Enhancing Color histogram for Image Retrieval

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Abstract—The conventional color histogram retrieval method is prone to lose the spatial information of colors. This paper proposes a novel color histogram approach for image retrieval. The histogram is built over groups of circular rings over the image. It keeps the advantages of the robust to the image rotation and scaling of the traditional histogram and incorporates the spatial information of pixels. An additional advantage is the consideration of perceptual sensitivity to the colors located in the central image by the use of a weighting factor of the histogram. The experimental results show that the recall and precision of this proposed approach is better than the others’ histogram methods.

Index Terms—content-based image retrieval, color histogram, spatial information

I. INTRODUCTION

The last decade has witnessed great interest in research on content-based image retrieval. Various approaches exploited texture, color, and shape etc. had been proposed and they are effective for Content-Based Image Retrieval (CBIR). The common ground for them is to extract a signature for every image based on its pixel values, and to define a rule for comparing images. Color histograms are among the most basic approaches and widely used in image retrieval for its effectiveness and efficiency. The advantage of using the histogram in image retrieval is its robustness to rotation and scaling of the image content.

However, color histogram is liable to lose the spatial information and therefore can’t distinguish those images with same color but different color distributions. Many literatures have investigated this question by integrating spatial information into the conventional color histogram. Pass and Zabih [1] divide the whole histogram into region histogram by means of color clustering. Hsu et al. [2] modify the color histogram by first selecting a set of representative colors and then analyzing the spatial information of the selected colors using maximum entropy quantization with event covering method. Colombo et al. [3] propose a concept called color coherence vector (CCV) to split histogram into two parts: coherent one and non-coherent one depending on the size of their connected component. Combining color with texture, shape and direction, this method escapes comparing color of different regions. Cinque et al. present a spatial-chromatic histogram considering the position and variances of color blocks in an image [4]. Huang [5] proposes color correlogram for refining histogram which distills the spatial correlation of colors. Recently, several other techniques have been introduced as well in which different color-related features are used as descriptors including the color feature hashing techniques [6], reference color table methods [7], and color adjacency graphs [8], etc. The sub-block histogram [9] retrieves images by separating an individual image into some blocks.

All the above approaches improve the traditional histogram by embedding the spatial information into the color histogram. However, the way of extracting colors from the image spoils the robustness to rotation and translation of the conventional histogram as seen with the position of color block adopted by Cinque et al. [4], and the shape and size of the predefined triangle used by Rickman and John Stonham [10]. Therefore these improvement methods spoil the merit of the conventional histogram.

In this paper, we enhance the traditional histogram by incorporating the spatial information to the histogram. The histogram is built over groups of circular rings over the image. It remains the advantages of the robust to the image rotation and scaling of the traditional histogram and integrates the spatial information of pixels. The experimental results show that the recall and precision of this proposed approach is better than the others’ histogram methods.

The rest of this paper is organized as follows: Section 2 introduces the novel color histogram. Experiments are shown and discussed in Section 3 followed the conclusion made in section 4.

II. ENHANCE THE TRADITIONAL HISTOGRAM WITH THE SPATIAL INFORMATION

Given a color space \( C \), the conventional color histogram \( H \) of image \( I \) is defined

\[
H_C(I) = \left\{ N(I,C_i) \right\}, \quad i \in \{1, \ldots, n\}.
\]

Where \( N(I,C_i) \) is the number of pixels of image \( I \) that fall into cell \( C_i \) and \( i \) indicates the color levels of color space \( C \). \( H_C(I) \) shows the proportion of pixels of each color within the image. See the definition of the conventional histogram, it is only dependent on the summations of pixel of each color and ignores the spatial distributions of colors completely. To incorporate spatial information into color histogram, color distribution or layout has to be considered.

We illustrate most frequently failed retrieval example using the traditional histogram in Fig 1. Suppose the total

\[
\text{Supported by: Program of the Shanghai Education Commission under Grant No.09YZ247 to WangXiaoling and Shanghai finance foundation (No. 11381A0005)}
\]

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AP-PROC-CS-09CN004

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quantity of the black color is equal in Fig1.(a) and Fig1.(b). Evidently, color distributions in the two cases are very distinctive. However, the conventional histogram method only considers the total amount of color. Consequently, the traditional histogram fails to distinguish them completely.

A simple idea is to divide all the pixels contained in each bin of the color histogram in spatial space so that an extended spatial color histogram can be derived. We propose a novel color-based histogram which is able to catch the spatial distribution of colors.

The histogram illustrated in Fig.2 is consists of a several of histograms over a groups of circular rings with different color in Fig.2. The width of each ring is one pixel.

The corresponding the histogram of Fig.1 is shown in Fig.3. Evidently, the number of pixels falling into the \( i \)th \((i = 1,2,\ldots,n)\) ring in Fig 3.(a) and Fig3.(b) is different enough, therefore, the novel histogram we proposed can be used to distinguish them correctly. We can conduct that it is capable of describing the spatial distribution of color properly.

It is easy to know such histogram has the advantage of being robust to the image rotation and scaling, which is very important to improvements algorithm on the traditional color histogram.

Next, we give its definition. Here, suppose the size of image \( I \) is \( M \times M \) where the remainder of \( M - 1 \) divided by 2 is 0 and \( M \geq 3 \). This condition guarantees the location of the first ring is in the center of image \( I \). Given a color space \( C \), the histogram is defined as

\[
H_C(I) = \{H_{R_i} \mid i \in [1,\ldots,n] \} \quad \text{(2)}
\]

Where \( H_{R_i} \) is the histogram of each ring. \( H_{R_1} \) is the histogram of center ring in image \( I \). The number of the rings \( n \) is obtained by

\[
\{ \max(0) \mid 0 < n \leq (M \times M) / 8 + 1 \} \quad \text{(3)}
\]

and \( n=1 \) indicates the first ring. We include the only one pixel in the center of the image as the first ring and also build its histogram. Another issue is the importance of different rings also differs. We design a method to assign weights for these rings in Equation (6).

According to the definition and the practical needs, users can build histogram as Fig.2 with 2, 3, etc. pixels of width. Of course, the number of rings will change accordingly. If the last ring without enough pixels width, then build histogram directly over this ring. In this paper, we adopt the 1 pixel width histogram.

In this study, we adopt the most commonly used Euclidian distance to measure two histograms

\[
d(H(I),H(Q)) = \sum_{i=1}^{n} d(H_{R_i}(I),H_{R_i}(Q)) \quad \text{(4)}
\]

Where \( n \) is defined in Equation (3).

An additional advantage of this histogram is the consideration of perceptual sensitivity to the colors located in the central image by the use of a weighting factor of the histogram as followings.

\[
d(H_{R_1}(I),H_{R_1}(Q)) = \sum_{j=1}^{n} W_j |H_{R_1}(I_j)-H_{R_1}(Q_j)|^2 \quad \text{(5)}
\]

Where \( j \) indicates the color levels of color space \( C \). \( W_j \) is the \( j \)th weight of \( H_{R_1} \). \( W_j \) is calculated as

\[
W_j = (1/j) \left( j = 1,2,\ldots,n \right) \quad \text{(6)}
\]

where \( n \) is defined in Equation (3). As we known, what an image expresses is often locates in the center of an image. The importance of the rings is inversely proportional to its distance to the center of the image. Furthermore, \( W_j \) needs to be normalized as

\[
W_j = (1/j) \sum_{j=1}^{n} 1/j \quad \text{(7)}
\]

Color figures will be appearing only in online publication. All figures will be black and white graphs in print publication.

V. EXPERIMENTAL RESULTS

A. Image database

We selected 2000 JPEG images in 10 classes from the website: http://db.stanford.edu/wangz/image.vary.jpg.tar as the database. The queries are specially chosen so as to include images of different views of the same scene, large changes in appearance, etc. We determine the relevant images based on its semantic and appearance.
B. Image preprocessing

Before experiment, all the RGB images are resized into (127×127), which satisfies the requirements described in section. In terms of search and retrieval efficiency, before experiment, the images, which have 2563 levels in the RGB color system, are firstly converted into the HSV color space and then quantitative into 72 color bins[11].

C. Performance evaluation

We make use of the Precision-Recall measure to evaluate the retrieval system. Precision is the fraction of retrieved images that are truly relevant to the query image and Recall is the fraction of relevant images that are actually retrieved.

D. Equations Experiment

In the HSV space, we compute our enhanced histogram, the traditional histogram, and the CCV histogram using 72 color bins for each image in the database. We adopt the Euclidian distance to measure their similarity.

Figure 4 illustrates three comparative query results using different methods, in which the first images are the query images.

As shown in Figure 4, we may conclude that our enhanced histogram outperforms the other two histograms; there are 30 relevant flower images in the image database. We have retrieved 19 of them in the top 20 images using our enhanced histogram, 11 using the traditional histogram and 16 using the CCV. Notice the ranks of the retrieved relevant images our enhanced histogram are also lower than other two. The main reason for this achievement is it’s incorporation of the spatial information.

Figure 5 shows the Precision and recall rate of the three schemes compared. It can be seen that our enhanced histogram significantly outperforms the other three schemes in terms of recall rate and precision. It verifies that the enhanced histogram is capable of reflecting the spatial information of color distribution.

(a) Enhanced histogram retrieval results

(b) Traditional histogram retrieval results

(c) CCV histogram retrieval results

Figure 4. Spatial division of the histogram

Figure 5. Precision and recall rate of the 3 schemes compared

III. IV CONCLUSIONS AND FUTURE WORK

In this paper, we enhance the traditional histogram by incorporating the spatial information with several rings of histograms. Not same as other improved approaches, this way to build the histogram guarantees no loss of the advantages of the traditional histogram. We found this idea is very effective to acquire the spatial information of an image and in future work we will design the method to determine a proper ring width in the histogram, for our future work and exploit its value for the shape, texture and etc.

REFERENCES


