Bark Classification Using RBPNN Based on Both Color and Texture Feature

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Summary
In this paper, a new scheme that merges color and texture information for bark image recognition is proposed. The feature vectors concerning color and texture are extracted using the multiresolution wavelet. In addition, the application of these features for bark classification using radial basis probabilistic network (RBPNN) and support vector machine (SVM) has been introduced. Finally, experimental results clearly show that the combining color and texture features that have employed wavelet filter bank for bark classification are more effective than other methods such as Histogram method, Co-occurrence matrices method and Auto-correlation method for bark image.

Key words:
Image classification, radial basis probabilistic network (RBPNN), SVM ,bark image ,pattern recognition

1.Introduction

Automatic plant species recognition is a very challenging problem in fields of pattern recognition, computer vision, plant taxonomy and ecology. A major challenge with this task is to find a robust and accurate method for extracting visual botanic features. There have been several approaches for plant species recognition based on the plant features of leaves, barks and flowers [1, 2, 3]. Here, we report our work on plant species recognition based on bark features, in particular, bark classification using color and wavelet filter texture features. Unlike the gray level approaches, color information is a powerful tool that can increase the efficiency and robustness of bark features extraction. Wavelet transform has been applied in diverse areas such as signal processing and image processing. Combinations of these features which have been extracted from bark image can be employed to improve classification accuracy of plant species recognition.

2. Two Dimensional Discrete Wavelet Transform

Application of wavelet transform in image processing is one of the most active areas in wavelet studies. The continuous wavelet transform (CWT) of a 1-D signal $f(x)$ is defined as:

$$(W_a f)(b) = \int f(x)\psi^*_{a,b}(x)dx \qquad \textbf{(1)}$$

where the wavelet $\psi_{a,b}$ is computed from the mother wavelet ψ by translation and dilation

$$\psi_{a,b} = \frac{1}{\sqrt{a}}\psi(\frac{x-b}{a}) \qquad \textbf{(1)}$$

(1) can be discreted by restraining a and b to a discrete lattice ($a = 2^n, b \in Z$). Typically, it is imposed that the transform should be non-redundant, complete and constitute a multiresolution representation of the original signal. Under these constraints, an efficient real-space implementation of the transform using quadrature mirror filters exists [4].
Two dimensional wavelet transform can be considered as an extension of 1D wavelet transform. Mathematically, wavelet transform is a convolution operation, which is equivalent to pass the pixel values of an image through a low pass filter and a high pass filter. A separable filter bank to the image can be expressed as follows:

$$\begin{aligned}
L_n(\vec{b}) &= [H_x * [H_y * L_{n-1}]_{\downarrow} 2,1]_{\downarrow 1,2}(\vec{b}) \\
D_{n1}(\vec{b}) &= [H_x * [G_y * L_{n-1}]_{\downarrow} 2,1]_{\downarrow 1,2}(\vec{b}) \\
D_{n2}(\vec{b}) &= [G_x * [H_y * L_{n-1}]_{\downarrow} 2,1]_{\downarrow 1,2}(\vec{b}) \\
D_{n3}(\vec{b}) &= [G_x * [G_y * L_{n-1}]_{\downarrow} 2,1]_{\downarrow 1,2}(\vec{b})
\end{aligned} \qquad \textbf{(3)}$$

where (*) denotes the convolution operator, $\downarrow 2,1(\downarrow 1,2)$ subsampling along the rows (columns) and $L_0 = I(\vec{x})$ is the original image. H and G are the low and bandpass filter respectively. L_n is obtained by low pass filtering and is therefore referred to as the low resolution image at scale n .The D_{ni} are obtained by bandpass filtering in a special direction and thus contain directional detail information at scale n ; they are referred to as the detail

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images. The original image I is thus represented by a set of subimages at several scales; $\{L_d, D_{ni} | i = 1,2,3, n = 1,2,...,d\}$ which is a multiscale representation of depth d of the image I .

For image that is a two dimensional signal, wavelet transform decomposes it into 4 frequency bands, namely, the LL1, HL1, LH1 and HH1 band. H and L denote a highpass and lowpass filter respectively. The approximated image LL is obtained by lowpass filtering in both row and column directions. The detailed images, LH, HL, and HH, contain high frequency components. To obtain the next coarse level of wavelet coefficients, the subband LL1 alone is further decomposed and critically sampled. Similarly, to obtain further decomposition, LL2 will be used. By decomposing the approximated image of each level into four subimages iteratively, a pyramidal image tree is acquired. This results in three-level wavelet decomposition as shown in Fig. 1.

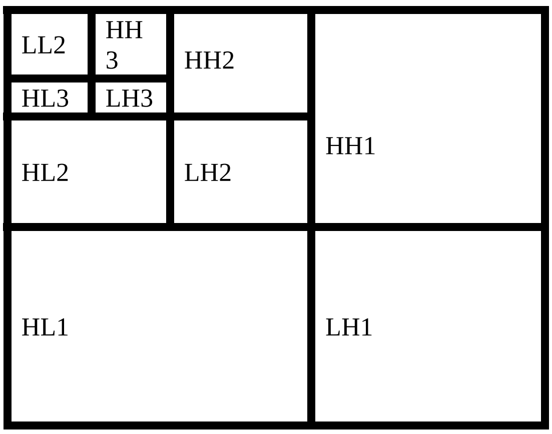

Fig. 1. A three-level wavelet analysis

The previous analysis can be applied to input bark images for distinguishing frequency layers. It is evident that at each resolution level three new feature channels are obtained, which are characterized by the given scale depth the horizontal, the vertical, and the diagonal components. As micro textures or macro textures have non-uniform pixel value variations, they are statistically characterized by the features in approximation and detailed images or in other words, the values in the sub-band images or their combinations or the derived features from these bands uniquely characterize a texture. The features obtained from these wavelet transformed images have been used to texture analysis, namely, classification. Different textures are distinguished based on these last two characteristics. We have used the energy calculated at the output of each channel as the following representative features vector:

$$e_i = \frac{1}{M \times N} \sum_{x=1}^{M} \sum_{y=1}^{N} I_i^2(x, y) \qquad (\mathbf{4})$$

where, $I_i(x, y)$ denotes an image obtained in i^{th} subband, with resolution $M \times N$ having been determined by the wavelet frame analysis and the dimension of the vector being $e = 3i$.

3. Wavelet-based bark feature set

Among various low-level features, the color information has been extensively studied because of its invariance with respect to image scaling and orientation. For an image, a color spectrum or histogram is the simple and efficient low-level feature. However, if we calculate directly in a triple-dimension color space (e.g., RGB), both the storage space and computing time will be much cost. So color quantization is necessary before extraction of the image color features. In our experiments, the steps for creating the color layout feature vector from an image are:

a) Convert the RGB value of bark image to the YCbCr color space. In this color space, luminance (brightness or intensity) information is stored as a single component denoted by Y). Chrominance (color) information is stored as two color-difference components (Cb and Cr). Cb represents the difference between the blue component and a reference value. Cr represents the difference between the red component and a reference value.

b) Extract the color feature components for each component using Daubechies 3rd wavelet filter at depth 3 as described in Section 2.

c) Then construct the color layout feature vector.

In this work, apart from the color, the texture of the image has also been taken into account [8]. The spatial texture feature extraction is independent from that of color. At first, we convert the RGB image to grayscale image. Thus, we use the gray-scale component of the image to obtain the spatial texture features from constructing the wavelet transform using three-level decomposition. The energy associated with each subband at each level is used to form the feature vector which has been shown in above, just the same as color features extraction.

4. Image data and radial basis function neural networks

Having extracted the color and texture features of bark image as described in section 2, we will recognize 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]. The RBPNN, shown in Fig.2, consists of four layers: one input layer, two hidden layers and one output layer. 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 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.

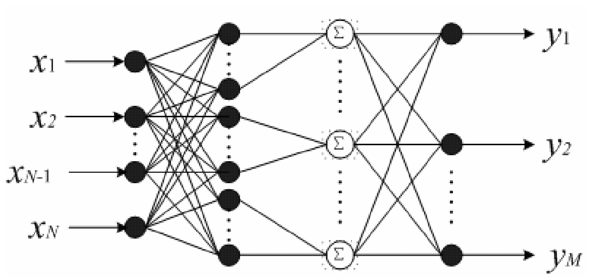

Fig.2 The topology scheme of the RBPNN

Orthogonal least square algorithms (OLSA) is used to train the network for the RBPNN. The algorithms can be expressed as the following equations in mathematics:

$$y_i^o = \sum_{k=1}^{M} w_{ik} h_k(x) \tag{4}$$

$$h_k(x) = \sum_{i=1}^{n_k} \phi_i(x, c_{ki}) = \sum_{i=1}^{n_k} \phi_i(\|x - c_{ki}\|_2)$$
$$k = 1,2,\cdots M \tag{5}$$

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 kth 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 numher for the training samples set; $\phi_i(\|x - c_{ki}\|_2)$ is the kemel function, generally Gaussian kernel function, which can be written as.

$$\phi_i(\|x - c_{ki}\|_2) = \exp(-\frac{\|x - c_{ki}\|_2^2}{\sigma_i^2}) \tag{6}$$

For m training samples, Eq.1 can be expressed as:

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

(7)

which also can be writed as:

$$Y^O = HW \tag{8}$$

From [5], the weight matrix $\mathbf{W}$ can be solved as follows:

$$\mathbf{W} = \mathbf{R}^{-1}\hat{\mathbf{Y}} \tag{9}$$

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

$$\mathbf{H} = \mathbf{Q}\begin{bmatrix} \mathbf{R} \\ \cdots \\ \mathbf{0} \end{bmatrix}, \mathbf{Q}^{\mathbf{T}}\mathbf{Y} = \begin{bmatrix} \hat{\mathbf{Y}} \\ \tilde{\mathbf{Y}} \end{bmatrix} \tag{10}$$

where $\mathbf{Q}$ is an $n \times n$ orthogonal matrix with orthogonal columns satisfying $\mathbf{Q}\mathbf{Q}^T = \mathbf{Q}^T\mathbf{Q} = \mathbf{I}$, and $\mathbf{R}$ is an $m \times m$ upper triangle matrix with the same rank as $\mathbf{H}$. In Eq. (9), $\hat{\mathbf{Y}}$ is a $(N-M) \times M$ matrix. Equation (9) expresses the orthogonal decomposition of the output matrix $\mathbf{H}$ of the second hidden layer of RBPNN.

The experiment database containing more than 300 pictures of bark is collected by us. These images were recorded at a resolution of 640 x 480 pixels, with a bit depth of 24 bits/pixel. Thus, 256 levels were available for each R, G, and B color plane. Some bark images are shown in Fig.2.

Fig. 3 Three kinds of original bark images

About 50% of plant bark samples are chosen randomly for each bark class to form a testing set and the remaining samples constitute the 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), a relatively bigger ROI with the size of 360×360 pixels is selected.

Our experiments compare different features measurements, such as auto-correlation method (ACM), co-occurrence matrices method (COMM), histogram method(HM), and then test the combination of color and texture with our bring forward methods[7].
The obtained average recognition rates are presented in Table 1.

Table 1: Average Recognition Rates for Different Bark Features and methods

Features Used	RBPNN (%)	SVM (%)
Auto-correlation method(ACM)	72.00	65.00
Co-occurrence matrices method (COMM)	77.00	75.00
Histogram method(HM)	65.00	62.00
Color & texture wavelet filter	84.68	82.26

From the classification performances shown in Table 1, we found that combining color and texture wavelet filter features can achieve better perform than others methods.

5.Conclusions

In this paper, a new method for bark classification based on textural and color features using RBPNN is presented. In this method, DWT is applied to a set of color bark images and energy features are extracted from the approximation and detailed regions of DWT decomposed images. It is found from the experiments that the accuracy of classification is improved much by combining color and texture features compared with other methods such as Histogram method, Co-occurrence matrices method and Auto-correlation method. The future study will focus on how to extract more efficient and optimum feature set from bark images, to improve the classification accuracy further.

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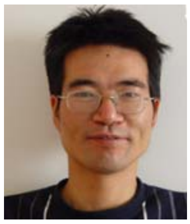

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