Computers and Electronics in Agriculture 140 (2017) 70–76

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

Rotation invariant wavelet descriptors, a new set of features to enhance plant leaves classification

Ehsan Yousefi, Yasser Baleghi *, Sayed Mahmoud Sakhaei

Department of Electrical & Computer Engineering, Babol Noshirvani University of Technology, Babol, Iran

A R T I C L E I N F O

Article history:
Received 25 April 2016
Received in revised form 26 May 2017
Accepted 27 May 2017
Available online 15 June 2017

Keywords:
Elliptic Fourier Descriptors
Feature extraction
Computer vision
Plant identification
Leaf recognition

A B S T R A C T

Automatic plant leaf recognition can play an important role in plant classification due to leaf's availability, stable features and good potential to discriminate different kinds of species. Amongst many leaf features like leaf venation, margin, texture and lamina, leaf shape is the most important one due to its better discriminative power and ease of analysis. One of the most common leaf shape descriptors is Elliptic Fourier Descriptor (EFD). In this paper a new shape descriptor is introduced as "Rotation Invariant Wavelet Descriptor" (RIWD). The performance of RIWD is compared with IEFD using Flavia dataset. MLP neural network is used as the classifier in this work. Results analysis shows better performance of the proposed feature in classification accuracy. Furthermore, an optimum feature vector is constructed using a set of textural and morphological features and the RIWD that reached 97.5% classification accuracy with low computational cost in comparison with many reported results in Flavia dataset.

1. Introduction

Plants are substantial for the survival of human society. Recently many species of plants are at the risk of extermination. Thus it is very essential to set up a dataset for plant variety protection (Wu et al., 2007). It is very beneficial to distinguish which plants are eatable and useful, and which ones produce irritation or even death. There are about 3 million species of plants that have been named and classified on earth (Harish et al., 2013).

Traditionally, professional taxonomists are trained to identify species and their relationships. They can examine specimens and assign taxonomic labels to them. However, a problem known as the "taxonomic impediment" (de Carvalho et al., 2007), is caused by deficiency of such experts. Moreover, an expert on one species or family may be unfamiliar with another. This has resulted in an increasing interest in automating the process of identification of plant species (Cope et al., 2012).

Automatic plant identification is a challenging task. Plant organs like flowers, fruits and leaves can be used for identification. Flowers and fruits are often only available for a few days or weeks of a year. Therefore, leaf recognition plays an important role in plant classification due to its availability, stable features and good potential to discriminate different kinds of species (Singh et al., 2010).

An image processing approach that leads to automatic segmentation of plant leaves can play an important role in such a task. Even some mobile applications are developed to do this (Grand-Brochier et al., 2015). Actually, leaf shape, venation, margin, texture and lamina (surface) are common leaf features involved in several applications (Cope et al., 2012). However, some researchers used part of those features only (Kadir et al., 2013).

Amongst the abovementioned leaf features, leaf shape is the most important one due to its better discriminative power and ease of analysis. Wu et al. (2007) used 5 basic geometric and 12 morphological features as leaf shape descriptors, PCA analysis and PNN as the classifier for leaf recognition. They also introduced a well-developed dataset called Flavia.

Flavia dataset was used by Singh et al. (2010) that did a research to compare Wu's algorithm with other methods including Support Vector Machine (SVM) and Fourier moments (Kadir et al., 2013).

Zernike moments, a set of shape descriptors, were implemented by Kulkarni et al. (2013). In this method, the extracted leaf features were combined with the Zernike moments. The focal improvements were based on the feature extraction techniques that included Zernike moments and the dual stage learning algorithm for training the classifier using Radial Basis Function neural network (Harish et al., 2013).

Wong et al. (2007) used Fourier descriptor as a similarity measure and support vector machine as pattern classifier for a large scale dataset. Yadav et al. (2008) reported retrieval and classification of various shapes using generic Fourier description.

* Corresponding author.
E-mail address: y.baleghi@nit.ac.ir (Y. Baleghi).

http://dx.doi.org/10.1016/j.compag.2017.05.031
0168-1699/

Prasad et al. (2016) proposed an RST-invariant shape profile transform called Angle View Projection (AVP) that is used in leaf recognition application. Discrete Cosine Transform (DCT) is then applied to the resultant signal to maintain the shape property of leaf while reducing its dimension using Principal Component Analysis (PCA). They reported promising results in Flavia dataset.

Apleaf is an android-based plant leaf identification system (Zhao et al., 2015). The feature extraction phase of this system uses pyramid histograms of oriented gradients (PHOG), HSV color features and their statistical moments and wavelet coefficients. The system was tested using ImageCLEF2012 dataset which contains 126 tree species from the French Mediterranean area.

During an international competition called LifeCLEF plant challenge, 7 research groups submitted their results for plant recognition on PlantCLEF 2015 dataset. This dataset includes 113,205 images from 41,794 observations of 1000 species of trees, herbs and ferns living in Western European regions. The detailed description of each submitted method and results can be found in Joly et al. (2015).

One of the most common leaf shape descriptors is Elliptic Fourier Descriptor (EFD). Mancuso (2015) used Elliptic Fourier Analysis and artificial neural networks for grapevine genotypes identification. Neto et al. (2006) used Elliptic Fourier (EF) and discriminant analysis to identify 4 plant species, based on leaf shape. Invariant Elliptic Fourier Descriptor (IEFD) is developed for cereal grains classification that is independent of size and rotation of the shape contour (Mebatsion et al., 2012b). The variation of grain types is also evaluated using IEFD and PCA (Mebatsion et al., 2012a). Moreover, a dozen of research works has been reviewed by Cope et al. (2012) that used variations of EFD for plant leaf identification.

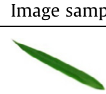
In this paper a new shape descriptor is introduced as "Rotation Invariant Wavelet Descriptor" (RIWD). The performance of RIWD is compared with IEFD using Flavia (Wu et al., 2007) dataset. Furthermore, an optimum feature vector is constructed using a set of textural and morphological features in combination with the mentioned descriptors to reach the best classification rate in Flavia dataset. MLP neural network is used as the classifier in this work.

2. Materials and methods

2.1. Dataset description

The Flavia dataset contains 32 different species, a total of 1907 leaves. A full description of the species names and the sample numbers for each one can be found in Wu et al. (2007). Table 1 shows a few samples of the dataset.

Table 1
Some Samples of Flavia Dataset.

Class name	Image sample 1	Image sample 2
Phyllostachys edulis (Carr.) Houz.		
Aesculus chinensis		
Berberis anhweiensis Ahrendt		
Cercis chinensis		
Acer palmatum		

2.2. Preprocessing

The images from dataset are converted to binary and preprocessed using morphological operations to eliminate some border errors. However for color features, the original images are used. The leaf contour is extracted from the preprocessed image, as shown in Fig. 1.

Flavia dataset contains leaf images in a clear background. This property leads to a simple segmentation process to prepare the object for feature extraction. Datasets containing leaf images with complex natural background require more intensive segmentation step. Assuming a perfect segmentation as the preprocessing stage, this work can be applied for feature extraction phase of any other leaf datasets with complex background.

2.3. Feature extraction

Feature extraction is one of the most important steps in leaf image recognition. In this section the new "Rotation Invariant Wavelet Descriptor" (RIWD) will be proposed after the review of IEFD, as the basis of this new idea. Finally some other morphological and textural features are introduced that will be concatenated to the mentioned descriptors to form a comprehensive feature vector and enhance the recognition performance.

2.3.1. Invariant elliptic Fourier descriptor

EFD was introduced as a powerful feature to represent the shape information of a closed contour (Kuhl and Giardina, 1982). Following (Soldea et al., 2010), a planar curve $C(t)$: $[0,T] \to R^2$ can be parameterized by t in Eq. (1).

$$C(t) = (x(t), y(t)) \tag{1}$$

Then $C(t)$ in Eq. (1) can be described using EFDs in Eq. (2).

$$\begin{pmatrix} x(t) \\ y(t) \end{pmatrix} = \sum_{i=0}^{\infty} \begin{pmatrix} a_i & b_i \\ c_i & d_i \end{pmatrix} \begin{pmatrix} \cos\left(\frac{2i\pi t}{T}\right) \\ \sin\left(\frac{2i\pi t}{T}\right) \end{pmatrix} \tag{2}$$

where a_i, b_i, c_i and d_i are the Elliptic Fourier Descriptors that are given in Eqs. (3)–(5).

$$a_0 = \frac{1}{T}\int_0^T x(t)dt,\ b_0 = 0,\ c_0 = \frac{1}{T}\int_0^T y(t)dt,\ d_0 = 0 \tag{3}$$

$$a_i = \frac{2}{T}\int_0^T x(t)\cos\left(\frac{2i\pi t}{T}\right)dt,\ b_i = \frac{2}{T}\int_0^T x(t)\sin\left(\frac{2i\pi t}{T}\right)dt \tag{4}$$

$$c_i = \frac{2}{T}\int_0^T y(t)\cos\left(\frac{2i\pi t}{T}\right)dt,\ d_i = \frac{2}{T}\int_0^T y(t)\sin\left(\frac{2i\pi t}{T}\right)dt \tag{5}$$

These coefficients are variable with scale and orientation of the contour. Therefore the normalized (Mebatsion and Paliwal, 2011) and standardized (Mebatsion et al., 2012b) forms of EFDs were proposed. The coefficients of ith harmonic in standardized form are given in Eq. (6) as $a_i^{**}, b_i^{**}, c_i^{**}$ and d_i^{**}.

$$\begin{bmatrix} a_i^{**} b_i^{**} \\ c_i^{**} d_i^{**} \end{bmatrix} = \frac{1}{E^*} \begin{bmatrix} \cos\psi & \sin\psi \\ -\sin\psi & \cos\psi \end{bmatrix} \begin{bmatrix} a_i b_i \\ c_i d_i \end{bmatrix} \begin{bmatrix} \cos i\vartheta & -\sin i\vartheta \\ \sin i\vartheta & \cos i\vartheta \end{bmatrix} \tag{6}$$

where

$$E^* = \sqrt{a_1^{*2} + c_1^{*2}} \tag{7}$$

$$\begin{bmatrix} a_1^* \\ c_1^* \end{bmatrix} = \begin{bmatrix} a_1 & b_1 \\ c_1 & d_1 \end{bmatrix} \begin{bmatrix} \cos\vartheta \\ \sin\vartheta \end{bmatrix} \tag{8}$$

$$\vartheta = \frac{1}{2}\tan^{-1}\frac{2(a_1 b_1 + c_1 d_1)}{(a_1^2 + c_1^2 - b_1^2 - d_1^2)} \quad 0 \leqslant \vartheta \leqslant \pi \tag{9}$$