ROTATION IN Variant TEXTURE CLASSIFICATION BASED ON A DIRECTIONAL FILTER BANK

Rong Duan, Hong Man and Ling Chen

Department of ECE, Stevens Institute of Technology
Hoboken, NJ 07030,
{rduan, hman, lchen}@stevens-tech.edu

ABSTRACT

This paper presents a rotation invariant texture classification method using a special directional filter bank (DFB). The new method extracts a set of coefficient vectors from directional subband domain, and models them with multivariate Gaussian density. Eigen-analysis is then applied to the covariance metrics of these density functions to form rotation invariant feature vectors. Classification is based on the distance between known and unknown feature vectors. Two distance measures are studied in this work, including the Kullback-Leibler distance and the Euclidean distance. Experimental results have shown that this DFB is very effective in capturing directional information of texture images, and the proposed rotation invariant feature generation and classification method can in fact achieve high classification accuracy on both non-rotated and rotated images.

1. INTRODUCTION

Texture classification is a fundamental building block of image analysis that is frequently applied in a variety of important applications, such as target recognition, robotic vision, image/video indexing and retrieval, and data mining etc. Texture classification has been an active research topic for several decades. However effective and efficient classification of rotated texture images remains to be a challenge. A number of methods for rotation invariant texture classification have been proposed [1], and most interests lie on rotation invariant feature extraction. Madiraju and Liu [2] proposed a method using eigen-analysis of local covariance of image blocks to obtain six rotation invariant features representing roughness, anisotropy and other high-order texture characteristics. Charalampidis and Kasparis [3] also introduced roughness features in directional wavelet domain based on fractal dimension (FD). The directional wavelet is implemented as linear combination of two orthogonal wavelets, which is referred to as "steerable wavelet". Steerable wavelet is also studied by Do and Vetterli in [4], in which a Gaussian hidden Markov tree (HMT) is used to model cross-scale wavelet coefficients. Rotation invariance is achieved by replacing covariance matrices in HMT parameter set with matrices of eigenvalues. Porter and Canagarajah [5] introduced a wavelet domain feature using circularly symmetric Gaussian Markov random field (GMRF) model for rotation invariance.

In this paper, we present a texture classification method based on the special properties of a unique directional filter bank (DFB) for feature generation. This DFB was developed by Bamberger [6] and improved by Park [7] to obtain visualizable subband domain representation.

2. DIRECTIONAL FILTER BANK

The directional filter bank [7] is able to partition the frequency plane into a set of equal-sized wedge-shaped passbands, as shown in Fig 1(a). It can be implemented efficiently through a series of two-band subband decompositions. At each stage of the two-band decomposition, two complementary fan filters are applied, and a special downsampling matrix Q is used to take samples lying on a quincunx lattice for the output. The fan filters at different stages are implemented through two different procedures. For the first two decomposition stages, the structure of the filter bank is shown in Fig 1(b), and for the following stages, the structure of the filter bank takes the form shown in Fig 1(c). In these structures, \( H_0(\omega) \) is a diamond filter and \( H_1(\omega) \) is its complement; Q represents a...
quincunx downsampling matrix. MOD in Fig 1(b) corresponds to a modulation of the input by \( \pi \) on either \( n_1 \) or \( n_2 \) direction in spatial domain, which shifts the diamond shape passband to fan shape passbands. In Fig 1(c), \( R \) represents a unitary frequency resampling (skewing) matrix that can reshape a diamond passband into different parallelogram passbands, and together with the passbands in the previous stages these will produce wedge-shaped passbands. After quincunx downsampling \( Q \) each directional subband takes shape of a rectangle. In traditional filter bank decomposition, each subband maintains the original image structure. With this DFB, the resampling matrix and the quincunx downsampling matrix causes the content of each subband skewed and rotated. A backsampling matrix \( B \) is therefore introduced in Fig 1(c) [7] to compensate this distortion and rearrange the subband coefficients so that each subband becomes visually proportional to the original image with only exception of ration aspect. Fig 2 provides examples of an eight-band DFB decomposition of the image STRAW at two rotation angles.

In texture analysis, discriminative information usually resides in high frequency regions. Although this DFB provides good directional resolution, it does not provide frequency resolution. Each subband covers the whole frequency spectrum. To avoid negative impact of low frequency variations, we apply a highpass prefiltering before the DFB.

3. FEATURE GENERATION IN DIRECTIONAL SUBBAND DOMAIN

Texture classification based on the directional filter bank was first reported in [8], in which the distribution of directional subband coefficients are modelled as zero-mean Gaussian density, and a variance is extracted from each subband to form the feature vector. For an eight-band decomposition, each image is represented by a vector of eight variance values. The conditional distribution of the feature vectors from each class is assumed to be a multivariate Gaussian density, with a mean vector and a covariance matrix that will not be affected by any rotation of the multivariate Gaussian density.

Based on this observation, we realize that the principal axes of the multivariate Gaussian density can be a good candidate for rotation invariant feature. The lengths of these principal axes are the eigenvalues of the covariance matrix, and if these eigenvalues are sorted according to their values, they can form a feature vector that will not be affected by any rotation of the multivariate Gaussian density.

An N-dimensional multivariate Gaussian density function has the form of

\[
p(x) = \frac{1}{(2\pi)^{N/2}|C|^{1/2}} \exp\left(-\frac{1}{2}(x - \mu)^T C^{-1} (x - \mu)\right),
\]

where \( x \) is the observation vector, \( \mu \) is the mean vector, and \( C \) is the covariance matrix. Then according to eigen decomposition theorem, the covariance matrix can be decomposed into the form

\[
C = U \Lambda U^T,
\]

where columns of \( U \) are the normalized eigenvectors of \( C \), and \( \Lambda \) is a diagonal matrix containing the corresponding eigenvalues \( \lambda_i \) for \( i = 1, \ldots, N \). The eigenvalues are sorted in descending order, and each of them representing the variance of the multivariate density along a principle axis determined by the corresponding eigenvector. The column vector \( v = [\lambda_1, \lambda_2, \ldots, \lambda_N]^T \) is then used as the feature vector to represent one particular image.

A further advantage of this feature vector is that its size can be easily reduced by keeping only a few largest eigenvalues, i.e. principle components, can still properly represent an image with less amount of information. This approach can effectively reduce the computation at both training and testing phases.

4. FEATURE CLASSIFICATION METHODS

In this work we implement two classifiers based on two popular distance measures. The Kullback-Leibler Distance (KLD) is com-
monly used to measure the distance between two probability density functions $p_i(x)$ and $p_j(x)$. In general it is defined in the form of "relative entropy",

$$D(p_i(x)||p_j(x)) = - \int p_i(x) \log \frac{p_j(x)}{p_i(x)} dx$$  \hspace{1cm} (3)

For two N-dimensional Gaussian pdfs, a close form expression of the KLD is given in [9],

$$D(p_i(\cdot; \mu_i, C_i)||p_j(\cdot; \mu_j, C_j)) = \frac{1}{2} \left[ \log \frac{\det C_j}{\det C_i} - N + \text{tr}(C_j^{-1} C_i) + (\mu_i - \mu_j)^T C_j^{-1} (\mu_i - \mu_j) \right],$$  \hspace{1cm} (4)

where $\mu_i, \mu_j$ are mean vectors, and $C_i, C_j$ are covariance matrices of the two Gaussian pdfs. According to our definition of feature vector, we essentially model each image with an N-dimensional Gaussian pdf with zero mean and no correlation among variables, as a result of the eigen-analysis. Therefore the KLD can be further simplified as

$$D(p_i(\cdot; C_i)||p_j(\cdot; C_j)) = \frac{1}{2} \sum_{k=1}^{N} \left( \frac{\lambda_{ik}}{\lambda_{jk}} - \log \frac{\lambda_{ik}}{\lambda_{jk}} \right) - \frac{N}{2},$$  \hspace{1cm} (5)

where $\lambda_{ik}$ and $\lambda_{jk}$ are the elements of the covariance matrices $C_i$ and $C_j$ for $k = 1, \ldots, N$.

To compare with the KLD, we also use the Euclidean distance in the test. Classification is based on the distance of two N-dimensional feature vectors $v_i$ and $v_j$,

$$D(v_i||v_j) = \sum_{k=1}^{N} (v_{ik} - v_{jk})^2,$$  \hspace{1cm} (6)

where $v_{ik}$ and $v_{jk}$ are the elements of the feature vectors $v_i$ and $v_j$ for $k = 1, \ldots, N$.

With the KLD or Euclidean distance, the classifiers are based on the nearest neighbor rule.
overlapping small images with size of ing and testing images, we partition each image into sixteen non-

representative structure.

containing heterogeneous texture, or image with no sufficient rep-

tations. It should be noted that we used all the images at all the

weave, our methods work remarkably well on all different orien-

tures with strong directional structures, e.g. bark, grass, straw and

ods achieve significant improvement on rotated images. For tex-

gles over all thirteen classes. It is clear that our proposed meth-

ods on images over all seven different angles. And Table

and classification method introduced in [8], and we applied the

feature vectors.

the 16-dimensional feature vectors. The second uses KLD on the

32

subbands, we split each subband into two

or

σ

pass filter with

9

ter to eliminate the effect of DC component. The highpass filter

images.

0

the

of which eleven training images are randomly chosen solely from

16

for each of the seven rotation angles, i.e.

o

,

30

, 90

, 120

, and 200

. In order to obtain sufficient number of train-

and testing images, we partition each image into sixteen non-

overlapping small images with size of 128 × 128. Therefore for

each of the thirteen classes we have 16 × 7 = 112 images, out

of which eleven training images are randomly chosen solely from the

0

(or non-rotated) images, and all the rest are used as testing

images.

Each 128 × 128 images is first passed through a highpass fil-

ter to eliminate the effect of DC component. The highpass filter is a complement of a 9 × 9 rotationally symmetric Gaussian low-

pass filter with \( \sigma = 2 \). The resulting image is then filtered by an

eight-band DFB, producing eight subbands with sizes of 64 × 32

or 32 × 64 as shown in Figure 2. In order to unify the sizes of subbands, we split each subband into two 32 × 32 small subbands

using subsampling. So totally there are sixteen such subbands for

each input image. Then a 16-dimensional feature vectors is calcu-

lated according to our feature generation method in Section 3.

Three classifiers are implemented. The first applies KLD on the

16-dimensional feature vectors. The second uses KLD on the

simplified 8-dimensional feature vectors, each of which contains

the largest eight components from a 16-dimensional feature vec-

tor. The third calculates Euclidean distance on the 16-dimensional

feature vectors.

For comparison, we also implemented the feature generation and classification method introduced in [8], and we applied the

same test conditions as used in our methods.

Table 1 shows the average classification results from various methods on images over all seven different angles. And Table

2 shows the average classification results for seven different an-

gles over all thirteen classes. It is clear that our proposed meth-

ods achieve significant improvement on rotated images. For tex-

tures with strong directional structures, e.g. bark, grass, straw and

weave, our methods work remarkably well on all different orienta-

tions. It should be noted that we used all the images at all the

rotation angles in these tests. We did not take away any image

containing heterogeneous texture, or image with no sufficient rep-

resentative structure.

<table>
<thead>
<tr>
<th>texture</th>
<th>KLD-16</th>
<th>KLD-8</th>
<th>Euclidean-16</th>
<th>[8]</th>
</tr>
</thead>
<tbody>
<tr>
<td>bark</td>
<td>0.9307</td>
<td>0.9406</td>
<td>0.8020</td>
<td>0.5644</td>
</tr>
<tr>
<td>brick</td>
<td>0.2475</td>
<td>0.1485</td>
<td>0.0690</td>
<td>0.0300</td>
</tr>
<tr>
<td>bubble</td>
<td>0.8515</td>
<td>0.8911</td>
<td>0.9010</td>
<td>0.6039</td>
</tr>
<tr>
<td>grass</td>
<td>0.9109</td>
<td>0.8911</td>
<td>0.8713</td>
<td>0.6634</td>
</tr>
<tr>
<td>leather</td>
<td>0.6535</td>
<td>0.7921</td>
<td>0.8119</td>
<td>0.3267</td>
</tr>
<tr>
<td>pigskin</td>
<td>0.4951</td>
<td>0.3267</td>
<td>0.5545</td>
<td>0.1584</td>
</tr>
<tr>
<td>raffia</td>
<td>0.3762</td>
<td>0.2475</td>
<td>0.3465</td>
<td>0.1683</td>
</tr>
<tr>
<td>sand</td>
<td>0.8515</td>
<td>0.8416</td>
<td>0.8713</td>
<td>0.9010</td>
</tr>
<tr>
<td>straw</td>
<td>0.9505</td>
<td>0.8317</td>
<td>0.7822</td>
<td>0.4158</td>
</tr>
<tr>
<td>water</td>
<td>0.7129</td>
<td>0.6435</td>
<td>0.5347</td>
<td>0.0396</td>
</tr>
<tr>
<td>weave</td>
<td>0.9505</td>
<td>0.9208</td>
<td>0.9406</td>
<td>0.0396</td>
</tr>
<tr>
<td>wood</td>
<td>0.7624</td>
<td>0.5149</td>
<td>0.6535</td>
<td>0.0495</td>
</tr>
<tr>
<td>wool</td>
<td>0.5644</td>
<td>0.7228</td>
<td>0.6733</td>
<td>0.1188</td>
</tr>
</tbody>
</table>

Table 1. Classification performance of rotated texture images aver-

ged over all seven different angles.

5. EXPERIMENTAL RESULTS

The Brodatz texture dataset [10] is used in our experiments. It contains thirteen classes of texture images with size of 512 × 512.

Each class was from a single texture photo, which was digitized for each of the seven rotation angles, i.e. 0°, 30°, 60°, 90°, 120°, 150° and 200°. In order to obtain sufficient number of train-

and testing images, we partition each image into sixteen non-

overlapping small images with size of 128 × 128. Therefore for

each of the thirteen classes we have 16 × 7 = 112 images, out

of which eleven training images are randomly chosen solely from the

0° (or non-rotated) images, and all the rest are used as testing

images.

In this paper we have presented a new rotation invariant feature generation method based on the directional filter bank. For each

image, the subband coefficients are modelled as a multi-variate Gaussian density, and the feature vector contains the eigenval-

ues of the covariance matrix. Three classifiers are implemented based on different distance measures. Experimental results clearly

demonstrated the possible performance improvement over an ex-

isting feature generation method based on the same filter bank.

6. CONCLUSION

In Table 2. Classification performance of images at different rotation

angles averaged over all thirteen classes.

angles.

0

 Rotation | KLD-16 | KLD-8 | Euclidean-16 | [8] |
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0°</td>
<td>0.8923</td>
<td>0.8769</td>
<td>0.8150</td>
<td>0.8000</td>
</tr>
<tr>
<td>30°</td>
<td>0.8173</td>
<td>0.7644</td>
<td>0.7355</td>
<td>0.3400</td>
</tr>
<tr>
<td>60°</td>
<td>0.7692</td>
<td>0.5961</td>
<td>0.5865</td>
<td>0.2010</td>
</tr>
<tr>
<td>90°</td>
<td>0.6923</td>
<td>0.7039</td>
<td>0.7130</td>
<td>0.2500</td>
</tr>
<tr>
<td>120°</td>
<td>0.4711</td>
<td>0.5433</td>
<td>0.7020</td>
<td>0.2060</td>
</tr>
<tr>
<td>150°</td>
<td>0.6250</td>
<td>0.5481</td>
<td>0.6200</td>
<td>0.3120</td>
</tr>
<tr>
<td>200°</td>
<td>0.8413</td>
<td>0.8029</td>
<td>0.7548</td>
<td>0.4180</td>
</tr>
</tbody>
</table>

Table 2. Classification performance of images at different rotation

angles averaged over all thirteen classes.

7. REFERENCES


[10] S. Uni. Southern California and I. P. Institute, "Rotated tex-