ROTATION-INVARIANT TEXTURE RECOGNITION BY ROTATION COMPENSATION AND WAVELET ANALYSIS

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ABSTRACT

A new rotation-invariant wavelet-based texture recognition scheme is proposed. In the previous rotation-invariant approaches, the focus is on adapting the wavelet transform or filter to rotated texture. In our approach, instead, we estimate the rotation of the texture with respect to some reference orientation, and then rotate the texture image back to the reference orientation before applying the wavelet analysis to extract features. With such rotation compensation, even very simple features (such as 1-level DWT and the subband energy) can be effective in achieving high classification accuracy as we demonstrate through our experiments.

Index Terms— texture recognition, wavelets, rotation-invariant, rotation compensation, intensity moment

1. INTRODUCTION

Texture recognition and classification is an important and challenging task in image processing. A number of early methods use the statistical property of the image to analyze textures, such as the co-occurrence matrix method [12]. Later on Gabor filter [13][14] and wavelet-based methods [1-6][15][16] become the classical methods for texture recognition. Other common methods include Gaussian Markov random field (GMRF) [17], local binary pattern (LBP) histogram [7], autoregressive model [18] and hidden Markov models [19][20]. Among all those methods, Gabor filter, and particularly, wavelet-based methods are perhaps the most popular ones. The reason for the popularity of the wavelet-based methods is that it provides a natural partition of the image spectrum into multiscale and oriented subbands via efficient transforms [2]. There has been a rich variety of the wavelet-based texture analysis methods such as wavelet transform, wavelet packets, complex wavelet transform, rotated wavelet filter and so forth. Most of the wavelet methods make use of the energy distribution among the subbands in frequency domain to identify texture. The subband energy may be used directly, or features may be extracted from the wavelet coefficients using techniques such as generalized Gaussian density model [2].

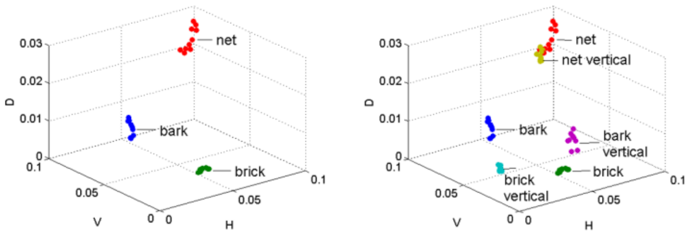
2. RELATED WORK

One of the classical methods for wavelet-based texture recognition, proposed by Chang and Kuo [1], is based on the idea of wavelet packets. In the traditional octave wavelet transform only the low-frequency channel is iteratively decomposed. However the textures may have dominant frequencies in the middle frequency channels. It is therefore better to detect the significant frequency channels of the texture and decompose them further. In the wavelet packets approach, each subband LL, HL, LH, HH can be further decomposed, depending on the energy of the subband. A criterion is used to decide whether a subband needs to be further decomposed. Finally the energy values at J most dominant channels are used as features for classification [1].

However the major drawback of this wavelet packets approach for texture recognition is that it is not rotation-invariant, i.e., the rotation of texture will severely affect its accuracy. Since recognizing texture irrespective of its orientation is a very important issue, many efforts have been devoted in literature to rotation-invariant texture recognition [8-11][17-24], such as those based on rotated wavelet filter (RWF) [8] and complex wavelet transform (CWT) [9]. But most of these methods are aimed at modifying the wavelet filter or transform to adapt to the rotation of the texture (i.e., trying to extract rotation-invariant features), without manipulating the rotated texture image itself. In this study, we propose a method to directly manipulate the rotated texture image itself before the feature extraction to obtain rotation-invariant recognition. Some other study also suggests the idea of orientation adjustment of the texture [24], and Radon transform is used for estimating the texture orientation. In our study we use a totally different method for texture orientation estimation – the intensity moment approach, which is very effective and has more explicit physical meaning than Radon transform.

(a) (b) (c)

Figure 1. (a) Net texture. (b) Brick texture. (c) Bark texture.



(a) (b)

Figure 2. (a) Feature space plot for three textures net, brick and bark. (b) Feature space plot for three textures net, brick and bark with rotation.

3. WAVELET-BASED TEXTURE RECOGNITION WITH ROTATION COMPENSATION

As mentioned above, wavelet is a good tool for texture recognition since it provides a natural partition of the image spectrum into multiscale and oriented subbands using an efficient transform. Recognition is based on the observation that the energy distribution among the subbands in frequency domain can identify texture. Using the *Rotation compensation* introduced later in this paper, even simple features can achieve very good classification performance. We apply a 1-level Discrete Wavelet Transform (DWT) on the original texture image; straight-forward extensions can be made easily, such as applying N-level DWT upon the image. We compute the average energy (l_1-norm) in each subband (LL, HL, LH, HH) as follows:

$$e = \frac{1}{MN} \sum_{m=1}^{M} \sum_{n=1}^{N} | x(m,n) | \tag{1}$$

where the subband image has dimension $M \times N$, and $x(m,n)$ is the wavelet coefficient at location (m,n). Then we normalize the subband energies by the energy of the LL channel (approximation channel) and use this normalized set of four subband energies as feature. Again, straight-forward extensions can be made if we consider a N-level DWT on the texture image, which could be an octave wavelet decomposition (where we only further decompose the low-frequency channel), or a full wavelet decomposition (where we further decompose every channel, possibly using parameters from only selected channels, such as eliminating the parameter of the HH channel), or a wavelet packets decomposition (where we further decompose any channels of interest, not necessarily the low-frequency channel).

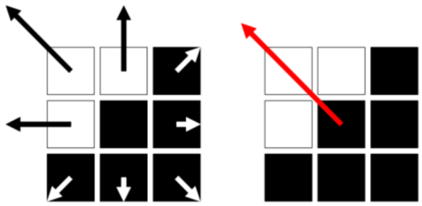
For the three textures (net, brick and bark) shown in Figure 1, the computed subband energies are (1.0000 0.0786 0.0748 0.0244) for the net texture, (1.0000 0.0403 0.0186 0.0035) for the brick texture, and (1.0000 0.0202 0.0524 0.0134) for the bark texture, respectively. If we plot them in the feature space as in Figure 2 (a), we can see that the three textures are well separated. Here the multiple points for each texture correspond to the feature points extracted from random locations within each original texture image, and apparently the features extracted from the same texture, regardless of their locations, are all clustered together.

However the rotation of texture places a major challenge for wavelet-based texture recognition, since wavelet transform is orientation-dependent and rotation-sensitive. For the same three textures in Figure 1, if we rotate each of them by 90° and apply the same wavelet analysis, it is clear from Figure 2 (b) that we can no longer separate them easily in the feature space. For example, the feature points corresponding to the rotated bark texture (bark vertical) are closer to the feature points of brick texture than to those of the unrotated bark texture. Therefore, dealing with texture rotation is an important issue in texture recognition and classification. Here we propose an approach called rotation compensation, i.e. we first estimate the rotation of the texture image with respect to some reference orientation, and then rotate it back before applying any further processing (such as DWT) on the image. In such a way the rotation-invariant texture recognition can be achieved.

The idea of rotation compensation or specifically rotation estimation is based on the concept of intensity moment and moment angle. In essence, the intensity moment measures the imbalance of the intensity distribution within a patch of certain scale around each pixel. In analogy with force moment, the intensity moment is calculated via the vector summation of the product between pixel intensity and vector distance to the patch center for each pixel within the patch (Figure 3).

$$\vec{M}(i_0, j_0) = \sum_{(i,j)\in D} I(i,j) \cdot \vec{L}(i,j) \tag{2}$$

In above D is the local patch or domain centered at (i_0, j_0), $I(i,j)$ and $\vec{L}(i,j)$ are the pixel intensity and the vector distance to the patch center (i_0, j_0) for each pixel (i,j), respectively, and $\vec{M}(i_0, j_0)$ is the intensity moment of the patch centered at (i_0, j_0). The intensity moment angle at each pixel is simply the direction of the intensity moment at that point or the "micro" orientation of the local image patch (in fact the raw direction of intensity moment is at the normal of the image local orientation, here we use the normal of this raw direction as the direction of intensity moment angle). Therefore if we generate the histogram of intensity moment angle, the major peak in the histogram



(a) (b)

Figure 3. Schematic illustration of intensity moment. Each block represents a pixel, dark block has lower intensity value than bright block. (a) Intensity moment and its direction of each pixel in the region with respect to the center pixel. (b) Total intensity moment and its direction of the region (or of the center pixel), note the raw intensity moment direction is at the normal of the image local orientation.

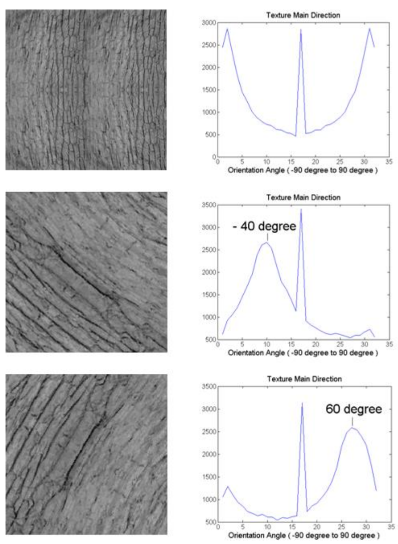


Figure 4. The bark texture with various orientations and the corresponding intensity moment angle histograms. We can see that the major peak of the histogram corresponds well with the main orientation of the texture image (ignore the thin peak at the center of the plot).

should indicate the main orientation of the texture. Figure 4 illustrates the relationship between the intensity moment angle histogram with the texture orientation. The major peak in the histogram (ignore the thin peak at the center or 0 degree as explained below) corresponds well with the main orientation of the texture image (with respect to the horizontal line).

For texture image, it is often the case that the majority portion of the local image patches have relatively uniform intensity distribution (i.e. zero degree orientation), only a small portion of the image patches exhibit a strong orientation which we can use to distinguish textures. This is why in most cases we will have a thin peak at the center or zero degree in the intensity moment angle histogram, and

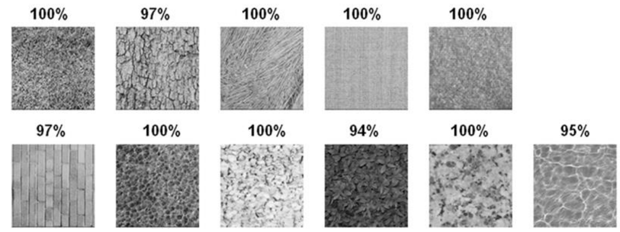


Figure 5. The classification accuracy with rotation compensation for 11 textures (from left to right, top to bottom, the textures are grass, bark, straw, cloth, wool, brick, foam plastic, sand, leaves, marble, water), with 100 random rotations for each texture.

that peak should be ignored since it is not the signature feature of the given texture. In the case that no major peak is found besides the peak at the center or zero degree we consider the texture orientation is at the zero degree.

Once we estimate the main orientation of the texture image, we rotate the texture image back to some reference orientation (for example, let the main orientation of the texture be along the horizontal line) and apply the wavelet-based feature extraction.

4. EXPERIMENTS

We use 11 textures from Brodatz texture database (last three textures are self-collected) as shown in Figure 5. For each texture, we randomly rotate it to obtain 100 samples with random rotations and then perform the classification. For the sample image, we perform 1-level DWT on it (with Daubechies-4 filter), and compute the average energy (l_1-norm) for each subband. The set of four energy values for the four subbands (normalized against the LL-channel) is used as feature. A training set of 100 randomly rotated texture images for each texture class is used as the labeled samples in the feature space (rotation compensation will be applied before extracting wavelet features), and k-Nearest Neighbor approach is employed for the classification. With the rotation compensation, the average classification accuracy is 98.5%, even though the feature we used is fairly simple – the 1-level DWT and corresponding subband energies. If the same feature and classification method are applied on the texture images without rotation compensation, the classification performance is dramatically poorer especially for the textures with strong orientation. For example, for the bark texture the classification accuracy is only 40% without rotation compensation, but improved to 97% with the rotation compensation. And the classification accuracy for brick is improved from 44% to 97%, water from 64% to 95% with the rotation compensation approach. Hence based on the simple features, the rotation compensation approach provides an effective and efficient way for rotation-invariant texture recognition.

For the larger dataset, we carried out experiments on 112 Brodatz textures (D1 – D112). As well we use 100 randomly rotated images within each texture class as the training samples, and 100 randomly rotated images within each texture class as the testing samples. The average classification accuracy is 83.1%. We should note that all the input textures are randomly rotated, and many textures within this database are similar to each other. Also the feature we use is fairly simple (1-level DWT and subband energy), the classification performance might be further improved if more sophisticated features are used. In comparison, the experiment carried out on the same database can also be found in [9], where they use 109 Brodatz textures (D1 – D112 except D13, D88, D96). The classification accuracy in their study is 62.04% based on DWT feature, 75.40% for DT-CWT (dual-tree complex wavelet transform) feature, and 77.63% for the combination of DT-RCWF (dual-tree rotated complex wavelet filter) and DT-CWT feature. Hence it is clear that with the help of rotation compensation as applied in this study, the classification accuracy can be improved considerably.

In [24] some scheme similar to ours is proposed and Radon transform is applied to adjust the texture orientation before the wavelet analysis. For 25 selected textures from Brodatz database, 90.8% - 96.8% accuracy is obtained (depending on the k value in k-NN classifier) with Daubechies-4 filter for wavelet analysis and the k-NN classifier. Based on the same textures and settings (we use k=10 for k-NN classifier) our method obtains an accuracy of 95.2%, which is comparable to the result in [24]. For another set of 60 textures from Brodatz database, 77.2% - 89.3% accuracy is obtained in [24], while our accuracy is 89.4%.

The same experiment is also conducted upon the real leave images as in Figure 6. The first six leave images are from VisTex texture database and the rest images are self-collected. The average classification accuracy is 99%. The individual accuracy for each texture is 99%, 100%, 100%, 100%, 92%, 99%, 100%, 100%, 100%, 100%, respectively.

5. CONCLUSION

Wavelet-based texture recognition is among the most effective and popular methods for texture analysis, which is due to the natural property of wavelet analysis that it can partition the image spectrum into multiscale and oriented subbands. However, original wavelet-based texture analysis is not rotation-invariant, and has difficulties in recognizing the same texture with different orientations. Therefore, it is important to develop a texture recognition scheme that is

Figure 6. The 10 real leave images. These are either from VisTex texture database or self-collected.

rotation-invariant. In this study, we have proposed a new texture recognition scheme based on the approach called rotation compensation. In essence, we first estimate the rotation of the texture image with respect to some reference orientation, and then rotate the texture image back before performing wavelet-based analysis. In such a way we compensate the change of orientation of the texture. Hence even with the simple feature, such as 1-level DWT and normalized subband energy, the classification scheme can obtain high accuracy.

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