Invariant Texture Classification Using Ridgelet Packets

G. Y. Chen and P. Bhattacharya
Concordia Institute for Information Systems Engineering,
Concordia University,
1455 De Maisonneuve West,
Montreal, Quebec, Canada H3G 1M8.
Email: {guang_c@cs.concordia.ca, prabir@ciise.concordia.ca.}

Abstract

In this paper, we propose a novel rotation invariant texture classification technique by using ridgelet packets. Ridgelet packets provide many orthonormal bases that can effectively capture directional features present in textures. The Fourier transform is good at eliminating the texture orientation differences. By combining these two tools, a very efficient rotation invariant texture classification technique is created. Experimental results show that the proposed method achieves very high classification rates and it outperforms two state-of-the-art methods for rotation invariant texture classification under both noise-free and noisy environments.

Keywords - Ridgelets, ridgelet packets, Fourier transform, feature extraction, texture classification.

1 Introduction

Texture classification has played an important role in many real life applications such as remote sensing, medical imaging, industrial inspection, image retrieval, document segmentation, etc. ([11] - [14]). Among all existing texture classification techniques, one very promising class of methods is to classify textures in the presence of different texture orientations. However, most of the proposed techniques assume that the texture has the same orientation, which is not always the case. In recent years, rotation invariant texture classification techniques have been the focus of interest, and many promising methods have been developed. However, the current available rotation invariant texture classification techniques still need improvement. Therefore, it is desirable to develop new rotation invariant texture classification techniques that have the potential to achieve higher classification rate.

In this paper, we investigate a new rotation texture classification technique by using ridgelet packets. Ridgelet packets are a better tool for the extraction of features based on line singularities as compared to point singularities as in the case of wavelets. Based on this observation, important features can be extracted so that better texture classification results can be achieved compared to the standard wavelet packet approach. We use the Fourier transform to eliminate the orientation difference in textures. Experimental results show that the proposed method achieves very high classification rate and it outperforms two previously developed methods for classifying both noise-free and noisy textures.

The organization of the paper is as follows. In section 2, we review the ridgelet transform and ridgelet packets. In section 3, we propose a rotation invariant texture classification technique by using ridgelet packets. In section 4, we conduct some experiments in order to demonstrate the effectiveness of the proposed method. Finally, in section 5 we draw the conclusions and give future work to be done.

2 The Ridgelet Transform and Ridgelet Packets

The ridgelet transform provides near-ideal sparsity of representation for smooth objects and objects with edges. It has been successfully applied in such applications as image processing and pattern recognition ([15] - [20]). For each \( a > 0 \), each \( b \in R \) and each \( \theta \in [0, 2\pi) \), the bivariate ridgelet \( \psi_{a,b,\theta} : R^2 \rightarrow R \) is defined as

\[
\psi_{a,b,\theta} = a^{-1/2} \psi((x_1 \cos \theta + x_2 \sin \theta - b)/a).
\]

where \( \psi(\cdot) \) is a wavelet function. A ridgelet is constant along the lines \( x_1 \cos \theta + x_2 \sin \theta = \text{constant} \). Transversing to these ridges it is a wavelet. Given an integrable bivariate image \( f(x_1, x_2) \), we can define its ridgelet coefficients as

\[
R(a, b, \theta) = \int \psi_{a,b,\theta} f(x_1, x_2) dx_1 dx_2.
\]
The ridgelet transform can be represented in term of the Radon transform. The Radon transform of an image \( f(x_1, x_2) \) is defined as

\[
RA(\theta, t) = \int f(x_1, x_2) \delta(x_1 \cos \theta + x_2 \sin \theta - t) dx_1 dx_2
\]

where \( \delta \) is the Dirac distribution. So the ridgelet transform is precisely the application of a 1-D wavelet transform to the slices of the Radon transform where the angular variable \( \theta \) is constant and \( t \) is varying. Ridgelets are different from wavelets in a sense that ridgelets exhibit very high directional sensitivity and are highly anisotropic.

The ridgelet packets library provides a large number of orthonormal bases [20]. Many of these bases align along specified ridges, making them very successful in extracting directional features. There are two ways to construct ridgelet packets: the frequency domain approach and the Radon domain approach. For the frequency domain approach, we can take a recursive dyadic partition of the polar Fourier domain into a collection of rectangular tiles with various widths and length. A wavelet can be applied in the ridge direction and a localized sinusoid in the traverse direction. For the Radon approach, we can take a 1-D wavelet packet in the ridge direction first. Since the spectrum magnitude of the 1-D Fourier transform is the same no matter how the signal is shifted, we take another 1-D Fourier transform in the traverse direction. In this way, we can extract rotation invariant features for effective rotation invariant texture classification. Note that the Radon approach given here is different from [20]. This is because our approach is well suited for extracting invariant features for texture classification.

3 Invariant Texture Classification by Using Ridgelet Packets

In this section, we propose a rotation invariant texture classification technique by using ridgelet packets. The Radon transform can be obtained by summing all the intensity values of those pixels that are within the circle tangent to boundaries of the square texture and on the line that is perpendicular to the ridge. The radial variable in the Radon domain is discretized using the same dimension as the diameter of the circle, and we select twice the dimension for the angle variable \( \theta \). We arrange the Radon slices in counterclockwise direction in terms of \( \theta \). Therefore, the same slice is saved twice: one in the normal order for orientation \( \theta \) \((0 \leq \theta < \pi)\) and the other one in reverse order for \( \theta + \pi \). After storing the slices in this way, we can only get circularly shifted rows for the Radon slice matrix no matter how the texture image is rotated. We apply a 1-D wavelet packet transform along the ridge direction so that we can have a multiresolution representation of the texture. In practical texture classification applications, only a few intermediate frequency wavelet subbands are frequently used in order to achieve high classification rates. Since the wavelet subbands could be circularly shifted along the angle direction, we perform a 1-D Fourier transform in the angle direction and take the spectrum magnitude. In this way, we have extracted rotation invariant features for the texture we are currently considering.

The steps of operations of the proposed method can be described as follows:

1. For texture of size \( n \times n \), discard all those pixels that are outside the surrounding circle with center \((n/2, n/2)\) and radius \( n/2 \).
2. Project the pattern in different orientations to get the Radon transform coefficients.
3. Perform a 1-D wavelet packet transform along the ridge direction.
4. Conduct a 1-D Fourier transform along the angle direction for each wavelet subband and get the Fourier spectrum magnitude of every subband.
5. Save these ridgelet packet features into the feature database.

The main advantages of our proposed texture classification technique are that we project the pattern onto different orientation slices so that important features can be extracted in the Radon slices. The wavelet packet transform on the Radon coefficients also gives us multiresolution representation in the feature space. An additional Fourier transform along the angle direction can effectively extract rotation invariant features. All these good properties combined in this descriptor, making it a very attractive choice in invariant texture classification. Experiments show that the method achieves high classification rates and it outperforms two previous methods under both noise-free and noisy environments.

4 Experimental Results

Experiments are conducted on a set of 25 natural textures from the Brodatz album [21]. These textures are shown in Fig. 1. Each texture is first scanned with 150 dpi resolution and 256 grey levels are obtained. Since rotation invariance is our main concern, we test the classification rate of the proposed method for different orientations. We first divide each \( 512 \times 512 \) texture into four \( 256 \times 256 \) nonoverlapping regions. Then, we extract 36 subsamples of size \( 128 \times 128 \) with different orientations \((0^\circ, \cdots, 350^\circ \text{ with } 10^\circ \text{ intervals})\) from each region. We use the textures with orientation \( 0^\circ \)...
for training and the textures with other orientations for testing. In this way, a dataset of $25 \times 4 = 100$ textures are used for training, and a dataset of $25 \times 4 \times 35 = 3500$ textures are used for testing. Nearest neighbor classifier is used in the classification phase. Daubechies-4 wavelet is used in this experiment. Since the high resolution wavelet coefficients are sensitive to noise, we adopt the 4th resolution scale of the ridgelet packet features as our invariant features for texture classification. Only half of the spectrum magnitude of the Fourier transform coefficients are kept because the Fourier spectrum is symmetric. The distance metric used is defined as

$$L_1(x, y) = \sum |x_i - y_i|.$$  

where $x$ and $y$ are feature vectors. We achieve 100% correct classification rate for classifying the above rotated textures. Pun and Lee obtained 100% classification rate in [14], and the multichannel Gabor filtering only got 87.50% classification rate. The classification rate here is defined as the percentage of classification that we assign the unknown texture to the correct texture class.

The performance of our proposed method is also tested on noisy textures. The noisy textures with different orientations are generated by adding Gaussian white noise to the noise-free textures. The signal-to-noise-ratio (SNR) is defined as

$$\text{SNR} = \frac{\sqrt{\sum_{i,j} (f_{i,j} - \text{avg}(f))^2}}{\sqrt{\sum_{i,j} (n_{i,j} - \text{avg}(n))^2}}$$

where $f$ is the noise-free texture, $n$ is the added white noise, and $\text{avg}(f)$ is the average value of the texture $f$. We conduct experiments for SNR = 0.5, 5, 10, 15, 20, and 25. Table 1 shows the recognition rates of noisy textures for different SNR’s. The results are also compared with the log-polar wavelet energy signatures [14] and the multichannel Gabor filtering in Table 2. It is clear that our proposed method is very robust to Gaussian white noise and it outperforms the log-polar wavelet energy signatures [14] and the multichannel Gabor filtering for all different noise levels.

5 Conclusions and Future Work

In this paper, we present a rotation invariant texture classification technique by using ridgelet packets. The main motivation of using ridgelet packets is that this is a much better tool for the extraction of features based on line singularities as compared to point singularities as in the case of wavelets. Based on this observation, important features can be extracted. Fourier spectrum magnitudes are used to achieve rotation invariance. Experiments show that our proposed method achieves very high classification rates and it outperforms two previous rotation invariant texture classification methods for both noise-free and noisy environments. Future work will be done by applying ridgelet packets to scale invariant texture classification.

Acknowledgments

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References


### Table 1. Texture classification rates (%) for different SNR’s.

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<thead>
<tr>
<th>SNR</th>
<th>Recognition Rate</th>
</tr>
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<tbody>
<tr>
<td>0.5</td>
<td>68</td>
</tr>
<tr>
<td>5</td>
<td>100</td>
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<tr>
<td>10</td>
<td>100</td>
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<td>15</td>
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<td>20</td>
<td>100</td>
</tr>
<tr>
<td>25</td>
<td>100</td>
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</table>

### Table 2. A comparison of average classification rates (%) for the new method, the log-polar wavelet energy signatures, and the multichannel Gabor filtering for noisy textures.

<table>
<thead>
<tr>
<th>Method</th>
<th>Classification Rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>New Method</td>
<td>94</td>
</tr>
<tr>
<td>Log-Polar Wavelet Energy Signature</td>
<td>75</td>
</tr>
<tr>
<td>MultiChannel Gabor Filtering</td>
<td>70</td>
</tr>
</tbody>
</table>


