

Bark Classification Based on Gabor Filter Features Using RBPNN Neural Network

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Abstract. This paper proposed a new method of extracting texture features based on Gabor wavelet. In addition, the application of these features for bark classification applying radial basis probabilistic network (RBPNN) has been introduced. In this method, the bark texture feature is firstly extracted by filtering the image with different orientations and scales filters, then the mean and standard deviation of the image output are computed, the image which have been filtered in the frequency domain. Finally, the obtained Gabor feature vectors are fed up into RBPNN for classification. Experimental results show that, first, features extracted using the proposed approach can be used for bark texture classification. Second, compared with radial basis function neural network (RBFNN), the RBPNN achieves higher recognition rate and better classification efficiency when the feature vectors have low-dimensions.

1 Introduction

Plant species identification is a process resulting in the assignment of each individual plant to a descending series of groups of related plants, as judged by common characteristics. It is important and essential to correctly and quickly recognize and identify the plant species in collecting and preserving genetic resources, discovery of new species, plant resource surveys and plant species database management, etc. Plant identification has had a very long history, from the dawn of human existence. However, so far, this time-consuming and troublesome task was mainly carried out by botanists. Currently, automatic plant recognition from color images is one of the most difficult tasks in computer vision because of lacking of proper models or representations for plant. In addition, different plants take on numerous biological variations, which farther increased the difficult of recognition.

Many plant barks show evident texture features, which can be used as one of useful features for plant recognition. From bark texture analysis, we can conclude that it is necessary to define a set meaningful feature for exploring the characteristics of the texture of bark. There have been several approaches for this problem such as spatial gray-level co-occurrence matrix [1], Gabor filter banks [2], combining grayscale and

binary texture [3]. Although these methods yield a promising result to bark texture analysis, but they fail to classify bark texture adequately. One of the most popular signal processing approaches for texture feature extraction is Gabor filters which can filtering both in the frequency and spatial domain. It has been proposed that Gabor filters can be used to model the responses of the human visual system. A bank of filters at different scales and orientations allows multichannel filtering of an image to extract frequency and orientation information. This can then be used to decompose the image into texture features.

2 Gabor Wavelets and Feature Extraction

2.1 Gabor Wavelets

A 2-D Gabor function is a Gaussian modulated by a complex sinusoid [4]. It can be specified by the frequency of the sinusoid ω and the standard deviation σ_x and σ_y , of the Gaussian envelope as:

$$g(X, Y) = \frac{1}{2\pi\sigma_x\sigma_y} \cdot \exp\left[-\frac{1}{2}\left(\frac{X^2}{\sigma_x^2} + \frac{Y^2}{\sigma_y^2}\right) + 2\pi j\omega X\right] \quad (1)$$

The frequency response of this filter is written as:

$$G(U, V) = \exp\left\{-\frac{1}{2}\left[\frac{(U - \omega)^2}{\sigma_u^2} + \frac{V^2}{\sigma_v^2}\right]\right\} \quad (2)$$

Where $\sigma_u = \frac{1}{2\pi\sigma_x}$, $\sigma_v = \frac{1}{2\pi\sigma_y}$

The self-similar Gabor wavelets are obtained through the generating functions:

$$g_{mn}(X, Y) = a^{-m} \cdot g(X', Y') \quad (3)$$

$$X' = a^{-m}(X \cos \theta + Y \sin \theta), Y' = a^{-m}(-X \sin \theta + Y \cos \theta)$$

$$\theta = \frac{n\pi}{N}, a > 1, m, n = \text{Integers}$$

Where m and n specify the scale and orientation of the wavelet, respectively, with $m = 0, 1, 2, \dots, M, n = 0, 1, 2, \dots, N - 1$ and M, N are the total number of scales and orientations.

The Gabor kernels in Eq.1 are all mutually similar since they can be generated from the same filter, also known as mother wavelet. As described above, Gabor filter can localize direction spatial frequency at θ . When applied to an image, the output responds maximally at those particular edges whose orientation is θ . That means Gabor filter is oriental selective to image. We can use this specialty to detect the edges at all orientations of an image.

2.2 Image Feature Extraction

The Gabor wavelet image representation is a convolution of that image within the same family of Gabor kernels in Eq.1. Let $I(x, y)$ be the gray level distribution of an image, and the convolution of image I together with a Gabor kernel g_{mn} is defined as follows:

$$W_{mn}(x, y) = \int I(x, y) g_{mn}^*(x - x_1, y - y_1) dx_1 dy_1 \tag{4}$$

Where * indicates the complex conjugate and W_{mn} is the convolution result corresponding to the Gabor kernel at orientation m and n . It is assumed that the local texture regions are spatially homogeneous, and the mean μ_{mn} and the standard deviation σ_{mn} of the magnitude of the transform coefficients are used to represent the

region for classification purposes: $\mu_{mn} = \int \int |W_{mn}(x, y)| dx dy$ and

$$\sigma_{mn} = \sqrt{\int \int (|W_{mn}(x, y)| - \mu_{mn})^2 dx dy}$$

A feature vector is now constructed using the mean μ_{mn} and standard deviation σ_{mn} of the output in the frequency domain as feature components.

$$\vec{f} = [\mu_{00} \sigma_{00} \mu_{01} \dots \mu_{35} \sigma_{35} \dots] \tag{5}$$

We use this feature vector as bark recognition feature vector.

3 Radial Basis Probabilistic Network (RBPNN) Classifier

After the Gabor features of bark image have been extracted which had described in section 2, the second task is that recognition of bark texture image using radial basis probabilistic network (RBPNN).

The RBPNN model is essentially developed from the radial basis function neural networks (RBFNN) and the probabilistic neural networks (PNN) [5], [6], [7], [8]. Therefore, the RBPNN possesses the common characteristics of the two original networks, i.e., the signal is concurrently feed-forwarded from the input layer to the output layer without any feedback connections within the network models. Moreover, the RBPNN avoids the disadvantages of the two original models to some extent. The RBPNN, shown in Fig.1, consists of four layers: one input layer, two hidden layers and one output layer. The first hidden layer is a nonlinear processing layer, which generally consists of hidden centers selected from a set of training samples. The second hidden layer selectively sums the first hidden layer outputs according to the categories to which the hidden centers belong. Generally, the corresponding weight values of the second hidden layer are 1's. For pattern recognition problems, the outputs in the second hidden layer need to be normalized. The last layer for RBPNN is simply the output layer, which completes the nonlinear mapping by carrying out

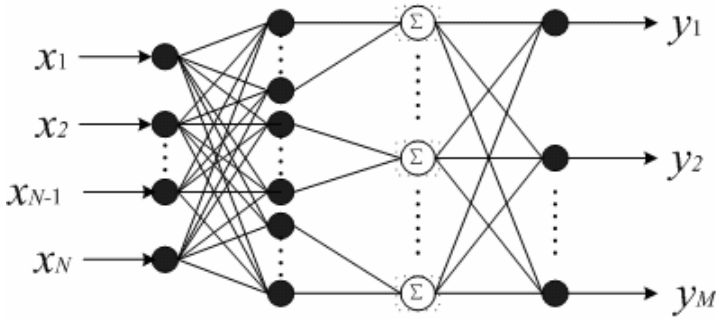


Fig. 1. The topology scheme of the RBPNN

tasks such as classification, approximation and prediction. In fact, the first hidden layer of the RBPNN has the vital role of performing the problem-solving task.

Training of the network for the RBPNN used orthogonal least square algorithms (OLSA). The advantages of recursive least square algorithms are that it can fast convergence and good convergent accuracy. The algorithms can be expressed as the following equation in mathematics:

$$y_i^o = \sum_{k=1}^M w_{ik} h_k(x) \quad (6)$$

$$h_k(x) = \sum_{i=1}^{n_k} \phi_i(x, c_{ki}) = \sum_{i=1}^{n_k} \phi_i(\|x - c_{ki}\|_2) \quad (7)$$

$, k = 1, 2, \dots, M$

Here, x is a given input vector, y_i^o is the output value of the i -th output neuron of neural network, $h_k(x)$ is the k -th output value of the second hidden layer of network; w_{ik} is the weight matrix between the k -th neuron of the second hidden layer and the i -th neuron of the output layer, c_{ki} represents the i -th hidden center vector for the k -th pattern class of the first hidden layer; n_k represents the number of hidden center vector for the k -th pattern class of the first hidden layer; $\|\bullet\|_2$ is Euclidean norm; and M denotes the number of the neurons of the output layer and the second hidden layer, or the pattern class number for the training samples set; $\phi_i(\|x - c_{ki}\|_2)$ is the kernel function, which is generally Gaussian kernel function can be written as.

$$\phi_i(\|x - c_{ki}\|_2) = \exp\left(-\frac{\|x - c_{ki}\|_2^2}{\sigma_i^2}\right) \quad (8)$$

For m training samples, Eq.6 can be expressed as:

$$\begin{bmatrix} y_{11}^o & y_{12}^o & \cdots & y_{1m}^o \\ y_{21}^o & y_{22}^o & \cdots & y_{2m}^o \\ \cdots & & & \\ y_{n1}^o & y_{n2}^o & & y_{nm}^o \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & \cdots & h_{1m} \\ h_{21} & h_{22} & \cdots & h_{2m} \\ \cdots & & & \\ h_{n1} & h_{n2} & & h_{nm} \end{bmatrix} \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1m} \\ w_{21} & w_{22} & \cdots & w_{2m} \\ \cdots & & & \\ w_{m1} & w_{m2} & & w_{mm} \end{bmatrix} \quad (9)$$

that also can be written as:

$$Y^o = HW \quad (10)$$

From [7], the weight matrix W can be solved as follows:

$$W = R^{-1}\hat{Y} \quad (11)$$

where R, \hat{Y} can be obtained as follows:

$$H = Q \begin{bmatrix} R \\ L \\ 0 \end{bmatrix}, Q^T Y = \begin{bmatrix} \hat{Y} \\ \tilde{Y} \end{bmatrix} \quad (12)$$

where Q is an $n \times n$ orthogonal matrix with orthogonal columns satisfying $QQ^T = Q^T Q = I$, and R is an $m \times m$ upper triangle matrix with the same rank as H . In Eq. (11), \hat{Y} is a $(N-M) \times M$ matrix. Equation (11) expresses the orthogonal decomposition of the output matrix H of the second hidden layer of RBPNN.

4 Image Data and Experimental Results

4.1 Image Data and Features Chosen

We have collected more than 300 pictures of bark in our image database. These images were recorded at a resolution of 640 x 480 pixels, with a bit depth of 16 bits/pixel. Thus, 256 levels were available for each R, G, and B color plane. The images were converted to JPEG format and grayscale intensity image before processing. Some bark images are shown in Fig.2.

Chosen randomly about 50% of plant bark samples for each bark class form a testing set and the remaining samples form a training set. By this partition, there are 248 samples in the training set and 17 character samples in the testing set. In addition, because the trunk of the tree is cylinder and the two sides of the pictures are possibly blurred, so the particularity of interests (ROI), we have select that is a relatively bigger ROI with the size of 350 x 400 pixels.



Fig. 2. Three kinds of original bark images

As we have discussed in section 2, the Gabor filter-based feature extraction method requires setting control parameters of Gabor filter. Hence a feature vector consists of different parameters will be obtained which contains the visual content of the image. To get the best result, the Gabor parameters were test for different values of the number of scales (m) and the number of orientations (n). The average recognition rates have been presented in Table 1.

The experiment has been made on a PC (PentiumIV-2.4GHz CPU, 512M RAM).The image features were calculated using subroutines written in Matlab 7.0 language. Software for Classifier of RBPNN, we use a conventional C++6.0 programming environment. Totally seventeen bark classes are used for identification. These were: retinispora, maple, Sophora japonica, dogbane, trumpet creeper, osier, pine, phoenix tree, camphor, poplar and willow, honey locust, palm, ginkgo, elm, etc. Every type of bark has half images for training, others for testing. We used the "quantity average recognition rate" defined as below to compare the results.

$$\text{Average Recognition Rate} = \frac{\text{Number of Bark Image Classified Truly}}{\text{Totat Number of Classified Bark Images}} \cdot \%$$

The obtained average recognition rates are presented in Table 1.

Table 1. Average Recognition Rates for Different Gabor Filter and SVM classifier

Gabor Filter Features Used	RBPNN	SVM
Orientation(n)=6, Scales(m)=4	63.71%	60.48%
Orientation(n)=6, Scales(m)=5	72.58%	78.22%
Orientation(n)=6, Scales(m)=6	79.03%	81.45%
Orientation(n)=6, Scales(m)=7	77.42%	83.06%
Orientation(n)=5, Scales(m)=4	62.90%	62.10%
Orientation(n)=5, Scales(m)=5	74.19%	77.42%
Orientation(n)=5, Scales(m)=6	76.61%	79.84%
Orientation(n)=5, Scales(m)=7	79.84%	81.45%
Orientation(n)=4, Scales(m)=4	66.13%	64.52%
Orientation(n)=4, Scales(m)=5	77.42%	76.61%
Orientation(n)=4, Scales(m)=6	79.84%	80.64%
Orientation(n)=4, Scales(m)=7	79.84%	82.26%
Orientation(n)=4, Scales(m)=8	80.65%	81.45%

From the classification performances shown in Table 1, we found that: 1) for each fixed spatial sampling resolution, there exists an optimal wavelength which achieves the best performance. We observed that the orientation $n=4$ achieves the better performance in bark recognition experiments. 2) While orientation $n=4$ and scales increasing, the average recognition rate of bark can be improved. 3) As for the spatial sampling resolutions, it seems that 4×8 sampling is enough for bark classification when used RBPNN classifier. Adopting the more Gabor image feature that can improve accuracy of bark classification, but it will lead to a time-consuming computation. 4) In order to compare the effectiveness of the Gabor features with that of the other classifier such as SVM, Our results show that RBPNN classifier can achieve more better when the feature vectors has low-dimensions such as the dimensions is fewer than 24, at the same time the SVM classifier can give better classification accuracy while the dimension of feature vectors is above 24.

5 Conclusion

This paper proposes a bark texture recognition algorithm, in which Gabor feature representation and RBPNN classifier are employed. The neural network which was trained using orthogonal least square algorithms is employed to classify such feature vectors and tested on different scales and different orientation. We have also found in experiments that RBPNN offers an accuracy of higher classification when the feature vectors have low-dimensions such as the dimensions is fewer than 24. When the dimension of the feature vectors is high, the RBPNN can give similar results as SVM. In the future, more effective feature extracted methods will be investigated for bark classification.

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