The Possibilities of Fuzzy Logic in Image Processing

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Abstract. It is not a surprise that image processing is a growing research field. Vision in general and images in particular have always played an important and essential role in human life. Not only as a way to communicate, but also for commercial, scientific, industrial and military applications. Many techniques have been introduced and developed to deal with all the challenges involved with image processing. In this paper, we will focus on techniques that find their origin in fuzzy set theory and fuzzy logic. We will show the possibilities of fuzzy logic in applications such as image retrieval, morphology and noise reduction by discussing some examples. Combined with other state-of-the-art techniques they deliver a useful contribution to current research.

1 Introduction

Images are one of the most important tools to carry and transfer information. The research field of image processing not only includes technologies for the capture and transfer of images, but also techniques to analyse these images. Among the wide variety of objectives, we mention the extraction of additional information from an image and practical applications such as image retrieval, edge detection, segmentation, noise reduction and compression.

But how can image processing be linked to fuzzy set theory and fuzzy logic? A first link can be found in the modeling of images. On the one hand, an n-dimensional image can be represented as a mapping from a universe $\mathcal{X}$ (a finite subset of $\mathbb{R}^n$, usually a $M \times N$-grid of points which we call pixels) to a set of values. The set of possible pixel values depends on whether the image is binary, grayscale or color. Binary images take values in $\{0, 1\}$ (black = 0; white = 1), grayscale images in $[0, 1]$ (values correspond to a shade of gray); the representation of color images depends on the specific color model, e.g. RGB, HSV, La*b* [26]. On the other hand, a fuzzy set A in a universe $\mathcal{X}$ is characterized by a membership function that associates a degree of membership $A(x) \in [0, 1]$ with each element x of $\mathcal{X}$ [38]. In other words: a fuzzy set A can be represented as a $\mathcal{X} - [0, 1]$ mapping, just like grayscale images. Consequently, techniques from fuzzy set theory can be applied to grayscale images.

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A second link can be found in the nature of (the information contained in) images. Image processing intrinsically encounters uncertainty and imprecision, e.g. to determine whether a pixel is an edge-pixel or not, to determine whether a pixel is contaminated with noise or not, or to express the degree to which two images are similar to each other. Fuzzy set theory and fuzzy logic are ideal tools to model this kind of imprecise information.

In this paper we will illustrate the possibilities of fuzzy logic in image processing applications such as image retrieval (Section 2), mathematical morphology (Section 3) and noise reduction (Section 4). We will focus on the first application, and briefly review the other two applications.

2 Similarity Measures and Image Retrieval

2.1 An Overview of Similarity Measures for Images

Objective quality measures or measures of comparison are of great importance in the field of image processing. Two applications immediately come to mind: (1) Image database retrieval: if you have a reference image, then you will need measures of comparison to select similar images from an image database, and (2) Algorithm comparison: similarity measures can serve as a tool to evaluate and to compare different algorithms designed to solve particular problems, such as noise reduction, deblurring, compression, and so on.

It is well-known that classical quality measures, such as the MSE, $RMSE$ (Root Mean Square Error) or the $PSNR$ (Peak Signal to Noise Ratio), do not always correspond to human visual observations. A first example is given in Figure 1. A second example is that it occurs that several distortions of a specific image (e.g. obtained by adding impulse noise, gaussian noise, enlightening, blurring, compression) have the same MSE (which would rank the images as "equally similar" w.r.t. the original image), while visual evaluation clearly shows that there is a distinction between the images.

To overcome these drawbacks, other measures have been proposed. Among the different proposals, we also encounter similarity measures that find their origin in fuzzy set theory. Extensive research w.r.t. the applicability of similarity measures for fuzzy sets in image processing has been performed [30,31]. This resulted in a set of 14 similarity measures, e.g. [5]:

$$M(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{\sum\limits_{(i,j)\in\mathcal{X}} \min(A(i,j), B(i,j))}{\sum\limits_{(i,j)\in\mathcal{X}} \max(A(i,j), B(i,j))}.$$

Note that we use minimum and maximum to model the intersection and union of two fuzzy sets, and the sigma count to model the cardinality of a fuzzy set.

Unfortunately, similarity measures that are applied directly to grayscale images do not show a convincing perceptual behaviour. Therefore two types of extensions have been proposed:

Fig. 1. The MSE does not always correspond to human evaluation of image comparison: left = original cameraman image, middle = cameraman image with 35% salt & pepper noise (MSE w.r.t. left image = 7071), right = monkey image (MSE w.r.t. left image = 5061

(1) Neighbourhood based measures [33]: each image is divided into blocks, the similarity between the corresponding blocks of the images is calculated using the similarity measures discussed above and finally these values are combined in a weighthed sum, where the weights depend on the homogenity of the block images: the higher the homogenity, the higher the weight.
(2) Histogram based measures [32]: the similarity measures discussed above can also be applied on image histograms, which can be normalized and/or ordered. In this way, the human sensitivity to frequencies can be taken into account.

The results obtained using these extensions are already much better. In order to incorporate the image characteristics in an even more optimal way we proposed combined similarity measures. These measures are constructed by combining (multiplying) neighbourhood-based similarity measures and similarity measures which are applied to ordered histograms. Extensive and scientifically guided psycho-visual experiments confirm the good and human-like results of these measures [36,37], which is a very important feature (see Figure 1).

The next step is the construction of human-like similarity measures for color images. A first attempt has been carried out in [34,35]. The existing grayscale similarity measures have however also been applied successfully in the context of color image retrieval, as is outlined in the next section.

2.2 Application: Image Retrieval

Image retrieval applications are important because the increasing availability of images and the corresponding growth of image databases and users, makes it a challenge to create automated and reliable image retrieval systems [2,3,14,19,27,29]. We consider the situation in which a reference image is available, and that similar images from a database have to be retrieved. A main drawback of most existing systems is that the images are characterized by textual descriptors (describing features like color, texture, morphological properties, and so on), which usually have to be made by a person [4,8,28]. Using histogram based similarity measures, we have developed a retrieval system that does succeed in extracting images from a database of images automatically, based on the similarity values only.

The characteristics of the system can be summarized as follows [18]:

– We use the HSI color space to model colors. The hue component is enough to recognize the color, except when the color is very pale or very somber. In order to perform an extraction based on dominant colors, we limit ourselves to 8 fundamental colors, that are modelled with trapezoidal fuzzy numbers [3]. In those cases where there is nearly no color present in the image we will use the intensity component to identify the dominant "color". Also for this component we use a fuzzy partition.
– We calculate the membership degree of all the pixels in every image with respect to the fundamental colors modelled by the trapezoidal fuzzy numbers. In that way we obtain 8 new "images".
– We consider the histogram of each of these 8 images, and normalize them by dividing all the values by the maximum value. In that way we obtain for each image 8 fuzzy sets, representing the frequency distribution of the membership degrees with respect to the 8 fundamental colors.
– We use a specific histogram-based similarity measure [32] to calculate the similarity between these different histograms.
– We combine the similarity values corresponding to the 8 histograms or colors by using the standard average as aggregation operator.
– We perform the same procedure w.r.t. the intensity component.
– The overall similarity between two images is defined as the average of the similarity value w.r.t. the hue component and the similarity value w.r.t. the intensity component.

Experimental results confirm the ability of the proposed system to retrieve color images from a database in a fast and automated way. One example is illustrated in Figure 2. We used a database of over 500 natural images of animals, flowers, buildings, cars, texture images, . . ., and we show the retrieval results (the 10 most similar images), together with the numerical results, using a flower image as query image. The results are quite good: the three most similar retrieved images are flowers in the same color as the one in the query image. The other retrieved images do not contain flowers but have a very similar layout, i.e., they all show an object with a natural background. This illustrates that the proposed approach has potential w.r.t. color image retrieval.

3 Mathematical Morphology

Mathematical morphology is a theory, based on topological and geometrical concepts, to process and analyze images. The basic morphological operators (dilation, erosion, opening and closing) resulted from this research, and form the fundamentals of this theory [25]. A morphological operator transforms an image into another image, using a structuring element which can be chosen by the user.

Fig. 2. Retrieval result for the natural image experiment

The goal is to retrieve additional information from the image (e.g. edges) or to improve the quality of the image (e.g. noise reduction).

By the 1980's, binary morphology was extended to grayscale morphology (there are two classical approaches: the threshold approach [25] and the umbra approach [11]), and the lattice-based framework was shaped. As a scientific branch, mathematical morphology expanded worldwide during the 1990's. It is also during that period that different models based on fuzzy set theory were introduced. Today, mathematical morphology remains a challenging research field.

The introduction of "fuzzy" morphology is based on the fact that the basic morphological operators make use of crisp set operators, or equivalently, crisp logical operators. Such expressions can easily be extended to the context of fuzzy sets. In the binary case, where the image and the structuring element are represented as crisp subsets of $\mathbb{R}^n$, the dilation and erosion are defined as follows [25]:

$$D(A,B) = \{y \in \mathbb{R}^n | T_y(B) \cap A \neq \emptyset\},$$
$$E(A,B) = \{y \in \mathbb{R}^n | T_y(B) \subseteq A\},$$

with $T_y(B) = \{x \in \mathbb{R}^n | x - y \in B\}$ the translation of B by the point y.

The binary dilation and erosion have a very nice geometrical interpretation. For example, the dilation $D(A,B)$ consists of all points y in $\mathbb{R}^n$ such that the translation $T_y(B)$ of the structuring element has a non-empty intersection with the image A. Consequently, the dilation will typically extend the contours of objects in the image, and fill up small gaps and channels. Similar interpretations can be made for the erosion.

Fuzzy techniques can now be used to extend these operations to grayscale images and structuring elements. This can be realised by fuzzifying the underlying logical operators, using conjunctors and implicators. A $[0,1]^2 - [0,1]$ mapping $\mathcal{C}$ is called a conjunctor if $\mathcal{C}(0,0) = \mathcal{C}(1,0) = \mathcal{C}(0,1) = 0$, $\mathcal{C}(1,1) = 1$, and if it has increasing partial mappings. Popular examples are $T_M(a,b) = \min(a,b)$, $T_P(a,b) = a \cdot b$ and $T_W(a,b) = \max(0, a+b-1)$, with $(a,b) \in [0,1]^2$. A $[0,1]^2 - [0,1]$ mapping $\mathcal{I}$ is called an implicator if $\mathcal{I}(0,0) = \mathcal{I}(0,1) = \mathcal{I}(1,1) = 1$, $\mathcal{I}(1,0) = 0$, and if it has decreasing first and increasing second partial mappings. Popular examples are $I_W(a,b) = \min(1, 1-a+b)$, $I_{KD}(a,b) = \max(1-a,b)$ and $I_R(a,b) = 1 - a + a \cdot b$, with $(a,b) \in [0,1]^2$. The resulting expressions for the fuzzy dilation and fuzzy erosion are as follows [7]:

$$D_{\mathcal{C}}(A,B)(y) = \sup_{x \in \mathbb{R}^n} \mathcal{C}(B(x-y), A(x)), \tag{1}$$
$$E_{\mathcal{I}}(A,B)(y) = \inf_{x \in \mathbb{R}^n} \mathcal{I}(B(x-y), A(x)), \tag{2}$$

with $A, B \in \mathcal{F}(\mathbb{R}^n)$ and with $\mathcal{C}$ a conjunctor and $\mathcal{I}$ an implicator.

Extensive studies [15] showed that the most general model of fuzzy mathematical morphology is the one based on the expressions above.

An application of fuzzy morphological operations is illustrated with the "cameraman" image in Figure 3. This figure shows the edge images (an edge image can be obtained by subtracting the eroded from the dilated image) for two different pairs of conjunctors and implicators. It also illustrates that the choice of

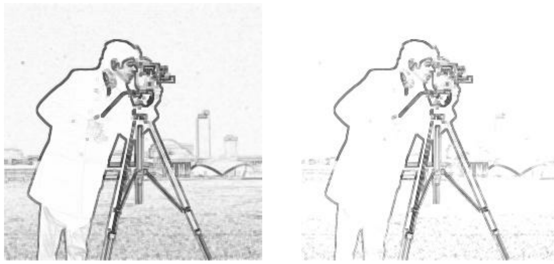

Fig. 3. Fuzzy morphological edge images for $(\mathcal{C},\mathcal{I}) = (T_M, I_{KD})$ (left) and $(\mathcal{C},\mathcal{I}) = (T_W, I_W)$ (right)

the fuzzy logical operators has a big influence on the result of the fuzzy morphological operators.

The next important step was the extension to and the use of fuzzy techniques for color morphology. Although a component-based approach, in which we apply grayscale operators on each color component separately, is straightforward, it also leads to disturbing artefacts because correlations between colors are not taken into account. Therefore, colors should be treated as vectors. A major problem is that one also has to define an ordering between the color vectors, in order to be able to extend concepts such as supremum and infimum; also the sum, difference and product of colors has to be defined if we want to extend fuzzy morphology to color images. Numerous orderings have been defined in different color spaces such as RGB, HSV and La*b*; our own ordering is discussed in [9]. This resulted in the setup of theoretical frameworks for (fuzzy) color morphology, in which pratical applications can now be studied [1,6,10,12,13].

4 Noise Reduction

Images can be contaminated with different types of noise. Among the most common types of noise we find impulse noise (e.g. salt & pepper noise), additive noise (e.g. gaussian noise) and multiplicative noise (e.g. speckle noise). It is a great challenge to develop algorithms that can remove noise from an image, without disturbing its content. The main disadvantage of classical filters is that they treat all the pixels in the same way, based on purely numerical information. This makes them incapable of taking into account any uncertainty and imprecision that usually occurs (e.g. not all the pixels will be contaminated with noise in the same way; one should be able to work with degrees of contamination).

The use of fuzzy techniques offers a solution. In general, a fuzzy filter for noise reduction uses both numerical information (just as classical filters) and linguistic information (modeled by fuzzy set theory; enabling us to work with e.g. “small” and “large” gradient values). This information is processed by a fuzzy rule base (approximate reasoning; enabling us to use rules such as “if most of the gradient

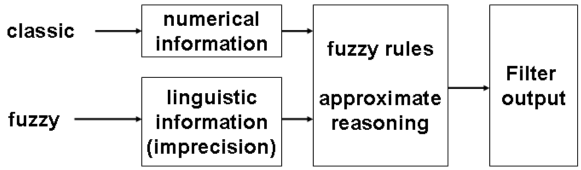

Fig. 4. Fuzzy filters use both numerical and linguistic information to process an image

values are large, then assume that the pixel is noisy"), resulting in a (defuzzified) filter output. The general scheme of fuzzy filters is shown in Figure 4.

Several proposals for noise reduction algorithms based on fuzzy set theory and fuzzy logic have been made. In [16,17] we have studied 38 different algorithms that were specifically designed for impulse noise and/or gaussian noise, and found out that the best performing filters always are based on fuzzy logic. The more recent construction of new fuzzy-logic-based filters resulted in new comparative studies, confirming that fuzzy logic is a very powerful tool for noise reduction [22], also for color images [20,23,24] and video sequences [39]. We illustrate the FIDRM filter, the Fuzzy Impulse Noise Detection and Reduction Method [21], which is designed for grayscale images, in Figure 5.

Fig. 5. The Lena image with 20% impulse noise (MSE = 3309,40), and the result of the FIDRM filter (MSE = 30,57)

In summary, fuzzy logic makes it possible to reason with uncertainty and imprecision (linguistic information), which is inherent to noise detection and reduction, which explains the very good results. On the other hand, quite a lot of research still has to be carried out: the continued development of new filters for noise reduction, for different types of noise (e.g. speckle noise gets less attention than impulse noise and gaussian noise), for different types of images (e.g. natural scenes, satellite images, medical images, ...), for different types of images (grayscale, color and video) and the necessary comparative studies to evaluate them w.r.t. each other, will require many future efforts.

5 Conclusion

In this paper, we have briefly outlined the possibilities offered by fuzzy logic in the field of image processing, in particular for image similarity and retrieval, mathematical morphology, and noise reduction

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