Similarity measures for content-based image retrieval based on intuitionistic fuzzy set theory

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***Abstract*—In this paper, a new intuitionistic fuzzy model for images based on the HSV color histogram is proposed. The image can be treated as an Attanassov's intuitionistic fuzzy set (IFS) with this new model. A new and simple calculation of similarity measurement called $IFSL_1$ based on similarity measurement of intuitionistic fuzzy set L_1 is presented. Unlike general fuzzy similarity measure that consider only the membership degree, the new intuitionistic similarity measure takes into account the membership degree, the non-membership degree and the hesitation degree, these have been found to be highly useful in dealing with vagueness. The similarity measure $IFSL_1$ is used for content-based image retrieval (CBIR). With the similarity measure $IFSL_1$, image retrieval can be carried out more rapidly than with many other existing similarity measurements and the results better coincide with human perception.**

***Index Terms*—Content-based image retrieval , Intuitionistic fuzzy set , Similarity measure , HSV color space , Image fuzzy model**

I. Introduction

Fuzziness is inherently embedded in nature and is reflected in the images. The theory of fuzzy sets (FS) proposed by Zadeh [1] in 1965 has already been applied to several areas of image processing in the last decade (e.g., filtering, image enhancement, region extraction and pattern recognition) [2]–[6]. The use of fuzzy set theory in image processing has been receiving greater attention for the following reasons [3], [7], [8]: 1) Images are the 2D projections of a visual 3D world and thus some information is lost during mapping; 2) Many images digitized by charge coupled devices (CCDs) and digital cameras will contribute noise to the image during image capture since there can be corrupted pixel elements in the camera sensors and acquisition and transmission errors; 3) Due to quantization of the hardware, the gray levels are imprecise. With the tremendous growth of digital images, content-based image retrieval (CBIR) has gained much attention in the last decade. In this paper, we will focus on fuzzy techniques for content-based image retrieval CBIR [7], [9]–[11].

In general, the CBIR systems are based on the extraction of various features which are used to index the image database. Retrieval can then be based on a user query to such a database to find the images that are most similar to the query based on various similarity metrics [7], [11]. Image retrieval using similarity measures has been observed to be an elegant technique for CBIR systems. Attempts have been made to identify objects (e.g., people, face, vehicles) to drive the matching process [7]. However, this is extremely difficult, since special algorithms are required for identifying each type of object. Thus, techniques that seek to identify objects are not widely applicable or easily extendable without significant effort. In a word, although retrieval processing can be approached on three levels (pixel-level, low-level features and high-level concepts), most practical approaches are still rooted in low level feature extraction and description. Of all the proposed approaches based on low level visual features (such as color, texture and shape), the color histogram is employed extensively because color is an effective and robust visual cue for distinguishing one object from another. In this paper, we concentrate our attention on building color histogram and histogram matching based on fuzzy techniques.

A color histogram is constructed by mapping each pixel onto a discrete color space containing N color bins. The common types of similarity measurement are the Euclidean distance, the histogram intersection, and the weighted distance metric. In [11], Chaira and Ray presented a scheme for fuzzy similarity based strategy to retrieve an image from color image database, after interpreting color histogram of a image as a fuzzy set. Compared to traditional similarity measurement, their scheme using membership function for finding the membership values of the pixels of the image and fuzzy similarity measure as the distance measures give improved results. Nevertheless, only ordinary fuzzy set theory was employed in their work. As we know, in ordinary fuzzy set theory, a degree of membership is assigned to each element, while the degree of non-membership is automatically equal to 1 minus the degree of membership. However, human

This work was supported by the National Basic Research Program of China 2011CB302400, the National Natural Science Foundation of China under Grant 61163023, 61175072 and 50863003, the Education Department of Jiangxi Province of China under Grant GJJ11284, and the Science and Technology Department of Jiangxi Province of China under grant CB200920364

doi:10.4304/jcp.7.7.1733-1742

beings often do not express the corresponding degree of non-membership as the complement to 1. Atanassov [12] introduced the concept of higher-order fuzzy sets, intuitionistic fuzzy sets (IFS), which reflects the fact that the degree of non-membership is not always equal to 1 minus the degree of membership, but allows for some degree of hesitation [6]. IFSs are described using two characteristic functions expressing the degree of membership (belongingness) and the degree of non-membership (non-belongingness) of elements of the universe to the IFS, which provides a flexible mathematical framework to cope with the hesitancy originating from imperfect or imprecise information. Similarity measures of intuitionistic fuzzy sets have received much attention from researchers [13]. Szmidt and Kacpryzk [14] proposed the use of distance measures between intuitionistic fuzzy sets that are the generalization of the Hamming distance and the Euclidean distance. Grzegorzewski [15] suggested Hamming distance and Euclidean distance based on the Hausdorff metric using intuitionistic fuzzy sets. Li and Cheng [6] introduced the similarity measures between two intuitionistic fuzzy sets and applied them to pattern recognition. Later, Liang and Shi [16] proposed several similarity measures to differentiate IFSs in a report in which they further discussed the relationships between these measures. Furthermore, Mitchell [8] interpreted IFSs as ensembles of ordered fuzzy sets from a statistical viewpoint to modify Li and Cheng's measure. Hung and Yang [17] proposed several reasonable similarity measures between two intuitionistic fuzzy sets induced by the L_p metric and demonstrated that the proposed measures perform well in pattern recognition problems.

In this paper, we introduced a novel extension to the original Chaira's fuzzy image model [11]. A new intuitionistic fuzzy model of images based on the HSV color histogram is proposed in which the image can be treated as an Attanassov intuitionistic fuzzy set (IFS). A new and simple calculation of the measure of similarity called $IFSL_1$ based on the intuitionistic fuzzy set L_1 similarity measure proposed by Hung and Yang [17] is presented. Unlike the general fuzzy set which considers only the membership degree, the new intuitionistic similarity measurement takes into account the membership degree, the non-membership degree and the hesitation degree. To demonstrate the applicability of the similarity measure $IFSL_1$ in practice, it has been used for a real image retrieval. The various experimental results show that the new measure is comparable to approaches in the literature. The main advantage of the proposed method is the high retrieval accuracy and low computational cost, while the only disadvantage is that a little more storage and time are required to build a histogram for the image features. However, considering that most existing CBIR systems create their features database beforehand and our method of calculation of the similarity measure contains only one additional operation and one comparison operation, the proposed approach has significant benefits.

The subsequent sections are constructed as follows. After introducing the histogram in Section 2, we briefly describe the fuzzy set, the intuitionistic fuzzy set and some related distance measures in Sections 3 and 4. In Section 5, a new intuitionistic fuzzy model of the image is proposed in the HSV color space and the image can be treated as an Attanassov intuitionistic fuzzy set. In order to measure the effectiveness of the similarity measure, extensive experiments are conducted in Section 6. Finally, conclusions are drawn in Section 7.

II. Histogram and Distance Measure

A. Histogram

The histogram of a gray image of size $M \times N$ represents the frequency of occurrence of a gray level i, $i = 0, 1, 2 \ldots, L-1$, with L the gray level in the image. The normalized histogram of a digital image A is a sequence $H_A = \{h_A(0), h_A(1), \ldots, h_A(i), \ldots, h_A(L-1)\}$,$i = \{0, 1, 2 \ldots, L-1\}$, such that $\sum_{i=0}^{L-1} h_A(i) = 1$ and $h_A(i)$ denotes the ratio of the number of counts of the ith gray level to the total number of pixels $M \times N$. It should be noted that the gray histogram be easily extended to the color histogram (multi-dimensional histogram) to handle color images described in color spaces like RGB or HSV.

B. Distance measure of histograms

It is well known that the distance measure and similarity measure are dual concepts. We do not distinguish between them in the following sections. There are many distance measures between two histograms, but some of them used in this paper are defined as follows.

The histogram intersection distance measure is defined as

$$D_1(H_A, H_B) = \sum\nolimits_{i=0}^{L-1} \min(h_A(i), h_B(i)) \quad (1)$$

where H_A and H_B are histograms of image A and B with bins numbered as $i = 0, 1, \ldots, L-1$ respectively, $h_A(i)$ and $h_B(i)$ denote histogram value of the ith bin of H_A and H_B, respectively.

The histogram Chi-Square distance measure is defined as

$$D_2(H_A, H_B) = \sum\nolimits_{i=0}^{L-1} (h_A(i) - h_B(i))/(h_A(i) + h_B(i)) \quad (2)$$

A popular distance measure between two histograms, i.e., Bhattacharyya coefficient, is defined as

$$D_3 = \sqrt{1 - \sum_{i=0}^{L-1} \sqrt{h_A(i) * h_B(i)}} \quad (3)$$

The correlation distance measure is defined as

$$D_4(H_A, H_B) = \sum_{i=0}^{L-1} \frac{(h_A(i) - \bar{h}_A(i))(h_B(i) - \bar{h}_B(i))}{\sqrt{\|h_A(i) - \bar{h}_A(i)\| \|h_B(i) - \bar{h}_B(i)\|}} \quad (4)$$

In [18], Perlibakas has discussed in detail the distance measures of histograms. Interested readers may refer to it for more details.

III. Fuzzy Set

A. Fuzzy Set

A fuzzy set A in a finite set $X = \{x_1, x_2 \dots x_n\}$ may be represented mathematically as

$$A = \{(x, u_A(x)) | x \in X\} \tag{5}$$

where the function $u_A(x) : X \rightarrow [0..1]$ is a measure of belongingness or degree of membership of an element x_i in the finite set X. Thus, the measure of non-belongingness is $1 - u_A(x)$.

B. Fuzzy image model based on the histogram

As previously mentioned, the normalized histogram of a digital image A is a sequence $H_A = \{h_A(0), h_A(1), \dots, h_A(i), \dots, h_A(L-1)\}, i = \{0, 1, 2 \dots, L-1\}$ and $h_A(i)$ is defined as the ratio of the number of counts of the ith gray level to the total number of pixels, obviously $h_A(i) \in [0..1]$. Therefore, from the point of view of fuzzy set theory, we can let $u_A(i) = h_A(i)$ denote the membership value of the ith gray level of the histogram of the image A, which represents the degree to which it belongs where $u_A(x) \in [0..1]$ with $u_A(i) = 1$ denoting full membership and $u_A(i) = 0$ denoting non-membership.

Therefore, a fuzzy gray image [3] may be represented as

$$A = \{i, u_A(i)\} \tag{6}$$

where $u_A(i)$ lies in the interval $[0..1]$ and $i = 0, 1, 2 \dots, L-1$.

C. Fuzzy similarity measures

There are many fuzzy similarity measures, but some of the similarity measures used in this paper are defined as follows:

1) Min-max ratio. The similarity between two fuzzy sets is given by

$$S_1(A, B) = \frac{\sum_{i=1}^{N} \min(u_A(i), u_B(i))}{\sum_{i=1}^{N} \max(u_A(i), u_B(i))} \tag{7}$$

where $u_A(i)$ and $u_B(i)$ are the membership values of the ith bin of histograms H_A and H_B , respectively. For an identical pair of fuzzy sets, the memberships are equal and the similarity value will be equal to 1.

2) Contrast enhancement. The similarity between two fuzzy sets is given by

$$S_2(A, B) = \frac{1}{N} * \sum_{i=1}^{N} (1 - |u_A(i) - u_B(i)|) \tag{8}$$

It is the same as the previous definition in that for an identical pair of fuzzy sets, the memberships are equal and the similarity value will be equal to 1.

3) Normalized absolute difference. The similarity between two fuzzy sets is given by

$$S_3(A, B) = 1 - \frac{\sum_{i=1}^{N} abs(u_A(i) - u_B(i))}{\sum_{i=1}^{N} (u_A(i) + u_B(i))} \tag{9}$$

4) Fuzzy divergence.

$$S_4(A, B) = \sum_{i=1}^{N} (2 - (1 - u_A(i) + u_B(i)) e^{u_A(i) - u_B(i)} - (1 - u_B(i) + u_A(i) e^{u_B(i) - u_A(i)})) \tag{10}$$

5) Inclusion measure.

$$S_5(A, B) = \frac{\sum_{i=1}^{N} \min(\min(u_A(i), u_B(i)), \min(1 - u_A(i), 1 - u_B(i)))}{\sum_{i=1}^{N} \max(\max(u_A(i), u_B(i)), \max(1 - (u_A(i), 1 - u_B(i)))} \tag{11}$$

6) GTI Model. Tolias et al. [19] proposed a generalized Tversky's index (GTI) as a similarity measure, this has been defined as

$$S_6(A, B, \alpha, \beta) = \frac{\sum_{i=1}^{N} \min(u_A(i) - u_B(i))}{\sum_{i=1}^{N} (\min(u_A(i) - u_B(i)) + \alpha \min(u_A(i), 1 - u_B(i) + \beta \min(1 - u_A(i), u_B(i))} \tag{12}$$

The parameters α, β determine the relative importance of the distinctive features in the similarity assessment. GTI provides a set theoretical index for similarity assessment based on human perception. In the default situation, the values of α, β have been set to 0.5.

IV. Intuitionistic fuzzy set

One goal of fuzzy set theory would be, according to Zadeh, to represent how the human mind perceives and manipulates information. The degree of non-belongingness in fuzzy sets is automatically just the complement to 1 of the membership degree. However, a human being who expresses the degree of membership of a given element in a fuzzy set very often does not express a corresponding degree of non-membership as the complement to 1. Thus Atanassov [12] introduces the concept of IFS to deal with vagueness.

A. Intuitionistic fuzzy set

An IFS A in X is defined as

$$A = \{(x, u_A(x), v_A(x)) | x \in X\} \tag{13}$$

where $v_A(x) : X \rightarrow [0, 1]$, with the condition $0 \leq u_A(x) + v_A(x) \leq 1$,$\forall x \in X$, the numbers $u_A(x)$ and $v_A(x)$ denoting the degree of membership and non-membership of x to X, respectively. Obviously, a fuzzy set A corresponds to the following IFS with

$$A = \{(x, u_A(x), 1 - v_A(x)) | x \in X\} \tag{14}$$

For each IFS A in X, we will call

$$\pi_A(x) = 1 - u_A(x) - v_A(x) \tag{15}$$

the intuitionistic index of x in X. It is a hesitancy degree of x to X. Obviously, $0 \leq \pi_A(x) \leq 1$.

B. Similarity measures of intuitionistic fuzzy sets

Some intuitionistic fuzzy distance measures are defined as follows:

1) Hamming distance.

$$S_7(A,B) = \sum \max\{|u_A(x_i) - u_B(x_i)|, |v_A(x_i) - v_B(x_i)|\} \tag{16}$$

2) Euclidean distance.

$$S_8(A,B) = \sqrt{\sum_{i=1}^{n} \max\{|u_A(x_i) - u_B(x_i)|^2, |v_A(x_i) - v_B(x_i)|^2\}} \tag{17}$$

3) Li and Cheng [6] define the similarity measure between IFSs A, B as

$$S_9(A,B) = \frac{1}{\sqrt[p]{n}} \sqrt[p]{\sum_{i=1}^{n} |m_A(x_i) - m_B(x_i)|^p} \tag{18}$$

where $m_A(x_i) = (u_A(x_i)+1-v_A(x_i))/2$ and $\varphi_B(x_i) = |(1-v_A(x_i))/2 - (1-v_B(x_i))/2|$

4) Liang and Shi [16] proposed the similarity measure between IFSs A, B as follows

$$S_{10}(A,B) = \frac{1}{\sqrt[p]{n}} \sqrt[p]{\sum_{i=1}^{n} |\varphi_A(x_i) - \varphi_B(x_i)|^p} \tag{19}$$

where $\varphi_A(x_i) = |u_A(x_i) - u_B(x_i)|/2$ and $\varphi_B(x_i) = |(1-v_A(x_i))/2 - (1-v_B(x_i))/2|$

5) L_p distance. Hung and Yang [17] proposed several reasonable measures to calculate the degree of similarity between IFSs, in which the proposed measures are induced by the L_p metric. We briefly introduce it as follows.

For an IFS A of $X = \{x_{1,}x_{2,} \cdots x_{n,}\}$, let $I_A(x_i)$ be a subinterval on [0, 1] given by

$$I_A(x_i) = [u_A(x_i), 1 - v_A(x_i)], i = 1, 2, \ldots n \tag{20}$$

Using the L_p metric definition, we have

$$d_p(I_A(x_i), I_B(x_i)) = (|u_A(x_i) - u_B(x_i)|^p + |v_A(x_i) - v_B(x_i)|^p)^{1/p} \tag{21}$$

Hence we can define the distance $L_p(A,B)$ between A and B as follows:

$$L_p(A,B) = \frac{1}{n} \sum_{i=1}^{n} d_p(I_A(x_i), I_B(x_i)) \tag{22}$$

C. $IFSL_1$ distance

It is well known that similarity measures can be generated from distance measures. In this paper, we apply the distance $IFSL_1$ as the similarity measurement and achieve some good results. According to EQ. (22), we have

$$L_1(A,B) = \frac{1}{n} \sum_{i=1}^{n} (|u_A(x_i) - u_B(x_i)| + |v_A(x_i) - v_B(x_i)|) \tag{23}$$

For IFS sets A and B, if $u_A \le u_B$, then $v_A \ge v_B$ or if $u_A \ge u_B$, then $v_A \le v_B$, so for $u_A \ge u_B$, we have

$$\begin{aligned} L_1(A,B) &= \frac{1}{n} \sum_{i=1}^{n} (u_A(x_i) - v_A(x_i)) - (u_B(x_i) - v_B(x_i)) \\ &= \frac{1}{n} \sum_{i=1}^{n} (u_A(x_i) - v_A(x_i)) - (u_B(x_i) - v_B(x_i)) \end{aligned} \tag{24}$$

or for $u_A < u_B$, we have

$$\begin{aligned} L_1(A,B) &= \frac{1}{n} \sum_{i=1}^{n} (u_B(x_i) - v_B(x_i)) - (u_A(x_i) - v_A(x_i)) \\ &= \frac{1}{n} \sum_{i=1}^{n} (u_B(x_i) - v_B(x_i)) - (u_A(x_i) - v_A(x_i)) \end{aligned} \tag{25}$$

Time reduction can be achieved by calculating the $u_A(x_i) - v_A(x_i)$ and $u_B(x_i) - v_B(x_i)$ in advance.

V. Intuitionistic fuzzy model of images

A. HSV Color Space

A color space is a method by which we can specify, create and visualize color. As we know, different color spaces are suitable for different applications. We prefer to use the HSV color space over alternative spaces such as RGB , CMYK or YCbCr. The reasons why HSV color space is selected in our work is as follows. 1) It is an extremely intuitive manner of specifying color. It corresponds better to how people experience color compared with RGB or other color spaces. It is very easy to select a desired hue and to then modify it slightly by adjustment of its saturation and intensity; 2) The supposed separation of the luminance component from chrominance (color) information is shown to have advantages in applications such as image processing. For instance, after the images were converted from RGB space to HSV space, we built an HSV color histogram with only $16 \times 4 \times 1$ bins that achieved the same effectiveness as $8 \times 8 \times 8$ bins in RGB color space, according to the data in the table II; 3) We gave just one bin for V (brightness), based on the fact that human beings are less sensitive to the V value of HSV color. 4) Finally, the most important reason is that HSV color space gives us a natural explanation of color distance or color neighborhood, thus we can easily compute non-membership of an appointed color.

B. Image fuzzy model in HSV color space

Let A be a color image of size $M \times N$ on which the HSV histogram has been built. This HSV histogram in our work is implemented by a multi-dimensional histogram. Let $H_A(h,v,s)$ be the number of pixels that fall in the (h,v,s)th bin. The histogram of a image represents the frequency of occurrence of a color in the HSV coordinate system, where $h \in [0..h\_bins-1]$, $s \in [0..s\_bins-1]$,$v \in [0..v\_bins-1]$.h_bins is the quantization bin number for

Hue, s_bins is the quantization bin number for Saturation and v_bins is the quantization bin number for Value.

Let $u_A(h,s,v) = H_A(h,v,s)$ denote the membership value or the degree of belongingness of the (h,v,s)th bin of the HSV color histogram of the image A, where $0 \leq u_A(h,s,v) \leq 1$. $u_A(h,s,v) = 1$ denotes full membership and $u_A(h,s,v) = 0$ denotes non-membership. A fuzzy color image in HSV color space can be represented as

$$A = \{(h,s,v), u_A(h,s,v)\} \tag{26}$$

where $u_A(h,s,v)$ lies in the interval [0..1]

Our motivation for the new intuitionistic fuzzy model of images is based on the following. In the HSV color space, Hue can be described as representing the position of a color in a color circle, in which colors change smoothly between the primary colors. Saturation refers to the dominance of hue in the color. So HSV color space gives us a natural explanation of color distances; for example the HSV coordinate (0,255,255) represents pure red, its complementary color is cyan which has the HSV coordinate (180,255,255). To look for the complementary color of an appointed color, what we need do is just add 180 degrees to the hue coordinate of the current color. Therefore, after we build color histogram, colors located at the bin (h,s,v) have its complementary colors located at $((h + h\_bins/2)\%h\_bins, s, v)$ The colors located between $((h + h\_bins/2)\%h\_bins, s, v)$ and $((h+h\_bins/2)\%h\_bins, s\_bins, v)$ can be taken as the non-member of the color at the bin (h,s,v), because they are the furthest colors in the HSV color space, defined as follows:

$$v_A(h,s,v) = \sum_{m=h-\nabla h}^{h+\nabla h} \sum_{n=s}^{s\_bins} \sum_{l=v-\nabla v}^{v+\nabla v} u_A((m + h\_bins/2)\%h\_bins, n, l) \tag{27}$$

where $u_A((m+h\_bins/2)\%h\_bins, n, l)$ are the number of pixels that falls in the $((m+h\_bins/2)\%h\_bins, n, l)$ bin of image A. ∇h ,∇v can be adjusted for different application contexts, we set the values of ∇h ,∇v to 0 in our work .

Due to humans being less sensitive to the V value of HSV, we can set 1 bin for V in the HSV color histograms, then the HSV color histogram was implemented with 2-D histogram in our work. After further simplification, if $u_A(h,s)$ denotes the membership value of the (h,s)th bin of the histogram of the image A, the non-membership value $v_A(h,s)$ can be defined as

$$= \begin{cases} \sum_{n=s-\nabla s}^{s\_bins} u_A((h + h\_bins/2)\%h\_bins, n) & s \leq \frac{s\_bins}{4} \\ \sum_{n=s}^{s\_bins} u_A((h + h\_bins/2)\%h\_bins, n) & \\ \frac{s\_bins}{4} \leq s \leq \frac{3s\_bins}{4} & \\ \sum_{n=0}^{\nabla s} u_A((h + h\_bins/2)\%h\_bins, n) & s \geq \frac{3s\_bins}{4} \end{cases} \tag{28}$$

Based on the above definition, an image intuitionistic fuzzy model can be defined as

$$A = \{(h,s), u_A(h,s), v_A(h,s)\} \tag{29}$$

where hesitation degree $\pi_A(x) = 1 - u_A(x) - v_A(x)$, and $v_A(h,s) \neq 1 - u_A(h,s)$ due to consideration of the degree of hesitation in the intuitionistic fuzzy set.

VI. Experimental results and analysis

In this section, we compare the performance of our intuitionistic fuzzy similarity measure based on the L_1 metric (called $IFSF_1$) in the HSV color space by comparison to some other state-of-the-art similarity measures.

A. Experimental setup

The software for experiments was all written on an OpenCV computer vision software development platform and run on a Intel Core(TM)2 2.8GHz processor with 3GB of memory under the Windows XP operating system. All the images were scaled to a $72*72$ pixel size using the nearest neighbor interpolation method in order to make the algorithms faster and to avoid later normalization of the histograms, which might result in loss of color quantity information.

To illustrate the image retrieval performance of our methods, comparison has been made with other similarity measures using the open image database from Konstantinidis et al. [7], which contains a total of 1188 images. The image database is online, available at the following URL: http://utopia.duth.gr/ konkonst. Some images in the database were selected from different WEB sites on the internet; others were scanned from personal photographs and many images were taken with several different digital cameras. The images in the collection are representative for the general requirements of an image retrieval system over the internet. The range of topics presented in the image database is quite wide and varies from several different landscapes to face, buildings, views, people, animals, furniture and other computer graphics which usually confuse image retrieval systems.

Usually precision and recall are used in CBIR system to measure retrieval performance. Precision (Pr) is the proportion of the relevant images retrieved N_r (similar to the query image) with respect to the total retrieved K_r, whereas recall (Re) is defined as the ratio of the number of correct images retrieved N_r to the total number of correct images N_t in the database. Due to the fact that we know in advance the number of similar images existing in the database and K_r, precision was taken as our main performance index.

$$Pr = N_r/K_r \ , Re = N_r/N_t \tag{30}$$

B. Comparative studies

The performance test of the similarity measure in Konstantinidis et al. [7], was based on the retrieval of image sets 1, 2 and 3 from an image database, but since

Konstantinidis did not give detailed query information about set 2, we have only compared our proposed intuitionistic fuzzy similarity measure with others using image sets 1 and 3. A retrieval image has been classified as accurate if it is perceived (to humans) to be similar to a given query image. Fig. 1 shows the results of the ranking of images in order of decreasing similarity using the method proposed by Konstantinidis [7]. The query image is at the extreme top left. The first image detects false after retrieval of 13 correct images. Fig. 2 shows the results with the same query image ranking the images in order of decreasing similarity with the method proposed in this paper. Our experiment results in only one false detection, i.e., the last one. Fig. 3 shows the results from ranking of the landscape images from the image database in order of decreasing similarity using the fuzzy linking method of Konstantinidis. The query image is at the extreme top left. Fig. 4 shows the results of the same query image, ranking the images in order of decreasing similarity using the method proposed in this paper. This result shows that our method also performs much better than that of Konstantinidis. The reasons are as follows: 1) As shown in Fig. 3, the query image mainly contains grassland and trees, but the content of many of the retrieval images does not contain the same information. By contrast, we have retrieved many photos which seemingly were taken in the same place but with a different view and background information as the query image in Fig. 4. Thus, the images we retrieved are more easily perceived by humans to be accurate than by the method used by Konstantinidis did. Konstantinidis gave a brief comparison with some other similarity measures (including the similarity measure proposed by Tico, Swain,and Liang [20]–[22]). They declared that the fuzzy linking methods outperform the others. Since we use the same image database as Konstantinidis and have achieved sometimes the same and sometimes even better precision, our proposed similarity method outperforms others.

In order to evaluate the precision of our proposed similarity measure compared with other similarity measures using our new image intuitionistic fuzzy model, a number of experimental tests were carried out. The scheme of the experiment was that every image in data set 3 of Konstantinidis was selected as the query image and the average precision treated as a general measure.of performance. It is obvious that this scheme will be more suitable for characterizing the performance of a specific similarity measure. The experimental data are shown in Table I. This data were acquired in the HSV color space with a 16*4*1 combination of histogram bins. We should note that the proposed method dominates almost all other fuzzy similarity measures or histogram matching distances except the D3(Bhattacharyya coefficient). This is due to the fact that our proposed method considers the degree of hesitation which makes it even less sensitive to changes of angle, scale variations, lighting variations and occlusions. The data in the gray column show that the performance is the worst when color information is

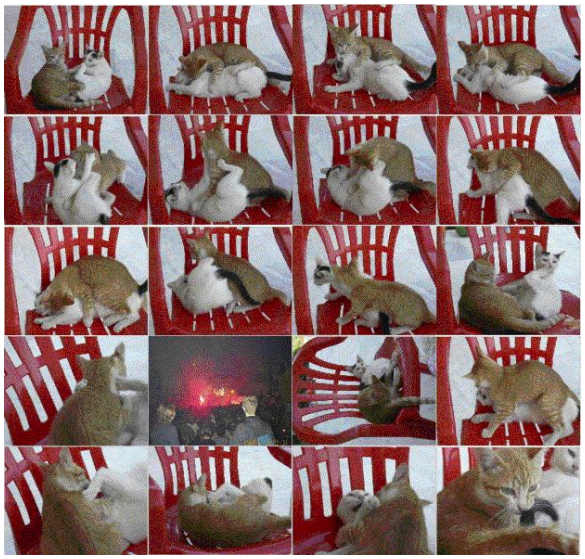

Fig. 1. The 20 retrieved images from data set 3 by the fuzzy linked method proposed by Konstantinidis [7]. The images are presented in descending similarity measure from left to right and from top to bottom.

Fig. 2. The 20 retrieved images from data set 3 by our proposed similarity measure. The images are presented in descending similarity measure from left to right and from top to bottom.

not considered. The data of columns D1(Intersection distance measure), D2(Chi-Square distance measure) and D4 (Correlation distance measure) [18] show that the performance of the traditional histogram matching was normal. The D3(Bhattacharyya similarity measure) achieves the best results of all, but this kind of similarity computation is very expensive. The data of columns S1(Min-max ratio), S2(Contrast enhancement), S3(Normalized absolute difference), S4(Fuzzy divergence), S6(GTI Index) are fuzzy similarity measures which only consider membership [3]. The data of columns S7(Hamming distance), S8(Euclidean distance), S9(Li similarity measure), S10(Liang similarity measure) [6], [16] are the intuitionistic fuzzy similarity measures. The new proposed measure

TABLE I
COMPARISON OF PERFORMANCE IN TERMS OF THE PRECISION WITH THE OTHER SIMILARITY MEASURES.

NO	D1	D2	D3	D4	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	new
1	40	85	85	100	85	95	95	95	90	95	95	85	95	90	95
2	5	35	35	80	35	35	35	35	40	35	35	55	45	40	45
3	15	100	100	100	100	100	100	100	100	100	100	85	95	100	100
4	50	90	90	100	90	95	95	95	90	95	95	85	95	90	95
5	50	100	100	100	100	95	95	95	100	95	95	85	95	100	100
6	45	95	95	100	95	100	100	100	95	100	100	85	95	95	100
7	45	90	90	100	90	95	95	95	95	95	95	85	95	95	95
8	30	95	95	100	95	95	95	95	100	95	95	85	95	100	95
9	40	100	100	100	100	95	95	95	100	95	95	90	100	100	100
10	35	100	100	100	100	95	95	95	100	95	95	95	100	100	100
11	30	95	95	100	95	95	95	95	95	95	95	80	95	95	95
12	40	85	85	100	85	100	100	100	90	100	100	75	90	90	100
13	45	95	95	100	95	100	100	100	95	100	100	90	95	95	100
14	30	95	95	100	95	95	95	95	100	95	95	100	100	100	95
15	30	90	90	95	90	95	95	95	95	95	95	85	100	95	100
16	35	60	60	95	60	100	100	100	80	100	100	85	100	80	95
17	10	95	95	95	95	95	95	95	100	95	95	90	100	100	100
18	30	95	95	100	95	100	100	100	95	100	100	85	100	95	100
19	5	50	50	100	50	90	90	90	60	90	90	40	50	60	85
20	40	90	90	100	90	95	95	95	100	95	95	85	95	100	95
Avg	32.5	87	87	98.25	87	93.25	93.25	93.25	91	93.25	93.25	82.5	91.75	91	94.5

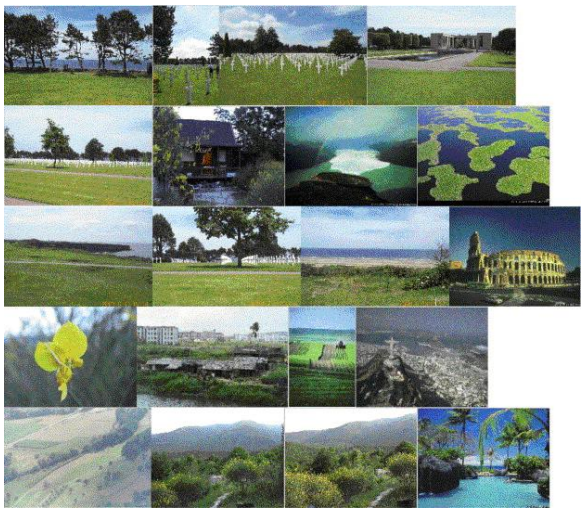

Fig. 3. The 20 retrieved images from data set 1 by the fuzzy linking method proposed by Konstantinidis [7]. The images are presented in descending similarity measure from left to right and from top to bottom.

Fig. 4. The 20 retrieved images from data set 1 by our proposed similarity measure. The images are presented in descending similarity measure from left to right and from top to bottom.

achieved top score throughout.

We tested the average performance of the intuitionistic fuzzy similarity measure on the different kinds of color space with other similarity measures and the experimental data is shown in Table II. The data in Table II show that it is robuster than other color spaces. The intuitionistic fuzzy similarity measure, amongst all the color space and different combination of bins, is very effective and can achieve the best precision of all the similarity measures except the Bhattacharyya coefficient. However, the Bhattacharyya coefficient needs more bins. For example, the precision of our method can reach 90.50% in the HSV color space with $4 \times 4 \times 1$ bins; the Bhattacharyya coefficient needs at least $6 \times 10 \times 10$ bins. In summary , our new intuitionistic fuzzy model has high computational efficiency, which dramatically decreases the data storage requirement without loss of accuracy.

It is very interesting to investigate how the similarity measures react to noise (e.g. salt and pepper noise / Gaussian noise / motion blur). A good similarity measure

TABLE II
COMPARISON OF PERFORMANCE IN TERMS OF THE AVERAGE PRECISION IN DIFFERENT COLOR SPACE AND WITH DIFFERENT COMBINATION OF BINS.

NO	D1	D2	D3	D4	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	new
HSV 16*4*1	87	87	98.25	87	93.25	93.25	93.25	91	93.25	93.25	82.5	91.75	91	94.25	94.5
HSV10*6*1	80.25	80.25	97	80.25	93.25	93.25	93.25	88.25	93.25	93.25	68.5	89.25	88.25	92.5	93.5
HSV 8*8*1	80.5	80.5	91.75	80.5	90	90	90	85.25	90	90	60	82.5	85.5	88.25	88.5
HSV 6*6*1	79.75	79.75	92	79.75	89.25	89.25	89.25	85.5	89.25	89.25	71	85.5	85.5	88	88.25
HSV 4*4*1	75.75	75.75	91	75.75	88.75	88.75	88.75	86	88.75	88.75	82.75	89.5	86	90.75	90.5
RGB 4*4*4	81.25	81.25	89.25	81.25	86.25	86.25	83.25	83.25	86.25	86.25	—	—	—	—	—
RGB 8*8*8	81.75	81.75	88.5	81.75	88.75	88.75	88.75	82.75	88.75	88.75	—	—	—	—	—
RGB 6*16*16	78.75	78.75	88.75	78.75	89.25	89.25	89.25	73.5	89.25	89.25	—	—	—	—	—
LAB3*5*5	73	73	92.25	73	88.5	88.5	88.5	81	89	88.25	—	—	—	—	—
LAB6*10*10	82	82	94.75	82	90	90	86	90	90	90.75	—	—	—	—	—
LAB12*20*20	69	69	92	69	89.25	89.25	89.25	78	89.25	89.25	—	—	—	—	—
LAB16*16*16	79.5	79.5	89.75	79.5	88.25	88.25	88.25	83.25	88.25	88.25	—	—	—	—	—
Luv 4*4*4	68.5	68.5	88.75	68.5	75.75	75.75	75.75	69	75.75	69.75	—	—	—	—	—
Luv 8*8*8	75.75	75.75	93	75.75	88.5	88.5	88.5	80	88.5	88.5	—	—	—	—	—
Luv 8*16*16	76.25	76.25	93.5	76.25	90.75	90.75	90.75	82	90.75	90.75	—	—	—	—	—
Ycrcb4*4*4	57	57	80.75	57	68.75	68.75	68.75	60	68.75	66.25	—	—	—	—	—
Ycrcb8*8*8	74.75	74.75	87.5	74.75	82.25	82.25	82.25	73.75	82.25	82.25	—	—	—	—	—

should not be greatly affected by noise and not decrease rapidly with respect to an increasing percentage of noise. Some special tasks were executed to test the robustness of the similarity measure with various noisy images as shown in Fig. 5. This includes one brightening of the image, four images contaminated by different densities of salt and pepper noise, five images blurred by a filter (which approximates the linear motion of a camera) and five images contaminated by Gaussian noise. The experimental results are shown in Table III in which the data was taken in HSV color space with $16 \times 4 \times 1$ histogram bins. The percentage accuracy of the proposed approach was decreased by about 0-80% in the tests but nonetheless the performance dominates other similarity measures. Thus, the similarity measure presented is robust to extreme changes in the images.

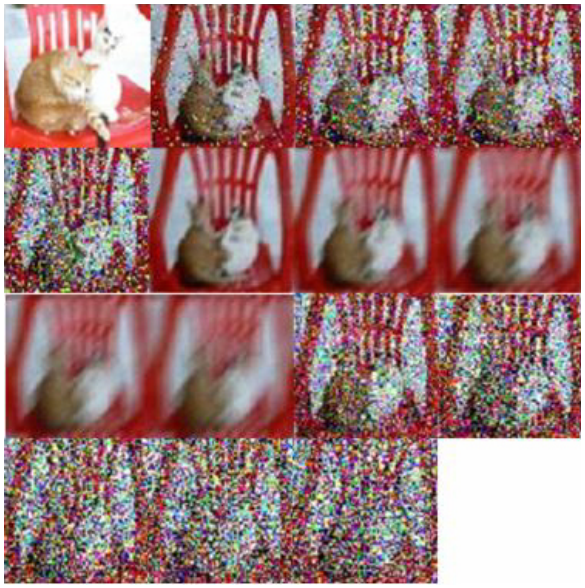

Fig. 5. Query images which have been contaminated with different types of noise. (1) brightened, (2)-(5) densities of salt and pepper noise 5%,15%, 20% and 30%, (6)-(10) blurred though filter which approximates the linear motion of a camera by a length 3, 6, 9, 12, 15 pixels with an angle of 45 degree in a counterclockwise direction, (11)-(15) Gaussian noise of =0.1, 0.2, 0.3, 0.4, 0.5.

C. Computational analysis

Our objective is to improve the effectiveness of the simple color histogram by introducing the intuitionistic fuzzy set theory based on a new intuitionistic fuzzy image model. At this point, we examine the performance of this proposed method including effectiveness and efficiency. Effectiveness is a measure of the relevance of the retrieved image to a query. We have employed precision to show the effectiveness of our new proposed method. Efficiency is a measure of the storage and computational cost requirements and responsiveness of a CBIR system. It is noted that in Konstantinidis' work on the L*a*b color space, their histogram consists of 10 bins by using the fuzzy logic rule, but his method needed 75 bins (3 bins for L, 5 bins for a and 5 bins for b) for initial building of the fuzzy linking histograms. Swain and Ballard's approach to the creation of the histogram needed 256 bins. Tico et al. worked on HSI color space to obtain the histogram. Their histogram consisted of 20 bins, 16 for hue and 4 for intensity. As we know, the fewer bins employed by the similarity function, the more computing time can be saved. In our work, 16 bins were employed (4 bins for H, 4 bins for S and 1 bin for V). We use equations EQ. (24) and EQ. (25) to calculate the similarity and because the values of $u_A(x_i) - v_A(x_i)$ and $u_B(x_i) - v_B(x_i)$ can be calculated before the query execution, our new proposed method consists only of one additional operation and its calculation cost is very low. In Table IV, the execution

TABLE III
COMPARISON OF PERFORMANCE IN TERMS OF THE PRECISION WHEN A DIFFERENT NOISY PHOTO WAS SELECTED AS QUERY IMAGE.

NO	D1	D2	D3	D4	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	new
1	55	55	85	55	75	75	75	55	75	75	50	65	55	80	80
2	95	95	100	95	100	100	100	95	100	100	45	85	95	95	95
3	60	60	80	60	80	80	80	50	80	80	0	15	50	60	65
4	35	35	40	35	55	55	55	30	55	55	0	5	30	35	40
5	40	40	0	40	25	25	25	20	25	25	0	5	20	10	25
6	100	100	100	100	100	100	100	100	100	100	80	100	100	100	100
7	100	100	100	100	100	100	100	100	100	100	90	100	100	100	100
8	95	95	100	95	100	100	100	95	100	100	90	100	95	100	100
9	70	70	95	70	90	90	90	80	90	90	60	90	80	100	100
10	45	45	85	45	80	80	80	65	80	80	40	50	65	85	85
11	20	20	25	20	50	50	50	35	50	50	0	5	35	25	35
12	20	20	0	20	30	30	30	10	30	30	0	5	10	10	20
13	20	20	0	20	5	5	5	5	5	5	0	0	5	0	5
14	15	15	0	15	0	0	0	5	0	0	0	0	0	0	0
15	5	5	0	5	0	0	0	0	0	0	0	0	0	0	0

TABLE IV
EXECUTION TIME(IN MILLISECONDS) OF KONSTANTINIDIS METHOD AND PROPOSED ONE.

Image retrieval results	Fig.1	Fig.2	Fig.3	Fig.4
Execution time	9.17ms	0.48ms	9.21ms	0.50ms

times for different image retrieval results are tabulated. It should be noted that the time of feature extraction is not included, because the feature database is always produced beforehand in CBIR system, and the time spent in this part can be ignored. It can be observed that the execution times of the proposed similarity measure $IFSL_1$ is significantly less than the fuzzy linking method (Konstantinidis method).

VII. CONCLUSION

In this paper, a new image fuzzy model based on the HSV color histogram is proposed. A new and simple calculation method of the similarity measure called $IFSL_1$ has also been presented. The novelty lies in the use of IFS theory in image retrieval after building a suitable image intuitionistic fuzzy model. Very few bins are required to describe the color distribution (color histogram) of the image, resulting in much faster computing. The $IFSL_1$ was compared to other fuzzy similarity measures and traditional histogram similarity measures and proved to be much more accurate and robust by way of several image retrieval tests. To achieve better results, future research will include spatial, texture and edge information factors. The proposed similarity measure represents an alternative to the CBIR system search engine.

ACKNOWLEDGMENT

The authors would like to thank the anonymous reviewers for their useful comments in improving the paper.

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