Recognition of Plant Leaves Using Support Vector Machine

Qing-Kui Man[1,2], Chun-Hou Zheng[3,*], Xiao-Feng Wang[2,4], and Feng-Yan Lin[1,2]

[1] Institute of Automation, Qufu Normal University, Rizhao, Shandong 276826, China
[2] Intelligent Computing Lab, Institute of Intelligent Machines, Chinese Academy of Sciences, Hefei, Anhui 230031, China
[3] College of Information and Communication Technology, Qufu Normal University
[4] Department of Computer Science and Technology, Hefei University, Hefei 230022, China
mqingkui@126.com, zhengch99@126.com

Abstract. A method using both color and texture feature to recognize plant leaf image is proposed in this paper. After image preprocessing, color feature and texture feature plant images are obtained, and then support vector machine (SVM) classifier is trained and used for plant images recognition. Experimental results show that using both color feature and texture feature to recognize plant image is possible, and the accuracy of recognition is fascinating.

Keywords: Support vector machine (SVM), Image segmentation, Digital wavelet transform.

1 Introduction

There are many kinds of plants that living on the earth. Plants play an important part in both our human life and other lives existing on the earth. Unfortunately, the categories of plant is becoming smaller and smaller. Fortunately, people are realizing the importance of protecting plant, they try all ways they can to protect plants that ever exist on the earth, but how can they do this work without knowing what kind of categories plant belongs to. Then a problem is: Since computer is more and more widely used in our daily life, how can we recognize the different kind of leaves using computer?

Plant classifying is an old subject in human history, which has developed rapidly, especially after human being came into the Computer Era. Plant classifying not only recognizes different plants and names of the plant, but also tells the difference of different plants, and builds system for classifying plant. It can also help researchers find origins, relations of species, and trends in evolution. At present, there are many modern experiment methods in plants classifying area, such as plant cellular taxonomy, cladistics of plant, and so on. Yet all these methods are not easy for non-professional staff, because these methods can't be easily used and the operation is very complex.

* Corresponding author.

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With the development of computer technology, digital image processing develops rapidly, so people want to use image processing and pattern recognition techniques to make up the deficiency of our recognition ability, in order that non-professional staffs can use computer to recognize variety of plants.

According to theory of plant taxonomy, it can be inferred that plant leaves are most useful and direct basis for distinguishing a plant from others, what's more, leaves can be very easily found and collected everywhere. By computing some efficient features of leaves and using a suitable pattern classifier, it is possible to recognize different plants successfully.

Till now, many works have focused on leaf feature extraction for recognition of plant. In [1], a method of recognizing leaf images based on shape features using a hyper-sphere classifier was introduced. In [5], the author gave out a method which combines different features based on centroid-contour distance curve, and adopted fuzzy integral for leaf image retrieval. Gu et.al[6] used the result of segmentation of leaf's skeleton to do leaf recognition. Among these methods, using leaf shape feature is the best way to recognize plant images [1], and the accuracy of recognizing is fascinating. Since image color and texture feature are two features that most sensitive to human vision, we select both of the two features as the feature to recognize plant image in this paper.

In this paper, a method of using color feature and texture feature to recognize plant image was proposed. That is, using color moments as the color feature and extracting texture feature of plant leaf image after wavelet high pass filter. Usually, the wavelet transform has the capability of mapping an image into a low-resolution image space and a series of detail image spaces. For the majority of images, their detail images indicate the noise or uselessness of the original ones. In this paper, information of leaf vein was extracted as the texture feature. Therefore, after extracting these features of leaves, different species of plants can be classified by using SVM.

The remainder is organized as follows: Section 2 describes something about image segmentation, and some definition of color moments and texture feature, especially wavelet transform. Section 3 describes the Support Vector Machine (SVM) in detail. Section 4 present the experimental results and demonstrates the feasibility and validity of the proposed method. Conclusions are included in Section 5.

2 Extracting Leaf Features

In this section, we will introduce something about image segmentation. After the segmentation, color moments and wavelet transform are introduced to represent images of plant leaf.

2.1 Image Segmentation

The images of plant leaf, which were gotten through camera, are always with complex background. The purpose of image segmentation is to get the region of interest (ROI), which will be used to extract color moments and other texture features. There are two kinds of background in the leaf images: one is simple, and the other is complicated. In this paper we select leaf image with simple background to test our algorithm that recognizing leaf images. After the procedure of image segmentation, a binary image of which ROI is displayed with 1 and background is displayed as 0 will be received.

For the leaf image with simple background, it can be seen that the gray level of pixels within leaf objects is distinctly different from that of pixels within the background. For the leaf images we collected ourselves are with simple background, we use adaptive threshold [10] method to segment them, and experimental results show that this method worked very well.

There are many kinds of image features that can be used to recognize leaf image, such as shape feature [1], color feature and texture feature. In this paper, we select color feature and texture feature to represent the leaf image.

2.2 Color Feature Extraction

Color moments have been successfully used in many color-based image retrieval systems [2], especially when the image contains just the image of leaf. The first order (mean), the second (variance) and the third order (skewness) color moments have been proved to efficient and effective in representing color distributions of images. Mathematically, the first three moments can be defined as:

$$\mu_k = \frac{1}{sum} \sum_{i=1}^{sum} p_i^k \tag{1}$$

$$\sigma_k = \left(\frac{1}{sum} \sum_{i=1}^{sum} (p_i^k - \mu_k)^2\right)^{1/2} \tag{2}$$

$$\delta_k = \left(\frac{1}{sum} \sum_{i=1}^{sum} (p_i^k - \mu_k)^3\right)^{1/3} \tag{3}$$

Where p_i^k is the value of the k-th color component of the image i-th pixel, and sum is the number of pixel that the region of interest contains.

For the reason that HSV color space is much closer to human vision than HIS color space [12], we extracted color moments from HSV color space in this paper.

2.3 Image Normalization

Texture feature is another important image feature to represent image. In this paper, we use wavelet transform to obtain the leaf vein on which the texture feature is based. Before wavelet transform, we do some preprocessing to normalize the leaf image [4]. The method of normalizing the image is summarized as follows:

(1)Compute the center coordinate $A(x_0, y_0)$ of plant image.

(2)Find the coordinate $B(x_1, y_1)$ which is farthest from the center coordinate.

(3)From coordinates $A(x_0, y_0)$ and $B(x_1, y_1)$, we can get $\theta = \arctan(\frac{y_1 - y_0}{x_1 - x_0})$.

(4)Rotate the plant image by θ.

The results of this preprocessing are shown in Fig.1.

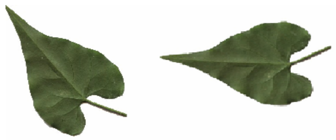

Fig. 1. Leaf image after normalization

2.4 Texture Feature Extraction

The wavelet transform (WT), a linear integral transform that maps $L^2(R^2) \to L^2(R^2)$, has emerged over the last two decades as a powerful new theoretical framework for the analysis and decomposition of signals and images at multi-resolutions [7]. Moreover, due to its both locations in time/space and frequency, this transform is completely differs from Fourier transform [8, 9].

Wavelet transform is defined as decomposition of a signal $f(t)$ using a series of elemental functions called as wavelets and scaling factors, which are created by scaling and translating a kernel function ψ (t) referred to as the mother wavelet:

$$\psi_{ab}(t) = \frac{1}{\sqrt{a}}\psi(\frac{t-b}{a}) \tag{4}$$

Where $a, b \in R, a \neq 0$ and the discrete wavelet representation (DWT) can be defined as:

$$W_f^d(j,k) = \int_{-\infty}^{\infty} \psi_{j,k}(x)\bar{f}(x)dt = \langle \psi_{j,k}, f \rangle \quad j,k \in Z \tag{5}$$

In this paper, we use wavelet transform in 2D, which simply use wavelet transform in 1D separately. 2D transform of an image $I = A_0 = f(x, y)$ of size $M \times N$ is:

$$A_j = \sum_x \sum_y f(x, y)\varphi(x, y).$$

$$D_{j1} = \sum_x \sum_y f(x, y)\psi^H(x, y).$$

$$D_{j2} = \sum_x \sum_y f(x, y)\psi^V(x, y).$$

$$D_{j1} = \sum_x \sum_y f(x, y)\psi^D(x, y).$$

That is, four quarter-size output sub-images, A_j, D_{j1}, D_{j2} and D_{j3}, are generated after wavelet transform.

After the Digital Wavelet Transform (DWT), we use high pass filter to obtain the leaf vein. Then we calculate leaf image's co-occurrence matrix which is used to calculate the texture feature. The result of this transform is shown in Fig.2. From the image after wavelet high pass filter, it is easy for us to find that leaf vein was more distinctive than in the original image, and the approximate part of the original image was filtered.

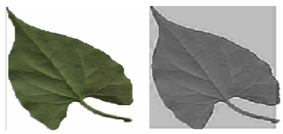

Fig. 2. Leaf image after wavelet high pass filter transform

Then we use the transformed image to extracted co-occurrence matrix. Texture features we get can be defined as following:

Entropy: $$ent = -\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p(i,j)\log_2 p(i,j) \tag{6}$$

Homogeneity: $$h = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} \frac{p(i,j)}{0.1+|i-j|} \tag{7}$$

Contraction: $$cont = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p(i,j)\,|i-j| \tag{8}$$

Based on co-occurrence matrix, in the four different directions of the image, i.e. the angles take different value: 0, 45, 90 and 135 degree, we can get texture features of plant images.

All the data we extracted as described in Section 2 are raw data. Both data that represent color feature and texture feature will be processed before training the classifier.

3 Support Vector Machine (SVM)

Support vector machine (SVM) [11] is a popular technique for classification, and using SVM to process multi-class problem is one of present research focuses.

A classification task usually involves with training and testing data which consist of some data instances. Each instance in the training set contains one “target value” (class labels) and several “attributes” (feature). The goal of SVM is to produce a model which predicts target value of data instances in the testing set which are given only the attributes.

Given a training set of instance-label pairs $(x_i, y_i), i = 1,...,l$ where $x_i \in R^n$ and $y_i \in \{1,-1\}^l$, the support vector machines (SVM) require the solution of the following optimization problem:

$$\min_{w,b,\xi} \frac{1}{2} w^T w + c \sum_{i=1}^{l} \xi$$

subject to $$y_i(w^T \phi(x_i) + b) \ge 1 - \xi_i, \ \xi \ge 0 .$$

Here training vectors x_i are mapped into higher (maybe infinite) dimensional space by the function ϕ. Then SVM finds a linear separating hyperplane with the maximal margin in this higher dimensional space. $c > 0$ is the penalty parameter of the error term. Furthermore, $K(x_i, x_j) \equiv \phi(x_i)^T \phi(x_j)$ is called the kernel function. Though new kernels are being proposed by researchers, the following are the four basic kernels:

Linear: $K(x_i, x_j) = x_i^T x_j$.

Polynomial: $K(x_i, x_j) = (\gamma x_i^T x_j + r)^d, \gamma > 0$.

Radial Basis Function (RBF): $K(x_i, x_j) = \exp(-\gamma \| x_i - x_j \|^2), \gamma > 0$.

Sigmoid: $K(x_i, x_j) = \tanh(\gamma x_i^T x_j + r)$.

Here, γ r and d are kernel parameters.

4 Experimental Results

In this section, we will select some features that we extracted through the procedure we describe above, such as image segmentation and wavelet transform, to do classification experiment, and select $K(x_i, x_j) = \exp(-\gamma \| x_i - x_j \|^2), \gamma > 0$ as the SVM kernel.

The following experiments are programmed using Microsoft Visual C++ 6.0, and run on Pentium 4 with the clock of 2.6 GHz and the RAM of 2G under Microsoft windows XP environment. Meanwhile, all of the results for the following figures and tables are the average of 50 experiments.

This database of the leaf images is built ourselves in our lab by the scanner and digital camera, including twenty four species. In this section, we take 500 leaf samples corresponding to 24 classes collected by ourselves such as seatung, ginkgo, etc (as shown in Fig.3). We selected data of color feature and texture features as the input data for training classifier SVM. Before training the classifier, we do some processing with the raw data [3]. We used z-score normalization to do data preprocess, which is defined as:

$$v' = (v - \bar{A}) / \sigma_A \tag{9}$$

Where $\bar{A}$ and σ_A are the mean and standard deviation of component A respectively.

Fig. 3. Leaf images used for experiment

Firstly, we only use color features to do experiment and find that the accuracy is more than 90 percent if number of categories is small, yet when the number grew to five or six the accuracy drop to 60 percent. This is because that the color of most plant leaf images are green, and in HSV color space, which is similar to human's vision, the difference between every two plants leaf image is very little, that's to say, color feature is not a good feature for plant leaf image recognition.

Secondly, we take only texture features as the experiment data. The result is that: the rate of recognition is satisfying. From the result, we can get the truth that texture of image is a good feature to recognize plant images.

Thirdly, because color is an important feature of the plant image, so we also use both of the two image features, color feature and texture feature, to do experiments. The result is fascinating: the right recognition accuracy is up to 92%.

Table 1. Results of leaf image recognition

	Accuracy			
	4 categories	6 categories	10 categories	24 categories
Using color feature	90%	63%	40%	Very low
Using texture feature	98%	96%	93.5%	84.6%
Using both feature	100%	100%	97.9%	92%

The result of our experiment is shown in table 1. From the table we can see that our method is competitive. In [1], the method authors proposed that using shape feature to recognize plant images can recognize more than 20 categories plants with average correct recognition rate up to 92.2%. Compared to that method, our way that using color feature and texture feature of plant image is very good.

5 Conclusions

In this paper, a way of using color feature and texture feature to recognize plant images was proposed, i.e. using color moments and texture feature of plant leaf image after wavelet high pass filter to recognize plant leaf images. The wavelet transform is of the capability of mapping an image into a low-resolution image space and a series of detail image spaces. However, in this paper, information of leaf vein was extracted after wavelet high pass filter to represent the texture feature. After computing these features of leaves, different species of plants was classified by using SVM. And the rate of recognizing plant using this method is satisfying. Our future work include selecting most suitable color feature and texture feature, as well as preprocessing the raw data we selected from leaf images, which will heighten the accuracy rate.

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