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# Feature Analysis of Quantized Histogram Color Features for Content-Based Image Retrieval Based on Laplacian Filter

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**Abstract.** Color is most prominent and widely used feature in content-based image retrieval (CBIR). It is most commonly extracted in images by using the histogram. Extraction of features from enhanced image gives good performance in image retrieval. In this paper a CBIR algorithm is proposed for the retrieval of images based on the Laplacian filter for enhancement of image using the statistical quantized color histogram features. The sharpening method using Laplacian filter is used for enhancement of image with significant information for retrieval. The statistical quantized color histogram features are extracted from sharpened grayscale image using different number of quantization bins. The color features are used in similarity measurement of the query image with database images for retrieval of similar images. The retrieval performance of the color features is analyzed for different number of quantization bins in terms of efficiency and accuracy. Experimental results using Corel image database show that the quantized color histogram features of Laplacian sharpened image are robust in retrieval.

**Keywords:** Content-Based Image Retrieval (CBIR), sharpened grayscale image, Laplacian filter, color histogram

## 1. Introduction

The current improvement in the digital storage media, image capturing devices like scanners, web cameras, digital cameras and rapid development in internet provide a huge collection of images. This leads to the retrieval of these images for visual information efficiently and effectively in different fields of life like medical, medicine, art, architecture, education, crime preventions. To achieve this purpose many image retrieval systems have been developed. The first approach for searching of images in image collection is text-based in which manually annotated images are retrieved by keywords. This approach has two drawbacks, first is to annotate huge number of images requires a lot of human labor and second is the different subjective perceptions of human for example Lilly flower can be annotated as water lilies, flowers in pond. Due to these disadvantages, another approach is emerged called content based image retrieval (CBIR) [1]. In the CBIR the images are retrieved automatically by the visual contents of images like color, shape and texture instead of annotated text. The CBIR systems have been developed which include commercial systems, production systems, research systems and some demonstration systems. For example QBIC, ADL, BDLP, Virage, AltaVista, SIMPLIcity, etc [3].

There are various low-level features which can be used for retrieval but one of them is color information which is widely used in CBIR by researchers. It is prominent and extensively studied feature. The main reason of its importance is that it has invariance to the orientation and scaling of image [12]. The color information of image can be extracted by different techniques but the mostly used and prominent technique is color histogram. It is extensively used for CBIR. the color histogram features are combined with shape features such as size, mean, variance of objects to get best retrieval [5]. The color histogram features are combined with statistical texture features like entropy, smoothness and uniformity to retrieve similar images in CBIR [4]. The color and the texture features are extracted by using color histogram and Gabor wavelet transform techniques [6]. The color histogram extracts global color features in RGB color space while local features are extracted by genetic algorithm (GA) in HSV color space. These features are combined to get high performance [7]. Analysis of features of color histogram using median filter to reduce noise and edge extraction method to keep the original edge information, is presented. Feature vector is created by taking average of pixels in each bin to retrieve images [2].

In this paper our main contribution is to analyze and show the performance of quantized histogram bins in terms of accuracy and efficiency for retrieval of similar images by using the quantized histogram statistical color features of Laplacian sharpened grayscale images. To the best of our knowledge, such a performance comparison of the histogram bins has not been reported in literature for the quantized histogram statistical color features of grayscale images. Our method starts with conversion of RGB color image to grayscale and then gets sharpened image with Laplacian filter. The color statistical features are extracted from histograms by quantizing into several bins and these features are combined to construct a feature vector to retrieve similar images from database. These vectors are used in similarity measurement to compare query image vector with database vectors. We demonstrate in this paper the comparison of quantized histogram bins to get best performance in terms of efficiency and accuracy using statistical color features of quantized histograms of sharpened grayscale image.

The rest of the paper is organized as such that section 2 discusses the proposed algorithm in detail, section 3 evaluates and compares the performance of several quantized histogram bins in the image retrieval experimental results and section 4 concludes this paper.

## 2. The Proposed Algorithm

In our proposed algorithm the quantized histogram color statistical features are extracted from the Laplacian sharpened images without using spatial information of images. Before feature extraction and similarity measurement the grayscale images are converted into enhanced image by using histogram equalized method and Laplacian filter to reduce noise. The block diagram of proposed algorithm with sharpened method is shown in Fig 1-A and Fig 1-B.

### 2.1 Preprocessing

The input RGB image is first converted into grayscale as shown in Fig. 1-A and Fig.1-B-a, to reduce the computations because it consists of only single plane while RGB consists of three planes Red, Green and Blue. Then it is again converted into histogram equalized image $f$ to get enhanced image in Fig 1-B-b. The image $f$ is filtered with Laplacian filter to get a filtered image $g_1$ with edges of objects in image as show in Fig. 1-B-c The Laplacian filter uses a mask w of 3×3 with -4 at the center. But all pixel values in $g_1$ are positive and these values must be negative because of the negative value -4 at the center of the mask. For this purpose the histogram equalized image $f$ is converted into real valued image $f_2$ as shown in Fig 1-B-d. This image $f_2$ is again filtered with Laplacian filter to get image $g_2$ with edges information as shown in Fig. 1-B-e. But during the filter process of image $g_2$, some amount of information is lost. To restore this information and get an enhanced and sharpened image $g$, this Laplacian filtered image $g_2$ is subtracted from the real valued image $f_2$ as defined by:

$$g = f_2 - g_2 \tag{1}$$

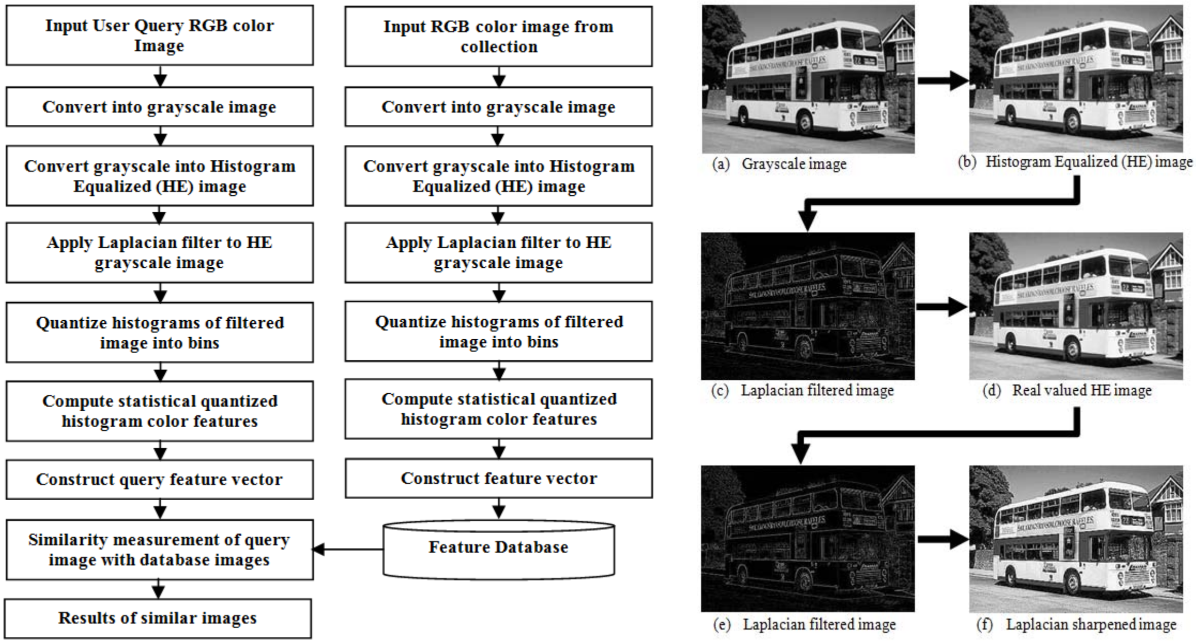
The filtration process is called sharpening of image [8].

### 2.2 Histogram Quantization

The histogram is defined as the frequencies of the pixels in grayscale image. The quantization is a process in which the histogram is divided into levels or bins. The sharpened filtered image is quantizing into 32, 16, 8 and 4 bins as shown in Fig 1-A and 1-B. As grayscale image consists of 256 levels, computation cost for the feature extraction in these 256 levels will be high. To reduce the computation cost, the histogram of image is reduced to different bins [5]. The histogram is then quantized into $L$ bins such that

$$H= \{h(b_1),\ h(b_2)\ \dots h\ (b_L)\ \} \tag{2}$$

Where $h(b_i)$ is the frequency of pixel values in bin $b_i$ and $H$ is the histogram of $L$ bins.




(A) (B)

Fig.1. (A) Block diagram of the proposed algorithm (B) Sharpening process using Laplacian filter

## 2.3 Feature Extraction

The statistical color features are considered useful for retrieval of similar images. These color features provide the information about the intensity level distribution in the image. The statistical color features mean and standard deviation are calculated by using distribution of intensity levels in histogram bins of $H$. Let $\mu_j$ is the mean and $\sigma_j$ is the standard deviation in a particular bin $j$, where $j$=1, 2, 3…, $L$, and then these two features can be calculated by using the statistical measurements [11] as:

$$\mu_j = \frac{1}{N}\sum_{i=1}^{N} x_{ji} \tag{3}$$

$$\sigma_j = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_{ji} - \mu_j)^2} \tag{4}$$

Where $x_{ji}$ is the pixel value in bin $j$ and pixel $i$ and $N$ is total number of pixels in each bin.

After the calculation of these texture features, the feature vector $FV$ of these values is constructed as:

$$FV = \{\mu_1, \mu_2 \ldots\ldots \mu_m,\ \sigma_1, \sigma_2 \ldots \sigma_m\} \tag{5}$$

The feature vectors of all images are constructed and are stored in database. The feature vector of the user query is constructed in the same way and compared with feature vectors of database for similarity and retrieval of relevant images. The block diagram of algorithm is shown in Fig. 1-A.

## 2.4 Similarity Measurement

Once the feature database of the images is created with feature vectors using (2), (3), (4) and (5), then the user can give an image as a query to retrieve the similar images from the database. The feature vector of the query image is also computed by using same (2), (3), (4) and (5) in the second step of same algorithm as shown in Fig. 1-A.

The similarity between the query image and the database images is measured by computing the distance between the query feature vector and the database feature vectors. For this purpose the Sum-of-Absolute Differences (SAD) [11], is used to calculate the difference between the query and database feature vectors for the similarity. Let query feature vector is represented by $Q_f$ and database feature vector by $D_f$ then the distance is calculated as:

$$\Delta d = \sum_{i=1}^{n} |(Q_f(i) - D_f(i))| \quad (6)$$

Where $n$ is the number of features, $i=1, 2..., n$. Both query and database images are similar for $\Delta d = 0$ and the small value of $\Delta d$ shows the relevant image to the query image.

## 3. Experimental Results

The proposed algorithm is tested by using Corel image database which is provided by James Wang et al [9], [10]. It is freely available for researchers. The database consists of 1000 images having 10 categories and each of which has 100 images. The categories of images consist of people, beaches, buildings, buses, dinosaurs, elephants, roses, horses, mountains, and foods. All these image categories are used in experiments. All images are in RGB color space and in JPEG format with size of 256×384 and 384×256 pixels.

The algorithm is performed in two steps in Fig 1-A. In first step all images are acquired one after another from the database for feature extraction. The extracted features are stored in database in the form of feature vectors using (5). In the second step the user is asked to input query image to retrieve relevant images from the database. The feature vector is constructed using (5) and compared with feature vectors of database by computing the similarity using (6). The relevant images are displayed to the user according to the query image.

In the experiments the two steps of proposed algorithm are performed for all proposed quantization of histograms into 32, 16, 8 and 4 bins separately using images of all 10 categories and the average precision and recall are calculated for all these images as shown in Table 1-A and Table 1-B.

Table 1 (A) Average precision (B) average recall of different histograms bins using 10 categories of images

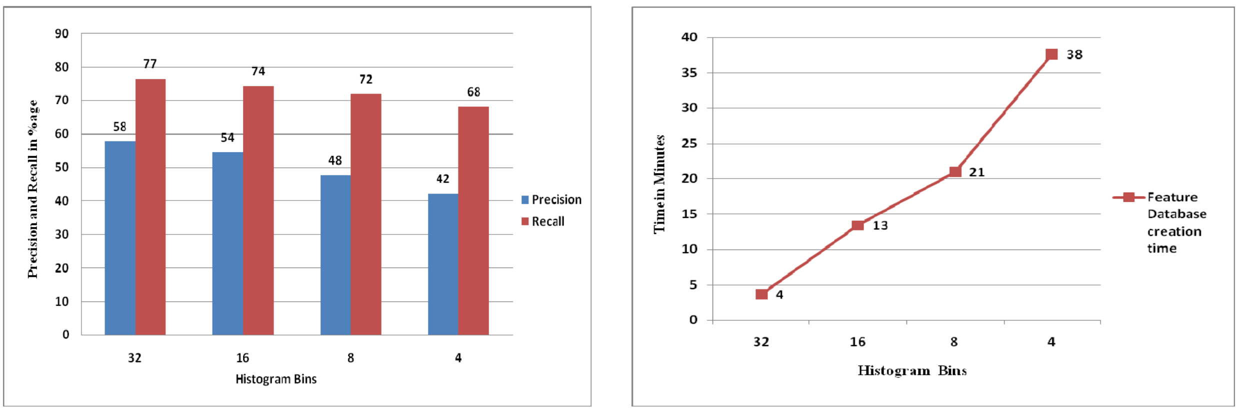
**A**

| S.No | Categories | 32 Bins | 16 Bins | 8 Bins | 4 Bins | Average |
|---|---|---|---|---|---|---|
| 1 | People | 78 | 44 | 44 | 33 | 50 |
| 2 | Beaches | 56 | 56 | 44 | 44 | 50 |
| 3 | Buildings | 56 | 56 | 44 | 44 | 50 |
| 4 | Buses | 67 | 56 | 44 | 44 | 53 |
| 5 | Dinosaurs | 89 | 89 | 67 | 67 | 78 |
| 6 | Elephants | 56 | 56 | 33 | 44 | 47 |
| 7 | Roses | 56 | 56 | 56 | 33 | 50 |
| 8 | Horses | 44 | 44 | 67 | 44 | 50 |
| 9 | Mountains | 44 | 44 | 44 | 33 | 42 |
| 10 | Foods | 33 | 44 | 33 | 33 | 36 |
| Average | | 58 | 54 | 48 | 42 | 51 |

**B**

| S.No | Categories | 32 Bins | 16 Bins | 8 Bins | 4 Bins | Average |
|---|---|---|---|---|---|---|
| 1 | People | 78 | 50 | 67 | 60 | 64 |
| 2 | Beaches | 71 | 71 | 80 | 67 | 72 |
| 3 | Buildings | 71 | 71 | 80 | 67 | 72 |
| 4 | Buses | 75 | 71 | 80 | 80 | 77 |
| 5 | Dinosaurs | 80 | 73 | 60 | 75 | 72 |
| 6 | Elephants | 71 | 83 | 60 | 67 | 70 |
| 7 | Roses | 83 | 83 | 71 | 75 | 78 |
| 8 | Horses | 80 | 80 | 67 | 57 | 71 |
| 9 | Mountains | 80 | 80 | 80 | 60 | 75 |
| 10 | Foods | 75 | 80 | 75 | 75 | 76 |
| Average | | 77 | 74 | 72 | 68 | 73 |

The results in Table 1-A, Table 1-B and Fig 2-a show that comparison of histogram quantization of 32, 16, 8 and 4 bins for 10 categories of images using statistical color features gives improved performance in terms of precision and recall such that 32 bins quantization gives good results as compared to other bins. The average precision for dinosaurs and buses while average recall for buses, roses and foods show good results.




(a) (b)

Fig. 2(a) Comparison of average precision and recall for different histogram bins (b) Feature database creation time for histogram bins

Figure 2(b) shows the processing time taken by the feature database creation. It is clear from the graph that as the number of bins is decreasing the time is increasing. It can be seen that the algorithm gives good results for 32 bins quantization not only in terms of precision and recall but also in execution time for feature extraction to create feature databse.

Figure 3 (a-c) shows the result of user queries. Each figure consists of a query image and the retrieved images from the database by using the proposed algorithm. The top single image is the query image and below 9 are the relevant images. The results show that proposed algorithm has good retrieval accuracy.

(a) (b) (c)

Fig.3. Query image results for (a) dinosaurs (b) elephants (c) roses

## 4. Conclusion

Color histogram quantization in bins has an impact on the performance of CBIR. In our proposed work, we have used Laplacian sharpened grayscale image for feature extraction because the energy is compensated in the sharpen method, which is lost by the Laplacian filter in the preprocessing of the grayscale image to get sharpen and enhanced image without noise. In the sharpening processing using Laplacian filter not only the noise is reduced while information is also preserved that gives a precise matching of images. The sharpened image is quantized into different bins like 32, 16, 8 and 4 bins. The statistical color features are extracted from bins and represented in feature vectors. These vectors are used in similarity measurement for retrieval of similar images. From the results we conclude that quantization histograms of 32 bins gives the best performance in terms of precision and recall of retrieved images as well as in processing time for feature database creation of 1000 images. After performing experiments for all images as query images our method gives good performance in terms of accuracy and efficiency.

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