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Performance Evolution of Texture Classification

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Abstract—

Textures 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 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. 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), Gaussian noise

I. Introduction

Texture is a property that represents the surface and structure of an Image. 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, colour, shape, size, etc. The term of texture is a somewhat misleading term in computer vision, which is not the normal meaning of the word. The texture of an image may be thought as something which describes the characteristic of the intensity surface of the image. Method of texture analysis is used to extract a set of features from an image.

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 is a real construct that defines local spatial organization of spatially varying spectral values that is repeated in a region of larger spatial scale.[1] Texture classification assigns a given texture to some texture classes. Two main classification methods are supervised an unsupervised classification. Supervised classification is provided examples of each texture class as a training set. A supervised classifier is trained using the set to learn a characterization for each texture class. Unsupervised classification does not require prior knowledge, which is able to automatically discover different classes from input textures. Another class is semi-supervised with only partial prior knowledge being available.

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. In this paper, the DWT is applied on a set of texture images and statistical features such as mean and standard deviation are extracted from the approximation and detail regions of DWT decomposed images, at different scales. The various combinations of the above statistical features are applied for texture classification and a set of best feature vectors are chosen. In order to improve the success rate of classification, the co- occurrence matrix is calculated for original image, approximation and detail sub-bands of 1-level DWT decomposed images and additional features are extracted. [2] These additional features are combined with the above chosen best wavelet statistical feature (WSF) sets and a detailed analysis is done using three different feature databases. It is found that the success rate is improved much by combining wavelet statistical and co-occurrence matrix features.

Techniques assume that the textures are captured from the same viewpoint. This is an unrealistic assumption in the real world. Robust rotation invariant features are the need of the day. In many applications, it is very difficult and impossible to ensure that surfaces captured have the same rotation between each other and such an assumption is rather restrictive in many practical applications. Therefore we consider rotation invariant texture features. Major Representative work can be divided into two categories: statistical methods model based method.

II. Discrete Wavelet Transform

The image is actually decomposed that is divided into four sub-bands and critically sub-sampled by Applying DWT as shown in Fig.(a). These sub bands labelled LH1, HL1 and HH1 represent the finest scale wavelet coefficients that is detail images while the sub-band LL1corresponds to coarse level coefficients i.e., approximation image. [2] 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 Figure2. (b).

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 Information 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 [3]. 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 this paper.

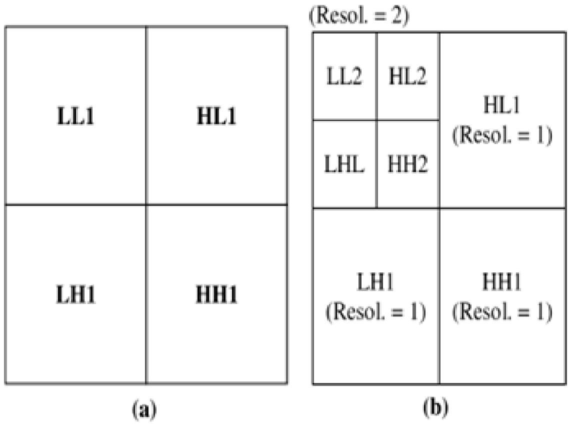

Fig.1 Image decomposition. (a) One-level, (b) two level.

III. METHODOLOGY

The steps defined in texture training and texture Classification are shown in Fig.(a) and (b) respectively.

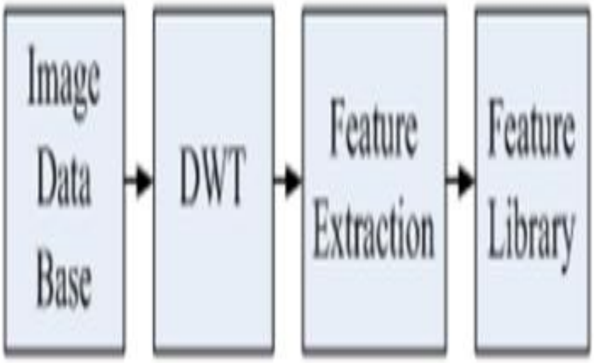

Fig. 2 (a) - Texture Training

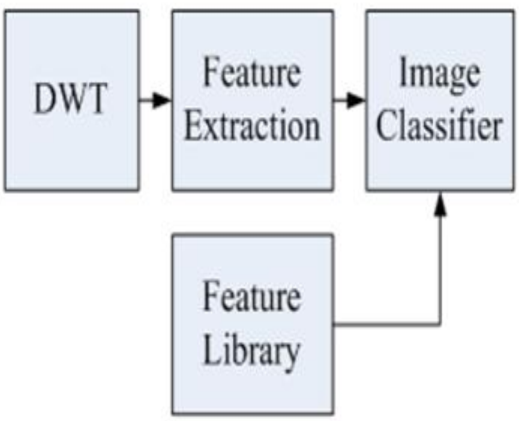

Fig.2 (b) - Texture Classification

A. 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.

$$mean(m) = \frac{1}{N^2} \sum_{i,j=1}^{N} p(i,j) \tag{1}$$

$$standard\,deviation(sd) = \sqrt{\frac{1}{N^2} \sum_{i,j=1}^{N} [p(i,j) - m]^2} \tag{2}$$

Where p(i;j) is the transformed value in (i;j) for any sub-band of size N×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.

B. 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 a distance vector formula, given in Eq.(3)

$$D(i) = \sum_{j=1}^{No.of\,features} abc[fj(x) - fj(i)] \tag{3}$$

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.

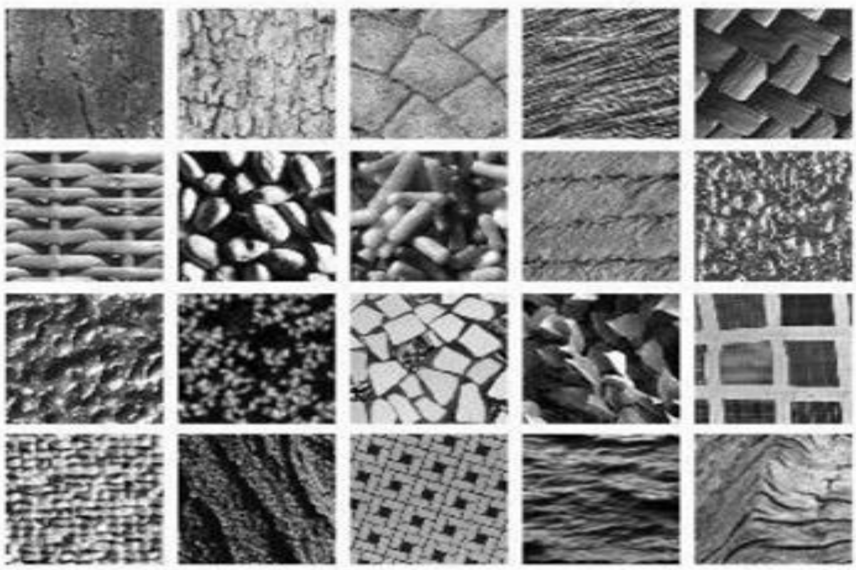

Fig.3-Texture Image Database: Bark-1, Bark 2,Cobble-1,Fabric-1,Fabric-2, Fabric-3, Food-1, Food-2, Dessert, Metal-1, Metal-2, Misc, Mosaic, Plant Leave, Rattier, Sand, Tile ,Water, Wood.

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 LLk, LHk, HLk and HHk (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., h = 0, 45, 90 and 135) and averaged, of original images, approximation and detail sub-bands of 1-level DWT decomposed texture images.

The second feature database (Feat-DB2) is created from a total of 1680 image regions of 20 texture images, constructed by dividing each 512×512 texture image into non-overlapping 4 256×256, 16 128×128 and 64 64×64 image regions and by extracting 24 WSFs and 35 WCFs, averaged over these 84 image regions. The third feature database (Feat-DB3) is obtained again from a total of 1680 image regions and it consists of three sub-databases derived by extracting 24 WSFs and 35 WCFs, averaged over 4 (256×256), 16 (128×128) and 64 (64×64) 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 1680 (i.e., 20×84) image regions of 20 texture images, shown in Fig. 3, In the first instance, texture classification is done with Feat-DB1using 14 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 84 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 92.02%, 87.86% and 97.68% respectively.

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

Sr.no.	Images	correct classification(5)							
		Feature vectors							
		F1	F2	F3	F4	F5	F6	F7	F8
1	Bark.0006	46.43	90.48	90.48	91.67	92.86	92.86	91.67	91.67
2	Brick.0000	97.62	96.43	100	100	100	100	100	100
3	Brick .0004	82.14	98.81	100	100	100	100	100	100
4	Clouds .0001	79.76	90.48	96.43	96.43	96.43	94.05	96.43	97.62
5	Fabric .0013	97.62	96.43	100	100	97.62	97.62	100	100
6	Fabric .0017	100	96.43	97.62	97.62	97.62	97.62	97.62	97.62
7	Flowers.0006	94.05	35.71	98.81	98.81	98.81	98.81	98.81	98.81
8	Food.0000	100	92.86	98.81	98.81	98.81	98.81	98.81	98.81
9	Food .0001	100	73.81	96.43	96.43	97.62	97.62	97.62	97.62
10	Grass .0001	86.9	77.38	100	80.95	78.56	78.56	79.76	80.95
11	Leaves .0012	90.48	91.67	100	96.43	91.67	91.67	94.05	96.43
12	Metal .0002	100	100	100	100	100	100	100	100
13	Metal .0004	86.9	100	98.81	100	98.81	98.81	100	100
14	Misc.0001	100	84.52	100	100	100	100	100	100
15	Misc .0002	97.62	91.67	98.81	98.81	97.62	97.62	98.81	98.81
16	Sand .0000	96.43	95.24	100	98.81	100	100	100	100
17	Sand .0002	89.29	91.67	98.81	100	97.62	96.43	97.62	97.62
18	Title .0008	97.62	97.62	100	98.81	100	100	100	100
19	Water .0005	97.62	83.33	100	100	97.62	98.81	100	100
20	Wood .0002	100	72.62	100	100	100	100	100	100
Number of image regions 1639 1643 Correctly classified			1546	1476	1641	1634		1632	1628
Mean success rate		92.02	87.86	97.68	97.86	97.14	97.14	97.56	97.80

- 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 nonoverlapping image regions: Feat-DB2).

- F5=WSF+WCFs (trained by three averaged feature sub-databases of 4 256 x 256, 16 128 x128 and 64 x 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).

V. Conclusion

The Mat lab based code is used to generate this paper results and that can be concluded that (i) when classification is done with FDB1,the mean success rate improved to 96.57% for a combination of WSFs and 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 change with different wavelet family and invariant rotation angle in database. Different algorithm of texture will use to classify the image and angle of images.

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