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Leaf Shape Identification Based Plant Biometrics

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Abstract

This paper presents a simple and computationally efficient method for plant species recognition using leaf image. This method works only for the plants with broad flat leaves which are more or less two dimensional in nature. The method consists of five major parts. First, images of leaf are acquired with digital camera or scanners. Then the user selects the base point of the leaf and a few reference points on the leaf blades. Based on these points the leaf shape is extracted from the background and a binary image is produced. After that the leaf is aligned horizontally with its base point on the left of the image. Then several morphological features, such as eccentricity, area, perimeter, major axis, minor axis, equivalent diameter, convex area and extent, are extracted. A unique set of features are extracted from the leaves by slicing across the major axis and parallel to the minor axis. Then the feature pointes are normalized by taking the ratio of the slice lengths and leaf lengths (major axis). These features are used as inputs to the probabilistic neural network. The network was trained with 1200 simple leaves from 30 different plant species. The proposed method has been tested using ten-fold cross-validation technique and the system shows 91.41% average recognition accuracy.

Keywords: Leaf identification, Plant biometrics, Plant recognition, Probabilistic neural network.

I. INTRODUCTION

Plants play a critical role in preserving the delicate balance of the environment. Unfortunately, the overwhelming development of human civilization has disrupted this balance to a greater extent than we realize. It is one of our biggest responsibilities to save the plants from various threats, restore the diverseness of the plant community and put everything back to balance. A computerized plant identification system can be very helpful in botanical garden or natural reserve park management, new plant species discovery, plant taxonomy, exotic plant detection, edible/poisonous plant identification and so on. A computer based plant identification or classification system can use different characteristics of the flora, starting at very simple level such as: shape and color of the leaf, flower and fruit type, branching style, root type, seasonality, outlook, to very complex such as cell and tissue structure, DNA and genetic structure. However, a simplified approach which requires very little work by the user to identify the plant is our concern. Our goal is to develop a computerized system that can identify species of the plant from leaf images. Presently the cell phones are capable of acquiring high quality images with their integrated digital camera, which makes the usability of such a system even wider. Adventurers, campers, trekkers or people in survival situation might also be able to make use of such a system.

A substantial amount of work has been done on leaf shape based plant classification and recognition. Wu et al. [1] extracted 12 commonly used digital morphological features which were orthogonalized into 5 principal variables. They used 1800 leaves to classify 32 kinds of plants. Wang et. al. [2] employed centroid-contour distance (CCD) curve, eccentricity and angle code histogram (ACH). Their experimental results on 1400 leaf images from 140 plants show that the proposed approach can achieve a better retrieval performance than both the curvature scale space (CSS) method and the modified Fourier descriptor (MFD) method. Fu et al. [3] also used centroid-contour distance curve to represent leaf shapes. Wang et al. [4] extracted seven Hu geometric moments and sixteen Zernike moments to represent leaf shape. Du et. al. [5] employed Douglas-Peucker approximation algorithm to extract leaf shape features. Ye et al. [6] used CCD (centroid-contour distance) curve to represent leaf shapes. Li et al. [7] applied snakes technique with cellular neural networks (CNN). Gu et al. [8] used the result of segmentation of leaf's skeleton based on the combination of wavelet transform (WT) and Gaussian interpolation. Wang et al. [9] extracted several geometric features like rectangularity, circularity, eccentricity and seven moment invariants for classification.

Some [1], [3], [10], approaches employed artificial neural network for its fast performance. Others [8], [9] employed k-nearest neighbor (k-NN) classifier to classify plants. Du et al. [10] introduced shape

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recognition based on radial basis probabilistic neural network which is trained by orthogonal least square algorithm (OLSA) and optimized by recursive OLSA. It performs plant recognition through modified Fourier descriptors of leaf shape. Mokhtarian and Abbasi [11] used curvature scale space image to represent leaf shapes and applied it to leaf classification with self-intersection.

The major contribution of this work is a robust and easy to implement method for plant species recognition from leaf image. It can identify the type of plant from a partially damaged or broken leaf. First, images of leaf are acquired with digital camera or scanners. Then the system requires the user to select the base point of the leaf and a few reference points on the leaf blades. After preprocessing is complete, a set of morphological features- eccentricity, entirety, area, perimeter, major axis, minor axis, equivalent diameter, convex area, extent were extracted from the leaves. Then, a set of unique features called Leaf Width Factor (LWF) is extracted from the leaves by slicing across the major axis and parallel to the minor axis. Then the feature pointes are normalized by taking the ratio of the slice lengths and leaf lengths (major axis). These features are used as inputs to the probabilistic neural networks. 1200 simple leaves belonging to 30 different plants have been used to train our system.

II. SYSTEM DESCRIPTION

A typical image based plant identification system is shown in Fig. 1 the major steps are discussed in the consecutive sub-sections.

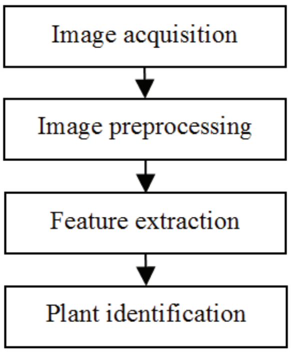

Fig. 1. System flowchart

A. Leaf image acquisition

The leaf images can be acquired using a scanner or digital camera, even one embedded in your cell-phone. There is no restriction on resolution and image format; however, a descent sized image with reasonable resolution is enough for the proposed method. The image can be an RGB image or a grayscale image. However, the image background needs be clean preferably white or any single colored with reasonable contrast with the leaf color and the leafstalk should be removed prior to image acquisition. For our experiment, we used the dataset collected by Wu et al. [1]. The dataset contains 1904 compressed RGB leaf images in JPEG format and 1600 by 1200 pixels resolution. All images were acquired using digital camera and have white background with no leafstalk. There are total 32 plant species; each plant species has around 40 to 60 sample leaves.

B. Image preprocessing

The main goal of preprocessing is to identify the leaf in an image and discarding all other information other than the leaf shape. This can be done with a little help from the user. The user can help identify the base-point and some reference points of the leaf.

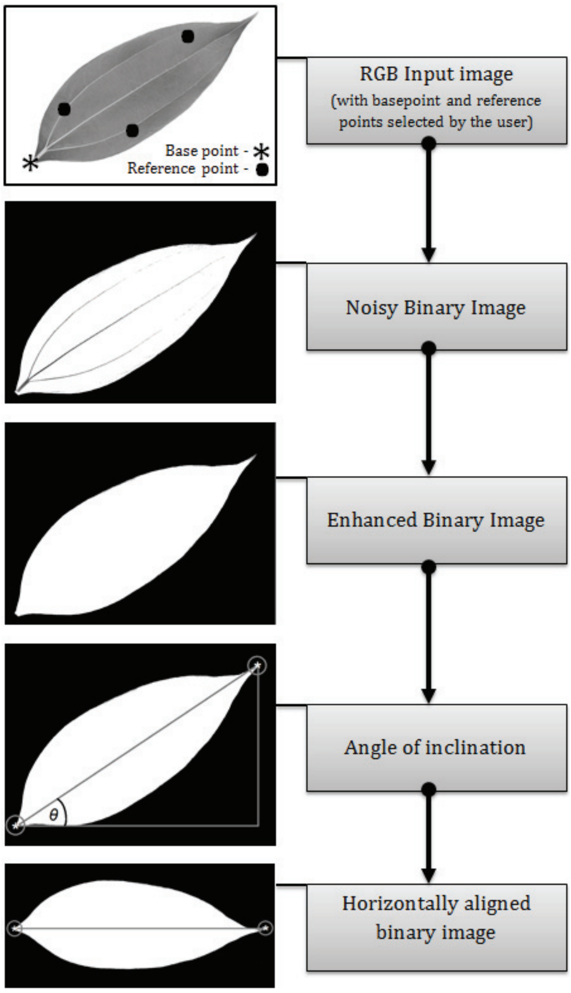

Fig. 2. Image pre-processing steps

Then the system uses the reference points and finds out the pixels that have similar value and connected to the reference points/pixels. Then the leaf is extracted from the background and a binary image is produced where the background pixels are set to 0 or black and the pixels within the leaf is set to 1 or white. Then the remaining black pixels within the leaf blade are removed to produce an enhanced binary image. Next, the tip of the leaf is located. This is done by finding out the furthest point (which is, in most cases, the tip of the leaf) from the base-point (selected by the user). Then the slope of the line connecting the base-point and the tip of the leaf is calculated. Finally the enhanced binary image is rotated according to the angle of inclination to make the leaf horizontally aligned. A pictorial representation of these steps is given in Fig. 2.

C. Feature extraction

Once the pre-processing is done, feature extraction is easy. Our method takes into account only the shape of the leaf. The line connecting the base and the tip of the leaf is the major axis. And the maximum width, which is perpendicular to the major axis, is considered the minor axis. These two axes of a leaf are shown in Fig. 3.

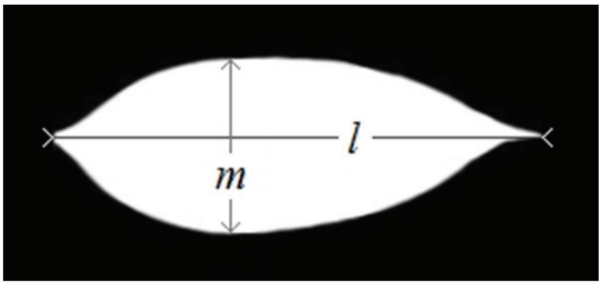

Fig. 3. Major axis *l* and minor axis *m* of a leaf

Having major and minor axis of a leaf determined, the *leaf width factor* of the leaf in hand is measured by slicing across the major axis and parallel to the minor axis, see Fig.4.

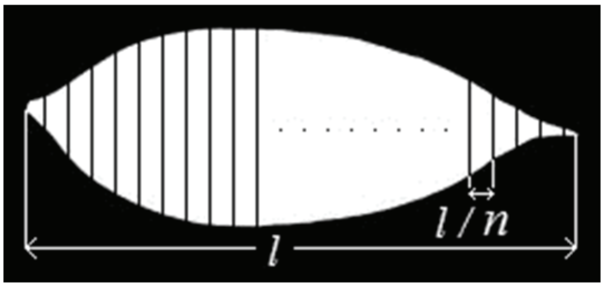

Fig. 4. Leaf Width Factor (LWF) extraction

Then the feature pointes are normalized by taking the ratio of the slice lengths and leaf lengths (major axis). The leaf is sliced, perpendicular to the major axis, into a number of vertical strips. Then for each strip, the ratio of length of strip and the length of the entire leaf is calculated. The ratio *R*, at column *c* is given by the following formula

$$R_c = \frac{W_c}{l} \tag{1}$$

Here W_c is the width of the leaf at column c and l is the length of the entire leaf.

In addition to the Leaf Width Factor, the following morphological features are extracted from the preprocessed leaf images. These features are discussed below.

1) Eccentricity: A scalar value which 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 ranges between 0 and 1.

2) Major axis: The line segment connecting the base and the tip of the leaf is the major axis, shown in Fig.3.

3) Minor axis: The maximum width, which is perpendicular to the major axis, is the minor axis of a leaf; see Fig.3.

4) Area: Area is the actual number of pixels in the region. The area of leaf in a preprocessed image is the number of white or '1' pixels. For example, the area of the region in the image segment, shown in Fig.5(a), is 56 pixels because it contains 56 white pixels.

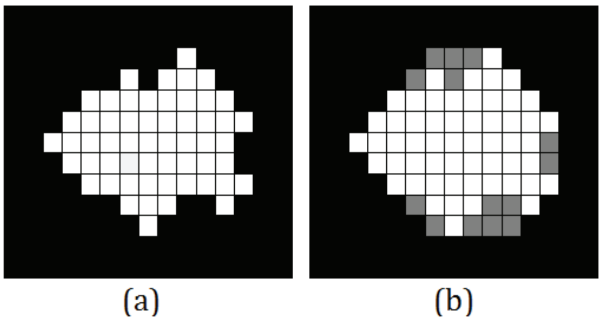

Fig. 5. (a) Area and (b) Convex area of a region

5) Convex area: Convex area specifies the number of white pixels in the 'Convex Image'. A convex image is a binary image that specifies the smallest convex polygon that can contain the region, with all pixels within the polygon filled in (i.e., set to 1). Fig. 5(b) shows the convex image with the pixels filled in (shown in gray pixels).

6) Entirety: Entirety of a leaf is calculated using the following formula,

$$\text{(Convex area - Area) / Area} \tag{2}$$

7) Perimeter: Perimeter of a leaf is the summation of the distances between each adjoining pair of pixels around the border of the leaf. The perimeter of a leaf is shown in gray pixels in Fig.6(a).

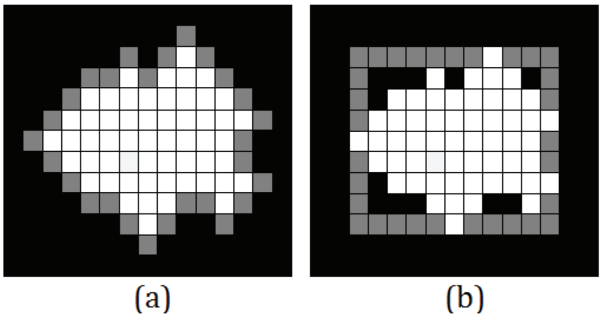

Fig. 6. (a) Perimeter and (b) Extent of a region

8) Extent: Extent of a leaf specifies the ratio of pixels in the region to pixels in the smallest rectangle containing the region. In Fig.6(b), the area of the smallest rectangle (shown using gray pixels) containing the region is 99 and the area of the region is 56. Thus, extent of the region is 56/99.

9) Equivalent diameter: Equivalent diameter specifies the diameter of a circle with the same area as the region. A region's equivalent diameter, D_E can be calculated using the formula,

$$D_E = \sqrt{(4 \times \text{Area} / \pi)} \tag{3}$$

D. Plant identification

The next task is to perform classification of these lower dimensional feature vectors. Neural networks are excellent in greater generalization. We applied probabilistic neural networks (PNN) for classification of leaf shape features for plant identification. The PNN, learns rapidly compared to the traditional back-propagation, and guarantees to converge to a Bayes classifier if enough training examples are provided, it also enables faster incremental training, and robust to noisy examples [12-14].

In Fig.7, R the number of elements (features) in the input vector. Q is the total number of training (inputs, output) pairs, this is also the number of neurons in layer 1 (radial basis layer), and, IW and b_1 are the weight matrix and bias vector of the redial basis layer. K is the number of classes of input data, and the number of neurons in layer 2 (competitive layer) and LW is the weight matrix of the competitive layer.

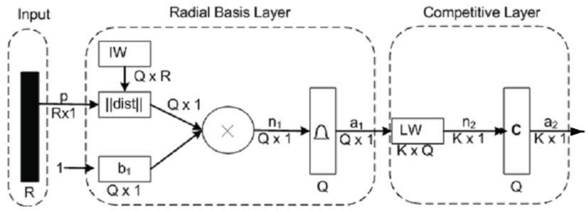

Fig. 7. A typical Probabilistic Neural Network

In the training phase, $IW = X^T$ where X is the training pattern matrix of size $R \times Q$ containing Q training patterns as column vectors. $LW = T$ where T is the training class matrix of size $K \times Q$ containing Q training class information as column vectors, here note that the entries to the matrix T are Boolean and if the i^{th} pattern (column) in X belongs to the class k then the k^{th} entry of the i^{th} column in matrix T is set to 1 and rest of the entries of that column is set to 0 to train the PNN and rest of the feature vectors are kept apart for testing. In this experiment $R = \{1, 2, \ldots, 100\}$, $Q = 30 \times 36$ and $K = 30$, and the value of R changes as we test the classification accuracy of different number of features.

In the testing phase, when a test input vector is presented the || *dist* || box produces a vector whose elements indicate how close the input is to the vectors of the training set. These elements are multiplied element by element by the bias, and passed as the argument n to the radial basis transfer function ($a_1(i)=\exp(-n_1(i)^2)$). An input vector close to a training vector is represented by a number close to 1 in the output vector a_1. In the second layer the multiplication $T * a_1$ sums the elements of a_1 due to each of the K input classes. Finally, the second-layer uses a comparative transfer function and produces a 1 corresponding to the largest element of n_2, and 0 elsewhere. It illustrates that, the network has classified the test input vector into a specific one of the K classes because that class had the maximum probability of being correct as it is most similar with an example of that class.

Total 1200 leaves, 30 plants with 36 leaves from each plant, were normalized and then used to train the probabilistic neural network. We recorded the accuracies of the system with different sizes of LWF, starting from 1 up to 20. The highest accuracy, 84.50%, occurs at the size 11. Therefore we decided to set the size of the LWF to 11. Fig. 8 shows the size of LWF versus the recognition accuracy curve.

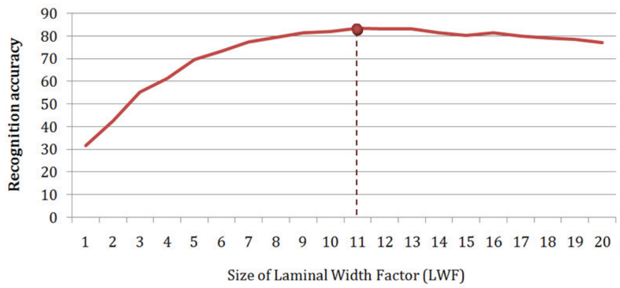

Fig. 8. Size of LWF vs. recognition accuracy curve.

III. EXPERIMENTAL RESULTS

The PNN was tested using 10-fold cross validation. For this validation purpose, we partitioned the leaf image dataset into 10 subsamples. Of the 10 subsamples, a single subsample is retained as the validation data for testing our method, and the remaining 9 subsamples were used as training data. The cross-validation process is then repeated 10 times (the folds), with each of the 10 subsamples used exactly once as the validation data. The 10 results from the folds were then averaged to produce a single estimation. The advantage of this method over repeated random sub-sampling is that all observations are used for both training and validation, and each observation is used for validation exactly once. The maximum recognition accuracy is 94% at 8th fold and the lowest is 87% at 7th fold, see Fig.9.

The average recognition accuracy of our method is 91.41%. Different features have been tested separately. The LWF gives the highest recognition accuracy. Table-I shows accuracies of different features extracted from simple leaves.

Table I. Accuracies using different features.

Feature	Accuracy, %
Leaf Width Factor (LWF)	84.50
Eccentricity	35.27
Entirety	28.08
Area / Major axis	28.0
Perimeter / Major axis	33.08
Minor axis / Major axis	33.16
Equivalent diameter / Major axis	31.16
Extent	20.58
	91.41

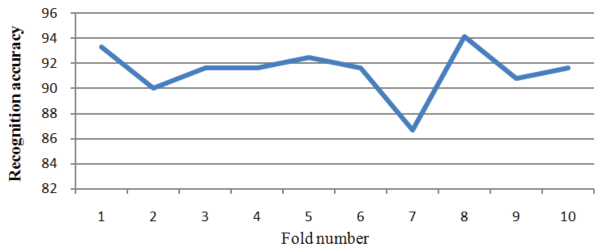

Fig. 9. Fold number vs. recognition accuracy curve.

We tested our system with partially damaged leaves. It was able to successfully identify the plants and recall the actual (undamaged) shapes of the leaves. Fig.10 shows the Graphical User Interface of our plant identification system (Chloris) displaying a search result with a partially damaged leaf.

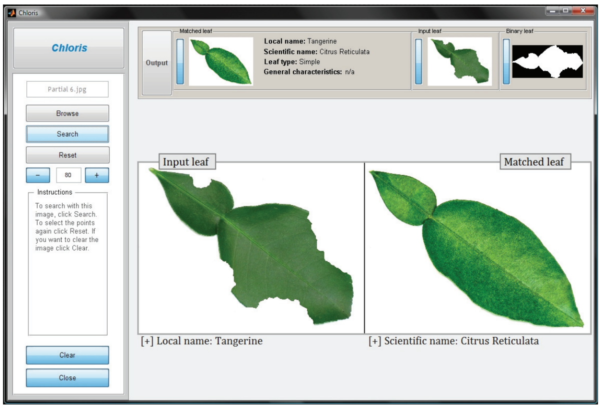

Fig. 10. Search result with a partially damaged leaf.

IV. CONCLUSIONS

Our system is no match to the human ability of plant identification. Human brain is far too powerful to be compared with our system. But when it comes to identifying a plant from hundreds and thousands leaf samples, a system like this can definitely be of use.

In this paper we presented a robust and computationally efficient method for plant species recognition from leaf image. Our system is intelligent enough to identify a plant from a partially damaged or broken leaf. 1200 simple leaves from 30 types of plants have been used to train our system. Using 10-fold cross validation our system shows 91.41% average recognition accuracy.

The biggest limitation of our system is, it requires user help in the pre-processing stage. Another limitation is its inability to work with images with complicated background. We would like to overcome these limitations in our future work and make the system even more robust.

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