Journal of Computational Information Systems 11: 1 (2015) 141–148
Available at http://www.Jofcis.com

Leaf Image Recognition Based on Wavelet and Fractal Dimension *

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Abstract

Recognition of plant leaf images is an important and difficult task. Extracting the texture feature of leaf images becomes the key to solve this problem in recent years. Considering some wavelet methods only focus on low-frequency sub-bands of images and some fractal dimension methods using a single exponent also cannot identify the images well, a novel wavelet fractal feature based approach for plant leaf images recognition is proposed. Firstly, the preprocessed leaf images are pyramid decomposed with 5/3 lifting wavelet transform and sub images are obtained. Then fractal dimensions of each sub images are calculated to be the wavelet fractal feature of leaf images. Finally back propagation artificial neural network is used to classify plant leaf images. The experimental results show that the proposed method can improve the performance for plant image recognition compared with methods using only wavelet or fractal dimension.

Keywords: Image Recognition; Feature Extraction; Lifting Wavelet Transform; Fractal Dimension

1 Introduction

Plants play an important role in the natural circle of life, humans cannot live without plants. Plant classification and identification has greatly significance for the research and protection of a large number of plants which are different from each other. Compared with other organs of the plant, leaves can be collected more easily, they contain many features such as shape, color and vein texture. So leaves are often chosen as the main organ to identify plants. With the development of digital image processing, machine vision and pattern recognition, some studies of plant identification based on leaf image have been done. Computer-aided plant classification can make up for the shortcomings of traditional manual identification methods to improve the efficiency and accuracy.

Due to its importance in feature classification, feature extraction has received considerable attention during the past decades. A large percentage of these works have involved the analysis of leaf shape with leaf texture having been ignored [1, 2]. However texture should also be taken into consideration. Texture is an important visual cue which widely exists in images and is hard to describe. Among the visual attributes that can be used to characterize an image, texture is one

*Project supported by the Fundamental Research Funds for the Central Universities (No. TD2014-01).

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DOI: 10.12733/jcis12815
January 1, 2015

of the most important as it describes the surface of an object in terms of the distribution of pixels over a region. Given the importance of the texture, many approaches have been developed in recent years. Currently, there are several most common methods for texture features extraction of leaf image such as Gray-Level Co-occurrence Matrix (GLCM) [3], wavelet transform, Gabor filter [4] and fractal dimension.

There are both advantages and disadvantages in these methods. The methods using wavelet transform can represent the image texture at multi-resolutions and combine space domain and frequency domain to analyze texture features. And it is also more in line with the human visual characteristics. However, the traditional wavelet transform methods just utilize the low-frequency sub-bands texture image information. They only keep an eye on the low-resolution images, while the detail images are ignored. But the high-frequency sub-bands of the image still contain detailed information about the texture [5]. The fractal methods apply fractal dimension as an index characterizing complicated geometric forms for which the details seemed more important than the gross image. It means that fractal dimension can describe detailed structure of the image at scale which is even smaller than the observation. Unlike topological dimensions, the fractal dimension can take non-integer values. In spite of its frequent utilization in image analysis and pattern recognition, the fractal dimension measure has limitations: objects and patterns with distinct geometric natures can be found that have equivalent or approximate fractal dimension. So a single exponent is not enough to describe the image [6].

Essentially, both fractal method and wavelet method are studies of nonlinear problems and related to self-similarity of object from some respect. Therefore this paper proposes a method based on wavelet transform and fractal dimension to overcome the above-mentioned limitations. Moreover this method is able to analyze the texture at multiple scales without losing details.

The rest of this paper is organized as follows: Section 2 introduces the details of the proposed method and gives the corresponding algorithm. Section 3 gives the experiment and results. Section 4 discusses the result and draws a conclusion.

2 Wavelet Fractal Feature Extraction

On the basis of the above discussion, in this part, we propose an approach for image feature extraction based on wavelet transform and fractal dimension. Firstly, the preprocessed images are decomposed by wavelet transform. Then fractal dimensions of the decomposed images are calculated including both coarse images and detail images. Finally, these wavelet fractal dimensions are used as the features of images.

2.1 Wavelet transform and lifting scheme

The first literature that relates to the wavelet transform is Haar wavelet which was proposed by the mathematician Haar in 1909. However, the concept of the wavelet did not exist at that time. In 1984 Morlet proposed the concept and then invented the term wavelet. Mallat proposed multi-resolution and the fast wavelet transform in 1988. Since then the wavelet transform had numerous applications in the signal and image processing field [7].

Sweldens proposed the lifting scheme for the construction of wavelets. The lifting scheme is also called as the second generation wavelet transform. Compare with the traditional fast wavelet transform algorithm, lifting scheme is more simple and efficient to calculate wavelet transforms. It does not require complex mathematical calculations and does not depend on Fourier transforms. It is able to implement reversible integer wavelet transforms.

Wavelets decomposition based on lifting scheme contains three steps as follows:

(1) Split: The original signal s is split into two subsets which do not overlap with each other. Usually two subsets are even sequence s_e and odd sequence s_o.

$$Split(s) = (s_e, s_o). \tag{1}$$

(2) Predict: The original signal is locally coherent, so odd sequence can be predicted by even sequence utilizing the correlation between them. In fact, the predict operator P could not predict precisely. The prediction set $P(s_e)$ could only get as close as possible to odd set s_o. It is also called as detail signal and reflects the degree of correlation of data. If the prediction is reasonable, the difference set d contains much less information than the original.

$$d = s_o - P(s_e). \tag{2}$$

(3) Update: After the split step, the feature of image is changed such as the average value. Thus an update step is needed. Detail signal d is used to update the set s_e to get coarse signal c through the update operator U.

$$c = s_e - U(d). \tag{3}$$

2.2 Fractal dimension and blanket method

The essential idea of fractal dimensions has a long history in mathematics, but the term itself was first used by Mandelbrot based on his 1967 paper on self-similarity in which he discussed fractional dimensions. The application of fractal dimension for non-fractal objects is common in image analysis and pattern recognition, where fractal dimension has been utilized for quantifying shape complexity, texture and geometric composition [8].

Determining the dimension of an object implies computing a value that better represents the dimensional space, to which it belongs. It is a challenging work. Mandelbrot proposed a method to determine the fractal dimensions based on Eq. (4) when he estimated the length of the coastline and its fractal characteristics. Peleg extended this method to estimate the surface area and proposed a blanket method [9].

Self-similarity is the most important feature of fractal. It is expressed as

$$M(\lambda) = k\lambda^{D-D_F}. \tag{4}$$

For a two dimensional image, λ is measure scale, $M(\lambda)$ is fractal surface area $A(\lambda)$, k is constant, $D = 2$, D_F is fractal dimensions. When analyze the fractal dimension in texture, the texture is regarded as point sets defined as (x, y, z) where x and y are pixel coordinates and z is the gray level of that pixel. All points in the three-dimensional space at distance ε from the surface are considered, covering the surface with a blanket of thickness 2ε. The surface area is then the volume occupied by the blanket divided by 2ε. According to Eq. (4), the self-similarity of the image could be expressed as

$$A_\varepsilon = k\varepsilon^{2-D_F}, \tag{5}$$

so

$$\log A(\varepsilon) = (2 - D_F)\log \varepsilon + \log k. \tag{6}$$

When plotting $A(\varepsilon)$ versus ε on a $\log - \log$ scale, one gets a straight line of slope. This curve does not have to be straight for non-fractal surfaces. The fractal dimensions could be estimate by the slope of the curve.

Detail steps are as follows:

Step 1. Define the covering blanket by its upper surface u_ε and its lower surface b_ε. Initialize the u_0 and b_0 given the gray level function $g(i, j)$.

$$u_0(i, j) = b_0(i, j) = g(i, j). \tag{7}$$

Step 2. Calculate the value of the upper surface and the lower surface, for $\varepsilon = 1, 2, 3, \ldots$ they are defined as

$$u_\varepsilon(i, j) = \max\{u_{\varepsilon-1}(i, j) + 1, \max u_{\varepsilon-1}(m, n) \mid d \leqslant 1\}, \tag{8}$$

and

$$b_\varepsilon(i, j) = \max\{b_{\varepsilon-1}(i, j) - 1, \max u_{\varepsilon-1}(m, n) \mid d \leqslant 1\}, \tag{9}$$

where d is the distance between point (m, n) and point (i, j), so point (m, n) are the four immediate neighbors of point (i, j) with distance less than one from point (i, j).

Step 3. Calculate the volume of the blanket.

$$V_\varepsilon = \sum_{i,j}(u_\varepsilon(i, j) - b_\varepsilon(i, j)). \tag{10}$$

Step 4. Calculate the surface area of the blanket.

$$A(\varepsilon) = \frac{V_\varepsilon - V_{\varepsilon-1}}{2}. \tag{11}$$

Step 5. Calculate the slope of the fitting straight line through the points $(\log \varepsilon, \log A(\varepsilon))$ as fractal dimensions.

3 Experiments and Results

The procedure of experiment contains two phase, training phase and testing phase. We divided the leaf images to two groups, one was training samples and the other was testing samples. First we preprocessed the images and then extract the features of the preprocessed images. In training phase, we used the features of training samples to train the classifiers. We used the trained classifiers and the features of testing samples to recognize the leaf. Finally, we got the recognition accuracy which proved the effectiveness of this method.

3.1 Dataset

The dataset used in our experiments was Flavia which was set up by Stephen and was shared online [10]. We chose 16 plant species of all, each consisting of 60 images. There was only one leaf in each image whose background is white with a resolution of 1600×1200 pixels and in JPG format. The images of each species were divided into training samples and testing samples. The number of training samples has effect on the results and is discussed in Section 3.5.

3.2 Preprocessing

Before extracting the feature, some preprocess work should be done to improve the quality of the image to prepare for the feature extraction and recognition. The colored images would be turned into gray-scale images, ignoring the color information, since the majorities of leaves are green. In practice, the variety of the change of nutrition, water, atmosphere and season can cause the change of the color. We used the weighted average method to calculate the gray scale as follows:

$$L = R \times 0.2989 + G \times 0.5870 + B \times 0.1141, \tag{12}$$

where R, G, B are three values of red, green and blue channel of the RGB image, the weight coefficients is the ratio of the three primary colors which is obtained in practice.

In the process of acquiring an image, it cannot avoid generating noise. The images include noise which could affect the result of feature extraction, so need to smooth image to eliminate noise. We used median filtering method whose main idea is to have a window which contains an odd number of points to slide, put the point needs to be calculated in the middle of the window, calculate all the value of points in the window as the gray value of the current point.

The wavelet decompose at each scale require the image size to be multiples of 2. So we should resize the image to 1024×1024.

3.3 Feature extraction

After pre-processing procedure, the images were decomposed by lifting wavelet transform mentioned above. We used 5/3 bi-orthogonal wavelet to decompose the images. The update operator and predict operator is expressed as follows:

$$d_{j-1} = s_{oj-1} - \frac{1}{2}(s_{ej-1} + s_{ej}). \tag{13}$$

$$c_{j-1} = s_{ej-1} + \frac{1}{4}(d_{j-1} + d_j). \tag{14}$$

The multiplication in Eq. (13) and Eq. (14) can be replaced by the shift operation, which could reduce the complexity of computation.

We applied pyramid decomposition which means that we decomposed the coarse images until the scale s equals depth. At each scale s, the decomposed images include horizontal detail images(h), vertical detail images(v), diagonal detail images(d) and coarse images(c). $3d + 1$ sub images were obtained after wavelet transform decomposition of depth d. Fig. 1 shows the structure of pyramid decomposition of depth 2. Then we used the method mentioned above to calculate the fractal dimension of all sub images.

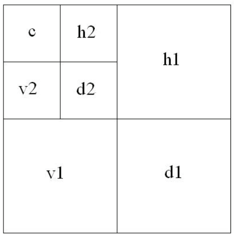
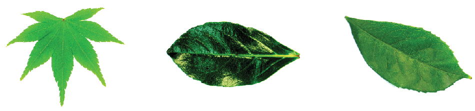


Fig. 1: Structure of pyramid decomposition

The fractal dimensions (fd) of original images in Fig. 2 and the fractal dimensions of their decomposed images ($hd1$, $vd1$, $dd1$, $cd1$) are listed in Table 1. This result implies that fractal dimensions could distinguish leaf images but sometimes a single fractal dimensions is not enough to describe the image.



(a) (b) (c)

Fig. 2: Three different species leaves

Table 1: Fractal dimensions of three leaves

Species	fd	hd1	vd1	dd1	cd1
a	2.46	2.03	2.06	2.08	2.61
b	2.48	2.12	2.19	2.23	2.59
c	2.26	2.09	2.13	2.16	2.36

The depth of decomposition determines the number of wavelet sub images which is same as the number of features we can extract from the images. It also affects the results and is discussed in Section 3.5.

3.4 Classifier

We used back propagation artificial neural network (BPANN) as a classifier, the structure of network include three layers, one input layer, one hidden layer and one output layer. The number of input layer nodes m is the number of feature extracted by wavelet fractal method. The number of output layer nodes n is the number of all species we need to identify. The number of hidden layer nodes is $\sqrt{mn}$. The transfer function is symmetrical function.

The result is shown in Table 2 comparing with the support vector machines (SVM) classifier and k-nearest neighbor (K-NN) classifier [11].

Table 2: Comparison with different classifier

Classifier	Accuracy(%)
K-NN	69.01
SVM	77.46
BPANN	91.19

3.5 Factors

As mentioned in Section 3.1 and 3.3, there are two main factors that affect the accuracy of recognition. The results are shown in Fig. 3 and Fig. 4.

- **The number of training samples** The classifier need training samples to learn the features of leaf images. If the number is not large enough, the classifier could not be trained well to recognize the leaf effectively. The accuracy increase along with the number of training samples.

- **The depth of decomposition** The depth of decomposition determines the number of features that could be extracted from leaf images. Only one feature could not describe the leaf well. However, too many features also have bad effect on recognition. The accuracy increases significantly before depth 2 and decreases slightly after depth 5.

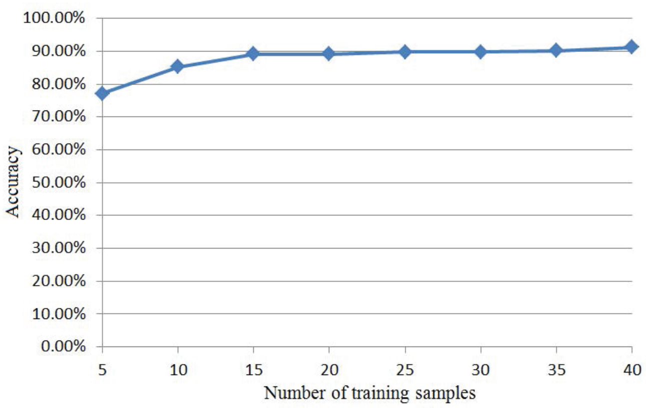


Fig. 3: Effect of number of training samples

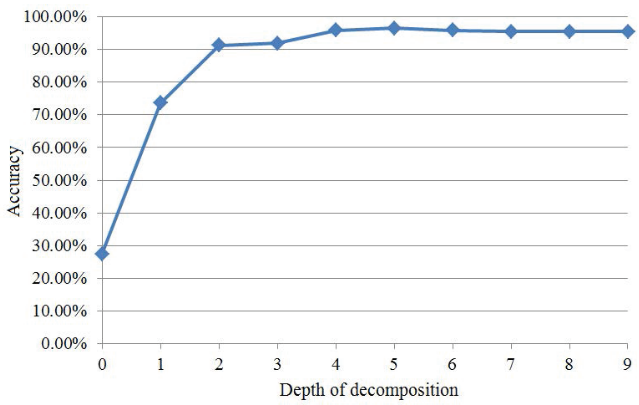


Fig. 4: Effect of depth of decomposition

So we chose 40 images as the train samples randomly and the remaining 20 images as testing samples. And depth 2 was selected as a proper depth of decomposition.

3.6 Comparison

We also did the performance comparison of our method with wavelet method [12] and fractal method. The result is listed in Table 3.

Table 3: Comparison with other methods

Method	Accuracy(%)
fractal	71.33
wavelet	85.46
our method	91.19

4 Conclusion

This paper proposes a method for plant leaf recognition based on wavelet transform and fractal dimension to overcome the limitations. This method is able to analyze the texture at multiple scales without losing details. First, decompose the preprocessed images by wavelet transform. Then calculate fractal dimensions of the decomposed images including both coarse images and detail images. Finally, use these wavelet fractal dimensions to form the input vector of BPANN classifier. BPANN is adopted for it has high recognition accuracy compared with SVM and K-NN classifier. Experimental result indicates that our method is workable with accuracy greater than 90% on 16 kinds of plant leaf images. Compared with other methods, this algorithm is fast in execution, efficient in recognition and easy in implementation. Future work is under consideration to improve it.

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