Fuzzy Color Histogram and Its Use in Color Image Retrieval

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***Abstract*—A conventional color histogram (CCH) considers neither the color similarity across different bins nor the color dissimilarity in the same bin. Therefore, it is sensitive to noisy interference such as illumination changes and quantization errors. Furthermore, CCHs large dimension or histogram bins requires large computation on histogram comparison. To address these concerns, this paper presents a new color histogram representation, called *fuzzy color histogram* (FCH), by considering the color similarity of each pixel's color associated to all the histogram bins through fuzzy-set membership function. A novel and fast approach for computing the membership values based on fuzzy c-means algorithm is introduced. The proposed FCH is further exploited in the application of image indexing and retrieval. Experimental results clearly show that FCH yields better retrieval results than CCH. Such computing methodology is fairly desirable for image retrieval over large image databases.**

***Index Terms*—Conventional color histogram, fuzzy c-means, fuzzy color histogram, illumination changes, image indexing and retrieval, membership matrix.**

I. Introduction

NUMEROUS methods about efficient image indexing and retrieval from image databases have been proposed for the applications such as digital library [1]–[3]. Low-level visual features such as color, texture, and shape are often employed to search relevant images based on the query image. Among these features, color constitutes a powerful visual cue and is one of the most salient and commonly used features in color image retrieval systems.

Swain and Ballard [4] have demonstrated the potential of using color histograms for color image indexing. Because each histogram bin represents a local color range in the given color space, color histogram represents the coarse distribution of the colors in an image. Two similar colors will be treated as identical provided that they are allocated into the same histogram bin. On the other hand, two colors will be considered totally different if they fall into two different bins even though they might be very similar to each other. This makes color histograms sensitive to noisy interference such as illumination changes and quantization errors. In this paper, we proposed a new color histogram, called *fuzzy color histogram* (FCH), to efficiently address the aforementioned issue.

In contrast with conventional color histogram (CCH) which assigns each pixel into one of the bins only, our FCH considers the color similarity information by spreading each pixel's total membership value to all the histogram bins. Furthermore, to save computation, we introduce an efficient method to compute these membership values using *fuzzy c-means* (FCM) clustering algorithm. Experimental results show that the obtained FCH is less sensitive to noisy interference such as lighting intensity changes and quantization errors than CCH.

Moreover, in contrast with quadratic histogram distance exploited for measuring the degree of similarity between CCHs, simple Euclidean distance measurement over their FCHs can yield similar retrieval results. This is a fairly attractive and desirable computing paradigm for the application of image indexing and retrieval especially over large image databases.

In the next section, we introduce related works of color histogram based methods for image indexing and retrieval. The concept of FCH is introduced in Section III. An efficient scheme to compute the required fuzzy membership values using FCM algorithm is introduced in Section IV. In Section V, we analyze the relationship between FCH and other color histograms. In Section VI, we analyze the experimental results of image retrieval based on FCH and discuss the parameter selection of FCH. Section VII concludes the paper.

II. Related Works

Color histograms are easy to compute, and they are invariant to the rotation and translation of image content. However, color histograms have several inherent problems for the task of image indexing and retrieval. The first concern is their sensitivity to noisy interference such as lighting intensity changes and quantization errors. The second problem is their high dimensionality on representation. Even with coarse quantization over a chosen color space, color histogram feature spaces often occupy more than one hundred dimensions (i.e., histogram bins) [5] which significantly increases the computation of distance measurement on the retrieval stage. Finally, color histograms do not include any spatial information and are therefore incompetent to support image indexing and retrieval based on local image contents. In the following, we briefly describe several existing approaches that have been attempting to address these concerns.

A. Sensitivity

Some approaches exploit the color histogram derived together with a similarity measurement chosen to make color

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histograms more robust to noisy interference. To identify objects based on their color histograms, Swain and Ballard [4] propose a *histogram intersection* method which is able to eliminate the influence of color contributed from the background pixels during the matching process in most cases. Although their method is robust to object occlusion and image resolution, but it is still sensitive to illumination changes [4].

Funt and Finlayson [6] propose a *color constant color indexing* method to extend Swain and Ballard's color indexing method to be illumination independent by establishing the histogram of color ratios. Since the illumination remains essentially constant locally, calculating the ratios of neighboring colors removes the illumination variation component. Similar extension can be found in Drew *et al.*'s work [7].

Cumulative color histogram [8] utilizes the spatial relationship of the histogram bins in the color space. Consequently, it is slightly more robust with respect to illumination changes than CCH [8]. In Section V, we will show that it can be viewed as a special case of our FCH.

QBIC [1] takes into account the perceptual color similarity between histogram bins through the measurement of *quadratic distance*, which is a weighted distance between two CCHs with each weight denoting the similarity between a pair of color histogram bins. It has been shown that such measurement is more closely related to human being's judgment on color similarity comparison, but on the expense of large computations.

B. Dimensionality

Many other approaches exploit their derived color histogram methods to facilitate the design of efficient database indexing schemes. Hafner *et al.* [9] generalize computationally simple similarity measures using *singular value decomposition* (SVD) method to compute quadratic histogram distance. It has been mathematically shown that SVD-based approach provides the lower bounds on the histogram distance measure. Mandal *et al.* [10] reduce the computational complexity of color histogram comparison by representing the histogram in terms of its moments. Experimental results also indicate that Legendre moments provide superior retrieval performance compared to regular moments [10].

C. Spatial Information

Some approaches strive to incorporate spatial information into color histograms by dividing each image into subregions and imposing positional constraints on image comparison in order to increase image discrimination power [11]–[14]. Smith and Chang's method [11] uses back projection of binary color sets to extract color regions. Each of these regions is efficiently represented by a binary color set and its location information as well. Stricker and Dimai's method [12] tessellates each image into five partially overlapping fuzzy regions and extracts the first two color moments of each region both weighted by the membership functions of the region, respectively, to form a feature vector for the image.

Other approaches augment histograms with local spatial properties. Pass and Zabih [15] propose a split histogram, called *color coherence vector* (CCV), where image pixels in a given histogram bin are partitioned into two classes based on their spatial coherence [16]. A pixel is considered as coherent pixel if it is part of a sizable contiguous region; otherwise, incoherent pixel. Huang *et al.* [17], [18] propose *color correlograms* to take into account the local color spatial correlation as well as the global distribution of this spatial correlation. In fact, a color correlogram of an image forms a table of statistics for color pairs, where the k-th entry for pair $\langle i, j\rangle$ specifies the probability of finding a pixel of color j from a pixel of color i at a distance k in the image.

All the above-mentioned approaches made some improvements over the CCH for the task of image indexing and retrieval. Our FCH proposed in this paper makes improvement on robustness (less sensitive to interference), efficiency (reduced dimension), and computation (less online computation consumed). The full development of FCH is presented as follows.

III. Fuzzy Color Histogram

In this paper, the color histogram is viewed as a color distribution from the probability viewpoint. Given a color space containing n color bins, the color histogram of image I containing N pixels is represented as $H(I) = [h_1, h_2, \ldots, h_n]$, where $h_i = N_i/N$ is the probability of a pixel in the image belonging to the ith color bin, and N_i is the total number of pixels in the ith color bin. According to the total probability theory, h_i can be defined as follows:

$$h_i = \sum_{j=1}^{N} P_{i\,|\,j} P_j = \frac{1}{N}\sum_{j=1}^{N} P_{i\,|\,j} \tag{1}$$

where P_j is the probability of a pixel selected from image I being the jth pixel, which is $1/N$, and $P_{i\,|\,j}$ is the conditional probability of the selected jth pixel belonging to the ith color bin.

In the context of CCH, $P_{i\,|\,j}$ is defined as

$$P_{i\,|\,j} = \begin{cases} 1, & \text{if the } j\text{th pixel is quantized into the } i\text{th color bin} \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

This definition leads to the boundary issue of CCH such that the histogram may undergo abrupt changes even though color variations are actually small. This reveals the reason why the CCH is sensitive to noisy interference such as illumination changes and quantization errors.

The proposed FCH essentially modifies probability $P_{i\,|\,j}$ as follows. Instead of using the probability $P_{i\,|\,j}$, we consider each of the N pixels in image I being related to all the n color bins via fuzzy-set membership function such that the degree of "belongingness" or "association" of the jth pixel to the ith color bin is determined by distributing the membership value of the jth pixel, μ_{ij}, to the ith color bin.

Definition (Fuzzy Color Histogram): The fuzzy color histogram (FCH) of image I can be expressed as $F(I) = [f_1, f_2, \ldots, f_n]$, where

$$f_i = \sum_{j=1}^{N} \mu_{ij} P_j = \frac{1}{N}\sum_{j=1}^{N} \mu_{ij}. \tag{3}$$

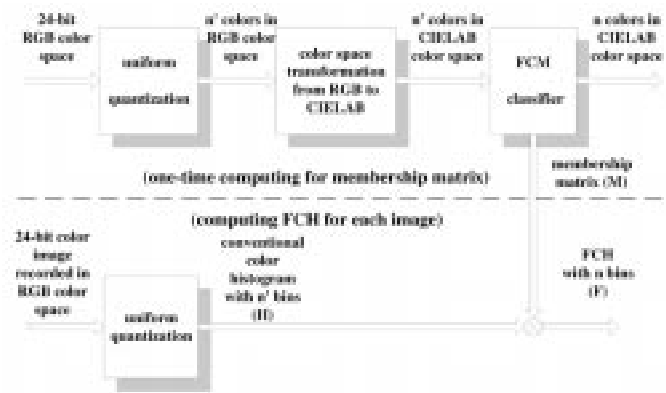

Fig. 1. Procedure diagram for computing FCH ($n' = 16^3 = 4096$ in our experiment).

P_j has been defined in (1), and μ_{ij} is the membership value of the jth pixel in the ith color bin.

In contrast with CCH, our FCH considers not only the similarity of different colors from different bins but also the dissimilarity of those colors assigned to the same bin. Therefore, FCH effectively alleviates the sensitivity to the noisy interference.

IV. FCH Computing

Equation (3) gives the definition of FCH, but it does not provide an applicable method to compute FCH. Given two colors i and j, Hafner *et al.* [9] measure their perceptual similarity in terms of the Euclidean distance between colors i and j represented in a chosen color space. However, the measurement does not consider the nonuniformity inherent in color space representation. To accurately quantify the perceptual color similarity between two colors recorded in a specific color space, the nonuniformity of that color space should be considered. For that, we choose the CIELAB color space which is one of perceptually uniform color spaces and has been increasingly exploited into many electronic color imaging systems (e.g., Postscript language and Adobe Photoshop) [19].

Since RGB color space has been most commonly used for representing color images, intuitively we need to perform nonlinear color space transformation from RGB to CIELAB pixel by pixel. Such pixel-wise transformation is computationally intensive for the entire image. Moreover, to compute the FCH of a color image, we need to compute each pixel's membership values with respect to all available color bins, respectively. Such direct approach is also not favorable because of its large computational load. To address the above-mentioned issues, we propose an efficient method to compute FCH based on *fuzzy c-means* (FCM) clustering algorithm [20]. The procedure diagram for computing FCH is illustrated in Fig. 1.

First, we perform fine uniform quantization in RGB color space by mapping all pixel colors to n' histogram bins. Here, the bin number n' is chosen to be large enough so that it makes the color difference between two adjacent bins small enough. Then, we transform the n' colors from RGB to CIELAB color space. Finally, we classify these n' colors in CIELAB color space to n clusters using FCM clustering technique (usually, $n \ll n'$; hence, a coarse quantization process), with each cluster representing an FCH bin. Through these steps, a pixel's membership value to an FCH bin can be represented by the corresponding fine color bin's membership value to the coarse color bin. Note that we only need to compute these membership values once, and they are represented as a membership matrix $M = [m_{ij}]_{n \times n'}$. Each element m_{ij} in M is the membership value of the jth fine color bin distributing to the ith coarse color bin. Thus, the FCH of an image can be directly computed from its CCH without computing membership values for each pixel. That is, given an n'-bin CCH $H_{n' \times 1}$, the corresponding n-bin FCH $F_{n \times 1}$ can be computed as follows:

$$F_{n \times 1} = M_{n \times n'} H_{n' \times 1} \tag{4}$$

where membership matrix M is pre-computed only once and can be used to generate FCH for each database image. We employ FCM clustering algorithm to not only classify the n' fine colors to n clusters but also obtain membership matrix M at the same time. For the latter, we explain how it works with more details as follows.

FCM is an unsupervised clustering algorithm that has been applied successfully to a number of problems involving feature analysis, clustering and classifier design. The FCM minimizes an objective function J_m, which is the weighted sum of squared errors within each group, and is defined as follows [21]:

$$J_m(U, V; X) = \sum_{k=1}^{n} \sum_{j=1}^{c} u_{ik}^m \|x_k - v_i\|_A^2, \quad 1 < m < \infty \tag{5}$$

where $V = [v_1, v_2, \ldots, v_c]^T$ is a vector of unknown cluster prototypes. The value of u_{ik} represents the membership of the data point x_k from the set $X = \{x_1, x_2, \ldots, x_n\}$ with respect to the ith cluster. The inner product defined by a norm matrix A defines a measurement of similarity between a data point and the cluster prototypes, respectively. A nondegenerate fuzzy c-partition of X is conveniently represented by a matrix $U = [u_{ik}]$. The weighting exponent m controls the extent of membership shared by c clusters.

It has been shown by Bezdek [20] that if $\|x_k - v_i\|_A > 0$ for all i and k and $m > 1$, then J_m could be minimized at (U, V) where

$$v_i = \frac{\sum_{k=1}^{n} (u_{ik})^m x_k}{\sum_{k=1}^{n} (u_{ik})^m}, \quad \text{for } 1 \le i \le c, \tag{6}$$

and

$$u_{ik} = \frac{1}{\sum_{j=1}^{c} \left(\frac{\|x_k - v_i\|_A^2}{\|x_k - v_j\|_A^2} \right)^{\frac{1}{m-1}}}, \quad \text{for } 1 \le i \le c \quad \text{and} \quad 1 \le k \le n. \tag{7}$$

Equations (6) and (7) cannot be solved analytically, but an approximate solution can be obtained by performing the following iterative procedures. (First, denote (l) as the iteration index.)

Algorithm (Fuzzy C-Means):

Step 1) Input the number of clusters c, the weighting exponent m, and error tolerance ϵ.
Step 2) Initialize the cluster centers v_i, for $1 \le i \le c$.
Step 3) Input data $X = \{x_1, x_2, \ldots, x_n\}$.
Step 4) Calculate the c cluster centers $\{v_i^{(l)}\}$ by (6).
Step 5) Update $U^{(l)}$ by (7).

Step 6) If $||U^{(l)} - U^{(l-1)}|| > \epsilon, l = l+1$ and return to Step 4; otherwise, stop.

In our work, we need to classify the n' fine colors in CCH into n clusters for FCH. Due to the perceptual uniformity of CIELAB color space, the inner product $||x_k - v_i||_A^2$ can be simply replaced by $||x_k - v_i||^2$, which is the Euclidean distance between the fine color x_k and the cluster center v_i. The fuzzy clustering result of FCM algorithm is represented by matrix $U = [u_{ik}]_{n \times n'}$, and u_{ik} is referred to as the grade of membership of color x_k with respect to cluster center v_i. Thus, the obtained matrix $U_{n \times n'}$ can be viewed as the desired membership matrix $M_{n \times n'}$ for computing FCH, i.e., $M_{n \times n'} = U_{n \times n'}$. Moreover, the weighting exponent m in FCM algorithm controls the extent or "spread" of membership shared among the fuzzy clusters. Therefore, we can use the parameter m to control the extent of similarity sharing among different color bins in FCH. The membership matrix M can be thus adjusted according to different image retrieval applications. In general, if higher noisy interference is involved, larger m value should be used.

V. Relationship Between FCH and Other Color Histograms

Cumulative color histogram [8] has been proven to be more robust to noisy interference than CCH. Given the color histogram H of image I, the corresponding cumulative color histogram is mathematically represented as $\tilde{H}(I) = [\tilde{h}_1, \tilde{h}_2, \ldots, \tilde{h}_n]$, where $\tilde{h}_i = \sum_{C_j \leq C_i} h_j$. Here, C_i and C_j are the representative color values of the ith and jth histogram bins, respectively. In RGB color space, $C_j = (r_j, g_j, b_j) \leq C_i = (r_i, g_i, b_i)$, if $r_j \leq r_i, g_j \leq g_i$ and $b_j \leq b_i$. In fact, we can describe cumulative color histogram in terms of *crisp* membership matrix $M = [m_{ij}]_{n \times n'}$ and $n' = n$, which is defined as follows:

$$m_{ij} = \begin{cases} 1, & \text{if } C_j \leq C_i \\ 0, & \text{otherwise.} \end{cases} \tag{8}$$

Therefore,

$$\tilde{H}_{n \times 1} = M_{n \times n} H_{n \times 1}. \tag{9}$$

For example, given an ordered color histogram with eight bins and $C_i < C_j$, where $i < j$, the membership matrix $M_{8 \times 8}$ of cumulative color histogram is

$$M_{8\times 8} = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \end{pmatrix}. \tag{10}$$

Note that inherently cumulative color histogram also considers the color similarity across all color bins. However, FCH is more general as its *fuzzy* (rather than *crisp*) membership matrix can be adjusted according to different noise interference and applications.

Quadratic histogram distance [1] provides more stable and consistent matching measurement than other similarity measures between two CCHs. Given two color images Q and T, the quadratic distance between their n-bin CCHs, H_Q and H_T, is given by

$$d_q^2(H_Q, H_T) = [H_Q - H_T]_{n \times 1}^T A_{n \times n} [H_Q - H_T]_{n \times 1} \tag{11}$$

where $A = [a_{ij}]_{n \times n}$ is a weighted similarity matrix and a_{ij} denotes perceptual similarity between color bins i and j. With a suitable membership matrix $M = [m_{ij}]_{n \times n'}$, the FCHs of images Q and T can be computed by (4), respectively. On the other hand, the squared Euclidean distance between their n-bin FCHs is

$$\begin{aligned} d_E^2(F_Q, F_T) &= [F_Q - F_T]_{n \times 1}^T [F_Q - F_T]_{n \times 1} \\ &= [H_Q - H_T]_{n' \times 1}^T M_{n \times n'}^T M_{n \times n'} [H_Q - H_T]_{n' \times 1} \\ &= [H_Q - H_T]_{n' \times 1}^T A_{n' \times n'} [H_Q - H_T]_{n' \times 1}. \end{aligned} \tag{12}$$

Compared with (11), the simple squared Euclidean distance between two n-bin FCHs is equivalent to the quadratic histogram distance between their n'-bin CCHs. Note that the computationally intensive matrix multiplication in computing quadratic distance of CCHs (11) is incurred at *online* retrieval stage. On the other hand, our FCH-based representation simply applies Euclidean distance measurement, and the matrix multiplication is desirably avoided at *online* retrieval stage, because it has already been performed in the *offline* indexing stage according to (4).

From (12), it also shows that our FCH-based measurement could preserve more detailed color similarity information than CCH-based quadratic distance measurement with the same number of histogram bins because $n \ll n'$. This indicates that it is possible to exploit FCH with fewer number of histogram bins to efficiently represent color distribution than CCH.

VI. Experimental Results of Image Retrieval

A. Retrieval Performance Evaluation Criterion

We evaluate the performance of image retrieval according to *normalized rank sum* (NRS) [22], which is defined as follows. From a manually predefined target image set $\{I_t\}$ containing n_t similar images stored in the database, a query image $I \in \{I_t\}$ is selected for performing image retrieval experiments. If all the images in the database were sorted according to the similarity measured with respect to query image I, the *rank* of each image corresponds to its location in the sorted list. When all the n_t images in the target image set $\{I_t\}$ appear in the first n_t locations in the sorted list, the ideal (or best) retrieval performance is achieved. The *rank sum* of the query image I, which is defined as the sum of the ranks of all the n_t target images (i.e., the denominator of (13)), denotes the performance of a retrieval method exploited. To compare the rank sums of target image sets with different set sizes, the NRS of image I is required and defined as

$$\text{NRS}(I) = \frac{n_t(n_t + 1)/2}{\sum_{t=1}^{n_t} \text{rank}(I_t)}. \tag{13}$$

Note that the rank sum in the denominator is normalized by $n_t(n_t+1)/2$ in the numerator—the rank sum when the retrieval

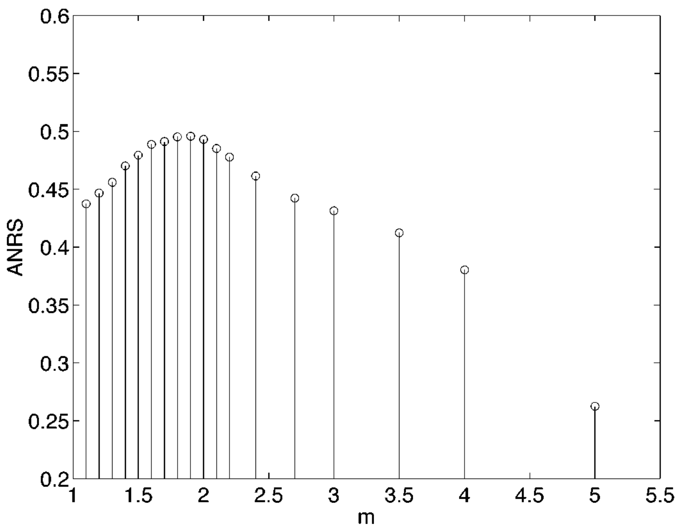

Fig. 2. ANRS values of image retrieval using FCHs with 18 different weighting exponents empirically determined, i.e., $m = 1.1, 1.2, 1.3, 1.4, 1.5, 1.6, 1.7, 1.8, 1.9, 2.0, 2.1, 2.2, 2.4, 2.7, 3.0, 3.5, 4.0$, and 5.0, respectively. (ANRS' range [0, 0.2] is omitted for the purpose of presentation.)

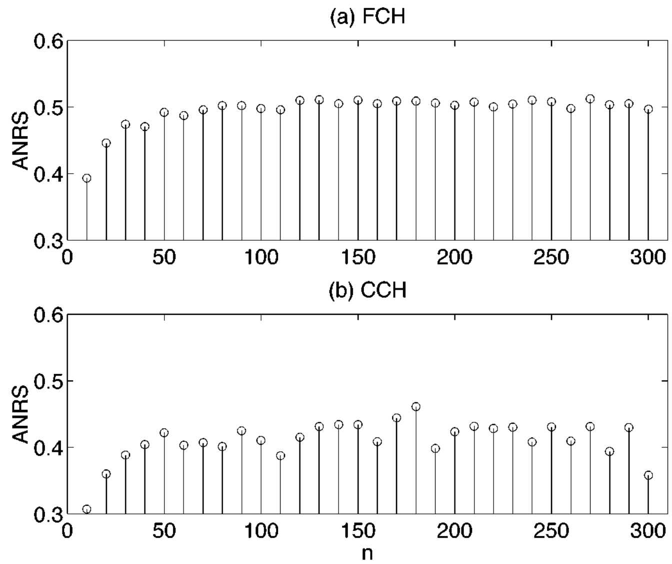

Fig. 3. ANRS values of image retrieval using (a) FCHs $(m = 1.9)$ and (b) CCHs with bin numbers $n = 10, 20, 30, \ldots, 290$, and 300, respectively. (ANRS' range [0, 0.3] is omitted for the purpose of presentation.)

performance is *ideal* as described earlier. As the NRS value is approaching one, it indicates that the retrieval performance is getting close to ideal. This makes the NRS measurement independent of the size of the target image set $\{I_t\}$. Also note that between two consecutive correctly retrieved images lie average $\lceil 1/\mathrm{NRS} \rceil - 1$ incorrectly retrieved images [23].

B. FCH Parameter Selection

In order to evaluate the performance of FCH representation exploited in image indexing and retrieval, we establish an image database containing about 500 color images with various sizes and a wide range of image content, such as nature scenes, animals, buildings, etc.

Our experiments for determining FCH parameter were carried out based on global color distribution of the entire image. For that, we selected 39 target sets from our image database based on their global color distribution. Each target image set contains a set of images having similar main object and background, but with some variations in position, viewing angle, illumination, etc.

According to the scheme on computing FCH as described in Section IV, we first uniformly quantize the given RGB color space into $n' = 16^3 = 4096$ color bins [24]. Thus, the weighting exponent m and bin number n are the two main parameters which jointly influence the performance of FCH-based image retrieval. In our experiments, we empirically chose 18 values of m and 30 values of n as shown in Figs. 2 and 3. With each of the 18×30 parameter combinations, the membership matrix was obtained using FCM algorithm, and the FCHs of all the database images were computed. Each image contained in the 39 target image sets was selected as the query image, and the NRS value of the query image was computed by using the Euclidean distance as the similarity measurement. Then, the *average* NRS (ANRS) value over the entire image database was computed. The ANRS value thus represents the performance of image retrieval based on FCHs with the given parameter combination—the larger the ANRS value, the better the parameter combination. For comparison, the ANRS values for CCHs were also obtained in the same way.

With the 18×30 parameter compositions, 18×30 ANRS values of FCH-based retrieval were obtained. We first determine the optimal m value as follows. For each of the 18 values, we averaged all the 30 ANRS values with different n values. The obtained 18 ANRS values are shown in Fig. 2. It suggests that the choice of $m = 1.9$ achieves the best retrieval performance in our experiments.

The 30 ANRS values of FCH-based retrieval with $m = 1.9$ under different n values are shown in Fig. 3(a), and the corresponding 30 ANRS values of CCH-based retrieval are shown in Fig. 3(b). Comparing these two subfigures, we can see that the retrieval performance using FCHs is better than the performance using CCHs under the same bin number. Moreover, it also indicates that the FCH-based image retrieval is less sensitive to the bin number changes. As the quantization errors are intimately related to the bin number used, these results demonstrate that FCH is more robust (i.e., less sensitive) to quantization errors than CCH.

C. Retrieval Sensitivity Under Lighting Intensity Changes

To study the robustness of FCH with respect to lighting intensity changes, we carry out the following image retrieval experiments. First, we select an image from the database as the query image. Then, the query image is processed by using, say, Photoshop to create ten images under lighting intensity changes with amount varying from $-25, -20, -15, -10, -5, +5, +10, +15, +20$ to $+25$, respectively. These ten images are then added back to the database. For comparison, both FCH (using $m = 1.9$) and CCH for database images are independently computed with 64 bins (i.e., $n = 64$) each. Finally, all the database images are sorted with

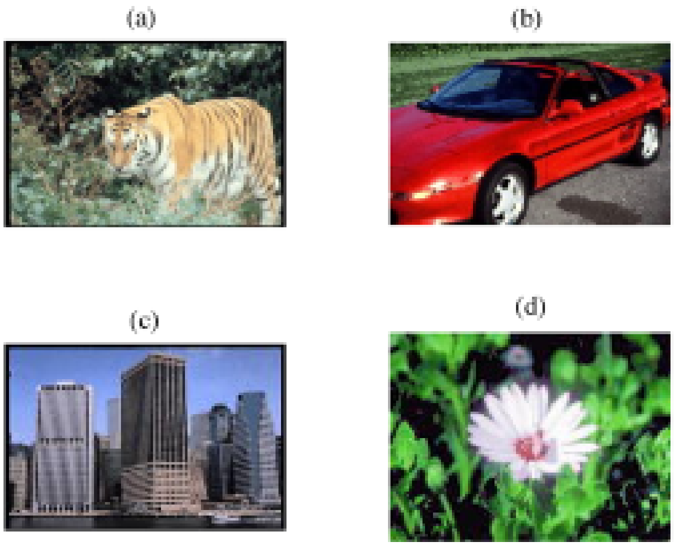

Fig. 4. Arbitrarily selected four query images for sensitivity studies under lighting intensity changes.

TABLE I
RANKS OF CORRESPONDING TEN PROCESSED IMAGES UNDER VARIOUS DEGREES OF LIGHTING INTENSITY CHANGES WITH RESPECT TO EACH QUERY IMAGE AS SHOWN IN FIG. 4

query image	feature	ranks of the corresponding 10 images									
(a)	FCH	4	6	10	16	17	23	29	36	69	141
	CCH	4	5	10	17	18	29	42	46	128	239
(b)	FCH	2	3	4	5	6	7	10	22	45	143
	CCH	2	3	5	6	9	12	18	22	121	390
(c)	FCH	3	4	5	6	7	8	10	14	19	31
	CCH	3	5	8	9	11	16	38	116	124	189
(d)	FCH	2	3	4	5	6	7	8	14	74	137
	CCH	2	3	4	5	6	7	16	18	91	370

respect to the query image based on the Euclidean distance measurement.

Four query images are arbitrarily selected from our image database as presented in Fig. 4. The experimental results are documented in Table I, which shows the ranks of the corresponding ten processed (i.e., under lighting intensity changes as previously mentioned) images. For the purpose of presentation, note that the entries of each row have been arranged from high to low in their ranks without considering their corresponding lighting intensity changes individually. The justification is quite clear that as long as the images from the target image set could be retrieved, the exact ordering among themselves is not important anymore. It clearly demonstrates that the ranks obtained by FCH are much higher than those obtained by CCH. Similar results and conclusion are also obtained from extended simulation experiments using other database images as the query images, respectively. Therefore, our proposed FCH is more robust to lighting intensity changes than CCH for the task of image indexing and retrieval.

Fig. 5. Top-left image is the query image with a user-selected local region indicated by the white-line bounding box. With respect to the selected local region, the 16 most similar images retrieved from a database containing about 500 color images. The retrieval criterion is based on the Euclidean distance between FCHs.

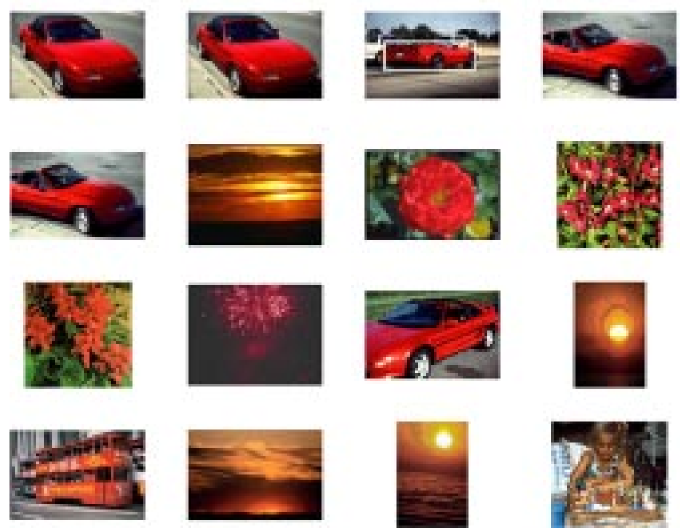

Fig. 6. Same experiments as those of Fig. 5 are conducted by exploiting CCHs. The retrieval criterion is based on the Euclidean distance between CCHs.

D. Regional Image Retrieval

Image indexing by localized or regional color distribution provides partial or subimage matching between images. For example, if the user is interested in finding all the images containing human faces regardless their backgrounds, the regional indexing approach would be more effective as the background information will be completely excluded for similarity matching. For that, we employ the hierarchical partition scheme proposed in Dimai's work [23] in our experiment.

For region-based image retrieval, the query object selected by the user from the query image should be matched by those database images that contain such object but appearing at different locations with possibly variable sizes and angles. To achieve this goal, we systematically partition each database image into subimages in order to increase the chances of

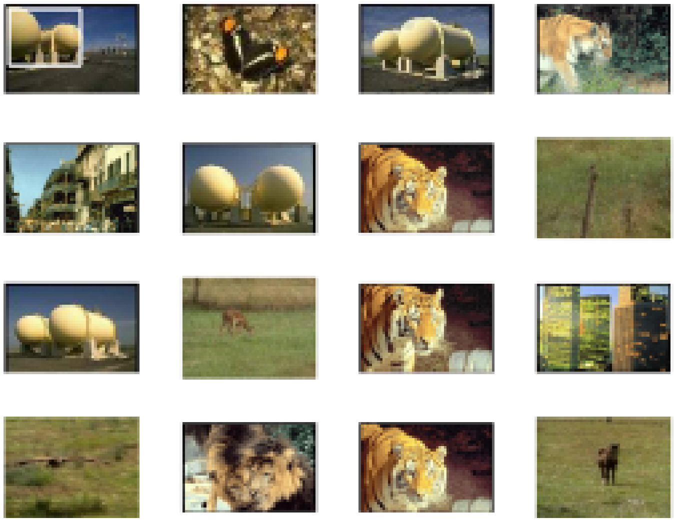

Fig. 7. Another retrieval result based on FCHs.

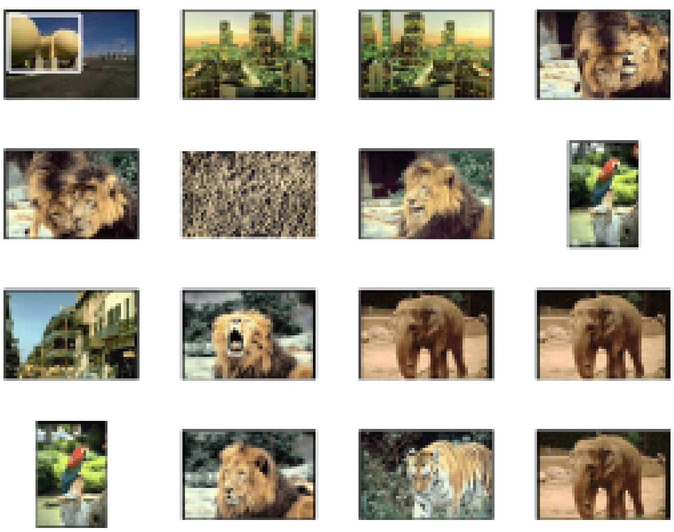

Fig. 8. Same experiments as those of Fig. 7 are conducted by exploiting CCHs. Note that the three target images as presented in Fig. 7 fail to be retrieved.

matching the query object from the query image. The methodology of dividing each database image into three hierarchical levels as introduced in [23] is adopted here and generates overlapping subimages. The highest level is the image itself, and the image is then equally portioned into 3×3 overlapping rectangle regions in the second level which has each side length be a half of the corresponding side length of the original image. Similarly, with finer partition, the lowest level is composed by 5×5 rectangle regions with each region having its side lengths being one-third of the image side lengths, respectively. Therefore, total 35 $(=1 + 9 + 25)$ rectangular regions are obtained for each database image.

For each of 35 regions, its 64-bin FCH (with $m = 1.9$) and 64-bin CCH are computed as the feature vector, respectively. We also employ the Euclidean distance as the similarity measure for both cases. The similarity between the query local image and a database image is measured by the minimum distance between the feature vectors of the query local image and all the 35 rectangle subregions of each database image.

TABLE II
RETRIEVAL PERFORMANCE (NRS VALUE) FOR 50 CCQs ON CCD USING FCH AND CCH, RESPECTIVELY

CCQ	CCH	FCH	CCQ	CCH	FCH
flower garden	0.0185	0.3846	quiz scene	0.3030	1
rock and sky	0.0053	0.2586	speaker	1	1
news anchor	0.9483	1	man and horse	0.9545	1
walking people	0.2122	0.6892	space earth	1	1
baldheaded man 1	0.9740	1	fountain	0.0473	0.1986
sports reporters	0.0366	0.2500	graphics before news	0.5056	1
congress	0.1023	0.3600	Ron Reagan	0.8182	0.5921
baldheaded man 2	0.1400	0.9215	basketball game overlay	1	1
castle	1	1	glass roof	0.0383	0.0319
black clothes lady	0.7241	1	snow clad mountain	0.1000	0.3030
singer	1	0.8824	outdoor/boats	0.0139	0.0345
strange hair	0.1685	0.8333	by the water	0.2000	0.6250
leather jacket people	0.4472	0.3846	couple	0.0142	1
man with placard	0.0439	0.4839	shop	0.0095	0.1556
people on the red	0.5769	0.2830	flower(indoor)	0.0156	0.1639
snake	1	0.9873	playing on the street	0.0493	0.1899
fish	1	1	road with trees/grass	0.0047	0.0481
tapirs	1	1	children/rock/grass	0.2128	0.0144
butterfly	1	1	Asian building	0.0044	0.0167
small monkey	0.9512	0.7723	containers	0.0041	0.2381
landscape image 1	0.1370	0.2381	sunset over lake	0.0203	0.0285
landscape image 2	0.2778	0.0323	big pipes	0.0321	0.0722
landscape image 3	1	1	man in white shirt	0.0084	0.0458
indoor image	0.1608	0.3035	wooden shack	0.0463	0.2727
anchor person	0.8407	0.9563	ruins	0.0059	0.0098

Our experimental results show that the performance of regional image retrieval by FCH is consistently better than or equivalent to that by CCH in general. Two examples are presented in Figs. 5 and 6 for demonstration. The first (i.e., top-left) picture in Fig. 5 is the query image with a selected local region indicated by the white-line bounding box imposed by the user. The images presented in Figs. 5 and 6 in the order of ranking show the retrieval results after searching for those images containing a "red car" from the database based on FCH's and CCH's representation, respectively. In Fig. 5, the 16 most similar images retrieved based on FCHs include all the 9 images containing a red car. Note that the last three "red car" images in Fig. 5 do not appear in the 16 most similar images retrieved by exploiting CCHs as shown in Fig. 6. Note that even the query image itself is not being ranked as the most relevant retrieval in Fig. 6, as it normally should be.

Another set of retrieval results are shown in Figs. 7 and 8. Note that the three target images in Fig. 7 (with ranking of third, sixth, and ninth, respectively) are failed to be retrieved in Fig. 8.

E. Image Retrieval Results on MPEG-7 Testing Database

Common color dataset (CCD) is established in MPEG-7 as the test database for conducting color core experiments [25]. Among the 5466 images contained in this database,

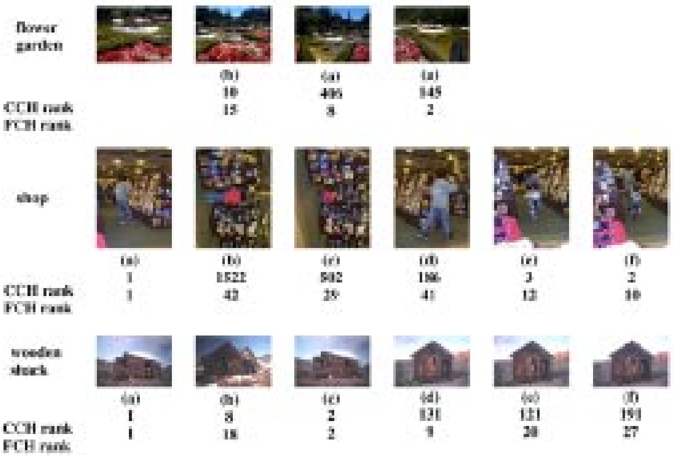

Fig. 9. Retrieval results of using three CCQs as shown in images (a) in each rows, based on FCH and CCH, respectively. The images (a)–(f) in each row are the corresponding GTS with respect to the query image (a) in the same row.

50 *common color queries* (CCQs) and their corresponding so-called *ground truth sets* (GTSs) are defined for the purpose of image retrieval based on color. As mentioned in Section IV, the value of m should be adjusted according to different image retrieval applications. Our experimental results indicate that FCH with $m = 1.2$ achieves best retrieval performance for these queries on CCD. Here, both FCH and CCH are computed based on global color distribution of the entire image. Table II documents the retrieval performance for these queries using 64-bin FCH $(m = 1.2)$ and 64-bin CCH, respectively. Note that FCH achieves better performance than CCH in most cases. Among these CCQs, three retrieval results are shown in Fig. 9. Comparing these results, we can see that FCH is less sensitive to noisy interference (i.e., small scene changes and illumination changes) than CCH experimented on this database.

VII. Conclusion

In this paper, we introduce a novel descriptor on representing color images, called *fuzzy color histogram* (FCH), with mathematical development. For computing FCHs, we propose an efficient method based on fuzzy c-means clustering algorithm performed on the color components recorded in the perceptually uniform CIELAB color space. Note that our proposed FCH is generic and can be directly employed in other color spaces and for various application fields as well. Experimental results show that our FCH is less sensitive and more robust than CCH on dealing with lighting intensity changes, quantization errors, region-of-interest image retrieval, and possibly other uncovered aspects in new applications.

From the observation of the interplay between FCH and quadratic histogram distance, our proposed FCH not only addresses the noise sensitivity issue of CCH but also avoids intensive online computation encountered in computing the quadratic histogram distance. The preliminary results of this work proposed to MPEG-7 [26] since the *retrieval sensitivity* was recognized as an indispensable issue that needs to be satisfactorily addressed.

Finally, exploiting FCH into other image processing frameworks and even extending similar soft clustering approach to other low-level visual features (e.g., shape, texture, etc.) are also recommended here.

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