A Robust Texture Descriptor using Multifractal Analysis with Gabor Filter

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ABSTRACT
Texture classification analysis and classification play an important role in the domain of content-based image retrieval, image segmentation, scene recognition and image/video analysis. This paper proposes a novel robust texture descriptor on variance in rotation, scale and illumination, which combines the dominant orientation analysis and multifractal analysis base on Gabor filter. The dominant orientations are extracted in corresponding Gaussian scales to handle the rotation variance, and then the scale and illumination invariant multifractal spectrum (MFS) is produced based on the multi-scale Gabor filters at the corresponding dominant orientation. The proposed approach is evaluated on Brodatz and Outex databases. The experiment results show that our method outperforms existing techniques under different condition variances.

Categories and Subject Descriptors
I.4.7 [Computing Methodologies]: Feature Measurement – Feature representation, Invariants, Texture.

General Terms
Algorithms, Performance, Experimentation.

Keywords
Texture classification, robust texture descriptor, dominant orientation analysis, Gabor filter, multifractal analysis.

1. INTRODUCTION
Texture classification is an important problem in image analysis, multimedia understanding, and computer vision, which have many potential applications in photo manage, scene recognition, image search, and image/video compression or segmentation. In recent years, many researchers have proposed robust texture description approaches for handling the variance in rotations, scales, and illuminations [1-10].

Generally speaking, the previous methods can be loosely divided into three main categories [1]: statistical methods, model based methods, and signal processing based methods. The statistical methods are earlier methods for texture classification, which focus on the statistical analysis of texture images, and characterize an image in terms of numerical features, for example, the second order gray level co-occurrence method [2], and texture spectrum methods [3]. In model based approaches, textures are represented as mathematical image perceptual models, and there methods focus on choosing a suitable model to characterize the selected textures and estimating the parameters of these models, for example, wavelet transforms and HMM model method[4], and the anisotropic circular Gaussian MRF model[5]. In signal processing based methods, local textures are extracted and analyzed by using local signal processing with maximizing the separation and discrimination among different textures representation. The representative works include wavelet packet frame [1], Discrete Wavelet Transform (DWT) [6], Gabor wavelets [7], LBP [8], and LBP-like methods [9][10].

In general their classification results are good as long as the training and test samples have identical or similar orientations and scales. The rotations and scaling of textures will vary in real-world, severely affecting the performance of the methods and suggesting the need for rotation invariant methods of texture classification. Recently, some rotation- and scale-invariant texture description and classification method were proposed [8,9]. However, their rotation-invariance could be guaranteed only in local neighbors rather than global scopes. Moreover, the illumination invariance usually is ignored by the previous methods.

In this paper, we propose a novel rotation-, illumination-, and scale-invariant texture description and classification method. Firstly, we compute dominant orientation base on the gradient orientation histogram of each scale, which is produced on the multi-scale Gaussian convolution. This extracts the global texture dominant orientation, since considering the whole texture image against the local region. Secondly, the Gabor images are computed with Gabor transform of multi-scale and the dominant orientation in the scale, and the multifractal spectrum (MFS) are extracted base on the Gabor images. Thirdly, the each scale MFS is used to train a probability SVM classifier. Thus, the classifier set, consisting of $ M \times C $ SVM classifiers ($ S $ denotes the number of scales and $ C $ denotes the number of texture category), are used to classify the query texture image. “Winner-take-all” strategy is employed, which the maximal probability result of classifier set is as the classification result. The framework of the proposed approach is shown in Fig.1.

There are two main contributions in our proposed approach. The first is the dominant orientation analysis in the multi-scale...
Figure 1. The framework of the proposed MFS-Gabor texture description approach.

gradient orientation histograms, which detects and describes the global texture orientation distribution for handling the global rotation variance of texture image. The second is the combination of multi-scale Gabor filter and multifractal analysis for effective description the texture, which combine the orientation description of Gabor filter, and illumination and geometrical transforms invariance of MFS.

Compared to previous work, the proposed texture descriptor enjoys several advantages, including (1) better robustness to global rotation variance (dominant orientation analysis); (2) robustness to geometric transformation and photometric variations (due to MFS); (3) better classification performance base on combination on the components. The proposed texture descriptor is applied to texture classification tasks and the experimental results on several texture datasets show its promising performance against several existing state-of-the-art methods.

2. DOMINANT ORIENTATION ANALYSIS

2.1 Dominant Orientation Analysis

Motivated by the robustness and invariance to illumination change and rotation in SIFT [11], we use the gradient orientation histogram to compute the dominant orientation in different Gaussian scales.

The $\sigma$th scale Gaussian image is defined as follows,

$$S^\sigma(x, y) = G(x, y, \sigma)^* I(x, y)$$

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right),$$

where $*$ is the convolution operation, $I(x, y)$ denotes the input image, $G(x, y, \sigma)$ is the Gaussian function, and $\sigma$ denotes the scale variable.

For the any pixel point $(x_0, y_0)$ of the $\sigma$th scale Gaussian image $S^\sigma(x, y)$, we compute the gradient magnitude, $m^\sigma(x_0, y_0)$, and the orientation, $\theta^\sigma(x_0, y_0)$, using the pixel differences, respectively,

$$m^\sigma(x_0, y_0) = \frac{\sqrt{(S^\sigma(x_0 + 1, y_0) - S^\sigma(x_0 - 1, y_0))^2 + (S^\sigma(x_0, y_0 + 1) - S^\sigma(x_0, y_0 - 1))^2}}{2\sigma},$$

$$\theta^\sigma(x_0, y_0) = \text{atan} \frac{S^\sigma(x_0, y_0 + 1) - S^\sigma(x_0, y_0 - 1)}{S^\sigma(x_0 + 1, y) - S^\sigma(x - 1, y)}.$$

According to the signs of $S^\sigma(x_0 + 1, y_0) - S^\sigma(x_0 - 1, y_0)$ and $S^\sigma(x_0, y_0 + 1) - S^\sigma(x_0, y_0 - 1)$, the gradient orientation $\theta^\sigma(x_0, y_0) \in [0, 2\pi)$, is quantized to 8 gradient orientations, covering 45 degrees each.

Similarly with SIFT descriptor, we align orientation histogram $H^\sigma$ in each scale $\sigma$, $H^\sigma(h_0^\sigma, h_1^\sigma, ..., h_7^\sigma)$ with the gradient orientation and gradient magnitude of each pixel, as follows,

$$h_i^\sigma = \sum (x', y'), \forall \theta^\sigma(x', y') \in \left\{ \frac{i\pi}{4}, \frac{(i+1)\pi}{4} \right\},$$

in which $i = 0, 1, ..., 7$ denotes the quantized orientation.

For each scale $\sigma$, the dominant orientation $\theta^\sigma$ is defined as follows,

$$\theta^\sigma = \max h_i^\sigma, \ i = 0, 1, ..., 7.$$

Figure 2. (a) Two textures image in different orientations (the difference of orientations is 90°); (b)-(c) the dominant orientations of the two images in scale 1 to 3, respectively, see Sec. 2.1 for details.

For computing dominant orientation (As shown in Fig. 2), our proposed method is similar with the SIFT description method, but there are two folds differences between with SIFT, (1) we compute the dominant orientations on the multi-scale gradient histogram for accurate description, while SIFT only extracts in the optimized scale; (2) the dominant orientations are computed in whole image against the local neighborhood of keypoint in SIFT.
2.2 Gabor Filter with Dominant Orientation Analysis

The Gabor filter can effectively present the texture characteristic in texture recognition [7]. Thus, we exploit the multi-scale Gabor filters with the dominant orientation to extract the feature of texture image. The Gabor filters we used are defined as follows [12],

$$
\psi_{u,v}(z) = \frac{k_{u,v}}{\sigma} e^{-k_{u,v}^2/2}\left[e^{i2\pi z} - e^{-\sigma^2/2}\right],
$$

where $u$ and $v$ define the orientation and scale of the Gabor filters, $z = (x,y)$, $k_{u,v} = k_u e^{i\phi_u}$ and $k_u = k_{\text{max}}/f^u$ give the frequency, $\phi_u = u\pi/8$, $\phi_u \in [0,\pi)$ gives the orientation. Note that, in the Equation 5, $u$ controls the scale of the Gabor filters and $v$ controls the orientation of the Gabor filters. In our algorithm, the parameters are as follows, $\sigma = 2\pi$, $k_{\text{max}} = \pi/2$, $f = \sqrt{2}$, $v \in \{0,1,...,M\}$, $u \in \{\sigma^1,\sigma^2,...,\sigma^M\}$, $M = 5$.

We get the Gabor images with the Gabor filter as follows,

$$
\{G_{s_i,\phi_i}, G_{s_2,\phi_2}, ..., G_{s_M,\phi_M}\},
$$
in which $s_i$ and $\phi_i$ denote the $i$th scale and the dominant orientation in this scale, respectively, and $G_{s_i,\phi_i}$ is the Gabor image of the $s_i$ scale and $\phi_i$ orientation.

3. CLASSIFIER FUSION BASE ON MULTIFRACTAL ANALYSIS

Considering the advantages of the multifractal analysis in texture recognition [13], we extract the statistical features using the multifractal analysis on Gabor image.

Multifractal analysis can robustly describe the irregular 2D functions. Multifractal analysis divides the space into multiple point sets, and the points have similar property (usually local density) in each set. The fractal dimension is a measurement that describes how a given element set $E$ appears to fill space when one zooms in to finer scales [14]. The multifractal spectrum (MFS) is the vector of the fractal dimensions of the point set of the image. The fractal dimension of each point set becomes an element of MFS (See [13] for more details).

We calculate the MFS for each Gabor image using the box-counting method, the same as [13] does. Thus, we get the bag of MFS for the given texture image $f$ as follows,

$$
\{\text{MFS}_{s_1,\phi_1}, \text{MFS}_{s_2,\phi_2}, ..., \text{MFS}_{s_M,\phi_M}\}.
$$
training set, to the validation set and to the test set are disjoint. The results are reported as the average value over the ten runs.

The precision, $p_c$ of classification in category $c$, and the average precision $AP$, are defined as follows,

$$\begin{align*}
    p_c &= \frac{N_{\text{correct}}}{N_{\text{total}}}, \\
    AP &= \frac{1}{M} \sum_{c=1}^{M} p_c,
\end{align*}$$

where $N_{\text{correct}}$ and $N_{\text{total}}$ denote the number of correct classification samples, and total number of samples in category $c (c=1,2,\ldots,C)$ respectively.

Table 1. The texture classification performances of the methods on Outex database with various conditions.

<table>
<thead>
<tr>
<th>Methods</th>
<th>O1</th>
<th>O2</th>
<th>O3</th>
<th>O4</th>
<th>O5</th>
<th>O6</th>
<th>O7</th>
<th>O8</th>
<th>AP1</th>
</tr>
</thead>
<tbody>
<tr>
<td>DWT</td>
<td>0.81</td>
<td>0.86</td>
<td>0.90</td>
<td>0.88</td>
<td>0.81</td>
<td>0.80</td>
<td>0.82</td>
<td>0.84</td>
<td>0.84</td>
</tr>
<tr>
<td>rL-LBP</td>
<td>0.83</td>
<td>0.87</td>
<td>0.91</td>
<td>0.93</td>
<td>0.83</td>
<td>0.84</td>
<td>0.82</td>
<td>0.88</td>
<td>0.86</td>
</tr>
<tr>
<td>LHBP</td>
<td>0.94</td>
<td>0.93</td>
<td>0.95</td>
<td>0.95</td>
<td>0.99</td>
<td>0.93</td>
<td>0.90</td>
<td>0.94</td>
<td>0.94</td>
</tr>
<tr>
<td>gMFS</td>
<td>0.94</td>
<td>0.95</td>
<td>0.97</td>
<td>0.94</td>
<td>0.99</td>
<td>0.96</td>
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</tbody>
</table>

Table 2. The texture classification performances of the methods on Brodatz database with various conditions.

<table>
<thead>
<tr>
<th>Methods</th>
<th>B1</th>
<th>B2</th>
<th>B3</th>
<th>B4</th>
<th>B5</th>
<th>B6</th>
<th>B7</th>
<th>B8</th>
<th>B9</th>
<th>B10</th>
<th>B11</th>
<th>B12</th>
<th>AP2</th>
</tr>
</thead>
<tbody>
<tr>
<td>DWT</td>
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<td>0.85</td>
<td>0.85</td>
<td>0.85</td>
<td>0.81</td>
<td>0.88</td>
<td>0.80</td>
<td>0.87</td>
<td>0.91</td>
<td>0.82</td>
<td>0.87</td>
<td></td>
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</tr>
<tr>
<td>rL-LBP</td>
<td>0.87</td>
<td>0.92</td>
<td>0.85</td>
<td>0.87</td>
<td>0.91</td>
<td>0.88</td>
<td>0.89</td>
<td>0.86</td>
<td>0.94</td>
<td>0.93</td>
<td>0.89</td>
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<td></td>
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<tr>
<td>LHBP</td>
<td>0.98</td>
<td>0.95</td>
<td>0.94</td>
<td>0.97</td>
<td>0.99</td>
<td>0.97</td>
<td>0.97</td>
<td>0.92</td>
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<td>0.98</td>
<td>0.96</td>
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<tr>
<td>gMFS</td>
<td>0.98</td>
<td>0.95</td>
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We compared our method against four methods including Hiremath et al. [6], Ojala et al. [8] and Xu et al. [10]. The first one is the DWT method by Hiremath et al. [6], which is based on a co-occurrence histogram of Haar wavelet coefficient. The second method is rotation-invariant LBP(rL-LBP) method by Ojala et al [8]. The basic idea is to extract the local pattern of gray texture image using weighted binary code. Then the similar patterns with different orientations are uniformed to handle the rotation variance of texture image. The third method is the local Haar binary pattern (LHBP) method by Xu et al. [10], which combines the Haar wavelet and local binary pattern. The basic idea is to extract the threshold local binary pattern from the multi-scale Haar wavelet coefficient to handle the illumination change. The dominant orientation analysis on Haar wavelet and the scale-adaptive strategy enforce the rotation- and scale-invariance.

Table 1 and Table 2 show the each category and the average classification precisions of our proposed method (namely “gMFS”) versus the compared methods on the Brodatz dataset and Outex dataset, respectively. The best results for each test suite are marked in bold font. From the tables, it is seen that the MFS-Gabor method clearly outperformed all the other methods on both Brodatz and Outex datasets. Moreover, our method is effective due to the MFS and multi-scale Gabor filter on the most categories. It shows that the proposed method is robust to the variance of illumination, scale and rotation in texture images. The reason is that the illumination change, rotation- and scale-invariance are achieved by the MFS, dominant orientation analysis and the winner-takes-all classification strategy, respectively.

5. CONCLUSIONS

In this paper we proposed a texture descriptor based on dominant orientation analysis and the multifractal analysis on Gabor filter. The proposed texture descriptor is robust to global rotation, scale and illuminant of texture images. Moreover, the rotation invariance is enforced by the dominant orientation analysis, the illumination invariance is improve by leveraging MFS base on multi-scale Gabor filter, and the scale invariance is achieved with the “winner-takes-all” classification scheme. The experiments showed that our proposed method performs excellently for texture classification on two public texture datasets.

6. ACKNOWLEDGMENTS

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7. REFERENCES


