Application of the Fuzzy Logic in Content-based Image Retrieval[1]

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ABSTRACT

This paper imports the fuzzy logic into image retrieval to deal with the vagueness and ambiguity of human judgment of image similarity. Our retrieval system has the following properties: firstly adopting the fuzzy language variables to describe the similarity degree of image features, not the features themselves; secondly making use of the fuzzy inference to instruct the weights assignment among various image features; thirdly expressing the subjectivity of human perceptions by fuzzy rules impliedly; lastly we propose an improvement on the traditional histogram called the Average Area Histogram (AAH) to represent color features. Experimentally we realized a fuzzy logic-based image retrieval system with good retrieval performance.

Keywords: Content-based Image Retrieval, Fuzzy Inference, Weight Assignment, Subjectivity of Human Perceptions

1. INTRODUCTION

Due to the development of computer networks and the low cost of large storage device, visual information has been widely used in many fields. How to retrieve the visual information efficiently has led to the rise of interest in techniques for retrieving images through image databases. Image Retrieval (IR) aims to retrieve similar or relevant images to the query image by means of image features or the keywords related with the query image. In the past, various approaches to image retrieval were proposed, most of which were Content-Based Image Retrieval (CBIR) that derives image features such as color, texture and shape or any combination of these. Some key issues involved in CBIR are as follows:

(1) Semantic gap between the high-level semantic and the low-level features of an image Human prefer to retrieve images according to the "semantic" or "concept" of an image. However, CBIR depends on the absolute distance of image features to retrieve similar images. Research has concealed that there exists a nonlinear relation between the high-level semantics and the low-level features. For instance, an image may be regarded as a similar (semantic) image although its' color and shape (low-level features) are not quite similar to the query image.

(2) Integration of various features Multi features outperform the single feature in image retrieval. Currently, most of the weight assignment of variuous features are conducted in a linear way according to the users' experience [1]. For example, if a user thinks that color is twice important as shape, he assigns 2/3 to the color weight and 1/3 the shape weight. Such precisie and fixed assignment of weights fails to reflect what human think. An effieient method to solve this problem is the famous User Relevance Feedback (URF) [2]. The deficiency of URF is that it imposes a heavy burden on user in retrieval.

(3) The users' subjective intentions Different user may have different perception of same images, which refers to the subjectivity of users' perceptions. The research of how to reflect it in image retrieval is rather few.

The property of the image retrieval requires the computer to retrieve images as what human thinking and not depend on the rigid distance metrics to decide the image similarity. Fuzzy logic is a powerful tool to realize this goal. Fuzzy logic has been widely used in image retrieval. Most researches adopt the fuzzy set to describe the properties of image features such as the coarse of textures [3][4], the shape size of the human's face [5] and the thickness of edges [6]. Different from the previous works, we emphasis on the followings: (1) adopting the fuzzy language variables to describe the similarity degree of image features, not the features themselves so as to infer the image similarity as human thinking; (2) making use of the fuzzy inference to instruct the weight assignments among various image features; (3) expressing the subjectivity of human perceptions by the fuzzy rules impliedly. Experimentally, we realize a fuzzy logic-

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based image retrieval system with good retrieval performance.

Color is one of the most salient and commonly used features in image retrieval. There are three major types of color feature representations: color moments [7], color histogram [8] and color sets [9]. Among these, the color histogram is the most popular for its' effectiveness and efficiency. However, the color histogram is liable to lose spatial information and therefore fails to distinguish images with same color but different color distributions [10]. Many researchers had investigated this problem by integrating spatial information into the conventional histogram. Pass and Zabih [11] divide the whole histogram into region histogram by means of color clustering. Colombo et al. [12] propose a concept called color coherence vector (CCV) to split histogram into two parts: the coherent one and the non-coherent one depending on the sizes of their connected components. Combining color with texture, shape and direction, this method escapes comparing color of different regions. Cinque et al. [13] present a spatial-chromatic histogram considering the position and variances of the color blocks in image. Rick Rickman and John Stonham [14] define the color tuple histogram. They use a predefined equilateral triangle of a fixed length and then randomly move the triangle on an image to calculate the frequency of each tuple of triple pixels. Hsu et al. [15] modify the color histogram by first selecting a set of representative colors and then analyzing the spatial information of the selected colors using maximum entropy quantization with event covering method. All the above methods attempt to improve the retrieval performance by integrating spatial information into histogram. However, the way of extracting colors from the image spoils the robustness to rotation and translation of the conventional histogram inevitably as seen with the partition of regions used by Pass and Zabih [11], the color block position parameter used by Cinque et al. [13] and the shape and size of the predefined triangle used by Rick Rickman and John Stonham [14]. Therefore these improvement methods spoil the merit of the conventional histogram. For the images with same color but different color distributions, we notice that the pixels of each color usually form several disconnected regions of different sizes, which can be used as a key to distinguish the images. In this paper, we present a novel histogram called the Average Area Histogram (AAH) based on the area features of the regions formed by the pixels of each color.

Section 2 introduces the components of the fuzzy logic-based image retrieval system. Section 3 describes the representations and matching methods of color and shape features respectively. Section 4 gives the fuzzy inference image matching method. Experiments are shown and discussed in Section 5 followed the conclusions made in section 6.

2. THE FUZZY LOGIC-BASED IMAGE RETRIEVAL

The fuzzy logic-based image retrieval system is composed of the following four parts illustrated in figure 1.

(1) Feature Extraction The color feature C is represented by the histogram in HSV-space. We adopt the traditional moment invariants to extract the shape feature S.

(2) Fuzzifier Suppose query image is Q and images from the database is I. The color distance $D_C(C_Q, C_I)$ and shape distance $D_S(S_Q, S_I)$ between image Q and I are two inputs of the fuzzy logic-based image retrieval system. Three fuzzy variables including "very similar", "similar" and "not similar" are used to describe the feature difference D_C and D_S. By such descriptions, we can infer the similarity of images in the same way as what human think.

(3) Fuzzy Inference According to the general knowledge of an object and the users' retrieval requirements, a fuzzy rule base including nine rules is created.

(4) Defuzzifier Output of the fuzzy system *Sim* is the similarity of two images and it is also described by three fuzzy variables including "very similar", "similar" and "not similar". We adopt the Center Of Gravity (COG) method to defuzzify the output.

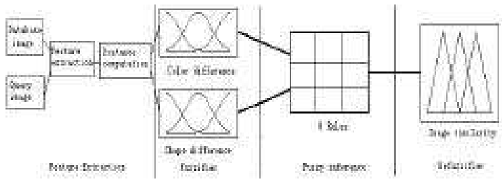

Fig.1. Fuzzy logic-based IR

3. FEATURE EXTRACTION

The color and shape representations and measurement methods are introduced in the following sections.

3.1 COLOR FEATURE DESCRIPTION

Given a color space C, the conventional histogram H of image I is defined as follow:

$$H_C(I) = \{N(I_i, C_i) \mid i \in [1,...,n]\} \qquad (1)$$

Where $N(I_i, C_i)$ is the number of pixels of I fall into cell C_i in the color space C and i is the gray level. $H_C(I)$ shows the proportion of pixels of each color within the image. The color difference $D_C(C_Q, C_I)$ is the histogram distance defined by Eq. (2) as follows:

$$D_C(C_Q, C_I) = d(H(I), H(Q)) = [\sum_{i=1}^{n} |H(I_i) - H(Q_i)|^2]^{1/2} \qquad (2)$$

Swain and Ballard [8] define a distance measure method called histogram intersection:

$$D_C(C_Q,C_I)=d(H(I),H(Q))=\sum_{i=1}^{n}\min(H(I_i)-H(Q_i)) \quad (3)$$

See the above distance measure methods, they only make use of the total amount of the pixels with color i to compare two histograms, not consider the different spatial distribution for color i in image I. See Eq. (2) and Eq. (3), the default coefficient of $H(I_i)$ and $H(Q_i)$ is 1, which means that the difference between the two histograms is just determined by the total number of pixels of each color. Actually, within each color bin, ther exists a spatial difference. To solve this problem, we present a novel histogram called Average Area Histogram (AAH). In the AAH, we integrate the area feature of the regions formed by each color into the conventional histogram.

Let D be the number of disconnected regions formed by the pixels with color i of image I in the color space C. Here we ignore the regions with only 1 pixel for they have no effect on the retrieval performance.

$$D(I,C_i)=\{N(C_{8i})\mid i\in[1,..,n]\} \quad (4)$$

Where $N(C_{8i})$ counts the number of disconnected regions formed by the pixels with color i through an 8-connectivity operation on image I. Then the average area histogram H^* can be defined as follow:

$$H^*_C(I)=\{\frac{N(I,C_i)}{D(I,C_i)}\mid i\in[1,..,n]\} \quad (5)$$

Where $N(I_i,C_i)$ counts the total number of pixels with color i in the image I, which can also be regarded as the area value of the regions formed by the pixels with color i. H^* then represents the average area value of these regions for color i.

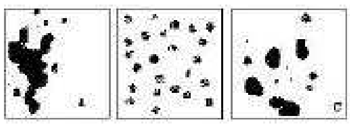

Fig.2 Regions formed by the pixels of identical color

Fig.2 illustrates three common cases where the pixels of color i form the connected and disconnected regions. For the three cases, suppose that the sum of these pixels is equal or close. The AAH can distinguish the three cases (A), (B) and (C) correctly. However, the conventional histogram method only considers the total amount of color i that is the sum of the areas of all the disconnected regions. Consequently, these three cases will be regarded as identical and thus be mismatched. In fact, the conventional histogram is only effective for case A. In most mismatching cases of the traditional histogram, it cannot distinguish the case (a) from case (b) while the AAH outperforms the traditional histogram to distinguish (a) from (b) and (a) from (c). Fig.4 shows the comparison of the traditional histogram and the AAH of image A and B illustrated in Fig.3. In Fig.4, (1) and (2) are the conventional histograms of the image (a) and (b) respectively, (3) and (4) are the AAH of them. Evidently, the AAH of image A and B is more dissimilar compared with their traditional histograms, which is consistent with the different contents in the image (a) and (b). In other words, the AAH is more suitable to reflect the real color distributions in the image than the traditional histogram.

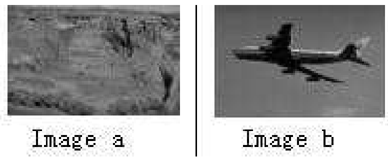

Fig.3 Image a and b

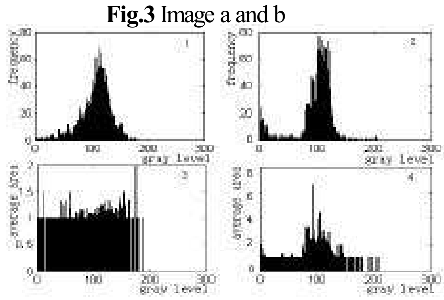

Fig.4 Traditional histogram and AAH comparison of image A and B

3.2. SHAPE FEATURE DESCRIPTION

In general, shape representation can be categorized into either boundary-based or region-based [16]. The former uses only the outer boundary characteristics of the entities while the latter uses the entire region. Well-known methods of the two types include the Fourier descriptors and the moment invariants [17] respectively.

In this paper, we adopt the moment invariants to describe the shape feature. Let f(x, y) be a binary image of an object, we define its (p+q)th order moment:

$$\mu_{pq}=\sum\sum(x-\mu_x)^p(y-\mu_y)^q f(x,y) \quad (6)$$

Where $\mu_x=\frac{\sum\sum xf(x,y)}{\sum\sum f(x,y)}$,

$\mu_y=\frac{\sum\sum yf(x,y)}{\sum\sum f(x,y)}$.

The normalized central moment is:

$$\eta_{pq}=\frac{\mu_{pq}}{\mu^r_{00}} \quad (7)$$

Where $r=\frac{p+q}{2}, p+q=2,3,\ldots$.

Based on the second and third order moments, we have the following seven invariant moments to describe a region:

(1) $\varphi_1=\eta_{20}+\eta_{02}$

(2) $\varphi_2=(\eta_{20}+\eta_{02})^2+4\eta^2_{11}$

(3) $\varphi_3=(\eta_{30}-3\eta_{12})^2+(3\eta_{21}-\eta_{03})^2$

$$(4)\ \varphi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$$

$$(5)\ \varphi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03}) + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$

$$(6)\ \varphi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \mu_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})$$

$$(7)\ \varphi_7 = (3\eta_{12} - \eta_{30})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$$

Then, a vector composed of the seven invariant moments $M = (\varphi_1, \varphi_2, \varphi_3, \varphi_4, \varphi_5, \varphi_6, \varphi_7)$ can be used to represent the region feature. The similarity of the shape feature can be computed by Eq. (8)

$$D_S(S_Q, S_I) = d(M(I), M(Q)) = [\sum_{i=1}^{7} (\varphi_{Ii} - \varphi_{Qi})^2]^{1/2} \quad (8)$$

4. FUZZY LOGIC-BASED IMAGE SIMILARITY MATCHING

4.1 Data Normalization

See Eq. (3) in section 3, if $D_C(C_Q, C_I)$ is close to 1, it indicates that the two images Q and I have strongly similar color. However, in the fuzzy inference, we assume that the feature distance which closes to 1 means "not similar". So we must convert $D(C_Q, C_I)$ through Eq. (9):

$$D_C(C_Q, C_I) = \| D_C(C_Q, C_I) - 1 \| \quad (9)$$

To satisfy the requirement of the Membership Grade Function used in the fuzzy logic-based image retrieval system, the shape difference $D_S(S_Q, S_I)$ needs to be transformed into range [0,1] with Gaussian normalization method [18].

$$D_S' = (\frac{D_S - m_{D_S}}{3\sigma_{D_S}} + 1) / 2 \quad (10)$$

Eq. (10) guarantees that 99 percents of D'_S fall into to range [0,1]. m_D and σ_D are the mean value and standard deviation of D_S respectively.

4.2 Fuzzy Inference of Image Similarity

In general, human accept and use the following experiences to retrieve images: if the feature difference of two images is no more than 20%, the two images are very similar, between 30%-50% similar, between 70%-90% or above not similar. The Membership Grade Function (MGF) to describe the similarity degree difference of the color and shape features is built according to the above experiences.

Next we will fuzzify the outputs and input of the system. Three fuzzy variables including "very similar", "similar" and "not similar" are used to describe the two inputs of the system. Their respective MGFs are Gauss MGF, Union Gauss MGF and Gauss MGF. The output of the system is the similarity of images, which is also described by three same fuzzy variables. Their respective MGFs are: Gauss MGF, Union Gauss MGF and Gauss MGF. Figure 5 shows the MGFs of the two inputs and one output of the fuzzy logic-based image retrieval system.

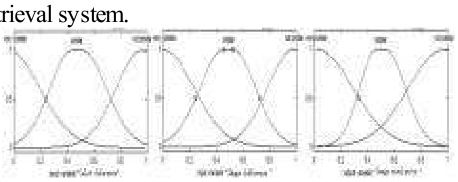

Fig.5 Membership functions of the two inputs and one output of our system

Once we acquire the fuzzy descriptions of the color difference and shape difference of the two images, the rule base including 9 rules can be built to make an inference of their similarity. The fuzzy relation matrix R is computed in Eq. (11). The inference can be conducted by R.

$$R = \cup (D_C \times D_S) \times S \quad (11)$$

These rules are consistent with the user's requirements and what his perceptions of an object. The weight of a rule reflects the user's confidence of it. For one user named A, he wants to retrieve all of the flower images with different color and shape to the query image named 5.jpg as shown in the top left corner of Fig.7. So he assumes that two images with similar color and very similar shape may be similar. According to his requirements, the fuzzy rules are shown in table 1. For another user named B, he just retrieves the flower images with strongly similar color to 5.jpg. So he may think that two images with similar color and very similar shape are not similar. The rules related to his requirements are shown in table 2. The differences of the two rule bases are illustrated in bold sequence number in table 1 and table 2. The two corresponding output surfaces are illustrated in Fig.6. Fig.7 shows their respective retrieval results (the top is for user A and the bottom user B). Obviously, the retrieval results satisfy the two users' subjective intentions and initial requirements. Each rule processes one of the possible situations of the color and shape features of two images. The 9 rules altogether deal with the weight assignments impliedly in the same way as what human think. In the fuzzy logic-based image retrieval system, the fuzzy inference processes all the 9 cases in a parallel manner, which makes the decision more reasonable.

Table 1. The fuzzy rules for user A

Rule	Input		Output	Weight
	D_C	D_S	S	
1	very similar	very similar	very similar	1
2	very similar	similar	similar	0.5
3	very similar	not similar	not similar	1
4	similar	very similar	not similar	1
5	similar	similar	similar	0.6
6	similar	not similar	not similar	1
7	not similar	very similar	not similar	1
8	not similar	similar	not similar	1
9	not similar	not similar	not similar	1

Table 2. The fuzzy rules for user B

Rule	Input		Output	Weight
	D_C	D_S	S	
1	very similar	very similar	very similar	1
2	very similar	similar	similar	1
3	very similar	not similar	not similar	1
4	similar	very similar	similar	0.3
5	similar	similar	similar	0.4
6	similar	not similar	not similar	1
7	not similar	very similar	similar	0.5
8	not similar	similar	not similar	1
9	not similar	not similar	not similar	1

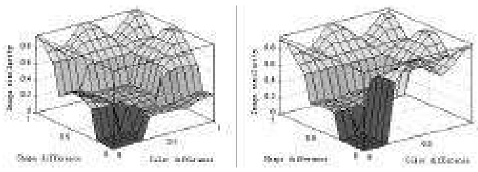

Fig.6 Output surface of the fuzzy inference of table 1 and table 2

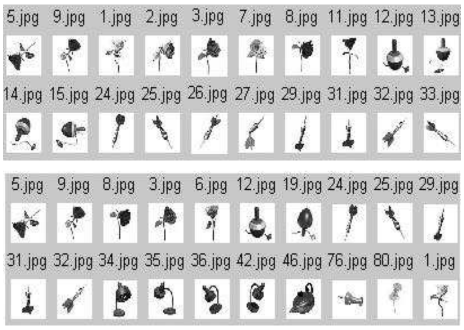

Fig.7 The retrieval results for user A and B

If different objects have same features variance scopes, the rule base will be similar and hence our proposed method has a good robustness to images categories. For example, for a stamp and a book images, their shape feature variance is very small for most of them are square; their color features variance is very large. Various colors are possible. Users' perceptions of their features will be close or similar, which makes the fuzzy rules are also similar or close.

5. EXPERIMENTS

5.1 Image Preprocessing

Before experiment, the color images in RGB-space are converted into HSV-space. An image database including 500 images involved in 48 categories are used in our experiment. Their color and shape features are extracted by he methods introduced in section 3 and stored in the database as the retrieval indexes. The experiments include two parts: one is for the AAH and the other for the fuzzy image retrieval.

5.2 Retrieval Performance

There are two principals to evaluate a retrieval system: the precision and the recall measures. Suppose $R(q)$ is the set of images relevant for the query q and $A(q)$ is the set of retrieved images. The precision of the result is the fraction of retrieved images that are truly relevant to the query:

$$P = \frac{|A(q)| \cap |R(q)|}{|A(q)|} \tag{12}$$

While the recall is the fraction of relevant images that are actually retrieved:

$$R = \frac{|A(q)| \cap |R(q)|}{|R(q)|} \tag{13}$$

To verify the efficiency of the AAH, the gray-scaled color space and the HSV color space are selected to perform the retrieval respectively. We adopt Eq. (2) as the distance metric for the gray level images and Eq. (3) for HSV-space images. Fig.8 and Fig.9 show the retrieval performance comparison of the three histograms in the two color spaces respectively. Result shows that our proposed histograms outperform the conventional histogram. The performance improvements come from the correct matching of those images that have similar color distribution as case (B) and (C) illustrated in Fig.2.

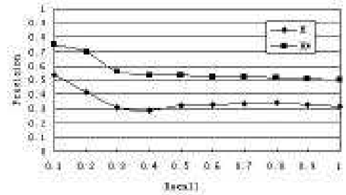

Fig.8 the average recall-precision performance of the two histograms in gray-level space

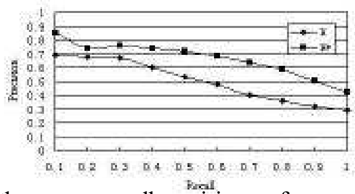

Fig.9 the average recall-precision performance of the two histograms in HSV-space

When retrieve images, user specifies each rules according to the importance of the color and shape feature to the query image as shown in table 1 or 2. Of course, we can also establish a rule base related with certain types of images before retrieval and make use of them in the retrieval time. Figure 10 illustrates the precision-recall of our proposed fuzzy logic-based image retrieval.

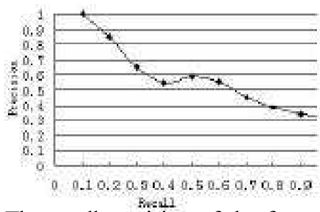

Fig.10 The recall-precision of the fuzzy logic-based image retrieval

The precision and recall verifies the efficiency and feasibility of applying the fuzzy method in the image retrieval. For the images with large appearance variety such as lamp, flower and knap etc., our proposed method has an average precision of above 41% vs. the top 20 images, which means that the fuzzy retrieval method has a good robustness to the image categories.

6. CONCLUSIONS

In this paper, a fuzzy logic-based image retrieval system based on color and shape features is presented. For the fuzzy inference integrates various features perfectly and reflects the user's subjective requirements, the experiments achieve good performance and demonstrate the efficiency and robustness of our scheme. If we apply this method for field-orientated image retrieval so as to embed the users' retrieval requirements into the fuzzy rules, we have reason to believe that the image retrieval performance will be improved.

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