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Content Based Image Retrieval by Using M-Band Wavelet based Texture Features

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Abstract: Biorthonormal M-band wavelet transform is used to decompose the image into MxM sub-bands for constructing the feature database in content-based image retrieval of 1856 Brodatz texture images. Texture features are obtained by computing the measure of energy, standard deviation and its combination on each band. Results are far superior and impressive than conventional two-band wavelet decomposition.

Index Terms: M-band wavelet, 2-band wavelet, Content-based image retrieval, image database, feature database, similarity, query image, texture analysis.

I. INTRODUCTION

Worldwide networking allows us to communicate, share, and learn information in the global manner. Digital library and multimedia databases are rapidly increasing; so efficient search algorithms need to be developed. Retrieval of image data has traditionally been based on human insertion of some text describing the scene, which can then be used for searching by using keywords based searching methods. This is very time consuming and difficult for describing every color, texture, shape, and object within the image. We know that an image speaks thousands of words [2]. So instead of manually annotated by text-based keywords, images would be indexed by their own visual contents, such as color, texture and shape. So researchers turned attention to content based retrieval methods.

Search techniques can be based on many features such as colour, shape, and texture but in this paper we concentrate only on the problem of finding good texture features. The main texture features currently used are derived from either Gabor wavelets or the conventional discrete wavelet transform. Alexandria project from UCSB [3] uses the mean and energy from Gabor wavelets for indexing photographic and satellite images, and SaFe project from Columbia [4] uses mean and the variance from the DWT. Extensive experiments on a large set of textured images show that retrieval performance is better using Gabor filters than using conventional orthogonal wavelets [3]. Recent development in wavelet theory has provided a promising alternative through multichannel filter banks that have several potential advantages over Gabor filters namely,

i). Wavelet filters cover exactly the complete frequency domain.
ii). Fast algorithms are readily available to facilitate computation.

Studies on successful application of wavelet theory on texture analysis have been reported using the multiresolution signal decomposition developed by Mallat [5]. He used quadrature mirror filters to relate information at different scales of decomposition of the embedded subspace representation. The work of Chang and Kuo [6] indicates that the texture features are more prevalent in the intermediate frequency band.

One of the drawbacks of standard wavelets is that they are not suitable for the analysis of high- frequency signals with relatively narrow bandwidth. So main motivation of the present work is to use the decomposition scheme based on M-band wavelets, which yield 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 is required for improving the retrieval accuracy. Previous approaches using M-band have been briefly discussed in section 2.
The main contributions of this paper are summarized as follows. Here we have investigated an M-band wavelet technique for content-based image retrieval by using the generalization of wavelet transforms to the M-band case. Large texture database of 1856 images is used to check the retrieval performance. All the database images were decomposed using complete and overcomplete representation of conventional 2-band wavelet and M-band (M=3) wavelet and features were computed on the decomposed sub-bands. A Manhattan distance metric and Mahalanobis distance metric were used to

discriminate 116 different textures. A detailed comparison of the retrieval performance-using feature measures such as standard deviation, energy. and combinations of both using Manhattan metric and Mahalanobis metric is presented. The result indicates that M-band wavelet improves retrieval performance significantly than conventional 2-band wavelet. The paper is organized as follows. In section 2 we will discuss M-band wavelets for image retrieval in brief. The proposed image retrieval procedure is given in section 3. Experimental Results are given in section 4, which is followed by the Conclusion.

2. Retrieval procedure for texture images

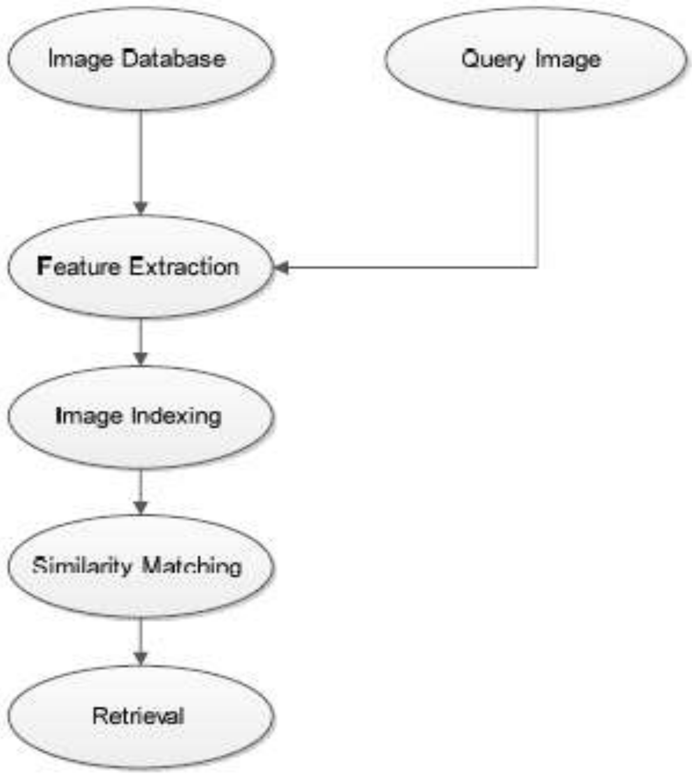

Fig.1: Flowchart of texture retrieval for CBIR

In this section texture image database used for experimental purpose, feature database creation and image retrieval method are discussed. General architecture of content-based image retrieval can be found in.

2.1Texture image database: The texture database used in the experimentation consists of 116 different textures. We have used 108 textures from Bordatz album, seven textures from USC database and one artificial texture. Size of each texture is 512x512. Each of 512x512 images is divided into sixteen 128x128 nonoverlapping subimages, thus creating a database of 1,856 patterns in the database.

2.2 Feature database creation: The database of 1856 texture images was analyzed using standard wavelet and 3-band wavelet filter banks. In 3-band decomposition each image was decomposed rowwise to give three different subbands of information corresponding to the three different subspaces. Subsequently the decomposition was performed columnwise. Thus at the first level of decomposition the original image was decomposed into $M^2 = 9$ sub-images. In a standard pyramidal wavelet analysis subsequent decompositions are performed only on the Vm sub-spaces spanned by the $\psi m(x)$ scaling functions and it translates. This would correspond to the upper left-hand corner sub-band of the figure and is also called a complete decomposition. In our analysis we also considered the overcomplete case where we decomposed every sub-band of coefficients, to give M^4 sub-bands at the second level of decomposition M^6, sub-bands at the third level of decomposition, in general we obtain M^{2n} sub-bands at the n^{th} level of decomposition. Table 1 shows the cumulative total number of subbands obtained after various levels of decomposition for the complete and overcomplete cases and different values of M=2and 3. The analysis was performed up to second level of decomposition for 3-band and up to third level of decomposition for standard 2-band wavelet.

For constructing the feature vector feature parameters such as Energy, Standard Deviation and combinations of both were computed separately on each sub-band and are stored in vector form. Length of feature vector will be equal to (No. of subbands × No. of feature parameters used in combination) elements. For creation of feature database above procedure is repeated for all the images of the image database and these feature vectors are stored in feature database.

Table 1

No. of bands	Level of decomposition	Complete case	Overcomplete case
2	1	4	4
	2	8	20
	3	12	84
3	1	9	9
	2	18	90

2.3 Image retrieval method: A query pattern is any one of the 1,856 patterns from image database. This pattern is then processed to compute the feature vector as in section (3.2). Then a Manhattan (city block) distance metric and Mahalanobis distance metric is used to compute the similarity or match value for given pair of images. Manhattan distance between query image and database image is given by

$$D_{qi}^{M} = \sum_{j=1}^{n} \left| f_{qj} - f_{ij} \right|$$

Where f_{qj} is the feature vector of the query image, f_{ij} is the feature vector of the database image, and is the length of feature vector. Similarly Mahalanobis distance between database image and query image is given by

$$D_{qi}^{Mah} = \sqrt{\left(f_{ij} - f_{qj}\right)' \left(c_{ij}\right)^{-1} \left(f_{ij} - f_{qj}\right)}$$

Where C_{ij} is the covariance matrix f_{ij}. It is obvious that the distance of an image from itself is zero. The distances are then stored in increasing order and the closest sets of patterns are then retrieved. In the ideal image. The performance is measured in terms of the average retrieval rate, which is defined as the average percentage number of patterns belongs to the same image as the query pattern in the top 16 matches.

3. Experimental Results

Table 2 provides a detailed comparison of average retrieval accuracy for 116 different textures using 3-band wavelet and conventional two-band wavelet for complete and overcomplete case. Table 2 also shows performance of feature parameter such as energy, standard deviation and combination of both using Manhattan distance and Mahalanobis distance metric. Table 2 indicates that there is significant improvement of average retrieval performance using 3-band wavelet than conventional 2-band wavelet. Retrieval accuracy of overcomplete case is better than the complete case. We observed that standard deviation as a feature measure alone gives best retrieval performance in complete case for 3-band wavelet as well as for conventional 2-band wavelet, while combination of standard deviation and energy gives best result in overcomplete case. Performance of Manhattan metric is better than Mahalanobis metric. Interesting thing noted that by using Mahalanobis metric retrieval performance decreases as number of features increases and vice versa in case of Manhattan metric. It is clear that best retrieval performance is 73.10% using overcomlpete 3-band wavelet case for the combination of standard deviation and energy feature measure and Manhattan distance metric. Previous work [3] indicates that Gabor feature gives retrieval performance close to 74% at the cost of very high computation time requirement. While proposed M-band wavelet method is fast and cost effective with almost equal retrieval performance as that of Gabor method. This makes a proposed method more suitable candidate for texture feature extraction in Content Based Image Retrieval. Fig.3 shows retrieval performance of 3-band wavelet and conventional 2-band wavelet according to the number of top matches considered. From that figure it is clear that the retrieval performance of 3-band wavelet for overcomplete case and complete case is far superior than conventional 2-band wavelet for overcomplete case and complete case. If the top 116(6% of the database) retrievals are considered the performance increases up to 93.75% using 3-band wavelet and up to 91.65% with conventional 2-band wavelet. Retrieved top twenty similar images from the database of 1856 images using 3-band wavelet for a sample query image is shown in Fig.2.

TABLE 2

Average retrieval accuracy of 116 different textures (Brodatz (108) +USC database (7) + artificial texture (1)) using different features for content-based image retrieval.

Feature	Complete case				Overcomplete case			
	Conventional 2-band Wavelet		*M*-band wavelet (*M*=3)		Conventional 2-band Wavelet		*M*-band wavelet (*M*=3)	
	Manhattan	Mahal-anobis	Manhattan	Mahal-anobis	Manhattan	Mahal-anobis	Manhattan	Mahal-anobis
Energy	45.80%	56.14%	53.77%	51.07%	65.63%	30.82%	64.22%	30.82%
Standard Deviation	56.79%	64.76%	69.50%	57.54%	68.97%	36.04%	72.14%	30.33%
Energy + Standard Deviation	53.50%	63.52%	69.12%	51.77%	69.27%	25.81%	**73.01%**	21.50%

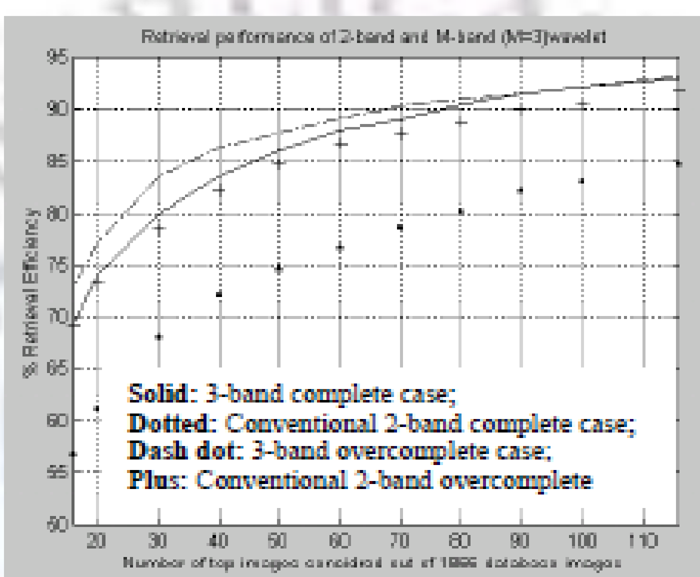

Fig. 2: Average retrieval rate according to no. of two image considered.

4. Conclusion

We have presented an M-band wavelet technique for content-based image retrieval. Large texture database of 1856 images is used to check the retrieval performance. All the database images were decomposed using complete and overcomplete representation of conventional 2-band wavelet and M-band (M=3) wavelet and features were computed on the decomposed sub-bands. A Manhattan distance metric and Mahalanobis distance metric were used to discriminate 116 different textures. A detailed comparison of the retrieval performance-using feature measures such as standard deviation, energy and combinations of both using Manhattan metric and Mahalanobis metric is presented. Amongst all these feature parameters we found that standard deviation alone gives best performance in complete case while combination of standard deviation and energy gives best performance in overcomplete case of conventional 2-band and M-band wavelet. Performance of Mahalanobis metric decreases as the feature vector length increases. Performance of Manhattan metric is better than Mahalanobis metric. The result indicates that M-band wavelet improves retrieval performance significantly than conventional 2-band wavelet. Previous work [3] indicates that Gabor feature gives retrieval performance close to 74% at the cost of very high computation time requirement. While proposed M-band wavelet method is fast and cost effective with almost equal retrieval performance as that of Gabor method. This makes a proposed method more suitable candidate for texture feature extraction in Content Based Image Retrieval.

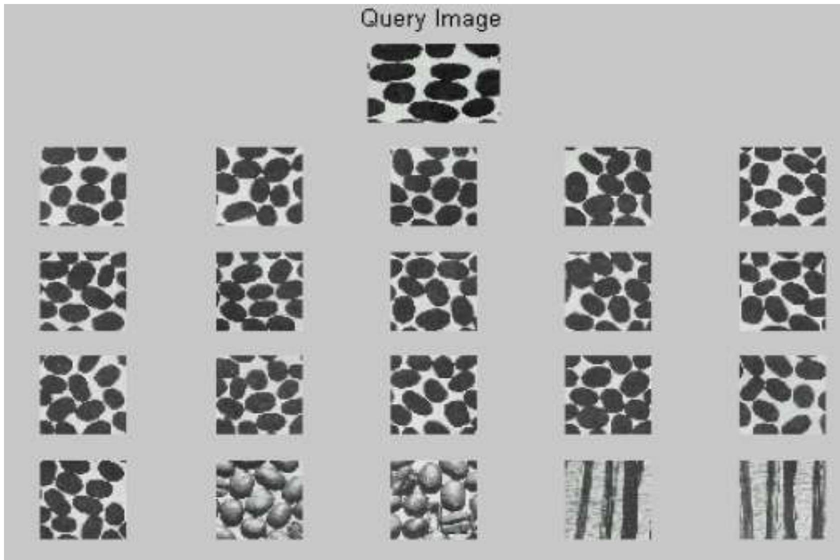

Fig. 3: Retrieved top twenty similar images from the database of 1856 images using 3-band wavelet.

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