Texture Classification of Gabor Filtering Images based of DST-Texton Template with LPboosting classifier

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ABSTRACT: *In this research, the importance of having a balanced basis of texture classified images are analyzed. It obtained on brodatz images even though the latter are more numerous on the web resources. The proposed algorithm shows a way to improve performance. A textual analysis of the Gabor filtered images based on the combination of text on co-occurrence matrix with shearlet band signatures based texture classification of 40 Brodatz texture images is presented. The entropy lineage parameters of redundant and interpolate at a certain point which congregating adjacent regions based on geometric properties then the classification is apprehended by comparing the similarity between the estimated distributions of all detail sub bands through the strong LPboosting classification with various weak classifier configurations. We show that the resulted texture features while incurring the maximum of the discriminative information. Our hybrid classification method significantly outperforms the existing texture descriptors and stipulates classification accuracy in the state-of-the-art real world imaging applications.*

Keywords: LPboost Classifier, Shearlet Transform, Gabor Filters, Texton Co-occurrence Matrix, Weak Classification

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1. Introduction

The annotation and requirement of texture content of the features to analyze the description of image is the effective method to classify the texture regions in multimedia technology. The process of isolating an image into various morphologically unique components analyzed with many scientific algorithms. The extraction of features in the image is based on the type of pattern to classify that involves low-level feature extraction through image descriptors such as shape, color and texture. There are many types of transformation such as wavelet, Curvelet, Fourier, discrete cosine transform and the discrete shearlet transformation to decompose the images into collection of sub bands. The neighboring gray level dependence matrix (NGLDM) is the initial method presented for computation of texture based on its spatial rotation in [1]. Another featureextraction method that based on features developed from the random field models with the maximum likelihood estimation (MLE) that act log-linear model for classifying the texture image in [2]. Similarly, the random field's concept applied in the remote sensing data by using Gaussian Markov random fields (GMRF) models in [3]. It is noted that the accuracies level is much improved by achieving through the simple minimum distance classifiers. The cooccurrence matrices based the sum and difference histograms of the texture image used to correlate the texture analysis in [4]. It showed that it reduce computation time and achieve higher accuracies in classification. The mathematical inner product space function named as rotational invariance applied in texture classification with the test and training samples based on the interpretation of texture image through its roughness. The texture analysis based on the texture spectrum through the application of grey level co-occurrence matrix (GLCM) approach that introduced a new concept for measuring the textural information known as texture unit in [6]. There are various existing approaches that are complicated such as second-order statistics, local linear descriptor transform. Gauss-Markov random fields or It discards the templates of internal frequency varying regions. The spatial filter banks such as Gabor, S-filter and Gaussian fails to correlate the texture features for evaluating the features. The evaluation result shows an effective in discriminating the performance of the texture spectrum by improving the spatial resolution in satellite image data for the remote sensing application. similarly, the radon transformation applied in the curvelet transformation for the Synthetic-aperture radar (SAR) images for speckle reduction through threshold coefficients of the sub band image. It yields accurate localization at higher computational cost. The DST and DWT are the pioneered method in decomposing the image for extracting the vital information. The combinations of shearlet and wavelet transform are used in this proposed method. It acts as a tool for processing the multi-dimensional data. [8-10].The proposed approach initially filter the texture image through the gabor filtering method and then it map the patterns named as "*texton*" in the texture image for effective classification that explained. The the hybrid of DST and DWT applied for effective decomposition of image in various sub bands to extract the information. Finally, the sub bands of various information discriminating in the Brodatz album based on feature extraction and then it undergoes classification with the minimax theory based LPboost classifier the accuracy of this system very well compared to other state of art techniques.

2. Gabor Filtering

Gabor filters to extract textures of different sizes and orientations (i.e. Gabor-based texture feature). A Gabor filter is defined by a twodimensional Gabor function, $g\,(x, y)$:

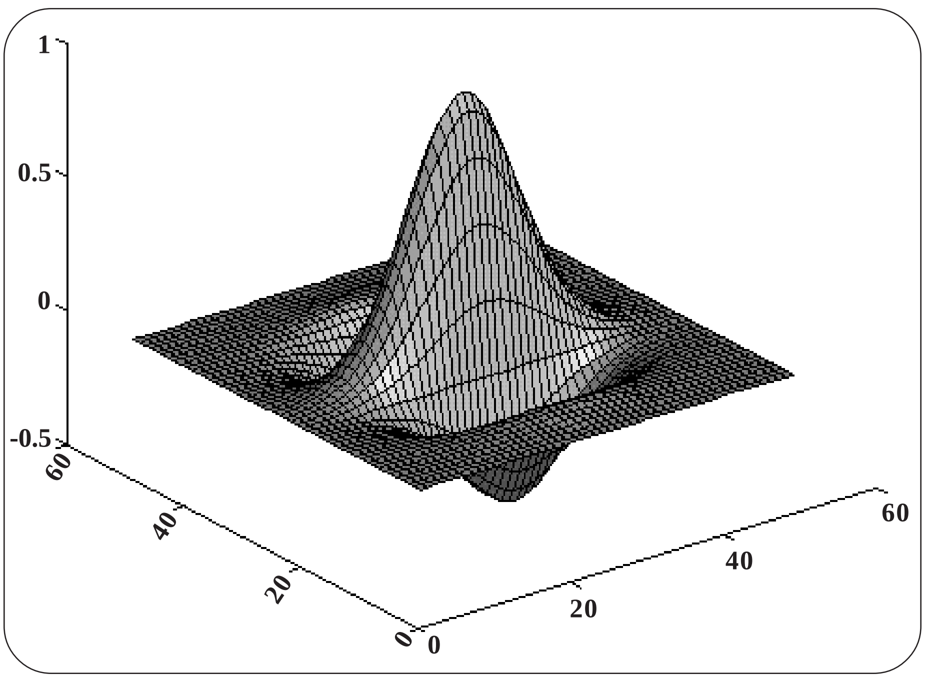

Figure 1. Real component of the 2-D Gabor function

$$g\,(x, y) = \left(\frac{1}{2\pi\sigma_x\sigma_y}\right) exp\left[-\frac{1}{2}\left(\frac{x^2}{\sigma_x^{\,2}}+\frac{y^2}{\sigma_y^{\,2}}\right)+2\pi jWx\right] \quad (1)$$

where σ_x and σ_y denote the scaling parameters of the filter in the horizontal (x) and vertical (y) directions, and W denotes central frequency of the filter. The Fourier transform of the Gabor function $g\,(x, y)$ is defined as:

$$G(u,v) = exp\left[-\frac{1}{2}\left(\frac{(u-W)^2}{\sigma_u^{\,2}}+\frac{v^2}{\sigma_y^{\,2}}\right)\right] \quad (2)$$

$$\text{where } \sigma_u = 1/2\pi\,\sigma_x \text{ and } \sigma_v = 1/2\pi\,\sigma_y$$

The Gabor filters can be obtained by dilations and rotations of $G(x, y)$ following a class of functions defined in:

$$g_{mn}(x, y) = a^{-m} G(x', y'),\ a > 1,\ m, n = \text{integer}$$
$$x' = a^{-m}(x\cos\theta + y\sin\theta),\ \text{and}\ y' = a^{-m}(-x\sin\theta + y\cos\theta) \tag{3}$$

where θ is the orientation of the wavelet and is defined by $\theta = n\pi / K$, and K denotes the total number of orientations. We generated six different orientations of Gabor filters ($K = 6$). The size of the filter is defined by a and m in Equation 3. These Gabor filters transformed the region $I(x, y)$ into $X_{mn}(x, y)$:

$$X_{mn}(x, y) = \int I(x_1, y_1) * (x - x_1, y - y_1)\, dx_1\, dy_1 \tag{4}$$

where * denotes the complex conjugate. Assuming that the local regions are spatially homogeneous, we can use the mean, u_{mn}, and standard deviation of these regions, σ_{mn}, as textural features.

$$\mu_{mn} = \int\int |W_{mn}(xy)|\, dxdy$$
$$\sigma_{mn} = \sqrt{\iint (|W_{mn}(xy)| - \mu_{mn})^2\, dxdy} \tag{5}$$

The general form of 2D Gabor wavelet with an identical modulation frequency of ω at both x and y directions and shift of m_x and m_y at x and y directions respectively can be as the product of Gabor wavelet in x and y directions.

Note σ plays the role of scaling factor and m role of shift parameter.

3. Texton co-occurrence matrix

The process of obtaining mapping the texton template patterns [11] to generate the pair wise term co-occurrences. Let N denote the number of different terms in the texture image. While the term co-occurrence matrix is an $N \times N$ symmetric matrix and assuming that term w appears independently from frequent terms (denoted as G), the distribution of co-occurrence of term w and the frequent terms is similar to the unconditional distribution of occurrence of the frequent terms. Conversely, if term w has a semantic relation with a particular set of terms $g \in G$, co-occurrence of term w and g is greater than expected, the distribution is said to be biased. The degree of bias of co-occurrence can be used as a indicator of term importance. However, if term frequency is small, the degree of biases is not reliable. The overall combination of the proposed system diagram is given in Figure 1. In a gray level image, the texton co-occurrence matrix (TCM) differentiates the features of pixel based on the interrelation to the textons. Let g be the unit vector corresponding to the G of the gray level in the image, then the following vectors co-ordinate with the function $f(x, y)$ [11]:

$$u = \frac{\partial G}{\partial x} g \tag{6}$$

To identify the texton in the original image, the texton templates are morphed the input image on various texton locations that generate the five unique combinations of texton component images. Finally, the component images are combined together into texton identified image by enumerating the boundary for all morphed regions that shown in Figure 3. The texton image T with the adjacent pixels $P_1 = (x_1, y_1)$ as well as $P = (x_2, y_2)$ and its corresponding weight of

$$v = \frac{\partial G}{\partial x} g \tag{7}$$

The dot products to the above vectors are given below:

$$g_{xx} = u^T u = \left|\frac{\partial G}{\partial x}\right|^2 \tag{8}$$

$$g_{yy} = v^T v = \left|\frac{\partial G}{\partial y}\right|^2 \tag{9}$$

$$g_{xy} = u^T v = \frac{\partial G}{\partial x} \bullet \frac{\partial G}{\partial y} \tag{10}$$

The $\theta(x, y)$ is the direction that changes with the vectors:

$$\theta(x,y) = \frac{1}{2}\tan^{-1}\left[\frac{2g_{xy}}{g_{xx}-g_{yy}}\right] \tag{11}$$

To identify the value ranges $C(x, y)$ from lower value to higher value of 0 to 255, the $G(x, y)$ is given below:

$$G(x,y) = \frac{1}{2}[(g_{xx}+g_{yy})] + [(g_{xx}-g_{yy})]\cos 2\theta + 2g_{xy}\sin 2\theta]\}^{\frac{1}{2}} \tag{12}$$

the pixels are $T(P_1) = w_1$ and $T(P_2) = w_2$. Similarly, the orientation angle of the image indicated as $\theta\ (P_1) = v_1$ and $\theta\ (P_2) = v_2$.Then, the group of texton image are undergoes to shearlet transform that decompose the image. The below matrix diagram shows the combination transition matrix that overlaps with the adjacency matrix. It exploits the texture image is overlapped by the different sets of texton template and the corresponding vertices generated through it for effective classification.

Adjacency Matrix:

$$\begin{array}{c|ccccccc|}
 & a & b & c & d & e & f & g \\
\hline
a & 0 & 1 & 1 & 1 & 1 & 1 & 1 \\
b & 1 & 0 & 1 & 0 & 1 & 0 & 1 \\
c & 1 & 1 & 0 & 0 & 0 & 1 & 1 \\
d & 1 & 0 & 0 & 0 & 1 & 1 & 1 \\
e & 1 & 1 & 0 & 1 & 0 & 1 & 0 \\
f & 1 & 0 & 1 & 1 & 1 & 0 & 0 \\
G & 1 & 1 & 1 & 1 & 0 & 0 & 0
\end{array}
\qquad
\begin{array}{c|ccccccc|}
 & a & b & c & d & e & f & g \\
\hline
a & 0 & 1/6 & 1/6 & 1/6 & 1/6 & 1/6 & 1/6 \\
b & 1/4 & 0 & 1/4 & 0 & 1/4 & 0 & 1/4 \\
c & 1/4 & 1/4 & 0 & 0 & 0 & 1/4 & 1/4 \\
d & 1/4 & 0 & 0 & 0 & 1/4 & 1/4 & 1/4 \\
e & 1/4 & 1/4 & 0 & 1/4 & 0 & 1/4 & 0 \\
f & 1/4 & 0 & 1/4 & 1/4 & 1/4 & 0 & 0 \\
G & 1/4 & 1/4 & 1/4 & 1/4 & 0 & 0 & 0
\end{array}$$

Vertices:

a	**b**	**c**	**d**	**e**	**f**	**g**
1 1 1 0	1 1 0 1	1 0 1 1	0 1 1 1	1 1 0 1	1 0 1 1	0 1 1 1
0 0 0 1	0 0 0 1	0 0 0 1	1 0 0 0	0 0 1 0	0 1 0 0	0 0 0 1
0 0 0 1	0 0 1 0	0 1 0 0	0 0 0 1	0 0 0 1	0 0 0 1	1 0 0 0

4. Discrete Shearlet Transform

The most significant step of any classification system is feature extraction. A new shearlet band signature, entropy is proposed based on discrete shearlet transform introduced. The group of $N*N$ database image that derived from the above texton sub space image. It consists of a finite sequence of values, $\{x[n_1, n_2]_{n_1, n_2=0}^{N-1, N-1}\}$ where $N \in \mathbb{N}$ Identifying the domain with the finite group $\mathbb{Z}_N^2$, the inner product of image x , y: $\mathbb{Z}_N^2 \rightarrow \mathbb{C}$ is defined as

$$(x, y) = \sum_{u=0}^{N-1}\sum_{v=0}^{N-1} x(u,v)\ \overline{y(u,v)} \tag{13}$$

Thus the discrete analog of $L^2(\mathbb{R}^2)$is $\mathbb{Z}_N^2$. Given an image $f \in l^2\mathbb{Z}_N^2$, $\hat{f}[k_1, k_2]$ let denote its 2D Discrete Fourier Transform (DFT):

$$\hat{f}[k_1, k_2] = \frac{1}{N}\sum_{n1,\, n2=0}^{N-1} f[n_1, n_2]\, e^{-2\Pi i\,(\frac{n1}{N}k1 + \frac{n1}{N}k2)} \tag{14}$$

The brackets in the equations [· , ·] denote arrays of indices, and parentheses [·,·] denote function evaluations. Then the interpretation of the numbers $\hat{f}[k_1, k_2]$ as samples $\hat{f}[k_1, k_2] = \hat{f}[k_1, k_2]$ is given by the following equation from the trigonometric polynomial.

$$\hat{f}(\xi_1, \xi_2) = \sum_{n1,\, n2=0}^{N-1} f[n_1, n_2]\, e^{-2\Pi i\,(\frac{n1}{N}\xi_1 + \frac{n1}{N}\xi_2)} \tag{15}$$

First, to compute

$$\hat{f}(\xi_1, \xi_2)\ \overline{V(2^{-2j}\xi_1, 2^{-2j}\xi_2)} \tag{16}$$

The most significant step of any classification system is feature extraction. A new shearlet band signature, entropy is proposed based on discrete shearlet transform introduced by Glenn Easley [13]. The wavelet series expansion of function $f(x) \in L^2(R)$

relative to wavelet $\psi(x)$ and scaling function $\phi(x)$. We can write

$$f(x) = \sum_k c_{j0}(k)\, \phi_{j0,k}(x) + \sum_{j=j0}^{\infty} \sum_k d_j(k)\, \psi_{j,k}(x) \tag{17}$$

where j_0 is an arbitrary starting scale and the $C_{j0}(k)$ are normally called the approximation or scaling coefficients, the $d_j(k)$ are called the detail or wavelet coefficients. The expansion coefficients are calculated as

$$C_{j0}(k) = \langle f(x), \tilde{\phi}_{j0,k}(x) \rangle = \int f(x)\, \tilde{\phi}_{j0,k}(x)\, dx \tag{18}$$

$$d_j(k) = \langle f(x), \tilde{\psi}_{j,k}(x) \rangle = \int f(x)\, \tilde{\psi}_{j,k}(x)\, dx \tag{19}$$

If the function being expanded is a sequence of numbers, like samples of a continuous function $f(x)$. The resulting coefficients are called the discrete wavelet transform (DWT) of $f(x)$. Then the series expansion defined in Equations **Error! Reference source not found. and Error! Reference source not found**. becomes the DWT transform pair

$$W_\phi(j_0, k) = \frac{1}{\sqrt{M}} \sum_{x=0}^{M-1} f(x)\, \tilde{\phi}_{j0,k}(x) \tag{20}$$

$$W_\psi(j, k) = \frac{1}{\sqrt{M}} \sum_{x=0}^{M-1} f(x)\, \tilde{\psi}_{j,k}(x) \tag{21}$$

For $j \geq j_0$ and

$$f(x) = \frac{1}{\sqrt{M}} \sum_k W_\phi(j_0, k)\, \phi_{j0,k}(x) + \frac{1}{\sqrt{M}} \sum_{j=j0}^{\infty} \sum_k W_\psi(j,k)\, \psi_{j,k}(x) \tag{22}$$

where $f(x)$, $\phi_{j0,k}(x)$, and $\psi_{j,k}(x)$ are functions of discrete variable $x = 0, 1, 2, ..., M-1$.

5. Strong LPboost Classifier

The boosting classifier optimizes the classification based on edges "γ". The LPboost strong classifier focus on the weak classifier for the extracted features based on the shearlet transform relative entropy. It bounds as the edges of the strong classifier in which "γ" are lesser for minimum edges based on the convergence rate. The distributions of the edge margin are linear for training the set of images based on the similar features. The entropy regularized parameters for the feature vector, η to update the distribution clearly.

6. Experimental Results

The performance evaluations of the proposed texture classification system are identified. From each original image, 128x128 pixel sized images are extracted with an overlap of 32 pixels between vertical and horizontal direction. From a single 640×640 texture image, 256 128×128 images are obtained. To carry out the proposed algorithm, 81 images are randomly selected from the 256 images. Among the 81 images, 40 images are randomly chosen to train the classifier and the remaining images are used to test the classifier. By applying the TCM, the sub band of decomposition transform sequence is identified very accurately. It iterated at various levels for uniformly decompose the images into equally spatial blocks. The Brodatz test images are divvied into various classes to generalize the texture classification experiment. The discriminate functions based on the LPboosting classification reduce the redundancy and misclassification. The classification rates abruptly increases as the training sets feature increases. It predominantly shows the efficient classification in the training images. Similarly, the collection of test images which identified by the subset homogenous pattern for classification. It improves the calculation and classification performance

7. Conclusion

In this study, the combination of texton cooccurrence matrix with shearlet band signatures based texture classification of 40 Brodatz texture images is presented. The feature extraction done more effectively and the sub-band are analyzed through the entropy measures and it undergoes for classification through LPboosting which provokes on weak classifier as the training images and then used to classify the testing imagesThe proposed system consistently achieves over 99.85% classification accuracy which is 0.16% higher than existing methods for accurate classification Experimental results show that the proposed

TCM based DST outperforms Wavelet and Gabor transform based classification systems.

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