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Content Based Image Retrieval Using Gabor Texture Feature and Color Histogram

Nitin Jain[1], Dr. S. S. Salankar*[2]
[1] Assistant Professor, Lokmanya Tilak College of Engineering, Navi Mumbai, India
[2]*Professor, G. H. Raisoni College of Engineering, Nagpur, India

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Abstract: In this paper, we present content based image retrieval using two features color and texture. Humans tend to differentiate images based on color, therefore color features are mostly used in CBIR. Color histogram is mostly used to represent color features but it cannot entirely characterize the image. Color Histogram is also rotation invariant about the view axis. Regularity, directionality, smoothness and coarseness are some of the texture properties perceived by human eye. Gabor filter, a tool for texture feature extraction has proved to be very effective in describing visual content via multi-resolution analysis. Texture feature extraction based on Gabor filter is used for CBIR.

Keywords: Content Based Image Retrieval, Feature Extraction, Color Histogram, Gabor Filter.

I. Introduction

In this era of information technology, 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. A large collection of images is referred to as image database. An image database is a system where image data are integrated and stored [1]. Image data include the raw images and information extracted from images by automated or computer assisted image analysis. The police maintain image database of criminals, crime scenes, and stolen items. In the medical profession, X-rays and scanned image database are kept for diagnosis, monitoring, and research purposes. In architectural and engineering design, image database exists for design projects, finished projects, and machine parts. In publishing and advertising, journalists create image databases for various events and activities such as sports, buildings, personalities, national and international events, and product advertisements. In historical research, image databases are created for archives in areas [1]. The CBIR technique uses image content to search and retrieve digital images stored in large database. Content based image retrieval is a set of techniques for retrieving semantically-relevant images from an image database based on automatically-derived image features [2] [3] [4].

The main goal of CBIR is efficiency during image indexing and retrieval, thereby reducing the need for human intervention in the indexing process. The computer must be able to retrieve images from a database without any human interruption on specific domain such color and texture. One of the main tasks for CBIR systems is similarity comparison; extracting feature of every image based on its pixel values and devising rules for comparing images. These features become the image representation for measuring similarity with other images in the database. An image is compared to other images by calculating the difference between their corresponding features. Some of the existing CBIR systems extract features from the entire image instead of certain regions in it. These features are referred to as Global features. Histogram search algorithms [3] characterize an image by its color distribution or histogram. The drawback of a global histogram representation is that information about object location, shape and texture is discarded. Color histogram search is sensitive to intensity variations and color distortions. The color layout approach attempts to overcome the drawback of histogram search. In simple color layout indexing [3], images are partitioned into blocks and the average color of each block is stored. Thus, the color layout is essentially a low resolution representation of the original image. In the field of computer vision and image processing, there is no clear-cut definition of texture.

This is because available texture definitions are based on texture analysis methods and the features extracted from the image. Texture properties are the visual patterns in an image that have properties of homogeneity that do not result from the presence of only a single color or intensity. The different texture properties as perceived by the human eye are, for example, regularity, directionality, smoothness, and coarseness, see Fig. 1.

Fig. 1: Images of Simple & Complex Texture

Since there is no accepted mathematical definition for texture, many different methods for computing texture features have been proposed over the years. Unfortunately, there is still no single method that works best with all types of textures. According to [5], the commonly used methods for texture feature description are statistical, model-based, and transform-based methods. The word transform refers to a mathematical representation of an image. There are several texture classifications using transform domain features in the past, such as discrete Fourier transform, discrete wavelet transforms, and Gabor wavelets. Gabor filter has been shown to be very efficient [5] and have also shown that image retrieval using Gabor features outperforms that using other transform features. In this paper, we present two features color and texture extraction algorithms. Color histogram is mostly used to represent color features but it cannot entirely characterize the image. Colour Histogram is also rotation invariant about the view axis. Gabor filter, a tool for texture feature extraction has proved to be very effective in describing visual content via multi-resolution analysis. Texture feature extraction based on Gabor filter is presented.

II. Color Histogram

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 purposes [6]. 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]. 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. GCH is known as a traditional method for retrieving color based images. Since it does not include color distribution of the regions, when two GCHs are compared, one might not always get a proper result when viewed in terms of similarity of images [9]. Fig. 2 shows the image with its color histogram.

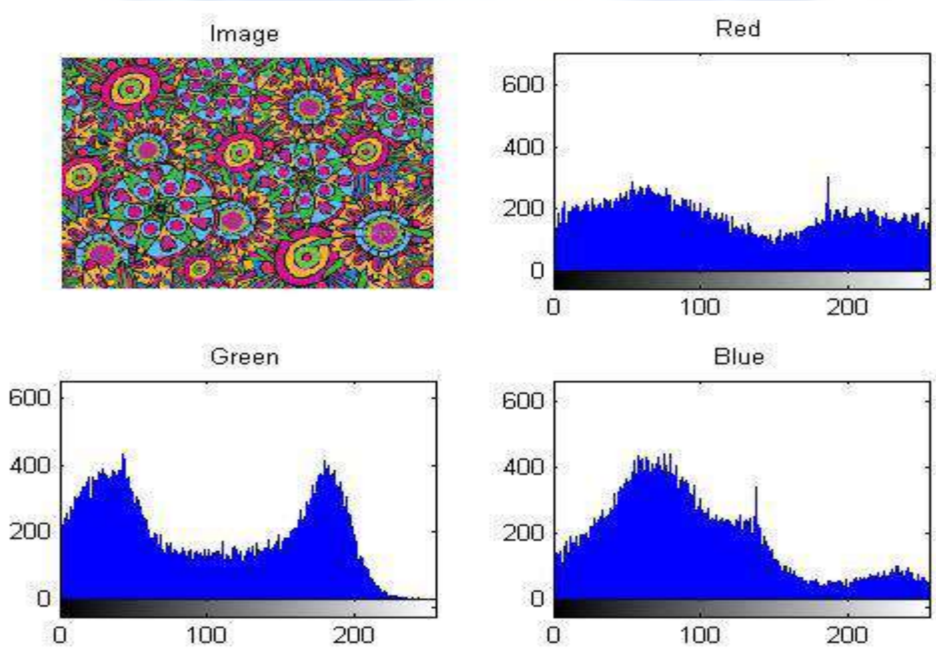

Fig. 2: Image and its corresponding color Histogram

III. Gabor Filter

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, and to extract texture features from image regions. 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 $\boldsymbol{\sigma_x}$ and σ_y, of the Gaussian envelope as:

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

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.

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

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

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

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

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 g_{mn} is defined as follows

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

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. Fig. 3 shows the response of the image to Gabor filter.

$$E(m,n) = \sum_x\sum_y |G_{mn}(x,y)| \quad (6)$$

$$\mu_{mn} = \frac{E(m,n)}{P \times Q} \quad (7)$$

$$\sigma_{mn} = \frac{\sqrt{\sum_x\sum_y(|G_{mn}(x,y)| - \mu_{mn})^2}}{P \times Q} \quad (8)$$

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 or regions that have homogenous texture, therefore the following mean μmn and standard deviation σmn 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 μmn and σmn as the feature components [5]. With M scales and N orientations used in common implementation the feature vector is given by Texture feature is computed using Gabor wavelets.

$$F_{Texture} = (\mu_{00}, \sigma_{00}, \mu_{01}, \sigma_{01}, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots, \mu_{MN}, \sigma_{MN}) \quad (9)$$

IV. Discussion

Gabor function is chosen as a tool for texture feature extraction because of its widely acclaimed efficiency in texture feature extraction. Gabor features performs better than that using pyramid-structured wavelet transform features, tree-structured wavelet transform features and multi-resolution simultaneous autoregressive model. A total of twenty-four wavelets are generated from the "mother" Gabor function given in equation 2 using four scales of frequency and six orientations. Redundancy, which is the consequence of the non-orthogonality of Gabor wavelets, is addressed by choosing the parameters of the filter bank to be set of frequencies and orientations that cover the entire spatial frequency space so as to capture texture information as much as possible in accordance with filter design in [5]. The lower and upper frequencies of the filters are set to 0.04 octaves and 0.5 octaves, respectively, the orientations are at intervals of 30 degrees, and the half-peak magnitudes of the filter responses in the frequency spectrum are constrained to touch each other [5]. Note that because of the symmetric property of the Gabor function, wavelets with center frequencies and orientation covering only half of the frequency spectrum are generated.

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 [4]. If the features extracted from the images are presented as multi-dimensional points, the distances between corresponding multi-dimensional points can be calculated. Euclidean distance is the most common metric used to measure the distance between two points in multi-dimensional space. When manipulating massive databases, a good indexing is a necessity. Processing every single item in a database when performing queries is extremely inefficient and slow. Raw image data is non-indexable as such, so the feature vectors must be used as the basis of the index. Precision, P, is defined as the ratio of the number of retrieved relevant images to the total number of retrieved images. Let the number of all retrieved images be n, and let r be the number of relevant images according to the query then the precision value is: P = r / n. Precision P measures the accuracy of the retrieval. Fig 3 shows the snapshot of the retrieved images.

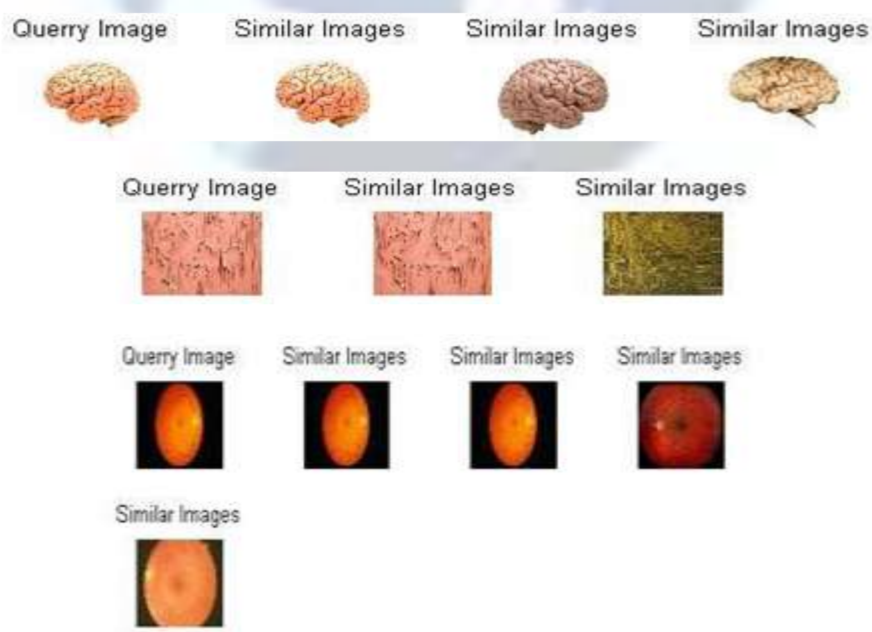

Fig. 3 Snapshot of Retrieved Images

Conclusions

In this paper, we presented CBIR system using two feature color and texture extraction algorithms. Color histogram is mostly used to represent color features but it cannot entirely characterize the image and is also rotation invariant about the view axis. We use Gabor filter, which is a powerful texture extraction technique either in describing the global content of an image. Color histogram as a global color feature and histogram intersection as color similarity metric combined with Gabor texture have been proved to give approximately as good retrieval results as that of region based retrieval systems.

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