ISSN No. 0976-5697

Volume 2, No. 3, May-June 2011

International Journal of Advanced Research in Computer Science

RESEARCH PAPER

Available Online at www.ijarcs.info

Extraction of Texture features Using Euclidean, Canberra and Both Distance

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Abstract: In this paper Cosine-modulated class of multiplicity M wavelet tight frames (WTF_s). In these WTF_s, the scaling function uniquely determines the wavelets. This is in contrast to general multiplicity M case, where one has to, for any given application, design the scaling function and the wavelets. Hsin used a modulated wavelet transform approach for texture segmentation and reported that texture segmentation performance can be improved with this approach. Guillemot and Onno had used Cosine-modulated wavelet for image compression. They have presented procedure for designing Cosine-modulated wavelets for arbitrary length filters. This procedure allows obtaining filters with high stopband attenuation even in the presence of additional regularity constraints. Their results show that these filter solution provide good performance in image compression. The advantages of the Cosine-modulated wavelet are their low design and implementation complexities, good filter quality, and ease in imposing the regularity conditions, which yields improved retrieval performance both in terms of accuracy and retrieval time. Feature extraction is one of the most important tasks for efficient and accurate image retrieval purpose. In this paper we are going to use Cosine-modulated wavelet transform based technique for extraction of texture features. The major advantages of Cosine-modulated wavelet transform are less implementation complexity, good filter quality, and ease in imposing the regularity conditions. Texture features are obtained by computing the energy, standard deviation and their combination on each subband of the decomposed image. To check the retrieval performance, texture database of 1856 textures is created from Brodatz album. Retrieval efficiency and accuracy using Cosine-modulated wavelet based features will be found to be superior to other existing methods.

Keywords: Cosine-modulated wavelet; Content-based image retrieval; Image database; Query image; Texture analysis

I. INTRODUCTION

Content-based image retrieval (CBIR) has been an active research topic in the last few years. Comparing to the traditional systems, which represent image contents only by keyword annotations, the CBIR systems perform retrieval based on the similarity defined in terms of visual features with more objectiveness. Although some new methods, such as the relevant feedback, have been developed to improve the performance of CBIR systems, low-level features do still play an important role and in some sense be the bottleneck for the development and application of CBIR techniques.

The advancement of information technology demands communication and sharing of visual information globally. This is made possible due to the development of global computer network in the form of World Wide Web. Storage of visual information or image database has wide applications such as entertainment, Film and video archives, finger print or face identification, geographical information systems, remote sensing, the most challenging tasks in content-based image retrieval (CBIR)[16]. Comprehensive and extensive literature survey on content-based image retrieval is presented by Rui et al. (1999), Smeulders et al. (2000) and Kokare et al. (2002a). Content-based image retrieval lies at the crossroads of multiple disciplines such as database, artificial intelligence, image processing, statistics, computer vision, high performance computing, and human–computer intelligent interaction. Efficient and accurate image retrieval necessitates development of image description techniques, which will not only describe an image uniquely but also should be computationally very efficient. An image is described by a set of features. These features represent various image characteristics such as color, texture, shape etc. Importance of texture feature is due to its presence in many real as well as synthetic data. As tigers and cheetahs have same colors but different texture patterns, so using color feature alone cannot clearly distinguish between them. This phenomenon gives clear justification for texture features to be used in content based image retrieval along with color and shape. Texture describes the content of many real world images: for example, clouds, trees, bricks, hair, fabric etc. all of which have textural characteristics.

II. RELATED WORK

A very basic issue in designing a CBIR system is to select the most effective image features to represent image contents. Many low-level features have been researched so far. Currently, the widely used features include color features, such as color correlogram , color moments, color histogram , and texture features, such as Gabor wavelet feature , MR-SAR(Multi Resolution Simultaneous Autoregressive) . As the color and texture features capture different aspects of images, their combination may be useful. Therefore, some pioneer works attempted to characterize the color and texture information of an image in one feature representation. Lakmann et al proposed a reduced covariance color texture model, which suggests a set of covariance matrices $CCij$ $(\Delta x,\Delta y)$ between different color channels i, j plus some color histogram to describe a color micro-texture. Palm et al proposed another scheme to combine the color and texture information together. It interprets the hue and saturation as polar coordinates, which allow the direct use of HSV color space for Fourier transform.

A novel low-level feature CTM(Color Texture Moments) for content-based image retrieval systems[22]. We adopt LFT as a texture representation scheme and derive eight characteristic maps for describing different aspects of co-occurrence relations of image pixels. Then we calculate the first and second moments of these maps as a representation for the distribution of natural color image pixels. We operate the LFT in the (SVcosH, SVsinH, V) color space since it not only corresponds to visual perception but also overcomes some shortcomings of the HSV color space. Experiments on an image library containing 10,000 Corel images and 200 queries demonstrate the effectiveness of the new method.

The main texture features currently used are derived from either Gabor wavelets or the conventional discrete wavelet transform. There is evidence that images are decomposed into a collection of band pass sub images by the simple visual cortical cells to form features for pattern recognition. Daugman (1980) reported that Gabor filters are suitable for such decomposition because impulse response of Gabor filter is similar to that of mammalian cortical cells. Manjunath and Ma (1996) reported Gabor wavelet based texture image retrieval results using four scales and six orientations. For constructing feature vector they used mean and standard deviation of the magnitude of the Gabor transform coefficients, resulting in a feature vector of size 24×2. Though Manjunath and Ma (1996) had done extensive experiments on a large set of textured images and shown that retrieval performance is better using Gabor filters than using conventional orthogonal wavelets, but the computational effort and storage requirement cause major problems. The basic requirement in content-based image retrieval for online application is that image feature extraction method should be computationally efficient with high retrieval accuracy and should require less storage space. Recent development in wavelet theory has provided a promising alternative through multi channel filter banks that have several potential advantages over Gabor filters namely, (i) Wavelet filters cover exactly the complete frequency domain. (ii) To facilitate computation fast algorithms are readily available. Studies on successful application of wavelet theory on texture analysis mainly use the multiresolution signal decomposition developed by Mallat (1989). He used quadrature mirror filters to relate information at different scales of decomposition of the embedded subspace representation. The work of Chang and Kuo (1993) indicates that the texture features are more prevalent in the intermediate frequency band. Smith and Chang (1996) used mean and the variance of discrete wavelet transform coefficients to develop fully automated content-based image retrieval system called VisualSEEk[17].

A drawback of standard wavelets is that they are not suitable for the analysis of high-frequency signals with relatively narrow bandwidth. Kokare et al. (2002b) used the decomposition scheme based on M-band wavelets, which yields improved retrieval performance. Unlike the standard wavelet decomposition, which gives a logarithmic frequency resolution, the M-band decomposition gives a mixture of a logarithmic and linear frequency resolution. Further as an additional advantage, M-band wavelet decomposition yields a large number of subbands, which improves the retrieval accuracy. One of the drawbacks with M-band wavelet in content-based image retrieval is that computational complexity increases and hence retrieval time with number of bands.

III. ANALYSIS OF PROBLEM

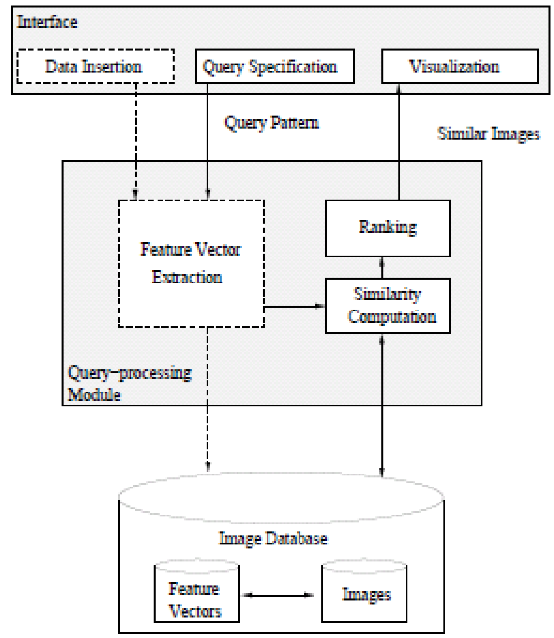

Figure1: Typical architecture of content based image retrieval system

Figure 1 shows a typical architecture of a content-based image retrieval system. Two main functionalities are supported: data insertion and query processing.

The data insertion subsystem is responsible for extracting appropriate features from images and storing them into the image database (see dashed modules and arrows)[19]. This process is usually performed off-line. The query processing, in turn, is organized as follows: the interface allows a user to specify a query by means of a query pattern and to visualize the retrieved similar images. The query-processing module extracts a feature vector from a query pattern and applies a metric (such as the Euclidean distance) to evaluate the similarity between the query image and the database images. Next, it ranks the database images in a decreasing order of similarity to the query image and forwards the most similar images to the interface module. Note that database images are often indexed according to their feature vectors by using structures such as M-tree or Slim-tree to speed up retrieval and similarity computation. Note that both the data insertion and the query processing functionalities use the feature vector extraction module.

IV. PROPOSED WORK

Gopinath and Burrus (1991) introduced Cosine-modulated class of multiplicity M wavelet tight frames (WTF_s). In these WTF_s, the scaling function uniquely determines the wavelets. This is in contrast to general multiplicity M case, where one has to, for any given application, design the scaling function and the wavelets. Hsin (2000) used a modulated wavelet transform approach for texture segmentation [6] and reported that texture segmentation performance can be improved with this approach. Guillemot and Onno (1994) had used Cosine-modulated wavelet for image compression. They have presented procedure for designing Cosine-modulated wavelets for arbitrary length filters[3]. This procedure allows obtaining filters with high stopband attenuation even in the presence of additional regularity constraints. Their results show that these filter solution provide good performance in image compression. The advantages of the Cosine-modulated wavelet are their low design and implementation complexities, good filter quality, and ease in imposing the regularity conditions, which yields improved retrieval performance both in terms of accuracy and retrieval time.

The main contributions of this paper are summarized as follows. First, in this paper we are presenting novel texture features for content-based image retrieval using Cosine-modulated wavelet transform[17]. Second, our approach of using the Canberra distance metric for similarity measurement improves the retrieval performance from 57.16% to 74.78% compared with the traditional Euclidean distance metric (where same features were used but Euclidean distance metric is used for similarity measurement). This shows that good performance in retrieval comes not just from a good set of features but also together with the use of suitable similarity measurement, which supports our approach. Another advantage of proposed method is that the retrieval time required is 6.69 times less than the Gabor based method, which is very important in CBIR. Third, a detailed comparison of the retrieval performance with standard Daubechies wavelet and Gabor wavelet method proposed by Manjunath and Ma (1996) is presented. The result indicates that retrieval performance of proposed method is superior to standard Daubechies wavelet and Gabor wavelet both in terms of accuracy and retrieval time. For large scale evaluation our retrieval results are checked on large database of 1856 images.

V. IMPLICATION

A. Cosine-modulated wavelet for content-based image retrieval

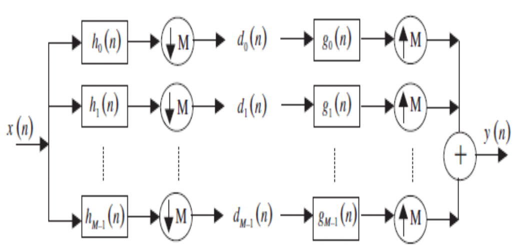

Figure2. M-channel Filter bank

Fig. 2 shows an M-channel filter bank with analysis filters h_i and synthesis filters g_i. Filter bank is said to be perfect reconstruction if y (n) = x (n). A perfect reconstruction filter bank is unitary if $g_i(n) = h_i(-n)$. Vaidyanathan (1992) reported that unitary (FIR) filter banks are practically important since they can be completely parameterized and efficiently implemented.Moreover, they give rise to orthonormal wavelet bases for L^2 (R). A unitary filter bank where the lowpass filter satisfies the additional linear constraints given in Eq. (1) gives rise to wavelet tight frames.

$$\sum_{k=0}^{N-1} h_0(k) = \sqrt{M} \qquad (1)$$

Where $h_0(k)$ is lowpass filter of length N, and the number of channels are M. This filter is the unitary scaling vector, and the remaining filters in the filter bank are the unitary wavelet vectors. The scaling and wavelet vectors determine the scaling function, $\psi_0(t)$ and the (M _ 1) wavelets, $\psi_i(t)$, are defined by

$$\psi_i(t) = \sqrt{M} \sum_k h_i(k)\, \psi_0(Mt-k) \qquad (2)$$

i $\in$*{0,…..,M-1}*

The (M _ 1) wavelets $\psi_i(t)$, i $\in${0,…..,M-1}, their translates and dilates by powers of M form a wavelet tight frame for L^2 (R) as reported by Gopinath and Burrus (1991) and Veterli and Herley (1992). For every function f (t) $\in L^2$ (R) one has

$$f(t) = \sum_{i=1}^{M-1} \sum_{j,k} \langle f, \psi_{i,j,k}(t) \rangle\, \psi_{i,j,k}(t) \qquad (3)$$

Where $\langle\rangle$ is an inner product and

$$\psi_{i,j,k}(t) = M^{j/2}\, \psi_i(M^j t-k)$$

A scaling vector is said to be K regular if its Z transform is of the form

$$H_0(z) = (1+z^{-1} + \cdots + z^{-(M-1)})^k P(z) \qquad (4)$$

for maximal possible K, and P(z) is a polynomial in z^{-1}. Steffen et al. (1993) had shown that the minimal length K-regular scaling vectors are generically of length N = MK and it can be constructed for all multiplicity M. The corresponding wavelet tight frames are called K-regular wavelet tight frames.

Modulated filter banks are special class of filter banks where the analysis and synthesis filters are obtained by modulation of prototype filters.

Koilpillai and Vaidyanathan (1992) had reported that Cosine-modulated FIR filter banks are the special class of unitary filter banks, where the analysis filters $h_i(n)$ are all Cosine-modulates of a low pass linear-phase prototype filter g(n). The fundamental idea behind Cosine-modulated filter banks is the following: In an M-channel filter bank[18], the analysis and synthesis filters are meant to approximate ideal M^{th} band filters, which are shown in Fig. 3. The passband of these filters occupy adjacent frequency channels that are $\frac{\pi}{M}$ apart. Given a real, prototype filter g(n) with passband in $[-\frac{\pi}{2M}, \frac{\pi}{2M}]$,if it is modulated by $\cos((2i+1)\frac{\pi}{2M} n + \varepsilon_i$ (where ε_i is arbitrary phase), has a passband

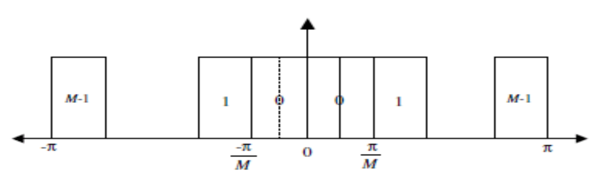

Figure 3.Ideal frequency responses in M-channel filter bank

equal to the desired band for the ith filter in Fig. 3. This technique gives rise to modulated filter banks [8](Eqs. (5) and (6))

$$h_i(n) = h(n)\cos\left(\frac{\pi}{2M}(2i+1)n + \varepsilon_i\right) \qquad (5)$$

and

$$g_i(n) = g(n)\cos\left(\frac{\pi}{2M}(2i+1)n + \gamma_i\right) \qquad (6)$$

Where ε_i and γ_i are phase factors. Several choices of ε_i and γ_i have been reported by Koilpillai and Vaidyanathan (1992) and Malvar (1990). In this work we have used filter coefficients designed by Gopinath and Burrus (1995) by assuming g(n)=h(n) with following phase factor.

$$h_i(n) = C_{i,n}\, g(n) \qquad (7)$$

Where g (n) is an even-symmetric prototype filter of length N = 2Mm for some nonnegative integer m and

$$C_{i,n}=\cos\left(\pi/2M\,(2i+1)\left(n-(N-1)/2\right)+\tau_i\right) \qquad (8)$$

The phase factor τ_i can be taken to be $(-1)^i \frac{\pi}{4}$. In the filtering stage we make use of filter coefficients for M = 2 to decompose the texture image in to four channels, corresponding to different direction and resolutions. After decomposing image with wavelet transform we get horizontal, vertical and diagonal information. Hsin (2000) has reported that diagonal filter gives strong response to textures with orientations at or close to $\pm 45^0$; the wavelet based features of similar textures with symmetric orientations are almost indistinguishable. Pattichis et al. (1997) reported that a large class of natural textures can be modeled as a quasiperiodic pattern and represented by modulated function, which motivates us to use Cosine modulated wavelet[4] for extracting texture features for content-based image retrieval.

The proposed image retrieval procedure is as follows:

B. Texture image database

The texture database used in our experiment consists of 1856 texture images. For creating this database 116 different textures classes will be used. We will use 108 textures from Brodatz (1966) texture photographic album, seven textures from USC database and one artificial texture. Size of each texture image is 512 × 512. Each 512 × 512 image is divided into sixteen 128 ×128 nonoverlapping subimages, thus creating a database of 1856 texture images[1].

C .Feature database creation

Each image from the database will be analyzed using standard Daubechies wavelet and Cosinemodulated wavelet filter banks. The analysis will performed up to third level (4 × 3 =12 subbands) of the wavelet decomposition. [11]For constructing the feature vector feature parameters such as energy, standard deviation and combinations of both will compute separately on each subband and will stored in vector form. The basic assumption of this approach is that the energy distribution in the frequency domain identifies a texture. Besides providing acceptable retrieval performance from large texture, this approach is partly supported by physiological studies of the visual cortex as reported by Hubel and Wiesel (1962) and Daugman (1980).

D. Image retrieval method

A query image is any one of the images from image database. This query image is processed to compute the feature vector as in Section B. Traditional Euclidean distance metric and Canberra distance metrics are used to compute the similarity or match value for given pair of images. If x and y are two d-dimensional feature vectors of database image and query image respectively

The idea is to apply image retrieval and then classify the resulting images to change their order.

• Need for tools that automatically extract semantic features from images: extract high level concepts contained in multimedia data.

VI. APPLICATION

A. Fingerprint identification

The use of CBIR can result in powerful services that can benefit biomedical information systems. Three large domains can instantly take advantage of CBIR techniques: teaching, research, and diagnostics. From the teaching perspective, searching tools can be used to find important cases to present to students. Research also can be enhanced by using services combining image content information with different kinds of data. For example, scientists can use mining tools to discover unusual patterns among textual (e.g., treatments reports, and patient records) and image content information. Similarity queries based on image content descriptors can also help the diagnostic process. Clinicians usually use similar cases for case-based reasoning in their clinical decision-making process. In this sense, while textual data can be used to find images of interest, visual features can be used to retrieve relevant information for a clinical case (e.g., comments, related literature, HTML pages, etc.).

B. Biodiversity Information Systems

Biologists gather many kinds of data for biodiversity studies, including spatial data, and images of living beings. Ideally, Biodiversity Information Systems (BIS) should help researchers to enhance or complete their knowledge and understanding about species and their habitats by combining textual, image content-based, and geographical queries. An example of such a query might start by providing an image as input (e.g., a photo of a fish) and then asking the system to *"Retrieve all database images containing fish whose fins are shaped like those of the fish in this photo"*. A combination of this query with textual and spatial predicates would consist of *"Show the drainages where the fish species with 'large eyes' coexists with fish whose fins are shaped like those of the fish in the photo"*.

C. Digital libraries

There are several digital libraries that support services based on image content. One example is the digital museum of butterflies, aimed at building a digital collection of Taiwanese butterflies. This digital library includes a module responsible for content-based image retrieval based on color, texture, and patterns. In a different image context, Zhu *et al.* present a content-based image retrieval digital library that supports geographical image retrieval. The system manages air photos which can be retrieved through texture descriptors.

Place names associated with retrieved images can be displayed by cross referencing with a Geographical Name Information System (GNIS) gazetteer. In this same domain, Bergman *et al.* describe architecture for storage and retrieval of satellite images and video data from a collection of heterogeneous archives. Other initiatives cover different concepts of the CBIR area. For example, while research presented in concentrates on new searching strategies for improving the effectiveness of CBIR systems, another popular focus is on proposing image descriptors.

D) Crime prevention
E) Medicine
F) Historical research
G) Face identification
H) Remote sensing
I) Film and video archieves
J) Geographical Information Systems

VII. EXPERIMENTAL RESULTS

A. Generate Database

The proposed CBIR system provides the offline feature extraction. We have used this option for extraction of features from images and stored it in database. By applying the find wavelet in 4*3 size i. e 12 sub bands of image, apply the cosine modulated feature on image[5]; apply to form the Energy & standard Deviation in vector form. In this way we found the total images values in the form vector stored in Database as text file. This is as shown below:

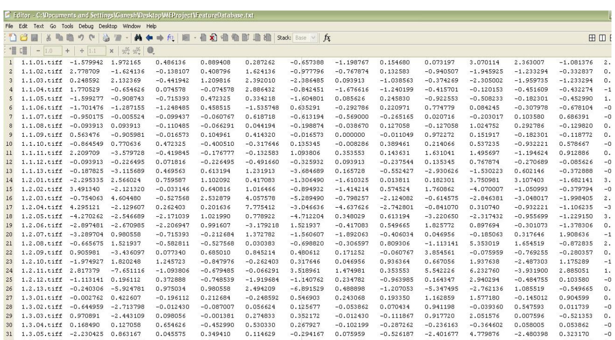

Figure 4: Generate Database of Different Images

B. Query Image

The proposed CBIR system provides Open Image option for submitting query image. When user selects option to open image then it is opened image after that it going to find the wavelet of that query image[11] which is shown as below figure

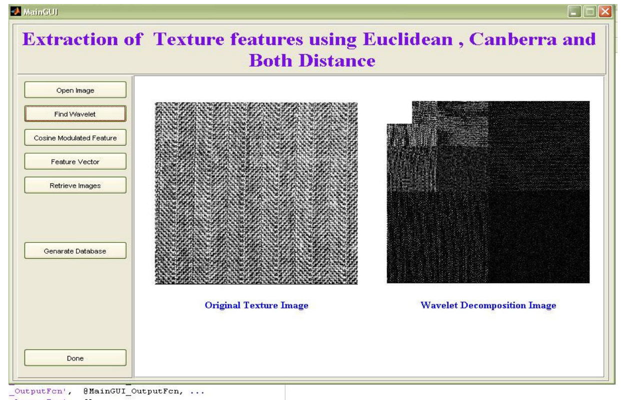

Figure 5: Wavelet of Query Image

C. *Cosine Modulated Wavelet Feature:*

In this CBIR after got the value of wavelet of query image now in this option it is going to find out the cosine modulated signal and reconstructed cosine signal[4]. It is shown in the below figure

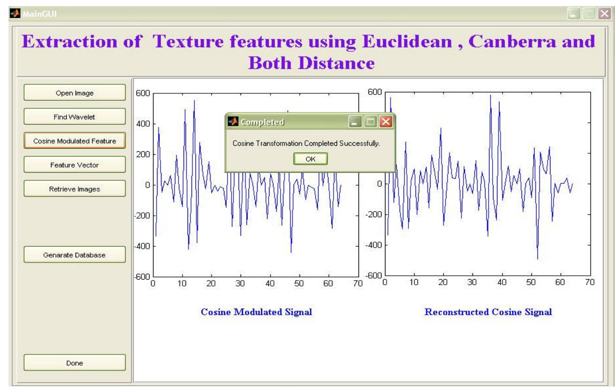

Figure 6: Cosine Modulated Features

D. Feature Vector

In this Feature vector is having the values of Energy and Standard Deviation of Query image

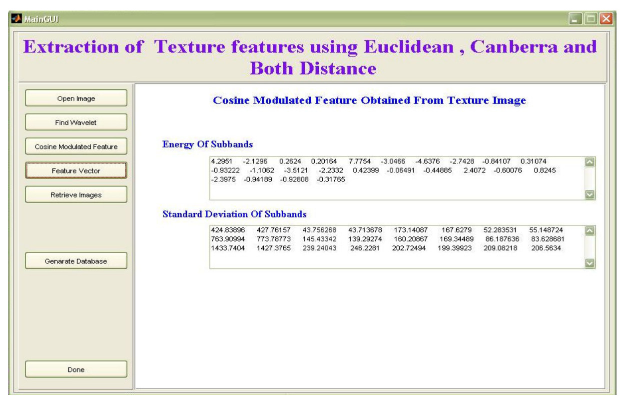

Figure 7: Feature Vector of Query Image

E. Retrieval Images by Euclidean distance

In this we got the approximate images of query image by Euclidean Distance

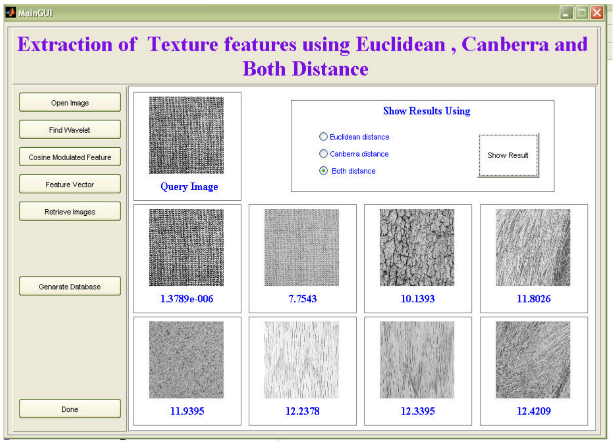

Figure 8: Retrieval Images by Euclidean distance

F. Retrieval Images by Canberra distance

In this we got the approximate images of query image by Canberra Distance

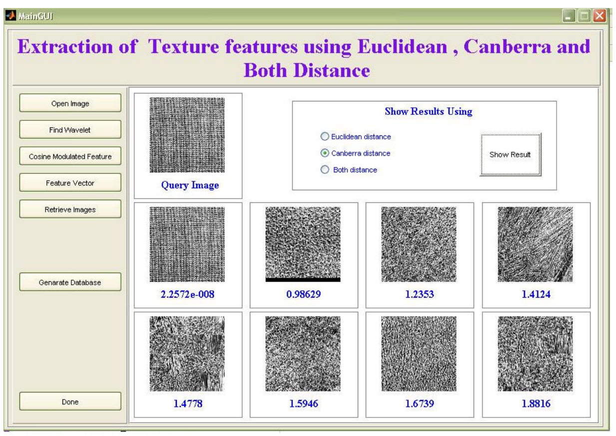

Figure 9: Retrieval Images by Canberra distance

G. *Retrieval Images by Both distance*

In this we got the approximate images of query image by Both Distance

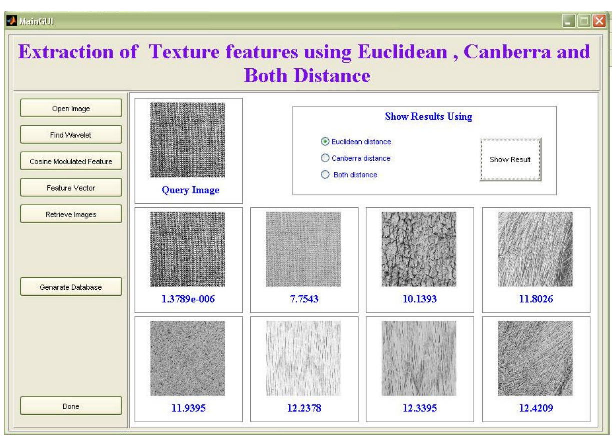

Figure 10: Retrieval Images by Both distances

VIII. CONCLUSION AND FUTURE WORK

This paper presents Extraction of texture feature using Euclidean, Canberra and Both distance. This paper mainly work with db1 wavelet. So for future enhancement can use the different wavelet and analysis the texture features.Currently this paper have Developed to find the results and effectiveness of image solution. In this paper can add the number of wavelet and that wave let can find out the images after that analysis could be performed. Enhancement of this paper is to analyze the performance with different wavelets.

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