A Fuzzy Approach on Image Complexity Measure

Enfoque Difuso Para la Medición de la Complejidad de Imágenes

Mario Ignacio Chacón Murguía, Alma Delia Corral Sáenz and Rafael Sandoval Rodríguez
Chihuahua Institute of Technology, DSP & Vision Laboratory
Av. Tecnológico 2909
Chihuahua, Chih., México C.P. 31310 Tel.4-13-74-74 Ext 112 y 114
mchacon@itchihuhahua.edu.mx

Article received on March 08, 2007; accepted on April 26, 2007

Abstract
This paper describes a novel fuzzy based approach to determine the complexity of an image which is independent of a human perception criterion. The proposed method determines the complexity of an image based on the analysis of its edge level percentages. First, the method determines the complexity class of an image from among three classes, *Little Complex, More or Less Complex,* and *Very Complex* using centroids obtained from a fuzzy clustering process. Second, the membership value for that class is computed by a set of interval mapping functions. The method is very robust and consistent since it does not incorporate any a priori human evaluation of complexity. Results of the method show a correlation with human complexity values obtained in an independent evaluation test; however, the values obtained with our method are consistent and not subject to the viewer's subjectivity. The paper also shows promising results in applying the method to an application of determining the edges of images when compared with a crisp image complexity method.
Keywords: Image complexity, Fuzzy logic, Image processing.

Resumen
Este artículo describe un nuevo enfoque basado en lógica difusa para determinar la complejidad de una imagen, el cual es independiente del criterio de la percepción humana. El método propuesto determinar la complejidad de una imagen mediante el análisis de los porcentajes de niveles de bordes de la imagen. El método determina primero la clase de complejidad de la imagen entre tres clases, *Poco Compleja*, *Más o Menos Compleja* y *Muy Compleja* usando centros de grupos obtenidos mediante un proceso de agrupamiento difuso. Después, el grado de pertenencia a esa clase es calculado mediante un conjunto de funciones de mapeo de intervalos. El método es muy robusto y consistente ya que no incorpora ninguna evaluación humana *a priori* de la complejidad. Los resultados del método muestran una correlación con los valores de complejidad asignados por observadores humanaos en una prueba de evaluación independiente, sin embargo, los valores obtenidos con el método propuesto son consistentes y no sujetos a la subjetividad del visor. El artículo presenta también resultados promisorios in la aplicación del método para la determinación de bordes de imágenes cuando se compara con un método de complejidad rígido.
Palabras clave: Complejidad de Imagen, Lógica Difusa, Procesamiento de Imágenes.

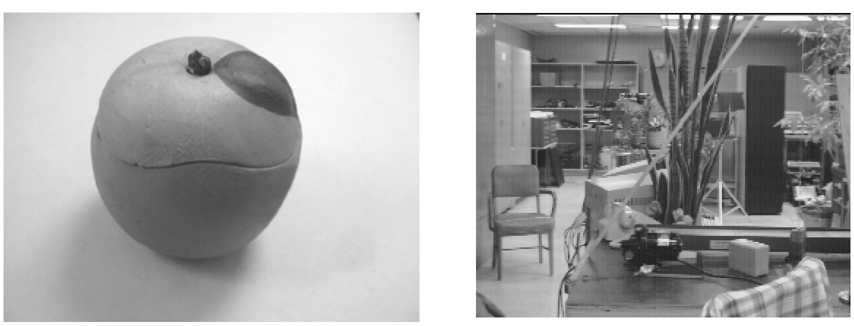
1 Introduction

Fuzzy logic was proposed by professor Zadeh as a new paradigm to the analysis of complex systems and processes [1]. As it is known, fuzzy logic is an extension of classic logic. In classic logic, membership of an element to a set is defined by the characteristic function that maps the element to true or false, that is, the element is a member or it is not a member of the set. Under this scheme, an element can only be a member of only one set, therefore, sets in classic logic are named crisp sets. On the other hand, in fuzzy logic, an element can be a member of different sets with different degrees of memberships. Membership of an element to the sets is determined by fuzzy membership functions or fuzzy sets. Fuzzy sets are functions that map an element of the universe of discourse to the interval [0, 1]. The value assigned by the membership function to an element of the universe of discourse is considered as the degree to which that element belongs to a set, 1 indicates the highest degree of membership. Membership functions are defined by knowledge engineering techniques that represent the knowledge of an expert, by data analysis, or using artificial neural networks. For a more complete description of fuzzy sets and fuzzy logic we encourage the reader to read [2], [3].

Fuzzy logic represents a new tool for solving real world problems. Real world problems in many cases are complex systems, and their mathematical representations require of the flexibility provided by fuzzy logic. Some of the advantages of fuzzy logic are its mathematical scheme to model subjectivity presented in real problems, and its potential to achieve concept computation. For example, spatial primitive relationships like, ”above”, “near”, “between”, have been represented with fuzzy logic [4]. Properties of objects and spatial relations modeled with fuzzy logic have also been investigated in the past [5]-[9]. Recently new spatial concepts like “surrounded by”, “between”, and “among” have been represented by fuzzy relations [10], [11]. These fuzzy models may be incorporated to other systems to achieve high level information processing. Fuzzy spatial relation models can improve the performance of vision systems for scene analysis. In fact there exist many computer vision applications that can take advantage of the fuzzy logic scheme [12]-[19]. A specific application is in high level image processing tasks. Image processing is applied to many problems including automatic target recognition (ATR), image retrieval, medical applications, image compression, remote sensing, industrial applications, surveillance, etc. and is being used to solve new and more complex problems every day. Certain applications deal with measures of various subjective parameters and a very important one is the complexity of an image. In this paper, our measure of image complexity is related to how much attention is required to detect and recognize objects by a person and to set relations among them [19]-[21]. For example, the image in Fig.1a is considered as *little complex* because basically there is just one object in the image. The image in Fig.1b is classified as *very complex* because it includes many objects. Image complexity measures have been used to achieve image processing tasks like, ATR, pattern recognition tasks, image retrieval, image compression, and edge detection, [22]-[27]; however, most of the image complexity measure methods are crisp methods and do not incorporate the advantages which fuzzy schemes contain in representing imprecision and uncertainty [1],[28],[29]. In some cases, complexity of an image is determined by human evaluation and then incorporated into the application. But human intervention, in the process to determine image complexity, may give misleading information. That is, the method may be affected by the subjective perception of the viewers. Therefore, the development of an image complexity measure method based on a fuzzy scheme and free of human evaluation is necessary and should yield more robust results.

The aim of this paper is to present a new method to determine image complexity which is based only on information obtained from the image independent of human evaluation. In order to generate a human independent scheme for determining the complexity of an image which avoids giving misleading information, the authors propose a new fuzzy image complexity measure scheme that is independent of human evaluation. The method presented is novel and is not similar to any other known method. In this paper a fuzzy complexity measure scheme is used as a criterion to detect image edges and the findings are compared with the results of using a crisp image complexity measure method.

The structure of the paper is as follows: Section II describes the general fuzzy complexity measure scheme to be used. Class complexity determination and in-class complexity membership are defined in Section III. Section IV describes an edge detection approach using the complexity measure method proposed, while Section V concludes with the results and conclusions.



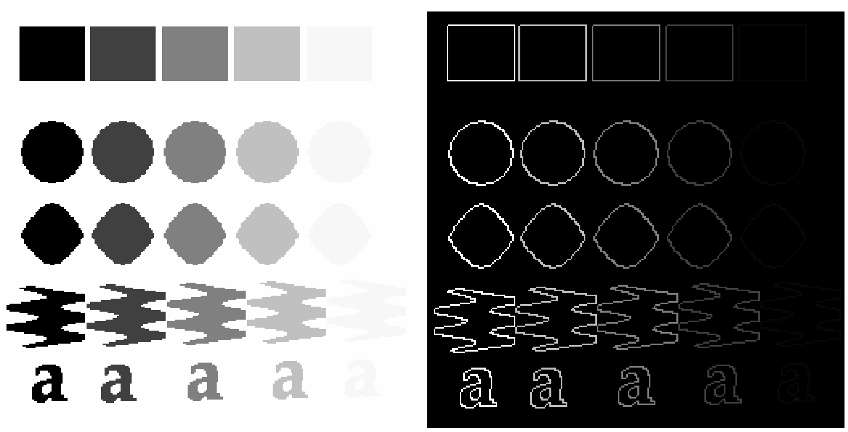
a) b)

Fig. 1. a) *Little complex* image, b) *Very complex* image

2 General Scheme of the Proposed Method

In a previous work [30], one of the authors described a fuzzy scheme to determine the complexity of an image. The model started with a pre-classification of an image data base into different levels of complexity based on human perception of the images. The performance of the model was dependent on the perception of complexity by the human viewers. In order to design a new human independent model, it was decided to define a procedure based only upon the image itself. The new approach consists of defining an image characteristic related to image complexity that can be evaluated by a computer program. The characteristic selected is the percentage of edge levels presented in the image. The level of an edge is defined as how much attention a person must use to detect the edge in an image. For example, edge level one corresponds to the edges that are easily detected by a person, edge level two requires more attention, and edge level *n* requires the most attention [31],[32]. Fig. 2a shows several objects with different edge level classification. For example, objects in column one, from left to right, could be considered as edge level one, objects in column two contain edge level two, etc. The image in Fig. 2b corresponds to the edges of the objects in the image of Fig 2a. Fig. 3 shows an image and the first five of its edge level decompositions. The procedure for decomposing an image into its different edge levels is documented in [33] and the process is totally independent of human perception.

Based on the edge level decomposition, the computation of image complexity is achieved in two steps. The first step consists of determining the image complexity based on three categories, *Little Complex (LC)*, *More or Less Complex (ML)*, and *Very complex (VC).* These categories were determined by analyzing a set of sample images using the fuzzy C-means process described in [35], [36]. It is important to remark that fuzzy membership functions, fuzzy sets, are not defined in this work to achieve this task. That is, there are not fuzzy sets to map the characteristic of the image into the three categories. This mapping is performed by the centroids obtained with the fuzzy C-means algorithm. The categories were defined in a previous work [36], and were shown to be sufficient measure of complexity. Once the image is classified into one of the three complexity classes the second step is to determine the membership of the image for that class. The result of this two step process is the complexity class of the image and its membership to the class. These two steps are described in further detail in the next section.



a) b)

Fig. 2. a) Objects with different edge levels. b) edges of a)

3 Class and In-class Complexity

3.1 Class Complexity

Assume that an image $I(x,y)$ is processed by a fuzzy edge level decomposition algorithm yielding three images, $I_{Ei}(x,y)$ $i=1,2,3$ which contain the edge levels 1 to 3, [33]. In this work only levels one through three are used since they have been shown to contain most of the information of the image [36]. Each image is then represented by a vector, E_k, as follows

$$\mathbf{E}_k = \begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix} \tag{1}$$

where k is the number of images in the data base, 150 for our example. The elements e_i, $i=1,2,3$ represent the percentage of edge levels 1, 2 and 3 contained in the image. Each image in the database is thus represented by a three dimensional vector as shown in Fig. 4, and groups of samples represent different levels of overall complexity.

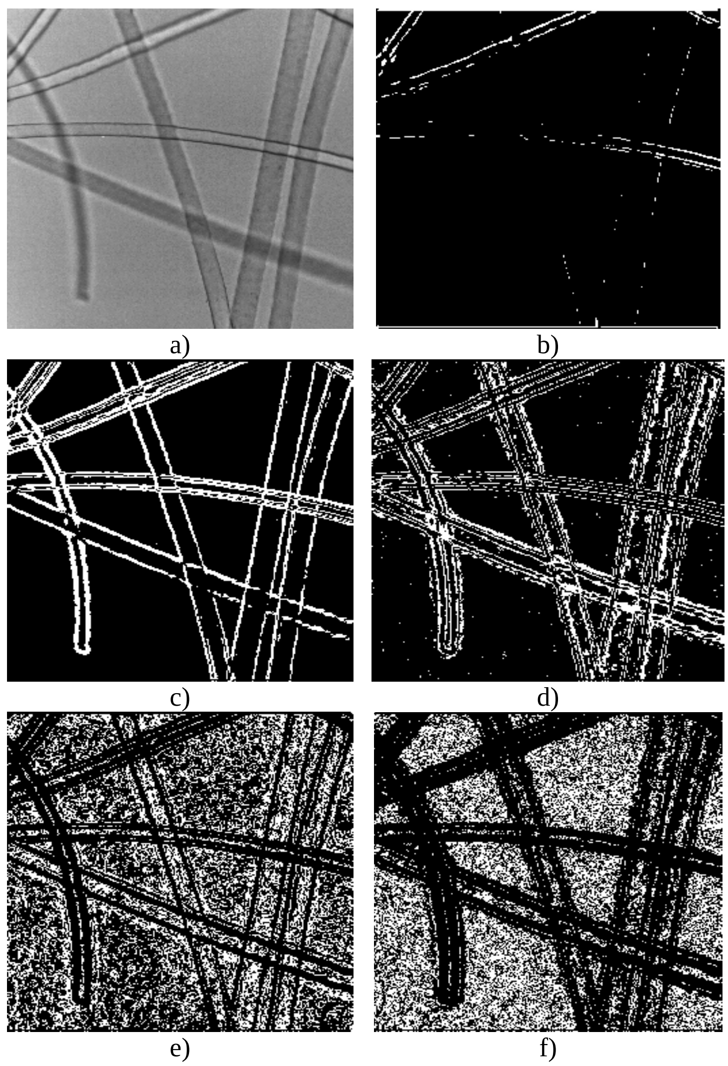


Fig. 3. a) Original image, edge level b) 1, c) 2, d) 3, e) 4, f) 5

Vectors close to the origin have little complexity while those positioned further from the origin are more complex. A fuzzy C-means algorithm [33] is applied to the data vectors which results in three centroids defined as the representative vectors: $\mathbf{V}_{LC}$, $\mathbf{V}_{ML}$, and $\mathbf{V}_{VC}$, corresponding to the three complexity classes *LC*, *ML*, and *VC*. The values of these vectors for our database are given in Table I. These centroids can be considered as the mapping function of the image into its class complexity, instead using fuzzy sets.

The complexity of an image can be now determined by using the metric distance between two vectors **E** and **V** defined as

$$d(\mathbf{E},\mathbf{V}) = |\mathbf{E}-\mathbf{V}| = \sqrt{\sum_{j=1}^{3}\left(e_j - v_j\right)^2} \tag{2}$$

An image represented by $\mathbf{E_k}$ has a complexity j if the distances between $\mathbf{E_k}$ and the representative centroids, $\mathbf{V}_{LC}$, $\mathbf{V}_{ML}$, and $\mathbf{V}_{VC}$ satisfy the following

$$d\left(\mathbf{E}_k, \mathbf{V}_j\right) < d\left(\mathbf{E}_k, \mathbf{V}_i\right) \quad i \neq j \quad i, j = \{LC, ML, VC\} \tag{3}$$

The complexity class of the image is thus determined; however, to generate useful information for future processing, it is also necessary to determine the membership of the image to this class. A description of this in-class value computation is described in the following section.

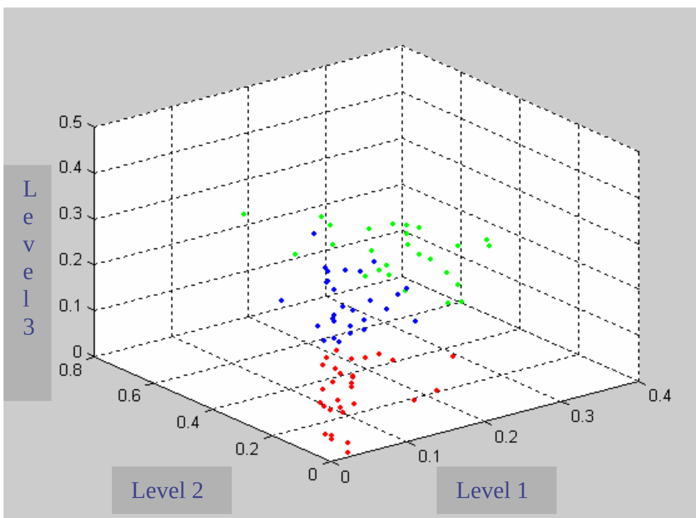


Fig. 4. Image complexity in the edge level domain

3.2 In-Class Complexity

In real image processing applications determination of the complexity class of an image may not be enough. In some cases it is required to obtain the complexity membership value of the image to a specific class. The in-class complexity is mapped into three regions corresponding to the classes, *LC*, *MC*, and *VC*, Fig 5.

Table 1. Representative vectors of complexity class

Class	Vectors		
	e_1	e_2	e_3
$\mathbf{V}_{LC}$ Little complex	0.044742	0.059438	0.11335
$\mathbf{V}_{ML}$ More or less complex	0.082103	0.15336	0.26409
$\mathbf{V}_{VC}$ Very complex	0.19526	0.27483	0.28762

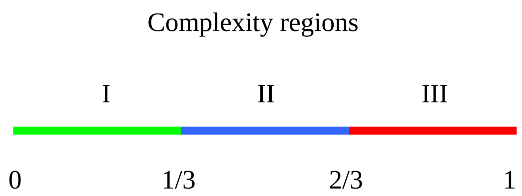


Fig. 5. Complexity region mapping

The three regions are shown in Table II.

Table 2. Complexity region mapping

Subintervals	Complexity class
I	Little complex
II	More or less complex
III	Very complex

To obtain membership values each of the three regions, *I*, *II*, and *III,* is divided into two subintervals, A and B, as shown in Fig 6. Where region A is to the left of the middle point of the subinterval, and region B is to the right of the middle point of the subinterval. For example if the distance from E_k to a class centroid is zero the in-class complexity equals the middle point of the region. If it is not zero then the procedure for determining the in-class membership is described in the following paragraph.

We remember again that the in-class complexity membership is determined not by fuzzy sets, but using the centroids of each class obtained with the fuzzy C-means algorithm. The in-class complexity value Ψ and its limits in the subintervals, A and B, are defined for this work as equally spaced, however they can be assigned in a different form if a different meaning is desired for the data clusters. The in-class complexity value Ψ and its limits of the subintervals for *Little Complex (LC)*, M*ore or Less Complex (MC)*, and ***V****ery* ***C****omplex (VC)* are defined next.

(A) For the *LC* case

$$if \quad |\mathbf{E}_{LCk}| < |\mathbf{V}_{LC}| \quad then \quad \Psi_{LCk} \in A_{LC} \tag{4}$$

$$if \quad |E_{LCk}| > |V_{LC}| \quad then \quad \Psi_{LCk} \in B_{LC} \tag{5}$$

The in-class complexity limits are

$$if \quad d(\mathbf{E}_{LCk}, \mathbf{V}_{LC}) = 0 \quad then \ \Psi_{LC} = \frac{1}{6} \tag{6}$$

$$if \quad d(\mathbf{E}_{LCk}, \mathbf{V}_{LC}) > \frac{1}{6} \quad the\ limit\ of\ \ \Psi_{LC} = \frac{1}{3} \tag{7}$$

$$if \quad d(\mathbf{E}_{LCk}, \mathbf{V}_{LC}) \leq \frac{1}{6} \quad the\ limit\ of\ \ \Psi_{LC} = 0 \tag{8}$$

The membership value is computed by (9)

$$\Psi_{LC} = \begin{cases} \frac{1}{6} & d(\mathbf{E}_{LCk}, \mathbf{V}_{LC}) = 0 \\ \max(0, \Psi_{LCN})\ AND & |\mathbf{E}_{LCk}| < |\mathbf{V}_{LC}| \\ \max(\Psi_{LCN}, \frac{1}{6}) & \\ \max(\frac{1}{6}, \Psi_{LCN})\ AND & |\mathbf{E}_{LCk}| > |\mathbf{V}_{LC}| \\ \min(\Psi_{LCN}, \frac{1}{3}) & \end{cases} \tag{9}$$

Where Ψ_{LCN} is the z-scores normalization of the complexity inside the subinterval defined by

$$\Psi_{LCN} = \frac{1}{6} \frac{d(\mathbf{E}_{\mathrm{LCk}}, \mathbf{V}_{\mathrm{LC}}) - \mu_{d(\mathbf{E}_{\mathrm{LCk}}, \mathbf{V}_{\mathrm{LC}})}}{\sigma_{d(\mathbf{E}_{\mathrm{LCk}}, \mathbf{V}_{\mathrm{LC}})}} \tag{10}$$

Where $\mu_{d(\mathbf{E}_{LCk}, \mathbf{V}_{LC})}$ is the mean of the distances between the samples $\mathbf{E}_{LCk}$ and the centroid $\mathbf{V}_{LC}$, and $\sigma_{d(\mathbf{E}_{LCk}, \mathbf{V}_{LC})}$ is the standard deviation.

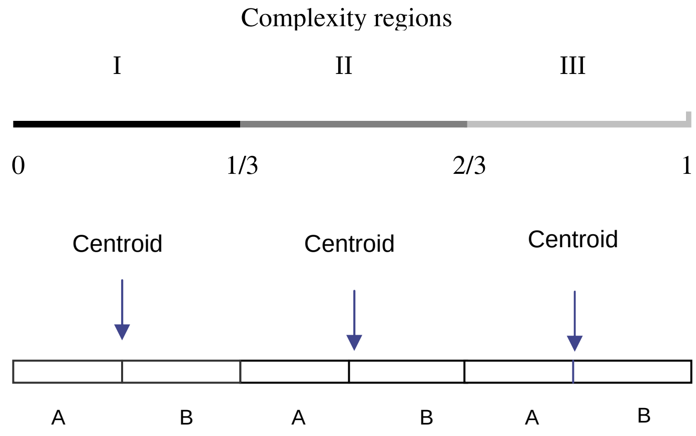


Fig. 6. Image complexity mapping into the interval [0,1]

ISSN 1405-5546

(B) For the *MC* case

$$if \quad |E_{MCk}| < |V_{MC}| \quad then \quad \Psi_{MCk} \in A_{MC} \tag{11}$$

$$if \quad |E_{MCk}| > |V_{MC}| \quad then \quad \Psi_{MCk} \in B_{MC} \tag{12}$$

The complexity limits are

$$if \quad d(\mathbf{E}_{MCk}, \mathbf{V}_{MC}) = 0 \quad then \quad \Psi_{MCk} = \frac{1}{2} \tag{13}$$

$$if \quad d(\mathbf{E}_{MCk}, \mathbf{V}_{MC}) > \frac{1}{2} \quad the\, limit\; of \quad \Psi_{MCk} = \frac{2}{3} \tag{14}$$

$$if \quad d(\mathbf{E}_{MCk}, \mathbf{V}_{MC}) \leq \frac{1}{2} \quad the\, limit\; of \quad \Psi_{MCk} = \frac{1}{3} \tag{15}$$

The membership value is computed by (16)

$$\Psi_{MC} = \begin{cases} \frac{1}{2} & d(\mathbf{E}_{MCk}, \mathbf{V}_{MC}) = 0 \\ \max(\frac{1}{3}, \Psi_{MCN}) \; AND & |\mathbf{E}_{MCk}| < |\mathbf{V}_{MC}| \\ \max(\Psi_{MCN}, \frac{1}{2}) & \\ \max(\frac{1}{2}, \Psi_{MCN}) \; AND & |\mathbf{E}_{MCk}| > |\mathbf{V}_{MC}| \\ \min(\Psi_{MCN}, \frac{2}{3}) & \end{cases} \tag{16}$$

and Ψ_{MC} is the z-scores normalization of the complexity inside the subinterval.

$$\Psi_{MCN} = \frac{1}{6} \frac{d(\mathbf{E}_{\mathrm{MCk}}, \mathbf{V}_{\mathrm{MC}}) - \mu_{d(\mathbf{E}_{\mathrm{MCk}}, \mathbf{V}_{\mathrm{MC}})}}{\sigma_{d(\mathbf{E}_{\mathrm{MCk}}, \mathbf{V}_{\mathrm{MC}})}} \tag{17}$$

(C) In the V*C* case

$$if \quad |\mathbf{E}_{VCk}| < |\mathbf{V}_{VC}| \quad then \quad \Psi_{VCk} \in A_{VC} \tag{18}$$

$$if \quad \left|\mathbf{E}_{VCk}\right| > \left|\mathbf{V}_{VC}\right| \quad then \;\; \Psi_{VCk} \in B_{VC} \tag{19}$$

The complexity limits are

$$if \quad d\left(\mathbf{E}_{VCk}, \mathbf{V}_{VC}\right) = 0 \quad then \;\; \Psi_{VCk} = \frac{5}{6} \tag{20}$$

$$if \quad d\left(\mathbf{E}_{VCk}, \mathbf{V}_{VC}\right) > \frac{5}{6} \quad the\, limit\, of \;\; \Psi_{VCk} = 1 \tag{21}$$

$$if \quad d\left(\mathbf{E}_{VCk}, \mathbf{V}_{VC}\right) \leq \frac{5}{6} \quad the\, limit\, of \;\; \Psi_{VCk} = \frac{2}{3} \tag{22}$$

The membership value computation is

$$\Psi_{VC} = \begin{cases} \dfrac{5}{6} & d\left(\mathbf{E}_{VCk}, \mathbf{V}_{VC}\right) = 0 \\ \max\left(\dfrac{2}{3}, \Psi_{VCN}\right) AND & \left|\mathbf{E}_{VCk}\right| < \left|\mathbf{V}_{VC}\right| \\ \max\left(\Psi_{VCN}, \dfrac{5}{6}\right) & \\ \max\left(\dfrac{5}{6}, \Psi_{VCN}\right) AND & \left|\mathbf{E}_{VCk}\right| > \left|\mathbf{V}_{VC}\right| \\ \min(\Psi_{VCN}, 1) & \end{cases} \tag{23}$$

and Ψ_{VC} is the z-scores normalization of the complexity inside the subinterval.

$$\Psi_{VCN} = \frac{1}{6} \frac{d\left(\mathbf{E}_{VCk}, \mathbf{V}_{VC}\right) - \mu_{d\left(\mathbf{E}_{VCk}, \mathbf{V}_{VC}\right)}}{\sigma_{d\left(\mathbf{E}_{VCk}, \mathbf{V}_{VC}\right)}} \tag{24}$$

The value of $1/6$ in Equations (10), (17) and (24) is a scale factor used because the interval $[0,1]$ is divided into 6 subintervals, and each subinterval is $1/6$.

The final complexity value is obtained by adding an offset accordingly to the image complexity class shown in Table III. The mapping of some of the $\boldsymbol{E_k}$ vectors in our database is shown in Figures 7a-c. Figure 7d corresponds to the complete mapping.

The method just described is human criterion free, that is, there is no human intervention in the method. The procedure can be applied to new images other than those originally in the data base to determine the complexity of those images based only on the information of the images. Thus no subjectivity is incorporated in the method in contrast to a procedure based on human perception criteria.

Table 3. Offset by class subinterval

Class	Subinterval	Offset
Little complex	A_1	0
	B_1	1/6
M. or L complex	A_2	1/3
	B_2	1/2
Very complex	A_3	2/3
	B_3	5/6

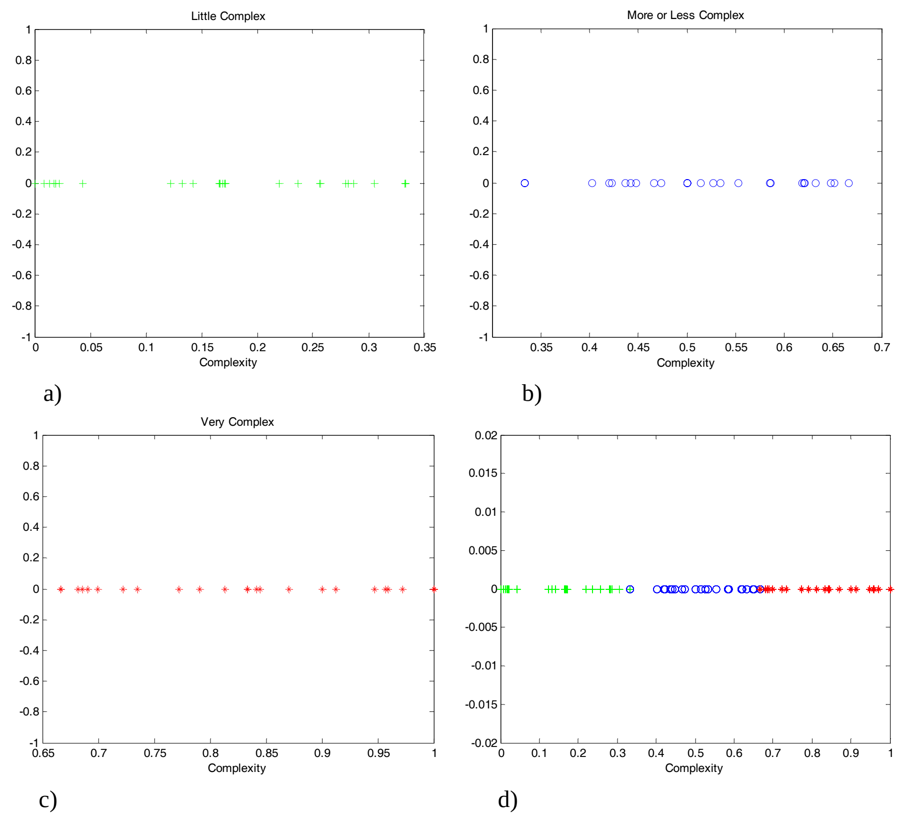


Fig. 7. Image to image complexity mapping. a) *Little complex* images, b) *More or less complex* images, c) *Very complex* images, and d) All together

In order to further illustrate the method, several images of the data base, with their respective complexity class, *Little Complex, More or Less Complex*, and *Very Complex,* and image complexity values in the interval (0,1), generated by the proposed method are shown in Fig. 8.

An experimental exercise that compares the performance of the method described in this paper against the performance of human viewers is illustrated next. This experiment was designed and performed since no previous work similar to the one described in this paper has been found in the literature so that we can offer comparative studies. The experiment consisted on the following steps. A subset of the image data base was selected. This subset included images with different complexity. Each image of the subset was presented to ten viewers. The image was exposed to the viewer during 5 seconds. After this time, the viewer had to assign the complexity class, *Little Complex, More or Less Complex*, and *Very Complex* of the image, and the membership to that class. The viewer determines the class complexity and membership accordingly to the criteria defined in this paper. These steps were repeated until the complete subset of images was analyzed by the ten viewers. Table IV shows a comparison between the results of the proposed method and the results

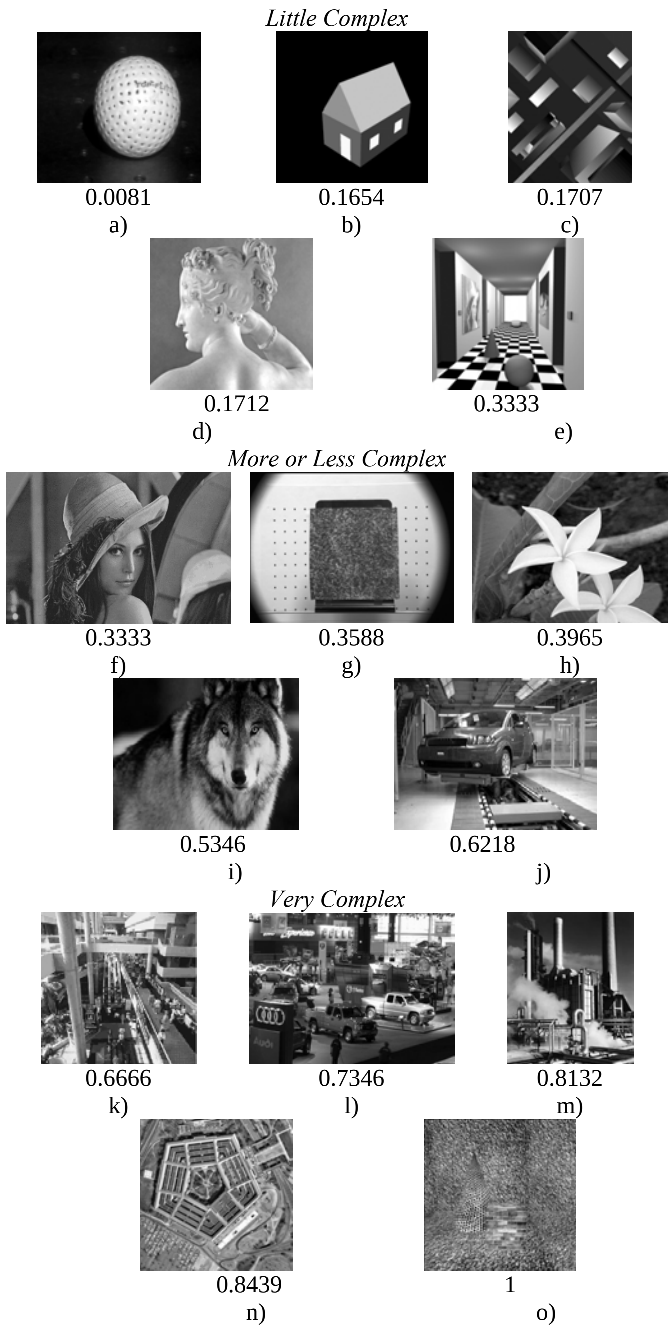


Fig. 8. Some images of the data base, their complexity class and complexity value

generated by the ten viewers on the computation of image complexity class, and image complexity values. According to Table IV there is some degree of correlation between the complexity classes obtained with the proposed method and the complexity classes assigned by human observers in some cases, see columns 4 and 6. However, it should be noticed from column three, that different human observers have different perception of the complexity class even the same subjective criterion of complexity was used by all the observers. This can be verified because only in two images, Fig.8.b and Fig.8o, did the observers assign the same class. An important advantage of the proposed method is that the complexity class assigned to the image is determined analytically and will not change since there is no human observer involved. The complexity value computed by our procedure is shown in Table IV column 4. Comparing these values with the values in the columns 5 to 7 we can see again the inherent variability of human perception.

While the procedure always computes the same complexity value of the image, the human observers have different perceptions of the complexity of the image. What is important to notice from Table IV is that the complexity values computed by the procedure are, in most cases, close to the average of the complexity values assigned by the observers. This finding assures us that the proposed method is simulating the human perception of image complexity with the advantage of discarding human subjectivity. This issue is very important in some industrial applications where human visual perception tasks are simulated by vision systems based on the model of human perception and yet requiring a system free of human criterions and decisions. The proposed method is highly recommended for this last type of applications.

4 Edge Detection Based on Complexity Measure

Finally, an image edge detection algorithm based in the complexity measure method proposed is described. This method was developed in order to demonstrate the applicability of our method in real applications. Fig. 9 illustrates the application of the described method in an edge detection algorithm. The edge detection algorithm determines the edges of images based on the computation of image complexity. Fig. 9a corresponds to edges obtained under a crisp image complexity measure.

The crisp method determines the crisp image complexity, equation (25), based only on the percentage of image pixels that are defined as edges by a gradient operator [33].

$$\Psi_{crips} = \frac{|\boldsymbol{S}_{il\nabla G}|}{\boldsymbol{MxN}} \qquad \boldsymbol{S}_{il\nabla G} = \{\boldsymbol{i}_{I\nabla G} : \|\boldsymbol{i}_{I\nabla G}\| > 0\} \tag{25}$$

Where $|\boldsymbol{S}_{il\nabla G}|$ is the cardinality of the set $\boldsymbol{S}_{il\nabla G}$ that is the set of pixels obtained

Table 4. Comparison between the proposed method and human criterions

Image	Class Assigned by the Proposed Method	Class Assigned by Human Observers	Complexity computed by the Proposed Method	Complexity Assigned by Human Perception		
				Minimum value	Average value	Maximum value
Fig.8a	LC	LC,MC	0.0081	0	0.25	0.6666
Fig.8b	LC	LC	0.1654	0	0.12	0.3333
Fig.8c	LC	LC,MC,VC	0.1707	0.25	0.34	0.6666
Fig.8d	LC	LC, MC	0.1712	0	0.33	0.3333
Fig.8e	LC	LC, MC	0.3333	0	0.37	0.35
Fig. 8f	MC	LC,MC,VC	0.3333	0.175	0.52	0.9
Fig.8g	MC	LC,MC,VC	0.3588	0.3	0.51	0.8
Fig.8h	MC	LC,MC	0.3965	0.225	0.43	0.6666
Fig. 8i	MC	LC,MC	0.5346	0.3	0.37	0.6666
Fig. 8j	MC	LC,MC,VC	0.6218	0.3333	0.58	0.8
Fig.8k	VC	MC,VC	0.6666	0.42	0.77	1
Fig. 8l	VC	MC,VC	0.7346	0.3333	0.67	0.9
Fig.8m	VC	LC,MC,VC	0.8132	0.25	0.53	0.7
Fig. 8n	VC	LC,VC	0.8439	0.275	0.75	1
Fig. 8o	VC	VC	1	0.9	0.99	1

from the original image after a gradient operator. Fig. 9b shows the edges obtained under the fuzzy complexity measure described in this paper. Once the image complexity is determined in both methods, the edges of the image are determined by the following four rules [33].

R1: If the image is LC then include border levels one, two, and three $\int_{i=1,2,3} IE_{i(x,y)}$

R2: If the image is VC then include border levels one, and two $\int_{i=1,2} IE_{i(x,y)}$

Where $IE_{i(x,y)}$ are the edge level images.

When an image is *MC*, we consider two possibilities. First, if the image is *MC* but closer to the *LC* interval then the rule is

$$R3:\quad \textit{Apply rule 1 and reduce edge level 3of edges that hold} \quad \left\| \frac{i_{I\nabla G}}{\max(I_{E3})} \right\| < \mu_{LC} \qquad \mathit{for} \quad i_{I\nabla G} \in I_{E3}$$

Second, if the image is *MC* but closer to the V*C* interval then the rule is

R4: Apply rule 2 and include edge level 3of edges that hold

$$\left\| \frac{i_{l\nabla G}}{\max(I_{E3})} \right\| < (1-\mu_{VC}) \quad for \quad i_{l\nabla G} \in I_{E3}$$

It can be noticed from Fig. 9 that the crisp approach tends to discard more information, whereas the fuzzy approach tends to preserve more. For example, the edges obtained by the proposed method in the first image in Fig.9 show edges in the back, neck and arm of the woman, that are easily perceived by a person. In the second image, Fig.9, the horizontal edge on the top, and the circular edge are preserved with the proposed method. These results are a consequence of the hard and soft modeling of information of the crisp and fuzzy approaches respectively.

5 Results and Conclusions

Fuzzy logic theory represents a new alternative to model human vision perception tasks. The flexibility of the fuzzy logic scheme to model visual perception concepts allows to image processing researchers to face new complex real world tasks. The work described in this paper represents and additional attempt to model visual perception concepts aimed to generate more human like systems. In this paper a new fuzzy image complexity measure, for the purpose of providing a human criterion free method, was described. The concept of fuzzy sets is substituted by centroids generated by the fuzzy C-means algorithm. That is, the method does not include definitions of fuzzy set to map an image into its complexity class and membership, instead the fuzzy centroids are used.

The fuzzy image complexity measure method has been implemented and tested on a variety of real images from a data base of 150 images. The method generates two partial results, first the "*complexity class*" of the image, *Little Complex, More or Less Complex*, or *Very Complex,* and second the membership value to that class. Based on these two results, the method provides the final complexity value of the image.

The main advantage of the method is that the model described does not include uncertainty generated by human perception of complexity. Therefore, the image complexity measure provided by the procedure is very consistent. The method developed is based on fuzzy image edge level analysis that is related to the overall image information content. Comparing the results of our method with that from human observers shows some correlation but at the same time the method is free of the variability and subjectivity which is always present when human observers are used. Based on our results our procedure is highly recommended in applications where a human independent complexity measure is required. The paper also demonstrated the applicability of the proposed method to an image edge detection task. Comparison of the results of the proposed method with a method based on a crisp measure of complexity illustrated the advantage of using the fuzzy method.

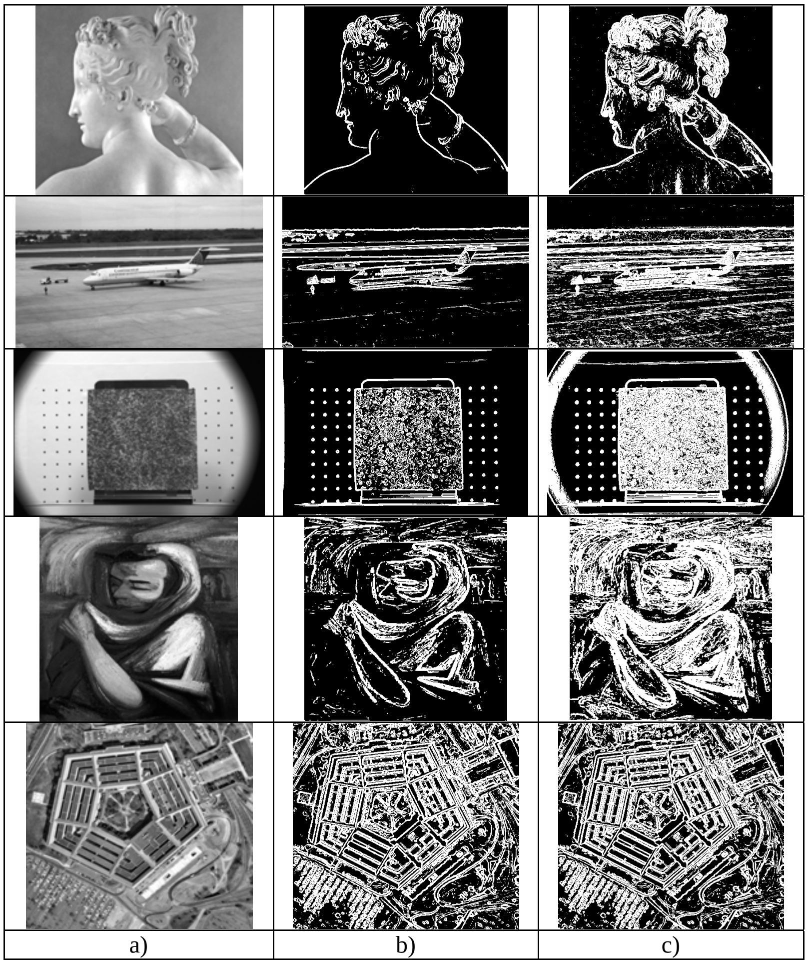


Fig. 9. Edge detection based on image complexity. a) Original, b) crisp complexity, b) proposed method

Acknowledgment

The authors appreciate the support of COSNET, and SEP-DGEST for the support of this research under grant 445.05-P.

References

1. **Zadeh L.**: Outline of a New Approach to the Analysis of Complex Systems and Processes, IEEE Tran. On Systems, Man, & Cybernetics 3(1) (1973) 28-44.
2. **Mendel J.**: Fuzzy Logic Systems for Engineering: A Tutorial, Proceedings of the IEEE 83(3) (1995) 345-377.
3. Kandel A., and Byatt W.: Fuzzy, Sets, Fuzzy Algebra, and Fuzzy Statistics, Proceedings of the IEEE 66(12) (1978) 1619-1639.
4. **Freeman J.**: The Modeling of spatial relations, Computer Graphics and Image Processing 4 (1975) 156-171.
5. **Krishnapuram R., Keller J. M.,** and **Ma Y.**: Quantitative Analysis of Properties and Spatial Relations of Fuzzy Image Regions, *IEEE Trans. on Fuzzy Systems* 1(3) (1993) 222-233.
6. **Miyajima K.,** and **Ralescu A.**: Spatial Organization in 2D Segmented Images: Representation and Recognition of Primitive Spatial Relations, Fuzzy Sets and Systems 65(2/3) (1994) 225-236.

7. **Matsakis P.,** and **Wendling L.**: A New Way to Represent the Relative Position Between Areal Objects, IEEE Trans. on Pattern Analysis and Machine Intelligence 21(7) (1999) 634-643.
8. **Matsakis P., Keller J., Wendling L., Marjamaa J.,** and **Sjahputera O.**, Linguistic Description of Relative Positions in Images, IEEE Trans. on Systems, Man and Cybernetics Part B 31(4) (2001) 573-588.
9. **Bloch I.**: ECVision- Specific Action Contribution to CCV Ontology: Dealing with Imprecise Spatial Information in Cognitive Vision (Unpublished manuscript, Ecole Nationale Supérieure des Télécommunications Département Traitement du Signal et des images, Paris France, 2003).
10. **Matsakis P.,** and **Andréfouet S.**: The fuzzy Between Line Between Among and Surround. In Proceeding of the 2002 IEEE International Conference on Fuzzy Systems, May 2002, 1596-1601.
11. **Bloch I.**: Fuzzy Spatial Relationships for Image Processing and Interpretation: a Review, Image and Vision Compute, 23 (2005) 89-110.
12. **Krishnapuram R.,** and **Keller J. M.**: Fuzzy Set Theoretic Approach to Computer Vision: An Overview. In: Proceedings of the FUZZ-IEEE, 1992, 135-142.
13. **Huntsberger T., Rangarajan C.,** and **Jayaramamurthy S.**: Representation of Uncertainty in Computer Vision Using Fuzzy Sets, IEEE Trans. On Computers C-35(2) (1986) 145-155.
14. **Lashkia V.**: Defect Detection in X-ray Images Using Fuzzy Reasoning, Image and Vision Computer 19 (2001) 261-269.
15. Pal S., and Sarbadhikari S.: Fuzzy Geometrical Features for Identifying Distorted Overlapping Fingerprints. In: Proceedings of the International Conference on Information, Communication and Signal, 1997, 1527-1531.
16. **Hata Y., Kobashi S., Hirano S., Kitagaki H.,** and **Mori E.**: Automated Segmentation of Human Brain MR Images Aided by Fuzzy Information Granulation and Fuzzy Inference, IEEE Trans. On System, Man, and Cybernetics C-30(3) (2000) 381-395.
17. **Ahmed M., Yamany S., Mohamed N., Farag A.,** and **Moriarty T.**: A Modified Fuzzy C-Means Algorithm for Bias field estimation and Segmentation of MRI Data, IEEE Trans. On Medical Imaging 21(3) (2002) 193-199.
18. **Park J.,** and **Yae H.**: Analysis of Active Features selection in Optic Nerve Data Using Labeled Fuzzy C-means Clustering. In: Proceedings of the IEEE International Joint Conference on Neural Networks, May 2002, 1178-1182.
19. **Ralescu A.,** and **Shanaham J.**, Perceptual Organization for Inferring Object Boundaries in an Image, Pattern Recognition 32 (1999) 1923-1933.
20. **Johnson J., Olshausen R.**: Time course of Neural Signatures of Object Recognition, Journal of Vision 3 (2003) 499-512.
21. **Boyle J., Maeder A.,** and **Boles W.**, Visual Perception. In: 9th International Conference on Neural Information Processing of low Quality Images, Vol 1, November, 2002, 153-157.
22. **Peters II R.,** and **Strickland R.**: Image Complexity Metrics for Automatic Target Recognizers. In: ATR System and Technology Conference, October 1990, 1- 17.
23. **Krishnapuram R., Medassani S., Jung S., Choi Y.,** and **Balasubramaniam R**., Content-Based Image Retrieval Based on a Fuzzy Approach, IEEE Transactions on Knowledge and Data Engineering 16(10) (2004) 1185-1199.
24. **Puniene J., Punys V.,** and **Punys J.**, Ultrasound and Angio Image Compression by Cosine and Wavelet Transforms, International Journal of Medical Informatics 64(2-3) (2001)473- 481.
25. **X. Yang,** and **C. Zhou**, Analysis of the Complexity of Remote Sensing Image and Its Role on Image Classification. In: Proceedings of the IEEE Geoscience and Remote Sensing Symposium (IGARSS 2000), July 2000, 2179–2181.
26. **Seong Y. K., Choi Y.,** and **Choi T.**, Scene-based Watermarking Method for Copy Protection Using Image Complexity and Motion Vector Amplitude. In: Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP '04), May 2004, 409 – 412.
27. **Auffarth B., Muto Y.,** and **Kunii Y.**: An artificial system for visual perception in autonomous Robots. In: Proceedings of the IEEE International Conference on Intelligent Engineering Systems, September 2005, 211-216.
28. **Zadeh L.**: Fuzzy Logic = Computing with Words, IEEE Trans. on Fuzzy Systems 4(2) (1996) 103-111.
29. **Hata Y., Kobashi S., Hirano S., Kitagaki H.,** and **Mori E.**: Automated Segmentation of Human Brain MR Images Aided by Fuzzy Information Granulation and Fuzzy Inference, IEEE Transactions on System Man, and Cybernetics C-30(3) (2000) 381-395.
30. **Chacón M., Aguilar L.,** and **Delgado A.**: Fuzzy Adaptive Edge Definition Based on the Complexity of the Image. In: Proceedings of the 10th IEEE International Conference on Fuzzy Systems, December 2001, 675-678.
31. **Milanese R., Pun T., Gil S.,** and **Bost J.-M.**: Exploiting Dynamic Aspects of Visual Perception for Object Recognition. In: Proceedings of the Perception to Action Conference, 1994, 193-205.
32. **Freeman W. J.**: A Neurobiological Theory of Meaning in Perception. In: Proceedings of the International Joint Conference, July 2003, 1373-1378.

33. **Chacón M.,** and **Aguilar L.**: A Fuzzy Approach to Edge Level Detection. In: Proceedings of the 10th IEEE International Conference on Fuzzy Systems, December 2001, 809-812.
34. **Bezdek J.** and **Pal K.**: Fuzzy Models for Pattern Recognition, Methods that Search for Structures in Data (IEEE Press 1991).
35. **Pakhira M., Bandyopadhyay S.,** and **Maulik U.**: Validity Index for Crisp and Fuzzy Cluster, Pattern Recognition 31 (2004) 487-501.
36. **Corral A. D.**: Modeling edge perception using fuzzy logic, Master Thesis, Chihuahua Institute of Technology, Mexico (2003).

Mario Chacon *received the B.Sc(1982) and MS degrees (1985) in EE from the Chihuahua Institute of Technology, Mexico and his Ph.D. in Electrical Engineering (1998) from New Mexico State University, USA. He has made research for the industry and universities and has more than 90 scientific and technical publications. He is a Senior member of the IEEE, he is member of the IEEE Computational Intelligence and Signal Processing Societies, and member of the Pattern Recognition Society. His current research interests include Computer Vision, Pattern Recognition, and Neural Networks and Fuzzy Logic applications to DSP.*

Alma Corral *received the B. Sc. degree in computational system engineering from the Universidad Autonoma de Chihuahua, Mexico, in 1999. She received the M. S. degree in Electrical Engineering with a major in digital signal processing and a minor in digital image processing at Instituto Tecnologico de Chihuahua, Mexico, in 2003. She is currently working for an automotive company at Chihuahua, Mexico. Her research interests focus on the development of techniques to simulate human visual perception and its applications.*

Rafael Sandoval *was born in Chihuahua, Mexico, in 1968. He received the B.Sc. and M.Sc. degrees in Electronic Engineering from the Chihuahua Institute of Technology, Mexico, in 1991 and 1994, respectively. He received the Ph. D. in Electrical Engineering from The University of New Mexico, USA, in 2005. His dissertation was on Teleautonomy of Mobile Robots. Currently, he is a research professor and chair of the Graduate Studies and Research Division at the Chihuahua Institute of Technology. His research interests are control and coordination of multiple robots, networked control systems, and intelligent sensor networks.*