ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 1, January 2013

A Leaf Recognition Technique for Plant Classification Using RBPNN and Zernike Moments

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ABSTRACT: Plants are among the earth's most useful and beautiful products of nature. Plants have been crucial to mankind's survival. The urgent need is that many plants are at the risk of extinction. About 50% of ayurvedic medicines are prepared using plant leaves and many of these plant species belong to the endanger group. So it is indispensable to set up a database for plant protection. We believe that the first step is to teach a computer how to classify plants. Leaf /plant identification has been a challenge for many researchers. Several researchers have proposed various techniques. In this paper we have proposed a novel framework for recognizing and identifying plants using shape, vein, color, texture features which are combined with Zernike movements. Radial basis probabilistic neural network (RBPNN) has been used as a classifier. To train RBPNN we use a dual stage training algorithm which significantly enhances the performance of the classifier. Simulation results on the Flavia leaf dataset indicates that the proposed method for leaf recognition yields an accuracy rate of 93.82%

Key words: Zernike moments (ZM), Dual stage training algorithm, Radial basis probabilistic neural network, Gray Level Co-occurance Matrix.

I Introduction

Plants form an essential part of life on Earth and provides with oxygen, food, medicine fuel, and much more. A thorough understanding of plants is vital to increase agricultural productivity and sustainability. With an unstoppable growing human population and a varying climate, there is an escalating threat to many ecosystems. It is therefore imperative to identify new or rare species and to measure their geographical extent as part of wider biodiversity projects. Hence the need of the hour is plant recognition and classification. Compared with other methods, such as cell and molecule biology methods, classification based on leaf image is the foremost choice for leaf plant classification. Sampling leaves and photoing them is inexpensive and expedient. We can easily transfer the leaf image to a computer and then the computer can extract necessary features automatically using image processing techniques and subsequently can recognize the plant /leaf using machine learning techniques.

II Feature Extraction

The following geometric features which have been used in leaf identification system are described as follows [13]

A. *Shape features*

Aspect ratio: Aspect ratio also called as eccentricity is defined as ratio between length of the leaf minor axis (w) and the length of the leaf major axis. It is notated as

$$\text{Aspect ratio} = w/l \tag{1}$$

Circularity: Circularity is ratio involving area of the leaf (a) and square of perimeter (p) of the leaf. It can be notated as

$$\text{Circularity} = a/p^2 \tag{2}$$

Irregularity: Irregularity or dispersion is defined as ratio between the radius of the maximum circle enclosing the region and the minimum circle that can be contained in

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the region. This feature is of paramount importance when the shape of the leaf is irregular. It is notated as

$$\text{Irregularity} = \frac{\max\left(\sqrt{(x_i-\bar{x})^2+(y_i-\bar{y})^2}\right)}{\min\left(\sqrt{(x_i-\bar{x})^2+(y_i-\bar{y})^2}\right)} \tag{3}$$

Solidity: Solidity is defined as ratio between the area of the leaf and the area of its convex hull. It is denoted as

$$\text{Solidity} = \frac{\text{area of leaf}}{\text{area of convex}} \tag{4}$$

B. Vein features

Vein features will be extracted by means of morphological operations performed on the gray scale image of the leaf. There are three different kinds of vein features which are computed as follows:

$$V1=A1/A \tag{5}$$

$$V2=A2/A \quad \text{and} \tag{6}$$

$$V3=A3/A \tag{7}$$

Here V1, V2, and V3 characterize the features of the vein; A1, A2, and A3 signify the total pixels of the vein, and A denotes total pixels present on the leaf.

C. Colour features/moments

Color moments are measures that can be effectively used to discriminate images based on their features of color. Color moments [1] are also very helpful to distinguish Color based image analysis techniques. The information of Color distribution in a image can be extracted by using the low order moments. Let P_{ij} is the i^{th} Color channel at the j^{th} image pixel. The four Color moments can be defined as:

Mean:

$$\mu = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} P_{ij} \tag{8}$$

Standard Deviation:

$$\sigma = \sqrt{\left(\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(p_{ij} - \mu\right)^2\right)} \tag{9}$$

Skewness

$$\theta = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(p_{ij}-\mu\right)^3}{MN\sigma^3} \tag{10}$$

Kurtosis

$$\gamma = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(p_{ij}-\mu\right)^4}{MN\sigma^4} - 3 \tag{11}$$

D. Texture features

An image texture is a set of metrics computed in image processing intended to enumerate the apparent texture of a leaf image. Leaf Image Texture gives information regarding the spatial arrangement of color or intensities in a leaf image or selected region of a leaf image. A diversity of techniques has been used for computing texture such as co-occurance matrix, Fractals, Gabor filters, variations of wavelet transform. Additional techniques have also been proposed for relating the local patterns using texture spectrum [11], for characterization of texture using a composition of edge information and co-occurance matrix properties [12]. The recognition of explicit textures in an image is achieved principally by modeling texture as a two-dimensional gray level variation. The resultant two dimensional arrays are called as Gray Level Co-occurance Matrix (GLCM).

1) *Extracting texture features of image using GLCM*

Normalized probability density Pδ(i,j) of the co-occurance matrices can be stated as follows.

$$P_{\delta}(i,j) = \frac{\#\{|(x,y),(x+d,y+d)\in S|f(x+y)=i,f(x+d,y+d)=j\}}{\#S} \tag{12}$$

Where, x, y = 0,1,…..N-1 are co-ordinates of the pixel, i, j = 0,1,…..L-1 are the gray levels, S is set of pixel pairs which have certain relationship in the image.
#S is the number of elements in S.

Pδ(i,j) is the probability density that the first pixel has intensity value i and the second j, which separated by distance δ=(dx, dy).

The GLCM is computed in four directions for δ=0°, δ=45°, δ=90°, δ=135°. Based on the GLCM four statistical parameters energy, contrast, entropy and correlation are calculated. Lastly a feature vector is obtained using the means and variances of all these parameters [7].

The steps for extracting texture features of image using GLCM can be given as below.

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1. Separate the R, G, B planes of image.

2. Repeat steps 3-6 for each plane.

3. Compute four GLCM matrices (directions for δ=0°,δ=45°, δ=90°, δ= 135°) as given by eq. (12)

4. For each GLCM matrix compute the statistical features Energy (Angular second moment), Entropy (ENT), Correlation (COR), Contrast (CON) [7, 8] as follows, where P (i , j) is probability density.

Energy: (Angular Second Moment (ASM)) which measures textural uniformity (i.e. pixel pairs repetitions is given by

$$\mathrm{ASM} = \sum\sum \mathrm{P}^2\,(\mathrm{i},\mathrm{j}) \tag{13}$$

Contrast (CON): Contrast indicates the variance of the gray level is given by

$$\mathrm{CON} = \sum\sum(\mathrm{i}-\mathrm{j})^2\mathrm{P}(\mathrm{i}-\mathrm{j}) \tag{14}$$

Entropy (ENT): This parameter measures the disorder of the image. For texturally uniform image, entropy is small.

$$\mathrm{ENT} = -\sum\sum \mathrm{P}\,(\mathrm{i},\mathrm{j})\log[\mathrm{P}(\mathrm{i},\mathrm{j})] \tag{15}$$

Correlation: (COR) is given by

$$\mathrm{COR} = \frac{\sum\sum \mathrm{ijP}\,(\mathrm{i}-\mathrm{j}) - \mu_x\mu_x}{\sigma_x\sigma_x} \tag{16}$$

Where μx, μ_y, σ_x, σ_y are the means and standard deviations of Px and Py respectively where Px is the sum of each row in co-occurance matrix and Py is the sum of each column in the co-occurance matrix.

5. After which we compute the feature vector using the means and variances of all the parameters.

6. Compute the feature vector considered is f={µASM, µENT, µCOR, µCON, σASM, σENT, σCOR, σCON} where σ is variance of the parameters andµ is mean.

E. Zernike Moments

As stated in the introduction, plants are generally recognized using the shape of the leaf. For this reason they cannot be appropriately described with the help of regular shape descriptors like circularity, linearity and so on. That's why we adopt Zernike moments. These moments have higher space feature vector and are normally of order N. If additional order of moments is considered, then we achieve better the recognition probability. If an image is presumed to be an object, its descriptors are recognized as its feature vectors.

The Zernike polynomials defined over the interior of a unit circle $x^2 + y^2 = 1$ are a set of complex and orthogonal polynomials. Zernike moment of order n and repetition m is defined as for a continuous image function f(x, y) are defined as

$$Anm = \frac{n+1}{\pi}\iint_{x^2+y^2\leq 1} f(x,y)\, V_{nm}^{*}(\rho,\theta)\, dxdy \tag{17}$$

in the *xy* image plane and

$$Anm = \frac{n+1}{\pi}\int_0^{2\pi}\int_0^1 f(\rho,\theta)R_{nm}(\rho)exp(-jm\theta)\rho d\rho d\theta \tag{18}$$

in polar coordinates. The real valued radial polynomial R_{nm} is defined as

$$R_{nm}(\rho) = \sum_{s=0}^{\frac{n-|m|}{2}}(-1^s)\frac{(n-S)!}{S!\left(\frac{n-|m|}{2}-S\right)!\left(\frac{n+|m|}{2}-S\right)!} \tag{19}$$

Using equation 19 we compute Zernike moments from order 2 to 10 for extracting the necessary features.

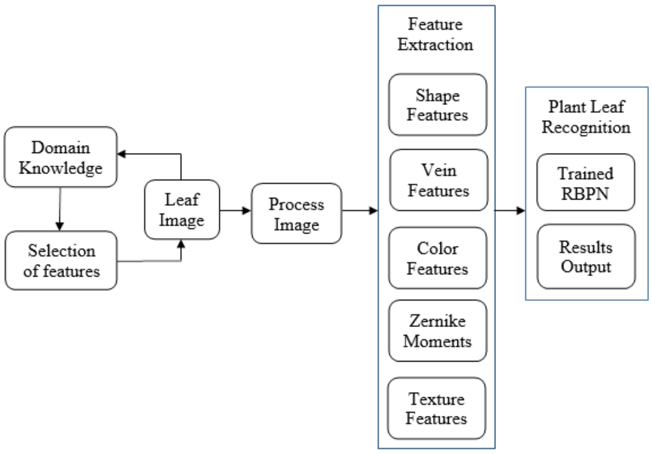

Fig. 1 Proposed System for leaf recognition

III PROPOSED SYSTEM

This paper implements a plant recognition algorithm by using easy to extract features like shape, vein, color, texture features which are combined with Zernike movements. The focal improvements are on feature extraction techniques that include Zernike movements and the dual stage learning algorithm for training the classifier namely Radial Basis Function neural network. The block diagram of the proposed technique is shown in Figure 1.Here in this research work 32 dissimilar leaf types from

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the well know Flavia dataset is used for recognizing the input leaf.

A. Radial basis probabilistic neural network

The radial basis probabilistic neural network (RBPNN) model, as shown in Figure 2, amalgamates the benefits of radial basis function neural networks (RBFNN) and probabilistic neural networks (PNN). The conception of a RBPNN involves four different layers: one input layer, two hidden layers and one output layer. The input layer consists of source (i.e., input) nodes. The first hidden layer consists of the hidden centers which are determined by input training sample set and normally is a non-linear processing layer. The second hidden layer discriminatorily sums the outputs of the first hidden layer. The second hidden layer commonly has the equivalent size as the output layer for a labeled pattern classification problem. Universally the weights between the first hidden layer and the second hidden layer of the network are ones or constants which may include zeros also. Explicitly these weights are commonly set as fixed values and necessarily do not require learning. The last layer is the output layer. Similar to the RBFNN, the selection of the number of neurons in the first hidden layer of the RBPNN is the prime concern for the network performance. By and large, the number of neurons in the first hidden layer is strongly correlated to the efficient performance of the RBPNN.

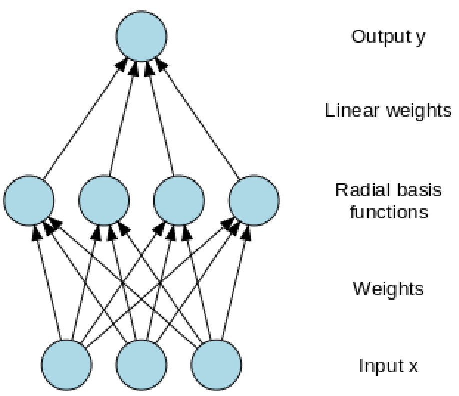

Fig. 2 Basic architecture of RBPNN

B. RBP neural network classifier design

The design of RBP neural networks classifier is mainly the difficult part of the entire research. In the input layer, the number of input nodes of the neural network is set equivalent to the number of feature vector elements. The number of nodes present in output layer is then set to the number of leaf image classes.

C. Dual stage learning algorithm

The training of the RBP neural networks can be made quicker by using a dual stage training algorithm. During the first stage of the training we resolve the output connection weights, which need the result of a set of linear equations that can be completed quickly. During the second stage, the parameters of the basis function which necessarily correspond to the RBP units are also found out using an unsupervised learning technique that requires the result of a set of nonlinear equations. Finally training of the RBP neural networks requires estimation of the output connection weights, centers, and widths of the RBP units.[13]

IV Experimental Results

To experiment the proposed method, a dataset named Flavia, which can be downloaded from http://flavia.sourceforge.net/, has been used. This dataset contains 32 kinds of plant leafs. Based on this dataset, 40 plants per species were employed to train the network, and 10 plants per species were used to test the performance of the proposed system. For each type of plant, 10 pieces of leaves from testing sets are used to test the accuracy of our algorithm. To calculate the overall accuracy of our system we have used the following formula.

Accuracy= NR/NT where NR is the number of images correctly recognized and NT is the total number of query input images.

From table no 1 we observe that using the Zernike moments from order 2 to 10 along with 5 shape features, mean of colors, standard deviation of colors, skewness of colors, 16 texture features, 3 vein features resulted in a highest accuracy of 93.82%.

Table 1

Accuracy of leaf image recognition using Zernike moments from order 2 to 10 and various combinational features.

Features	Accuracy
ZM+ 5 shape features + mean of colors + standard deviation of colors + skewness of colors + kurtosis of colors + 16 texture features	91.50%

ZM + 5 shape features + mean of colors + standard deviation of colors + skewness of colors + 16 texture features	92.00%
ZM + 3 geometric features + 12 texture features	89.86%
ZM+ 5 shape features + mean of colors + standard deviation of colors + skewness of colors + 16 texture features + 3 vein features	93.82%
ZM+ 5 shape features + mean of colors + standard deviation of colors + skewness of colors + kurtosis of colors + 16 texture features + 3 vein features	93.29%

V. COMPARISON WITH OTHER SYSTEMS

To compare our proposed technique with several researches who have used Flavia dataset, we have listed the proposed technique and their results as given in Table.2 Based on the table, the proposed systems that uses Zernike moments are certainly encouraging for plant identification.

TABLE.2

COMPARISON OF PROPOSED LEAF RECOGNITION SYSTEMS WITH OTHER SYSTEMS

Scheme	Accuracy
Proposed in [3]	71%
1-NN in [4]	93%
k-NN (k = 5) in [4]	86%
RBPNN in [4]	91%
MMC in [2]	91%
k-NN (k = 4) in [2]	92%
MMC in [5]	92%
BPNN in [5]	92%
BPNN in [5]	92%
MLNN in [6]	94 %
Flavia[9]	90%
Zernike moments[10]	93.44%
Proposed method	93.82%

VI. CONCLUSION

We conclude that incorporating Zernike moments for feature descriptors is a feasible alternative for classifying structurally complex images. They offer exceptional invariance features and reveal enhanced performance than other moment based solutions. However the only negative aspect of Zernike moments is their costly computation, which makes them inapt for some problems. Nevertheless they can be computed in parallel and as the computational performance of computers increase, the time necessary for their calculation perhaps won't be a problem in the nearby future. The use of dual stage learning algorithm, for training, of the RBP neural networks is faster, than the other methods that are used to train multilayer neural networks. Also the use of dual stage learning method results in faster convergence during the training phase.

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