AN EFFICIENT CONTENT BASED IMAGE RETRIEVAL SYSTEM AND THE SELECTING OPTIMAL ORIENTIATIONS OF GABOR WAVELET FOR CBIR SYSTEM

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ABSTRACT

In the past few decades, with the growth of the World Wide Web, extensive information in the form of images and videos are available for anyone, easy access to information has resulted, the need to have a system in which images and videos are retrieved based on their content. Features are extracted to specify the content in a unique way. In this work we proposed a system which is based on Gabor Wavelet, Color Correlogram and HSV histogram features, in this paper we show that, the precision rate can be increased by selecting most discriminating Gabor orientations and number of scales of GWT. In order to assess the performance of different number of orientations along with the other features we apply the proposed system on Wang image data base and for similarity measure between images we use Manhattan distance measure. With the proposed system we achieve good results and simple nature of features make the system computationally efficient.

Keywords: *Content Based Image Retrieval, HSV histogram & Average Precision Rate*

INTRODUCTION

In this age of digital technology, all sphere of human life uses images for efficient services. This searching of image is of two types, one is text based and the other is content based. Text based retrieval is subjected to keyword, tags, which may vary from user to user and also depend on user query text language and the worse problem is that image annotation is greatly affected by human perception. Keeping these problems in view, new approach namely content based image retrieval was firstly proposed by Florence. Visual features of images are the basis of CBIR system. From its introduction till now new approaches have been developed. In CBIR system, certain features of all images are extracted and stored in feature vectors. The length of feature vector depends on the number of features computed for each image. Content Based Image retrieval is an application of Computer vision technique for the retrieval of similar images to that of query image. When a query image is presented to system same feature of image will be computed and then a matching process takes place and similar images to that of query image is presented to the user.

The extraction of useful features and usage of efficient matching process plays a vital role in retrieval rate and efficiency of CBIR system. For texture feature extraction Gabor wavelet has been used by many researchers (Yalvrthi, Veerswami & Sheela, 2017) but did not investigated the effect of orientations and scales on the precision rate of the CBIR. In this paper we use Gabor wavelet, Color-Correlogram and HSV histogram, the effect of varying the number of scales and orientations in Gabor Wavelet on retrieval result and Average Precision Rate has also been investigated and for similarity measure we use Manhattan Distance.

LITRATURE REVIEW

Now a days Content Based Image Retrieval (CBIR) is one of the hot research field of image processing, which is also known as query by image content (QBIC). In literature it is also refer as Content Based Visual Information retrieved (CBVIR) (Harralic, 1973). The rapid advancement in Multimedia production storage, transmission along easy information has opened up tremendous opportunity for various computer-based video and image retrieval from a huge amount of data in a data base. To search for images and videos from databases in remote locations, fast recovery of images from the database is an important issue that needs to be addressed. High recovery rate and lower computational complexity are the main features of the good CBIR system. A lot of CBIR systems have been proposed till now. In (GM & Prasetyo, 2015) image is retrieve based on the criteria that is defined by the user. The evaluation is based on similarity between shapes, color, and edge pattern (Said & Khurshid, 2017). The survey (Wengang & Houqiang, 2017) report a notable growth on research publications on this topic. In conventional image data bases, image retrieving is based on keywords searching as images in these databases are text-annotating.

The disadvantage of keyword based searching is that is subjective to user and dependable on language also the content of an image cannot be described through fixed set of words. To avoid these problems efficient content based image retrieval is the need of the day. Visual features like color, shape, texture etc. can be used in indexing of CBIR system. For the extraction of visual features, there are several techniques in literature, efficiency of the system depends on how these features are extracted. A query image is presented to the system, same features are extracted from the query image that is extracted from the images in database and store in feature data base, some degree of similarity or a classifier is used to classify and extract images similar to query from image Data Base. Many system has been developed QBIC (Smeulders, Worring, Santini & Gupta, 2000), Photo Book (Pentland, Picard & Sclaroff, 1996), MARS (Saravanan & Srinivasan, 2012), NeTra (Saravanan & Srinivasan, 2010), PicHunter (Saravanan & Srinivasan, 2012). Different approaches for capturing content information of an image are described in (Manjunath, Ohm, Vasudevan & Yamada, 2001).

One certain approach involves constructing the image in DCT domain as in (Burkhardt & Ming, 2015) and in (Chang, 2007) it is further demonstrated the improvement of image retrieval in DCT domain wherein the image feature is obtained through the JPEG standard compression. In another approach an image description scheme such as MPEG-7 Visual Content Descriptor (VCD) is required to give description of content of the image (Guo & Heri, 2013). Here we present our proposed system, we use Gabor wavelet, Color-Correlogram and HSV histogram, the effect of varying the number of orientations and scales in Gabor Wavelet on retrieval result and Average

Precision Rate has also been investigated and for similarity measure we use Manhattan Distance. The rest of the paper is organized as, section 2 discusses proposed system architecture and section 3 discusses Results and Evaluation criteria and in section 4 conclusions has been drawn.

RESEARCH METHODOLOGY

In this section we will discuss our approach for the content based image retrieval. Block Diagram of the proposed system is shown in figure 1.In features extraction we use Gabor Wavelet, color correlogram and HSV histogram. We generate the results by varying number of scales of Gabor Wavelet to 4 and the numbers of orientations from two to 8 are used while the other two features namely HSV Histogram and Color-Correlogram remain unchanged, the Precision Rate is calculated for each number of orientations, for each class. The detail of Gabor Wavelet HSV Histogram and Color-Correlogram are given below.

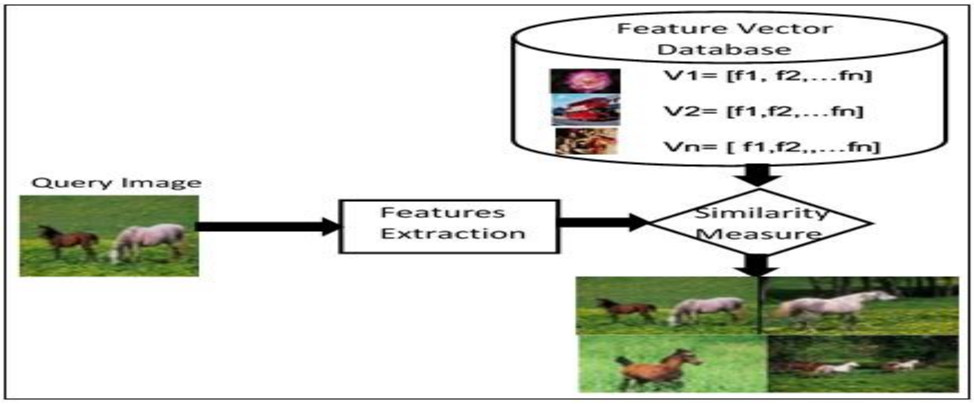
Gabor Wavelet

Gabor wavelet is suitable for image because images are non-stationary signals i-e having variation, in an image if the data is changing very rapidly on a short distance scale then the image have high frequency components If the image has large low frequency components, the large-scale features of the image is more important. For example a relatively simple object that occupies most of the image. For color images, the measure (now a 2D matrix) of the frequency content with respect to color / chrominance: it shows how the values change quickly or slowly. When the component or the amount of matrix of the frequency is small, the color changes gradually

Now, the human eye is insensitive to progressive changes in color and sensitive intensity. So we can ignore the gradual changes in color and delete the data without noticing the human eye. In CBIR system we use these frequency changes as features and we can compare two images by the amount and pattern of changes. For detection of these changes Fourier transform is used. We take the Fourier transform of the signal and see the frequency spectrum, for stationary signals, the Fourier transformation works well, but for non-stationary signals, to see the signal in the frequency domain, the loss of time localization is lost, the solution is derived from a Fourier transform that is called Short Time Fourier Transform (STFT). The signal underlying window of the STFT is stationary is the assumption while using STFT the problem occurs in selection of the window size.

In Gabor Wavelet, the size of the tunable window results in a pair of time-frequency resolution having different dimensions and the size are related to the analytical frequency. Among the different basic wavelets, the Gabor function offers an optimal resolution at the same time (spatial) and the frequency domain, and the Gabor wavelet transform seems to be the best basis for extracting local characteristics for several reasons (Linlin & Li, 2006) . The Gabor wavelet can be considered as scale and orientations tunable texture detector since they only respond to some specifically oriented texture in some specific scale and orientations.

Figure 1 Block Diagram of proposed CBIR System



Here in this work we use 2 to 8 orientations and 1 to 4 scales as shown in figure 2. For given image, $img\ (x, y)$ discrete Gabor wavelet transform is given by a convolution

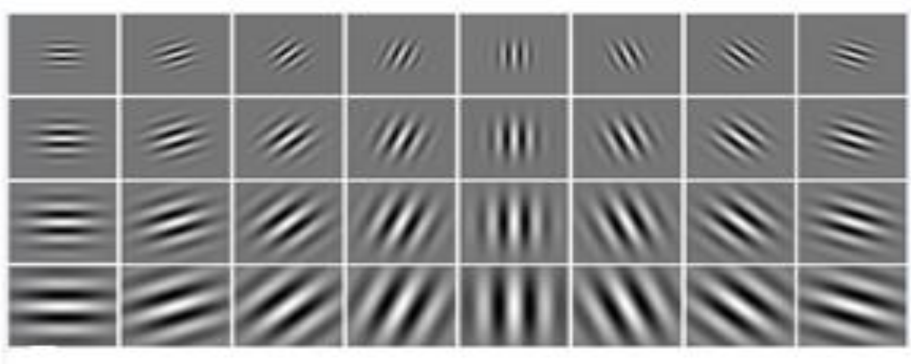
$$G_{mn}(x,y) = \sum_r \sum_w img(x-r, y-w)\Psi_{mn}\,(r,w) \qquad (1)$$

And

$$\Psi_{mn}(x,y) = \frac{1}{2\lambda\sigma_x\sigma_y} exp\left[-\frac{1}{2}\left(\frac{(x-x1)^2}{\sigma_x^2} + \frac{(y-y1)^2}{\sigma_y^2}\right)\right].exp(j2\lambda Wx) \qquad (2)$$

Here, the filter mask size variables is represented by r and w, Ψmn is a complex conjugate of Ψ_{mn} and is generated from mother wavelet given in equation 2 through dilation and rotation, which is a class of self-similar functions. In equation 2, σ_x and σ_y represents the standard deviation of Gaussian envelopes in the orientations of x, y and modulation frequency is represented by W. x1 and y1 are the shifting parameters.

Figure 2 Eight orientations and four scales of Gabor wavelet

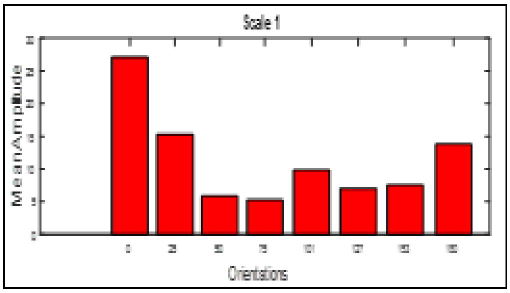


Feature extraction for retrieval the transformed coefficients are used for measuring distance or compressed representations, but not for reconstruction, so the orthogonal constraint could be omitted. There are host of features we can get from the Gabor wavelet, here in this work we only extract Mean Amplitude and Mean Square Energy for 4 scales and 2 to 8 orientations in which the 8 orientations comes the dominant orientations for Wang data Base. In figure 3 to 6, mean amplitude of Gabor coefficients versus orientations is shown it can be seen that mean amplitude is highest at 0^0,25^0, 75^0, 101^0, 153^0 and 180^0 while using scale 4. Instead of taking all possible orientations we can take all those orientations which have highest amplitude.

Color-Correlogram

The widely used feature in CBIR system is color, for color information extraction, RGB color histogram and color moments are widely used techniques. Using color as feature, the spatial information of the color is important (Haung, Ravi, & Mandar, 1999). The disadvantage in RGB color histogram method is that it does not contain any spatial information of the color it only preserves the frequency of occurring of a color in an image and about their spatial information. In (Jing, Ravi, mandar, & Ramin, 2006) a new technique for color extraction is proposed called Color-Correlogram.

Figure 3 (a) Mean Amplitude for scale 1 (b) Mean Square Energy for Scale 1



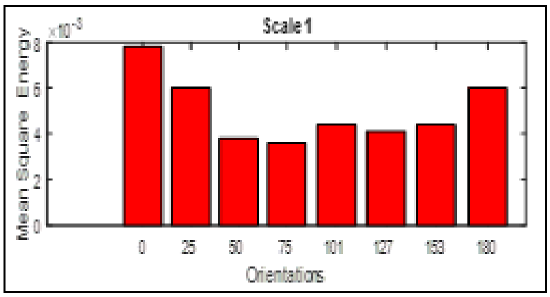
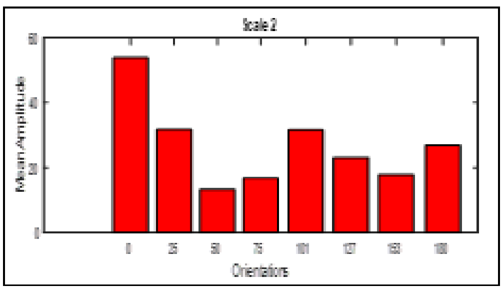


Figure 4 (a) Mean Amplitude for scale 2 (b) Mean Square Energy for Scale 2



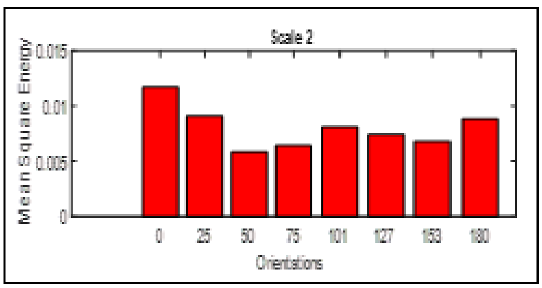
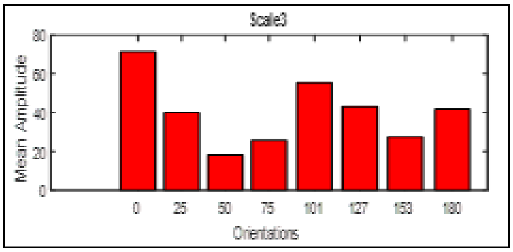


Figure 5 (a) Mean Amplitude for scale 3



(b) Mean Square Energy for Scale 3

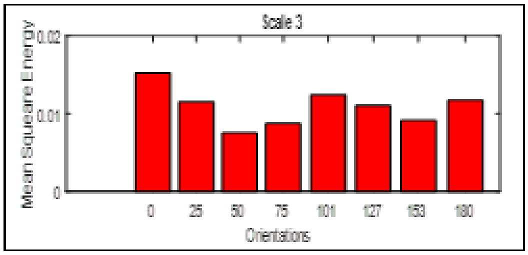
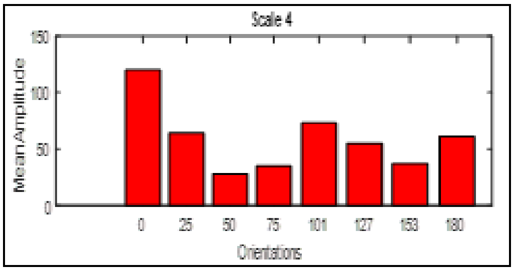
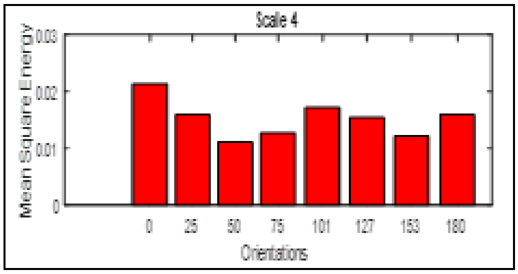


Figure 6 (a) Mean Amplitude for scale 4

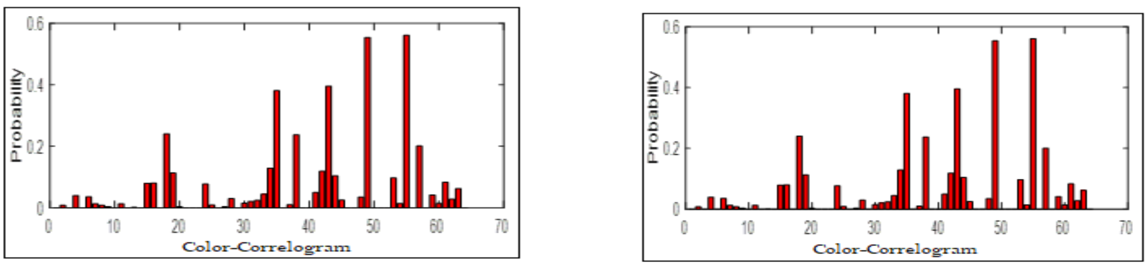


(b) Mean Square Energy for Scale 4



Tolerating large changes in appearance and shape cause by viewing position and zooming, as it preserves spatial information. Detail of Color-Correlogram is given in (Said & Khurshid, 2017) For color correlogram it is necessary to quantize all images to same level so that the feature vector length of all images have same length, here in this work, the image is quantized to 64 color so the length of the Correlogram feature vector must be 64. Figure 7 shows the correlogram of query image. We use four distances 1,3,5,7 the distance is D_8 distance.

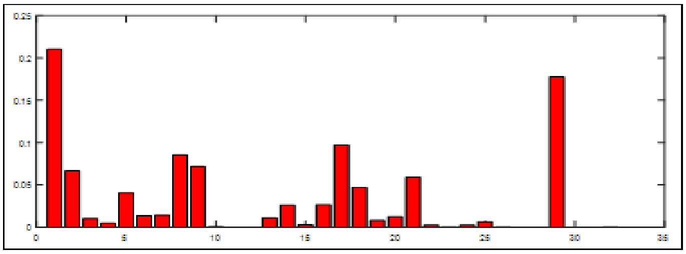
Figure 7 Color-Correlogram of Query Image



HSV Histogram

The histogram is another most used feature in the content base image retrieval task. It gives information about the distribution of color in image. It is insensitive to rotation and translation of image. Color image is composed of pixel, each of them can be represented by three components namely, hue, value and saturation, in HSV color space and with Red, Green and Blue in RGB color space. For each pixel of an image we find the distribution of pixel for each quantized bin, known as histogram. Discriminative power can be increase by increasing the number of bins which will increase the computational cost. In this work, with 8 level of quantization for hue (H), 2 for saturation (S) and 2 for value (V), we computed the histogram of HSV color space. After finding the feature vector we normalized it sum away that it sum up to one. The size of feature vector is 1x32. As shown in figure 8.

Figure 8 HSV Histogram of Query Image



EXPERIEMENTAL SETUP

The image data Base contain 1000 images. The images were partitioned in 10 classes namely food, mountains, elephants, building, flowers, beach, dinosaur, people, horses and buses. Figure 9 shows sample images from the data Base (Wang). Ten Images of each class were given as query images the query is chosen such as to represent different situations of the same scene and the Precision is calculated for each class.There is a large variations in intra-category image data in various categories, which offer a major challenge for the robustness of the CBIR system. The number of scales of Gabor Wavelet is varied from scale 1 to 4. Scale 1 is 16×16 Gaussian window, scale 2 is 32×32, scale 3 is 64× 64 and scale 4 is 128×128 Gaussian window and the numbers of orientations from two to 8 are used while the other two features namely HSV Histogram and Color-Correlogram remain unchanged, the Precision Rate is calculated for each number of orientations, for each class is tabulated in table 1.

Figure 9 Sample Images of Wang Data Base

Experimental Result

Setting the above experimental setup Average Precision Rate is calculated as given in equation 3 and tabulated in Table 1.

$$ARR = \frac{1}{R_n Q_r} \sum_{x=1}^{R_n} n_x(Q_r) \qquad (3)$$

Larger the average precision rate, indicate better performance of the system. To retrieve, one query image fed to the system and the features are extracted. These features are now compared with all the features stored in the database to get the similar images. For similarity measure we use Manhattan distance as given in equation 4.

$$Man \; = \sum\nolimits_{r=1}^{m} \frac{|t.fv(r) - q.fv(r)|}{1 + t.fv(r) + q.fv(r)} \qquad (4)$$

Here, the combine feature vector of the images in the data base term as target image is represented by $.fv$. i.e. target feature vector and the query image feature vector is represented by $q.fv$ i.e. query feature vector, of which we want to find similar images.

CONCLUSION

In this work, we proposed a CBIR system and investigated the effect of number of orientations and Scales of Gabor Wavelet, on the precision rate of CBIR system. The system performance is evaluated on Wang image data base in which the number of scales is used from 1 to 4 and increasing the number of orientations from 2 to 8 and APR is tabulated. It is concluded that increasing the number of orientations and increasing window size does not increase the Precision rate although it increases the precision rate of some classes but on average the Precision decreases because more than needed features act as noise and degraded the system. So for the Wang image database the number of dominant orientations are 8. By increasing number of orientations more than 8 the APR decreases.

Table 1 Precision Rate for 10 categories

Category/Class	**Number of Orientations 2 Precision Rate**	**Number of Orientations 4 Precision Rate**	**Number of Orientations 6 Precision Rate**	**Number of Orientations 8 Precision Rate**
People	.033	.423	0.723	0.654
Beach	.138	.325	0.721	0.699
Building	.095	.411	0.745	0.696
Bus	.120	.398	0.698	0.693
Dinosaur	.198	.833	.845	.994
Elephant	.171	.324	.543	.693
Flower	.489	.891	.852	.995
Horse	.326	.645	.988	.988
Mountain	.099	.424	.634	.698
Food	.128	.519	.810	.719
APR	0.1797	0.5193	0.756	**0.793**

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