Fusion of Rotation-Invariant Texture Features for Scene Recognition

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Abstract: Multichannel Gabor filters (MGFs) and Markov random fields (MRFs) are two common methods for texture classification. However, the two above methods make the implicit assumption that textures are acquired in the same viewpoint, which is unsuitable for rotation-invariant texture classification. In this paper, rotation-invariant (RI) texture features are developed based on MGF and MRF. A novel algorithm using the neighborhood-oscillating tabu search (NOTS) is proposed to fuse RI MGF and MRF features, compared with the sequential forward floating selection method. Experimental results indicate that the fused RI MGF/MRF features achieved by NOTS have much higher discrimination than pure features in terms of classification accuracy.
Keywords: rotation-invariant, texture classification, tabu search.

1. Introduction

With the advent of very high resolution sensors such as QuickBird, conceptual objects like urban or residential areas usually show significant variations in their pixel values, causing lower classification accuracies when solely using per-pixel classification based upon spectral comparisons. Texture analysis provides a complementary tool for those applications in which the spectral information is not sufficient for identification or classification of spectrally heterogeneous landscape units [1]. Texture reflects the local variability of grey levels in the spatial domain and reveals the information about the object structures in the natural environment. Over the last two decades, many approaches for texture feature extraction have been developed including statistical analysis methods, signal processing techniques such as multichannel Gabor filters (MGFs) [2], stochastic models such as Markov random fields (MRFs) [3], and geometrical methods.

However, the majority of approaches to texture classification assume, either explicitly or implicitly, that texture images are acquired from the same viewpoint. This gives a limitation of these methods. It is very difficult to impossible to ensure that images captured have the same rotation between each other. Furthermore, in high spatial resolution imagery, the land cover unit like a house or pond can be arranged in different orientation in space. Thus, rotation-invariant texture analysis is highly desirable from a practical and theoretical point of view. This paper focuses on the use of two common techniques for extraction of texture features: MGFs and MRFs. MGFs are capable of obtaining multi-scale texture information corresponding to different scales and orientations, whereas MRFs measure the interdependency of neighboring pixels within a texture. Because of inherent dependency on directions, both of methods are then further developed to allow textures to be classified at any orientation.

It is found that features derived from the above two methods are very different in nature and have low inter-feature correlations [4]. The combined rotation-invariant (RI) MGF and MRF texture features may provide richer texture information than pure features. However, the combined features without selection will produce more dimensions, which may downgrade the performance of the classifiers and lead to even worse classification accuracy than pure features [5]. In order to reduce data dimensions and improve classification quality, the combination of different features should be processed by feature selection. In this paper, the neighborhood-oscillating tabu search (NOTS) algorithm is proposed to select an optimal feature subset from the pooled RI MGF and MRF features, compared with other conventional algorithms such as the sequential forward floating selection (SFFS) method.

The remainder of the paper is organized as follows. Next section describes the RI texture feature extraction methods of MGF and MRF. Section 3 introduces the NOTS algorithm for solving the RI MGF/MRF feature fusion problem. Experimental results are given in Section 4 and conclusions drawn in Section 5.

2. Two Approaches to Rotation–Invariant (RI) Texture Features

In this section, two approaches to rotation-invariant (RI) texture features: the multichannel Gabor filtering (MGF) approach and the Markov random field (MRF) approach. In both cases, feature computation is based on a moving kernel of a fixed size, where window size is chosen experimentally in the preprocessing phase and depends highly on

the particular data used in a study [6]. There is a trade-off between application of too large and too small a window. The window size chosen for experiments is 17×17 pixels.

1) The Multichannel Gabor Filtering (MGF) Approach

Gabor filtering is popular for texture analysis owing to its appealing simplicity and optimum joint spatial/spatial-frequency localization. A multichannel filtering method is used based on Gabor filters with six different orientations (0°, 30°, 60°, 90°, 120°, and 150°) and four high-radial frequencies (64√2, 32√2, 16√2, and 8√2 cycles per image), resulting in 24-dimensional (24-D) MGF feature vectors [2, 7]. These Gabor filters in spatial-frequency domain are shown in Fig. 1(a). For MGF, each texture can be thought of as containing a narrow range of frequency and orientation components. By filtering the image with multiple filters tuned to dominant frequency and orientation component of the textures, it is possible to locate each texture. Brodatz texture D49 (straw screening) is selected as the original texture. Fig. 1(b) with size 256 × 256 is composed of four samples by rotating the texture with four angles (0°, 45°, 90°, and 135°) in the counterclockwise direction. And the MGF feature images corresponding to 64√2 cycles per image and all the six orientations (0°, 30°, 60°, 90°, 120°, and 150°) are shown in Fig. 1(c)-(h), respectively. From Fig. 1, we can see that the general MGF features are rotation-variant, and unsuitable for rotation-invariant texture classification. For rotation-invariant texture analysis, if only textures belong to the same types, texture features achieved are expected to be same. Therefore, the 24 direction features are then transformed to 12 RI MGF features: for each center frequency, the mean, standard deviation and sum of perpendicular ratios are calculated.

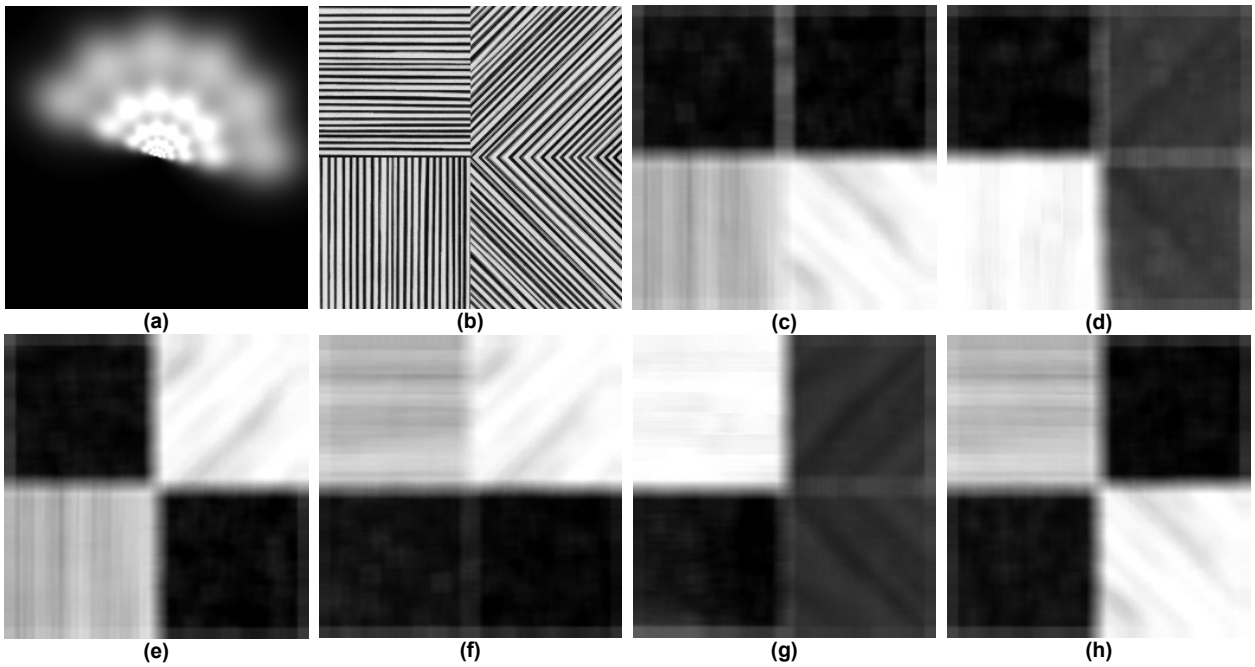


Fig. 1. Multi-channel Gabor filters and examples of filtered images: (a) the filter bank in the spatial-frequency domain; (b) the 256×256 image consisting of Brodatz D49 texture samples, at four different orientations (0°, 45°, 90°, and 135°); (c)-(h) MGF feature images for (b) corresponding to 64√2 cycles per image and six orientations (0°, 30°. 60°, 90°, 120°, and 150°).

2) The Markov Random Field (MRF) Approach

Markov random Fields (MRFs) are recognized for being effective for texture analysis as they use a finite number of parameters to characterize spatial interactions of pixels to describe an image region. A typical MRF model is the Gaussian MRF (GMRF) model, which is widely used for modeling textures. The GMRF model assumes $y(s)$, the intensity of pixel s, as a linear combination of intensities of its neighboring pixels and an additive Gaussian noise [8]. The symmetric GMRF model with an asymmetrical neighbor set η obeys the following formula:

$$y(s)-u=\sum_{r\in\eta}\theta(r)\left[\left(y(s+r)-u\right)+\left(y(s-r)+u\right)\right]+e(s)\ , \qquad (1)$$

where u is the mean of variable $y(s)$, $\theta(r)$s are the model parameters, and $e(s)$ is a Gaussian noise sequence with mean zero and variance ξ.

The effectiveness of the GMRF approach depends heavily on the neighbor set used. There are two types of neighborhood systems presented [9]: the rectangular neighborhood system and the circular neighborhood system. This paper uses the circular neighborhood system in view of its good performance in obtaining high-quality texture features. For one concentric circle, τ is denoted as the number of neighbors and an angular spacing between two nearest

neighbors is set by $2\pi/\tau$. Different concentric circles can have different angular intervals, and the angular spacing of inner circles can be bigger than that of outside circles. In our case, we fix $\tau = 8\lambda$, where λ is the circle number of neighbor sets. The values of the neighbors that are not exactly located on the image grid are calculated by interpolation. The circular neighbor sets for a 1st, 2nd, and 3rd GMRF model are shown in Fig. 2.

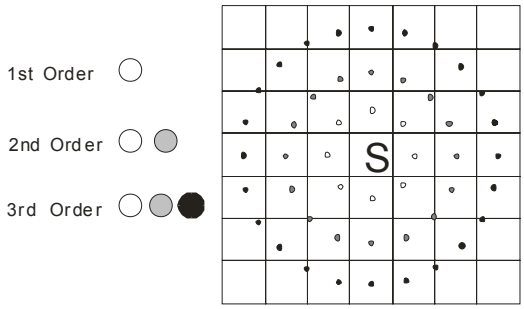


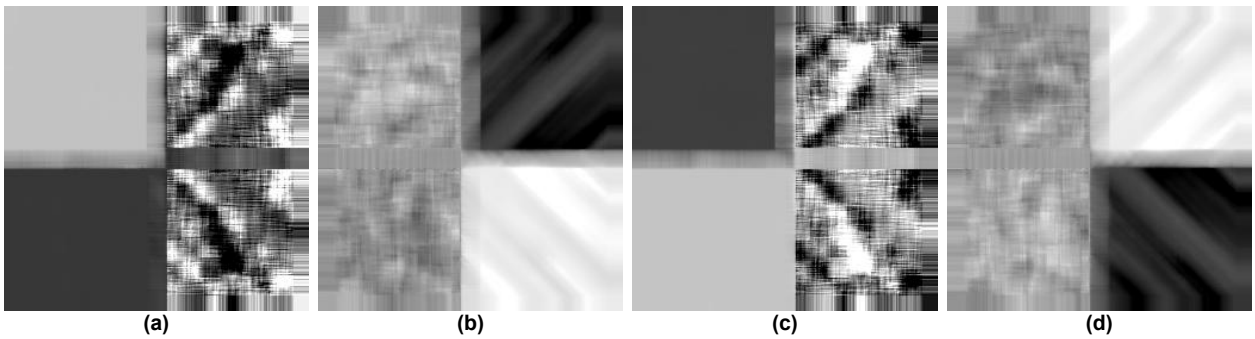
Fig. 2. Circular neighbor sets for GMRF models.

The estimation of the parameters $\theta(r)$s and variance ξ is the key step in extracting texture features using the GMRF model. In order to overcome the singularity problem, we use the approximate least square estimate method designed by Deng and Clausi [9]. After the model parameters $\theta(r)$s are calculated, the variance ξ can be computed by

$$\xi = \frac{1}{M}\sum_{s\in R}\left[\left(i(s)-u\right)-\sum_{r\in\eta}\theta(r)\left[\left(i(s+r)-u\right)+\left(i(s-r)-u\right)\right]\right]^2, \tag{2}$$

where R is a window of the input image, M denotes the number of pixels in R.

In our experiments, the 3rd order GMRF model is used to extract texture features. There are a total of 24 parameters: 4 parameters (i.e. corresponding to 0°, 45°, 90°, and 135° in the clockwise direction) over the first circle, 8 parameters over the second circle, and 12 parameters over the third circle. As a result, each window produces a 25-D feature vector (24 parameters plus the variance) which is associated with the center pixel of the window. When we observe Eq. (1) and Eq. (2), we see that GMRF parameters have strong orientation selectivity whereas the variance is independent of orientations. Fig. 3 displays the result of the four GMRF parameters on the first circle extracted from Fig. 1(b). However, in rotation-invariant texture analysis, we care about the types of textures rather than textures with varying spatial orientation. Fig. 1(b) contains four texture samples of the same type and different orientations, and for each texture sample, texture features are expected to be same. GMRF parameters are not rotation-invariant, which are undesirable in scene recognition applications. Therefore, the 24 directional parameters are converted into 6 RI features: for each circle, the mean and standard deviation are computed. As a result, 7-D RI MRF feature vectors (the 6 RI features plus the variance) are yielded.



(a) (b) (c) (d)

Fig. 3. The result of the extraction of GMRF parameters for Fig. 1(b): (a)-(d) the parameters over the first circle corresponding to 0°, 45°, 90°, and 135° in the clockwise direction, respectively.

3. RI Texture Feature Fusion

The fusion of complementary texture features are expected to improve the classification results. For the sake of differentiation from RI MGF (MRF) features, we denote the rotation-variant MGF (MRF) features as traditional MGF (MRF) features. It has been proved that the fused traditional MGF/MRF features can generate an improved classification in view of their low inter-feature correlations [4, 5]. A low correlation coefficient between different types of features indicates the potential to produce improved results. In Section 4, the correlation relationship between RI MGF and MRF features is investigated, and an improved performance is expected to obtain by fusing the two types of RI texture features.

Feature fusion typically involves two stages: combination and selection. Feature selection is performed to choose an

optimal feature subset when combining different types of features. The classification accuracy, i.e. the Kappa coefficient (κ), is used as the criterion for feature selection and the classification process is based on the widely used multivariate Gaussian Bayes classifier. Among many feature selection methods found in the literature [10, 11], Tabu search has been considered to be a promising tool in that it can search more extensively in the feasible domain by moving away from the local optimal solutions. Some parameters used in the tabu search need to be selected carefully, such as neighborhood size and tabu list's length. An adaptive tabu tenure strategy has been introduced by Korycinski *et al* [12]. In this paper, we emphasize on the problem of the search neighborhood search size.

Traditional neighborhoods have specified size, generated by reversing a certain number of features' states [11]. The neighborhood size results from a compromise. On the one hand, larger the size, deeper is the access to the neighborhood. On the other hand, smaller the size, higher is the computational efficiency. To overcome this problem, we design an oscillating neighborhood scheme by introducing the idea of the oscillating search algorithm [13]. The tabu search method with the oscillating neighborhood scheme is named as the neighborhood-oscillating tabu search (NOTS) algorithm, which is put forward to fuse the RI MGF and MRF texture features. Let G denote the global best solution so far, C the current best solution, TL the tabu list, d the oscillation cycle depth, D the specified limit of oscillation cycle depth, t the number of none improvement at the current move and T the maximum of consecutive rejections. The NOTS algorithm is detailed as follows:

Step 1. (Initialization): Generate the initial set X. Let $G = X$, $C = X$, and $t = 0$.

Step 2. (Tabu moves): Pick the best non-tabu neighbor in the dynamic neighborhoods using the oscillating search method. In the oscillating search, if the current feature set is better than C but belongs to TL, the present search does not make any improvement. The oscillating search algorithm stops if C is better than G or the value of d exceeds D.

Step 3. (Output): If $C > G$ is true, let $G = C$ and $t = 0$; else let $t = t + 1$. The termination condition is predefined number of consecutive rejections, that is, if $t \geq T$ is satisfied, stop and output the global best solution G, else let $TL = TL \cup C$ and go back to Step 2.

4. Experimental Results

A QuickBird image of the suburban area in Peking, China, is studied. Four texture chips are selected, each representing a specific land-cover type of this area: residential area and three kinds of fields. Each texture is rotated counterclockwise at four orientations: 0°, 45°, 90°, and 135°. Fig. 4(a) is organized as four lines, and each line contains an array of the same four classes with different rotations. The size of each image chip in Fig. 4(a) is 90 × 90 pixels. As demonstrated in Section 2, a 12-D RI MGF feature vector and a 7-D RI MRF feature vector are obtained for each pixel of Fig. 4(a). The correspondence between feature numbers and feature meanings is given in Tables 1-2. Fig. 4(b) is a false color image composed of Feature 1, 4, and 7. And Fig. 4(c) presents one RI MRF feature image of the variance. The correlation relationship between the two types of RI features is examined: the average inter-feature correlation coefficient is 0.0459, which suggests that RI MGF features are not well correlated with the RI MRF features, and the combined features have the potential to offer richer texture information than the pure features.

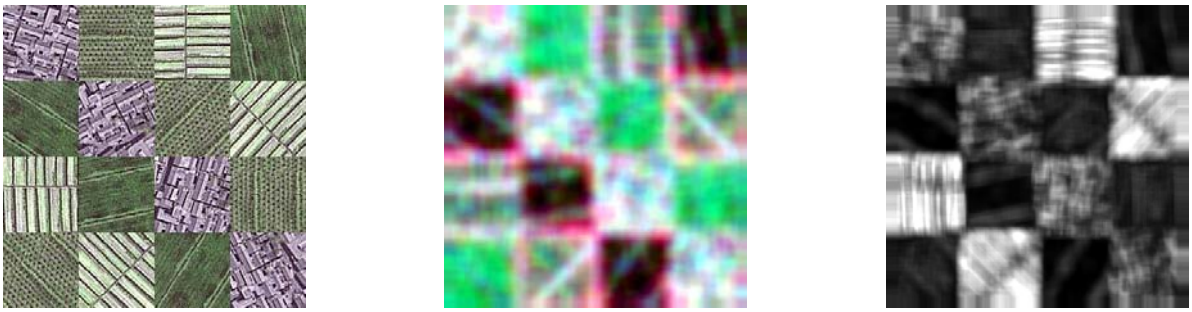
Different RI texture features is used in the classification. Since different features have different range of possible values, the classification may be based primarily on the features with wider range of values. For this reason, we normalize each feature by its standard deviation. In the common experiments found in the literature [14], training is based on multiple rotation angles. This paper considers a more challenging setup, where the texture classifier is trained at only one particular rotation angle: 0°. The fused MGF/MRF features by means of NOTS achieve a Kappa coefficient of 0.7982 with an overall accuracy 84.86%, and the results are listed in Table 3. And its corresponding classified image is shown in Fig. 5(c). The results using the sequential floating forward selection (SFFS) method [15], which is considered as a powerful tool for feature selection, are also shown in the same table for comparison. It is found that the obtained feature subset by NOTS is better than that by SFFS. The SFFS method is likely to trap into a local optimal solution. For SFFS, the local optimal solution {19, 4, 3, and 13} is obtained at the third running time.

Table 1. Identification of RI MGF texture features.

Feature number	Feature Meaning
1, 2, 3	Mean, standard deviation, and sum of perpendicular ratios for the frequency 64√2
4, 5, 6	Mean, standard deviation, and sum of perpendicular ratios for the frequency 32√2
7, 8, 9	Mean, standard deviation, and sum of perpendicular ratios for the frequency 16√2
10, 11, 12	Mean, standard deviation, and sum of perpendicular ratios for the frequency 8√2

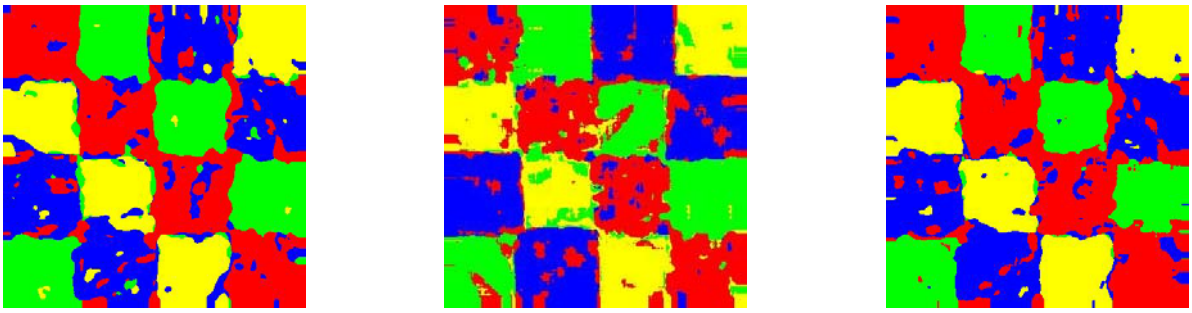
Table 2. Identification of RI MRF texture features.

Feature number	Feature Meaning
13, 14	Mean, standard deviation of model parameters over the first circle
15, 16	Mean, standard deviation of model parameters over the second circle
17, 18	Mean, standard deviation of model parameters over the third circle
19	Variance of the MRF model



(a) (b) (c)

Fig. 4. The input texture image and its RI texture feature images: (a) the image constructed with a total of 16 texture samples from the same four classes but from different rotations; (b) the false color image composed of Feature 1, 4, and 7; (c) the extracted RI MRF feature of the variance.



(a) (b) (c)

Fig. 5. The classified results using different features for Fig. 4(a): (a) features selected from RI MGF features with NOTS; (b) features selected from RI MRF features with NOTS; (c) the fused RI MGF/MRF features with NOTS.

The next SFFS running result is {19, 4, 3, 13, and 17} with a Kappa coefficient of 0.7521, and then the search is trapped into the local optimum. However, since the NOTS algorithm allows the search to move away from the local optimum, it always outperforms the conventional methods.

What's more, the comparison between the nonfused RI texture features with the fused MGF/MRF features is made. For each type of RI features (MGF or MRF), we employ the NOTS algorithm to selecting an optimal feature subset. Then the selected pure features are employed to texture classification. Their results are summarized in Table 4. And Fig. 5(a) and Fig. 5(b) correspond to the classified images for the RI MGF and MRF features, respectively. Comparing the results in Table 3 and Table 4, two remarks are made. One is the NOTS is more robust than SFFS. The other is the fused RI MGF/MRF features with NOTS obtain higher classification accuracy than either RI MGF or MRF features solely.

In addition, the experiments also show that some percentages of misclassifications are contributed by the border effect, inherent to texture analysis and which introduces important errors in the transition areas between texture units. Further work should be done to reduce this effect.

Table 3. Results for the fused RI MGF/MRF features using the SFFS and NOTS algorithms, respectively.

Feature selection methods	Features selected	Kappa coefficient	Overall accuracy
SFFS	19, 4, 3, and 13	0.7560	81.70%
NOTS	4, 6, 8, 5, 1,17, 2,and 3	0.7982	84.86%

Table 4. Results for the selected pure features with the NOTS algorithm.

Feature type	Dimensions of selected features	Kappa coefficient	Overall accuracy
RI MGF features	8	0.7726	82.94%
RI MRF features	3	0.7514	81.35%

5. Conclusions

This paper develops RI MGF and MRF features for rotation-invariant texture classification. And their integration is based on the observation that the weak correlation between them offers the potential for fusing the features and producing an improved classification. The NOTS algorithm is proposed to fuse features, compared with the SFFS method. It is observed that NOTS would not trap into a local optimal solution and is able to find an optimal feature subset effectively. The experimental results demonstrate the fused RI MGF/MRF features attained by NOTS outperform pure features solely. The fusion of the RI MGF/MRF features is capable of obtaining higher classification

accuracy. The approach described in this paper is proven to be an effective method of rotation-invariant texture classification.

Acknowledgments

This work was supported by the 973 Project of the People's Republic of China (Project Number 2003CB415205), and the National Natural Science Foundation of China (Project Number 40471088).

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