Rotation and Scale Invariant Color Image Retrieval Using Fuzzy Clustering

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Abstract

Color is one of the most important image features used in content-based image retrieval (CBIR). This paper proposes a robust and effective color feature known as ring-based fuzzy histogram (RFH), which reduces noise sensitivity in conventional color histograms (CCH) by using two stages of fuzzy clustering. By partitioning images into rings, RFH can capture an image's spatial information, and is robust to rotation and scale variations. This paper also presents details about the extraction of RFH. The fuzzy histogram extracted from the whole image is used to filter out highly dissimilar images during the image retrieval process, leading to a reduced query response time. Experiments results show that the proposed feature is, in general, compact; robust to changes due to images rotation or image scaling; and robust to illumination changes and quantization noise. It also outperforms CCH and other recently published proposal, such as fuzzy color histogram [6].

1. Introduction

Color is an important image feature for the task of content-based image retrieval. In the early 1990's, Swain and Ballard [14] were among the first to propose the use of conventional color histogram (*CCH*) in image retrieval. It maps the colors in an image into a discrete color space containing n colors. Color histograms are easy to compute, relatively robust to image distortions, (such as those due to rotation). However, there are also problems with the color histograms: First, the number of color bins needed in *CCH* is large and thus a comparatively large space is needed to store each image. Second, intersection-based similarity measurement leads to the sensitiveness to quantization errors and illumination changes (e.g., two colors will fall into different histogram bins even when they are very similar). Third, CCH doesn't include important details (such as spatial information) of images [6].

Some clustering methods had been employed to reduce the dimensionality of the color histogram. Examples here include hierarchical clustering, color naming system, supervised clustering, and uniform quantization.

To improve the robustness of the color histogram, [14] proposed a similarity measurement based on histogram intersection with the aim of eliminating the influence of background color in the match results. Although the method is robust to object occlusion and image resolution, it is still largely sensitive to changes in illumination. [7] assumed a linear spectral reflectance model to derive a set of illumination-independent moment invariants of color distributions. Other methods extended color indexing by using the distribution of color ratios. Invariance to illumination conditions is achieved on the assumption of locally constant illumination [4][10]. Though effective, their computation is time-consuming.

Trying to address both of two problems mentioned above, the method of Fuzzy Color Histogram (*FCH)* is proposed by applying fuzziness to color histograms [6]. Each pixel's color is associated to all the histogram bins through the function of fuzzy membership. The experiments showed that requiring less storage space, *FCH* is less sensitive to noise interference, such as illumination changes and quantization errors than *CCH*. However, this approach *FCH* simply ignored the quantization error introduced in the process of uniform quantization, which impaired its robustness to noise interference. Besides, it doesn't incorporate spatial information in the image feature, which leads to ambiguities when comparing similarities by histograms.

Common methods incorporate spatial information by dividing images to different blocks [2][5][13]. Yet such methods are not robust to image rotations. Other methods try to integrate spatial information without partitioning the image [8] [11] [12]. These methods typically have some special restrictions (eg. the number of representative colors [8], or the number of "sufficiently present" colors [12], should not be large). They are also usually time-consuming to implement. To our knowledge, there is still no commonly accepted method to incorporate spatial information with color features, while at the same time maintaining rotation and scale invariance.

In this paper, we propose a new image feature, called ring-based fuzzy histogram (*RFH*). Images are partitioned into concentric rings with varying radial distances first, in order to integrate spatial information while holding the property of rotation invariance. Two steps of fuzziness, fuzzy smoothening and fuzzy quantization, are introduced to *CCH*, to make the histogram more robust to noise interference. Experiments show that *RFH* generally outperforms *FCH* and *CCH* in the robustness to noise interference and in the subject discriminability.

This paper is organized as follows. In the next section, we present the details on the two steps of fuzziness in problem of color quantization. Section 3 describes the ring-partitioning method applied on the image, as well as the extraction process of *RFH*. Experimental results are provided in Section 4. Section 5 concludes the paper.

2. Fuzzy color quantization

To reduce the dimensionality of the resulting color histogram features, an appropriate method should be employed to quantize the color values. In this section, we describe a two-step approach to introducing fuzziness in problem of color quantization. First, the image is taken through an initial process of fuzzy color smoothening. Based on this, we perform fuzzy quantization using a perceptually-uniform color space, the $CIE(L^*, u^*, v^*)$ color space.

2.1. Fuzzy histogram smoothening

For color image in *RGB* space, there are usually 256 levels of colors in each channel. This number is not necessary for most color image recognition applications. Color levels are reduced from 256 levels/channel to 16 levels/channel through method of uniform quantization in our work. However, it could introduce quantization error during the process of quantization.

In order to lessen the quantization error, we first introduce fuzziness in our framework by the use of a fuzzy smoothening function on 4096(16*16*16)-bin RGB color histogram. For a given color level, we associate with it a fuzzy membership function *f*. Thus, given the *i*-th color level p_i, the membership function $f_i(j)$ defines the degree to which the *j*-th color level is similar to p_j, where the values in $f_i(j)$ are normalized to be in the range [0 1]. Expectedly, the degree of similarity should be inversely proportional to the inter-color distance between p_i and p_j. The natural choice for this function is the Gaussian smoothening function:

$$f_i(j) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{d(i,j)}{2\sigma^2}\right) \tag{1}$$

where, σ^2 is the variance, and $d(i,j)$ is a distance measure.

Typically, the distance measure is the *L2*-norm: $d(i,j) = \|p_i - p_j\|$. Given the membership function, the conventional color histogram *H* can now be smoothened as follows:

$$H'(i) = \sum_{j=1}^{n} H(j) f_i(j) \tag{2}$$

This is essentially a convolution operation. Thus, for image *M*, we can represent the fuzzy smoothened histogram as $H'(M) = H * f_i$, where * denotes the convolution operator.

The resulting histogram after the fuzzy smoothening has been termed "fuzzy paradigm-based histograms" in [15]. This approach has also been used by some authors for the purpose of reducing quantization noise [9]. We note that the above smoothening can be performed either on the *RGB* or on the CIE(L^*,u^*,v^*) space.

2.2. Fuzzy color clustering

To further improve efficiency, the histogram with 4096 bins can still be reduced with less bins. However, simply using fewer bins could lead to a significant loss in the color information. Therefore an appropriate quantization technique is required to reduce this potential loss, while still providing a more compact representation. We note two important observations in choosing a clustering method for the purpose of image retrieval.

First, a fine clustering method works better in a perceptually uniform color space, (such as the CIE (L^*, u^*, v^*) space used in the work); Second, color bins in *RGB* color histogram have a proportional spacing between them. And the proportional spacing between bins is lost after the nonlinear transformation from the *RGB* space to the CIE(L^*, u^*, v^*)space. Thus, uniform quantization (i.e., uniformly dividing the data equally to different clusters) is not appropriate in clustering colors in the CIE (L^*, u^*, v^*) space.

Fuzzy clustering method was shown to be effective for non-regularly distributed data points [1]. It was also shown to improve the performance of color image retrieval [3][6]. Therefore, we use Fuzzy C-Means (*FCM*) clustering method to cluster the color bins in the CIE (L^*, u^*, v^*) space. The *FCM* algorithm attempts to partition a finite collection of elements $X = \{x_1, x_2, ..., x_n\}$ into a finite collection of *c* fuzzy clusters with respect to some given criterion. A detailed description and implementation of the *FCM* algorithm can be found in [1].

2.3. Color quantization using fuzzy clustering

The procedure of color histogram quantization is described as follows:

1) Perform uniform quantization to the *RGB* color histogram, which reduces the color levels from 256 bins/channel to 16 bins/channel. We call this step *coarse quantization*.
2) Combine 3-D histogram to 1-D histogram and compute the index number of each bin in the 1-D histogram.
3) Using Gaussian smoothening function to smoothen the 4096-bin color histogram.
4) Convert the 4096 colors from *RGB* space to the CIE (L*,u*,v*) coordinates.
5) Cluster the 4096 color bins to *c* color clusters/bins by fuzzy quantization, using the *FCM* algorithm, where *c* is the required number of color clusters. We call this step *fine quantization*.

The 3D to 1D mapping in step 2 is performed using a simple relation:

$$f(r, g, b) = b \times 16^2 + g \times 16 + r \ , \qquad (3)$$

where r, g, b are the respective color values in the 3D RGB space,. $f(r, g, b)$ is the index number of the bin. 16 levels in each of the 3 channels lead to 4096 different levels at the 1D representation

The choice of the parameter *c*, the needed number of clusters will typically be application dependent. In this work, we performed a performance comparison using different values of *c*, (*c*=32, 64, 128). Results show that retrieval performance is only marginally improved beyond *c* = 64, (see section on results).

In step 5, a mapping table between the 4096 CIE(*L**,*u**,*v**) values and the *c* color clusters is generated. It serves as a mapping between the 4096 *RGB* values and the *c* fuzzy color clusters. The mapping table is computed offline only once, and is represented as a partition matrix *U*:

$$U = \{u_{ij}, i = 1,2,...,c, j = 1,2,...4096\} \ , \qquad (4)$$

where u_{ij} represents the degree of membership (or association) of the *j*-th color value (from 4096 possible RGB values) with the *i*-th color cluster (out of c clusters). Thus, each row of *U* represents a fuzzy membership function.

A quantized histogram (so called *fuzzy histogram*) could be computed directly from the conventional histogram, using simple matrix multiplication:

$$\underset{1\times c}{FH} = \underset{1\times 4096}{H} \times \underset{4096\times c}{U^T} \qquad (5)$$

where, *FH* is an *c*-bin *fuzzy histogram*, *H* is vector representing 4096-bin normalized *RGB* color histogram Since normalized RGB color histogram *H* is scale invariant, the *fuzzy histogram* *FH* is also scale invariant.

3. Ring partitioning and ring-based fuzzy histogram

As mentioned in Section 2, a number of approaches attempted to integrate spatial information with color histograms by dividing images into sub-blocks and comparing the features extracted from the sub-blocks. Yet the features in these methods are not rotation invariant. In this section, we present a new partition method. The method is easy to implement. More importantly, the image features extracted from the resulting partitions possess the important property of rotation invariance.

3.1. Ring partitioning method

Image rotating about uncertain point by angle θ_0 can be considered as rotating about the center of the image frame by angle θ_0 and then shifting by an amount that depends on the position of the uncertain point. For simplicity, we only consider rotating about the centroid. Translation is a concern which is beyond the scope of the present work.

A number of rings are used to partition the image to sub-regions. The rings are concentric, centered at the center of the image frame. The areas between neighboring rings are the sub-regions based on which the image features will be extracted. In order to more easily partition the image circular wise, polar transformation is applied to each image. With polar transform, rotation in the Cartesian space can be performed as planar shifts in the polar coordinates.

3.2. Polar images

A polar image can be constructed as follows: for a given $L_1 \times L_2$ image $f(x, y)$, scan the image in two dimensions. First, scan *M* times along the angular direction, evenly distributed from 0^o to 360^o. Second, scan *M* times along the radial direction, evenly distributed from 0 to $N/2$, where $N = \max(L_1, L_2)$ (see Fig. 1).

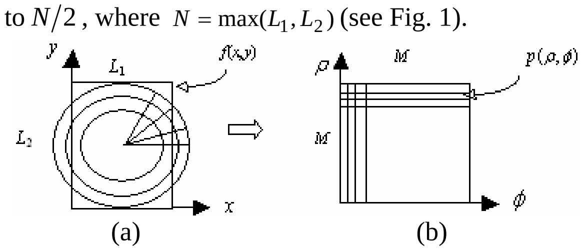

Figure 1. **The polar transformation: (a)** $L_1 \times L_2$ **image** $f(x, y)$ **in Cartesian coordinates; (b)equivalent** $M \times M$ **polar image** $p(\rho, \phi)$ **in polar coordinates.**

For the example of $f(x, y)$ in (a), we have $L_1 < L_2 \Rightarrow N = L_2$. For the regions of rings that fall out of the square area of $f(x, y)$ in (a), theirs color values are set to be 0 in the corresponding positions in the polar image, $p(\rho, \phi)$.

Formally, $p(\rho, \phi)$ can be computed as:

$$p(\rho, \phi) = f(\lfloor N/2 + \rho\cos(2\pi\phi/M)\rfloor, \lfloor N/2 - \rho\sin(2\pi\phi/M)\rfloor) \quad (6)$$

where $\lfloor x \rfloor$ represents the smallest integer that is not greater than *x*. Note that rotation in Cartesian space corresponds to a simple cyclic column shift in the polar space.

3.3. Ring-based fuzzy histogram

We partition the polar image to several sub-regions (or layers), where each region/layer is composed of the same number of consecutive rows in the polar image. Rotation and scale invariance can be achieved by computing fuzzy histograms from each sub-region in the polar image. We call these histograms *Rring-based Fuzzy Histograms* (*RFH*). Essentially, *RFH* is a set of fuzzy histograms defined as follows:

$$RFH = \{FH_0, FH_1, FH_2, ..., FH_m\}, \quad (7)$$

where, FH_0 is the *c*-bin *fuzzy histogram* of the whole polar image $p(\rho, \phi)$. $FH_i (i = 1,2,..,m)$ is the *c*-bin *fuzzy histogram* of the *i*-th sub-region in the polar image, *m* is the total number of sub-regions.

There are two kinds of *RFH* features: the global features FH_0, and the regional features $FH_i (i = 1,2,..,m)$.

1) Global features: FH_0 is the first component of *RFH*. This is a global feature that describes the color statistics from the entire image. For a given query image *q*, and a database image *d*, we define below a normalized distance $D(q, d)$ between them based on FH_0:

$$D(q, d) = \frac{\sum_{j=1}^{c} \left| FH_0^q(j) - FH_0^d(j) \right|}{1 + \sum_{j=1}^{c} [FH_0^q(j) + FH_0^d(j)]} \quad (8)$$

where *j* is the bin position in the *c*-bin *fuzzy histogram*.

We use the global feature FH_0 to filter out images that differ significantly from the query – in terms of their general color statistics. Since spatial information about the image is maintained in $FH_i (i = 1,2,..,m)$, in a sense, using FH_0 in this way can be viewed as using the image's general color information as a pre-filter before using detailed spatial information for further processing. This proved to be time saving during retrieval, and also improves the retrieval accuracy.

2) Region features: After pre-filtering the database images, $FH_i (i = 1,2,..,m)$ are then used to further prune out dissimilar images. To decide the value of *m*, there are several factors taken into consideration. First, with a bigger value of *m*, color image is partitioned by more rings, thus more spatial information is kept in FH_i. This is helpful to filter out those images that are visually dissimilar, but have similar global color statistics. Second, if the value of *m* is too big, each area of the ring-region gets small. Thus a small translation of the color image will have a significant influence on the contents of those ring-regions. As a result, the *RFH* from these areas will be less robust to small image translations. Third, FH_i with a bigger *m* surely takes more storage space and more computing time. Consider the 3 factors, an optimal number of rings needs to balance the positive and negative effects listed ahead. The value of *m* will be decided in the experiments.

The overall normalized distance between the query image I_q and the database image I_d is as follows:

$$D(I_q, I_d) = \sum_{i=1}^{m} w_i \frac{\sum_{j=1}^{c} \left| FH_i^q(j) - FH_i^d(j) \right|}{1 + \sum_{j=1}^{c} [FH_i^q(j) + FH_i^d(j)]} \quad (9)$$

where $\sum_{i=1}^{m} w_i = 1$, and w_i is the weighting factor for the *i*-th sub-region of the polar image. The choice of w_i will depend on the importance associated with each sub-region. In our experiments, we assume that each sub-region provides roughly equal contribution to the similarity measure, and hence use $w_i = 1/m$.

4. Experiments

4.1. Construction of test databases

Three test image databases were constructed to evaluate the performance of the proposed *RFH* on three grounds: general discrimination ability, rotation invariance, and robustness to illumination changes in the retrieval of similar images. The databases are called *general database*, *rotation database* and *illumination database* respectively. With each of the three databases, all the 1,500 images with different subjects are used as queries. Similar images are retrieved by comparing the query with the database images. Retrieval results from all queries in one database contribute to the average performance of all the queries in this database.

4.2. Measurement of retrieval performance

We use a precision-recall (*P-R*) graph to evaluate the retrieval performance of different image descriptors in rotation and scale test databases. Precision *P*, and recall *R* are defined respectively as follows:

$$P = \frac{|C_q|}{|B_q|}\,;\ R = \frac{C_q}{D_q} \tag{10}$$

For a given query, we can set the recall to different values, and then calculate the corresponding precision values. From all query results, we plot their average precision value for each recall in the *P-R* graph.

4.3. Results

1) General Database: To check the effect of the number of rings on the performance of *RFH*, we carried out a good number of experiments on the general database, using different number of rings to partition the color images. Fig.2 shows the overall *P-R* performance comparison.

The optimal number of rings will typically be application dependent. From Fig. 2, *RFH* with 4 rings produced the best overall *P-R* performance. Thus, for the remaining experiments, we fixed the number of ring partitions to 4. Due to the fact that similar images in the database are often in different size, the ability to retrieve these images demonstrates that *RFH* is robust to scale changes of images (i.e. scale invariant).

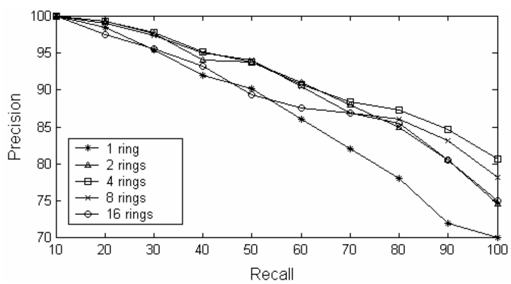

Figure 2. **Performance of *RFH* using different number of rings to partition the images.**

From Fig. 2, *RFH* has the poorest *P-R* performance when using just one ring. Since this corresponds to using only the global feature (i.e. no regional information is used), it illustrates the importance of spatial information in color-based image retrieval.

To test the subjective discriminability of *RFH*, *FCH* and *CCH*, we perform a series of experiments on general database using the three features. For each pre-set recall value, average precision value of different feature is listed in Table 1.

Table 1. ***P-R* performance of *RFH*, *FCH* and *CCH*. For *RFH* and *FCH*, the number of bins refers to the stage of fine-grained (fuzzy) quantization (i.e. the number of fuzzy clusters *c*).**

Recall (%)	10	20	30	40	50	60	70	80	90	100
RFH (32 bins)	100	98.5	96.7	94.0	91.3	90.5	88.5	85.9	83.4	78.5
RFH (64 bins)	100	99.3	97.8	95.1	93.8	92.7	88.4	87.3	85.6	81.6
RFH (128bins)	100	99.5	98.2	97.4	94.5	92.3	90.9	87.7	86.5	82.3
FCH (32 bins)	100	97.4	96.7	93.7	92.5	90.9	87.0	84.5	83.7	77.4
FCH (64 bins)	100	98.2	97.9	95.0	92.6	90.0	87.5	86.9	84.0	79.3
FCH (128 bins)	100	99.4	97.8	94.4	91.5	90.7	87.7	87.1	84.2	80.3
CCH (32bins)	100	97.7	92.1	89.0	86.4	80	77.5	75.5	70.4	65.5
CCH (64 bins,)	100	98.2	93.4	90.3	86.6	84.5	83.8	76.5	73.4	70.9
CCH (128bins)	100	98.9	94.5	91.7	88.6	87.9	85.1	82.1	79.5	77.4

Several conclusions can be drawn from the table above. First, under the same number of bins, *RFH* achieves better *P-R* performance than *CCH* and *FCH*. This implies that by incorporating spatial information, *RFH* is more accurate at retrieving similar images. Second, performance curves for *RFH* and *FCH* are closer than the results with *CCH*. This implies that, *RFH* and *FCH* are less sensitive to changes in the number of bins (i.e. clusters) used. As amount of quantization error is mostly dependent on the number of bins used, the implication is that *RFH* and *FCH* features are more robust to image noise and quantization errors than *CCH*. Third, for *RFH*, retrieval performance with 64 bins is close to the performance with 128 bins. For the rest of this section, we report results for 64 bins.

2) Rotation Database: We also compare the performance of *RFH* with histogram features that are based on block partitioning. To avoid the influence of factors other than rotation, for the block-based color features, we also extract fuzzy histograms from the partitioned blocks. Besides, we compare the performance of *RFH* with that of *FCH* on rotation test database.

Fig.3 presents the overall precision-recall charts for the three features using the rotation databases.

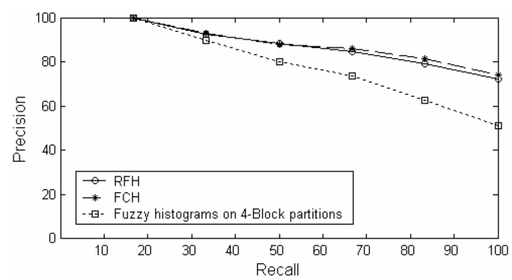

Figure 3. **Precision-recall plots using the three approaches to integrating spatial color features.**

When compared with the feature based on block partitioning, *RFH* with ring partitioning and *FCH* can produce higher precisions for many of the different recall values. The difference in performance increases with larger recall values. We can tell from above figure that *RFH* is robust to image rotations, and its robustness to image rotation is close to that of *FCH*.

3) Illumination Database: To compare the robustness of *RFH*, *CCH* and *FCH* to illumination variations, we performed tests on the illumination database by using the 3 features. For each feature, all database images are sorted based on their Euclidean distance to a query image. Fig.4 shows four randomly selected query images. Table 2, 3 and 4 list the ranks of the corresponding 10 images when using respective queries.

Comparing the retrieval results by using different features, similar images rank notably higher in Table 2 than in Table 3 and Table 4, which implies that *RFH* is more robust to illumination changes.

(a) (b) (c) (d)

Figure 4. **Query images from the illumination database**

Table 2. **Retrieval results by *RFH***

Original images	Ranks of the corresponding 10 images									
a	2	3	4	5	6	8	10	17	22	35
b	2	3	5	6	8	10	14	20	44	78
c	2	3	4	5	6	10	19	22	66	110
d	4	6	10	14	17	20	22	40	71	157

Table 3. **Retrieval results by *FCH***

Original images	Ranks of the corresponding 10 images									
a	2	3	4	6	7	10	14	17	20	60
b	2	4	5	6	11	14	17	28	66	121
c	2	3	4	5	6	9	17	23	73	127
d	4	7	13	14	19	26	32	41	96	178

Table 4. **Retrieval results by *CCH***

Original images	Ranks of the corresponding 10 images									
a	2	3	4	5	11	16	17	25	39	173
b	2	3	4	7	9	15	25	57	120	270
c	3	4	7	8	13	19	37	47	184	323
d	4	5	11	13	21	24	41	91	124	197

5. Conclusion

In this paper, we propose using the image feature known as *RFH*. To improve robustness, fuzziness is introduced in the histogram generation process in two steps. First, fuzzy smoothening is applied to the image histogram after coarse quantization, reducing the quantization errors introduced during the process of coarse quantization. At a later stage of fine quantization, *FCM* algorithm is used to cluster the histogram bins (4096 bins in the work) into a relatively low dimensional space. To integrate spatial information to the feature while holding the property of rotation invariance, ring-partitioning is applied to polar-form images and *RFH* is then constructed as a set of fuzzy histograms for the ring-partitions. To speed up the query process, the fuzzy histogram of the whole polar image is used as a global feature to filter out the highly dissimilar images, before performing the more time-consuming analysis of the region-based fuzzy histograms.

Experiment results show that, with introduction of two stages of fuzziness, *RFH* is more robust to noise and illumination changes than *FCH* and *CCH*; with spatial information integrated, *RFH* outperforms *FCH* and *CCH* in subject discriminability; with the ring-partitioning method, *RFH* is more robust to image rotations than traditional block-partitioning method.

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6. References

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