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Leaf Recognition Algorithm Using MLP Neural Network Based Image Processing

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Abstract

In this paper, we employ Multilayer Perceptron with image and data processing techniques and neural network to implement a general purpose automated leaf recognition. Sampling leaves and photoing them are low cost and convenient. One can easily transfer the leaf image to a computer and a computer can extract features automatically in image processing techniques. This paper implements a leaf recognition algorithm using easy-to-extract features and high efficient recognition algorithm. Our main improvements are on feature extraction and the classifier. All features are extracted from digital leaf image. With only one exception, all features can be extracted automatically.

Keywords: Multilayer priciptron, segmentation, featu-re extraction, segmentation, leaf recognition, plant classi-fication..

Introduction

Plants exist everywhere we live, as well as places without us. Many of them carry significant information for the development of human society. The urgent situation is that many plants are at the risk of extinction. So it is very necessary to set up a database for plant protection [1]–[4]. We believe that the first step is to teach a computer how to classify plants. Compared with other methods, such as cell and molecule biology methods, classification based on leaf image is a better choice. Sampling leaves and photoing them are lowcost and convenient. One can easily transfer the leaf image to a computer and a computer can extract features automatically in image processing techniques. Some systems employ descriptions used by botanists [5]–[7]. But it is not easy to extract and transfer those features to a computer automatically.This paper tries to prevent human interference in feature extraction. It is also a long discussed topic on how to extract or measure leaf features [7]-[8]. That makes the application of pattern recognition in this field a new challenge [1] [11]. According to Du *et al.* [1], data acquisition from living plant automatically by the computer has not been implemented. Several other approaches used their pre-defined features. *Miao et al.* proposed an evidence-theory-based rose classification [3] involving many features of roses.. proposed a modified dynamic programming algorithm for leaf shape matching [12]. *Ye et al.* compared the similarity between features to classify plants [2].

Many approaches above employ k-nearest neighbor (k-NN) classifier [1] while some papers adopted Artificial Neural Network (ANN). *Du et al.* introduced a shape recognition approach based on radial basis probabilistic neural network which is trained by orthogonal least square algorithm (OLSA) and optimized by recursive OLSA [14]. It performs plant recognition through modified Fourier descriptors of leaf shape.Previous work have some disadvantages. Some are only applicable to certain species [3] [11]. As expert system, some methods compare the similarity between features [2]. It requires pre-process work of human to enter keys manually. This problem also happens on methods extracting features used by botanists [6] [11]. Among all approaches, ANN has the fastest speed and best accuracy for classification work. [14] indicates that ANN classifiers (MLPN, BPNN, RBFNN and RBPNN) run faster than k-NN (k=1, 4) and MMC hypersphere classifier while ANN classifiers advance other classifiers on accuracy. So we adopt ANN as our classifier. This paper implements a leaf recognition algorithm using easy-to-extract features and high efficient recognition algorithm. Our main improvements are on feature extraction and the classifier. All features are extracted from digital leaf image. With only one exception, all features can be

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extracted automatically. Following fig. shows the flow diagram of Leaf recognition algorithm using neural network based image processing. The algorithm including Capture digital leaf image, process leaf image, extract features, train MLP, Test MLP & compare results. A multilayer perceptron (MLP) is a feed forward artificial neural network model that maps sets of input data onto a set of appropriate output. The flow diagram of proposed sheme is as shown follows.

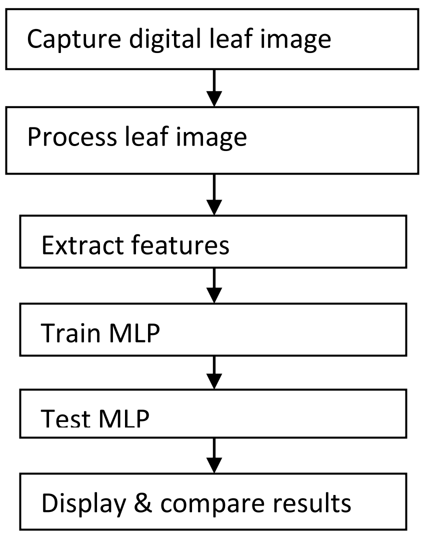

Fig. 1. Flow diagram of proposed scheme

Image Pre-Processing

A.Converting RGB image to binary image

The leaf image is acquired by scanners or digital cameras. Since we have not found any digitizing device to save the image in a lossless compression format, the image format here is JPEG.

All leaf images are in 256 x 256 resolution. There is no restriction on leaf direction when photoing.

An RGB image is firstly converted into a grayscale image. Eq. 1 is the formula used to convert RGB value of a pixel into
its grayscale value.

gray = 0.2989*R + 0.5870* G + 0.1140* B (1)

where R, G, B correspond to the color of the pixel, respectively.

B.Boundary Enhancement

When mentioning the leaf shape, the first thing appears in your mind might be the margin of a leaf. Convolving the image with a Laplacian filter of following 3 × 3 spatial mask:

0 1 0
1 −4 1
0 1 0

we can have the margin of the leaf image. To make boundary as a black curve on white background, the "0" "1" value of pixels is swapped.

Feature Extraction

In this paper, 10 commonly used digital morphological features (so that a computer can obtain feature values quickly and automatically).

1) Major Axis Length : Scalar specifying the length (in pixels) of the major axis of the ellipse that has the same normalized second central moments as the region. This property is supported only for 2-D input label matrices.

2) Minor Axis Length : The length (in pixels) of the minor axis of the ellipse that has the same normalized second central moments as the region. This property is supported only for 2-D input label matrices.

3) Eccentricity: The value 0 and 1 for leaf defines , Scalar that specifies the eccentricity of the ellipse that has the same second-moments as the region. The eccentricity is the ratio of the distance between the foci of the ellipse and its major axis length. The value is between 0 and 1. (0 and 1 are degenerate cases; an ellipse whose eccentricity is 0 is actually a circle, while an ellipse whose eccentricity is 1 is a line segment.) This property is supported only for 2-D input label matrices.

4) Orientation: Scalar:The angle (in degrees ranging from -90 to 90 degrees) between the *x*-axis and the major axis of the ellipse that has the same second-moments as the region. This property is supported only for 2-D input label matrices.

5) Convex Area: Scalar that specifies the number of pixels in 'ConvexImage'. This property is supported only for 2-D input label matrices.

6) Filled Area: Scalar specifying the number of on pixels in Filled image. 'Filled image' Binary image (logical) of the same size as the bounding box of the region.

7) Equiv Diameter: Scalar that specifies the diameter of a circle with the same area as the region. Computed assqrt(4*Area/pi). This property is supported only for 2-D input label matrices.

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8) Solidity : Scalar specifying the proportion of the pixels in the convex hull that are also in the region. Computed as Area/ConvexArea. This property is supported only for 2-D input label matrices.
9) Extent: Scalar that specifies the ratio of pixels in the region to pixels in the total bounding box. Computed as the Area divided by the area of the bounding box. This property is supported only for 2-D input label matrices.
10) Perimeter: Scalar the distance around the boundary of the region. regionprops computes the perimeter by calculating the distance between each adjoining pair of pixels around the border of the region. If the image contains discontiguous regions, regionprops returns unexpected results.

Proposed Scheme

A. Multilayer priciptron

A multilayer perceptron (MLP) is a feed forward artificial neural network model that maps sets of input data onto a set of appropriate output. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called back propagation for training the network MLP is modification of the standard linear perceptron, which can distinguish data that is not linearly separable. The multilayer perception neural network is built up of simple components. In the beginning, we will describe a single input neuron which will then be extended to multiple inputs. Next, we will stack these neurons together to produce layers. Finally, the layers are cascaded together to form the network.

B. Single input neuron

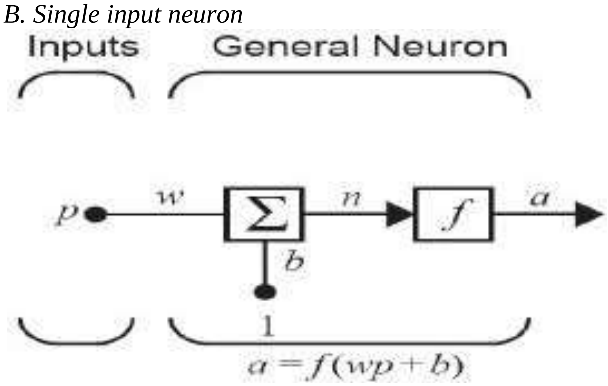

Fig. 2 Single input neuron

The scalar input *p* is multiplied by the scalar weight *W* to form *Wp*, one of the terms that is sent to the summer. The other input, 1, is multiplied by a bias *b* and then passed to the summer. The summer output n often referred to as the net input, goes into a transfer function f which produces the scalar neuron output a (sometimes "activation function" is used rather than transfer function and offset rather than bias). Typically the transfer function is chosen by the designer and then the parameters w and b will be adjusted by some learning rule so that the neuron input/output relationship meet some specific goal. The transfer function may be a linear or nonlinear function of n. A particular transfer function is chosen to satisfy some specification of the problem that the neuron is attempting to solve. One of the most commonly used functions is the log-sigmoid transfer function. This transfer function takes the input.

C. Multiple input neuron

Typically, a neuron has more than one input. than one input. A neuron with R inputs. The neuron has a bias b, which is sum-med with the weight inputs to form the net input *n*: n=W1,1p1+W1,2p2+...+W1,RpR+b
This expression can be written in matrix form as: n =Wp +b.
Where the matrix W for the single neuron case has only one row. Now the neuron output can be written as: a = f(Wp + b).
A particular convention in assigning the indices of the elements of the weight matrix has been adopted . The first index indicates the particular neuron destination for the weight. The second index indicates the source of the signal fed to the neuron.

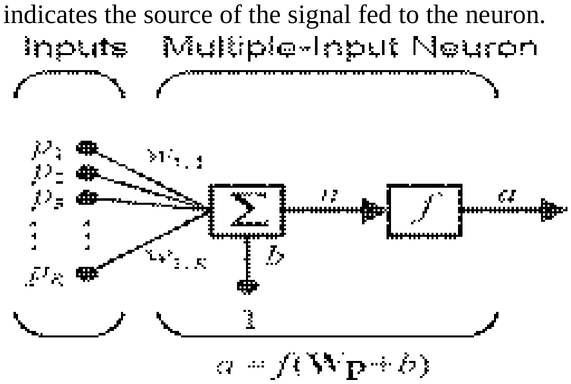

Fig. 3. Multiple input neuron

Thus, the indices in W1,2 say that this weight represents the connection to the first (and only) neuron from the second source. A multiple-input neuron using abbreviated notation the input vector p is represented by the solid vertical bar at left. The dimensions of p are displayed below the variable as *Rx1*, indicating that the input is a single vector of R elements.

D. Multilayer Perceptron Architecture

The network diagram shown above is a full-connected, three layer, feed-forward, perceptron neural network. "Fully conne-ted " means that the output from each input and hidden neuron is

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distributed to all of the neurons in the following layer. "Fe-ed forward" means that the values only move from input to hidden to output layers; no values are fed back to earlier layers (a Reccurent network allows values to fed backward).

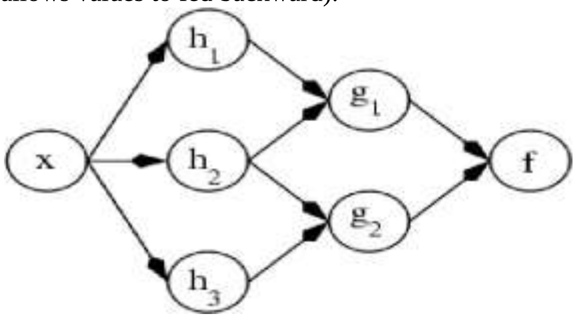

Fig. 4. Multilayer priciptron architecture

All neural networks have an input layer and an output layer, but the number of hidden layers may vary. Here is a diagram of a perceptron network with two hidden layers and four total layers. When there is more than one hidden layer, the output from one hidden layer is fed into the next hidden layer and separate weights are applied to the sum going into each layer. Fig. 4. Shows the multilayer priciptron architecture, no. of hidden layers never fixed they may vary. The multilayer priciptron neuron, fully connected to each other.

E. Working Steps

1) Leaf Segmentation
2) Feature Extraction
3) Classifier
4) Classification

The proposed method has training and classification phases. In the training phase, from a given set of training images (segmented) the texture features are extracted and used to train the system using a Multilayer Perceptron neural network. In the classification phase, given a test image, the leaf is segmented and the texture features are extracted. These features are queried to the Multilayer Perceptron neural network to know the leaf class label.

1) Leaf segmentation

The first step in leaf classification is to segment the leaf image by removing the unwanted background region. In ge neral, autonomous segmentation is one of the most difficult tasks in image processing. Leaves in images are often surrounded by greenery in the background. In order to avoid matching the green background region, rather than the desired foreground region, the image has to be segmented.

2) Feature Extraction

Color- All colors are seen as variable combinations of the three primary colours, namely, Red(R), Green (G) and Blue (B). The RGB and its variant like HSI being widely used in computer vision systems (CVS), Hue(H), Saturation(S), Intensity(I).

Algorithm of feature extraction
Colour Feature Extraction
Input: Original 24-bit colour image.
Output: 18 colour features.
Start
Step 1: Separate the RGB components from the original 24-bit input colour image.
Step2: Obtain the HSI components from RGB components using the equations
Step 3: Compute mean, variance, and range for each RGB and HIS components.
Stop.

3) Classifier

In the classification of natural scenes, there is often the problem that features we want to classify occur at different scales. We propose a novel way of measuring the distortion between two images, one being the original and the other processed. The measurements are used as features in classifier design. Using this classifier we are able to classify the given images into different categories based on their features.

Experimental Result

In the classification of leaf ,we have taken 32 leaf's of samples for recognition of leafs,out of that 32 leaf sample one leaf sample shows the example of segmented result,are as shown in following figures. The first image shows The input image (original image), second image shows the edge detection image & last image shows the segmented result in leaf segmentation it removes the unwanted region the first step in leaf classification is to segment the leaf image by removing the unwanted background region. In general autonomus segmentation is one of the most difficult task in image processing. Leaves in images are often surrounded by greenery in the background region, rather than desired foreground region, the image has to be segmented.

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Fig. 5. Sample leaf segmented result example

Following graph shows that, the graph between Train leaf image & Test leaf image for Match leaf sample..

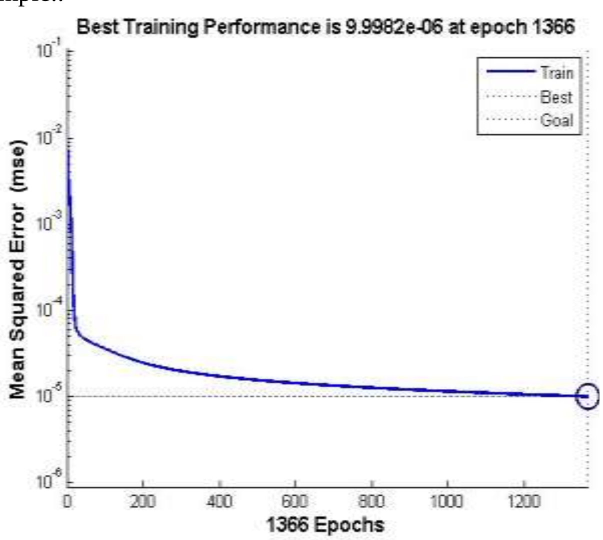

Fig. 6. Training of neural network for match reslts for Test leaf.

The Match result of leaf from training & testing of leaf obtained result are in following image.

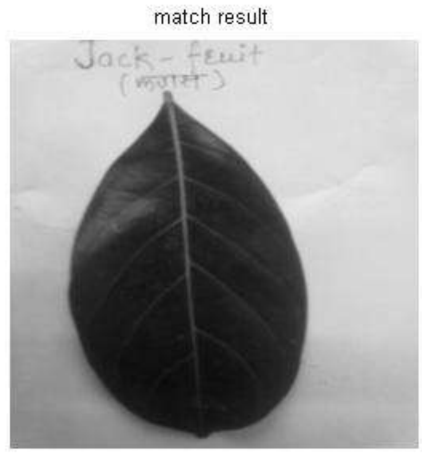

Fig. 7. Match result of leaf sample

Conclusion

This paper introduces a neural network approach for leaf recognition. The computer can automatically recognize leaf by transferring the leaf sample to the computer. MLP is adopted for its fast training speed and simple structure. Ten features are extracted and later processed form the input vector of MLP. Experimental result indicates that algorithm is workable with an accuracy greater than 94%. Compared with other methods, this algorithm is fast in execution, efficient in recognition and easy in implementation.

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