

# Fuzzy color quantization and its application in Content-based image retrieval

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*Abstract:* - A fuzzy approach to color quantization and its application in content-based image indexing and retrieval is presented in this paper. There are some drawbacks associated with traditional color histogram such as color quantization. The goal in this paper is to develop an effective method to overcome several limitations, which are related to traditional color histogram. In the proposed method, fuzzy logic is used to quantize color space and apply it in color histogram construction. The objective is to eliminate error quantization effect that causes poor results due to varying lighting conditions and gamma nonlinearity effect. Experimental results on a database of 1000 images are reported.

*Key-Words:* - Fuzzy color quantization, Color histogram, Image indexing, Content-based image retrieval.

## 1 Introduction

With rapid advances in the computer technology, the sizes of image databases have been extremely increased. Nowadays, there is a great need for efficient image indexing and retrieval techniques. In recent years, there has been an immense interest in the development of image retrieval techniques based on image content. Many techniques have been developed [1,2], and some content-based image retrieval ,CBIR, systems have been introduced[3,4].

The color feature is one of the most widely used visual features in content-based image retrieval. It is relatively robust to background complication and independent of image size and orientation. Descriptors for the color feature are mostly statistics of color distribution, e.g., the color histogram, the average color and color moments. The color histogram is the most basic color content representation, which describes statistical color distributions by quantizing the color space. Given a discrete color space defined by some color axes, the color histogram is obtained by counting the number of times each color occurs in the image array [5]. If the colors in the image  $I$  are mapped into a discrete color space, containing  $n$  colors, then the histogram  $H(I)$  is a vector  $(h_{c1}, h_{c2}, \dots, h_{cn})$ , where each element  $h_{cj}$  represents the probability of having the color  $c_j$  in the image  $I$ .

For the first time, Swain and Ballard [5] proposed the method, called color indexing, which identified objects using color histogram intersection. The color axes used for histogram were the three opponent colors. Each color channel was split into 16

intervals giving  $16*16*16=4069$  bins. Color histogram became very popular due to its advantages [6]:

- **Robustness:** the color histogram is invariant to rotation of the image on the view axis, and changes in small steps when rotate otherwise or scaled. It is also insensitive to changes in image and histogram resolution and occlusion.
- **Effectiveness:** there is high percentage of relevance between the query image and the retrieved image.
- **Implementation simplicity:** the construction of the color histogram is simple scanning of the image, to get the color values, and the building of the histogram using color components as indices.
- **Computational simplicity:**the histogram computation has  $O(M^2)$  complexity for images of sizes  $M*M$ . The complexity for a single image match is linear,  $O(n)$ , where  $n$  represents the number of different color or resolution of the histogram.
- **Low storage requirements:** assuming color quantization, the size of color histogram is significantly smaller than the image itself.

However using the color histogram for indexing has a number of drawbacks:

- **Spatial information:** a color histogram describes the global color distribution in an image; no spatial information is available [7].
- **Color quantization:** histograms require quantization to reduce the dimensionality. A typical 24-bit color image generates a histogram with  $2^{24}$  bins, which requires at least 2 M bytes of storage space, depending on the resolution. Due to quantization error

perceptually similar colors may be quantized into different bins and perceptually different color may be quantized into the same bin[7,8].

- **Between colors similarity:** The color histograms do not capture the similarity between colors.

### 1.1 Spatial information

As abovementioned, the histogram captures global color activity, and color layout information of an image is not shown in its color histogram. This causes the false positives to increase. This is especially critical in large image databases, where many images have almost the same color histogram [9]. Recently, several approaches have incorporated color layout information with color histogram to overcome its weakness[10-15]. One way is to divide the image into different regions and calculate color features for each region [16-19]. Huang et al. [9] proposed the color correlogram for image indexing. A color correlogram of an image is a matrix indexed by color pairs, where the  $k$ th entry for  $(i,j)$  specifies the probability of finding a pixel of color  $i$  at the distance  $k$  from a pixel of color  $j$ . Since the computation of the color correlogram is very time consuming, the use of color autocorrelogram is recommended which is a vector that only includes the diagonal entries of color correlogram matrix.

Pass and zabih[20] described a split histogram called color coherence vector (CCV). Each one of its buckets  $j$  contains pixels having a given color  $j$  and two classes based on the pixels spatial coherence. A pixel is coherent if the size of its connected component exceeds a threshold  $T$ ; otherwise, the pixel is incoherent. The feature is also extended by successive refinement, with buckets of a CCV further subdivided on the base of additional features. Rao et al. [21] generalized the color spatial distribution by computing the color histogram with specific geometric relationships between pixels of each color histogram bucket. Cinque et al. [22] proposed a spatial-chromatic histogram in which the average position of each color and its standard deviation are extracted to include spatial information into the color histogram.

Malki et al. [18] suggested a multi-resolution quad-tree approach for image indexing based on region queries without segmentation. In their method, color histograms are computed on sub-images of the quad-tree representation, yielding a high dimensional feature vector. Nezamabadi-pour and Kabir [23] presented an indexing technique that employs local chromatic distribution based on description of uniformity and non-uniformity concept for  $4*4$  non-overlapping image blocks. The non-uniform blocks are edgy blocks while the uniform blocks are homogeneous. For the pixels in each uniform block, the average of each color

component is found to assign a representative color to that block. Then the histogram of uni-color uniform blocks of the image, HUCUB, is constructed. For each non-uniform block, they used two representative colors. Then the histogram of bi-color non-uniform Blocks of the image, HBCNB, is generated. Each entry  $(i,j)$  of HBCNB represents the number of blocks having colors  $i$  and  $j$  as their representative colors. The histogram of bi-color blocks represents the distribution of local color adjacency within image. To consider the between colors similarity, Hanfer et al. [24] suggested the usage of a more sophisticated quadratic form of distance measure which tries to capture the perceptual similarity between any two colors.

### 1.2 Color quantization problem

As aforementioned to achieve high storage and retrieval efficiency, the number of histogram bins used is normally much smaller than the total number of colors used to represent images. Therefore, a number of colors have to be grouped into one bin. This is called color quantization [8]. There are three types of quantization that apply in CBIR: Linear quantization, vector quantization, VQ, and lookup table quantization. In linear quantization each color components is quantized into several intervals separately without considering other components. In VQ each pixels is considered as a vector and using a clustering technique, pixels are quantized into several bins. The lookup table quantization is performed by considering several pre-defined colors and assigning any color to one of existing colors based on a metric.

There are three main problems associated with color quantization. Firstly, Color histograms can provide false retrieval results in the presence of gamma nonlinearity [7]. In general, an image database can contain images acquired from many unknown sources and can pass through a number of stages from the moment it is captured to the moment it is displayed. These stages introduce a multiplicative nonlinearity due to gamma nonlinearity of the various equipments. For image retrieval this can cause very poor performance[7]. Secondly, changeable lighting condition can provide different color histograms for captured images from the same image and increase false retrieval results [6]. Finally, a color may belong to more than one bins of histogram, and this point does not consider in computing color histograms.

However, color quantization and no consideration of between colors similarity can cause capturing images from the same scene produce different histograms under varying lighting conditions and gamma nonlinearity effect. Considering a case that two images have been captured in different lighting

conditions, from the same scene. In this case, it is possible to be a small relocation in color components of two images. Therefore, due to quantization the measured similarity between two images based on color histogram may be decreased. For more explanation, Fig.1 is used. supposing that many pixels of one of the images ( called as image 1) in color space  $x_1x_2$  have color coordination specified by *circle* sign in Fig. 1. A 2-Dimensional color space is used for a better presentation of the problem. The color coordination of these pixels in image 2 that captured from the same scene under different lighting condition are relocated to color coordination specified by *square* sign in Fig 1. Fig 2. shows that each color components of  $x_1$  and  $x_2$  are quantized linearly into 3 intervals. After quantizing, these pixels of image 1 and image 2 are assigned to bins 4 and 8 respectively. Therefore, if the similarity of these images based on their color histograms is computed, the results may be unsatisfactory.

In the current work, the goal is to develop an effective method to overcome several limitations, which are related to traditional color histogram. In the proposed method, fuzzy logic is used to quantize color space and apply it in color histogram construction. The objective is to eliminate error quantization effect that causes poor results due to varying lighting conditions and gamma nonlinearity effect. The reminder of the paper is organized as follows:

Section 2 describes applied color space. The proposed method is presented in section 3. Section 4 concerns with the experimental setup and obtained results. Finally a conclusion is given in section 5.

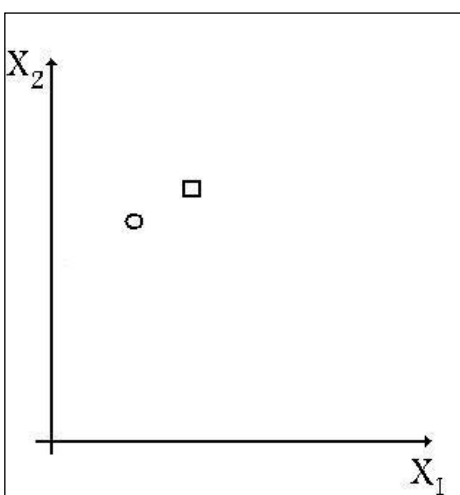


Fig.1 The color coordination of some pixels of two images that captured from a scene from different lighting conditions.

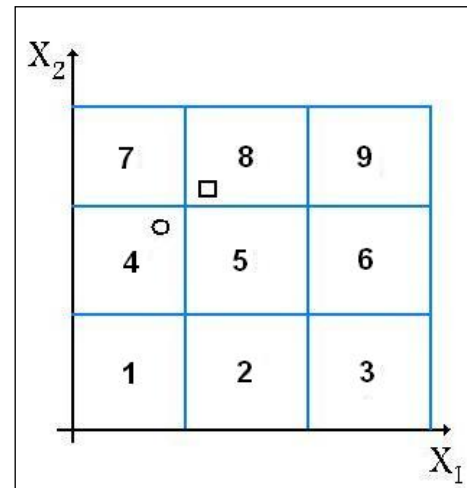


Fig.2 Each color component has been quantized linearly into 3 intervals. Circle and square signs are substituted for some pixels of image 1 and image 2 respectively.

## 2 Color space

The selection of color space in calculating color histogram can greatly influence the efficiency of the retrieval process. There are several commonly used color spaces, such as RGB, CIE, HSV, HSI and Munsell color spaces. The RGB color space is extensively used to represent images. This space does not correspond to the human way of perceiving the colors and dose not separate the luminance component from the chrominance ones. We have used HSV color space, which is common for image retrieval systems [12,16,17,23,25,26]. In HSV space, the colors can be matched in a way that is fairly consistent with human perception [16,25]. In this space, Hue is used to distinguish colors, Saturation is the percentage of white light added to a pure color and Value refers to the perceived light intensity. In HSV space, each color is represented by a three dimensional vector '(h,s,v)', where  $h \in [0,360)$  is Hue, and  $s \in [0,1]$  and  $v \in [0,1]$  are Saturation and Value, respectively. The HSV hex-cone is shown in Fig. 3. The conversion from RGB to HSV is performed with the Eqs. 1-3. The important advantages of HSV space are as follows [27]: good compatibility with human intuition, separability of chromatic and achromatic components, and possibility of preferring one component to other.

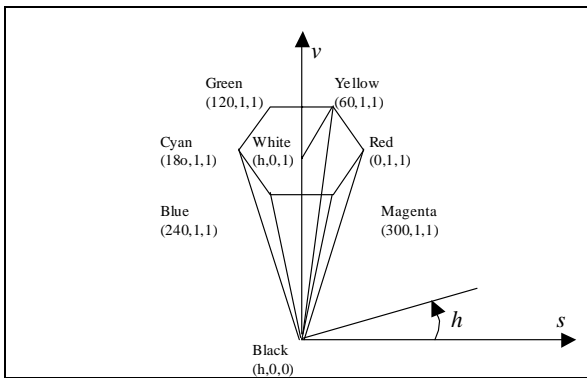


Fig.3 The HSV color space

$$\theta = \cos^{-1} \left\{ \frac{[(R-G) + (R-B)]/2}{\sqrt{(R-G)^2 + (R-B)(G-B)}} \right\} \quad (1)$$

$$H = \begin{cases} \theta & \text{if } B \leq G \\ 360 - \theta & \text{if } B > G \end{cases}$$

$$S = 1 - \frac{\min(R, G, B)}{\max(R, G, B)} \quad (2)$$

$$V = \max(R, G, B) \quad (3)$$

Since the human visual system is more sensitive to hue than saturation and value, hue axis should be quantized into smaller intervals than saturation and value axes. In this work, we quantized HSV space into 6 uniform intervals for hue, 3 for saturation and 3 for value [23]. This results in 54 bins for the color histogram.

### 3 The proposed method

The fuzzy logic is used to describe fuzzy color quantization to overcome some problems associated with traditional color histograms, TCH, constructed based on hard quantization. As abovementioned, the TCH is obtained by counting the number of times each color occurs in the image and normalized by the total number of image pixels. Each element  $h_{cj}$  of TCH can be formulized using Eq. 4.

$$h_{cj} = \frac{1}{N \cdot M} \sum_{x=1}^N \sum_{y=1}^M \mu_j(x, y) \quad (4)$$

$$\text{where } \mu_j(x, y) = \begin{cases} 1, & \text{if the pixel}(x,y)\text{is quantized} \\ & \text{into the } c_j \text{th color bin} \\ 0, & \text{otherwise} \end{cases}$$

Here M and N are length(row) and width(column) of the Image to be processed, respectively.  $\mu_j(x, y)$  is the degree association of pixel (x,y) to color  $c_j$ . As the Eq. 4 shows, in hard quantization each pixel is belong to only one bin.

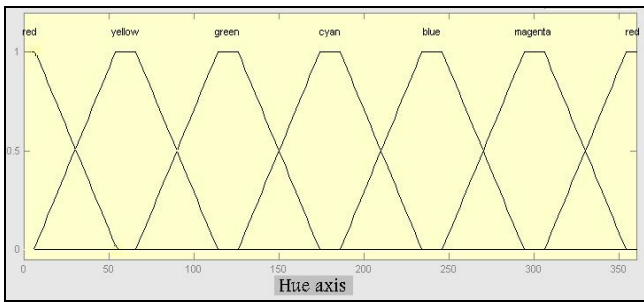
In the proposed method each color component is quantized based on its considered membership functions. According to considered membership functions, each component may belong to several intervals with different degree association. For example, Fig.4 shows the trapezoid membership functions for hue, saturation and value axes. As aforementioned hue has important information than other axes. Therefore, in the current work, we consider 6, 3 and 3 membership functions for hue, saturation and value axes, respectively. This results in 54 bins for the proposed color histogram.

Using the proposed color quantization, the color histogram is obtained by summing the degree association of each pixel in the image to every bin and normalized by the total number of image pixels. Each element  $h_{cj}$  of proposed color histogram can be formulized using Eq. 5.

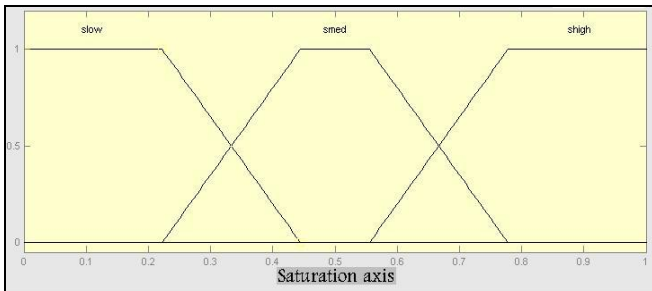
$$h_{cj} = \frac{1}{N \cdot M} \sum_{x=1}^N \sum_{y=1}^M \mu_j(x, y) \quad (5)$$

$$\text{where } \mu_j(x, y) = \mu_{hj}(x, y) \times \mu_{sj}(x, y) \times \mu_{vj}(x, y)$$

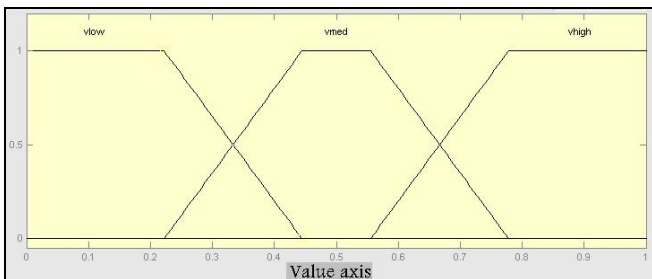
Here,  $\mu_{hj}(x, y)$ ,  $\mu_{sj}(x, y)$  and  $\mu_{vj}(x, y)$  are the degree association of hue, saturation and value components of pixel in location of (x,y) to bin  $c_j$  respectively. For example, if it is desired to calculate the degree associated with a color pixel to bin  $c_j$ , in which hue is "cyan", saturation is "smed" and value is "vlow" (see Fig. 4), the degree associated with hue, saturation and value components of the pixel to "cyan", "smed" and "vlow" respectively must be computed and multiply them to obtain the degree associated with the color pixel to bin  $c_j$ .



(a) hue



(b) saturation



(c) value

Fig.4 Trapezoid membership functions

## 4 EXPERIMENTAL RESULTS AND EVALUATION

The proposed method was developed in Matlab 6.5 language using a Pentium PC, 2 GHz. In our experiments, the “query-by-example” method, QBE, is used where the user specifies an image, and the system tries to retrieve the most similar images from the database. When a user presents a query image, its proposed color histogram is extracted. Then, the feature database is searched for the most similar images to the query image.

### 4.1 Image database

The proposed method is implemented on a database of 1000 images taken from the Corel collection. These

images are arranged in 10 semantic groups: people, lions, elephants, horses, flowers, foods, mountains, monuments, interior design and buses. All images are in JPEG format and of sizes 256\*384 and 384\*256.

### 4.2 Similarity measure

Different types of distance measures are studied and surveyed [2,28-32]. In this work, Several similarity measures including  $L_1$ ,  $L_2$ ,  $L_\infty$  [33], and,  $\chi^2$  [2] are studied. It is found among these measures,  $\chi^2$  is the best.

$$\chi^2 = \sum_{i=1}^{54} \left( \frac{F^Q(i) - F^T(i)}{F^Q(i) + F^T(i)} \right)^2 \quad (6)$$

Where  $F^Q$  and  $F^T$  denote the feature vector of query image and target image respectively.

### 4.3 Evaluation Method

The most common evaluation measures are different types of precision and recall. In this paper, the retrieval efficiency is used [28]. If the number of images retrieved is lower than the number of relevant images, retrieval efficiency represents the precision, otherwise the recall (Eq. 7).

$$\left( \begin{array}{l} \text{Retrieval} \\ \text{Efficiency} \end{array} \right) = \left\{ \begin{array}{l} \frac{\text{No. of relevant images retrieved}}{\text{Total no. of images retrieved}} \\ \quad ; \text{ If No. of retrieved images} < \text{No. of relevant images} \\ \\ \frac{\text{No. of relevant images retrieved}}{\text{Total no. of relevant images}} \\ \quad ; \text{ Otherwise} \end{array} \right. \quad (7)$$

### 4.4 Results

The considered query set includes 500 images of various types. In order to test the proposed indexing method, it is compared with a traditional color histogram method, TCH, with 54 quantization levels in the HSV space. The experimental results are summarized in Table.1, where the average retrieval efficiencies, for 500 queries, are reported. The Table.1 shows that the proposed method makes better results than TCH method. The retrieval results for 2 sample queries are given in Figs. 5 and 6, where the most similar images retrieved, are presented.



Table 1. Average retrieval efficiency versus the number of images retrieved, computed over 500 queries.

Number of retrieved images	TCH	Proposed Method
1	0.802	<b>0.824</b>
5	0.716	<b>0.736</b>
10	0.705	<b>0.726</b>
20	0.639	<b>0.674</b>
30	0.605	<b>0.636</b>
40	0.574	<b>0.606</b>
50	0.552	<b>0.572</b>
60	0.523	<b>0.545</b>
70	0.501	<b>0.519</b>
80	0.479	<b>0.499</b>
90	0.460	<b>0.479</b>
100	0.441	<b>0.460</b>

### 5 Conclusion

Content-based image retrieval is one of the most attractive fields in the computer vision area and many researches have been interested to work in this field. Promising advantages of color histogram make it as a significant feature in image indexing and retrieval. There are some drawbacks associated with color histogram. In this paper using fuzzy color quantization, it is tried to overcome some weakness of traditional color histogram. The proposed indexing method is tested on a database of 1000 images and yielded promising results. It seems that the key feature of the proposed method is fuzzy quantization of color components for building the color histogram.



Fig.5 Sample query 1: The image on the top left is the query. Ordered from left to right and top to bottom are the images retrieved



Fig.6 Sample query 2: The image on the top left is the query. Ordered from left to right and top to bottom are the images retrieved.

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