Wavelet Based Texture Analysis And Classification With Linear Regration Model

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Abstract

The Wavelet Transform is a multiresolution analysis tool commonly applied to texture analysis and classification and also Wavelet based pre-processing is a very successful method providing proper Image Enhancement and remove noise without considerable change in overall intensity level. The Wavelet Transform mostly used for contrast enhancement in noisy environments. In this paper we propose a texture analysis with the linear regression model based on the wavelet transform. This method is motivated by the observation that there exists a distinctive correlation between the samples images, belonging to the same kind of texture, at different frequency regions obtained by 2-D wavelet transform. Experimentally, it was observed that this correlation varies from texture to texture. The linear regression model is employed to analyze this correlation and extract texture features that characterize the samples. Our method considers not only the frequency regions but also the correlation between these regions. In contrast the tree structured wavelet transform (TSWT) do not consider the correlation between different frequency regions. Experiments show that our method significantly improves the texture classification rate in comparison with the, TSWT, Gabor Transform and GLCM with Gabor and some recently proposed methods derived from these.

Index Terms—Linear regression, texture analysis, texture classification, wavelet transforms.

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.

Texture provides essential information for many image classification tasks. Much research has been done on texture classification during the last three decades [1]-[4]. In the 1980s, most traditional approaches included gray level co-occurrence matrices (GLCM) [5], second-order statistic method [6], Gauss–Markov random field [7], and local linear transform [8], which are restricted to the analysis of spatial relations between neighbourhood pixels in a small image region. As a consequence, their performance is the best for the class of so called micro-textures [9]. With a study on human vision system, researchers begin to develop the multi-resolution texture analysis models, such as the wavelet transform and the Gabor transform. Extensive research has demonstrated that these approaches based on the multi-resolution analysis could achieve reasonably good performance, so they have already been widely applied to texture analysis and classification. The most common multi-resolution analysis approach is to transform a texture image into local spatial/frequency representation by wrapping this image with a bank of filters with some tuned parameters.

This property coincides with the study that the human visual system can be modelled as a set of channels. This clearly motivates researchers to study how to extract more discriminable texture feature based on the multi-resolution techniques. Currently the wavelet transform and the Gabor transform are the most popular multi-resolution methods. Compared to the wavelet transform [10]-[13], the Gabor transforms needs to select the filter parameters according to different texture. There is a trade-off between redundancy and completeness in the design of the Gabor filters because of none Orthogonality. The Gabor transform is also limited to its filtering area. Consequently, we choose the wavelet transform to obtain the spectral information of the texture image. Texture image at different scales and use the statistics of the spectral information as the texture descriptor, they ignore the texture structural information. In this paper, it is found that there exists a distinctive correlation between some sample textures images, belonging to the same kind of texture, at different frequency regions obtained by 2-D wavelet packet transform. Experimentally it is demonstrated that this correlation varies from texture to texture. A new texture classification method, in which the simple linear regression model is employed into analyzing this correlation, is presented. Experiments show that this method significantly improves the texture classification rate in comparison with the multiresolution methods, including TSWT, the Gabor transform [14]-[16], and some recently proposed methods. The most common multiresolution analysis approach is to transform a texture image into local spatial/frequency representation by wrapping this image with a bank of filters with some tuned parameters. This property coincides with the study that the human visual system can be modelled as a set of channels. This clearly motivates researchers to study how to extract more discriminable texture feature based on the multiresolution techniques [17-[18]. Currently, the wavelet transform and the Gabor transform are the most popular multiresolution methods.

In this paper, it is found that there exists a distinctive correlation between some sample texture images, belonging to the same kind of texture, at different frequency regions obtained by 2-D wavelet Packet transforms. Experimentally it is demonstrated that this correlation varies from texture to texture. A new texture classification method, in which the simple linear regression model is employed into analyzing this rate in comparison with the multiresolution methods including PSWT, TSWT, the Gabor transform, and some recently proposed methods.

This paper is organized as follows. The brief review about 2-D wavelet transform and an application of the correlation between different frequency regions to texture analysis are described in Section II.

Several multiresolution techniques, such as, TSWT, and the Gabor and GLCM transform, and our method are compared. Finally, the conclusions are summarized in Section III.

II. TEXTURE ANALYSIS WITH LINEA REGRESSION MODEL

A. Two-Dimensional Wavelet Packet Transform:

The wavelet transform provides a precise and unifying framework for the analysis and characterization of a signal at different scales. It is described as a multiresolution analysis tool for the finite energy function. It can be implemented efficiently with the pyramid-structured wavelet transform and the wavelet packet transform. The pyramid-structured wavelet Performs further decomposition of a signal only in the low frequency regions. Adversely, the wavelet packet transform decomposes a signal in all low and high frequency regions. As the extension of the 1-D wavelet transform, the 2-D wavelet transform can be carried out by the tensor product of two 1-D wavelet base functions along the horizontal and vertical directions, and the corresponding filters can be expressed as h L L(k,l) = h(k)h(l), h L H(k,l) = h(k)h(l), h H L(k,l) = g(k)h(l) and h H H(k,l) = g(k)g(l). An image can be decomposed into four sub images by convolving the image with these filters. These four sub images characterize the frequency information of the image in the LL, LH, HL, and HH frequency regions respectively. The 2-D PSWT can be constructed by the whole process of repeating decomposition in the LL regions, whereas the 2-D wavelet packet transform decomposes all frequency regions to achieve a full decomposition, as shown in Fig. 1 and 2, Therefore, the 2-D PSWT depicts the characteristics of the image in the LL regions and the 2-D wavelet packet trans- form describes the properties of the image in all regions. Most of the research in the multiresolution analysis based on the wavelet domain focuses on directly extracting the energy values from the sub images and uses them to characterize the texture image. In this paper, the mean of the magnitude of the sub-image coefficients is used as its energy.

In this paper the mean of the magnitude of the sub image coefficients is used as its energy. That is, if the sub image is x(m,n),with $1 \le m \le M$ and$1 \le n \le N$ its energy can be represented

$$E=(1/MN)\sum_{i=1}^{M}\sum_{j=1}^{N}X(i,j) \qquad 1.0$$

Where x(i,j) is the pixel value of the sub image.

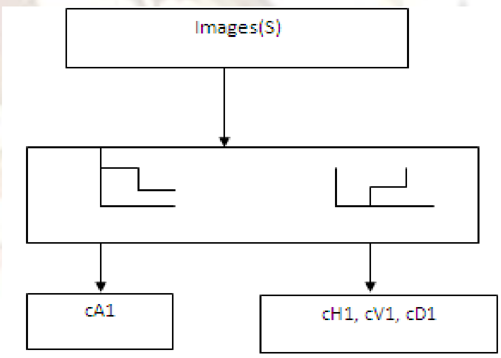

Fig.1:Flow Chart Level using Decomposition.

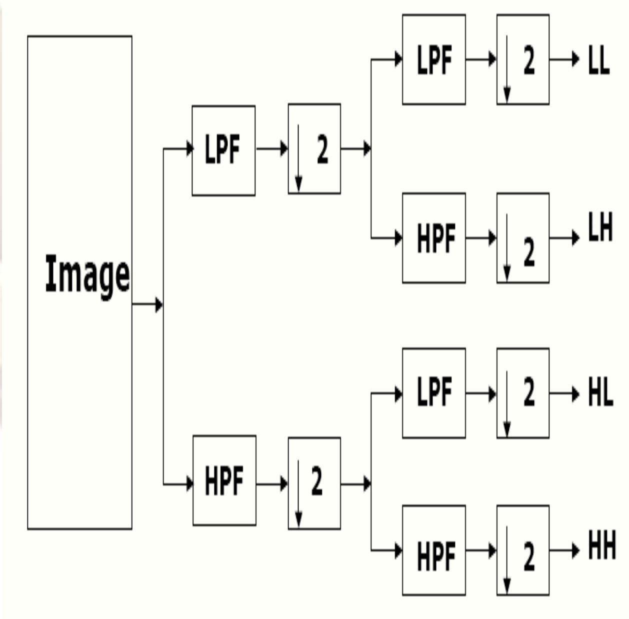

Fig.2 decomposition of image in HL, LL, HH, LH region

B. **Analysis of Correlation between Frequency channels.**

Given that there are some sample texture images from the same kind of texture, these images should have the same spatial relation between neighbourhood pixels as this texture. These images are all decomposed to obtain the same frequency regions by 2-D wavelet transform. The most common approach is to calculate all frequency regions' energy values of every image with the energy function and to characterize this texture by the statistics of these energy values. This approach ignores the spatial relation of these sample texture images. In this study, we capture this inherent texture property by learning a number of sample texture images. From a statistical perspective, a frequency region of a sample texture image can be viewed as a random variable and the energy values of this frequency region can be treated as the random values of this variable Experimentally it is found that there exists a distinctive correlation between different variables (frequency regions).

As a powerful multiresolution analysis tool, the2-D wavelet transform has proved useful in texture analysis, classification, and segmentation. The 2-D PSWT performs further decomposition of a texture image only in the low frequency regions. Consequently it is not suitable for images whose dominant frequency information is located in the middle or high frequency regions. Although the 2-D wavelet packet transform characterizes the information in all frequency regions, this representation is redundant. On the other hand, in order to generate a sparse representation, the 2-D TSWT decomposes the image dynamically in the low and high frequency regions whose energies are higher than a predetermined threshold. However, it ignores the correlation between different frequency regions. We use 2-D wavelet packet transform to obtain all frequency information of a texture image in this paper The detail is described as follow. First, the original image is decomposed into four sub-images, which can be viewed as the parent node and the four children nodes in a tree and named as O, A, B, C, and D respectively, as shown in Fig. 3.

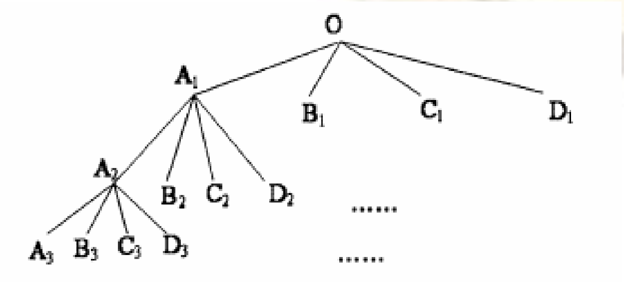

Fig. 3 Tree Representation

They symbolize the original image, LL, LH, HL, and HH frequency regions.

C) Linear Regression Model:

In the above subsection, the correlation between different frequency regions has been validated as a sort of effective texture characteristic. In this section, we employ the simple linear regression model to analyze the correlation. Suppose that we have a set of the random data $(X_1 Y_1)$T…… (X_n Y_n)T, for two numerical variables X and Y and suppose that we regard X as a cause of Y. From the simple linear regression analysis, the distribution of the random data approximately appears a straight line in X, Y space when X and Y are perfectly related linearly. There is a linear function that captures the systematic relationship between two variables. This line function (also called the simple linear regression equation) can be given as follows:

yˆ= a * x + b

Where yˆ is called a fitted value of y.

We exploit the simple linear regression model to extract the texture features from the correlation in the frequency channel pairs. The channel-pair list includes all channel pairs with T. For two frequency channels of one channel pair in the list, we take out their energy values from the channel-energy matrix M and then consider these energy values as the random data$(X_1 Y_1)$T,... , (X_n Y_n)T, for two variables X and Y.The distribution of these energy values should also represent a straight line in X,Y space. In general, the wavelet packet transform generates a multiresolution texture representation including all frequency channels of a texture image with the complete and orthogonal wavelet basis functions which have a "reasonably well controlled" spatial/frequency localization property. Our method absorbs this advantage of the wavelet packet transform. The difference between our method and other multiresolution based texture analysis methods are PSWT loses the middle and high frequency information. TSWT does not take into the account the correlation between different frequency channels. The Gabor transform uses a fixed n umber of filter masks with predetermined frequency and bandwidth parameters. In contrast, our method not only thinks about all frequency channels but also analyzes the correlation between them with the simple linear regression model. So, it can be viewed as a very useful multiresolution method.

III. EXPERIMENTAL RESULT

In this section, we will verify the performance. we used 40 textures .Every original image is of size 640X640 pixels with 256 gray levels. 81 sample images of size 128 with an overlap32 pixels between vertically and horizontally adjacent images are extracted from each original colour image and used in the experiments, and the mean of every image is removed before the processing. These 3240 texture images are separated to two sets being used as the training set with 1600 images and the test set with 1640 images, respectively. We compare our method with other traditional multi-resolutionion methods, such as . The tree-structured wavelet transforms and Gabor and Gabor plus GLCM.

In the classification algorithm of TSWT, its feature is constructed by the energy of all frequency regions in the third scale and its controllable parameters like decomposition constant and comparison constant, are empirically set to 0.15 and 10, respectively. We implement the Gabor transform obtained form by convolving an image with a set of functions by appropriate dilations and rotations of the Gabor mother function. The average retrieval rate defined in our method is different from that of other methods .Because we use threshold based comparison in one dimension. All query samples are processed by our method and respectively assigned to the corresponding texture. We count the samples of this texture, which are assigned to the right texture, and get the average percentage number as the average retrieval rate of this texture. In view of our methods, the distance, where is the query sample and is a texture from the database, is firstly computed with the feature vectors discussed above. The distances are then sorted in increasing order and the closet set of patterns is then retrieved. In the ideal case all the top 41 retrievals are from the texture. The sample retrieval rate same is defined as the average percentage number of samples belonging to the same texture as the query sample in the top 41 matches. The average retrieval rate of a texture is the average number of all sample retrieval rates of this texture. Several different distances similarity measures, like Euclidean, Bayesian, Mahalanobis, can be explored to obtain different results for other The different distances are applied to different methods in our experiment on behalf of their reasonably good performances Table 4 shows the retrieval accuracy of these different multiresolution methods for 40 textures. Fig. 4 gives a graph illustrating the retrieval performance as a function of texture here Gabor based performance is very poor. However, the average accuracy of our method is still first class, highly 96.86%, and much greater than other methods 94.16% (TSWT), 84.45% GLCK and Gabor), 76.429% (the Gabor transform), respectively. In summery TSWT keeps much more information of the spectral resolution in high frequency regions, so it can get better performance than the Gabor,GLCM transform. Gabor with GLCM Excellent performance compared to TSWT, GLCM, and Gabor. A very broad class of filters whose parameters are much more suitable for textures in our Database. However, our method considers not only all the frequency information of the Texture but also the correlation between them. Therefore, it can achieve the best result in Comparison with TSWT, GLCM and Gabor, Transform The way of combining the multiresolution methods, like the wavelet transform and the Gabor transform, and the statistic-based methods, like GLCM, can achieve the super multi-resolution methods because they take the texture primitives into account. In particular, the combination of the wavelet transform and GLCM excels our method in many textures though its average correct rate is still slightly lower than mine. This dramatic trait can be illuminated that the wavelet transform captures the frequency information of the texture image at different scales and GLCM characterizes the local spatial properties of the texture. However this approach leads to space increase the feature dimension and brings in the computation complexity in classification scheme, even the curse of dimensionality. Feature reduction like principle component analysis (PCA) alleviates the curse to some extent at the cost of affecting the performance [19] our method is to take advantage of the texture inherent in the learning phase. Thus relation characteristic, our classification algorithm simply takes the threshold comparison in one dimension space in order to avoid the difficulty in choosing a distance function that is suitable for the distributions of the multidimensional texture features Furthermore, it is obvious that the simple threshold comparison in one dimension space greatly diminishes the great computation

Complexity in comparison with the distance measure similarities in high-dimensional space images, respectively.

IV. CONCLUSION

In this paper, a new approach to texture analysis and classification with the simple linear regression model based on the wavelet transform is presented and its good performance on the classification accuracy is demonstrated in the experiments. Although the traditional multi-resolution methods, like TSWT, the Gabor transform, are suitable for some textures, our method is natural and effective for much more textures. While the fuse of the Gabor transform and GLCM is confined to the Gabor filter, the way of combining the wavelet transform with GLCM obtains the excellent performance very close to our method. However, our method surpasses them in the classification scheme because it adopts the simple threshold comparison and the leave-one-out algorithm. It is worthwhile to point out several distinctive characteristics of this new method. To begin with, our method provides all frequent channels of the quasi-periodicity texture in comparison with PSWT, Gabor, So, it is able to characterize much more spectral information of the texture at different multi-resolution. Next, the correlation of different frequent channels can be applied in this method through the simple linear regression model. In contrast, TSWT does not consider the correlation between different frequent regions though it also keeps more frequent information and employs the energy criterion to get over the over complete decomposition.

Therefore, this texture intrinsic characteristic helps our method go beyond TSWT. Furthermore, most of the research in the multi-resolution analysis directly computes the energy values from the sub images and extracts the features to characterize the texture image at the multi-dimension space, and, yet, our method employs the correlation between different frequency regions to construct the texture feature. So, it employs the threshold comparison in one dimension space rather than some distance measures in the multi-dimension space. Therefore, it is very easy and fast to examine the change of different frequent channels for texture image. Our current work has focused so far on the simple linear regression model which is used to employ the linear correlation. More thorough theoretical analysis of the linear correlation is expected in the future. In addition, the application of this method to texture segmentation is under our current investigation. Due to our method being quite sensitive to noise shown from Section, it is the urgent requirement of achieving its noisy invariance. In this paper, a new approach to texture analysis with the simple linear regression model based on the wavelet transform is presented. Although the traditional multiresolution methods, like PSWT, TSWT, the Gabor transform are suitable for some textures, our method is natural and effective for much more textures.

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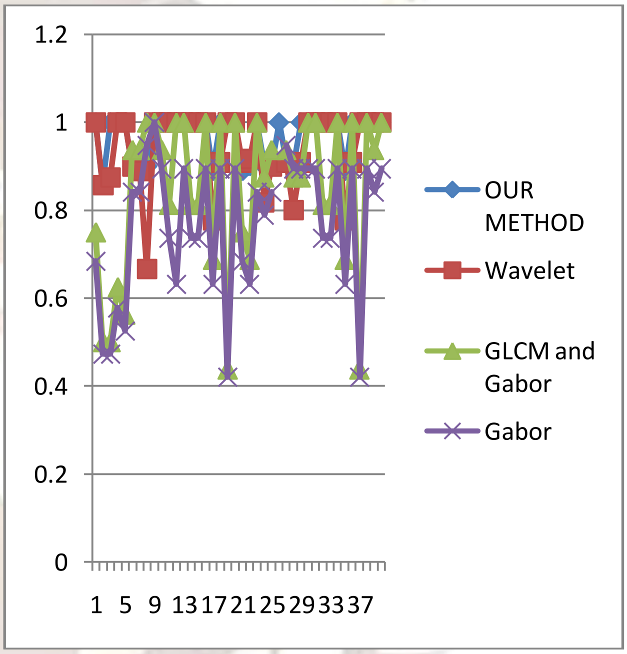

Fig.4. Comparison of classification rate using different methods.

TABLE 5. COMPARISSON OF THE EXPERIMENTAL RESULT USING DIFFERENT METHODS.

IMAGE	OUR METHOD	TSWT	GLCM and Gabor	Gabor
DSCOO779.JPG	1	1	0.75	0.6842
DSCOO782.JPG	0.8571	0.8571	0.5	0.4737
DSCOO786.JPG	1	0.875	0.5	0.4737
DSCOO787.JPG	1	1	0.625	0.5789
DSCOO790.JPG	1	1	0.5625	0.5263
DSCOO814.JPG	0.9	0.9	0.9375	0.8421
DSCOO815.JPG	0.9091	0.8889	0.9375	0.8421
DSCOO819.JPG	0.9	0.6667	1	0.9474
DSCOO820.JPG	1	1	1	1
DSCOO821.JPG	1	1	0.9375	0.8947
DSCOO823.JPG	1	1	0.8125	0.7368
DSCOO824.JPG	1	1	1	0.6316
DSCOO826.JPG	1	1	1	0.8947
DSCOO827.JPG	1	1	0.8125	0.7368
DSCOO829.JPG	1	1	0.8125	0.7368
DSCOO832.JPG	1	1	1	0.8947
DSCOO833.JPG	0.8889	0.7778	0.6875	0.6316
DSCOO834.JPG	1	0.9091	1	0.8947
DSCOO835.JPG	1	1	0.4375	0.4211
DSCOO840.JPG	1	1	1	0.8947
DSCOO844.JPG	0.8889	0.9091	0.75	0.6842
DSCOO845.JPG	0.9	0.9167	0.6875	0.6316
DSCOO846.JPG	1	1	1	0.8421
DSCOO851.JPG	0.9	0.8182	0.875	0.7895
DSCOO852.JPG	0.9	0.9	0.9375	0.8421
DSCOO853.JPG	1	0.9	0.9375	0.8421
DSCOO873.JPG	0.9091	0.9091	0.9375	0.9474
DSCOO874.JPG	0.9	0.8	0.875	0.8947
DSCOO875.JPG	1	0.9091	0.875	0.8947
DSCOO824.JPG	1	1	1	0.8947
DSCOO826.JPG	1	1	1	0.8947
DSCOO827.JPG	1	1	0.8125	0.7368
DSCOO829.JPG	1	1	0.8125	0.7368
DSCOO832.JPG	1	1	1	0.8947
DSCOO833.JPG	0.8889	0.7778	0.6875	0.6316
DSCOO834.JPG	1	0.9091	1	0.8947
DSCOO835.JPG	1	1	0.4375	0.4211
DSCOO840.JPG	1	1	1	0.8947
DSCOO843.JPG	1	1	0.9375	0.8421
DSCOO850.JPG	1	1	1	0.8947
AVERAGE	96.86%	94.16%	84.45%	76.92%

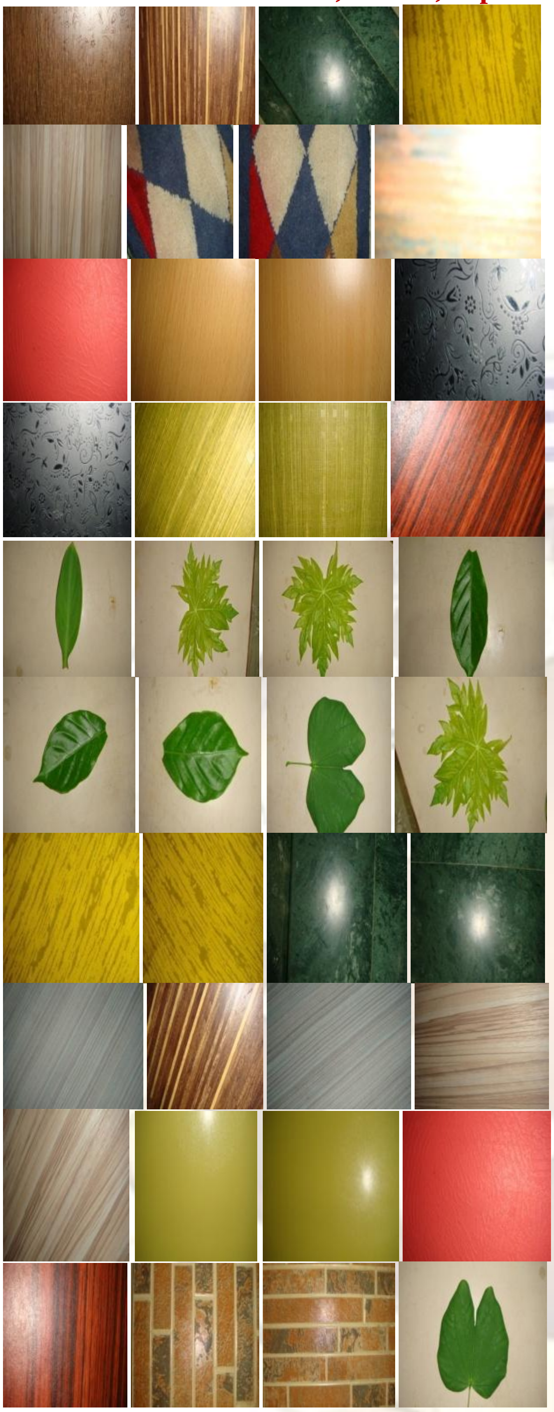

Fig.6. Forty Texture used in this experiment.

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REFERENCES

[1] Y. Rui, T. S. Huang, and S. F. Chang, "Image retrieval: Current techniques, promising directions, and open issues," J. Vis. Common. Image Represent. vol. 10, pp. 39–62 1999.

[2] R. Randen and J. H. Husøy, "Filtering for texture classification: A comparative study," *IEEE Trans. Pattern Anal. Mach. Intell., vol. 21, no. 4, pp. 291–310, Apr.*

[3] J. Zhang and T. Tan, "Brief review of invariant texture analysis methods," Pattern *Recognition. vol. 35, pp. 735–747, 2002.*

[4] C.-C. Chen and C.-C. Chen, "Filtering methods for texture discrimination," Pattern Recognit. Lett., vol. 20, pp. 783–790, 1999.

[5] R.M.Haralick, K.Shanmugan, and I. Dinstein,"Textural features for image classification," IEEE Trans. Syst. Man Cybern., vol. SMC-6, no. 6, pp. 610–621, Nov. 1973.

[6] P. C. Chen and T. Pavlidis, "Segmentation by texture using correlation," IEEE Trans. Pattern Anal. Mach. Intell., vol. 5, no. 1, pp. 64–69, Jan. 1983.

[7] 7R. L. Kashyap and R. Chellappa, "Estimation and choice of neighbors in spatial- interaction models of images," IEEE Trans. Inf. Theory, vol. 29, no. 1, pp. 60–72, Jan. *1983.*

[8] M.Unser,"Local linear transforms for texture measurements, "Signal Process. vol.11,pp.61–79,1986.-400,

[9] M. Unser, "Texture classification and segmentation using wavel Frames, M. Unser, "Texture classification and segmentation using wavel Frames,

[10] T.ChangandC.-C.J.Kuo,"A wavelet transform approach to texture analysis," in Proc. IEEE ICASSP, Mar. 1992, vol. 4, no. 23–26, pp.661–664.

[11] ChangandC.-C.J.Kuo,"Tree-structured wavelet transform for textured image Segmentation,"Proc.SPIE,vol.1770,pp.394–405,1992.

[12] T.Chang andC.-C.J.Kuo, "Texture analysis and classification with tree-structured wavelet transform,"IEEE Trans.Image Process., vol. 2,no.4,pp.429–441,Oct.1993.

[13] G.H.Wu, Y.J.Zhang, andX.G.Lin,"Wavelet transform-based texture classification Feature weighting,"Proc.IEEEInt.Conf.Image Processing,vol.4,no.10,pp.435 439,1999.

[14] W.Y.Maand B.S.Manjunath,"A comparison of wavelet transform features for texture Image annotation," Proc. IEEE Int. Conf. Image Processing, vol.2, no.23–26,pp.256259,Oct.1995.

[15] W.Y.MaandB.S.Manjunath,"Texture features and learning similarity," Proc.IEEECVPR, .18–20,pp.425–430,Jun.1996.

[16] B. S. Manjunath and W. Y. Ma, "Texture feature for browsing and retrieval of image Data, IEEE rans. Pattern Anal .Mach. Intel vol.18,no.8,pp.837–842,Aug.1996.

[17] D.A.ClausiandH.Deng,"Desing-based texture feature fusion using gabor filters and co- occurrence probabilities," IEEE Trans. Image. process.,vol.14,no.7,pp.925–936,Jul.2005.

[18] G. Van de Wouwer, P. Scheunders, and D. Van Dyck, "Statistical texture characterization from discrete wavelet representation," IEEE Trans.Image,Vol 8,no.4,,pp,592- 598,Apr.1999.

[19] Timothy K. Shih, Lawrence Y. Deng, Ching-Sheng Wang, and Sheng-En Yeh, "Conten- base Image Retrieval with Intensive Signature via Affine Invariant Transformation", Dept. of Computer Science and Information Engineering Tamkang University.