Abstract— Content-Based Image Retrieval (CBIR) Systems are becoming increasingly important and finding application in diverse areas of discipline. Due to disturbing factors present in images, e.g. non-uniform illumination and lightening intensities, the retrieval results are not always satisfactory. In this paper, we discuss how fuzzy set theory can be used to formulate an efficient image signature. This signature is 1-D Fuzzy Color Histogram (FCH) consisting of a small number of bins. The signature is obtained from image contents by considering the contribution of each pixel's color to all the histogram bins through the use of fuzzy-sets membership functions. Experimental results on a database of over 10,000 images demonstrate that the proposed system is less sensitive to light intensity changes and more robust than the Conventional Color Histogram (CCH) in retrieval precision.


1. INTRODUCTION

The continually increasing demand for multimedia storage and retrieval has led to the need of fast image retrieval systems. Content-based Image Retrieval (CBIR) system is a search engine for retrieving desired images from a large collection on the basis of features (such as color, texture, and shape) that can be automatically extracted from the images themselves. The features used for retrieval can be either primitive or semantic, but the extraction process must be automatic to avoid user subjectivity. CBIR systems are used in medical imagery, satellite image, graphics, digital library, government documents, and trademarks [1].

Every CBIR system consists of three stages; Image pre-processing, features extraction and similarity measure. The first stage is needed for image segmentation, de-noising normalization or conversion of image into a different color space. The second stage is features extraction, where the visual image is converted to 1-D vector. In most of the cases the features are color, texture, geometric shapes, sketches or spatial relationships. In this stage images are transformed into the selected features space. The key to a good retrieval system is the selection of features space. It is important that the selected features represent the image as close as possible. The third stage which is the retrieval stage, the selected features are used for retrieval of the most similar images. Distance measure between the query image and images in the database is computed. The dimension of the image signature must have two important properties. It must as representative to the image as possible and must be of a reasonable dimension. These two properties are required to obtain accurate retrieval and avoid curse of dimensionality and high computation costs. The third stage is the similarity measure between the query image and images in the database. This can be performed by measuring distance between the signature of the query and all signatures in the database. There are many methods for measuring similarities between images, but the most popular distance measure is City block, which is simple and suitable for large databases. CBIR has been subject to research for many years and most of the proposed systems have relied on color histogram as image signature [1][3]. While color histograms are easy to compute, they lead to a high dimensional features vector which results in high computation costs. In addition to high dimensionality, color histograms do not preserve spatial information such as relative position of objects in the image. Several methods have been proposed to reduce features vector dimension such as using the most dominant colors [4][5] and color moments[6]. Although some of these methods produced a compact signature, they have their own drawbacks. The Dominant color representation consists of considering representative colors and their distribution in the different image regions by segmenting the image into different color regions. There is not yet optimal technique for image
segmentation which works for all kinds of images [7]. Another limitation of dominant color descriptor is that it does not handle spatial relation between image regions [8].

Color moments use mean and standard deviation and higher-order-moment of the distribution in each color band as a feature to characterize the color information. In [6] Hu’s seven color moments were used as image features. Color moments could be used to narrow down the search space before other expensive color features are used. In [9], it has been shown that color moments performances was worse than color histogram.

Due to it simplicity, CCH of the image has been used extensively, since it provides a fast retrieval results and overcomes many image variations such as rotation and scaling. However, color histogram does not preserve special information of the image. To overcome this problem image are divided into several regions and a color histogram is generated for each region. This will increase the size and complexity of image signature. Recently, more attention was given to FCH [10][11]. Unlike CCH, FCH considers the contribution of each pixel into every bin in the histogram, making image signatures less sensitive to intensity and light changes.

In this paper, a fuzzy color histogram generation technique using HSV (Hue, Saturation and Value) color space is proposed for image retrieval. The fuzzy color histogram retains a perceptually smooth color transition by considering the color similarity information by spreading each pixel membership to the neighboring histogram bins. In an attempt to overcome the drawback of the histogram techniques of color image retrieval which consider only global properties and hence cannot effectively define an image, a scheme to capture local properties has been developed for more accurate retrieval. The original image is divides into two subimages and FCH for every subimage is generated. The two FCH’s generated are then combined into a 1-D vector to search database for similar images. For feature similarity checking, the Manhattan distance is used.

This paper is organized as follows: Section II describes the HSV color space. Section III is for fuzzy set and fuzzy variables. Section IV is for image signature using FCH. Section V for image experimental results and section VI conclusions.

II. COLOR SPACE

Most of image processing applications treat images as collections of pixels comprised of red, green and blue (RGB) values. This is very convenient for display purposes, since computer monitors output color by combining different amounts of red, green and blue. However, human do not perceived colors this way. Colors are perceived in terms of Hue (H), Saturation(S), and Value (V). Using HSV usually referred to as perceptual color space. The advantages of HSV over RGB space is that HSV represent color the way they are perceived by the human vision system. There are many perceptual color spaces, including the PANTONE Color System, the Munsell Color System, HSV color space, HLS (Hue, Lightness, Saturation)color space, CYM(Cyan, yellow, Magenta) and others [12].

As shown in fig.1, HSV color space can be envisioned as a cone with its apex pointing downward. Viewed from the circular side of the cone, Hue is defined as an angle moving around the color circle shown at the top edge of the cone cone’s top edge. Hues are represented by the angle of each color in the cone relative to the 0° line, which is traditionally assigned to be red. The saturation is represented as the distance from the center of the circle. Saturation increases in a radial manner away from the central vertical axis. Highly saturated colors are on the outer edge of the cone, whereas low saturated colors are at the center. The brightness is determined by the colors vertical position in the cone. At the lower end of the cone, there is no brightness and all colors are black.

![Figure (1) HSV color space representation](image)

**Color Conversion**

Given a color defined by \((R, G, B)\) where \(R, G,\) and \(B\) are between 0 to 255, an equivalent \((H, S, V)\) color can be determined as follows: Let \(Max=Max\) \(R, G, B\) and
III. FUZZY VARIABLES

In the conventional RGB histogram method, three 256-bin histograms are created representing red, green and blue. Queries and images are compared using histogram intersection in each channel and the mean value is computed. Measuring the distance between two images will require 768 operations. There are two problems arise with this algorithm. First, it is very sensitive to lighting conditions due to the nature of the RGB color space. Secondly, the computational time is costly and the accuracy of the method is not acceptable for many applications. To overcome the sensitivity and the computation cost problems, we propose a novel method that uses small number FCH in HSV color space. To overcome the sensitivity of histogram signature to pixel movements, FCH considers the contribution of each pixel into all bins, hence reducing the sensitivity of the signature. Hue is represented by 6 sets as shown in fig.2.

\[
H = \begin{cases} 
\left(\frac{G - B}{\text{max} - \text{min}}\right) \times 60, & \text{if } R = \text{max} \\
\left(2 + \frac{B - R}{\text{max} - \text{min}}\right) \times 60, & \text{if } G = \text{max} \\
\left(4 + \frac{R - G}{\text{max} - \text{min}}\right) \times 60, & \text{if } B = \text{max} \\
\text{Undefined}, & \text{if } R = G = B
\end{cases}
\]

\[
S = \begin{cases} 
0, & \text{if } \text{max} = 0 \\
\left(\frac{\text{max} - \text{min}}{\text{max}}\right) \times 255, & \text{otherwise}
\end{cases}
\]

\[
V = \{ \text{max} \}
\]

The Saturation value corresponds to the distance from the center of the circle. Colors on the edge of the circle are fully saturated and the center of the circle contains no saturation—it's white. Fig.3 shows the range of saturation values for the color blue, as if extracted from the circle shown in Fig.1.

The saturation variable is represented by 3 linguistic variable, low, medium and high distances from the center.

The Value portion contains the brightness of the selected color, and it ranges from 255 (fully bright) to 0 (black). Again, it is represented using 3 fuzzy values similar to the saturation except the low, medium and high here correspond to the distance from the apex of the cone. Fig.4 shows the color blue as its Value coordinate changes from 0 to 255.

Black, Gray and white colors are represented by 3 separate bins since they are not included in the
hue bins and the value of the Hue is undefined when colors are equal, as shown in Fig. 5.

![Figure (5) Hue representation for R=G=B](image)

For all membership functions, we have used Triangle membership defined in Fig. 6:

![Figure (6) A Triangular membership function](image)

\[ \mu_A(x) = \begin{cases} 0, & \text{if } x \leq a \\ \frac{x-a}{g-a}, & \text{if } x \in [a, b] \\ \frac{b-x}{g-b}, & \text{if } x \in [b, g] \\ 0, & \text{if } x \geq g \end{cases} \]

Where \( \theta \) is the center and \( x \) is the value of the function.

The centers of the hue are defined from eq. 1. For example, when Red is max, hue will take the value from 0 to 60 or from 330 to 360. The same applies for all other membership functions shown in Fig’s 3, 4, and 5 with the shown centers.

Once pixels are converted to HSV space, the fuzzy color histogram is constructed from the fuzzy rules as follows:

Let Hue defines a fuzzy variable with a universe of discourse \([0,360]\) with 6 fuzzy sets described using a term names such as red, yellow, green, cyan, blue, and magenta along with a fuzzy set that represents that term using eq(4). As shown in Fig. 2. The other two fuzzy variables are the saturation and the values. Both are represented by 3 fuzzy sets named as low, medium and high saturation. Their universe of discourse is defined from 0 to 255. The variable saturation represents the distance from the center of the upper cone circle while the value represents the distance from the apex of the cone.

IV. FUZZY COLOR HISTOGRAM (FCH)

The fuzzy color histogram is constructed from fuzzy rules which are fuzzy rules represented by IF-THEN constructions that have the general form of "IF A THEN B" where A and B are (collections of) propositions containing linguistic variables. A is called the premise and B is the consequence of the rule. In effect, the use of linguistic variables and fuzzy IF-THEN- rules exploits the tolerance for imprecision and uncertainty. In this respect, we construct the FCH from the fuzzy rules as follows:

\[
\text{for } i=0,...,5, j=0,...,2
\]

\[ IF \ x \ is \ A_i \ and \ y \ is \ B_j \ THEN \ D_{i,j} \]

The output of the premise part is \( \text{min}(\mu(x, A_i), \mu(x, B_j)) \) while the consequence part represents the increase of the FCH bin which corresponds to the rule. For example, bin number \( i*6+j*3 \) is incremented by the minimum membership of the premises part of the rule is IF-THEN. The value of the premises is computed as follows:

If we have an RGB pixel \((123, 243, 82)\) which correspond to HSV \((105, 169, 243)\). This value will activate the following rule. The value \( H=105 \) will belong to the two sets namely the yellow and green. The membership of the \( H \) in the yellow and green set is computed by eq.4. Center as 120 for the green and 60 for the yellow so \( \mu_{\text{Yellow}}(H)=0.25 \) and \( \mu_{\text{Green}}(H)=0.75 \). The saturation is 169 which have membership in the medium and the high terms. Its membership \( \mu_{\text{medium}}(S) =0.32 \) and \( \mu_{\text{high}}(S)=0.68 \). Six rules will be activated. If Hue is green and Saturation is Medium (the bin representing green Hue and medium Saturation is incremented by:

\[
\text{min}(\mu_{\text{Green Hue}}, \mu_{\text{medium Saturation}}(x))
\]

Since any value could activate up to 6 rules, all bins
corresponding to activated rules are incremented the same way.

If hue is undefined, meaning R=G=B, The 3 bins of the FCH are incremented by the memberships of the gray values of Fig.5.

Finally the image will be represented by a vector of part1 of the image(6 hue×3 saturation×1 value + 3 Gray scale= 21) + part2 of the image(6 hue×3 saturation×1 value + 3 Gray scale= 21) =42 bins. Each bin contains accumulated values of the corresponding fuzzy rules.

V. EXPERIMENTAL RESULTS

Once image descriptors have been defined the crucial task is to find an appropriate metric in the descriptor space. The degree of similarity is then proportional to the inverse of the distance. In this work, we use City Block as a similarity measure between images signatures defined as follows:

\[ d(q, I) = | \sum_{i=0}^{N-1} (q_i - I_{R, 1}) | \]  (5)

q is the query signature vector, I is the images signature vector and N is the dimension of the feature vector. Instead of exact matching, CBIR will calculate the visual similarities between the query and all images in the database. Accordingly, the retrieval results will be a list of images ranked by their similarity to the query image. After retrieval, images are sorted in an ascending order based on their distance from the query image.

A. Lightning Intensity test

We evaluate the performance of image retrieval according to Normalized Rank Sum (NRS) [11]. The database is manually divided into sets; each set contains a number of similar images. When a query image belonging to set is selected to test the performance of the CBIR system, CBIR will respond by a list of images sorted by the distance from the query image. The rank of each image corresponds to its order in the retrieved list. The normalized rank sum is defined as follows:

\[ \frac{\sum_{i=0}^{n-1} \text{ranks}( I_{i \in S} )}{\sum_{j=0}^{m-1} \text{ranks}( I_{j \in R} )} \]  (6)

Where S denotes sum of ranks in the set and R sum of ranks retrieved from set. If all images are retrieved according to their expected order, the NSR will be equal 1 (the ideal result).

To evaluate the performance of the system under light intensity changes, we have randomly selected 10 images and changed their intensity by±10%,±15%,±20%,±25%,±30%, and ±35%. From each image in Fig. 7, thirteen images are created from each image and added to the database. Each image is queried once. The retrieval result is sorted in ascending and the NSR is computed using eq. 6. Results obtained using NRS are listed in Table 1.

\[ \text{Figure.7 Sample of the selected images for testing} \]

They are comparison of the NSR obtained using FCH and CCH. It can be seen that the proposed system can retrieve with light intensity change with higher accuracy.

B. VARY Image Benchmark

VARY is an image collection with about 10,000 general-purpose images [9]. We manually defined 20 similarity image sets form this collection. These sets are in different image categories and each set contains 10-15 images. Our experiments use these similarity image sets for search quality evaluation. We first select query from the group, the CBIR then will come up with a list of images sorted by their similarity to the query image. The evaluation of the retrieval results is performed using Eq.6. This is repeated several times for each group and the average of the retrieval results is
Table 1. Results obtained by querying images with different light intensity using FCH and CCH.

The same experiment is repeated using CCH in RGB domain [12]. The CCH consists of 768 bins representing all colors in the RGB color space. To measure the retrieval speed, the retrieval experiment is repeated several times and the average retrieval time is calculated. Table 2 shows results obtained using Pintum4 with 3.6 MHZ.

Table 2. Retrieval accuracy and speed of FCH and CCH.

<table>
<thead>
<tr>
<th>No</th>
<th>Number of comparisons</th>
<th>Retrieval Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>FCH 42</td>
<td>4 sec</td>
</tr>
<tr>
<td></td>
<td>CCH 768</td>
<td>19 sec</td>
</tr>
</tbody>
</table>

Fig. 8. Sample query with the retrieved results.
VI. CONCLUSIONS

In this paper, we have reported a novel approach to color image signature. The approach is based on the application of fuzzy set theory and fuzzy rules on the color image retrieval. Fuzzy sets theory was applied to images in the HSV color space to obtain a compact 1-D color representation of the images. The match between two image is the distance measure between their signatures. The system was tested on image database containing about 10,000 images. It was found that the proposed signature is more robust to light intensity changes and can perform accurate image retrieval in present of intensity changes of up to ±35%. The proposed system was also compared with other image signatures such as CCH and the results clearly show that our proposed image signature outperforms the CCH signature.

REFERENCES