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Content Based Image Retrieval Technique on Texture and Shape Analysis using Wavelet Feature and Clustering Model

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Abstract: The project proposes the image retrieval technique based on Gray Level Co-occurrence Matrix (GLCM) and Shape features. The main target of Content-based Image Retrieval (CBIR) is to get accurate results with lower computational time. The need for efficient content-based image retrieval has increased tremendously in many application areas such as biomedicine, military, commerce, education, and web image classification and searching. CBIR technology overcomes the defects of traditional text-based image retrieval technology, such as heavy workload and strong subjectivity. It makes full use of image content features which are analyzed and extracted automatically by computer to achieve the effective retrieval. Using a single feature for image retrieval cannot be a good solution for the accuracy and efficiency. This paper discusses on the comparative method used in colour histogram based on two major methods used frequently in CBIR which are normal colour histogram using GLCM, and colour histogram using K-Means. Using Euclidean distance, similarity between queried image and the candidate images are calculated. The colour histogram with K-Means method had high accuracy and precise compared to GLCM. Future work will be made to add more features that are famous in CBIR which is texture features extraction using discrete wavelet based entropy measurement in order to get better results.

Keywords: Image Retrieval, Wavelet Feature, Clustering Model.

Introduction

Image retrieval techniques are useful in many image-processing applications. Content-based image retrieval systems work with whole images and searching is based on comparison of the query. General techniques for image retrieval are color, texture and shape. These techniques are applied to get an image from the image database. They are not concerned with the various resolutions of the images, size and spatial color distribution. Hence all these methods are not appropriate to the art image retrieval. Moreover shape based retrievals are useful only in the limited domain.

The content and metadata based system gives images using an effective image retrieval technique. Many other image retrieval systems use global features like color, shape and texture. The primary goal of this paper is to reduce the computation time and user interaction. The conventional CBIR systems also display the large amount of results at the end of the process this will drove the user to spend more time to analyze the output images. In our proposed system we compute texture feature and color feature for compute the similarity between query and database images. This integrated approach will reduce the output results to a certain levels based on the user threshold value.

Content-based Image Retrieval

In contrast to the text-based approach of the systems, CBIR operates on a totally different principle, retrieving stored images from a collection by comparing features automatically extracted from the images themselves. The common features used are mathematical measures of color, texture or shape. A typical system that allows users to formulate queries by submitting an example of the type of image being sought, though some offer alternatives such as selection from a palette or sketch input. The system then identifies those stored images whose feature values match those of the query most closely, and displays thumbnails of these images on the screen. Some of the more commonly used types of feature used for image retrieval are described below.

A. Color Feature Based Retrieval

Several methods for retrieving images on the basis of color similarity are variations on the same basic idea. Each image added to the collection is analyzed to compute a color histogram, which shows the proportion of pixels of each color within the image. The color histogram for each image is then stored in the database. At search time, the user can either specify the desired proportion of each color or submit an example image from which a color histogram is calculated. Either way, the matching process then retrieves those images whose color histograms match those of the query most closely. The matching technique most commonly used is histogram intersection. Variants of this technique are now used in a high proportion of current CBIR systems. Modified techniques include the use of cumulative color histograms, combining histogram intersection with some element of spatial matching, and the use of region-based color querying. The results from some of these systems can look quite impressive. Red Green Blue (RGB), Hue Saturation Value (HSV) color conversion models are commonly used here.

B. Texture Based Image Retrieval

A variety of techniques have been used for measuring texture similarity; the best established rely on comparing values of what are known as second-order statistics calculated from query and stored images. Essentially, these calculate the relative brightness of selected pairs of pixels from each image. From these it is possible to calculate measures of image texture such as the degree of contrast, coarseness, directionality and regularity, or periodicity, directionality and randomness. There are three principal approaches used to describe texture; statistical, structural and spectral.

The most popular statistical representations of texture is Co-occurrence Matrix which explores the grey level spatial dependence of texture [2]. Haralick proposed the following texture features:

1. *Energy*: It is a gray-scale image texture measure of homogeneity changing, reflecting the distribution of image gray-scale uniformity of weight and texture.

$$E = \sum_x \sum_y p(x, y)^2$$

where, $p(x,y)$ is the GLCM.

2. *Contrast*: Contrast is the main diagonal near the moment of inertia, which measure the value of the matrix is distributed and images of local changes in number, reflecting the image clarity and texture of shadow depth.

$$\text{Contrast} \qquad I = \sum\sum (x-y)^2 p(x, y)$$

3. *Entropy*: It measures image texture randomness, when the space co-occurrence matrix for all values is equal, it achieved the minimum value.

$$S = -\sum_x \sum_y p(x, y) \log p(x, y)$$

4. *Correlation Coefficient*: Measures the joint probability occurrence of the specified pixel pairs.

Correlation = sum (sum ((x-μx) (y-μy) p(x, y)/σxσy))

5. *Homogeneity*: Measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

Homogenity = sum (sum (p(x , y) / (1 + [x-y])))

Clustering Technique

Segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image.Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture.

A. Clustering Methods

The K-means algorithm is an iterative technique that is used to partition an image into K clusters. The flow chart of K-means algorithm is shown in figure 1 and the basic algorithm is:

1. Pick K cluster centers, either randomly or based on some heuristic.
2. Assign each pixel in the image to the cluster that minimizes the distance between the pixel and the cluster center.
3. Re-compute the cluster centers by averaging all of the pixels in the cluster.
4. Repeat steps 2 and 3 until convergence is attained.

In this case, distance is the squared or absolute difference between a pixel and a cluster center. The difference is typically based on pixel color, intensity, texture, and location, or a weighted combination of these factors. K can be

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selected manually, randomly, or by a heuristic. This algorithm is guaranteed to converge, but it may not return the optimal solution. The quality of the solution depends on the initial set of clusters and the value of K.

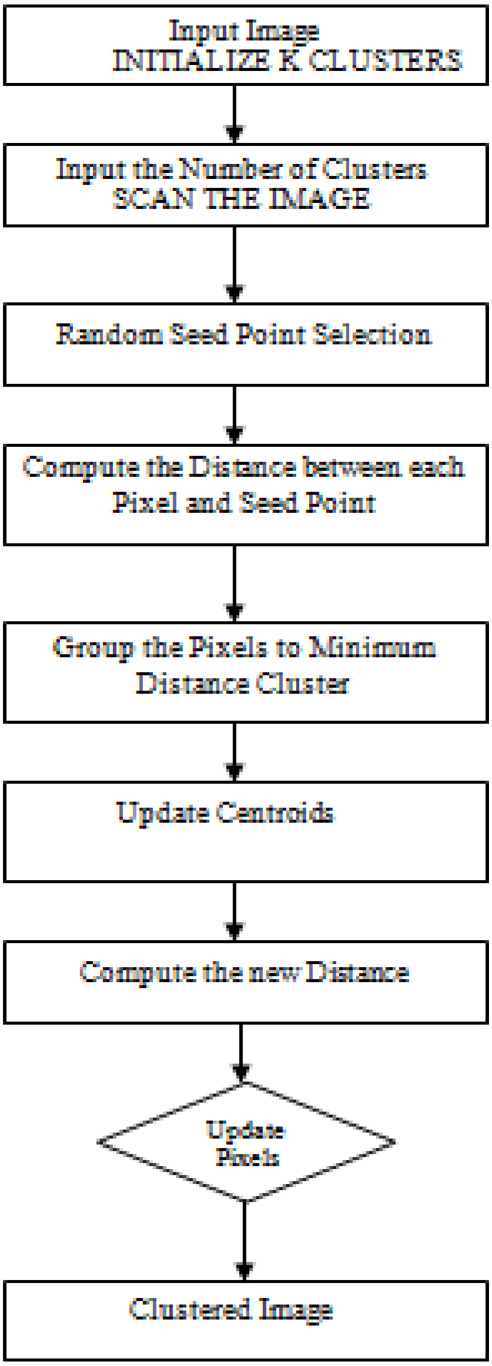


Figure 1: Flowchart of K-means Algorithm

Discrete Wavelet Transform

A. Wavelets

A wavelet is a waveform of an effectively limited duration that has an average value of zero. Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. A function can be called a wavelet if it possesses the following properties:

1. The function integrates to zero, or equivalently, its Fourier transform denoted as is $\psi(\omega)$ zero at the origin:

$$\int_{-\infty}^{\infty} \psi(x)dx = 0$$

2. It is square integrable, or equivalently, has finite energy:

$$\int_{-\infty}^{\infty} | \psi(x) |^2 dx < \infty$$

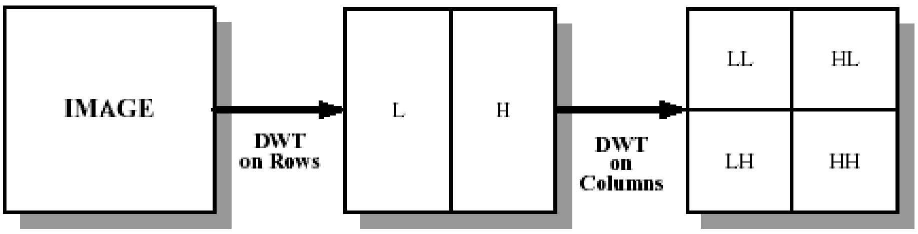
3. The Fourier transform must satisfy the admissibility condition given by

$$C = \int_{-\infty}^{\infty} \frac{|\psi(\omega)|^2}{\omega} d\omega < \infty$$

1)**Discrete Wavelet Transforms**

The 1-D Discrete Wavelet Transform (DWT) can be extended to 2-D transform using separable wavelet filters. With separable filters, applying a 1-D transform to all the rows of the input and then repeating on all of the columns can compute the 2-D transform. When one-level 2-D DWT is applied to an image, four transform coefficient sets are created. As depicted in figure 2, the four sets are LL, HL, LH, and HH, where the first letter corresponds to applying either a low pass or high pass filter to the rows, and the second letter refers to the filter applied to the columns.

The Two-Dimensional DWT (2D-DWT) converts images from spatial domain to frequency domain. At each level of the wavelet decomposition, each column of an image is first transformed using a 1D vertical analysis filter-bank. The same filter-bank is then applied horizontally to each row of the filtered and sub sampled data.



(a) (b) (c)

Figure 2: Block Diagram of DWT (a) Original Image (b) Output Image after the 1-D applied on Row Input (c) Output Image after the Second 1-D applied on Row Input.

One-level of wavelet decomposition produces four filtered sub bands. The upper and lower areas of figure 2 (b), respectively, represent the low pass and high pass coefficients after vertical 1D-DWT and subsampling. The result of the horizontal 1D-DWT and subsampling to form a 2D-DWT output image is shown in figure 2 (c).

B. Entropy Measurement

The Entropy will be finding for all sub band coefficients entropy measurement was used to extract significant information for texture pattern. Entropy measurement is giving by equation,

$$\text{Entropy} = -\sum_{i,j} C(i,j) \log C(i,j)$$

Results

Simulations are carried out on MATLAB software with Graphical User Interface (GUI) support. Figure 3 shows the GLCM based colour histogram analysis done using the content based image retrieval system with wavelet feature extraction.

Figure 3: GLCM based Colour Histogram Analysis

Figure 4 shows the shape based image retrieval system using content based image retrieval system with wavelet feature extraction. Figure 5 shows the wavelet feature based retrieval system using content based image retrieval system with wavelet feature extraction. Table 1 shows the comparison of GLCM and K-means method.

Figure 4: Shape based Image Retrieval System

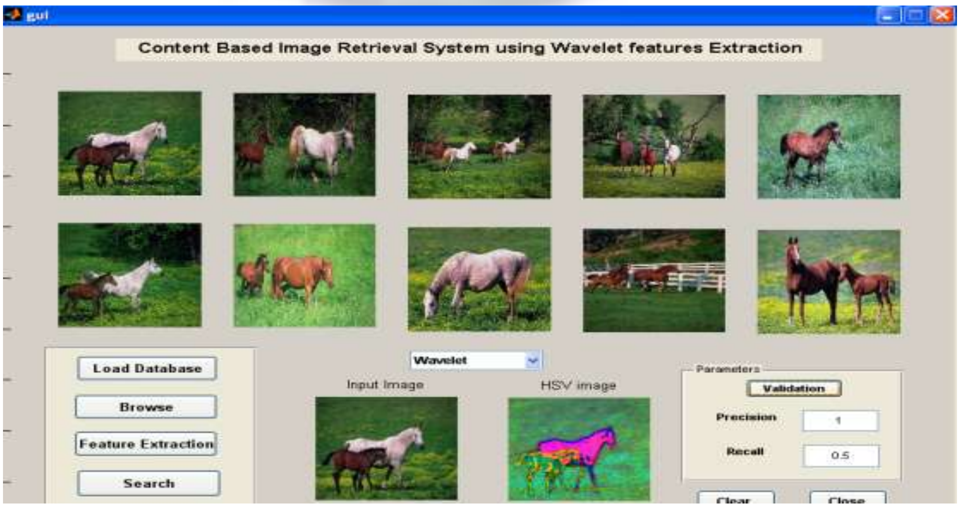


Figure 5: Wavelet Feature based Retrieval System

Table 1: Comparison of GLCM and K-means

Method	Parameters	Value
GLCM	Precision	0.50
	Recall	0.25
K-means	Precision	0.70

Conclusion

The project presented the image retrieval technique based on image contents shape and texture features. Here, the color histogram features are analyzed based on GLCM which used effectively to describe the color features. It provides the rules that gray scale of a pair of pixels appears in a certain distance away in a certain direction. The shape of image was analyzed by clustering model which was compared with GLCM based retrieval. Finally, a practical result proved that the better retrieval performance obtained for maximum test images based on shape features compared to texture features. The system can be further enhanced by analyzing pattern using wavelet filters.

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