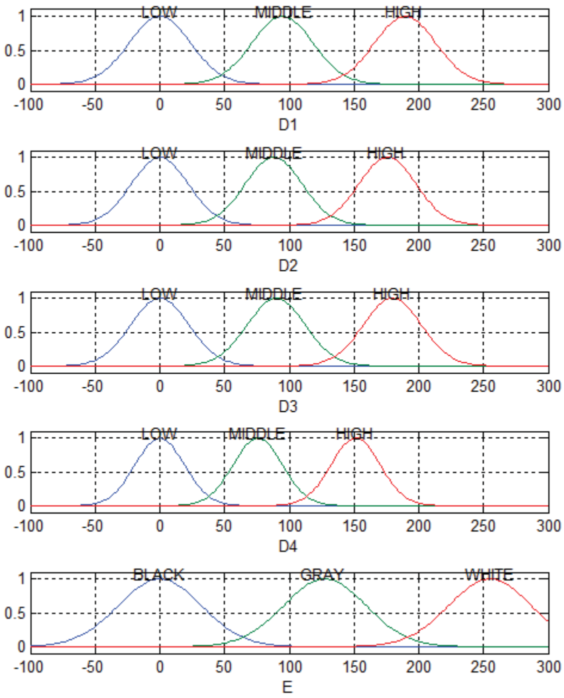

Figure 3: Linguistic variables for the TIFIS corresponding to the image in Fig. 2.

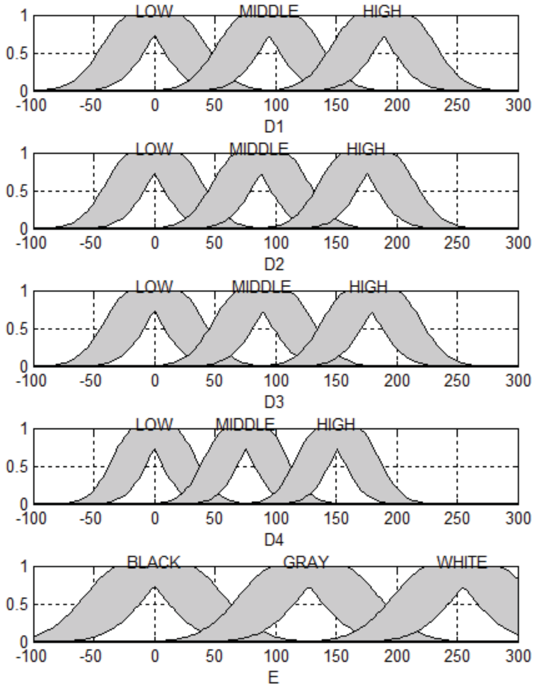

Figure 4: Linguistic variables for the IT2FIS corresponding to the image in Fig. 2, with $FOUd_i=0.4*dmiddle_i$

3.2 Interval type-2 linguistic variables

As we previously mentioned, the edge detection method proposed in this paper can be adapted to images with different contrast levels, but particularly the use of interval type-2 fuzzy sets enables us to handle the uncertainty by adding some FOU to the membership functions [17].

To compare the improvement of the edge detector using interval type-2 fuzzy sets, we build an IT2FIS using the same parameters than the TIFS [18]. The membership functions were obtained with Equations (6)-(14), but adding different sizes of FOU.

We made tests using different sizes of the FOU for the input variables D_i, using $dmiddle_i$, as parameter to obtain the values respect to the image contrast, in a proportional manner. The FOU sizes for D_i, then can be obtained using (15).

$$FOUd_i = \varepsilon * dmiddle_i \tag{15}$$

where ε is in (0,1)

The FOU for the output variable *E*, was calculated in a similar way to the inputs variables. In this case, we obtain the FOU values using *egray* as parameter (16).

$$FOUe = \varepsilon * egray \tag{16}$$

where ε is in (0,1)

The plot in Fig. 4, shows the linguistic variables with interval type-2 membership functions where the value for ε is *0.4*, adding $FOUd_i/2$ for inputs D_i and $FOUe_i/2$ for the output *E*, at each side of the center of the membership functions; then all the functions are symmetric.

3.3 The rules

The task of the fuzzy inference systems is to estimate a value for each pixel, which better describes the relation with its neighborhood.

1. If (D1 is HIGH) or (D2 is HIGH) or (D3 is HIGH) or (D4 is HIGH) then (E is WHITE)
2. If (D1 is MIDDLE) or (D2 is MIDDLE) or (D3 is MIDDLE) or (D4 is MIDDLE) then (E is WHITE)
3. If (D1 is LOW) and (D2 is LOW) and (D3 is LOW) and (D4 is LOW) then (E is BLACK)

The first rule establishes that a high gradient in any direction means an edge, the second rule is similar to the first one, because after many experiments with different images, a medium magnitude of the gradient in any direction results also in an edge, and the third rule is only to confirm the first two, because all derivatives with low magnitude means a homogeneous region in the image, that means there are not edge in this pixel. In Fig. 5 the solution surfaces for the TIFIS and IT2FIS are shown.

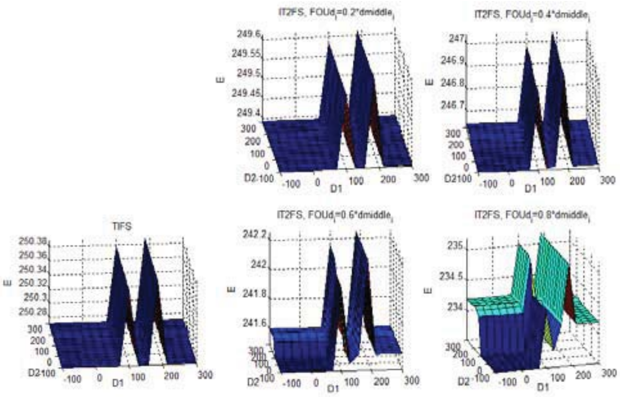

Figure 5: The solution surfaces for the image in Fig. 2, for TIFIS and IT2FIS with different FOU sizes.

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4 Experimental results

For a better appreciation of the results, we developed some programs in Matlab to obtain the edge image, under the same conditions. In all the images the morphological gradients were obtained with (2) and (3), then using the morphological gradient (MG) the edges were calculated with (5). For the fuzzy methods T1FIS and IT2FIS we use a fuzzy inference system instead of the gradient (5).

We choose Gaussian membership functions for all the variables of the both FIS (TIFIS and ITFIS), only for an easy configuration, because as we explained in section three we used the values obtained with the morphological gradient of each particular image to estimate the parameters for the membership functions.

For the first test, we used a sample of the ORL databases of faces, and selected arbitrary values for the FOU, only to demonstrate that the images obtained using IT2FIS are better that the images obtained with TIFIS. In the example of Fig. 6, we see the changes on the images with different values of the FOU. The best image is the one obtained with FOU=40, while the image obtained with T1FIS looses some details. For all the tests the use of the FIS's improve the results of the MG traditional method.

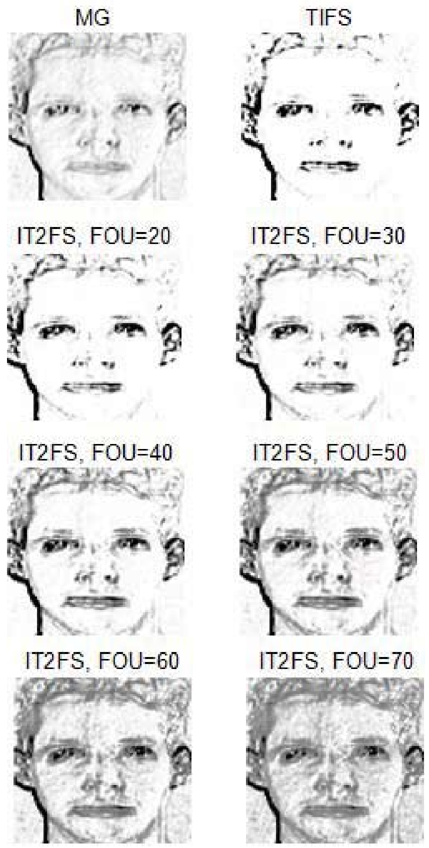

Figure 6: Edges images obtained using Morphological Gradient (MG), and the same method improved with a type-1 fuzzy system (TIFIS), and an interval type-2 fuzzy system (IT2FIS), with arbitrary FOU values.

For a better analysis of the results we plot frequency histograms for each result in Fig. 6. The histograms show that the images obtained with the IT2FIS when the FOU is increased, between 30 and 40, found more pixels corresponding to the edges preserving more details than T1FIS, but when the FOU increases more than 40, the pixels near white decreases, showing more noise in the background.

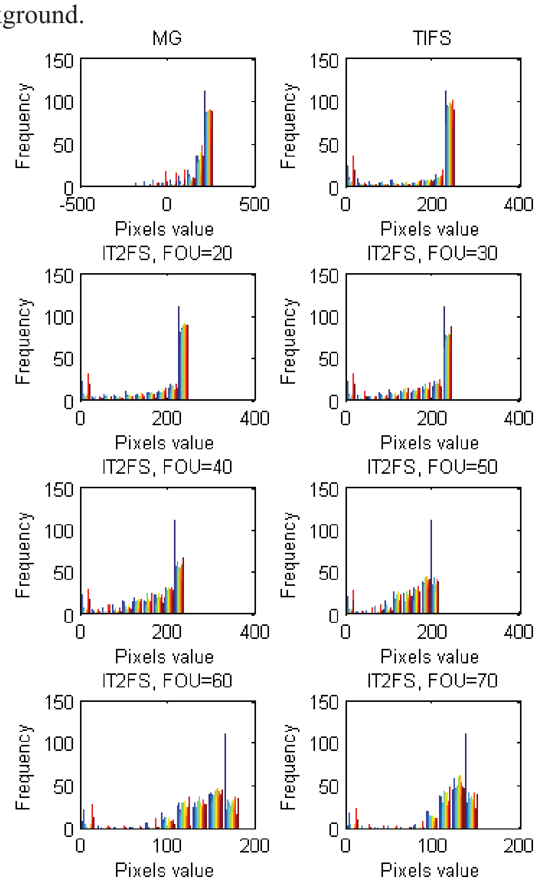

Figure 7: The frequency histograms correspond of the images shown in Fig. 6.

The second test, shown in Fig. 8, was made with an image used as benchmark for edge detection algorithms, and confirms the results obtained in Fig. 6.

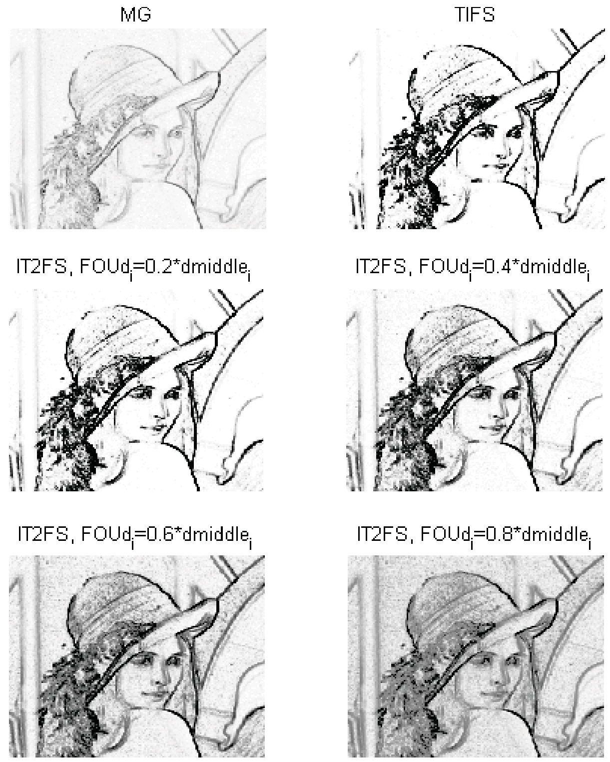

Figure 8: Edges achieved with FOU values obtained directly of the original image with equations (15) and (16).

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As we can see in Fig. 8 and Fig. 9, the edges can be seen better with the TIFIS method than de morphological gradient method, but more details of the image can be seen with the IT2FIS method when $FOUd_i=0.4*dmiddle_i$. Obviously the images obtained with a FOU near 0 are similar to the images obtained with the T1FIS. The image with $FOUd_i \geq 0.6*dmiddle_i$ show more details, but includes some textures that are not desired for edge detection.

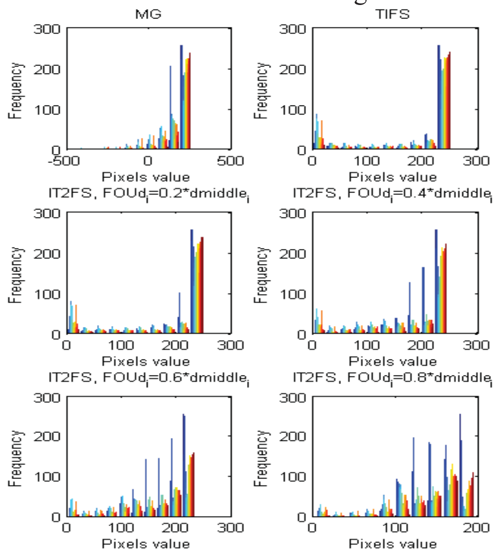

Figure 9: The frequency histograms correspond of the images shown in Fig. 8.

The parameters used for the T1FIS and IT2FIS in the tests of Fig. 8 and Fig. 9, were calculated with equations (6)-(16) and have the following values:

$dlow_1=0,\quad dmiddle_1=105.9,\quad dhigh_1=211.9,\quad \sigma_1=26.4$
$dlow_1=0,\quad dmiddle_2=109.6,\quad dhigh_2=219.2,\quad \sigma_2=27.4$
$dlow_1=0,\quad dmiddle_3=107.5,\quad dhigh_3=215.0,\quad \sigma_3=26.8$
$dlow_1=0,\quad dmiddle_4=74.6,\quad dhigh_4=149.2,\quad \sigma_4=18.6$
$\sigma e=31.8$

In Table I we show the numeric values of the FOUs used in the experiment below.

TABLE I: FOU values for the tests shown in Fig. 8.

FACTOR	$FOUd_1$	$FOUd_2$	$FOUd_3$	$FOUd_4$	FOUE
0.2	21.1	21.9	21.5	14.9	25.5
0.4	42.3	43.8	43.0	29.8	51.0
0.6	63.5	65.7	64.5	44.7	76.5
0.8	84.7	87.6	86.0	59.6	102

Figure 10: The original images used for the tests shown in Table II.

To finish the tests in this work, we repeat the same experiment with the images shown in Fig. 10, and compare the results with traditional algorithms [19] like the Canny and Sobel methods, as we can see in Table II.

TABLE II: Tests with Canny and Sobel methods using the Matlab defaults, and the best result using MG+IT2FIS.

Canny	Sobel	MG+IT2FIS

For all the tests we used the default parameters of Matlab. One of the images is a sample of the ORL database of faces

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[20], which is a set of images that are usually considered to compare the behavior of different image processing methods [21].
The other images are some of the typical images used for evaluation of edge detection algorithms, and were obtained them in the USC-SIPI Image Database [21].

In order to compare the results with the Canny and Sobel algorithms, we made modifications on the rules consequents, to obtain white edges and black background as the Matlab algorithms do it.

In all the tests we can observe that the images obtained with our method preserve more details of the original images than the traditional methods; that is good for the human observation. In the other hand, the images obtained with MG+IT2FIS are better to use in an image recognition application, because the training algorithm have more information to learn the image pattern. We can conclude that using interval type-2 fuzzy logic can improve edge detection in benchmark images, and for this reason it can be considered a good alternative for image processing.

5 Conclusions

The experiments presented in this paper show that the use of fuzzy inference systems can improve traditional methods for image processing. In particular, the morphological gradient method for edge detection, considered as one of the basic ones, when enhanced with an interval type-2 fuzzy inference system, results in a combination with satisfactory results. Especially the capability of the IT2FIS to model uncertainty in the morphological gradient and gray tone values for the edges achieved better images than the obtained with the T1FIS, because preserves more details of the original image.

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