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Plant leaf recognition using texture and shape features with neural classifiers ☆

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ABSTRACT

This paper proposes a novel methodology of characterizing and recognizing plant leaves using a combination of texture and shape features. Texture of the leaf is modeled using Gabor filter and gray level co-occurrence matrix (GLCM) while shape of the leaf is captured using a set of curvelet transform coefficients together with invariant moments. Since these features are in general sensitive to the orientation and scaling of the leaf image, a pre-processing stage prior to feature extraction is applied to make corrections for varying translation, rotation and scaling factors. Efficacy of the proposed methods is studied by using two neural classifiers: a neuro-fuzzy controller (NFC) and a feed-forward back-propagation multi-layered perceptron (MLP) to discriminate between 31 classes of leaves. The features have been applied individually as well as in combination to investigate how recognition accuracies can be improved. Experimental results demonstrate that the proposed approach is effective in recognizing leaves with varying texture, shape, size and orientations to an acceptable degree.

1. Introduction

Plants play a crucial role in Earth's ecology by providing sustenance, shelter and maintaining a healthy breathable atmosphere. Plants also have important medicinal properties and are used for alternative energy sources like bio-fuel. Building a plant database for quick and efficient classification and recognition is an important step toward their conservation and preservation. This is especially significant as many plant species are at the brink of extinction due to incessant de-forestation to pave the way for modernization. In recent years computer vision and pattern recognition techniques have been utilized to prepare digital plant cataloging systems for recognizing plant species in efficient ways. From this perspective, the current work proposes an innovative scheme of a plant recognition system based on digital images of plant leaves. People recognize a specific plant type by prominent characteristics of its leaf like shape and texture. Data modeling techniques have been employed here to represent these characteristics using a set of computer recognizable features. Shape of the leaf is represented by Curvelet transform coefficients together with Invariant Moments, while texture is modeled with Gabor filter outputs and metrics derived from Gray Level Co-occurrence Matrices. Features are subsequently fed to two neural based classifiers to discriminate them into a number of predefined classes. Experimentations are done using features individually as well as in various combinations to study optimal conditions. The organization of the paper is as follows: Section 2 discusses an overview of related works, Section 3 outlines the proposed approach with discussions on feature computations and classification schemes, Section 4 provides details of the dataset and experimental results obtained, Section 5 compares the proposed approach vis-à-vis some other contemporary approaches, Section 6 brings up the overall conclusions and scopes for future research.

2. Previous works

A number of features and parameters have been proposed for plant leaf classification. Sakai [21] employed geometrical parameters like length, width, area, perimeter to classify leaf types. Shape based approaches have been used to classify leaves based on their contours [7,23]. Colors have been combined with shape [19] for weed detection in fields, while shape and texture based techniques have been used to differentiate between lobed and unlobed leaves [4]. Shape, color and texture have also been jointly used [3,14]. Different data modeling techniques used include curvature scale space [1], fuzzy logic [24], fractal dimensions [9], Fourier analysis [28], wavelets [25], curvelets [20] and Zernike moments [13]. A variety of classifiers have also been used viz. neural networks [18,27], support vector machines [2], nearest neighbors [15], and K-means [22].

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3. Proposed approach

The approach proposed here uses a combination of texture and shape modeling techniques, since these are thought to be significant parameters for discrimination. Texture of a plant leaf is captured using complex Gabor filter (GF) and gray level co-occurrence matrix (GLCM) while shape of the leaf is captured using curvelet transforms (CT) and invariant moments (IM). The feature values generated are however sensitive to the size and orientation of the leaf image. To make them invariant to translation, rotation and scaling, a pre-processing step is used to standardize these parameters before the features are calculated. The steps performed are outlined as follows

1 Preprocessing
2 Feature extraction
  2.1 Texture based modeling
    2.1.1 Gabor filter (GF)
    2.1.2 Gray level co-occurrence matrix (GLCM)
  2.2 Shape based modeling
    2.2.1 Curvelet transform (CT)
    2.2.2 Invariant moments (IM)
  2.3 Combined modeling
3 Classification
  3.1 Neuro fuzzy controller (NFC)
  3.2 Multi-layered perceptron (MLP)

A block diagram depicting the major nodes of the system and data flow is shown in Fig. 1. The raw color image *I* is preprocessed (PP) to standardize its scale and orientation producing a standardized slot number *s* together with a binary signal (pb) and a grayscale signal (pg). The signal pg fed to a Gabor Filter (GF) block generates an imaginary component (igg) from which a set of GLCM based features (FT) are calculated to model the texture of the image. The signal pb is subjected to a curvelet transform (CT) decomposition and a set of curvelet coefficients (CC1, CC2, CC3) are used to generate invariant moments (IM) to compute shape based features (FS). The features are stored in the database (DB) and subsequently fed to a set of neural classifiers (CL) for classification.

3.1. Pre-processing (PP)

The objective of the pre-processing step is to standardize the scale and orientation of the image before feature computation. The raw image (*I*) is typically a color image oriented at a random angle and having a random size (see Fig. 2). The image is first converted to grayscale (gs) and binary (bw) forms. To make features rotation-invariant, the angle by which the major axis of the leaf is oriented with respect to the horizontal is extracted from the image and used to rotate it so that the major axis is aligned with the horizontal line (rg). The white bounding rectangle is removed to superimpose the leaf over a homogeneous background (cg). At this point even though the leaf is horizontal, it can have varying translation factors with respect to the origin. To make the features translation-invariant, the background is shrunk until the leaf just fits within the bounding rectangle (pg and pb). To make the features scale-invariant, the image is rescaled to standard dimensions, called 'slots'. Since the ratio of major axis to minor axis (*R*), henceforth called 'aspect ratio' is different for different leaf types, rescaling to a single size will produce distortions due to non-uniform scaling. Hence a scheme is devised so that the leaf can be scaled to one of 7 pre-determined slots (*s*) based on different values of this ratio, with no or minor distortions. The output of the pre-processing block for each leaf image is its slot number (*s*), the grayscale version (pg) and the binary version (pb).

The slot number assigned to each class along with aspect ratio is tabulated in Table 1. For $R > 13$ the system was found to produce unreliable results, hence only slots 1–6 are used here.

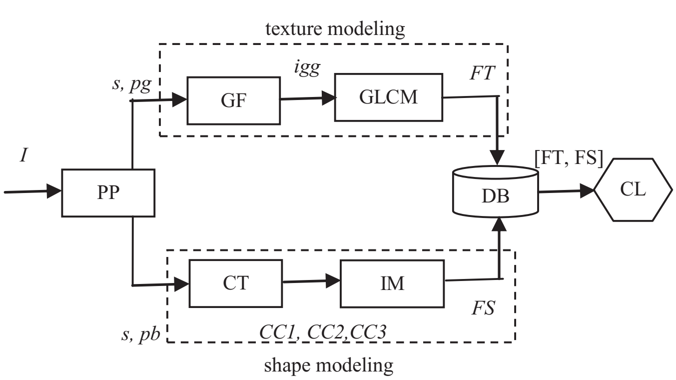

Fig. 1. Major blocks and dataflow of the proposed system.

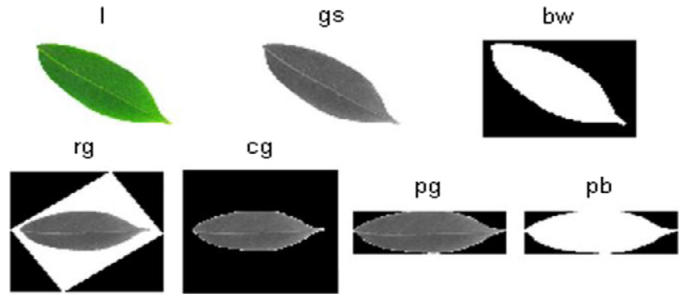

Fig. 2. Preprocessing steps.

Table 1
Predefined scaling dimensions mapped to slots.

Slot	R = (major axis length)/(minor axis length)	Size ($M \times N$)
1	$R \le 1.4$	300, 300
2	$1.4 < R \le 2$	200, 300
3	$2 < R \le 2.4$	140, 300
4	$2.4 < R \le 3$	100, 300
5	$3 < R \le 5$	65, 300
6	$5 < R \le 13$	45, 300
7	$R > 13$	10, 300

3.2. Gabor filter (GF)

A complex Gabor filter is defined as the product of a Gaussian kernel and a complex sinusoid. A 2D Gaussian curve *g* with a spread of σ in both *x* and *y* directions is represented as below:

$$g(x, y, \sigma) = \frac{1}{2\pi\sigma^2} \cdot \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \tag{1}$$

The complex sinusoid is defined as follows, where *u* denotes spatial frequency, θ the orientation and φ the phase shift ($j = \sqrt{-1}$).

$$s(x, y, u, \theta, \varphi) = \exp\{j2\pi\,(x \cdot u\cos\theta + y \cdot u\sin\theta) + \varphi\} \tag{2}$$

The complex Gabor function *h* is therefore

$$h(x, y, \sigma, u, \theta, \varphi) = g(x, y, \sigma) \cdot s(x, y, u, \theta, \varphi) \tag{3}$$

A grayscale image $I(x, y)$ is convolved with Gabor filter *h* with experimentally determined parameters to produce a set of complex signals *J*.

$$J(x, y) = I(x, y) \otimes h(x, y, \sigma, u, \theta, \varphi) \tag{4}$$

The real (rgg) and imaginary (igg) parts of the signal are separated out.

$$\begin{aligned} \mathrm{rgg}(x, y) &= \mathrm{Re}\{J(x, y)\} \\ \mathrm{igg}(x, y) &= \mathrm{Im}\{J(x, y)\} \end{aligned} \tag{5}$$