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# Content Based Image Retrieval Using Combined Color & Texture Features

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***Abstract:*** *In this paper, combined color and texture features for content based image retrieval is presented. Humans tend to differentiate images based on color and texture features such as regularity, directionality and smoothness. Color histogram is mostly used to represent color features but it cannot entirely characterize the image. Gabor filter, a tool for texture feature extraction has proved to be very effective in describing visual content via multi-resolution analysis. We present the use color histogram for color feature extraction, Gabor Wavelet for texture feature extraction and provide comprehensive experimental evaluation. The results clearly indicate that combined Color and Gabor texture features provide best retrieval precision.*

***Keywords:*** *Content Based Image Retrieval; Gabor Wavelet Transform; Color Histogram.*

## I. Introduction

Retrieval of image data based on pictorial queries is an interesting and challenging problem. All areas of human life including commerce, government, academics, hospitals, crime prevention, surveillance, engineering, architecture, journalism, fashion and graphic design, and historical research use images for efficient services [1]. A large collection of images is referred to as image database. An image database is a system where image data are integrated and stored. Content based image retrieval (CBIR) system extracts images from image database by automated or computer assisted image analysis. The recent emergence of multimedia databases and digital libraries clearly indicates the importance of CBIR. While manual image annotations can be used to a certain extent to help image search, the feasibility of such an approach to large databases is a questionable issue. In some cases, such as face or texture patterns, simple textual descriptions can be ambiguous and often inadequate for database search [2]. The CBIR technique uses image content to search and retrieve digital images stored in large database. The main goal of CBIR is efficiency during image indexing and retrieval, thereby reducing the need for human intervention in the process [3][4]. The objective of this study is to evaluate the performance of CBIR system based on use of combined color and texture features.

In this paper, we present an image retrieval system based on the combination of color and texture features for image retrieval. The color feature is expressed through color histogram and the texture feature is established through wavelets. The color feature is invariant with translation and rotation and the use of wavelet transformation not only reduces the processing time, by decomposing the image, but also extracts the edge structure of an image in different directions. The combined wavelet transformation and color histogram, gives a better image retrieval system, which is suitable for a CBIR system.

### *A. Color Features*

Color is a powerful descriptor that simplifies object identification, and is one of the most frequently used visual features for content-based image retrieval. To extract the color features from the content of an image, a proper color space and an effective color descriptor have to be determined. The purpose of a color space is to facilitate the specification of colors. Each color in the color space is a single point represented in a coordinate system. Several color spaces, such as RGB, HSV, CIE L*a*b, and CIE L*u*v, have been developed for different purpose [6] [9]. Although there is no agreement on which color space is the best for CBIR, an appropriate color system is required to ensure perceptual uniformity. Therefore, the RGB color space, a widely used system for representing color images, is not suitable for CBIR because it is a perceptually non-uniform and device-dependent system [7]. HSV colour model for colour feature extraction in image retrieval methods because of its distinguable feature from RGB colour space, as HSV colour space being closer to human visual perception. Moreover, a simple non-linear transform can be used to turn RGB into HSV. The most commonly used method to represent color feature of an image is the color histogram. A color histogram is a type of bar graph, where the height of each bar represents an amount of particular color of the color space being used in the image [6]. The bars in a color histogram are named as bins and they represent the x-axis. The number of bins depends on the number of colors there are in an image. The number of pixels in each bin denotes y-axis, which shows how many pixels in an image are of a particular color. The color histogram can not only easily characterize the global and regional distribution of colors in an image, but also be invariant to rotation about the view axis. In color histograms, quantization is a process where number of bins is reduced by taking colors that are similar to each other and placing them in the same bin. Quantizing reduces the space required to store the histogram information and time to compare the histograms. Obviously, quantization reduces the information regarding the content of images; this is the tradeoff between space, processing time, and accuracy in results [8]. Color histograms are classified into two types, global color histogram (GCH) and local color histogram (LCH). A GCH takes color histogram of whole image and thus represents information regarding the whole image, without concerning color distribution of regions in the image. In the contrary, an LCH divides an image into fixed blocks or regions, and takes the color histogram of each of those blocks. LCH contains more information about an image, but when comparing images, it is computationally expensive. Color quantization reduces the number of distinct colors used in an image, usually with the intention that the new image should be as visually similar as possible to the original image. In order to reduce the computation, without a significant reduction in image quality, color moments as mean, standard deviation and skew are measured that can used to differentiate images based on their features of color. Once calculated, these moments provide measurement for color similarity between images. These values of similarity can then be compared to the values of images indexed in a database for tasks like image retrieval.

### *B. Image Decomposition using Wavelet Transform*

Wavelet transformations are based on small waves, called wavelets, of varying frequency and limited duration. It is a mathematical tool used for the hierarchical decomposition of an image and to transform an image from spatial domain to frequency domain. They allow certain functions in terms of a coarse overall shape, plus details that range from broad to narrow for an image, curve or a surface. In this paper, we use Gabor wavelets to compute image features; because they are have been found to perform well in practice.

Gabor filters transform is a good multi-resolution approach that represents the texture of an image in an effective way using multiple orientations and scales. This approach has a spatial property that is similar to mammalian perceptual vision, thereby providing researchers a good opportunity to use it in image processing. Gabor filters are found to perform better than wavelet transform and other multi-resolution approaches in representing textures and retrieving images due to its multiple orientation approach [5]. We use the Gabor filter approach to extract global texture features from the whole image. A Gabor function is obtained by modulating a complex sinusoid by a Gaussian envelope. For the case of one dimensional (1-D) signals, a 1-D sinusoid is modulated with a Gaussian. This filter will therefore respond to some frequency, but only in a localized part of the signal. The 2-D Gabor function can be specified by the frequency of the sinusoid W and the standard deviation $\sigma_x$ and $\sigma_y$, of the Gaussian envelope as:

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} e^{\left(\frac{-1}{2}\left(\frac{x^2}{\sigma_x{}^2}+\frac{y^2}{\sigma_y{}^2}\right)+2\pi j\, w_x\right)} \quad (1)$$

Gabor functions form a complete but non-orthogonal basis set. Expanding a signal using this basis provides a localized frequency description. Wavelets are families of basis functions generated by dilations (scaling) and translations of a basic wavelet called the mother wavelet. The basis functions are themselves basic functional building block of any wavelet family. A class of self-similar functions referred to as Gabor wavelets, is now considered. Let g(x,y) be the mother Gabor wavelet, then this self-similar filter dictionary can be obtained by appropriate dilations and rotations of g(x,y) through the generating function.

$$g_{mn}(x,y) = a^{-m} g(\acute{x},\acute{y}) \quad (2)$$

Where m and n are integers specifying the scale and orientation of the wavelets, respectively, with m = 0, 1, 2, ..., M −1, n = 0, 1, 2, ..., N −1, M and N are the total number of scales and orientations, respectively. And

$$\acute{x} = a^{-m}(x cos\theta + y sin\theta) \quad (3)$$

$$\acute{y} = a^{-m}(-x sin\theta + y cos\theta) \quad (4)$$

Where $a > 1$ and $\theta = 2\pi / N$. The non-orthogonality of the Gabor wavelets implies that there is redundant information in the filtered images, and the following strategy is used to reduce this redundancy [5]. Let $f_l$ and $f_h$ denote the lower and upper center frequencies of interest, then the Gabor filter design strategy is to ensure that the half-peak magnitude support of the filter responses in the frequency spectrum touch each other. In our implementation, we used the following constants as commonly used in the literature $f_l = 0.05$ and $f_h = 0.4$. The Gabor wavelet image representation is a convolution of that image within the same family of Gabor kernels given in Equation 2. Let I (x, y) be the gray level distribution of an image, the convolution of the image I together with a Gabor kernel is defined as follows

$G_{mn}(x,y) = \sum_s \sum_t I(x-s, y-t) g_{mn}(s,t)$ (5)

Where, s and t are the filter mask size variables, $g^{*}_{mn}$ is the complex conjugate of the mother Gabor function $g_{mn}$, and $G_{mn}$ is the convolution result corresponding to the Gabor kernel at orientation m and scale n. After applying Gabor filters on the image with different orientation at different scale, we obtain an array of magnitudes. These magnitudes represent the energy content at different scale and orientation of the image. The main purpose of texture-based retrieval is to find images or regions with similar texture. It is assumed that we are interested in images that have homogenous texture, therefore the following mean $\mu_{mn}$ and standard deviation $\sigma_{mn}$ of the magnitude of the transformed coefficients are used to represent the homogenous texture feature of the region. A feature vector F (texture representation) is created using $\mu_{mn}$ and $\sigma_{mn}$ as the feature components [5].

$E_{mn} = \sum_x \sum_y |G_{mn}(x,y)|$ (6)

$\mu_{mn} = \frac{E_{mn}}{PxQ}$ (7)

$|G_{mn}(x,y)| - \mu_{mn}$

$2$

(8)

$\sum_y$

$\sum_x$

$\sqrt{\phantom{x}}$

$\sigma_{mn} =$

$F = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01}, \ldots, \mu_{mn}, \sigma_{mn})$ (9)

## II. Algorithm for the method

### *A. Color Features Extraction*

Steps for obtaining color features using color histogram is as follows

1. Convert RGB into HSV color space of an image.
2. Color quantization is carried out using CH by assigning 8 levels to hue, 8 to saturation and 8 to value to give a quantized HSV space with $8 \times 8 \times 8 = 512$ histogram bins.
3. Obtained normalized histogram.
4. Obtained color moments for H, S and V color space.
5. Repeat step 1 – 4 for images in database.

### *B. Texture Features Extraction*

Steps for obtaining texture features using Gabor wavelet transform is as follows

1. Split the image into R, G and B color space
2. Obtained the approximate, horizontal, vertical and diagonal coefficients using Gabor wavelet transformation for each R, G and B.
3. Combined the approximate, horizontal, vertical and diagonal coefficients of R, G, and B respectively.
4. Obtained texture features using equation 6, 7 and 8 for diagonal coefficients only
6. Repeat step 1 – 4 for images in database.

### *C. Feature Vector*

Steps for obtaining combined feature vector of color and texture is as follows

1. Mean, standard deviation and skew for H, S and V color space and three texture features are combined into a single vector for similarity measurement.
2. Repeat step 1 for images in database.

### *D. Similarity Measurement*

Steps for measurement of similarity using intersection distance of query image and images in database.

1. Obtained combined feature vector for color and texture above steps for query image.
2. Repeat step 1 for images in database.
3. Calculate the similarity matrix using intersection distance of query image and the image present in the database.
4. Repeat step 3 for all the images in the database.
5. Retrieve the images based on similarity index.

## III. Performance Evaluation

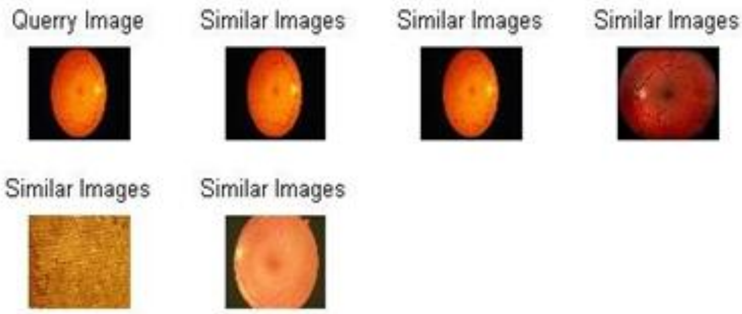
The performance of retrieval system is measured using the standard procedure in terms of the precision (P) and recall (R) values. Recall measures the ability of the system to retrieve all the models that are relevant, while precision measures the ability of the system to retrieve only the models that are relevant. The number of relevant items retrieved is the number of the returned images that are similar to the query image in this case. The number of relevant items in the collection is the number of images that are in the same particular category with the query image. The total number of items retrieved is the number of images that are returned by the search engine. P and R are defined as

$$P = \frac{numberofrelevantimagesretrieved}{totalnumberofimagesretrieved} \qquad (10)$$

$$R = \frac{numberofrelevantimagesretrieved}{totalnumberofrele\quad vantimages} \qquad (11)$$

## IV. Experimental Results and Discussion

The proposed method is applied on a general-purpose set of containing 500 images of the database, in JPEG format of size 300 x 350. These images are grouped into five different categories with each containing 100 images. The images in the same category are considered as similar images. The five different categories are: (i) brain, (ii) retina, (iii) coins, (iv) sun and (v) leaves. The objective of the paper is to design a CBIR system that is simple to use, easy to handle large Image data bases, and fastest to retrieve images using low-level features such as color and texture. The similarity between two images (represented by their feature values) is defined by a similarity measure. Selection of similarity metrics has a direct impact on the performance of content-based image retrieval. The kind of feature vectors selected determines the kind of measurement that will be used to compare their similarity. If the features extracted from the images are presented as multi-dimensional points, the distances between corresponding multi-dimensional points can be calculated. Fig 1 shows the snapshot of the retrieved images of retina and brain. Table 1 and 2 shows the precision and recall for the technique described in this paper and comparison of results with other techniques respectively. The experiments were carried on Intel core i5, 2.4 GHz processor with 4GB RAM.




(a)


(b)

**Fig. 1.** Retrieved Images (a) Retina (b) flowers

**Precision and Recall**

| ***Image Categories*** | ***Precision*** | ***Recall*** |
|---|---|---|
| Brain | 0.58 | 0.9 |
| Retina | 0.44 | 0.94 |
| Coins | 0.8 | 0.94 |
| Sun | 0.4 | 0.9 |
| flowers | 0.64 | 0.8 |
| Average | 0.572 | 0.896 |

**Comparison of image retrieval techniques**

| ***Parameter*** | ***Our Work*** | ***[10]*** | ***[11]*** |
|---|---|---|---|
| Average Precision | 0.572 | 0.545 | 0.55 |

## V. Conclusion

In this paper, we presented combined color and texture features for content based image retrieval. In order to reduce the computation, without a significant reduction in image quality, color moments as mean, standard deviation and skew are measured that can used to differentiate images based on their features of color. Gabor Wavelet transform was used to decompose the image into approximate, horizontal, vertical and diagonal components. It is assumed that we are interested in images that have homogenous texture; therefore the following mean and standard deviation of the magnitude of the transformed diagonal coefficients are used to represent the homogenous texture feature of the region. Combined color and texture features are used to obtain similarity matrix using intersection distance of query image and the image present in the database. The experimental result shows that the method presented in this paper achieves precision of 0.572 with only length of feature vector 12 and retrieval time of 24.66 seconds on 100 images in database. The work can be further extended by considering all wavelet coefficients for similarity measurement.

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