Color Matching for Image Retrieval

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Abstract

Color is an important attribute for image matching and retrieval. We present two new color matching methods, reference color table method, and a distance method, for image retrieval. Both these methods and an existing method 'histogram intersection' were implemented and tested for a database size of 170 color images. To compare the efficacy of each method, a figure of merit, called 'Efficiency of Retrieval' is defined. The results show that the both the new methods perform better than the existing method, and that the reference color table method gives the best results.

Keywords: *Color, Matching, Distance, Measure, Retrieval.*

1 Introduction

Color is an important attribute for image matching and retrieval [NBE$^+$93]. Traditionally, color images were not used widely due to the large storage and high computational requirements. With advances in technology, the computing & storage costs are rapidly decreasing. As a result, color images are increasingly being used in many applications.

The motivation for our work is to develop efficient color matching techniques so that image retrieval based on color can be effective and fast. This is required in image databases and image information systems like multimedia databases, trademarks databases, face image databases etc. Our problem is as follows: assume that we have a large number of color images in the database. Given a query image, we would like to obtain a list of images from the database which are most "similar" in color to the query image. For solving this problem, we need two things – first, a feature which represents the color information of the image and second, a similarity measure to compute the similarity between features of two images.

The rest of the paper is organized as follows: Section 2 is on image retrieval model, section 3 is a brief review of past work, Sections 4 describes the proposed methods, test results and discussion are given in section 5. Conclusions and scope for future work are given in section 6.

2 An Image Retrieval Model

Figure 1 shows a block schematic of an image archival and retrieval scheme. In essence, image matching and retrieval is based on some characteristic features of image class under consideration. The input images are analyzed to extract the features and these features are used to store in the image database, along with the original images. These features could, for example, be shape features, texture features or color features. Whenever an image is submitted for search, it is analyzed and its features are extracted. These extracted features are matched against those

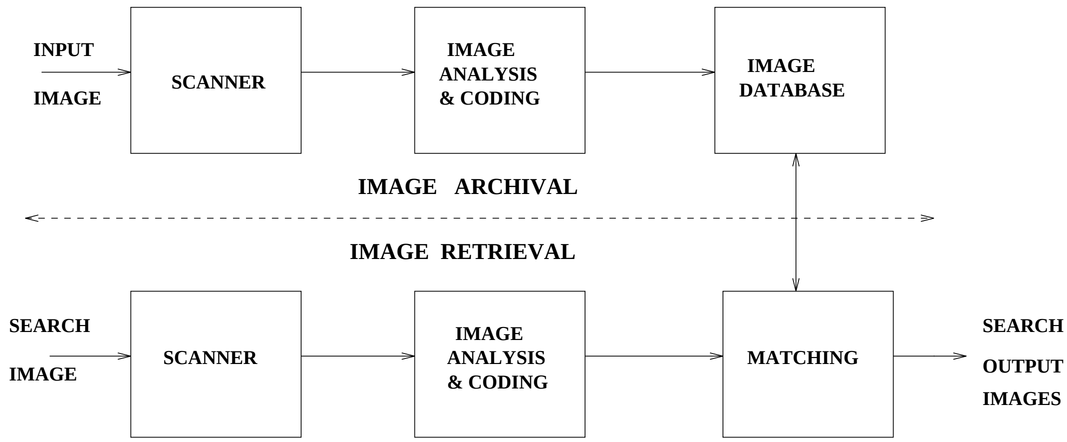

Figure 1: An Image Retrieval Model

in the database. A set of closely matching images are brought out as the result of search output.

An important criterion for testing the efficacy of the search and retrieval is that the output must include all the similar images. The list may have other images as well, but that is not very important. The important thing is that the similar ones should not be missed in the search process. Such a criterion is important in many applications like trademark registration, fingerprint identification etc., where the system brings out the short list and the final decision is taken by the human expert in the loop. In this paper, we present an efficient method for image matching when color is used as the feature for matching purpose.

3 Past Work

Recently there has been an increased interest in color research e.g., classification [CR93, ABS90], segmentation [Hea92]. Swain and Ballard [SB91] have proposed a color matching method in their paper on 'color indexing'. Their method, called *histogram intersection*, is based on matching of color histograms and the core idea in their technique is to compute:

$$H(I, M) = \frac{\sum_{j=1}^{n} min(I_j, M_j)}{\sum_{j=1}^{n} M_j} \tag{1}$$

where $H(I, M)$ is the match value, I and M, are image (query image) and model (an image in the database) histograms respectively, each containing n bins. The match value is computed for every model histogram and the value is closer to unity if the model image is more similar. It is obvious that a match value of unity is obtained for an image compared with itself. It is clear that for this approach, the feature $\bar{\mathbf{f}}$ used to characterize the color information of an image is the 3-D color histogram $h(x, y, z)$ and the similarity measure between features is given by the match value as shown in eqn. (1).

4 Proposed Methods

The two new methods proposed are Distance Method, and Reference Color Method. Both these methods are explained in the following sections 4.1 and 4.2.

4.1 The Distance Method

As seen earlier, the histogram intersection technique takes into account every color bin of the 3-D color histogram of the two images compared and it does a very detailed comparison. However, for many synthesized images like trademark images, flags, textile design patterns etc., there are large regions of uniform color. Therefore the 3-D histogram will have a few dominant peaks and the rest of the bins do not capture much color information of the image. Hence a detailed comparison for such images is not required. Also, our observation has been that there is some noise introduced during the process of scanning color images. Hence, a fine comparison is not necessary and may even produce incorrect results. We therefore propose a new method which does a coarse comparison of the color histograms of the query and model images.

The feature we use for capturing the color information is the mean value, μ, of the 1-D histograms of each of the three color components of the image. These components could be R, G and B for the RGB representation or the three opponent color axes – rg, by and wb [SB91] given by:

$$rg = R - G; \quad by = 2 * B - R - G; \quad wb = R + G + B \tag{2}$$

Therefore, the feature vector $\overline{\mathbf{f}}$ for characterizing a RGB image will be:

$$\overline{\mathbf{f}} = (\mu_R, \mu_G, \mu_B) \tag{3}$$

We can normalize the histogram by considering the relative fraction of pixels (compared to the total number of pixels in the image) in each bin of the histogram. We can then use a distance measure to compute the similarity or match value for a given pair of images. Depending on the type of the distance measure used – Manhattan (city block) or Euclidean, we have the following measures:

$$D^M_{q,i} = |\overline{\mathbf{f_q}} - \overline{\mathbf{f_i}}| = \sum_{R,G,B} |\mu_q - \mu_i| \tag{4}$$

$$D^E_{q,i} = \sqrt{(\overline{\mathbf{f_q}} - \overline{\mathbf{f_i}})^2} = \sqrt{\sum_{R,G,B} (\mu_q - \mu_i)^2} \tag{5}$$

where $D^M_{q,i}$ is the Manhattan distance between the query image and a database image, $D^E_{q,i}$ is the Euclidean distance between the query image and a database image, $\overline{\mathbf{f_q}}$ is the color feature vector of the query image and $\overline{\mathbf{f_i}}$ is the color feature vector of the database image. Note that a similar feature and distance measures can be deduced for color images using any other representation scheme, like the opponent color axes. It is obvious that the distance of an image from itself is zero.

4.2 Reference Color Table Method

The distance method computes a coarse feature measure and uses a relative distance measure for a given pair of images. It involves less computation and gives fast &

Color	R	G	B	Color	R	G	B
Black	0	0	0	SlateBlue	128	128	255
DarkBlue	0	0	128	LawnGreen	128	255	0
Blue	0	0	255	PaleGreen	128	255	128
DarkGreen	0	128	0	LightCyan	128	255	255
Turquoise	0	128	128	Red	255	0	0
SkyBlue	0	128	255	Maroon	255	0	128
Green	0	255	0	Magenta	255	0	255
SpringGreen	0	255	128	Orange	255	128	0
Cyan	0	255	255	Pink	255	128	128
Brown	128	0	0	LightMagenta	255	128	255
Violet	128	0	128	Yellow	255	255	0
MarineBlue	128	0	255	LightYellow	255	255	128
OliveDrab	128	128	0	White	255	255	255
Grey	128	128	128				

Table 1: Reference Color Table

reasonably accurate results. The histogram intersection method is highly granular and it carries out a detailed comparison of all the histogram bins in the 3D color representation but is susceptible to noise. The Reference Color Table method can be considered as an intermediate approach to the distance method and histogram intersection approaches, which reduces the detail of histogram matching yet retains the speed & robustness of the distance method.

In the Reference Color Table method, we define a set (table) of reference colors. This set of colors is selected such that all the colors in the database are approximately covered perceptually. Table 1 shows the color table which we have used for our database. For every image in the database, we compute a histogram for this set of colors, 27 in our case. For this purpose, each pixel in the color image is classified against the colors in the color table and assigned the nearest color. A simple city-block distance is used to compute the nearest color in the reference table. Then the histogram of the pixels with the newly assigned colors is computed. If the color table selected is good, the 'new image' after assigning the nearest color from the table, will perceptually be the same as the original image. So, for this method, the color feature chosen is this reduced color histogram based on the colors of the reference table. Therefore,

$$\bar{\mathbf{f}} = (\lambda_1, \lambda_2, ..., \lambda_n) \tag{6}$$

where λ_i is the relative pixel frequency (with respect to the total number of pixels) for the i^{th} reference table color in the image. The size of the reference color table is n. This feature is computed for all the images in the database.

For a particular query image, the reference color histogram feature described above is first computed. Then, the image is matched against all images in the database to obtain the similarity measure with each image in the database. For computing the similarity, we use a weighted distance measure:

$$D_{q,i} = \omega\sqrt{(\bar{\mathbf{f}}_{\mathbf{q}} - \bar{\mathbf{f}}_{\mathbf{i}})^2} \tag{7}$$

which leads to:

$$D_{q,i} = \sum_{i=1}^{n} \omega_i \sqrt{(\lambda_i^Q - \lambda_i^I)^2} \text{ where } \omega_i = \begin{cases} \lambda_i^Q & \text{if } \lambda_i^Q, \lambda_i^I > 0 \\ 1 & \text{if } \lambda_i^Q \text{ or } \lambda_i^I = 0 \end{cases} \tag{8}$$

where $\mathbf{f_q}$ and $\mathbf{f_i}$ are the color features of the query image and database image respectively. Note that λ_i^Q and λ_i^I are the i^{th} reference color relative pixel frequency of the query and database images respectively. n is the number of colors in the reference color table. Note ω is the weight factor used. For a particular color, if both of the histogram bins are non-zero, then the weight ω_i used is λ_i^Q since we want to take the relative proportion of color i in that image. If either of the corresponding histogram bins have a value of zero (which means that color is missing), then ω_i is taken to be unity. In this case the relative difference of the two bins is used as a *push factor* to separate the two images in the similarity measure. It is obvious here that the distance of an image from itself is zero.

Method	Feature Computation	Matching
Histogram Intersection	$O(M^2)$	$O(K)$
Distance Measure	$O(M^2)$	$O(1)$
Reference Color Table	$O(M^2)$	$O(L)$

Table 2: Comparison of Computational Complexity of different methods.

4.3 Computational Complexity

We need to consider the computational complexity of both feature computation and matching. Feature computation is a one time effort for building the database whereas matching is done for every query. A comparison of the computational complexity of the three methods is given in Table 2. The size of the input image is assumed to be $M \times M$ pixels, K (= 2048 in [SB91]) is the number of colors used in Histogram Intersection method, L (= 27) is the number of colors in the Reference Color Table.

Though all three methods have $O(M^2)$ complexity for feature computation, the Reference Color Table (RCT) method has the largest constant. However, it is easy to reduce this constant by exploiting coherence in the input image. Usually, a given image will have only a few colors of the RCT. We have observed that typically an image has about three to five different colors. The classification of each pixel color to the RCT color can be done once and this information can be re-used for all subsequent pixels of the same color. This significantly reduces the time for feature computation. From Table 2, it can be seen that for the matching part, both of our methods have a better complexity.

5 Test Results and Discussion

We implemented both the new methods and the existing histogram intersection method and tested them on two databases. We first used one database of 100 airline trademark images and then tested on another database of 70 flag images of different countries. For the histogram intersection and the distance method we quantized all the images to have $16 \times 16 \times 16$ levels for both RGB and opponent color axes (OPP) representations. We used the Euclidean distance measure, $D^E_{q,i}$ (eqn. 5) for the testing since our preliminary results indicated it to be a superior distance measure.

For the reference color table method, the images were first transformed such that each pixel is assigned the nearest color value from the reference color table. The database was built where the normalized histograms of the transformed images were stored.

We designed the tests in this manner: we picked 10 query images each for both the databases which represented the population well. For each of these query images, we manually listed the similar images found in the database. Let N be the number of such images. Then we applied all three techniques to each query image against all images in the database to obtain *short lists* of similar images. The summary of results are presented in table 3. For any query, we define the efficiency of retrieval, η_T, for a given short list of size T as follows:

$$\eta_T = \begin{cases} \frac{n}{N} & \text{if } N \leq T \\ \frac{n}{T} & \text{if } N > T \end{cases} \tag{9}$$

where n is the number of similar images retrieved in the short list (subset of N similar images) and N is the total number of similar images in the database. Table 2 represents the retrieval efficiency, η_T, for both the methods, averaged over 10 queries. We have presented the results for short list sizes of $T = 5,\ 10,\ 15$ and 20.

It is evident from table 3 that the efficiency of the distance method and the reference color table methods are superior to that of the histogram intersection method. The reference color table method gives best results among the three methods under consideration. The reason for the color table method's better performance compared to the distance method is that it uses an absolute distance measure (due to comparison against a reference) compared to the relative distance metric used by the distance method. Also, if the reference color table is well chosen, then the reference histogram is a better feature perceptually, than the means of the three 1-D histograms.

For example, consider the airline trademarks images database represented with the opponent color axes. For a short list of size $T = 15$, the efficiency for the histogram intersection method is 0.713 while it is 0.986 for the distance measure technique & 0.987 for the reference color table method. This means that, on the average, 71.3% percent of the similar images were present in the short list for the histogram intersection method. The corresponding figure for the distance measure technique is 98.6% and for the reference color table method is 98.7%. We did a few queries for the combined database of airlines and flags and the results were similar to the individual ones. Figure 2 shows a sample query image for the airline database with a short list of size $T = 10$ for all the three methods.

The proposed methods although not invariant to lighting condition, are not very sensitive to it. As long as the light is white light, variations in intensity should not matter. This is because white light will ensure the same proportionality of chromal reflection, and hence preserve the color information.

6 Conclusions and Future Work

We have presented two new methods of color matching for the purpose of image retrieval using the color feature. We have experimentally found that our techniques perform better than the histogram matching technique on synthetic images. The reference color table method allows users to define a specific color table for the application at hand. With an appropriately defined reference color table, it gives the best results possible. The advantage of distance method is that it is computationally much simpler, and gives fast yet reasonably accurate results. Of course, in any

Matching Method	Color Repr.	Airlines DB				Flags DB			
		T=5	T=10	T=15	T=20	T=5	T=10	T=15	T=20
Histogram Intersection	RGB	0.605	0.720	0.700	0.814	0.450	0.657	0.782	0.873
	OPP	0.547	0.645	0.713	0.771	0.475	0.625	0.778	0.868
Distance Measure	RGB	0.860	0.963	0.946	1.000	0.802	0.942	0.967	0.967
	OPP	0.880	0.925	0.986	0.993	0.612	0.837	0.958	0.983
Ref. Color Table		0.930	0.987	0.987	1.000	0.943	0.986	0.988	1.000

Table 3: Average Retrieval Efficiency η_T of different methods over 10 queries. Parameter T indicates the selected value of output short list size.

practical image information system, color would be one of the many features used for indexing and searching data. Our techniques appear suitable for such a purpose. We are planning to incorporate the color feature in our Trademarks image database which uses shape, text and phonetics as other features [WMG$^+$94]. One aspect which we have not considered is *indexing* the database using the color feature. This would be absolutely essential for efficient searching in a very large database. Currently, both histogram intersection and our methods require a linear search through the database which can be very time-consuming for a large database. We are working on developing efficient techniques for indexing using color features.

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Fig 2: Sample Query Results