Classification Based on Gabor Filter Using RBPNN Classification *

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Abstract

In this paper, a color pattern recognition technique that is suitable for multicolor images of bark has been analyzed and evaluated. To extract the bark texture features, Gabor filter the image has been filtered with four orientations and six scales filters, and then the mean and standard deviation of the image output are computed. In addition, the obtained Gabor feature vectors are fed up into radial basis function neural network (RBPNN) for classification. The performance of color space features is found to be better than that of the features which just extracted from gray image. The experimental results show this approach can be used to automatically identify the plant categories more effective.

1. Introduction

Recognizing plants from imagery is a complex task due to their irregular nature.The availability of a rapid and accurate method to recognize and classify bark images also becomes necessary. Plant identification can use some features that like as: the fruit, seeds or capsules, leaf shape or cell structure, etc. At the same time, many plant barks show evident color texture features, which can be used as one of useful features for plant recognition. Therefore, developing an effective method to preliminarily classify textures based on the textural characteristics will greatly help the design of a plant identification system. Bark image has shown some texture properties. Texture refers to some characteristic like smoothness, coarseness and regularity of a region. It is an important image features and often provides useful cues for surface and object. A great number of texture analysis methods have been proposed over decades, such as multi-channel filtering features, fractal based features and co-occurrence features [1,2,3], and these methods can capture different texture properties of the images at different levels. Chetverikov[4]defined a simple window differencing operator to the texture features obtained from simple filtering operations. This allows one to detect the boundaries of defects in the texture. Dewaele et al. [5] used signal processing methods to detect point defects and line defects in texture images. They have sparse convolution masks in which the bank of filters are adaptively selected depending upon the image to be analyzed. Texture features are computed from the filtered images. A Mahalanobis distance classifier is used to classify the defective areas. Chen and Jain [6] used a structural approach to defect detection in textured images. They extract a skeletal structure from images, and by detecting anomalies in certain statistical features in these skeletons, defects in the texture are identified. Fractals and spatial autocorrelation are two spatial analytical techniques used to measure geometric complexity[7] and conveniently describe many irregular, fragmented patterns found in nature[8].Conners et al. [9] utilized texture analysis methods to detect defects in lumber wood automatically. The defect detection is performed by dividing the image into subwindows and classifying each subwindow into

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one of the defect categories such as knot, decay, mineral streak, etc. In this paper, we brief overview color space and describe fundamentals of 2-D Gabor filters (wavelets) at first. Texture representation and based on the output of Gabor filters in different color space is computed. Finally, the obtained Gabor feature vectors are fed up into radial basis function neural network(RBPNN) for classification.

2. Overview color space and Gabor filters

2.1. Color Space

Color representation is a problem of significant importance in the fields of computer vision and image processing. There are several color space transformations. They attempt to obtain a better representation of the color. Commonly used color spaces for image include RGB,YIQ, L*u*v*, HSV (or HSL, HSB), and the opponent. The various color spaces exist because they present color information in ways that make certain calculations more convenient or because they provide a way to identify colors that is more intuitive. Model RGB is based on fact that almost all the colors can be expressed by mixing in the fixed proportions of three selected clusters of light of the properly chosen width of spectrum. This standard defined a three-dimensional space where three values, called tristimulus values, define a color. Three of components (r, g, b) (r=Red, g=Green, b=Blue) are the identification of color in the model RGB. The RGB model simplifies the design of computer graphics systems but is not ideal for all applications. The red, green, and blue color components are highly correlated. In 1931 the CIE developed the XYZ color system, also called the "norm color system". This system is often represented as a two-dimensional graphic, which more or less corresponds to the shape of a sail. The red components of a color are tallied along the horizontal axis of the coordinate plane and the green components along the vertical axis. In this way every color can be assigned a particular point on the coordinate plane. In the NTSC (National Television System Committee) color space, image data consists of three components: luminance (Y), hue (I), and saturation (Q). NTSC color space also called YIQ color space, formerly used in the NTSC television standard. I stands for in-phase, while Q stands for quadrature, referring to the components used in quadrature amplitude modulation. NTSC now uses the YUV color space, which is also used by other systems such as PAL. I and Q can be thought of as a second pair of axes on the same graph, rotated 33; therefore IQ and UV represent different coordinate systems on the same plane. This formula approximates the conversion from the RGB color space to YIQ. R, G and B are defined on a scale from zero to one:

$$\begin{bmatrix} Y \\ I \\ Q \end{bmatrix} = \begin{bmatrix} 0.299 & 0.587 & 0.114 \\ 0.595716 & -0.274453 & -0.321263 \\ 0.211456 & -0.522591 & 0.311135 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

The YCbCr color space is widely used for digital video. In this format, luminance information is stored as a single component (Y), and chrominance 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. To make the conversion from RGB to YCbCr:

$$\begin{aligned} Y &= 0.299R + 0.87G + 0.114B \\ C_b &= -0.16874R - 0.33126G + 0.5B \\ C_r &= 0.5R - 0.41869G - 0.08131B \end{aligned} \tag{2}$$

(2) The HSV color space (hue, saturation, value) is often used by people who are selecting colors (e.g., of paints or inks) from a color wheel or palette, because it corresponds better to how people experience color than the RGB color space does. In HSV space, a maximum value means that the color is at its brightest. In HLS space, a maximum value for lightness means that the color is white, regardless of the current values of the hue and saturation components. The brightest, most intense color in HLS space occurs at a lightness value of exactly half the maximum.

2.2. Gabor filters

One of the crucial aspects of texture classification is the extraction of proper and representative textural features. Here, we consider the features generated by Gabor filters [10]. Recently, Gabor filters have received considerable attention because the characteristics of certain cells in the visual cortex of some mammels can be approximated by these filters. The Gabor wavelets are of similar shape as the receptive fields of simple cells in the primary visual cortex (V1). They are localized in both space and frequency domains and have the shape of plane waves restricted by a Gaussian envelope function. Basically, Gabor filters are a group of wavelets, with each wavelet capturing energy at a specific frequency and a specific direction. Expanding a signal using this basis provides a localized frequency description, therefore capturing local features/energy of the signal. Texture features can then be extracted from this group of energy distributions. A particular Gabor elementary function can be used as the mother wavelet to generate a whole family of Gabor wavelets. A two-dimensional Gabor function and its Fourier transform can be written as:

$$g(x,y) = \frac{1}{2\pi\sigma_x\sigma_y} exp\left[-0.5\left(\frac{x^2}{\sigma_x} + \frac{y^2}{\sigma_y}\right)\right] + 2\pi j W_x \tag{3}$$

$$G(u,v) = exp\left\{-0.5\left[\frac{(u-W)^2}{\sigma_u^2} + \frac{v^2}{\sigma_v^2}\right]\right\} \quad (4)$$

where $j = \sqrt{-1}$, $\sigma_u = 1/2\pi\sigma_x$, and $\sigma_v = 1/2\pi\sigma_y$. Gabor functions form a complete but nonorthogonal basis set. Expanding a signal using this basis provides a localized frequency description. Let $g(x,y)$ be the mother Gabor wavelet, then this self-similar filter dictionary can be obtained by appropriate dilations and rotations of $g(x,y)$ through the generation function:

$$g_{mn}(x,y) = a^{-m} g(x', y') \quad (5)$$

where$a \geq 1, m, n = integer$,

$$\begin{aligned} y' &= a^{-m}(-x * \cos\theta + y * \sin\theta) \\ x' &= a^{-m}(-x * \cos\theta + y * \sin\theta) \end{aligned} \quad (6)$$

where $\theta = \frac{n\pi}{k}$, n and k indicate the orientation and scale of the filter respectively. is the total number of orientations and is the total number of scales in the filter bank. The scale factor is meant to ensure that the energy is independent of [4]. For a given image , the decomposed image at scale and orientation is :

$$W_{mn}(x,y) = \int\int I(x,y) g_{mn}^*(x - x_1, y - y_1) dx_1 dy_1 \quad (7)$$

where indicates the complex conjugate. It is assumed that the local texture regions are spatially homogeneous, and the mean and the standard deviation of the magnitude of the transform coefficients are used to represent the region for classification purposes:

$$\begin{aligned} \mu_{mn} &= \int\int |W_{mn}(x,y)| dxdy \\ \sigma_{mn} &= \int\int \left|(W_{mn}(x,y) - \mu_{mn})^2\right| dxdy \end{aligned} \quad (8)$$

A feature vector is now constructed using μ_{mn} and σ_{mn} as feature components. The texture descriptor for k scales and n orientations is given by:

$$features = [\mu_{00}, \sigma_{00}, \mu_{11}, \sigma_{11}, \ldots, \mu_{nk}, \sigma_{nk}] \quad (9)$$

While the size of the filter bank is application dependent, experimentation has shown that a bank of filters tuned to combinations of four scales, and six orientations, at 60-degree intervals, is sufficient for the analysis of bark image.

3. The results of RBPNN classifier

In this paper, radial basis probabilistic network (RBPNN) has been used for recognition of bark texture image. The RBPNN model is essentially developed from the radial basis function neural networks (RBFNN) and the probabilistic neural networks (PNN), more detail can be found in literature [11][12]. 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 database contains 300 bark images. In this experiment, there are 100 testing image50% of it for training and 50% of it for validation. Some bark sample images are shown in Fig.1.

Figure 1. Two kinds of original bark images

In our experiment, we use six scales (k) and four orientations (n), which result in a feature vector of 48. 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, gingkgo, 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.

Average recognition rates=Number of Bark Image Classified Truely/Total Number of Classified Bark Image$*$ 100%

The average recognition rates have been presented in Fig.2. In order to compare average recognition with different classifiers such as SVM (Support Vector Machine), and the corresponding results are shown in Figure 3. From the clas-

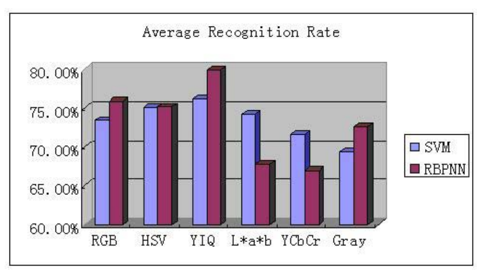

Figure 2. Average Recognition Rate in Different Color Space

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sification performances shown in Figure 3, we found that: 1) for different color space, there exists an optimal choice which achieves the best recognition rate. We observed that in YIQ color space can achieves the better performance in bark recognition experiments. 2) In contrast to only use gray information in image, increased color channel information can improve average recognition rate.3) As for the spatial sampling resolutions, adopting the more Gabor image feature that can improve accuracy of bark classification, but it will lead to a time-consuming computation.

4. Conclusion

This paper proposes a bark texture recognition algorithm, in which Gabor feature representation in different color space is extracted and RBPNN classifier are employed. After extracting the bark texture features, Gabor filter the image has been filtered with four orientations and six scales filters, and then the mean and standard deviation of the image output are computed. Finally, the obtained Gabor feature vectors are fed up into radial basis function neural network (RBPNN) for classification. This paper also demonstrates that when a bank of Gabor filters is applied to an image, there are strong relationships between the outputs of the different filters. These relationships are used to devise a new texture feature which is capable of describing texture information in a concise manner. The performance of color space features is found to be better than that of the features which just extracted from gray image. The experimental results show this approach can be used to automatically identify the plant categories. The future study will focus on how to extract more efficient features from bark images to improve the classification accuracy further.

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