Content Based Image Retrieval Using Various Distance Metrics

Sanjay Patil[1] and Sanjay Talbar[2]

[1] Department of Electronics Engg.
Padmabhushan Vasantdada Patil Pratisthan's
College Of Engg., Sion-Chunabhatti, Mumbai. PIN 400 022, India
sanjayashri@rediffmail.com
[2] Shri Guru Gobind Singhji College of Engineering and Technology,
Vishnupuri, Nanded, PIN 431 606, India
sntalbar@yahoo.com

Abstract. Content based image retrieval (CBIR) provides an effective way to search the images from the databases. The feature extraction and similarity measures are the two key parameters for retrieval performance. A similarity measure plays an important role in image retrieval. This paper compares six different distance metrics such as Euclidean, Manhattan, Canberra, Bray-Curtis, Square chord, Square chi-squared distances to find the best similarity measure for image retrieval. Using pyramid structured wavelet decomposition, energy levels are calculated. These energy levels are compared by calculating distance between query image and database images using above mentioned seven different similarity metrics. A large image database from Brodatz album is used for retrieval purpose. Experimental results shows the superiority of Canberra, Bray-Curtis, Square chord, and Square Chi-squared distances over the conventional Euclidean and Manhattan distances.

Keywords: Content based image retrieval, Distance metrics, Similarity measures, Image features.

1 Introduction

Content based image retrieval has been an active and fast growing research area since 1990's. It is a technique which uses visual contents (color, texture, shape etc.) of the image to search images from large scale image database according to users applications. Before going in details of this system, we briefly discuss evolution of the content based image retrieval system. In the early 1990's due to advances in internet and new digital image technologies, number of digital images produced by scientific, educational, medical, industrial and other applications available to users increased rapidly [1].

In 1979, a conference on Database Techniques for Pictorial applications was held in Florence. This was the beginning of attraction and attention of researchers in the field of image database management technologies. But still research area in this era was not so active. In February 1992, United Nations National Science Foundation

R. Kannan and F. Andres (Eds.): ICDEM 2010, LNCS 6411, pp. 154–161, 2012.

(USNSF) organized a workshop in Redwood, California to highlight research areas for visual information management systems and its applications in various fields [2]. Since then many researchers started work in this area. Development of methods which would increase retrieval accuracy and reduce retrieval time is the main challenges in CBIR.

Early techniques were not generally based on visual features but on the textual annotation of images. The images were first annotated by text and then searched using text based approach. However in many situations, text annotation scheme is inefficient. For the huge image data the vast amount of labor required in manual annotation. Also describing every visual feature within the images is very time consuming and difficult. We know that, image speaks thousands of the words. So instead of manual annotations by text based keywords, images are indexed by their own visual features such as color, texture, shape the etc.

2 Architecture of Typical CBIR System

The general architecture of CBIR system is shown in fig.1. For the given image database, first extract features of individual one. The features can be visual features like color, texture, shape, region or spatial features or some compressed domain features. The extracted features are described by feature vectors. These feature vectors are then stored to form Image feature database.

For a given query image, we similarly extract its features and form a feature vector. This feature vector is matched with the already stored vectors in image feature database. The distance between the feature vector of the query image and those of the images in the database are then calculated. Obviously the distance of a query image with itself is zero if it is in database. The distances are then stored in increasing order and retrieval is performed with the help of indexing scheme.

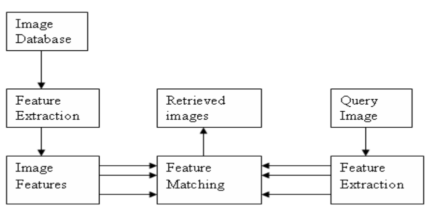

Fig. 1. Architecture of CBIR system

3 Image Features

A large amount of image database is added every moment of time, so the effective and efficient image retrieval system is needed. There are many features used in content based image retrieval but four of them are considered to be the main features. These features are color, texture, shape, and spatial properties. However, spatial properties are not generally taken into account, so main features to derive are color, texture, and shape [4].

3.1 Texture

There is one of the most important features of an image. It is characterized by the spatial distribution of gray levels in a neighborhood. In order to capture the spatial dependence of gray-level values, which contribute to the perception of texture, a two-dimensional dependence texture analysis matrix is taken into consideration. This two-dimensional matrix is obtained by decoding the image file; jpeg, bmp, etc.

3.2 Texture Representation and Features

The most popular statistical representations of texture are:

- Co-occurrence Matrix
- Tamura Texture
- Wavelet Transform

In the early 1970s, the co-occurrence matrix representation of texture features was proposed by Haralick *et al* [5]. In this approach, they highlighted the grey level spatial dependence of texture. Based on the orientation and the distance between image pixels, a co-occurrence matrix was first constructed and then meaningful statistics from the matrix are extracted. Many other researchers experimentally found out that contrast, inverse defence moment and entropy had the great discriminatory power.

Tamura *et al* [6] explored the texture representation which motivated by the psychological studies in human visual perception of texture. They found that in psychological studies computation approximation to the visual texture properties are important. The comparison between Tamura texture representation and co-occurrence matrix representation concluded that all the texture properties in Tamara texture representation are visually more meaningful. This characteristic gives tamura texture representation more importance in image retrieval.

In the early 1990s, many researchers began to use of the wavelet transform in texture representation. Smith and Chang [7] used the mean and variance extracted from the wavelet sub bands for texture representation. Chang and Kuo [8] was used tree structured wavelet transform to achieve better retrieval performance. Gross *et al* [9] used the wavelet transform combined with K-L transform and Kohenen maps to perform texture analysis. Kunda *et al* [10] proposed texture analysis using wavelet transform with a co-occurrence matrix to take advantage of both statistics based and transform based analysis.

4 Similarity Measures

Similarity measures also termed as distance metric plays important role in Content based image retrieval. Content-based image retrieval calculates visual similarities between a query image and images in a database. Therefore, the retrieval result is not a single image but a number of images ranked by their similarities with the query image. Different *similarity measures* will affect retrieval performances of an image retrieval system significantly so, it is important to find best distance metric for CBIR system. The query image will be more similar to the database images if the distance is smaller. If x and y are two d-dimensional feature vectors of database image and query image respectively, then the distance metrics are given by[11],

i. Euclidean distance, $$d_E(x, y) = \sqrt{\sum_{i=1}^{d} (x_i - y_i)^2} \tag{1}$$

ii .Manhattan distance, $$d_{MAN}(x, y) = \sum_{i=1}^{d} |x_i - y_i| \tag{2}$$

The Manhattan Distance was proposed in [13] for computing the dissimilarity scores between color images.

iii. Canberra Distance, $$d_C(x, y) = \sum_{i=1}^{d} \frac{|x_i - y_i|}{|x_i| + |y_i|} \tag{3}$$

iv. Bray –Curtis distance, $$d_{BC}(x, y) = \sum_{i=1}^{d} \frac{|x_i - y_i|}{x_i + y_i} \tag{4}$$

In the equation (3) and (4) the distance value will never be more than one, being equal to one when one of the attributes is zero. It avoids scaling effect and proved to be good metrics for retrieval performance.

v. Square chord distance,

$$d_{SC}(x, y) = \sum_{i=1}^{d} \left(\sqrt{x_i} - \sqrt{y_i}\right)^2 \tag{5}$$

vi. Square Chi-Squared distance,

$$d_{CHI}(x, y) = \sum_{i=1}^{d} \frac{(x_i - y_i)^2}{x_i + y_i} \tag{6}$$

The distance equations given in (5) and (6) respectively may also useful in image retrieval systems.

5 Retrieval Technique Used for Texture Images

In this section texture image database used for retrieval and image retrieval method are discussed.

5.1 Texture Image Database

We have used 108 textures from Brodatz texture album. Each texture pattern is containing set of nine images. So there are 972 different texture patterns [14]. The size of each texture is 643X 643. Each of 643X643 images is resized to 256X256 and saved in bitmap file format. The size conversion is done as in the databases generalised image size is 256X256 so we have developed software accordingly. Some of the specimen texture images in the database with set of their 9 different patterns are shown in figure 2.

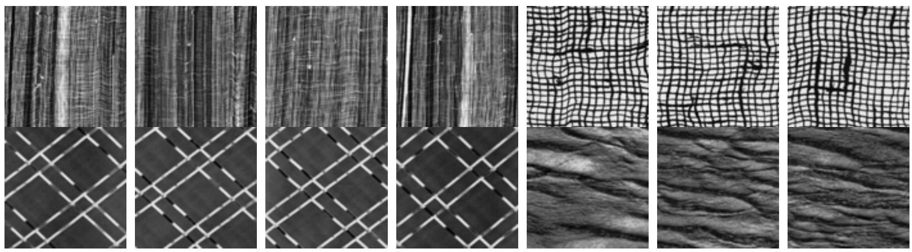

Fig. 2. Specimen texture images with 9 different patterns from Brodatz album

We used a method called the pyramid-structured wavelet transform for texture retrieval. It recursively decomposes sub signals in the low frequency bands. It is most significant for textures with dominant frequency bands. For this reason, it is mostly suitable for signals consisting of components with information concentrated in lower frequency bands [13]. As most of the image information exists in lower sub-bands, the pyramid-structured wavelet transform is highly efficient. The flow graph of pyramid structured wavelet transform is shown in figure 3.

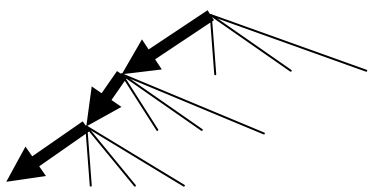

Fig. 3. Pyramid-structured wavelet transform

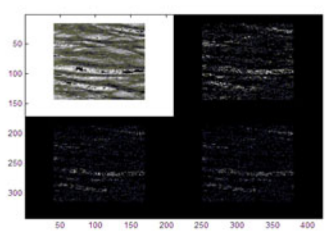

Fig. 4. First level wavelet decomposition of input image

Using the pyramid-structured wavelet transform, the texture image is decomposed into four sub images, in low-low, low-high, high-low and high-high sub-bands. The first level decomposition of input image is shown in figure 4. At this point, the energy level of each sub-band is calculated. This is first level decomposition. Using the low-low sub-band for further decomposition, we reached fifth level decomposition. The reason for this is the basic assumption that the energy of an image is concentrated in the low-low band. For this cause we used Daubechies wavelet as wavelet function.

5.2 Distance Algorithm

The query image is one of the 972 patterns from image database. The query image is decomposed and energies of the first dominant k-bands are determined. Similarly, all images in the database are decomposed and the first dominant k-band energies are calculated. Then distance between query image and database image is determined using different distance metrics [13]. This process is repeated until all the images in the database have been compared with the query image. It is obvious that the distance of an image from itself is zero. The distances are in the increasing order for the closest sets of pattern are then retrieved. Ideally, the nine topmost images are displayed as a result of the texture retrieval which is from same texture pattern. Using the above algorithm, the query image is searched for in the image database. The distances are calculated between the query image and every image in the database.

6 Experimental Results

We have done the experiment with different distance metrics on the same set of images and compared the images with smaller distances. The image D371 is query image which is shown in figure 5. There are 9 similar images to the query image which retrieved sequently with the increasing distance which is depicted in the figure 7. The table 1 shows the retrieved images and their distances from query image for different distance metrics. It is observed from the table 1, the distance of query image from itself is zero. Also, it is clear that square chord and square chi-squared distances retrieve images with smallest distances as compared to traditional Euclidean or Manhattan distances. The proposed retrieval system has been implemented in Matlab7.5 version on a Core2Duo, 2GHz processor. The figure 6 gives top 10 retrieved images from the database of 972 images for the given query image.

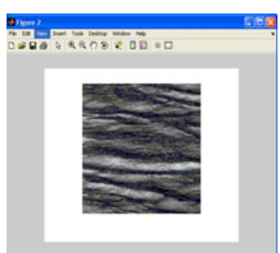

Fig. 5. The Query Image

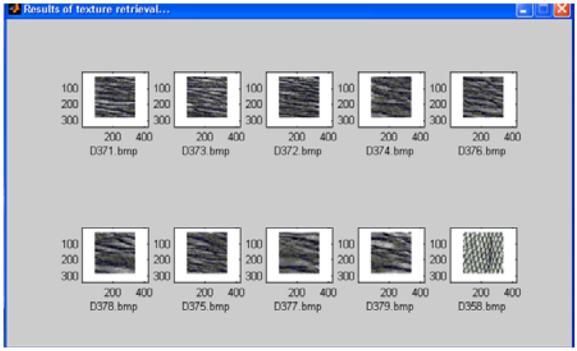

Fig. 6. Top 10 retrieved similar images from the database

Table 1. Retrieved images and their distances from query image

Retrieved Images	**Distance between query image and database image for different Distance Metrics**					
	Euclidean	**Manhattan**	**Canberra**	**Bray-Curtis**	**Square Chord**	**Square Chi-squared**
D371.bmp	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
D373.bmp	0.3480	0.7369	0.0317	0.0317	1.12×10^{-4}	0.0040
D372.bmp	0.3679	0.6275	0.0273	0.0273	1.30×10^{-4}	8.29×10^{-4}
D374.bmp	0.4403	0.7746	0.0334	0.0334	1.79×10^{-4}	0.0083
D376.bmp	0.4685	0.9669	0.0420	0.0420	2.07×10^{-4}	0.0076
D378.bmp	0.4707	0.8385	0.0360	0.0360	2.09×10^{-4}	0.0112
D375.bmp	0.4828	0.8350	0.0365	0.0365	2.24×10^{-4}	0.0067
D377.bmp	0.9706	1.6366	0.0707	0.0707	8.80×10^{-4}	0.0340
D379.bmp	1.0460	2.1135	0.0905	0.0905	0.0011	0.0504
D358.bmp	1.7690	3.0113	0.2341	0.2341	0.0017	0.0927

7 Conclusions

We have compared in detail six different distance metrics such as Euclidean, Manhattan, Canberra, Bray-Curtis, Square chord, Square chi-squared distances for texture image retrieval. A large database of 972 texture images is used. Using pyramid structured wavelet decomposition, energy levels are calculated. These energy levels are compared and distances between query image and database images are calculated using above mentioned six different distance metrics. From the results it is concluded that performance of Square chord and Square Chi-squared distances is better than the conventional Euclidean and Manhattan distances. Also Canberra and Bray-Curtis retrieves images with distances less than one, which avoids scaling effect as mentioned earlier.

References

1. Gudivada, V.N., Raghavan, V.V.: Content-based image retrieval systems. IEEE Computer 28(9), 18–22 (1995)
2. Kokare, M., Chatterji, B.N., Biswas, P.K.: A survey on current content based image retrieval methods. IETE Journal of Research 48(3&4), 261–271 (2002)
3. Long, F., Zhang, H., DagaFeng, D.: Fundamentals of content based image retrieval
4. Birgale, L., Kokare, M.: Color and texture features for CBIR. In: Proceedings of the International Conference on Computer Graphics, Imaging and Visualisation (2006)
5. Haralick, R.M., Shanmugam, K., Dinstein, I.: Texture features for image classification. IEEE Trans. on Sys. Man. and Cyb. SMC-3(6) (1973)
6. Tamura, H., Mori, S., Yamawaki, T.: Texture features corresponding to visual perception. IEEE Trans. on Systems, Man, and Cybernetics Smc-8(6) (June 1978)
7. Smith, J.R., Chang, S.F.: Transform features for texture classification and discrimination in large image databases. In: Proc. IEEE International Conference on Image Processing (1994)
8. Chang, T., Kuo, C.-C.J.: Texture analysis and classification with tree-structured wavelet transform. IEEE Transactions Image Processing 2(4), 429–441 (1993)
9. Gross, M.H., Koch, R., Lippert, L., Dreger, A.: Multiscale image texture analysis in wavelet spaces. In: Proc. IEEE Int. Conf. on Image Proc. (1994)
10. Kundu, A., Chen, J.-L.: Texture classification using qmf bank-based subband decomposition. CVGIP Graphical Models and Image Processing 54(5), 369–384 (1992)
11. Kokare, M., Chatterji, B.N., Biswas, P.K.: Comparison of Similarity Metrics for Texture Image Retrieval. In: TENCON (2003)
12. Swain, M., Ballard, D.: Color indexing. lnternatiunal Journal of Compurer Vision 17(1), 11–32 (1991)
13. Siddique, S.: A Wavelet Based Technique for Analysis and Classification of Texture Images. Carleton University, Ottawa, Canada, Proj. Rep. 70.593 (2002)
14. Brodatz, P.: Textures: A photographic album for artists and designers. Dover, New York (1966)