Texture Image Classification Using Gabor and LBP Feature

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Abstract. This paper presents a feature fusion based texture image classification method simultaneously using Gabor and Local Binary Patterns (LBP) feature. LBP and Gabor wavelets are two widely used two successful local image representation methods. This paper proposes two kinds of feature fusion methods, which perform in feature level and matching score level, respectively. We show that combining the two successful local image representations, i.e. Gabor wavelets and LBP, gives considerably better performance than either alone. Experiment results on MIT texture database demonstrate the effectiveness of our method.

Keywords: texture image classification, gabor wavelets, LBP.

1 Introduction

The textures exist in natural scenes captured in the image. The image texture is defined as a function of the spatial variation in gray values. The texture analysis is useful in a variety of applications, and it has been a subject of intense study by many researchers [1]. One immediate application of image texture is the recognition of image regions using texture properties. Image textures are one way that can be used to help in segmentation or classification of images. The goal of texture classification then is to produce a classification map of the input image where each uniform textured region is identified with the texture class it belongs to. Texture classification for images has been a hot research topic in computer vision for many years [2]. The texture classification has many potential applications. However, despite many potential areas of application for texture analysis in industry, there is only a limited number of successful examples. A major problem is that textures in the real world are often not uniform, because it changes in orientation, scale or other visual appearance.

Many appearance based approaches have been proposed to deal with texture classification problems. PCA [3] and LDA [4] are two widely used appearance based approaches, which have been the state of the art texture classification techniques. The PCA method extracts the features from the image matrix by projecting the image matrix along the projection axes that are the eigen-vectors of the covariance matrix. As the results, a texture subspace is constructed to represent the texture image. Similarly, LDA constructs a discriminant subspace, which is constructed to

J.-S. Pan et al. (eds.), *Intelligent Data Analysis and Its Applications, Volume 1*,
Advances in Intelligent Systems and Computing 297,
DOI: 10.1007/978-3-319-07776-5_35,

distinguish optimally textures of different subjects. In 2003, an improved PCA technique named two-dimensional PCA (2DPCA) was proposed by Yang et al. [5]. The 2DPCA directly extracts the features from the image matrix by projecting the image matrix along the projection axes that are the eigen-vectors of the 2D images covariance matrix. As the covariance matrix of 2DPCA has a lower dimensionality than that of PCA, 2DPCA is computationally more efficient than PCA. Motivated by 2DPCA, Xu et al. proposed to combine two solution schemes of 2DPCA to extract features from matrixes. Gao and Zhang et al. propose the two-dimensional independent component analysis (2DICA) that directly evaluates the two correlated demixing matrices from the image matrix without matrix-to-vector transformation.

The Gabor wavelets [6,7] based image preprocessing method achieves great success in texture classification. The Gabor wavelets, whose kernels are similar to the response of the two-dimensional receptive field profiles of the mammalian simple cortical cell, exhibit the desirable characteristics of spatial locality and orientation selectivity. The Gabor transformed image is represented by the convolution results of the image matrix with the Gabor wavelet. Since the Gabor features are extracted in local regions, they are less sensitive to variations of illumination than the holistic features.

LBP is a feature extraction method which considers both shape and texture information to represent the images [8]. A straight forward extraction of the feature vector (histogram) is adopted in LBP. The Local Binary Pattern (LBP) features are extracted and concatenated into a single feature histogram efficiently representing the image. The textures of the regions are locally encoded by the LBP patterns. The idea behind using the LBP features is that the texture images can be seen as composition of micro-patterns which are invariant with respect to monotonic grey scale transformations [9]. There is an extension to the original operator, in which it defined the so-called uniform patterns: an LBP is ‘uniform’ if it contains at most one 0-1 and one 1-0 transition when viewed as a circular bit.

In this paper, we seek to integrate the Gabor feature and LBP feature for texture classification. In texture image classification applications, when we get multiple feature sets of the pattern samples, it is very important to achieve a desirable recognition performance based on the feature sets. Feature fusion technology has been developed rapidly in the past years. There are mainly the following types of feature fusion strategies, which are fusion in data level fusion, fusion in feature level fusion, fusion in matching sore level fusion and fusion in decision level fusion. Data fusion simply combines different domains of raw data to form a new raw data, but it is difficult to implement in practice because of the following reasons: the feature sets of multiple modalities may be incompatible. Decision fusion combines multiple classifiers, but it is difficulty to achieve good performance. So we employ the fusion frameworks in feature level and matching score level, which has been applied to texture image classification.

The paper is organized as follows. In the next section we give a review of related work. Section 3 describes our method. In section 4, we give a number of experiment results. Section 5 offers our conclusions.

2 Related Works

2.1 Gabor Transform Method

Gabor filters have been used extensively in image processing, texture analysis for the excellent property of simulating the receptive fields of simple cells in the visual cortex. The Gabor filter is generated from a wavelet expansion of the Gabor kernels, exhibit desirable characteristics of spatial locality and orientation selectivity. Figure 1 gives an example of Gabor filter.

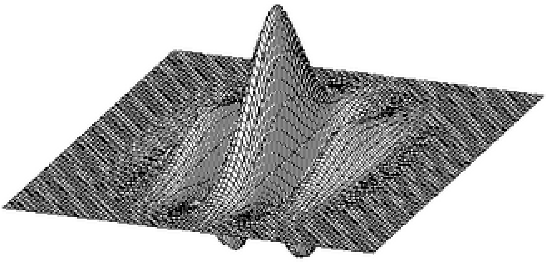


Fig. 1. An example of Gabor filter

The Gabor filter takes the form of a complex plane wave modulated by a Gaussian envelope function. The Gabor filter we used can be formulated in spatial-frequency domain as:

$$\psi_{u,v}(z) = \frac{\| k_{u,v} \|}{\sigma^2} e^{(-\|k_{u,v}\|^2 \|z\|^2 / 2\sigma^2)} [e^{izk_{u,v}} - e^{-\sigma^2/2}]$$

where, $z = (x, y)$, $\sigma = 2\pi$, $k_{u,v} = \begin{pmatrix} k_v \cos\phi_u \\ k_v \sin\phi_u \end{pmatrix}$, k_v and ϕ_u controls the scale and orientation of the Gabor wavelet, respectively. The first term in the brackets of the above Eq. is the oscillatory part of the kernel and the second compensates is the DC value. Let image matrix $I(z)(z = (x, y))$ be a image matrix, and then the Gabor transformed image is represented as the convolution of $I(z)$ with the Gabor wavelet $\psi_{u,v}(z)$, which can be defined as the following equation:

$$O_{u,v}(z) = I(z) * \psi_{u,v}(z)$$

The image matrix $I(z)$ is corresponding to 40 Gabor transformed images ($O_{k_0,\phi_0}(z)$, $O_{k_0,\phi_1}(z)$, …, O_{k_4,ϕ_7}).

2.2 LBP

- **LBP Coding**

Ojiala et al. [9] proposed the LBP operator in 1996. Local Binary Pattern (LBP) features have performed very well in various applications, including texture classification and segmentation. The LBP operator takes a local neighborhood around each pixel, thresholds the pixels of the neighborhood at the value of the central pixel and uses the resulting binary-valued image patch as a local image descriptor. The original LBP operator labels the pixels of an image by thresholding the 3-by-3 neighborhood of each pixel with the center pixel value and considering the result as a binary number. It was originally defined for 3×3 neighborhoods, giving 8 bit codes based on the 8 pixels. The resulting LBP can be expressed in the decimal form as

$$LBP(x_c, y_c) = \sum_{n=0}^{7} s(i_n - i_c)2^n$$

where n runs over the 8 neighbors of the central pixel, i_c and i_n are the gray-level values of the central pixel and the surrounding pixel, and s(x) is 1 if x>0; otherwise, s(x) is 0. Researchers have made an extension of the original operator. The operator was extended to use neighborhood of different sizes, to capture dominant features at different scales. Using circular neighborhoods and interpolating the pixel values allow any radius and number of pixels in the neighborhood. Figure 2 gives an example of LBP coding on a pixel.

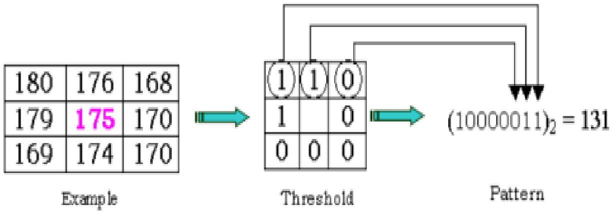


Fig. 2. LBP coding on a pixel

- **The Uniform Patterns in LBP**

It is noticed that most of the texture information was contained in a small subset of LBP patterns. These patterns, called uniform patterns, contain at most two bitwise 0 to 1 or 1 to 0 transitions (circular binary code). 11111111, 00000110 or 10000111 are for instance uniform patterns. They mainly represent primitive micro-features such as lines, edges, corners. The uniform patterns represent local primitives such as edges and corners. It was observed that most of the texture information was contained in the uniform patterns.

People usually label the patterns which have more than 2 transitions with a single label yields an LBP operator, which produces much less patterns without losing too much information. The following figure shows the 56 uniform patterns, and the two remaining uniform patterns are 11111111 and 00000000.

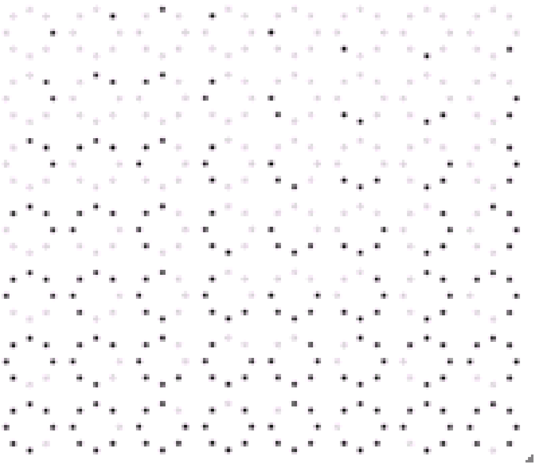
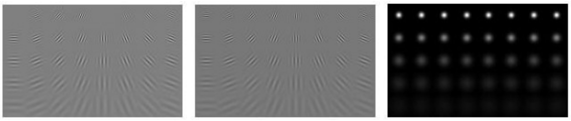


Fig. 3. The 56 uniform patterns. The black point means ‘1’ and the white point means ‘0’.

3 Our Method

In this section, we propose two feature fusion methods in feature level and matching score level, respectively. The first stage of the two fusion methods is same. They employ the Gabor transform and LBP coding methods to get the features.

For extracting discriminative information as much as possible, a bank of Gabor filters with several orientations and scales is chosen to extract the features from the image. 5 scales and 8 orientations are used in this paper, i.e.: $k_0 = \pi / 2^{0/2}, k_1 = \pi / 2^{1/2}, \ldots, k_4 = \pi / 2^{4/2}$ and $\phi_0 = 0\pi/8, \phi_1 = \pi/8, \ldots, \phi_7 = 7\pi/8$. We show the real part, imaginary part and the magnitude of the 40 Gabor filters (5 scales and 8 orientations) in Fig. 4:



(a) (b) (c)

Fig. 4. (a) The real part of the 40 Gabor filters, (b) The imaginary part of the 40 Gabor filters, (c) The magnitude of the 40 Gabor filters

One of the potential problems existing in Gabor feature is that it is redundant and too high-dimensional. For the example: if the size of the image size is 100×80, the number of the Gabor features will reach (100×5)×(80×8), which is incredibly large for the following feature extraction and classification method. Additionally, no evidence is found that every Gabor feature dose favor to improve classification accuracy. It is meaningful to conduct feature dimension reduction on all the Gabor features. As each Gabor transformed matrix is corresponding to a Gabor filter, we equate the feature dimension reduction to the selection of Gabor filters. Dozens of Gabor filters are usually adopted for constructing the ensemble Gabor transformed matrix, so exhaustive search is too time-consuming to get the solution. We design a heuristic search algorithm with forward selection. In our algorithm, the sum of the absolute values of the eigen-values of $G_w^{-1}G_b$ is used to evaluate the quality of the selected subset, where G_w, G_b are the between-class and within-class scatter matrices of 2DLDA respectively. Employing this criterion ensures that the new ensemble Gabor transformed matrix has the maximum Fisher's ratio, which is favorable for improving the classification accuracy of the training samples. The Gabor filter selection algorithm follows these steps:

Step 1. Initialize the parameter v that is the number of the filters to be selected.

Step 2. Select the first Gabor filter ψ_{s_1} from the Gabor filter set { $\psi_1,\psi_2,\ldots,\psi_k$ } according to the criterion.

Step 3. There are $k-1$ choices for selecting the second Gabor filter. Denote the Gabor transformed matrix corresponding to ψ_i as O_i. For each choice such as ψ_i, we ensemble the two Gabor transformed images of each training sample as the matrix [O_{s_1}, O_i]. Then, we calculate the value of the criterion function for the choice of ψ_i. ψ_{s_2} is selected as the second optimal Gabor filter, which has the maximum criterion function value among the $k-1$ choices.

Step 4. When the number of the Gabor filters selected reaches v, the algorithm terminates, otherwise, go to Step 5.

Step 5. Supposing t Gabor filters has been selected, then there are $k-t$ choices for selecting the ($t+1$)th Gabor filter. For each choice such as ψ_i, we ensemble the $t+1$ Gabor transformed images of each training sample as the matrix [$O_{s_1}, O_{s_2},\ldots,O_{s_t},O_i$]. Then, we calculate the criterion function for the choice of ψ_i. $\psi_{s_{(t+1)}}$ is selected as the ($t+1$)th Gabor filter, which has the maximum criterion function value among the $k-t$ choices.

By the above algorithm, v optimal Gabor filters ($\psi_{s_1},\psi_{s_2},\ldots,\psi_{s_v}$) are selected. Our optimal ensemble Gabor transformed image is constructed by the form of [$O_{s_1}, O_{s_2},\ldots,O_{s_v}$].

The individual sample image is divided into several small non-overlapping blocks with same size. Histograms of LBP codes are calculated over each block and then concatenated into a single histogram representing the image.

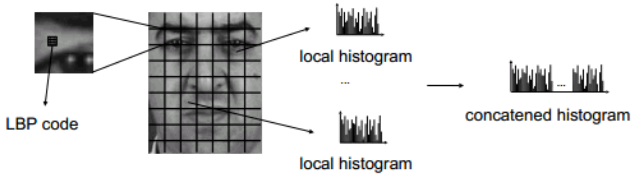


Fig. 5. Block based LBP

For the fusion method in feature level, the key stage is how to effectively combine the features. The simplest combination method is directly merged the Gabor feature vector and the LBP feature vector into one feature vector. The distance e denotes the matching score in our method. If $p = \arg\min_i e(i)$, then the testing sample is classified into the p-th subject. The following figure shows the framework of the fusion method in feature level.

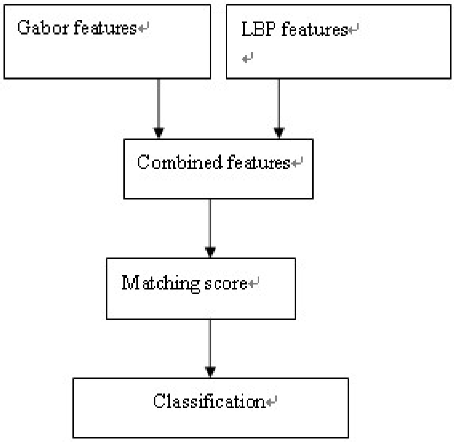


Fig. 6. The framework of the fusion method in feature level

For the fusion method in matching score level, the matching score in the two channels (Gabor feature and LBP) are computed, respectively. After getting the two matching scores e_1, e_2 of the test sample to the training image, Let $e(i) = ce_1(i) + (1-c)e_2(i)$. If $p = \arg\min_i e(i)$, then the testing sample is classified into the p-th subject.

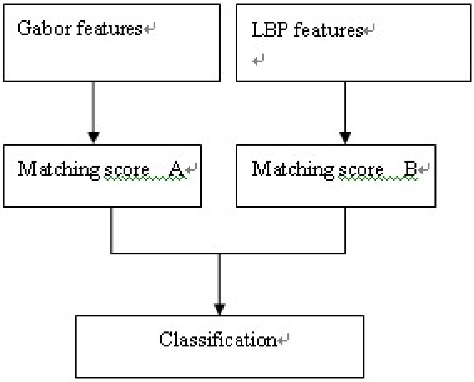


Fig. 7. The framework of the fusion method in Matching score level

4 Experiments

We assess the performance of our method on the MIT texture database, which includes 40 texture images. Figure 8 shows some images from this database. Each image has the same resolution of 512 × 512. Figure 8 shows some images from this database. We divided each image into 4 sub images with the size of 256 × 256. Figure 9 presents the 4 sub images obtained from the original image.

Fig. 8. Some images from this database

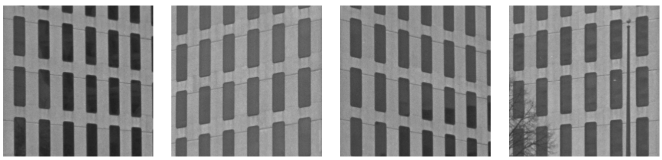
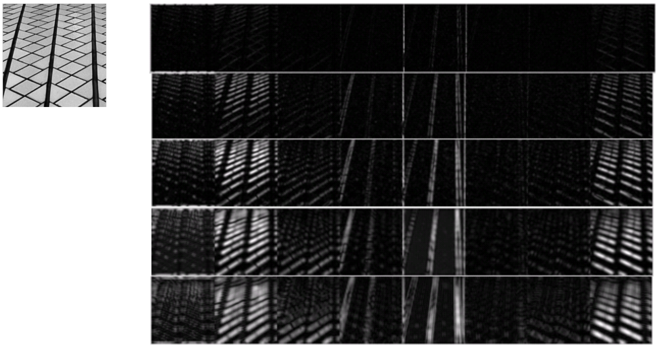


Fig. 9. 4 Sub images obtained from the original image

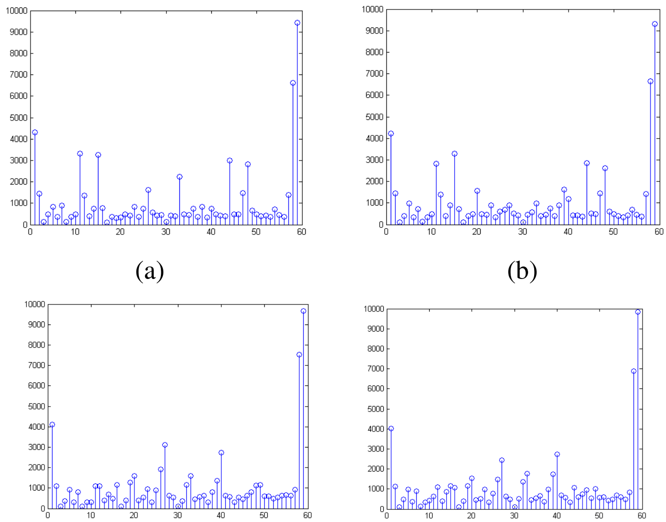
First, we use the 40 Gabor filters mentioned in section 3 to generate the Gabor feature of each image. Some examples of preprocessed images are shown in figure 10.



(a) (b)

Fig. 10. (a) a sub-image from the MIT texture database (b) the Gabor features of the left image

LBP also has been used for image representation. LBP histograms are extracted from the LBP coding image. It was observed that most of the texture information was contained in the uniform patterns. It has been noted that viewing the non-uniform patterns as one pattern produces much less patterns and does not lose too much information. so uniform patterns was used to reduce the length of LBP histograms. Figure 11 presents some 59-bin histograms obtained from the corresponding LBP coding images.



(a) (b)

(c) (d)

Fig. 11. (a) and (b) are the histograms of the two sub-images with the same texture. (c) and (d) are the histograms of the two sub-images with the same texture

As the comparisons, the state of the art image reorientation methods including original feature, DCT, Gabor wavelets. In the fusion method in the matching score level, we set e_1 be 0.1, 0.2, …,0.9. Among all the values of the parameter, we chose the one that has the maximum classification accuracy. The classification accuracies of these methods are presented in the following table.

Table 1. The classification accuracies on MIT texture database

methods	classification accuracy (%)
original feature	20.62
DCT (25 features)	34.38
DCT (100 features)	30.63
DCT (400 features)	26.25
DCT (65536 features)	20.62
Gabor (2621 features)	70.36
Gabor (655 features)	66.25
Fusing LBP and Gabor in feature level	98.75
Fusing LBP and Gabor in matching score level	98.75

5 Conclusions

This paper seeks to integrate the Gabor wavelets and LBP image presentation methods for texture classification. For achieving this aim, we proposed an optimal Gabor representation method and employed two feature fusion methods. The optimal Gabor representation method extracts the most representative and discriminative information from Gabor features. The two feature fusion methods are simple and effective. The results of the experiments carried on MIT texture database show that our method our method has strong ability in classifying texture images.

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