Available online at www.elixirpublishers.com (Elixir International Journal)

Electrical Engineering

Elixir Elec. Engg. 106 (2017) 46710-46713

ISSN: 2229-712X

Review on Computer aided plant species identification based on leaf images

Komal Thanvi and Gopal Gawande
SSGMCE,Shegaon,India.

ARTICLE INFO

Article history:
Received: 8 April 2017;
Received in revised form: 8 May 2017;
Accepted: 18 May 2017;

Keywords
MEW: Middle European Woody, DMF: Digital Morphological Features,
NN: neural network,
ANN: Artificial Neural Networks,
FF-NN: Feed Forward Neural Networks.

ABSTRACT

Number of plant species, in present time, is on the verge of extinction. Thus owing to this threat to plant species their identification has become very important. This paper presents a technique that has been implemented for the identification of plant species based on leaf images. The plant species identification involves three steps such as preprocessing, feature extraction and classification.

Introduction

There are many types of plant species on earth. Unfortunately, as human progress, more number of plant species are at the verge of extinction. Therefore, it has become very important to correctly and quickly recognize maximum number of plant species in order to understand, manage and document them before it's too late. Correctly identification of plant species requires expert knowledge that can be provided only by botanists. However, due to the limited number of botanists, it has become necessary to acquire some of the knowledge of different species and automate the recognition process.

Plants play a vital role in the environment. Without plants there will be no existence of the earth's ecology. To overcome the threat to plant species extinction, to protect plants and to catalogue various species of flora diversities, a plant data base is very important. There is huge volume of plant species over the entire world. In order to handle these large volumes of information, development of a rapid and competent classification technique has become an active area of research[1].Moreover , along with the conservation feature, recognition of plants is also essential to exploit their medicinal properties and use them as sources of alternative energy sources like bio-fuel. There are different ways to recognize a plant viz. flower, root, leaf, fruit etc. Recently, computer vision and pattern recognition techniques have been applied towards automated process of Plant recognition [2].

There are many foliar characteristics recognized by botanists (Ellis et al., 2009), but in pattern recognition three main suites of characters are used represented by:

- Leaf contour
- Leaf surface texture e includes primarily venation, hairs, and rough leaves
- Features unavailable from single leaf image (leaf arrangement on stem (axis), heterophylly presence, blade reverse side)[2]

Literature Review

ArunPriya C.proposed a approach by means of deriving common digital morphological features. Total of 12 DMF(digital Morphological features) were extracted which were reduced to 5 features using principal component analysis. These features were given as input to support vector machines for final classification. This classifier was also compared with k-NN classifier. The SVM classifier provides with better accuracy and also reduces the execution time. Accuracy of 94.5% and 96.8% have been obtained.

Xiao-Feng Wang et al., [11] proposed a technique of recognizing leaf images depending on shape features through a hypersphere classifier. Initially, the author employed image segmentation to the leaf images. Then a total of eight geometric features are extracted and seven moment invariants for classification. Ultimately, a moving center hypersphere classifier is presented to handle these shape features. Thus, there are more than 20 classes of plant leaves productively classified. The average correct recognition rate is up to 92.2 percent.

Xiao Gu et al., [10] proposed a unique approach for leaf recognition by means of the result of segmentation of leaf's skeleton. It is based on the integration of Wavelet Transform (WT) and Gaussian interpolation. After this three classifiers, a nearest neighbor classifier (1-NN), a k -nearest neighbor classifier (k- NN) and a radial basis probabilistic neural network (RBPNN) are employed. These classifiers are employed based on Run-length Features (RF) obtained from the skeleton to identify the leaves. Ultimately, the efficiency of this approach is illustrated by several experiments.

Tele:
E-mail address: komalthanvi@gmail.com

The results reveal that the skeleton can be effectively extracted from the entire leaf, which significantly improves the recognition ratesUsing the Template

Dataset used.

The most important publicly available data sets are:[2]

Flavia had originally 1800 samples of 32 species, most of them are common plants in the Yangtze Delta, China, introduced in (Wuet al., 2007). It now has 1907 samples of 33 species, the images contain only blades, without petioles. It can be downloaded from Flavia (2009).

The Swedish data set are introduced by So¨ derkvist (2001), it contains 75 samples from each of the 15 species of Swedish trees. It can be downloaded from Sweden (2012).

ICL (Intelligent Computing Laboratory) e the introductory paper (Hu, Jia, Ling, & Huang, 2012) presented 6000 samples (30 samples from each of the 200 species) growing in China. Currently 16,851 samples from 220 species can be downloaded from ICL (2010); the individual species have from 26 to 1078 samples.

ImageCLEF (Cross Language Evaluation Forum) e aims to provide an evaluation forum for the cross-language annotation and retrieval of images. ImageCLEF (2011) includes plant images of 71 tree species from the French Mediterranean area. It contains 6436 pictures subdivided into 3different groups of pictures: scans (3070), scan-like photos (897) and free natural photos (2469). They can be downloaded from ImageCLEF (2011). The data set was used e.g. in Yahiaoui, Mzoughi, & Boujemaa, 2012).

Middle European Woody Plants (MEW) contains native or frequently cultivated trees and shrubs of the Central Europe Region. The current number of species in the data set reaches 153 including at least 50 samples per species and a total of 9745 samples; the data set can be downloaded from MEW2012 (2012).

Out of these available dataset we have worked on MEW and flavia. 15 and 32 samples of MEW and flavia has been processed and classified successfully.

Approach for leaf recognition

Approach consists of three parts:

- Pre-processing of image
- Feature Extraction
- Classification

Pre-processing of image:

The leaves available in MEW dataset are already preprocessed and have gone through following steps. Leaves were scanned at 300-DPI resolution, 24-bit colour with solid white background in lossless compression format PNG. The used scanners: Epson Perfection V331, Mustek ScanExpress A3 USB 2400 Pro2 and Hewlett Packard scanjet 3500c3.The colour images were then converted to gray level images and then were thresholded using Otsu's Threshold.

The leaves of flavia dataset the leaves were preprocessed. For preprocessing the RGB leaves were converted to gay scale images which to thresholded to obtain a black and white image. Then the edge of black and white image was detected. Finally for feature extraction complement of edge extracted image was used.

Feature Extraction.

In our approach we extracted total of 22 features:

1. Entropy :

Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. Entropy is defined as

-sum(p.*log2(p))

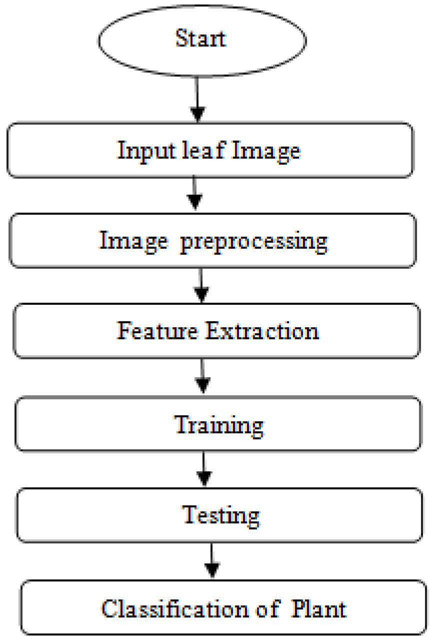

Figure 1. Flowchart.

where p contains the histogram counts.

2. Mean:

Mean gives the average of all pixel values. It provides the central tendency of pixel values.

3. Standard deviation:

Standard deviation is a statistic that is used as a measure of the dispersion or variation in a distribution. It is equal to the square root of the arithmetic mean of the squares of the deviations from the arithmetic mean.

4. Skewness:

Skewness is used to measure of the asymmetry of the data around the sample mean. If skewness is negative, the data are spread out more to the left of the mean than to the right. However if skewness is positive, the data are spread out more to the right. The skewness of the normal distribution or any distribution which is perfectly symmetric is zero.

The skewness of a distribution is denoted by S and is defined as

$$\frac{E(x-u)^3}{\sigma^3}$$

Where μ is the mean of x, σ is the standard deviation of x, and E(t) represents the expected value of the quantity t. skewness computes a sample version of this population value.

5. Area:

It corresponds to total number of pixels in a binary image having value one. It can be represented as A.

6. Eccentricity:

Eccentricity is a parameter associated with every conic section. It can be thought of as a measure of that shows how much the conic section deviates from being circular.

7. Orientation:

It is the angle (in degrees ranging from -90 to 90 degrees) between the x-axis and the major axis

8. Major axis length/Physiological length:

The distance between the two terminals of main vein of the leaf. It can be represented as PL.

9. Minor axis length/Physiological width:

Drawing a line passing through the two terminals of the main vein, one can plot infinite lines orthogonal to that line. The number of intersection pairs between those lines and the leaf margin is also infinite.

The longest distance between points of those intersection pairs is defined at the physiological width. It can be represented as LW.

10. Perimeter:
Leaf perimeter is computed by counting the number of pixels comprising of leaf margin.

11. Euler number:
Specifies the number of objects in the region minus the number of holes in those objects

12. Smooth factor:
The effect of noises to image area is used to illustrate the smoothness of leaf image. Smooth factor is given as the ratio between area of leaf image smoothed by 5 × 5 rectangular averaging filter and the one smoothed by 2 × 2 rectangular averaging filter.

13. Form factor:
This feature illustrates the difference between a leaf and a circle. It is given by 4πA/P2, where A is the leaf area and P is the perimeter of the leaf margin.

14. Aspect ratio:
It is the ratio of physiological length LP to physiological width LW, thus LP/LW.

15. Rectangularity:
Rectangularity illustrates the similarity between a leaf and a rectangle. It is defined as LP*LW/A, where LP represents physiological length, LW denotes the physiological width and A is the leaf area.

16. Narrow factor:
Narrow factor is the ratio of the diameter and physiological length of the leaf i.e. LP, and thus is given by Diameter/LP.

17. Perimeter ratio of diameter:
Ratio of perimeter to diameter, denoting the ratio of leaf perimeter P and leaf diameter, is computed by P/diameter.

18. Perimeter ratio of physiological length and width:
This feature is the ratio of leaf perimeter P and the sum of physiological length LP and physiological width LW, thus P/(LP +LW).

19. Convex area:
Scalar that specifies the number of pixels in 'Convex Image'

20. Solidity:
It is computed as Area/Convex Area.

21. Filled area:
It is a Scalar that specifies the number of on pixels in a Filled Image.

22. Extent:
It specifies the ratio of pixels in the region to pixels in the total bounding box. It can be computed as the Area divided by the area of the bounding box.

Classification

The ANN represents information-processing systems formed by interconnecting simple-processing units called neurons. Each neuron is an independent processing unit that transforms its input data via a function called activation function. The connections between neurons are characterized by weight values that represent the memory of the network. By modifying these weights according to some learning rule, the ANN can be trained to recognize any pattern giving the training data.

The network architecture plays a very important role in the performance of ANN and usually depends on the problem at hand. Several types of neural network structures have been proposed in the literature (Filippetti et al., 2004; Tung et al., 2009) for classification purposes, the most popular one is the multilayer perceptron which is used in the present study. This network with a simple architecture may be used for both modeling and classification tasks. The layers are fully interconnected in one direction from the input layer towards the output layer. The number of neurons in the input and output layers is governed by the number of inputs and outputs of the pattern to be recognized. However, the number of neurons in the middle layer can be selected depending upon the applications. Input patterns are exposed to the network whose output is compared with the target values to calculate the error which is corrected in the next pass by adjusting the synaptic weights. In the proposed work, a three-layer FF-NN is selected for classification of an plant species as this problem of fault diagnosis is likely a highly complex nonlinear mapping problem because both the inputs and outputs are multiple variables without clear linear relationships. A three-layer feedforward network has proven to have the capability of approximating any function regardless of its complexity. Figure 1 shows the architecture of a FF-NN.

Table 1.

Sr No.	Feature	MEW Dataset		Flavia Dataset	
		Aesculus hippocastanum 1	**Ulmus pumila 9**	**1001 leaf**	**1551 leaf**
1	Entropy	0.992255	0.970212	0.029215	0.246297
2	Mean	0.551763	0.601255	0.99703	0.959123
3	Standard deviation	0.497313	0.48964	0.05442	0.198004
4	Skewness	3.308534	2.316819	0.180449	-2.35974
5	Area	591047	209823	1914297	1841517
6	Eccentricity	0.813697	0.835919	0.660859	0.655961
7	Orientation	85.6721	-82.0646	0.158506	-0.38337
8	Major axis length	1171.764	703.2768	1847.668	1866.12
9	Minor Axis length	681.1334	385.9953	1386.694	1408.537
10	Perimeter	4197	2310	1	1
11	Euler number	1	1	1	1
12	Smooth Factor	0.16	0.16	0.16	0.16
13	Form Factor	0.421652	0.494127	24055766	23350365
14	Aspect Ratio	1.720315	1.821983	1.332427	1.324864
15	Rectang-ularity	1.350362	1.293765	1.338428	1.427356
16	Narrow Factor	0.740331	0.734946	0.844959	0.820547
17	Perimeter ratio of diameter	4.838078	4.469206	0.000641	0.000653
18	Perimeter ratio of physiological length and width	2.058102	1.893214	0.000293	0.000294
19	Convex Area	659885	225137	1920000	1920000
20	Solidity	0.895682	0.931979	0.99703	0.959123
21	Filled Area	591047	209823	1920000	1920000
22	Extent	0.554017	0.605579	0.99703	0.959123

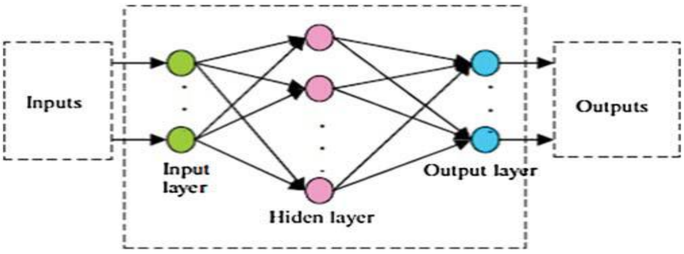

Figure 2. 3-layer FF-NN

Result

All 22 features for all samples of both the datasets were extracted. Values for few leaves samples from both the datasets are shown in table 1.

These features were given as input to simple FF-NN classifier. The classifier selected consisted of only three layers.. Details of classification are shown in table 2.

Table 2.

Sr no	Classifier	Number of neurons	Dataset	Classification accuracy
1	FF-NN	10	MEW	95.2%
2	FF-NN	14	Flavia	86.5%

Acknowledgment

The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g”. Avoid the stilted expression, “One of us (R. B. G.) thanks . . .” Instead, try “R. B. G. thanks”. Put applicable sponsor acknowledgments here; DO NOT place them on the first page of your paper or as a footnote.

References

1. Jyotismita Chaki, and Ranjan Parekh, “Plant Leaf Recognition using Shape based Features and Neural Network classifiers,” International Journal of Advanced Computer Science and Applications (IJACSA), 2011, vol. 2, no. 10.
2. Petr Novotny and Tomas Suk,”Leaf recognition of woody species in central Europe”,Elsevier journal,2013
3. J. Pan, and Y. He,”Recognition of plants by leaves digital image and neural network,” International Conference on Computer Science and Software Engineering, 2008, vol. 4, pp. 906 – 910.
4. N. Kumar, S. Pandey, A. Bhattacharya, and P.S. Ahuja, “Do leaf surface characteristics affect agro bacterium infection in tea,” J. Biosci., vol. 29, no. 3, 2004, pp. 309–317.
5. Ji-Xiang Du,De-Shuang Huang, Xiao-Feng Wang, and Xiao Gu, “Computer-aided plant species identification (capsi) based on leaf shape matching technique,” Transactions of the Institute of Measurement and Control, vol. 28, 2006, pp. 275-284.
6. Y. Li, Q. Zhu, Y. Cao, and C. Wang, “A Leaf Vein Extraction Method based on Snakes Technique,” Proceedings of IEEE International Conference on Neural Networks and Brain, 2005.
7. H. Fu, and Z. Chi, “Combined thresholding and Neural Network Approach for Vein Pattern Extraction from Leaf Images,” IEEE Proceedings-Vision, Image and Signal Processing, 2006, vol. 153, no. 6.
8. J.-X. Du, X.-F. Wang, and G.-J. Zhang, “Leaf shape based plant species recognition,” Applied Mathematics and Computation, 2007, vol. 185.
9. F. Gouveia, V. Filipe, M. Reis, C. Couto, and J. Bulas-Cruz, “Biometry: the characterization of chestnut-tree leaves using computer vision,” Proceedings of IEEE International Symposium on Industrial Electronics, 1997
10. Xiao Gu, Ji-Xiang Du, and Xiao-Feng Wang, “Leaf Recognition Based on the Combination of Wavelet Transform and Gaussian Interpolation,” Advances in Intelligent Computing, vol. 3644, 2005, pp. 253-262.
11. Xiao-Feng Wang, Ji-Xiang Du, and Guo-Jun Zhang, “Recognition of Leaf Images Based on Shape Features Using a Hypersphere Classifier,”Advances in Intelligent computing, vol. 3644, 2005, pp. 87-96.
12. http://flavia.sf.net.
13. MEW2012. (2012). Download middle European woods. http://zoi.utia.cas.cz/node/662.