TEXTURE BASED IMAGE INDEXING AND RETRIEVAL

N. Gnaneswara Rao[1] and V. Vijaya Kumar[2]
[1]*Associate Professor, Dept of CSE, Gudlavalleru Engg. College, Gudlavalleru, A.P., India*

[2]*Professor & Head, Dept of CSE ,RGM College of Engg & Technology, Nandyal, A.P., India*

Keywords: Texture, Content based Image Retrieval.

Abstract: The Content Based Image Retrieval (CBIR) has been an active research area. Given a collection of images it is to retrieve the images based on a query image, which is specified by content. The present method uses a new technique based on wavelet transformations by which a feature vector characterizing texture of the images is constructed. Our method derives 10 feature vectors for each image characterizing the texture of sub image from only three iterations of wavelet transforms. A clustering method ROCK is modified and used to cluster the group of images based on feature vectors of sub images of database by considering the minimum Euclidean distance. This modified ROCK is used to minimize searching process. Our experiments are conducted on a variety of garments images and successful matching results are obtained.

1 INTRODUCTION

With the steady growth of computer power, rapidly declining cost of storage and ever-increasing access to the Internet, digital acquisition of information has become increasingly popular in recent years. Digital information is preferable to analog formats because of convenient sharing and distribution properties. This trend has motivated research in image databases, which were nearly ignored by traditional computer systems due to the enormous amount of data necessary to represent images and the difficulty of automatically analyzing images. Currently, storage is less of an issue since huge storage capacity is available at low cost. However, effective indexing and searching of large-scale image databases remains as a challenge for computer systems.

The Content Based Image Retrieval System CBIR (Antani et al., 2002), (Kherfi and Ziou, 2004) is a system, which retrieves the images from an image collection where the retrieval is based on a query, which is specified by content and not by index or address. Alternatively, if given a collection of images the function of CBIR is to retrieve the images based on a query, which is specified by content and not by index or address. The query image is an image in which a user is interested and wants to find similar images from the image collection. The CBIR system retrieves relevant images from an image collection based on automatic derived features. The derived features include primitive features like texture, color and shape. The features may also be logical features like identity of objects shown, abstract features like significance of some scene depicted etc.There are many general-purpose image search engines. In the commercial domain, IBM QBIC (Faloutsos et al., 1994), (ICASSPW, 1993) is one of the earliest developed systems. Recently, additional systems have been developed at IBM T.J. Watson (Smith and Li, 2000), VIRAGE (Grupta and Rain, 1997), NEC AMORE (Mukherjea et al., 1999), Bell Laboratory (Natsev et al., 1999), Interpix (Yahoo), Excalibur, and Scour.net. In the academic domain, MIT Photobook (Pentland et al., 1994), (Picard and Kabir, 1993) is one of the earliest. Berkeley Blobworld (Carson et al., 1999), Columbia VisualSEEK and Web SEEK (Smith and Chang, 1997), CMU Informedia (Stevens et al., 1994), UCSB NeTra (Ma and Manjunath, 1997), UCSD, Stanford (EMD (Rubner et al., 1997), WBIIS (Wang et al., 1998) are some of the recent systems. The proposed CBIR system can be extended at the other primitive feature vectors like, color and shape.

The present method implemented basically by three steps. First, for each image in the image collection, a feature vector characterizing texture of the image is computed based on the Wavelet transformation method. The Wavelet

Gnaneswara Rao N. and Vijaya Kumar V. (2007).
TEXTURE BASED IMAGE INDEXING AND RETRIEVAL.
In *Proceedings of the Second International Conference on Computer Vision Theory and Applications*, pages 177-181
DOI: 10.5220/0002065801770181

transformations are used because they capture the local level texture features quite efficiently. Where 10 feature vectors are stored in a feature database, Second, using clustering algorithm to construct indexed image database based on the texture feature vectors obtained from wavelet transformation, and finally, given a query image, its feature vector is computed, compared to the feature vectors in the feature database, and images most similar to the query image are returned to the user. Every care has been taken to ensure that the features and the similarity measure used to compare two feature vectors are efficient enough to match similar images and to discriminate dissimilar ones. The main aim of this approach is that not even a single relevant image should be missed in the output as well as to minimize the number of irrelevant images.
The steps involved in the methodology are listed below:

- Wavelet transformation is used for feature extraction.
- Precomputing the texture feature vectors for all the images in the database using haar wavelet.
- Clustering the images based on feature vectors using modified ROCK clustering algorithm.
- Computing the feature vector of the query image as and when presented.
- Comparing query image with indexed data base, identifying the closest cluster for the query image and retrieves those images.
- Presenting the result as the thumbnail set of images.

2 EXTRACTION OF FEATURE VECTOR

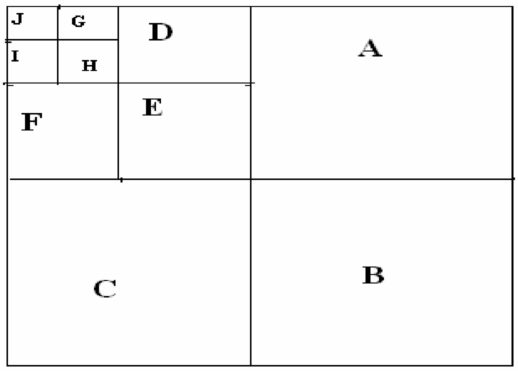
Texture is another important property of images. Various texture representations have been investigated in pattern recognition and computer vision. Basically, texture representation methods can be classified into two categories: structural and statistical. Structural methods, including morphological operator and adjacency graph, describe texture by identifying structural primitives and their placement rules. They tend to be most effective when applied to textures that are very regular. Statistical methods, including Fourier power spectra, co-occurrence matrices, shift-invariant principal component analysis (SPCA), Tamura feature, Wold decomposition, Markov random field, fractal model, and multi-resolution filtering techniques such as Gabor and wavelet transform, characterize texture by the statistical distribution of the image intensity.

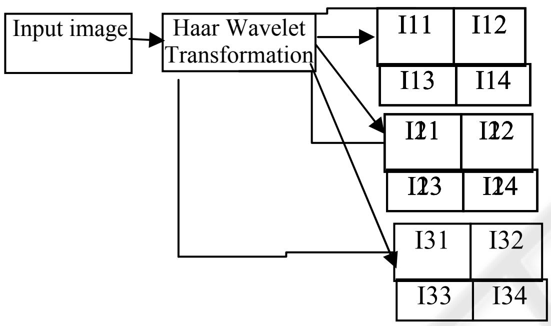
The Extraction of feature vector is the most crucial step in the whole CBIR system. This is because these feature vectors are used in all the subsequent modules of the system. It is to be realized that the image itself plays no part in the following modules. It is the feature vectors that are dealt with. The quality of the output drastically improves as the feature vectors that are used are made more effective in representing the image. The fact that the quality of the output is a true reflection of the quality of the feature vector is very much evident in our experiments.
The Feature vector generation (Natsev et al., 1999), (Wang et al., 1998) has been tried in two different ways. One way was to use wavelets (Daubechies, 1992), (Meyer, 1993), (Natsev et al., 1999) to compute energies whose values were classified.

Haar Wavelets
The Wavelets are useful for hierarchically decomposing functions in ways that are both efficient and theoretically sound. Broadly speaking, a wavelet representation of a function consists of a coarse overall approximation together with detail coefficients that influence the function at various scaled (Kherfi and Ziou, 2004). The wavelet transform has excellent energy compaction and de-correlation properties, which can be used to effectively generate compact representations that exploit the structure of data. By using wavelet sub band decomposition, and storing only the most important sub bands (that is, the top coefficients), we can compute fixed-size low-dimensional feature vectors independent of resolution, image size and dithering effects. Also, wavelets are robust with respect to color intensity shifts, and can capture both texture and shape information efficiently. Furthermore, wavelet transforms can be computed in linear time, thus allowing for very fast algorithms.

In this paper, we compute feature vectors using Haar wavelets because they are the fastest to compute and have been found to perform well in practice (Natsev et al., 1999), (ICASSPW, 1993). Haar wavelets enable us to speed up the wavelet computation phase for thousands of sliding windows of varying sizes in an image. They also facilitate the development of efficient incremental algorithms for computing wavelet transforms for larger windows in terms of the ones for smaller windows. One disadvantage of Haar wavelets is that it tends to produce large number of signatures for all windows in image. We proposed the modified the Haar wavelet transformation overcomes that reducing signatures only calculating 10 for the image in our method.

In our feature vector computation process, we applied Wavelet Transformations only three times to get 10 sub images of input image in the following way.





In each iteration $Ii_{2...4}$ images are saved and Ii_1 sub image is again subjected to wavelet Transformation instead of entire image for three iterations, by which 10 sub images of input image are obtained. Sub image I_{11} is further divided into sub images I_{21} ... I_{24} in the second iteration. The sub image I_{21} is further divided into I_{31} I_{32} I_{33} I_{34} in the third iteration. All sub images are normalized to maintain the uniform size.

Algorithm for calculating wavelet signatures

1. Let I be the image of size w×w
2. Divide the image I into four bands I_1,I_2,I_3,I_4 based on Haar wavelet of size w/2×w/2
3. Compute Signatures f_r for I_2,I_3,I_4
4. Now take the image I_1 and divide it into 4 bands namely $I_{11},I_{12},I_{13},I_{14}$ of size w/4×w/4
5. Compute signatures f_r for I_{12},I_{13},I_{14}
6. Again take the I_{11} and divide it into 4 bands namely $I_{111},I_{112},I_{113},I_{114}$ of size w/8×w/8.
7. Now we obtain 10 signatures then stop the process.

The texture feature vectors (signatures) are computed from sub image as follows,

$$f_r = \sqrt{\frac{\sum c_{ij}^2}{i \times j}}$$

Where f_r is the computed 1-d texture feature vector(signature) of the sub image, C_{ij} is the representation of the intensity value of all elements of sub image and i × j is the size of the sub image.

3 INDEXING OF IMAGES

Another important issue in content-based image retrieval is effective indexing (Antani et al., 2002), (Wang et al., 1998) and fast searching of images based on visual features. Because the feature vectors of images tend to have high dimensionality and therefore are not well suited to traditional indexing structures, dimension reduction is usually used before setting up an efficient indexing scheme.

The basis of the clustering method in indexed image data base is that, the images belonging to the same cluster are similar or relevant to each other when compared to images belonging to different clusters. We clustered the images using modified ROCK (Guha, 1999).The modified ROCK allow us to minimize the undesirable results of the ROCK algorithm. The feature vector of each image is a vector of size 10.The Euclidean distance measure is used to measure the similarity between feature vectors of query image and indexed database image. In the present method we calculated representative Feature vector of Cluster (F_C) as the minimum Euclidean distance, which resulted in good cluster-matching results. The representative feature vector of cluster(F_C) is computed from the following equation.

$$F_{ci} = \min|F_i - \sum F_j|$$

Where j =1,2,….n and j ≠ i, and i=1,2,..n.

F_{ci} denotes representative feature vector of cluster i,and F_i,F_j represents feature vector of the given cluster.

Query by example allows the user to formulate a query by providing an example image. The system converts the example image into an internal representation of features. Images stored in the database with similar features are then searched. Query by example can be further classified into query by external image example, if the query image is not in the database, and query by internal image example, if otherwise. For query by internal image, all relationships between images can be pre-computed. The main advantage of query by example is that the user is not required to provide an explicit description of the target, which is instead computed by the system. It is suitable for applications where the target is an image of the same object or set of objects under different viewing conditions. Most of the current systems provide this form of querying.

4 RESULTS

As a case study the proposed method is applied on the following Garments images. Figure 1 shows the query image. Table1 shows the feature vector values or feature vectors of sub images of fig.2.

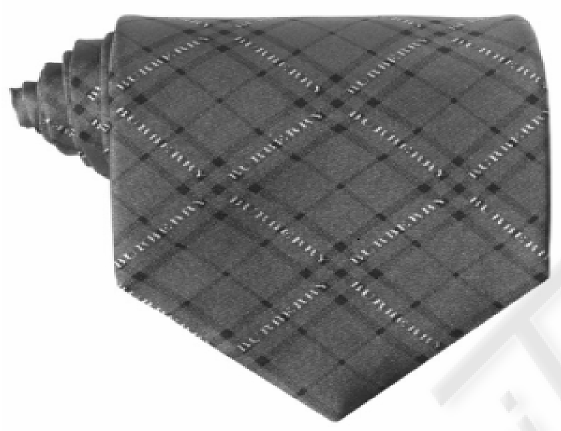


Figure 1: Query image.

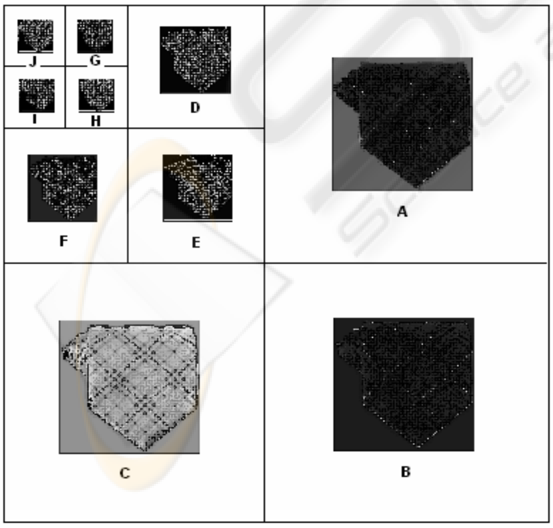


Figure 2: Sub Images of figure 1.

Table 1: Feature vectors of figure 2.

Sub image number	10-digit feature vector or FV
I_A	92.889603
I_B	45.284988
I_C	568.128662
I_D	23.954145
I_E	54.004360
I_F	75.862289
I_J	25.402018
I_G	20.730150
I_H	20.200342
I_I	23.954145

The clustered images from the database, are shown in figure 3. The figure 3 clearly represents matching images with the original (query) image and it has removed all nonrelevant images.

Figure 3: Clustered Image Set.

Choice of the Image-Collection

The reason behind choosing such an image collection is that such garments provide us a wide variety of texture, color and Texture. These three constitute the primitive features of an image. As mentioned earlier, our CBIR system operates on level-1 of feature extraction and thus this appeared to be the most convincing collection to test the system.

The downloaded images were subjected to further treatment to suit our system. The images were scaled to a size of 300 * 300 (width, height in terms of pixels) and were converted to 256-color Bitmap images in Gray scale format.

5 CONCLUSION

By deriving ten feature vectors or feature vectors from wavelet transformation in three iterations reduces overall time complexity than previous methods. The new method proposed in our study for clustering effectively minimizes the undesirable results and gives a good matching pattern, that will be having zero or a minimum set of nonrelevant images.

REFERENCES

Sameer Antani, Rangachar Kasturi, and Ramesh Jain. A Survey on the Use of Pattern Recognition Methods for Abstraction, Indexing and Retrieval of Images and Video. *Pattern Recognition*,35:945–965, 2002.

I. Daubechies, *Ten Lectures on Wavelets*, Capital City Press, 1992.

Faloutsos, R. Barber, M. Flickner, J. Hafner, W. Niblack, D. Petkovic, W. Equitz, ``Efficient and effective querying by image content," *Journal of Intelligent Information Systems: Integrating Artificial Intelligence and Database Technologies*, vol. 3, no. 3-4, pp. 231-62, July 1994.

Gupta, R. Jain, "Visual information retrieval," *Comm. Assoc. Comp. Mach.*, vol. 40, no. 5, pp. 70-79, May 1997

Guha S.,Rastogi R., and Shim K.ROCK: A robust clustering algorithm for categorical attributes. In proceedingConclusions of the IEEE International Conference on data engineering,Sydney,March 1999.

W. Y. Ma, B. Manjunath, "NaTra: A toolbox for navigating large image databases", *Proc. IEEE Int. Conf. Image Processing*, pp. 568-71, 1997.

Y. Meyer, *Wavelets AlgoConclusion rithms and Applications*, SIAM, Philadelphia, 1993.

S. Mukherjea, K. Hirata, Y. Hara, "AMORE: a World Wide Web image retrieval engine," World Wide Web, vol. 2, no. 3, pp. 115-32, Baltzer, 1999.

A. Natsev, R. Rastogi, K. Shim, ``WALRUS: A similarity retrieval algorithm for image databases," *SIGMOD*, Philadelphia, PA, 1999.

ICASSPW. Niblack, R. Barber, W. Equitz, M. Flickner, E. Glasman, D. Petkovic, P. Yanker, C. Faloutsos, G. Taubin, ``The QBIC project: querying images by content using color, texture, and Texture," *Proc. SPIE - Int. Soc. Opt. Eng., in Storage and Retrieval for Image and Video Database*, vol. 1908, pp. 173-87, San Jose, February, 1993.

A. Pentland, R. W. Picard, S. Sclaroff, `Photobook: tools for content-based manipulation of image databases," *SPIE Storage and Retrieval Image and Video Databases II*, vol. 2185, pp. 34-47, San Jose, February 7-8, 1994.

R. W. Picard, T. Kabir, ``Finding similar patterns in large image databases," *IEEE*, Minneapolis, vol. V, pp. 161-64, 1993.

Y. Rubner, L. J. Guibas, C. Tomasi, ``The earth mover's distance, Shimulti-dimensional scaling, and color-based image retrieval," *Proceedings of the ARPA Image Understanding Workshop*, pp. 661-668, New Orleans, LA, May 1997.

Carson, M. Thomas, S. Belongie, J. M. Hellerstein, J. Malik, ``Blob world: a system for region-based image indexing and retrieval," *Third Int. Conf. on Visual Information Systems*, D. P. Huijsmans, A. W.M. Smeulders (eds.), Springer, Amsterdam, The Netherlands, June 2-4, 1999.

J. R. Smith, S. -F. Chang, "An image and video search engine for the World-Wide Web," *Storage and Retrieval for Image and Video Databases V (Sethi, I K and Jain, R C, eds), Proc SPIE 3022*, pp. 84-95, 1997.

J. R. Smith, C. S. Li, "Image classification and querying using composite region templates," *Journal of Computer Vision and Image Understanding*, 2000, to appear.

S. Stevens, M. Christel, H. Wactlar, "Informedia: improving access to digital video," Interactions, vol. 1, no. 4, pp. 67-71, 1994.

J. Z. Wang, G. Wiederhold, O.Firschein, X. W. Sha, ``Content-based image indexing and searching using Daubechies' wavelets," *International Journal of Digital Libraries*, vol. 1, no. 4, pp. 311-328, 1998.

M. L. Kherfi and D. Ziou, universit´e de sherbrooke, A. Bernardi, Laboratoires Universitaires Bell," Image Retrieval from the World Wide Web: Issues, Techniques, and Systems In ,ACM Computing Surveys, Vol. 36, No. 1, March 2004, pp. 35–67.