A Multi-layer Data Model for Image Retrieval Based on Fuzzy Features

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Abstract: - Content-based image retrieval is one of the main research directions in information retrieval and digital library. However, the low-level image features used in traditional content-based image systems lack of semantics meanings of users. In this paper, we propose a multi-layer image data model to combine the low-level image features and high-level linguistic meanings. We analyze and represent an image as fuzzy features including fuzzy colors, fuzzy shapes and fuzzy spatial relationships. Then the linguistic fuzzy concept is used to measure the similarity of image features. Through the descriptions of fuzzy linguistic image features, the semantic relevant images can be retrieved. Further, based on the fuzzy features, we also present a new method of relevance feedback to improve the effectiveness of image retrieval.

Key-Words: - Image database, image retrieval, multi-layer, data model, fuzzy feature, similarity matching

1 Introduction

Effective image retrieval is an important technique for many applications. The traditional retrieval method uses text to annotate images and retrieves them by keywords matching. In contrast with the annotation-based method, the content-based image retrieval method usually uses low-level image features to measure the similarity between images. The low-level image features include colors, shapes, and textures, which can be extracted by image processing techniques automatically. Although the content-based retrieval method overcomes part of drawbacks in the annotation-based method, it loses the high-level semantic meaning of images due to the usage of low-level features. That is, the cognitive gap between low-level image features and high-level concept becomes a new problem in content-based image retrieval. The other problem is the subjectivity of human perception. The desirable images of the users depend not only on low-level image features but also on individual requirements of users. For different users, or even the same user under different situations, may perceive different visual content for the same image. However, low-level features can only describe objective characteristics of images. It is still far from the human perception and subjectivity of users.

Many researches on content-based image retrieval have been done in the past years. Some well-known representative systems like QBIC [4][8], Virage [1], and VisualSEEk [13] which are developed to retrieve similar images based on low-level image contents. The extracted contents of images in the above systems include color histogram, color moments, color sets, moment invariants, finite element method, Gabor wavelet transform and spatial positions. In order to overcome the cognitive gap between low-level features and human high-level concepts, further, consider human perception, the relevance feedback mechanism is used to integrate the human factor and low-level features.

In this paper, we develop a multi-layer image data model and adopt the fuzzy concept to develop the fuzzy colors, the fuzzy shapes and the fuzzy spatial relationships. Fuzzy similarity matching algorithms are also designed to evaluate the similarity degrees between the query image and the target image. The process of image retrieval consists of three main stages: The first stage segments images into some significant regions and analyzes the regions by fuzzy features. The second stage matches the region-pairs and measures the similarity between the query image and target images. At last, through the proposed mechanism of relevance feedback, the user can mark the relevant and irrelevant images to retrieve the target images fitting his(her) requirements.

2 The Multi-Layer Image Data Model

The proposed multi-layer image data model is shown in Figure 1. There are five layers in the model: Image feature layer, object feature layer, fuzzy feature layer, linguistic object layer, and high/low mapping layer. We describe each layer in detail in the following.

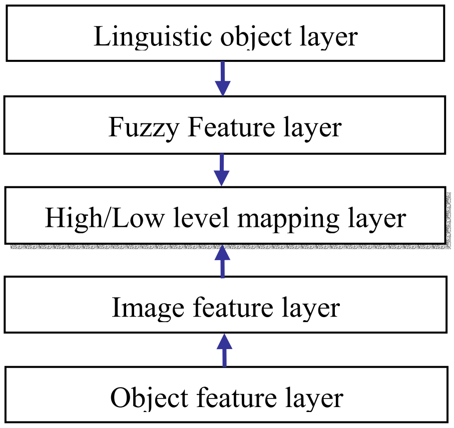

Figure 1: A multi-layer image data model

Image feature layer: This layer describes the basic image low-level features of raw images.
Object feature layer: Raw image data in image layer generally should be processed in advance by segmentation or other image features analysis. After segmentation, we extract regions from images. The significant regions then stand for meaningful objects.
Fuzzy feature layer: This layer defines fuzzy concepts for describing low-level image features including fuzzy colors, fuzzy shapes and fuzzy spatial relationships.
Linguistic object layer: This layer integrates distinct fuzzy features for a significant region and forms a meaningful linguistic object.
High/Low level mapping layer: In this layer, we map the regions with low-level image features to the linguistic objects with fuzzy features. An effective mapping mechanism will be able to describe the high-level meaning of image precisely.

3 Analyses of Image Fuzzy Features

We will proposed the definition of the fuzzy features and propose the mapping mechanism between high and low levels.

3.1 The Fuzzy Colors

The color coordinate system we used for measuring similarity of colors is the HLS. Given a color represented by the RGB color coordinate system, (R, G, B), the values of R, G, and B are all integers in the range of [0, 255] and represent the values of red, green and blue, respectively. We define the relative intensity value (r, g, b) for (R, G, B) as:

$$r = \frac{R}{255}, g = \frac{G}{255}, b = \frac{B}{255}.$$

Let $I_{max} = max\{r, g, b\}$ and $I_{min} = min\{r, g, b\}$. The values of hue(H), lightness(L) and saturation (S) can be transformed from the values of R, G and B by the following formulas:

$$H = \begin{cases} 60*(\frac{g-b}{I_{\max} - I_{\min}}) & \text{if } r = I_{\max} \\ 60*(2 + \frac{b-r}{I_{\max} - I_{\min}}) & \text{if } g = I_{\max} \\ 60*(4 + \frac{r-g}{I_{\max} - I_{\min}}) & \text{if } b = I_{\max} \\ \text{undefine} & \text{if } I_{\max} = I_{\min} \end{cases} \quad (1)$$

$$H = H + 360 \quad \text{if } H < 0 \quad (2)$$

$$L = \frac{I_{\max} + I_{\min}}{2} \quad (3)$$

$$S = \begin{cases} 0 & \text{if } I_{\max} = I_{\min} \\ \frac{I_{\max} - I_{\min}}{I_{\max} + I_{\min}} \cdot L & \text{if } L \le 0.5 \\ \frac{I_{\max} - I_{\min}}{2 - I_{\max} - I_{\min}} \cdot L & \text{otherwise.} \end{cases} \quad (4)$$

Kawamura *et al.* [5] utilized color attributes hue and tone to design a fuzzy based approach for color specification. Sugano [14] made use of color attributes including hue and tone to design expression model of subjective color impressions. The usage of color attributes hue and tone to reflect human's subjectivity is easier than the RGB color space system. Hence, we define fuzzy colors based on the combination of hue and tone to construct fuzzy colors for achieving human visual perception.

A fuzzy set A can be defined by a membership function as:

$$\mu_A : X \rightarrow [0,1]$$

where [0, 1] denotes the interval of real numbers from 0 to 1. The function can also be generalized to any real interval instead of [0,1].

We define the fuzzy set of hue, fuzzy set of lightness, and fuzzy set of saturation. Then we use the fuzzy set of hue, fuzzy set of lightness, and fuzzy set of saturation to construct the set of hierarchical fuzzy colors. Fuzzy colors are composed by fuzzy set of hue and fuzzy set of tone. We combine fuzzy set of lightness and fuzzy set of saturation into the fuzzy set of tone. After that, the fuzzy set of hue is combined with the fuzzy set of tone to construct fuzzy colors.

3.1.1 The Fuzzy Set of Hue

Let $\mathbf{H}=\{H_i \mid i=1, 2, \ldots, h\}$ be the set of hue obtained by feature clustering in Section 3. For a hue H the fuzzy set of hue $\widetilde{H}$ is represented as

$$\widetilde{H}=(\mu_{H_1}(x)/H_1+\mu_{H_2}(x)/H_2+\ldots+\mu_{H_h}(x)/H_h) \\ =\sum_{i=1}^{h}\mu_{H_i}(x)/H_i\ , \tag{5}$$

where x is the value of the hue H defined in equations (1) and (2).

3.1.2 The Fuzzy Set of Tone

Since tone is constructed by lightness and saturation, we first define the fuzzy sets of lightness and saturation and then combine the two fuzzy sets to be the fuzzy set of tone.

Let $\mathbf{L}=\{L_i \mid i=1, 2, \ldots, l\}$ be the set of lightness obtained by feature clustering in Section 3. For a lightness L, the fuzzy set of $\widetilde{L}$ is represented as

$$\widetilde{L}=(\mu_{L_1}(y)/L_1+\mu_{L_2}(y)/L_2+\ldots+\mu_{L_l}(y)/H_l) \\ =\sum_{i=1}^{l}\mu_{L_i}(y)/L_i\ , \tag{6}$$

where y is the value of the lightness L defined in equation (3).

Let $\mathbf{S}=\{S_i \mid i=1, 2, \ldots, s\}$ be the set of saturation obtained by feature clustering. For a saturation S, the fuzzy set $\widetilde{S}$ is represented as

$$\widetilde{S}=(\mu_{S_1}(z)/S_1+\mu_{S_2}(z)/S_2+\ldots+\mu_{S_s}(z)/S_s) \\ =\sum_{i=1}^{s}\mu_{S_i}(z)/S_i\ , \tag{7}$$

where z is the value of the saturation S defined in equation (4).

After the fuzzy sets of lightness and saturation are defined, we use the two fuzzy sets to compose the fuzzy set of tone. Let T_{ij} be the region composed by L_i and S_j inside the tone plane. The fuzzy set of tone $\widetilde{T}$ is represented as

$$\widetilde{T}=\sum_{i=1}^{l}\sum_{j=1}^{s}\mu_{T_{ij}}(y,z)/T_{ij}\ . \tag{8}$$

We further define the membership functions for the fuzzy set of tone as the product of the membership grade of lightness and the membership grade of saturation, as follow:

$$\mu_{T_{ij}}(y,z)=\mu_{L_i}(y)\cdot\mu_{S_j}(z)\,, \tag{9}$$

where y and z are the values of lightness and saturation obtained in equations (3) and (4), respectively. μ_{L_i} and μ_{S_j} are the membership functions of lightness L_i and saturation S_j, respectively.

3.1.3 Construction of Fuzzy Colors

A fuzzy color is constructed by a element of fuzzy set hue and a element of fuzzy set tone. Assume that there are h elements of fuzzy set hue and t elements of fuzzy set tone. Let $C=\{C_{ij} \mid 1 \le i \le h \text{ and } 1 \le j \le t\}$ be the set of fuzzy colors constructed by the h hues and t tones. The fuzzy set of fuzzy color

$$\widetilde{C}=\sum_{i=1}^{h}\sum_{j=1}^{t}\mu_{C_{ij}}(x,y,z)/C_{ij}\ , \tag{10}$$

where x is defined in equation (1) and (2), y and z are defined in equation (3) and (4), respectively.

The membership degree for the fuzzy color are defined as follow

$$\mu_{C_{ij}}(x,y,z)=\mu_{H_i}(x)\cdot\mu_{T_j}(y,z)\,, \tag{11}$$

where μ_{H_i} is the membership function of hue H_i and μ_{T_j} is defined in equation (9).

3.1.4 Similarity Measure of Fuzzy Colors

We designed a fuzzy similarity measure to evaluate the similarity between two fuzzy colors. The fuzzy similarity measure is based on the membership grades of fuzzy colors. For two given specified colors $Color_1 = (R_1, G_1, B_1)$ and $Color_2 = (R_2, G_2, B_2)$, the corresponding values in HLS space are $C_1 = (h_1, l_1, s_1)$ and $C_2 = (h_2, l_2, s_2)$, respectively. From equations (19) the fuzzy color $\widetilde{C}_1$ of color C_1 and $\widetilde{C}_2$ of color C_2 are

$$\widetilde{C}_1=\sum_{i}^{h}\sum_{j}^{t}\mu_{C_{ij}}(h_1,l_1,s_1)/C_{ij}\ ,$$
$$\widetilde{C}_2=\sum_{i}^{h}\sum_{j}^{t}\mu_{C_{ij}}(h_2,l_2,s_2)/C_{ij}\ .$$

Then, the fuzzy similarity measure is defined as follows

$$Sim(\widetilde{C}_1,\widetilde{C}_2)=\frac{\sum_{i=1}^{h}\sum_{j=1}^{t}\min(\mu_{C_{ij}}(h_1,l_1,s_1),\mu_{C_{ij}}(h_2,l_2,s_2))}{\sum_{i=1}^{h}\sum_{j=1}^{t}\max(\mu_{C_{ij}}(h_1,l_1,s_1),\mu_{C_{ij}}(h_2,l_2,s_2))} \quad (12)$$

The value of $Sim(\widetilde{C}_1,\widetilde{C}_2)$ is in the range of [0, 1].

3.2 The Fuzzy Shapes

The invariant moment proposed by Hu [5], is one of the important shape features of image objects. The invariant moment of one image object will not be changed via rotating or scaling transformation. Let the size of an image f is $M\times N$ and $f(x, y)$ is the color value of pixel at position (x, y). Then, the moment m_{pq} of pth order in x-axis direction and the qth order in y-axis direction is:

$$m_{pq}=\sum_{x=0}^{M}\sum_{y=0}^{N}x^p y^q f(x,y)\,. \quad (13)$$

If the central coordinate is $(\hat{x},\hat{y})$, then the normalized central moment η_{pq} becomes:

$$\eta_{pq}=\frac{\sum_{x=0}^{M}\sum_{y=0}^{N}(x-\hat{x})^p(y-\hat{y})^q f(x,y)}{\left[\sum_{x=0}^{M}\sum_{y=0}^{N}f(x,y)\right]^{[(p+q)/2+1]}}\,. \quad (14)$$

We use the seven invariant moments to describe the shape feature of an object. The definitions of seven invariant moments are as follows:

$$\phi_1=\eta_{20}+\eta_{02}\,,$$
$$\phi_2=(\eta_{20}-\eta_{02})^2+4\eta_{11}^2\,,$$
$$\phi_3=(\eta_{30}-3\eta_{12})^2+(3\eta_{21}-\eta_{32})^2\,,$$
$$\phi_4=(\eta_{30}+\eta_{12})^2+(\eta_{21}+\eta_{32})^2\,,$$
$$\phi_5=(\eta_{30}-3\eta_{12})(\eta_{30}+\eta_{12})[(\eta_{30}+\eta_{12})^2-3(\eta_{21}+\eta_{03})^2]$$
$$+(3\eta_{21}-\eta_{03})(\eta_{21}-\eta_{03})[3(\eta_{30}+\eta_{12})^2-(\eta_{21}+\eta_{03})^2],$$
$$\phi_6=(\eta_{20}+\eta_{02})[(\eta_{30}+\eta_{12})^2-(\eta_{21}+\eta_{03})^2]+$$
$$4\eta_{11}^2(\eta_{30}+\eta_{12})(\eta_{21}+\eta_{03})^2],$$
$$\phi_7=(\eta_{21}-3\eta_{03})(\eta_{30}+\eta_{12})[(\eta_{30}+\eta_{12})^2-3(\eta_{21}+\eta_{03})^2]+$$
$$(\eta_{30}-3\eta_{21})(\eta_{21}+\eta_{03})[3(\eta_{30}+\eta_{12})^2-(\eta_{21}+\eta_{03})^2].$$

3.2.1 Construction of Fuzzy Shapes

Let $\mathbf{P}=\{P_1, P_2, \ldots, P_k\}$ be k fuzzy shapes. We define each fuzzy shape seven invariant moments as a vector, then the magnitude of each vector are define as:

$$D_i=\sqrt{\phi_{i1}{}^2+\phi_{i2}{}^2+\ldots+\phi_{i7}{}^2}\,. \quad (15)$$

where D_i is the magnitude of moments vector of i-th fuzzy shape.

3.2.2 Similarity Measure of Fuzzy Shapes

Let $O=\{\phi_{O1}, \phi_{O2}, \ldots, \phi_{O7}\}$ be a given seven invariant moments of shape O_i. The membership function that shape belongs to different defined fuzzy shapes is

$$\mu_{P_i}(O)=\begin{cases}1-\dfrac{d_i}{D_i} & \text{if } d_i<D_i;\\ 0 & \text{else,}\end{cases} \quad (16)$$

where

$$d_i=\sqrt{(\phi_{i1}-\phi_{O1})^2+(\phi_{i2}-\phi_{O2})^2+\ldots+(\phi_{i7}-\phi_{O7})^2}\,,$$

and i=1, … k.

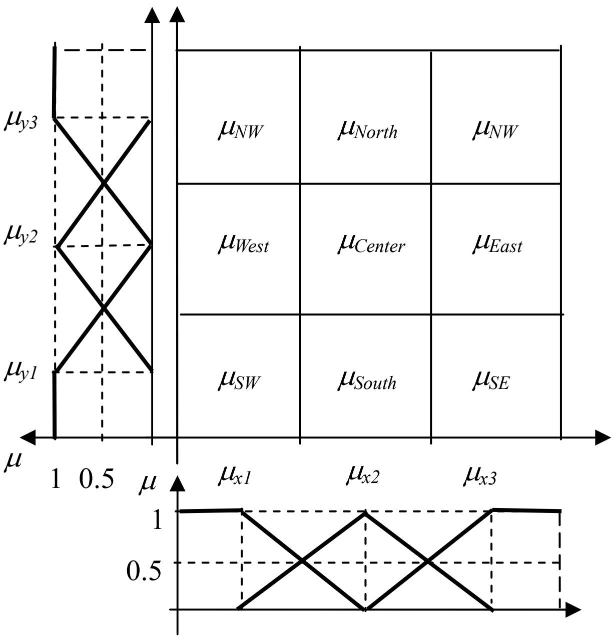

Figure 2: The fuzzy spatial relationships

3.3 The Fuzzy Spatial Relationships

We define membership function of nine relative fuzzy spatial relationships as Figure 2. For a given object O_i the nine membership degrees is defined as follows:

$$\mu_{SW}(O_i) = \min\{\mu_{x1}(O_i), \mu_{y1}(O_i)\},$$
$$\mu_{West}(O_i) = \min\{\mu_{x1}(O_i), \mu_{y2}(O_i)\},$$
$$\mu_{NW}(O_i) = \min\{\mu_{x1}(O_i), \mu_{y3}(O_i)\},$$
$$\mu_{South}(O_i) = \min\{\mu_{x2}(O_i), \mu_{y1}(O_i)\},$$
$$\mu_{Center}(O_i) = \min\{\mu_{x2}(O_i), \mu_{y2}(O_i)\},$$
$$\mu_{North}(O_i) = \min\{\mu_{x2}(O_i), \mu_{y3}(O_i)\},$$
$$\mu_{SE}(O_i) = \min\{\mu_{x3}(O_i), \mu_{y1}(O_i)\},$$
$$\mu_{East}(O_i) = \min\{\mu_{x3}(O_i), \mu_{y2}(O_i)\},$$
$$\mu_{NE}(O_i) = \min\{\mu_{x3}(O_i), \mu_{y3}(O_i)\}.$$

4 The Similarity Matching Algorithms

In this section we will propose fuzzy image matching algorithms to evaluate the fuzzy match degrees of images. There are three main stages. In the first stage, we segments images into some significant regions and analyzes the regions by fuzzy features using the method in [3]. The second stage matches the object-pairs and measures the similarity between the query image and target images. We will propose a region-pairs matching algorithm and a similar image matching algorithm. At last, we proposed a mechanism of relevance feedback based on fuzzy features. The proposed algorithm is thus suitable for images with uncertain objects and satisfies users' linguistic requirements.

We also develop the fuzzy similarity measure for different image features. The fuzzy color similarity measure *SimColor* between two objects is defined as

$$SimColor(O_i, O_j) = \frac{\sum_{i=1}^{12} \min\{\mu_{Ci}(O_i), \mu_{Ci}(O_j)\}}{\sum_{i=1}^{12} \max\{\mu_{Ci}(O_i), \mu_{Ci}(O_j)\}}. \quad (17)$$

Then, we defined fuzzy shape similarity measure *SimShape* between two objects as

$$SimShape(O_i, O_j) = \frac{\sum_{l=1}^{k} \min\{\mu_{p_l}(O_i), \mu_{p_l}(O_j)\}}{\sum_{l=1}^{k} \max\{\mu_{p_l}(O_i), \mu_{p_l}(O_j)\}}. \quad (18)$$

Let $\mathbf{SP}_i = \{\mu_{SW}(O_i), \mu_{south}(O_i), \dots, \mu_{NE}(O_i)\}$
and $\mathbf{SP_j} = \{\mu_{SW}(O_j), \mu_{south}(O_j), \dots, \mu_{NE}(O_j)\}$.
The fuzzy spatial relationship similarity measure *SimSpatial* between two objects is defined as

$$SimSpatial(O_i, O_j) = \frac{\sum_{\mu_i \in SP_i, \mu_j \in SP_j} \min\{\mu_i(O_i), \mu_j(O_j)\}}{\sum_{\mu_i \in SP_i, \mu_j \in SP_j} \max\{\mu_i(O_i), \mu_j(O_j)\}}. \quad (19)$$

The object-pairs matching algorithm and the image similarity matching algorithm are described as follows.

Algorithm: object-pairs matching algorithm
Input: the object sets of image *Q* and *D*.
Output: a set of matched object-pairs.
{
  for *i* = 1 to *m*
  for *j* = 1 to *n*
    Compute *SimColor*(O_i^Q, O_j^D)
    Compute *SimShape*(O_i^Q, O_j^D)
    $R_i[j] = \min\{ SimColor(O_i^Q, O_j^D),$
      $SimShape(O_i^Q, O_j^D)\}$
    $R_i[a] = \max_{1 \le j \le n}\{R_i[j]\}$
    Match object O_i^Q of query image *Q* to object O_a^D of database image *D*.
}

Algorithm: Image similarity matching algorithm
Input: The matched object-pairs
  $\{(O_1^Q, O_1^D), (O_2^Q, O_2^D), \dots, (O_m^Q, O_m^D)\}$.
Output: *Sim*(*Q*, *D*), the similar degree of *Q* and *D*.
{
  for *i*=1 to *m*
    Compute *SimColor*(O_i^Q, O_i^D)
    Compute *SimShape*(O_i^Q, O_i^D)
    Compute *SimSpatial*(O_i^Q, O_i^D)
    $R[i] = \min\{SimColor(O_i^Q, O_i^D),$
      $SimShape(O_i^Q, O_i^D),$
      $SimSpatial(O_i^Q, O_i^D)\}$
    $Sim(Q, D) = \max_{1 \le i \le m} R[i]$
}

After the matching objects in images and measure the similarity of images, the similar images can be retrieved from the image database and ranked by their degrees of similarity. For further matching the user's semantic requirements, we propose the following relevance feedback method to improve the ranking of retrieving results.

Algorithm: fuzzy relevance feedback algorithm.
Input: a set of relevance images O_j and a set of non-relevance images N_j
Output: similarity degree between images P and Q.

{
for $i = 1$ to m
$R_1[i] = Sim(P, Q_i)$
for $j = 1$ to n
$R_2[j] = 1 - Sim(P, N_j)$
$Sim_1 = Sim(Q, P)$
$Sim_2 = \min_{1 \le i \le m} R_1[i]$
$Sim_3 = \min_{1 \le j \le n} R_2[j]$
$Sim(Q, P) = \max\{Sim_1, Sim_2, Sim_3\}$
}

5 Conclusions

Content-based image retrieval is one of the important techniques for retrieving multimedia data. It is difficult for researchers to create the so-called fully automatic image retrieval to capture human perception. In this paper, we proposed a multi-layer image retrieval data model. We also develop the corresponding mapping method to implement each layer using fuzzy features. In query processing, we use fuzzy-based matching method to retrieve similar images from image databases. We also build the system and make experiments to show that the proposed approach is effective and efficient. For the high-level concept, combining proper ontology to improve the model is direction of our future work. Also, extending the model to video data such as MPEG-7 standard should be natural and expected.

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