CBIR USING COLOR HISTOGRAM PROCESSING

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ABSTRACT

Advances in data storage and image acquisition technologies have enabled the creation of large image datasets. In this scenario, it is necessary to develop appropriate information systems to efficiently manage these collections. The most common approaches use Content-Based Image Retrieval (CBIR). The goal of CBIR systems is to support image retrieval based on *content* e.g., shape, color, texture. In this paper color extraction and comparison were performed using the three color histograms, conventional color histogram (CCH), invariant color histogram (ICH) and fuzzy color histogram (FCH) .The conventional color histogram (CCH) of an image indicates the frequency of occurrence of every color in an image. The appealing aspect of the CCH is its simplicity and ease of computation. There are however, several difficulties associated with the CCH. The first of these is the high dimensionality of the CCH, even after drastic quantization of the color space. Another downside of the CCH is that it does not take into consideration color similarity across different bins and cannot handle rotation and translation. To address the problem of rotation and translation an invariant color histograms(ICH) based on the color gradients is used and to address the problem of spatial relationship fuzzy linking color histogram (FCH) is used.

Keywords: *conventional color histogram, invariant color histogram, fuzzy linking color histogram*

1. INTRODUCTION

Content-based image retrieval plays a central role in the application areas such as multimedia database systems in recent years. The work focused on using low-level features like color, texture, shape and spatial layout for image representation[1]. Among all the visual features, color is perhaps the most distinguishing one in many applications. It may be represented by a color histogram [2], color moments [3], color correlogram [4].

The conventional color histogram (CCH) of an image indicates the frequency of occurrence of every color in an image. The appealing aspect of the CCH is its simplicity and ease of computation. There are however, several difficulties associated with the CCH. The first of these is the high dimensionality of the CCH, even after drastic quantization of the color space. Another downside of the CCH is that it does not take into consideration color similarity across different bins and cannot handle rotation and translation.

To address the problem of rotation and translation an invariant color histograms based on the color gradients[5] is used and to address the problem of spatial relationship *fuzzy color histogram* (FCH)[6,7] is used, by considering the color similarity of each pixel's color associated to all the histogram bins through fuzzy-set membership function. In comparison with the conventional color histogram (CCH), which assigns each pixel into one of the bins only, FCH spreads each pixel's total membership value to all the histogram bins.

2. PRINCIPLE OF CBIR

Content-based image retrieval, also known as query by image content and content-based visual information retrieval is the application of computer vision to the image retrieval problem, that is, the problem of searching for digital images in large databases. Content-based means that the search makes use of the contents of the images themselves, rather than relying on human-input metadata such as captions or keywords. A *content-based image retrieval system* (CBIR) is a piece of software that implements CBIR.

In CBIR each image that is stored in the database has its features extracted and compared to the features of the query image. It involves two steps.

- **Feature Extraction:**
  The first step in this process is to extract the image features to a distinguishable extent.
- **Matching:**
  The second step involves matching these features to yield a result that is visually similar.

2.1. Block Diagram

Basic idea behind CBIR is that, when building an image database, feature vectors from images (the features can be color, shape, texture, region or spatial features, features in some compressed domain, etc.) are to be extracted and then store the vectors in another database for future use. When given a query image its feature vectors are computed. If the distance between feature vectors of the query image and image in the database is small enough, the corresponding image in the database is to be considered as a match to the query. The search is usually based on similarity rather than on exact match and the retrieval results are then ranked accordingly to a similarity index.

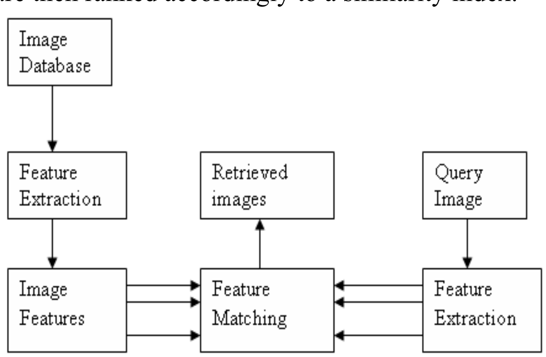


Fig.1 Block Diagram of CBIR

3. FEATURE EXTRACTION

3.1. Conventional Color Histogram

The approach more frequently adopted for CBIR systems is based on the conventional color histogram (CCH), which contains occurrences of each color obtained counting all image pixels having that color. Each pixel is associated to a specific histogram bin only on the basis of its own color, and color similarity across different bins or color dissimilarity in the same bin are not taken into account.

Since any pixel in the image can be described by three components in a certain colour space(for instance, red, green and blue components in RGB space or hue, saturation and value in HSV space), a histogram, i.e., the distribution of the number of pixels for each quantized bin, can be defined for each component. Clearly, the more bins a color histogram contains the more discrimination power it has. However, a histogram with large number of bins will not only increase the computational cost, but will also be in appropriate for building efficient indexes for image data base.

Quantization in terms of color histograms refers to the process of reducing the number of bins by taking colors that are very similar to each other and putting them in the same bin. By default the maximum number of bins one can obtain using the histogram function in MatLab is 256. For the purpose of saving time when trying to compare color histograms, one can quantize the number of bins. Obviously quantization reduces the information regarding the content of images but as was mentioned this is the tradeoff when one wants to reduce processing time.

The conventional color histogram (CCH) of an image indicates the frequency of occurrence of every color in an image. The appealing aspect of the CCH is its simplicity and ease of computation. There are however, several difficulties associated with the CCH viz .,a) CCH is sensitive to noisy interferences such as illumination changes and quantization errors; b) large dimension of CCH involves large computation on indexing, c)It does not take into consideration color similarity across different bins and cannot handle rotation and translation. To address the problem of rotation and translation an invariant color histograms based on the color gradients is used and to address the problem of spatial relationship fuzzy color histogram (FCH) is used.

3.2. Invariant Color Histogram

Color histograms have been widely used for object recognition. Though in practice these histograms often vary slowly under changes in viewpoint, it is clear that the color histogram generated from an image surface is intimately tied up with the geometry of that surface, and the viewing position. A method is developed to create color histogram based on the color gradients and it is invariant under any mapping of the surface which

Vol6. No1. (pp 116 - 122)

is *locally* affine, and thus a very wide class of viewpoint changes or deformations[5].

3.2.1. local affine approximations

Given two corresponding points in two images, one can change coordinate systems such that both points lie at the origin in their respective systems. Assuming that the transformation between the two images is continuous, it is locally linear. Note that this is a weak assumption, satisfied by transformations such as homographies, changes in viewpoint or smooth deformations. Thus, for *infinitesimal* **x** the local affine transformation as

$$X = HX'$$

Where

$$H = \begin{bmatrix} A & B \\ C & D \end{bmatrix}$$

Here, **x'** and **x** are the points in the first and second coordinate systems, respectively.

3.2.2. differential area from gradients

By definition, the differential area in the first coordinate system is

$$da' = dx'dy'$$

Then find the corresponding area in the second coordinate system.

$$da = \left|\frac{\partial X}{\partial x'} \times \frac{\partial X}{\partial y'}\right| = |AD - BC|\ dx'dy'$$

3.2.3. invariant color histograms

Denote the image intensity function in one color channel by

$$f(x, y) = f'(x', y')$$

Using standard calculus, we can relate the image derivatives.

$$\frac{\partial f'}{\partial x'} = \frac{\partial f}{\partial x}\frac{\partial x}{\partial x'} + \frac{\partial f}{\partial y}\frac{\partial y}{\partial x'}$$

$$\frac{\partial f'}{\partial y'} = \frac{\partial f}{\partial x}\frac{\partial x}{\partial y'} + \frac{\partial f}{\partial y}\frac{\partial y}{\partial y'}$$

$$f_x' = f_x A + f_y C$$
$$f_y' = f_x B + f_y D$$

Denoting the image intensity function in a second Color by g. The derivatives will obey the same constraints as above.

$$g'_x = g_x A + g_y C$$
$$g'_y = g_x B + g_y D$$

Now, given all derivatives, it is possible to solve for each of *A*, *B*, *C*, and *D*.

$$A = \frac{f_y g_x' - g_y f_x'}{f_x g_y - g_x f_y},\quad B = \frac{f_y g_y' - g_y f_y'}{f_x g_y - g_x f_y}$$

$$C = \frac{f_c g_x' - g_c f_x'}{f_x g_y - g_x f_y},\quad D = \frac{f_c g_y' - g_c f_y'}{f_x g_y - g_x f_y}$$

Hence

$$\frac{da}{da'} = |AD - CB| = \frac{f_x' g_y' - f_y' g_x'}{f_x g_y - f_y g_x}$$

We can now see a direct relationship between the color derivatives, and the differential areas.

$$da\left|f_x g_y - f_y g_x\right| = da'\left|f_x' g_y' - f_y' g_x'\right|$$

This is the key relationship that is used to construct invariant color histograms. If integrals over the areas in both images with a given color are taken, these integrals will be equal, and so no correspondence is required. If the color of pixel **x** is some integer xc, then,

$$\int_{X:x_c=c} \left|f_x(X)g_y(X) - f_y(X)g_x(X)\right| da = \int_{X':x'_c=c} \left|f'_x(X')g'_y(X') - f'_y(X')g'_x(X')\right| da'$$

Intuitively, the contribution in the integral in the above equation will be largest when there are significant gradient magnitudes in both color channels, and these gradients are in different directions.

Vol6. No1. (pp 116 - 122)

3.2.4. Algorithm

Using the above equations a simple algorithm to create deformation invariant color histograms. In this histogram the influence of each pixel is weighted by a function of the derivatives.

$$h_c = \sum_{s:s_c=c} w(s)$$

$$w(s) = \left| f_x(s)g_y(s) - f_y(s)g_x(s) \right|$$

5 color bins in each of the three color channels are used, resulting in a total of 125 bins. Using such a coarse sampling of the color space is principally for display purposes. In our experiments, it was possible to accurately recover histograms with many more colors. This method requires derivatives in two color channels, *f* and *g*. Here, red is used for one channel, and the average of green and blue for the other. Derivatives are taken in the simplest possible way, through convolution with the filters.

$$\begin{bmatrix} -1 & 0 & 1 \end{bmatrix} \quad \text{and} \quad \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix}$$

3.3. Fuzzy Color Histogram

The classic histogram is a global statistical feature, which describes the intensity distribution for a given image. Its main advantage is that it is fast to manipulate, store and compare and insensitive to rotation and scale. On the other hand, it is also quite unreliable as it is sensitive to even small changes in the scene of the image. In color image processing, the histogram consists of three components, respect to the three components of the color space.

A histogram is created by dividing a color space into a number of bins and then by counting the number of pixels of the image that belong to each bin. It is usually thought that in order for an image retrieval system to perform satisfyingly, the number of regions that the color space is divided into is quite large and thus the colors represented by neighboring regions have relatively small differences. As a result, the perceptually similar colors problem appears, images which are similar to each other but have small differences in scene or contain noise will produce histograms with dissimilar adjacent bins and vice versa due to the small distance that the regions are separated from each other.

In order to present a solution to this problem , the FCH uses a small number of bins produced by linking the triplet from the L*a*b* color space into a single histogram by means of a fuzzy expert system[7]. The a* and b* components are considered to have more weight than L* as it is mostly the combination of the two which provides the color information of an image. One of the reasons why the L*a*b* color space was selected is that it is a perceptually uniform color space which approximates the way that humans perceive color.

In L*a*b*, L* stands for luminance, a* represents relative greenness-redness and b* represents relative blueness-yellowness. All colors and grey levels can be expressed throughout a combination of the three components. However, L* does not contribute in providing any unique color but for shades of colors, white, black and grey. Thus, the L* component receives a lower weight with respect to the other two components of the triplet. According to the work mentioned in [7] ,in order for the CBIR system to work effectively the a* and b* components should be subdivided into five regions representing green, greenish, the middle of the component, reddish and red for a*, blue, bluish, the middle of the component, yellowish and yellow for b*, whereas L* should be subdivided into only three regions: dark dim and bright areas. The fuzzification of the input is accomplished by using triangular shaped built-in membership functions (MF) for the three input components (L*, a*, b*) as shown in fig .2.

The Mamdani type of fuzzy inference is used in which the fuzzy sets from the output MFs of each rule are combined through the aggregation operator which is set to max and the resulting fuzzy set is defuzzified to produce the output of the system. The implication factor which determines the process of shaping the fuzzy set in the output MFs based on the results of the input MFs is set to min and the OR and AND operators are set to max and min, respectively.

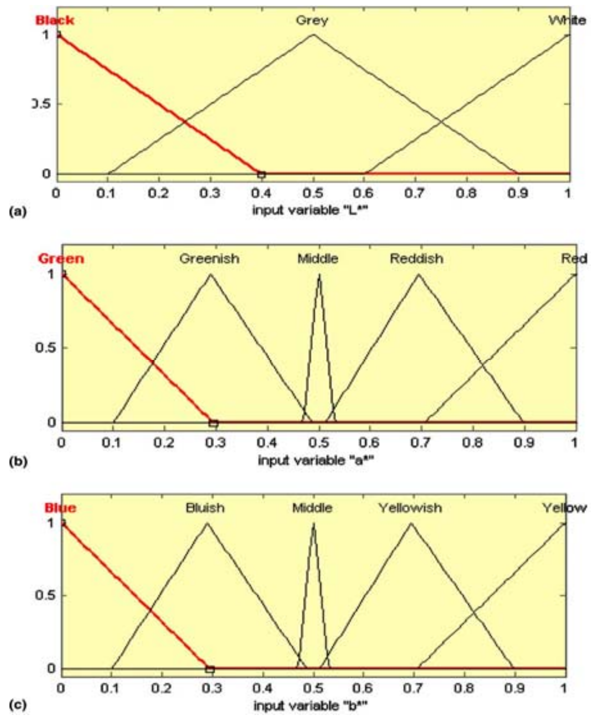


Fig.2 Membership functions of L*, a* and b*.

The output of the system has only 10 equally divided MFs. So, the final fuzzy histogram consists of only 10 bins approximately representing black, dark grey, red, brown, yellow, green, blue, cyan, magenta and white as shown in fig.3.

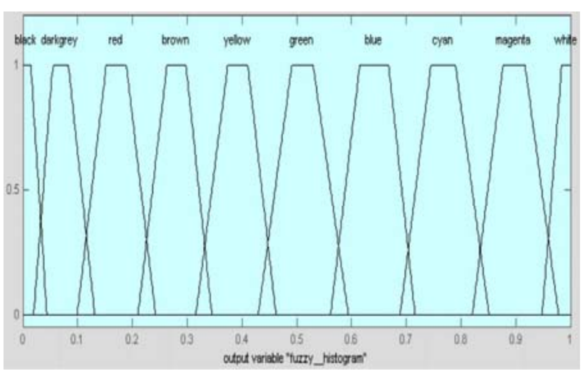


Fig.3 Membership functions of the output of the fuzzy system

The defuzzification phase is performed using the lom (largest of maximum). The fuzzy linking of the three components is made according to 27 fuzzy rules which leads to the output of the system[7].

4. FEATURE MATCHING

4.1. Similarity Measure For FCH and CCH:

Content-based image retrieval calculates visual similarities between a query image and images in a database. Accordingly, the retrieval result is not a single image but a list of images ranked by their similarities. The result is not a single image, but a list of images that have been developed for image retrieval based on empirical estimates of the distribution of features in recent years. Different *similarity/distance measures* will affect retrieval performances of an image retrieval system significantly.

4.1.1. minkowski– form distance:

If each dimension or image features vector is independent of each other and is of equal importance, the *Minkowski – form distance Lp* is appropriate for calculating the distance between two images., Let $D(I, J)$ be the distance measure between the query image I and the image J in the database; and $fi(I)$ as the number of pixels in bin i of I .This distance is defined as:

$$D(I,J) = \left(\sum |f_i(I) - f_i(J)|^p\right)^{1/p}$$

When p=1, 2 and ∞, D(I, J) is the L1, L2 (also called Euclidean distance) and L∞ distance respectively. Minkowski-form distance is the mot widely used metric for image retrieval. Euclidean Distance measure is used in FCH.

4.1.2. quadratic Form (QF) distance:

The Minkowski distance treats all bins of the feature histogram entirely independently and does not account for the fact that certain pairs of bins correspond to features which are perceptually more similar than other pairs. To solve this problem, *quadratic form distance* is introduced:

$$D(I,J) = \sqrt{(F_I - F_J)^T A (F_I - F_J)}$$

Where A = [a_{ij}] is a similarity matrix, and a_{ij} denotes the similarity between bin i and j
FI and **FJ** are vectors that list all the entries in *fi* (I) and *fi* (J).

Quadratic form distance has been used in many retrieval systems for color histogram-based image retrieval. It has been shown that quadratic form distance can lead to perceptually more desirable results than Euclidean distance and histogram intersection method as it considers the cross similarity between colors.

Vol6. No1. (pp 116 - 122)

A simple distance metric involving the subtraction of the number of pixels in the 1st bin of one histogram from the 1st bin of another histogram and so on is not adequate. This metric is referred to as a *Minkowski-Form Distance Metric*, shown below, which only compares the same bins between color histograms.

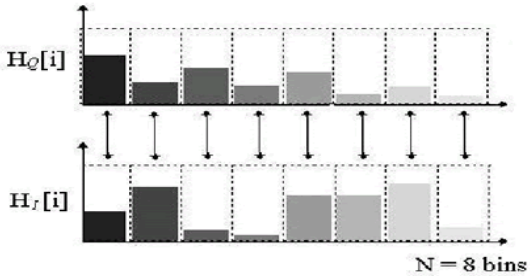


Figure 4 : Minkowski Distance Approach

This is the main reason for using the quadratic distance metric. More precisely it is the middle term of the equation or similarity matrix ***A*** that helps us overcome the problem of different color maps. The similarity matrix is obtained through a complex algorithm:

$$a_{q,i} = 1 - \frac{\left[\left(v_q - v_i\right)^2 + \left(s_q \cos\left(h_q\right) - s_i \cos\left(h_i\right)\right)^2 + \left(s_q \sin\left(h_q\right) - s_i \sin\left(h_i\right)\right)^2\right]^{\frac{1}{2}}}{\sqrt{5}}$$

which basically compares one color bin of H_Q with all those of H_I to try and find out which color bin is the most similar, as shown below:

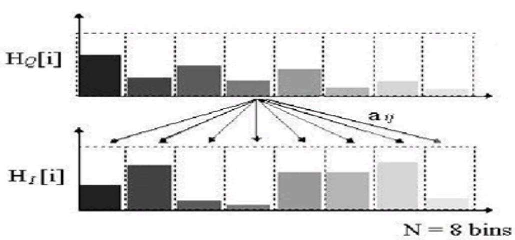


Figure 5: Quadratic Distance Approach

This is continued until we have compared all the color bins of H_Q. In doing so we get an ***N* x *N*** matrix, ***N*** representing the number of bins. What indicates whether the color patterns of two histograms are similar is the diagonal of the matrix, shown below. If the diagonal entirely consists of ones then the color patterns are identical. The further the numbers in the diagonal are from one, the less similar the color patterns are. Thus the problem of comparing totally unrelated bins is solved. This distance measure is used in CCH.

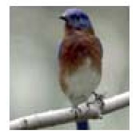
5 . RESULTS

5.1. Database

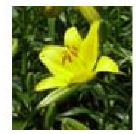

flower3.bmp

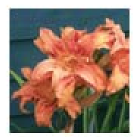

tiger1.bmp


bird3.bmp

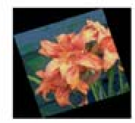

bird1.bmp

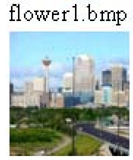

tiger2.bmp

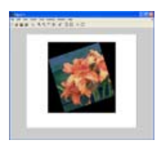

flower2.bmp


flower1.bmp


building1.bmp


orinent.bmp


Building3.bmp



Query
Fig. 5(a)

5.2 Retrieved Images

with CCH **with ICH**

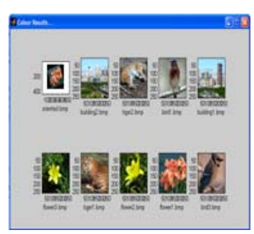


Fig.5(b)

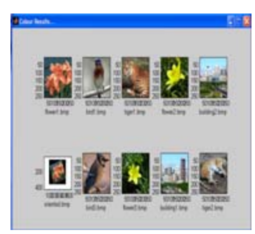


Fig.5(c)

Vol6. No1. (pp 116 - 122)

Retrieved Images with FCH

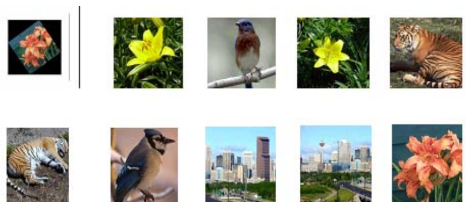


Fig.5(d)

6. CONCLUSION

The conventional color histogram with quadratic form (QF) distance as similarity measure and the fuzzy color histogram with Euclidean Distance almost similar in their performance. But they couldn't respond well to shifted or translated images.

In order to overcome this problem invariant color histogram technique is used makes which use of gradients in different channels that weight that weight the influence of a pixel on the histogram to cancel out the changes induced by deformations. When a rotated image is given as the query, the original image is retrieved as the closest match as shown in the results.

To reduce the large variations between neighboring bins of conventional color histograms, fuzzy color histograms are adopted which consists of only ten bins. It is less sensitive to various changes in the images such lightning variations and noise.

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