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CLASSIFICATION OF TEXTURES WITH AND WITHOUT ROTATION ANGLES: A DAUBECHIES WAVELET BASED APPROACH

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Abstract- Textures play important roles in many image processing applications, since images of real objects often do not exhibit regions of uniform and smooth intensities, but variations of intensities with certain repeated structures or patterns, referred to as visual texture. The textural patterns or structures mainly result from the physical surface properties, such as roughness or oriented structured of a tactile quality. It is widely recognized that a visual texture, which can easily perceive, is very difficult to define. The difficulty results mainly from the fact that different people can define textures in applications dependent ways or with different perceptual motivations, and they are not generally agreed upon single definition of texture [1]. The development in multi-resolution analysis such as Gabor and wavelet transform help to overcome this difficulty. In this paper it describes that, texture classification using Wavelet Statistical Features (WSF), Wavelet Co-occurrence Features (WCF) and a combination of wavelet statistical features and co-occurrence features of wavelet transformed images with different feature databases can results better [2]. Several Image degrading parameters are introduced in the image to be classified for verifying the features. Wavelet based decomposing is used to classify the image with code prepared in MATLAB.

***Keywords**- Wavelet, Texture Classification, Wavelet Statistical Features (WSF), Wavelet Co-occurrence Features (WCF), Histogram Equalization, Background Subtraction,Range filtering, Blurring and Dilation of image.*

I. INTRODUCTION

Texture is a property that represents the surface and structure of an Image. Generally speaking, Texture can be defined as a regular repetition of an element or pattern on a surface. Image textures are complex visual patterns composed of entities or regions with sub-patterns with the characteristics of brightness, color, shape, size, etc. An image region has a constant texture if a set of its characteristics are constant, slowly changing or approximately periodic [3]. Texture can be regarded as a similarity grouping in an image [4]. Because texture has so many different dimensions, there is no single method of texture representation that is adequate for a variety of textures. Texture analysis is a major step in texture classification, image segmentation and image shape identification tasks. Image segmentation and shape identification are usually the preprocessing steps for target or object recognition in an image. Texture analysis refers to a class of mathematical procedures and models that characterize the spatial variations within imagery as a means of extracting information. Texture is a real construct that defines local spatial organization of spatially varying spectral values that is repeated in a region of larger spatial scale. Thus, the perception of texture is a function of spatial and radiometric scales. Descriptors providing measures of properties such as smoothness, coarseness and regularity are used to quantify the texture content of an object. Since an image is made up of pixels, texture can be defined as an entity consisting of mutually related pixels and group of pixels. This group of pixels is called as texture primitives or texture elements [5]. Consider all the fact discussed above, texture classification is difficult task in special domain; here, texture classification is proposed with the help of wavelet transform. Texture classification using wavelet statistical features, wavelet co-occurrence features and a combination of wavelet statistical features and co-occurrence features of wavelet transformed images with different feature databases is performed and discussed.

II. DISCRETE WAVELET TRANSFORM

The image is decomposed into four sub-bands and critically sub-sampled by applying DWT as shown in Fig. 1(a). These sub-bands labeled LH1, HL1 and HH1 represent the finest scale wavelet coefficients i.e., detail images while the sub-band LL1 corresponds to coarse level coefficients i.e., approximation image. To obtain the next coarse level of wavelet coefficients, the sub-band LL1alone is further decomposed and critically sampled. This results in two-level wavelet decomposition as shown in Fig. 1(b).

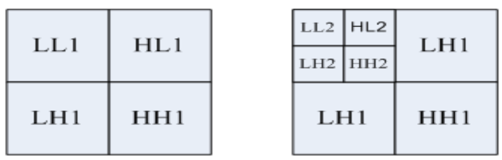

Fig. 1 – Image Decomposition (a) One Layer (b) Two Layer

Similarly, to obtain further decomposition, LL2 will be used. This process continues until some final scale is reached. The values or transformed coefficients in approximation and detail images (sub-band images) are the essential features, which are shown here as useful for texture analysis and discrimination. As micro-textures or macro-textures have non-uniform gray level variations, they are statistically characterized by the features in approximation and detail images [2]. The values in the sub-band images or their combinations or the derived features from these bands uniquely characterize a texture. The features obtained from these wavelet transformed images are shown to be used for texture analysis, namely, classification and are discussed later in the paper.

III. METHODOLOGY

The steps involved in texture training and texture classification are shown in Fig. 2(a) and (b) respectively.

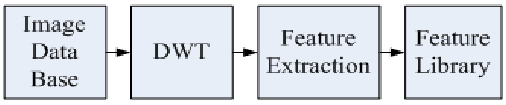

Fig. 2(a) - Texture Training

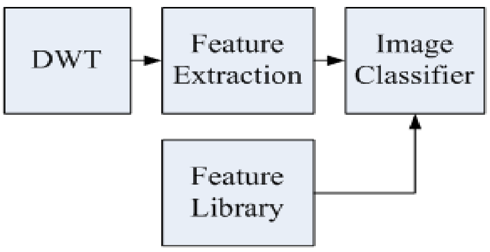

Fig. 2 (b) - Texture Classification

Texture Training: In the texture training, the known texture images are decomposed using DWT. Then, mean and standard deviation of approximation and detail sub-bands of three level decomposed images (i.e., LLk, LHk, HLk and HHk; for k = 1; 2; 3) are calculated as features using the formulas given in the Eqs. (1) and (2) respectively and stored in features library.

$$\text{Mean (m)} = \frac{1}{N^2} \sum_{i,j=1}^{N} p(i, j) \qquad (1)$$

$$\text{SD} = \sqrt{\frac{1}{N^2} \sum_{i,j=1}^{N} [\, p(i, j) - m]^2} \qquad (2)$$

Where $p(i, j)$ is the transformed value in (i; j) for any sub-band of size N x N. Using this procedure, from any texture image, the features (up to k-level sub-bands) are computed and stored in the features library which are further used in texture classification phase. Using a combination of the above WSFs, texture classification is performed which yielded good result.

In order to improve the correct classification rate further, it is proposed to find co-occurrence matrix features for original image, approximation and detail sub-bands of 1-level DWT decomposed images (i.e., LL1, LH1, HL1 and HH1). The various co-occurrence features such as contrast, energy, entropy, local homogeneity, cluster shade, cluster prominence and maximum probability, as suggested by Haralick et al. (1973) [5], are calculated from the co-occurrence matrix C (i; j) using the formulas.

Texture Classification: Here, the unknown texture is decomposed using DWT and a similar set of wavelet statistical and co-occurrence matrix features are extracted and compared with the corresponding feature values stored in the features library using distance vector formula given in Eq. (3).

$$D(i) = \sum_{j=1}^{\text{No.of feature}} f_j(x) - f_j(i) \qquad (3)$$

Where, $fj(x)$ represents the features of unknown texture while fj(i) represents the features of known ith texture in the library. Then, the unknown texture is classified as ith texture, if the distance D(i) is minimum among all textures, available in the library.

IV. RESULT AND DISCUSSION

Experiments are conducted with 98 monochrome texture images, each of size 512x512, image database shown in Fig. 3. For comparative analysis, texture classification is done using different feature vectors for three different feature databases.

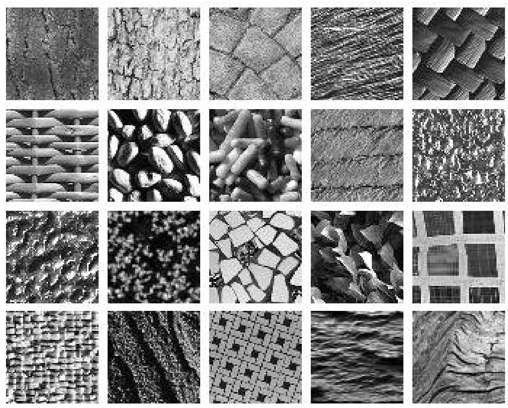

Fig. 3 – Texture Image Database: Bark-1, Bark 2,Cobble-1,Fabric-1, Fabric-2, Fabric-3, Food-1, Food-2, Dessert, Metal-1, Metal-2, Misc, Mosaic, Plant Leave, Rattier, Sand, Tile ,Water, Wood

The first feature database (FDB-1) is created from 20 1024x1024 original texture images by extracting (i) 32 Wavelet Statistical Features (WSFs) such as mean and standard deviation of LL_k, LH_k, HL_k and HH_k (for k = 1; 2; 3; 4) sub-bands of four-level DWT decomposed texture images and (ii) 35 wavelet co-occurrence features (WCF) such as contrast, energy, entropy, local homogeneity, cluster shade, cluster prominence and maximum probability, derived from co-occurrence matrices, computed for different angles (i.e., θ = 0, 22.5, 45, 67.5, 90, 112.5, 135, 157.5, and 180) and averaged, of original images, approximation and detail sub-bands of 1-level DWT decomposed texture images.

The second feature database (FDB2) is created from a total of 6800 image regions of 20 texture images, constructed by dividing each 1024x1024 texture image into non-overlapping 4-512x512, 16-256x256, 64-128x128 and 256- 64x64 image regions and by extracting 32 WSFs and 35 WCFs, averaged over these 340 image regions.

TABLE I : Results of texture classification using wavelet statistical and co-occurrence features (with 6800 image regions)

Table 1 : Results of texture classification using wavelet statistical and co-occurrence features (with 6800 image regions)

Sr. No.	Image	Correct Classification (%)							
		Feature Vectors							
		F1	F2	F3	F4	F5	F6	F7	F8
1	Bark 1	95.83	96.94	96.67	87.50	99.72	89.17	87.78	92.50
2	Bark 2	92.22	87.78	92.22	99.17	88.89	92.22	88.89	90.00
3	Cobble 1	91.39	85.83	96.67	98.89	98.33	83.89	99.72	95.28
4	Fabric 1	86.39	82.78	99.17	99.44	98.06	96.39	83.89	90.00
5	Fabric 2	91.11	87.50	93.33	84.44	96.94	96.67	97.78	96.11
6	Fabric 3	100.00	82.78	92.78	83.61	81.39	90.00	91.39	90.83
7	Food 1	90.00	80.56	93.06	91.67	87.50	95.28	86.67	92.22
8	Food 2	93.89	88.61	81.67	92.22	86.11	88.33	98.06	84.72
9	Dessert	90.00	76.67	98.89	94.17	92.78	94.72	91.11	87.50
10	Metal 1	95.28	68.06	98.06	86.39	83.06	83.33	89.44	86.39
11	Metal 2	84.72	79.44	94.17	88.06	87.78	90.56	96.39	97.22
12	Misc	85.28	91.94	86.67	86.94	97.50	93.61	87.50	99.72
13	Mosaic	82.22	81.94	87.22	83.06	85.28	83.33	99.44	92.78
14	Plant Leave	94.44	79.44	81.94	82.22	81.11	81.67	91.39	98.06
15	Quilt	88.33	75.28	90.56	91.11	100.00	86.94	95.56	99.72
16	Rattier	96.11	68.33	92.50	86.67	92.22	89.17	93.89	93.06
17	Sand	95.00	76.67	94.72	100.00	85.28	95.28	84.44	96.11
18	Tile	82.50	80.28	80.56	94.72	89.17	83.06	96.94	88.33
19	Water	90.56	79.44	83.89	91.67	95.00	98.33	97.50	90.00
20	Wood	94.44	85.28	89.44	94.44	91.39	84.72	81.11	90.83
Number of Images Correctly Classified		6551	5888	6567	6539	6543	6468	6620	6665
Mass Success Rate		96.34	86.59	96.57	96.16	96.22	95.12	97.35	98.01

F1=wavelet statistical features (WSF)—(trained by features of 512 x512 original images: Feat-DB1).
F2=wavelet co-occurrence features (WCF)—(trained by features of 512 x512 original images: Feat-DB1).

F3=WSF +WCFs (trained by features of 512 x 512 original images: Feat-DB1).
F4=WSF+WCFs (trained by averaged features of 4 256 x 256, 16 128 x128 and 64 64 x 64 non-overlapping image regions: Feat-DB2).
F5=WSF+WCFs (trained by three averaged feature sub-databases of 4 256 x 256, 16 128 x128 and 64 64 x64 non-overlapped image regions: Feat-DB3).
F6=WSF+WCFs (trained by averaged features of 64 64 x 64 non-overlapping image regions: Feat-DB3).
F7=WSF+WCFs (trained by averaged features of 16 128 x128 non-overlapping image regions: Feat-DB3).

F8=WSF+WCFs (trained by averaged features of 4 256 x256 non-overlapping image regions: Feat-DB3).

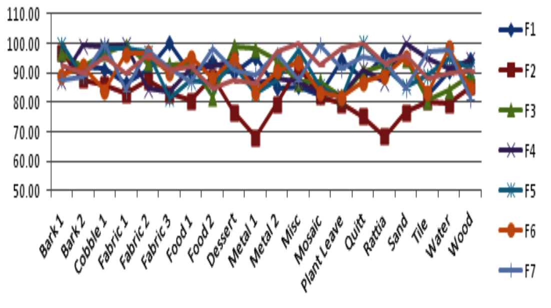

Fig. 4- Mean Success Rate for database

The third feature database (FDB3) is obtained again from a total of 6800 image regions and it consists of three sub-databases derived by extracting 32 WSFs and 35 WCFs, averaged over 4-512x512, 16-256x256, 64-128x128 and 256-64x64 image regions respectively and either all these three different sub-databases are used based on the size of unknown image (or) one at a time during the classification.

Texture classification is done with a total of 6800 (i.e., 20--340) image regions of 20 texture images, shown in Fig. 3. In the first instance, texture classification is done with DB1 using 24 WSFs (feature vector–F1), 17 WCFs (feature vector–F2) and a combination of WSFs and WCFs (feature vector–F3) and the results are summarized in Table 1, where each entry corresponds to the average correct classification rate of all the 340 image regions of different sizes, discussed earlier.

From the Table 1, it is observed that the mean success rate for feature vectors F1, F2 and F3 are 96.34%, 86.59% and 96.57% respectively. In the second instance, again the combination of WSFs and WCFs (feature vector–F4) are used to classify images with FDB2 and it is found that the mean success rate is 96.16%. Next, classification is carried out with FDB3 using the same combination of WSFs and WCFs. In feature vector F5, the 6800 image regions are classified by comparing one of the three feature sub-databases based on their size. But, in feature vectors F6, F7 and F8 all the 6800 image regions are classified by comparing trained averaged features of 64x64, 128x128, 256x256 and 512x512 image regions respectively, irrespective of their size.

The mean success rate of feature vectors F5, F6, F7 and F8 are 96.22%, 95.12%, 97.35% and 98.01% respectively. The graphical analysis of texture classification results are shown is Fig. 4.

Lastly the noise is introduced in the image to be classified and again classification is done with the given database and the Wavelet Statistical feature (F1) gives more accurate result as compared with the other Features.

Texture classification without rotation angles: Here, the unknown texture is decomposed using DWT and a similar set of wavelet statistical and co-occurrence matrix features are extracted and compared with the corresponding feature values stored in the features library using distance vector formula given in Eq. (4).

$$D(i) = \sum_{j=1}^{\text{No.of feature}} f_j(x) - f_j(i) \qquad (4)$$

Where, fj(x) represents the features of unknown texture while fj(i) represents the features of known ith texture in the library. Then, the unknown texture is classified as ith texture, if the distance D(i) is minimum among all textures, available in the library. The main difference is the rotation is excluded and this will result in direct classification of the image which is shown in the figure below.

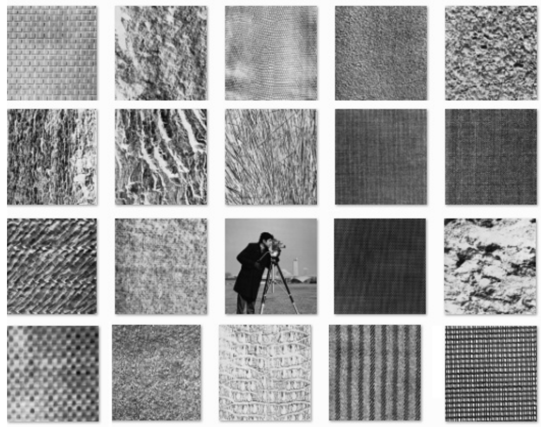

Fig. 5- Database of images excluding (Cameraman.tiff) Matlab, 2011

Here for the classification the image (cameraman.tiff), is inserted in database to check the correct classification.

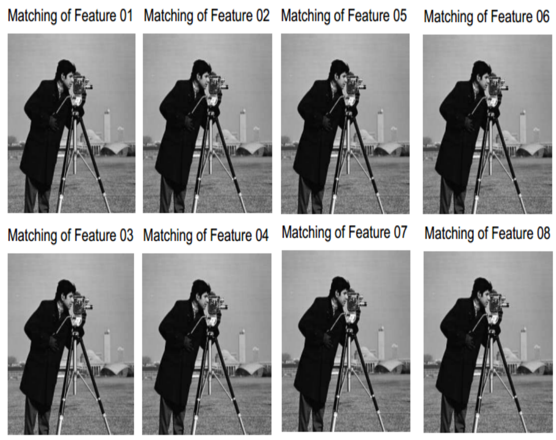

Fig. 5-Correct classification of image.

The main difference here is the rotation angle is excluded. This gives complete visualization of images that are classified by classifier. As for a good classifier the features should be efficient enough which, are the combination of Wavelet Statistical and Co-occurrence Features. Hence from Features (F1 to F8), all are classified correctly by distance vector formula as classifier as stated in equation (3).

Further the image to be classified is introduced with, (i) Histogram Equalization, (ii) Background Subtraction, (iii) Range Filtering (iv), Image Blurring (v), Image Dilate.

The below figure shows the visualization of image classification, if the image to be classified is histogram equalization and its features are compared with the image stored in the database. In the database the figure (Cameraman.tiff) is inserted for the correct visualization of image that is classified. After introducing the above stated parameters the image is applied for classification. The following figure (6) shows the classification result of image with Histogram equalization Background Subtraction and Range Filtering.

Fig: 6. correct classification of image form Histogram Equalization, Background Subtraction and Range Filtering.

Now the image is introduced with the Blurring, which means that the features of the blurred image are applied for classification. The basic intuition behind this is to analyze, which statistical features gives correct features after decomposition so that, for the classifier it is easy to classify.

The below results show the classification result of classifier in figure (7).

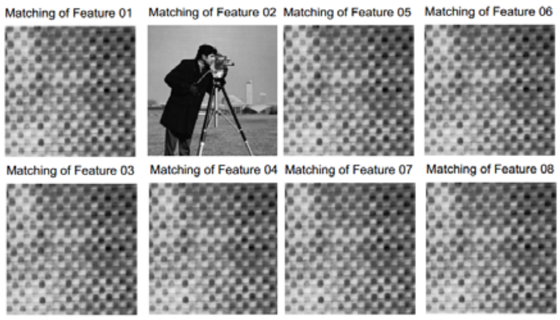

Fig: 6. correct classification of blurred image for Feature Vector (F2) by classifier.

The feature vector (F3) includes combination of Wavelet Statistical Feature and Wavelet Co-occurrence Feature, which is efficient to give perfect features of the blurred image applied to the classifier for the classification.

Now the image is Dilate and applied for the classification. The below results shows the results of the classifier. The Feature Vectors (F2, F3, F5, F7 and F8) gives correct Features for classification.

Fig: 6. correct classification for Dilated image of (cameraman) given to classifier.

Features	Parameters			
	Histogram Equalization	Background Subtraction	Blurring	Dilate
F1	100	100	75	73
F2	100	100	100	100
F3	100	100	75	100
F4	100	100	75	70
F5	100	100	75	100
F6	100	100	75	100
F7	100	100	75	100
F8	100	100	75	70
Classification Percentage of features in parameters				

TABLE II: Classification Rate of Features against several parameters

V. CONCLUSION

The Matlab based code is used to generate the above mentioned results, and that can be concluded as under: (i) When classification is done with FDB1, the mean success rate is improved to 96.57% for a combination of WSFs and WCFs compared to that of WSFs (or) WCFs. (ii) When classification is done with FDB2, the mean success rate is slightly reduced to 96.16%. (iii) When classification is done with FDB3, the highest mean success rate (i.e., 98.01%) is obtained. The research work is focused on algorithmic development and future work is to change different wavelet family to generate the result and achieve higher mean success rate. Lastly the Features are analyzed by introducing several image degrading parameters and results are shown above states that F1 features F1and F2 are efficient for classification in Histogram Equalization and Background Subtraction.

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