Image-to-Image Retrieval with Similarity Measures

Mrs Manisha Ballal[1], Prof. Potdar G.P.[2]

ME student (IT), Pune Institute of Computer Technology, Pune, India[1]
Asst. Professor, Pune Institute of Computer Technology, Pune, India[2]

Abstract: **The most important thought of this project is to present competent, immediate, and accurate CBIR using simple and strong man machine interface by means of images. In other terms the aim is to locate content-based image features that are efficient enough to allow us to do texture based image retrieval where an input image is applied as the starting point to search in an image dataset for conceptually similar images. This is a non-trivial task since users usually do not have a good example at hand when they begin to search for images. Indexing ability of the proposed methods ensures their appropriateness in large-scale image datasets. Our system improves the retrieval performance and better matches.**

Keywords: ***CBIR, haar wavelet, indexing,curvelet algorithm***

I. INTRODUCTION

In content based image queries, example images, unclear drawings of the desired colors; simple outline sketches; are recommended and analyze. We suppose that draw sketches are usually easier and quicker to generate than a complete color description of the picture. And they can be generated for subjective preferred images, while model images may or may not be at give when searching.The main goal of the CBIR is to find images which are similar to the query image. Texture analysis is one of the major components of image processing and work as the backbone for many applications such as remote sensing, quality inspection, medical imaging, etc. [2].Here we proposed amethod in which texture features are used for efficient image retrieval.The Haar wavelet transform, in this application is one way of compressing images so they take fewer gaps when stored and transmitted.Our system, reduce the physical size of the files without mortifying the superiority of the image to an undesirable level using image compression techniques. This leads to compressed version of an image, lessening in file size allows extra images to be stored in a certain amount of disk or memory space.

II. RELATED WORK

Content-based image retrieval (CBIR) supports both known image search and novel image search. However, in both cases CBIR requires a query image to start with that is similar to the final result. Without such a query image, it is difficult to achieve good retrieval quality. The degree of matching achieved and the elastic deformation energy spent by the sketch to achieve such a match are used to derive a measure of similarity between the input image and the images in the database and to rank images to be displayed. However the expense of the optimization step to fit the model limits the scalability of the approach, making it inappropriate for use in interactive TBIR systems.

A. *Indexing and Clustering*

Wehavedescribedaclusteringalgorithmwhichclusterrsimagefoundationonthesimilarity measure of image features (for example, similarity by object shape etc). The algorithm classifies groups of images based on all possible ways the user is able to query the database. This clustering algorithm smooths the progress of outline finding method by use of clusters in combination with multi-dimensional indexes. Clustering is made on calculating the distance of the new images, rank their distances in ascending order.

B. *Haar wavelet Descriptor*

Wavelets are mathematical tools for hierarchically decaying functions. In recent years Wavelet Transform has been proved to be a very helpful tool for image processing. The Haar Transform (HT) is one of the simplest and basic transformations from the space domain to a local frequency domain. A HT decomposes each signal into two components, one is called average and the other is known as difference. To understand averaging and differencing.[5] The formula for average is, av1=(av1,av2,av3…….avn/2) at one level of signal legth n i.efq=(fq1,fq2,…….fqn) fq is frequency. i.eavn= ,n=(1,2,3,….n/2).--------eq(1) and the first detail sub-signal.df1=(df1,df2,df3…..dfn/2). at the same level is given as dfn= ,n=(1,2,3,….n/2).--------eq(2).

The haar wavelet transform produces four areas A, H, V and D respectively. A (approximation area) includes information about the global properties of analysed image. Removal of spectral coefficients from this area leads to the biggest distortion in original image. H (horizontal area) includes information about the vertical lines hidden in image. Removal of spectral coefficients from this area excludes horizontal details from original image.V (vertical area) contains information about the horizontal lines hidden in image. [3].

III. SYSTEM ARCHITECTURE

In general, an image retrieval system generally provides a user interface for communicating with the user. It collects the necessary information, including the query image, from the user and displays the retrieval results. Our system works, in four steps:

1. Querying: The user gives an input image as the query for the system.
2. Feature Extraction: The system extract the low level feature from the input image.

3. Curvelet Algorithm: This algorithm is used for texture feature extraction.
4. Similarity Measure: Comparison of input image and the stored images are through on feature extracted.

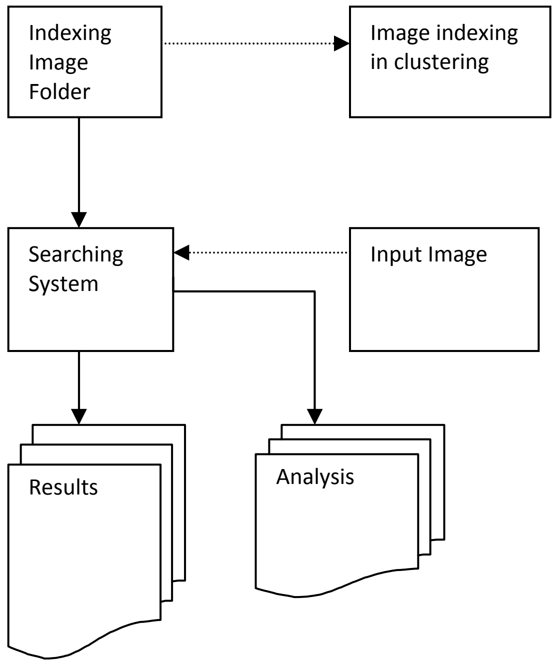

Fig. 1 System overview

IV. CURVELET ALGORITHM

In this paper we are using a multiscale transform called Curvelet transform which is designed to handle curve discontinuities. The idea is to partitioning the curves into collection of ridge fragments and then handles each fragment using the ridgelet transform. The curvelet transform is applied on a set of texture images. One group feature vector can be constructed by the mean and variance of the Curvelet Statistical Features (CSFs), which are derived from the sub-bands of the curvelet decomposition and are used for classification. The experimental result shows that the success rate is improved much when compared with traditional methods.

To overcome the weakness of wavelets in higher dimensions, a new system of representations named ridgelets which deal effectively with line singularities in two dimensions. The idea is to map a line singularity into a point singularity using the Radon transform. Then, the wavelet transform can be used to effectively handle the point singularity in the Radon domain. So, Ridgelet transform allows representing edges and other singularities along lines in a more efficient way than wavelet transform, for a given accuracy of reconstruction [7].

As curvelet transform extends the ridgelet transform to multiple scale analysis. So we start from the definition of ridgelet transform. [6].

Given an image function f(x, y), the continuous ridgelet transform is given as

$$R_f(a,b,\theta)=\iint \psi_{a,b,\theta}(x,y)f(x,y)\,dxdy \quad (1)$$

Where $a>0$ is the scale, $b\in R$ is the translation and $\theta \in[0,2\pi)$ is the orientation.

The ridgelet is defined as:

$$\psi_{a,b,\theta}(x,y)=a^{-1/2}\psi\left(\frac{x\cos\theta+y\sin\theta-b}{a}\right)$$

In A new multiscale transform named curvelet transform which was designed to represent edges and other singularities along curves much more efficiently than traditional transforms, i.e., using fewer coefficients for a given accuracy of reconstruction. There are no losses of information in curvelet transform.

The continuous curvelet transform can be defined by a pair of windows $W(r)$ (a radial window) and $V(t)$ (an angular window), with variables Was a frequency-domain variable, and r and θ as polar coordinates in the frequency-domain.[21].

$$\sum_{J=-\infty}^{\infty} W^2(2^J r) = 1 \qquad r>0$$

$$\sum_{J=-\infty}^{\infty} V^2(t-l) = 1 \qquad t\in r$$

In Image processing edges are curved rather than straight lines and Curvelet transform is a multi-scale representation of data which is most suitable method for objects with curves. Curvelet transform is designed to handle curve discontinuities. In this transform the image could be decomposed into a set of wavelet bands, (collection of ridge fragments) and then each fragment is handled using ridgelet transform. The block size of image can be changed at each scale level. These formal properties are very similar to the results expected from an orthonormal basis, and reflect an underlying stability of representation.

The curvelet transform involves following steps:

1. Sub-band decomposition
2. Smooth partitioning
3. Renormalization
4. Ridgelet analysis

The features of images data are extracted from images. These features are used to compare with database features through matching the similarity using Euclean Distance. The results are ranking according to the degree of similarity.

In this paper project, the curvelet transform is applied on a set of texture images. One group feature vector can be constructed by the mean and variance of the Curvelet Statistical Features (CSFs), which are derived from the sub-bands of the curvelet decomposition and are used for classification. The experimental result shows that the success rate is improved much when compared with traditional methods.

V. SIMILARITY MEASURES

In Content based image retrieval system query image is input from the user. Then system has to compare this image with the images in the database. In this first low-features of the query image are extracted and feature descriptor is formed. This descriptor of the query image is compared with the feature descriptor of the images in the database. Similar images should have similar descriptor. To check this similarity we have used Euclidean distance similarity measure matrix

Euclidean distance is the most common metric for measuring the distance between two vectors and is discussed and implemented in a number of content based image retrieval approaches. It is applicable when the image feature vector elements are equally important and the feature vectors are independent of one another. The Euclidean distance can simply be described as the ordinary distance between two values. It is given by the square root of the sum of the squares of the differences between vector components.[5]

It is one the similarity measure metric.

If $u = (x_1, y_1)$ and $v = (x_2, y_2)$

Then the Euclidean distance between u and v is given by,

$$EU(u,v) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

Instead of two dimensions, if the points have n-dimensions, such as $a = (x_1, x_2, \dots, x_n)$and b= $(y_1, y_2, \dots, y_n)$. Then the distance between a and b can be given as,

$$EU(a,b) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \ \dots + (x_n - y_n)^2}$$

$$EU(a,b) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}.$$

VI. Experimental Setup And Results

Our Experiment is carried out on the image compression using haar wavelet. The compression technique is used to find the interested edge point required to our key value algorithm , after finding the key values of the it's check with the stored images edges and find the similarity between them and display the result.

Indexing is done on files which stored the related images and the features are stored in the featured array. Our system performance and retrieval of image is fast as compared to the existing system. The correctness of the correspondence between the query and retrieved image is taken as performance measure

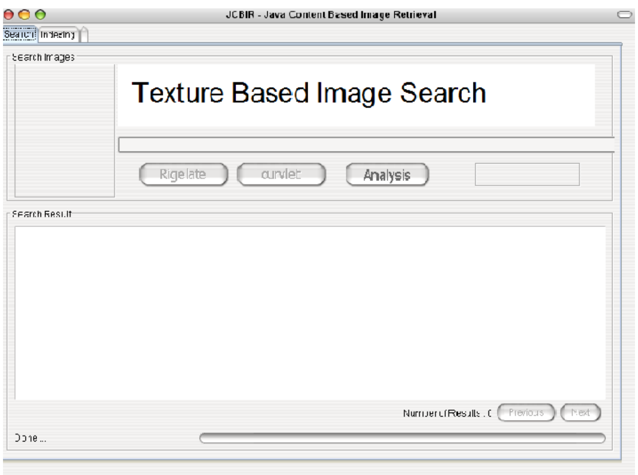

Fig. 2 Main Screen

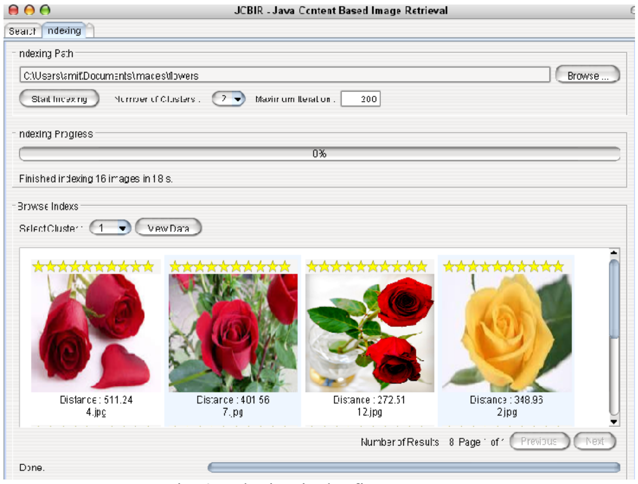

Fig. 3 Indexing is the first step

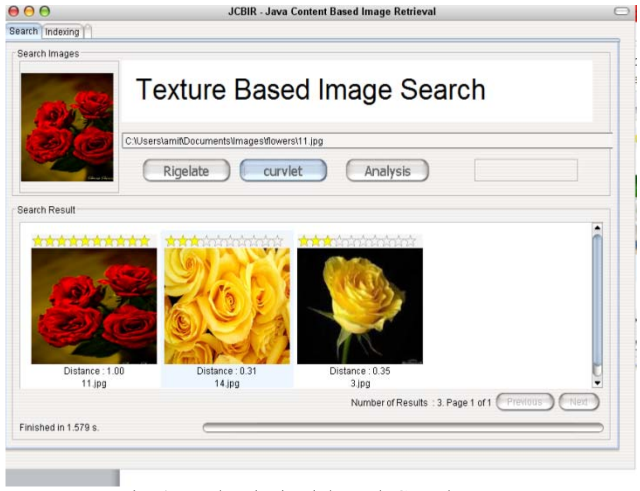

Fig. 4 Results obtained through Curvelet

VII. Searching And Indexing Analysis

We had perform some test on the collection of different images set, time taken for searching and indexing the result on the desired qeury.The graph below shows the behavior of the search results from dataset and indexing results.

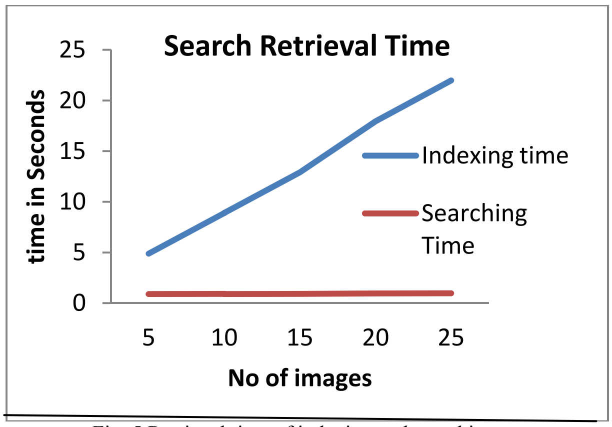

Fig. 5 Retrieval time of indexing and searching

It shows that as number of images increases it takes time to indexing while in case of searching time is decreases because of the indexing is done before .

VIII. CONCLUSION AND FUTURE WORK

Retrieving images from a large collection of image dataset is still the challenge in the Content Based Image Retrieval. In texture Based Image Retrieval, a query image is mapped to a similar image in the image dataset. After feature extraction from the query image using our algorithm, we found that the performance of the system is improved and the accuracy of the similar images is better. In future, we will work on rotation and scale invariance to improve curvelet retrieval performance. Semantic learning is another issue to be considered in future. Working on large texture image dataset is still to achieve.

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