Aggregate Features Approach for Texture Analysis

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***Abstract*--Texture analysis is significant field in image processing and computer vision. Shape and texture has groovy correlation and texture can be defined by shape descriptor.**
Three individual approach Zernike moment, which is orthogonal shape signifier, Gabor features and Haralick features are utilized for texture analysis. Another approach is applied by aggregating all the features for texture analysis. Texture is defined by features which are extracted using Gabor filter, GLCM and Zernike moments. Classification of texture are done using back-propagation neural network. Individual approach is applied on texture images and accuracy is determined. By combining all approaches overall result is improved.

***Index Terms*—Texture analysis, texture classification, Gabor filter, Zernike moments, GLCM.**

I. Introduction

To understand, model and process texture, and ultimately to simulate human visual learning process using computer technologies are major goals of texture research in computer vision.

Texture is group of pixel (texton) repeated at particularly frequency in specified orientation. Visually texture is defined by its smoothness, fineness or coarseness. Texture analysis is defined as the sectionalization of texture features extracted from particular texture region.

II. Related Work

Analyzing texture information is interpreted as texture analysis and classifying texture based on classes of texture the process is defined as texture classification. Texture classification is part of the process texture analysis.

Heralick et al [1][2] present the statistical approach based on second order joint probability distribution. Textures tell apart based on 19 statistical features derived from gray level co-occurrence matrix (GLCM). Dedy Septiadi [3] also used GLCM to check surface roughness by texture features measure by correlation and information correlation.

Alan Bovik et al [5] has presented approach based on Gabor filter. Gabor filter is spatial domain directional filter. Basically, for any texture there should be particular frequency correlated with that and that particular direction along with frequency should be easily estimated by Gabor filter. So particular texture in image is emphasized by applying respective Gabor filter.

K. I. Kim et al [6] has proposed texture classification based on kernel principle component analysis. It is basically nonlinear mapping technique which mapped non linear sample data to linear feature space and the principle component analysis done later on. For supervised classification nearest neighbor (NN) classifier is used.

Guoliang Fan et al [7] present texture analysis based on Discrete Wavelet Transform (DWT). After finding DWT of an texture image wavelet energy signature is found. And one feature vector is created for each texture image. Classification performance is experimented for Independent Mixture Model (IMM), Hidden Markov Tree (HMT) and HMT-3S in which three DWT subbands are merged into one structure using graphical grouping technique for more statistical characterization of DWT. Chi-Man Pun et al [8] proposed rotation and scale invariant texture classification based on log polar transform and wavelet packet transform. Rotation change in texture image is converted into shifting of row in log polar image. And adaptive row shift invariant wavelet packet transform is performed then log-polar wavelet energy signatures extracted from each subband of wavelet coefficients used as texture feature to classify each texture correctly.

Rob J. Dekker et al [9] has proposed approach for texture analysis and classification based on texture measures like mean intensity, variance, weighted rank fill ratio and semivariograms are found from texture samples. Then each texture image is classified using k-nearest neighbor classifier by feeding texture measure as input.

Christodoulos et al [10] has define approach using combining different types of texture features derived from statistical features like mean , median, standard deviation, skewness and kurtosis, Heralick features from gray level co-occurrence matrix (GLCM) , gray-level difference statistics, neighborhood gray tone difference matrix, statistical feature matrix, Laws' texture energy measures, fractals, and Fourier power spectrum. The neural network self organizing feature map (SOFM) classifier and the statistical K-nearest neighbor (KNN) classifier were used for the classification of the clods images having different types of textures. Guillaume Rellier

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et al [11] has proposed probabilistic model for each texture using multivariate Gaussian markov random field and to test likeliness of these models on the sample texture data.
Zhi-Zhong Wang et al [12] presented new approach for texture analysis based on Linear Regression Model Based on Wavelet Transform. By obtaining different frequency region from 2D wavelet packet transform between two sample texture image classifiable correlation arrived and linear regression model is utilized to examine this correlation and texture feature which demonstrate exactly correct ample of texture.

III. Gray level co-occurrence matrix (GLCM)

Co-occurrence features are defined useful property for texture analysis. To capture the spatial habituation of gray-level values, which contribute to the perception of texture, Co-occurrence matrix, which has two dimensions habituation, is used. Since texture feature depend on location as well as value of the pixels. It can be measure using intensity or gray level values of image or color value of image.

A. GLCM features

Often size of GLCM are Fairly large and sparse so set of features is calculated from GLCM which are called Haralick features [1][2]. There are basically 19 features from that four features are most efficient.

$$\text{Energy} = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1} g^2(i,j) \tag{1}$$

$$\text{Entropy} = \sum_{j=0}^{N_g-1} g(i,j)\log\left(g(i,j)\right) \tag{2}$$

$$\text{Contrast} = \sum_{j=0}^{N_g-1} g(i,j)\left(i-j\right)^2 \tag{3}$$

$$\text{Correlation} = \frac{\sum_{j=0}^{N_g-1} g(i,j)(ij)-\mu_x\mu_y}{\sigma_x\sigma_y} \tag{4}$$

IV. Gabor Filter

Large Gabor filter is basically sine wave modulated by Gaussian envelope [13]. Gabor filter is tunable means frequency and orientation of filter is easily adjustable. In 2-D Gabor filter G(x,y) can be convolved with image I(x,y) resultant image is with emphasized texture information.
Two-dimensional Gabor function is defined as [14][15]:

$$G\left(x,y\right)=e^{\left(-\pi\left(p^2x^2+q^2y^2\right)\right)}.e^{\left(j\left(2\pi F\left(x\cos w+y\sin w\right)\right)\right)} \tag{5}$$

Where, parameter p and q also define spreading of Gaussian envelope in x and y direction respectively. F is radial frequency of the sinusoid and w specifies the orientation of the Gabor filters.

V. Zernike Moments

Each and every texture is defined by characteristics of shade, gray level distribution and importantly Shape or its geometry. From so many decades, in computer vision and image and object matching Moment are used as good and efficient descriptor [16][17]. Zernike moments are orthogonal moments and image can be representing by it effectively.
The Zernike polynomials are a set of complex, orthogonal polynomials defined over the interior of a unit circle $x^2 + y^2 = 1$ [18][19],

$$V_{nm}(x,y)=V_{nm}(\rho,\theta)R_{nm}(\rho)e^{jm\theta} \tag{6}$$

$$R_{nm}(\rho)=\sum_{s=0}^{\frac{n-|m|}{2}}(-1)^s\frac{(n-s)!}{s!\left(\frac{n+|m|}{2}-s\right)!\left(\frac{n-|m|}{2}-s\right)!}\rho^{n-2s} \tag{7}$$

where n is a non-negative integer, m is an integer such that $n-|m|$ is even and $|m|\le n$,

$\rho=\sqrt{x^2+y^2}$ and $\theta=\tan^{-1}\frac{y}{x}$.

The Zernike moment of order n with repetition m is projecting the image function onto the basis set,:

$$A_{mn}=\frac{n+1}{\pi}\sum_x\sum_y f(x,y)V_{mn}(x,y),x^2+y^2\le 1 \tag{8}$$

VI. Experimental Assemble

A. Learning and Classification Stage

Three individual classification approach and aggregate approach of all these methods have been evaluated employing neural network. In learning phase, neural network is trained using multi-dimensional feature vector by aggregating Zernike moment, Gabor features and Haralick features. In our approach back propagation feed forward neural network is used.

B. Training images

Different types of textured image considered in this experiment taken from Brodatz texture collection [20]. We have considered 100 different types of texture from Brodatz database and each texture image consider 9 sample images for same type of textures. So total 900 images considered in our paper. From that image set 500 image are used to train the neural network classifier and 400 images are used to test the accuracy of neural network.

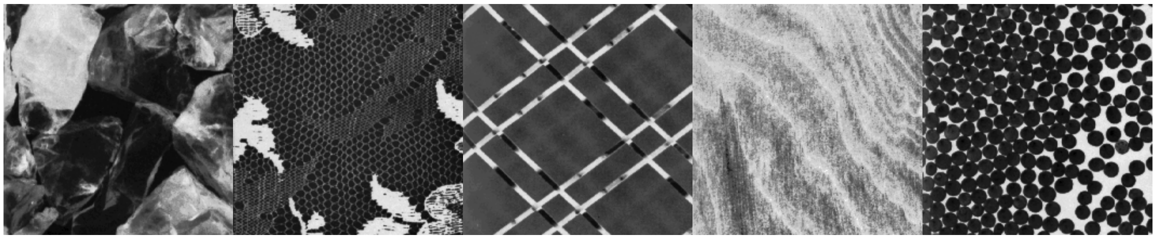

Fig 1 Image from Brodatz database (left to right) D99_02, D42_01, D47_01, D71_01 and D67_01

TABLE 1
RESULTS OF FEATURES EXTRACTION FOR DIFFERENT TEXTURE IMAGES

Image	Gabor				Zernike Moments				Co-occurrence			
D99_02	3.8132 e-05	- 10.3834	7085.68	0.0169	1312602	243489	884090	355410	0.1998	- 2.1936	0.2460	0.8927
D42_01	3.6453 e-05	- 10.4259	7255.18	0.0147	1051550	82912.7	800995	186705	0.2041	- 2.0682	0.6387	0.7979
D47_01	3.6772 e-05	- 10.4749	7699.53	0.0123	1200232	50090.7	1185047	826803	0.5080	- 1.3991	0.3324	0.9059
D71_01	2.778 e-05	- 10.5917	7499.45	0.0145	2381105	106769	2387623	70850.4	0.1242	- 2.3761	0.5098	0.7773
D67_01	5.4248e-05	- 10.1676	7713.92	0.01142	932410	43995	869638	18140.8	0.3924	- 1.8395	1.1942	0.8288

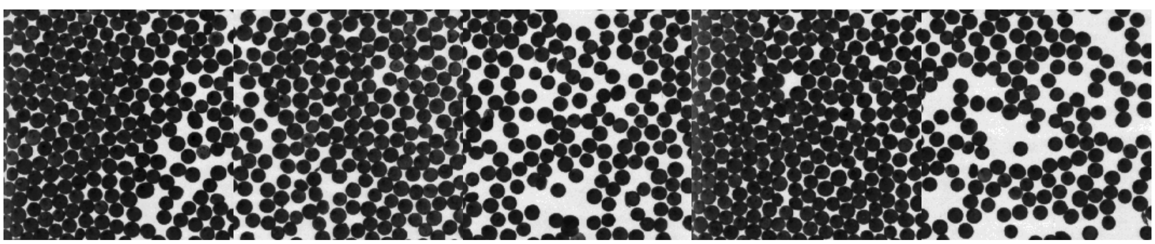

Fig. 2 Image from Brodatz database (left to right) D67_01, D67_02, D67_03, D67_04 and D67_05

TABLE 2
RESULTS OF FEATURES EXTRACTION FOR DIFFERENT IMAGES HAVING SAME TEXTURE

	Gabor				Zernike Moments				Co-occurrence			
D67_01	5.4248 e-05	- 10.1676	7713.92	0.01542	1532410	43995	869638	18140.8	0.3924	- 1.8395	1.1942	0.8288
D67_02	5.0907 e-05	- 10.3210	7495.85	0.01542	1548 626	104608	1649053	62258.5	0.3980	- 1.9086	1.2817	0.8412
D67_03	5.5412 e-05	- 10.2693	7277.76	0.01531	1547 985	99764.7	1105938	54969	0.3281	- 1.9349	1.2637	0.8236
D67_04	5.1844 e-05	- 10.1845	7574.39	0.01589	1490 718	160784	920007	80727	0.3684	- 1.8751	1.1935	0.8349
D67_05	5.7494e-05	- 10.3797	7889.08	0.01575	1574 264	114637	1740149	106832	0.3973	- 1.8635	1.1940	0.8536

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TABLE 3
COMPARISON OF TEXTURE ANALYSIS METHODS

Method	Co-occurrence Matrix	Gabor filter	Zernike moments	Combine Approach
Total Test images	400	400	400	400
Classify correctly	258	324	329	389
Classify incorrectly	142	76	71	22
Accuracy (%)	64.5	81	82.25	97.25

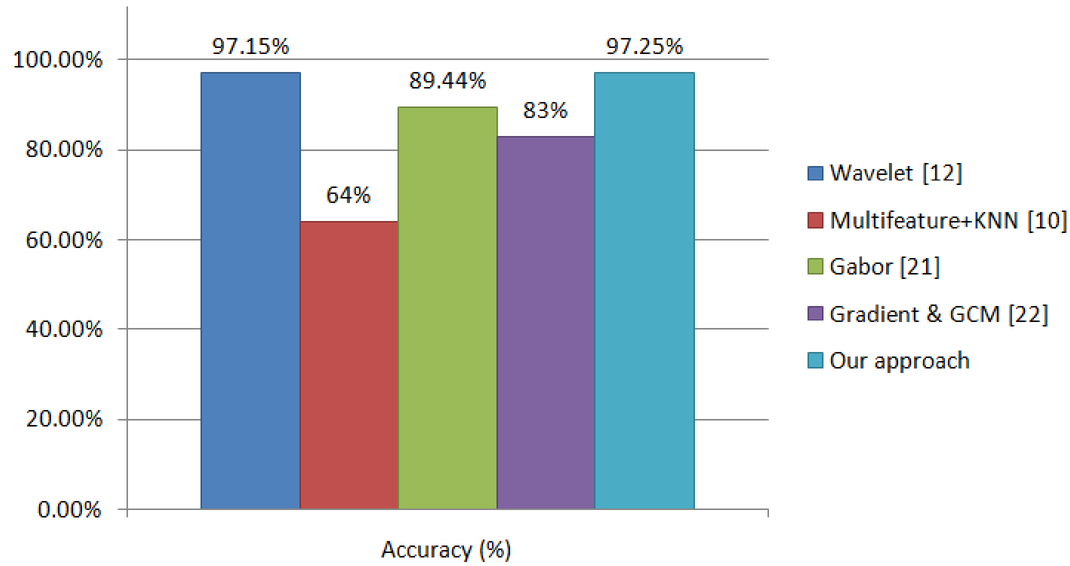

Fig. 3 Comparative analysis

C. Results and Discussion

Table 1 is showing results of feature extraction using Gabor filter, co-occurrence matrix and Zernike moments. Four features of Gabor filter four of Co-occurrence matrix and four features of Zernike moments are considered in our research work. Table 1 interpret that features are enough to differentiate classes of textures as they are having too much dissimilarity between them.

Table 2 is showing results of feature extraction of images having same texture and it can be easily interpreted from the feature value that they have good similarity.

Table 3 is showing comparative analysis for texture analysis method with proposed method. Individually all the approaches are applied first then finally combined proposed approach is used for texture analysis, which gives effective results in term of accuracy.

D. Comparative Analysis

Figure 3 is showing comparative analysis of our approach with proposed approach. And graph shows that our method is working efficiently.

VII. CONCLUSION

In this paper, texture analysis approach is proposed based on features calculated from Co-occurrence matrix, Zernike moment and Gabor filtered image. Individually performance of each feature is not effective as they are working together effectively on texture analysis. Results are showing that proposed algorithm got 97.25% successful classification accuracy.

Future work can be done by considering affine translation of texture images and how these features can be made invariant to this translation.

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