Texture Recognition by Fusion of Optimized Moment Based and Gabor Energy Features

Naeem Qaiser, Mutawarra Hussain, Amir Hussain* and Nadeem Qaiser**
Department of Computer and Information Sciences,

Pakistan Institute of Engineering and Applied Sciences, Pakistan

*Computational Intelligence Research Group, University of Stirling, UK.

** Department of Electrical Engineering,
Pakistan Institute of Engineering and Applied Sciences, Pakistan

Abstract— Use of a single technique for the extraction of diverse features in a texture image usually shows limited capabilities for texture description. Texture features extracted using different techniques can be merged in an attempt to enhance their texture description capability. This paper explores the fusion of optimized moment and Gabor energy texture features. The Fisher linear discriminant analysis is used to show that the discrimination effectiveness of the features increases as a result of the proposed fusion. Preliminary simulation results have been validated experimentally through the classification and segmentation of real texture images.
Keywords—Moment based texture features, Gabor energy features, Texture classification, Fisher's criterion Texture Segmentation, Fusion

1 Introduction

Texture is an attribute whose study is significantly different from the study of other image attributes. It is an aspect so easy to be recognized visually but hard enough to be characterized verbally. In fact, no formal scientific definition of texture exists [1]. Most of the texture analysis methods utilize statistical, spectral and structural approaches [2][3][4][5]. One of the statistical approaches is moment based feature extraction which has shown promising results especially for segmenting texture having identical second order statistics [3]. Gabor filters have also demonstrated their capabilities in characterizing texture information for segmentation and classification purposes [5][6][7][8][9]. These kinds of texture features alone might, however, have limited power in describing textures. Different texture features are therefore merged to enhance texture description capability. Clausi [9] proposed a design-based method to fuse Gabor filter and grey level co-occurrence probability (GLCP) features for improved texture recognition.

This article explores the fusion of Gabor energy and optimized moment based texture features for improved texture segmentation. The following aspects are the prime focus of this research work; i) Theoretical and experimental analysis of the fusion of the said technique after examining the limitation of both the methods, ii) Introduction of more comprehensive strategy to optimize moment based texture features and iii) Results verification through multiple validation procedures.

Organization of the paper is as follows: Section 2 briefly explains related previous work on optimized moment based texture features. Next, Gabor features are discussed briefly in Section 3. Section 4 gives the theoretical and experimental background of this work and finally the results and conclusion have been summarized in Section 5 and Section 6 respectively.

2 Optimized Moment Based Texture Features

Moments computed over some bounded region have well defined geometric interpretations and thus can be used for texture feature extraction. Tuceryan [3] proposed the following algorithm for texture segmentation using moments:

- Compute image moments within a window around each pixel.
- Compute the texture features from these moments by applying a non-linear transformation followed by an averaging operation.
- Perform unsupervised clustering to classify every pixel in the image using feature vectors obtained in the previous step

This technique proposes specific masks to compute moments using normalized coordinates within local regions. The resulting features are sensitive to the size of the moment window and the averaging window. As the window size gets larger, more global features are detected. On the other hand accurate segmentation requires a small window. This suggests that the window size could possibly be tied to the contents of the image for optimization.

The issue of optimum window size computation, using the Fourier spectrum, has been investigated in [10] and a generalized yet simple to implement framework has been proposed. Fourier data in its polar form has been exploited in order to relate the optimum window for different moment masks with the spectral contents of an image.

3 Gabor Based Texture Features

Local spectrum based texture features have extensively been used for segmentation and classification purposes [5][6][7][8] and [11]. In most of these studies the relation to the local spectrum is established through features which are obtained by filtering with a set of two-dimensional Gabor filters. This type of filter is linear, localized in nature and is characterized by an orientation and a spatial frequency. A Gabor filter acts as a band pass filter with certain optimal joint localization properties in both the spatial domain and the spatial frequency domain [11]. Typically, a multi-channel filtering scheme is used: an image is filtered with a set of Gabor filters with different preferred orientations and spatial frequencies. And then the Gabor filter output is transformed into new feature set which can be used directly as input to a classification or segmentation operator. Depending upon the transformation, called post processing, features can be categorized as linear Gabor features, thresholded Gabor features, Gabor-energy features, complex moment features and grating operator cell features [11]. We have used Gabor energy features in our experimentation.

4 Theoretical and Experimental Background

Generally, in texture analysis, Gabor filters are implemented in a pseudo wavelet scheme. This scheme has an excellent ability to describe textures having low frequencies. The drawback associated with the scheme is that at higher frequency Gabor filters cover a lot of evenly distributed impulsive noise due to a greater spread of filter (in the spatial-frequency domain). Thus exhibit more sensitivity to impulsive noise at higher frequencies and generate highly variable features. Moments based features are statistical in nature and do not weight the local region in Gaussian fashion and hence are less sensitive to additive impulsive noise. However, moments are not as good as Gabor filters for texture description at lower frequency. This suggests that moment based features optimized for higher frequency can be merged with Gabor for better texture recognition. The following subsections discuss the proposed feature set and also the validation procedures and tools which have been exploited to evaluate the reliability and robustness of the proposed feature set.

4.2 Proposed Feature Set

The use of various combinations of Gabor features with different values of preferred frequencies and orientations has been reported in the literature [6]-[8], and [11]. In our experimentation, we used four preferred spatial frequencies of 19, 27, 43 and 75 cycles per image (image of size 256 × 256) and four preferred orientations [$\theta=k(\pi/4)$, k=0,1,2,3] for Gabor-energy features, resulting in 16-dimensional feature vector. The resulting feature set is then merged with five moment features [10] making 21-dimensional fused feature set. We optimized the moment feature as follows: i) The size of moment mask is optimized for highest frequency (75 cycles per image), giving moment masks of size 5 to 7 [10], ii) The size of the averaging window is chosen so that it can cover most of the energy of highest frequency Gabor filter used in the pseudo wavelet scheme.. In this experimentation $\sigma/\lambda=0.56$ is used for Gabor filters [9], that is, σ used for Gabor filter with highest frequency (3.41 pixels per cycle) is 1.9 pixels and as most of the energy of a Gaussian envelop lies in $\pm 3\sigma$, therefore for $\sigma=1.9$ pixels, we chose averaging window of size 11×11.

4.3 Validation Procedures

The following subsections briefly explain the procedures used to validate the results obtained in this research work.

4.3.1 Fisher Criterion

Texture is such an attribute which shows a degree of variance in almost all real images. That is why, the feature vectors computed for different pixels in a texture image using a given operator are not identical; they rather form a cluster in the multi-dimensional feature space. Larger the distance between two clusters corresponding two different types of texture, better the discrimination properties of the texture operator that produced the feature vectors. This distance has, however, to be considered in relation to the size of the clusters. In order to determine the distance between two clusters of feature vectors, it is sufficient to look at their projection on a line, under the assumption that this projection maximizes the separability of the clusters in the one-dimensional space. A linear trans-formation that realizes this projection was first introduced by Fisher [12] and is called the Fisher's linear discriminant function. It has the following form:

$$y = (\vec{\mu}_1 - \vec{\mu}_2) S^{-1} \vec{x} , \quad (1)$$

where $\vec{\mu}_1$ and $\vec{\mu}_2$ are the means of the two clusters and S is the pooled covariance matrix. The distance between two clusters relative to their compactness can be expressed as single quantity called Fisher's criterion and is defined as

$$f = \frac{|\eta_1 - \eta_2|}{\sqrt{\sigma_1^2 + \sigma_2^2}}, \qquad (2)$$

where σ_1 and σ_2 are the standard deviations of the distribution of the projected feature vectors of the respective clusters and η_1 and η_2 are the projections of the means $\vec{\mu}_1$ and $\vec{\mu}_2$.

4.3.2 Classification

The curse of dimensionality states that increasing the dimensionality of the feature space first enhances classification accuracy, but rapidly leads to sparseness of the training data and to poor representation of the vector densities, and thereby decreasing the classification performance [13]. The results for supervised texture classification, with individual and proposed feature sets have been presented, to prove that proposed feature set has enhanced accuracy of classification without increasing the sparseness of training data, and also that the fusion of the features does not come up with increased redundancy. Probabilistic Neural Network (PNN) has been used for this purpose.

4.3.3 Segmentation

The unsupervised classification, using Competitive Learning Network (CLN) to segment images having more than one texture, has been performed to demonstrate that the proposed technique is a useful tool for real applications. CLNs have lateral inhibitory connections at some layers to implement competitive learning [14]. The dimension of the features is reduced by employing Principal Component Analysis (PCA) to obtain an optimal feature set and these features are then fed to CLN for segmentation

5 Results and Discussion

The overall impact of impulsive noise on individual techniques and the proposed feature set has been demonstrated through a comprehensive experimental example. In this experimentation, four synthesized texture pairs were used. In each pair, one is a simple vertically oriented sine pattern while the other is a composite of vertically and horizontally-oriented identical type of sine patterns. These texture images are then added with additive impulsive noise (salt and pepper) with a noise density ($\sigma = 0.01$). The four variants of these pairs, used in this experimentation, are with the four different frequencies (19, 27, 43 and 75 cycles per image) to which the Gabor filters were tuned for. Similarly the window sizes, used for moment features, were also optimized for these frequencies. Figure 1 shows one of these texture pairs (19 cycles per image) and Table 1 gives the Fisher's criterion values for each pair.

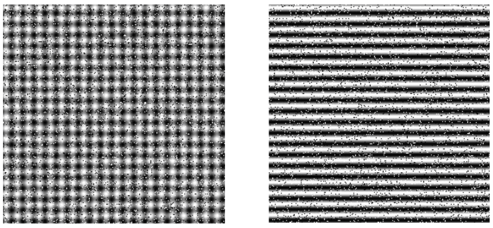

Figure 1. Synthetic texture pair (19 Cycles per image) with impulsive noise

The results show that Gabor energy features are better than moment features for low and medium frequency textures. However, the discrimination power of Gabor energy features falls more rapidly (as compared with moment features) when the frequency of the texture increases.

Table 1. Fisher's Criterion Values for patterns (Figure 1)

	Fisher's Criterion Values			
	Pair 1	Pair 2	Pair 3	Pair 4
Gabor	27.437	24.458	12.519	4.496
Moment	14.410	13.584	12.790	10.026
Fused	28.062	25.132	16.632	13.648

In order to evaluate the discrimination capability of the proposed set we have also experimented with the real images taken from Brodatz album [15] and Official Web Site of University of Southern California: Institute of Signal and Image Processing [16] (Figure 2). The reason to select these images was to investigate the relative weaknesses and strengths of moment based and Gabor texture features. This set of test images includes synthetic textures, real images of man made structures and real images of textures existing in nature.

The performance of moment based, Gabor energy and fused texture features has been evaluated according to the Fisher criterion by looking at the pair-wise separability of the feature clusters corresponding to six test textures shown in Figure 2 (Image 1-6). Table 1 summarizes the statistics of pair wise Fisher's criterion value in each case. Figure 3 illustrates the results of Optimized moment Gabor energy, and fused texture features respectively when classified using a probabilistic neural network for four textures (Image 1-6, Figure 2). In the process of classification, using PNN, 5% of 2000 pixels (chosen randomly from each image) were used as the training set and the entire set of 2000 pixels were classified after the network had been trained. Both the Fisher's criterion values and classification results shows that fused features give better texture discrimination capabilities.

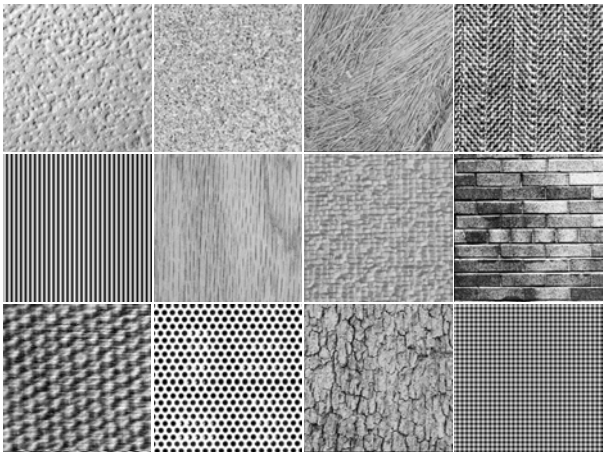

Figure 2. Set of 12 texture images used in experimentation ; Row 1: {Image 1 (rough wall), Image 2 (sand), Image 3 (straw D15), Image 4 (herringbone weave D16)}, Row 2: {Image 5 (sine pattern), Image 6 (Wood grain D68), Image7 (Raffia D84), Image 8 (Brick wall D94)}, Row 3: {Image 9 (cotton canvas D77), Image 10 (hexagonal array), Image 11 (bark D12), Image 12 (composite sine pattern)}

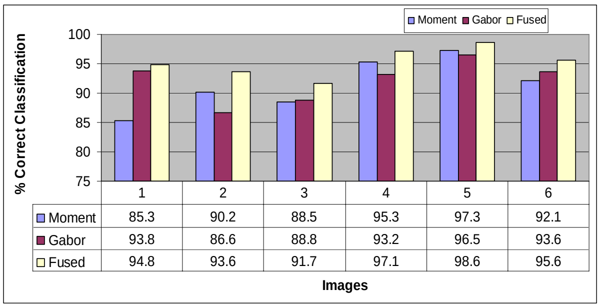

Figure 3. Percentage of the correctly classified pixels using PNN.

For segmentation of textured images we proceeded as follows:

First the dimension of the fused features was reduced from 21 to 9. For this purpose PCA was employed and 9 features with most dominating eigen values were selected. The reduction of the features not only removes the redundant features but lowers the computational cost of the classification stage as well.

Then these features were classified in an unsupervised manner using CLN, labeling all the pixels in the segmented image.

Figure 4 shows the segmentation results of six textures in a group of four textures (3 images). These results indicate that some textures are better discriminated by Gabor features and some by moment features but in all the cases proposed feature set shows the best performance. Figure 5 shows the segmentation of an image comprising six different textures. These results have exclusively been presented here to demonstrate that the resulted features are crisp enough to be classified promisingly even by a six class unsupervised classifier and are performing better than the individual feature sets.

Table 2. Statistics (pair-wise) of Fisher's criterion value, M (Moment), G (Gabor) and F (Fused)

Image	Image 2			Image 3			Image 4			Image 5			Image 6		
	M	G	F	M	G	F	M	G	F	M	G	F	M	G	F
1	3.25	5.25	6.35	3.58	2.87	4.96	10.90	7.98	14.97	15.85	22.54	28.87	4.87	5.93	8.39
2	---	---	---	6.23	3.12	7.87	11.99	6.06	14.04	18.05	15.21	22.66	8.99	5.97	11.64
3	---	---	---	---	---	---	4.06	6.11	8.25	14.98	12.89	21.68	10.01	4.02	10.77
4	---	---	---	---	---	---	---	---	---	10.02	20.88	22.67	23.85	7.92	28.05
5	---	---	---	---	---	---	---	---	---	---	---	---	6.93	12.96	18.23

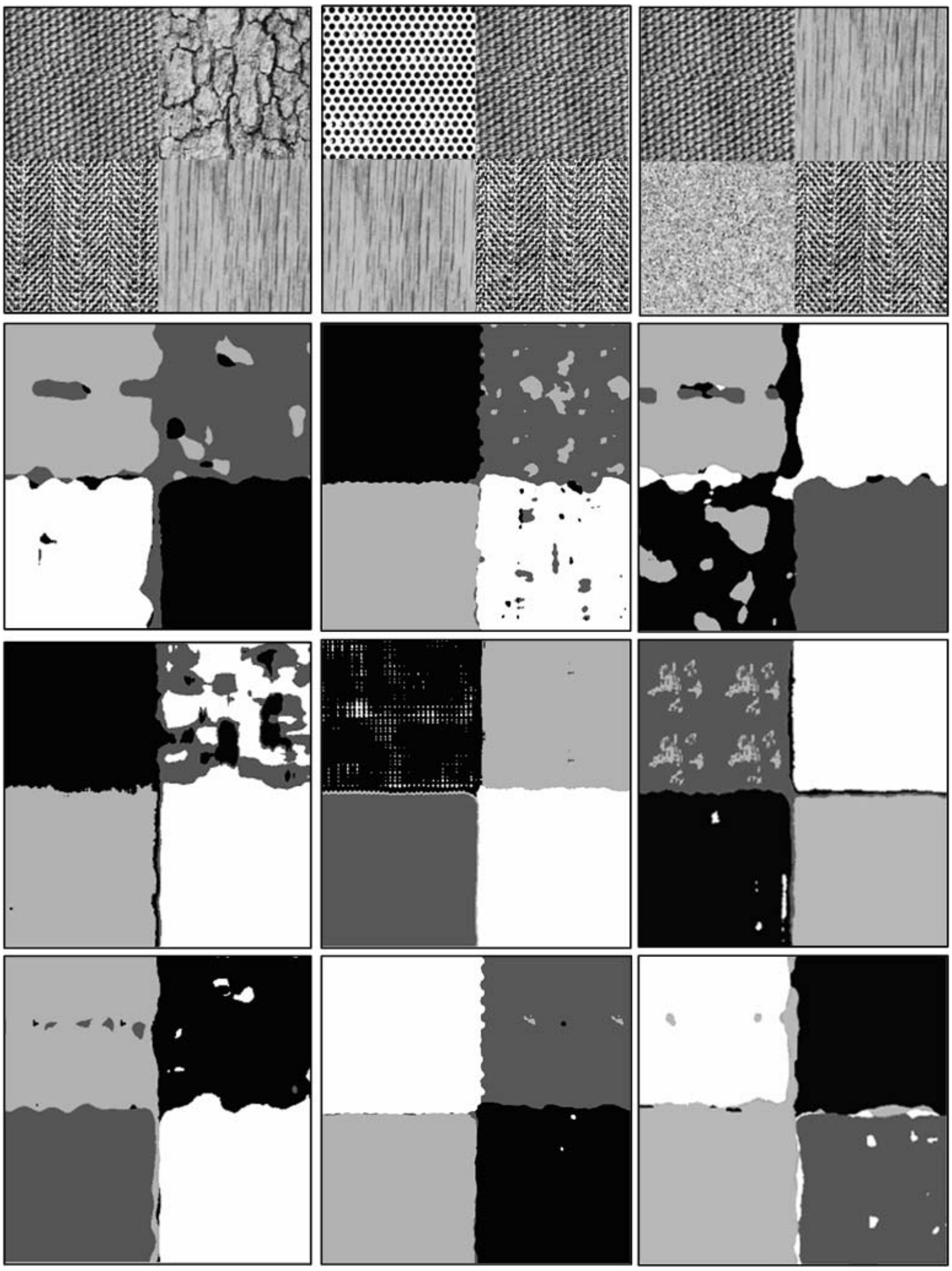

Figure 4. Original images (Row 1), segmented results using; moments (Row 2), Gabor (Row 3) and fused features (Row 4)

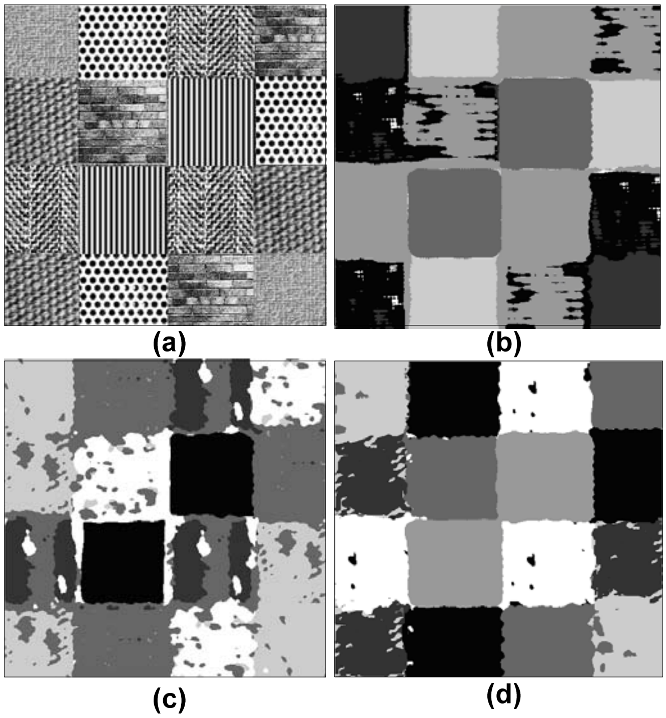

Figure 5. Segmentation results of six texture image (a), using moments (b), Gabor (c), and fused features (d)

6 Conclusions

This chapter proposes the fusion of optimized moment based and Gabor energy texture features for better texture description. The fusion is based on the experimental analysis of each method so as to combine robust and reliable features. The robustness of the proposed solution has been established through the experimentation on synthesized textures having known characteristics. Subsequently, the results have been validated through the analysis of benchmark textures taken from Brodatz album. Discriminant analysis, classification and segmentation results using fused features indicate significant improvement over the individual methods.

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