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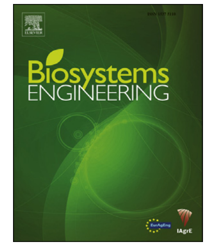

Research Paper

Automatic classification of plants based on their leaves

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The proposed algorithm identifies a plant in three distinct stages i) pre-processing ii) feature extraction iii) classification. Different leaf features, such as morphological features, Fourier descriptors and a newly proposed shape-defining feature, are extracted. These features become the input vector of the artificial neural network (ANN). The algorithm is trained with 817 samples of leaves from 14 different fruit trees and gives more than 96% accuracy. To verify the effectiveness of the algorithm, it has also been tested on Flavia and ICL datasets and it gives 96% accuracy on both the datasets.

1. Introduction

Automatic classification of plants is an important step for solving general problems like yield prediction, growth estimation and health prediction. Traditionally, botanists classify plants based on their floral parts (Mishra, Maurya, Singh, & Misra, 2012), fruits and leaves. Flowers and fruits may not be the best choice for automatic plant identification as they appear during a limited period. However, leaves are numerous in number and are present for most of the year, which make them suitable for computerised plant classification.

Leaf features that have been used in the literature include different statistical features like eccentricity, aspect ratio, circularity, roundness perimeter etc., and leaves have also been identified using Fourier descriptors (Neto, Meyer, Jones, & Samal, 2006; Singh, Gupta, & Gupta, 2010), wavelets (Gu, Du, & Wang, 2005; Im, Nishida, & Kunii, 1998); vein structure, saw-toothed pattern, texture of a leaf (Rashad, El-Desouky, & Khawasik, 2011); centroid contour distance

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(Bong, Sulong, & Rahim, 2013; Wang, Chi, & Feng, 2003); and leaf colour (Kadir, Nugroho, Susanto, & Santosa, 2011).

Du, Wang, and Zhang (2007) extracted different morphological features and Hu moments but did not use the contour information. Some of the features like aspect ratio and rectangularity were based upon the physiological length and width of the leaf, which require a human operator to mark the extreme points on the leaf image. Wu et al. (2007) used morphological features and the vein features to classify plants. Although the selected features gave accuracy as high as 90%, the features still required physiological length and width.

Neto et al. (2006) used Elliptic Fourier technique to analyse the shape of a leaf to classify different plant species at different stages of growth. Although the system was fully automatic, the accuracy it could achieve was almost 88.4%.

Beghin, Cope, Remagnino, and Barman (2010) combined the shape and texture features to make a feature set. The accuracy they could achieve was almost 81%. Different classification techniques like support vector machines (SVM) (Zhang, Yanne, & Liang, 2011), probabilistic neural network (PNN) (Kadir et al., 2011; Wu et al., 2007), moving media centres hyperspheres (MMC) (Du et al., 2007; Zhang et al., 2004) and ANN with back-propagation (Heymans, Onema, & Kuti, 1991; Satti, Satya, & Sharma, 2013) have been used for plant classification.

Here we propose an algorithm which automatically classifies a plant based on its leaf. For this research, we have created a database in the laboratory consisting of leaves of 14 different fruit trees. We identify different morphological features, Fourier descriptors and a newly developed feature, called shape-defining feature (SDF), for classification. SDF's basic purpose is to retrieve the shape of a leaf along with its fine serrations. The proposed algorithm uses ANN with back propagation as a classifier as it is more general than PNN and less sensitive to noise than SVM. To verify its effectiveness the algorithm has also been tested on Flavia (Wu et al., 2007) and ICL (Intelligent Computing Laboratory, Chinese Academy of Sciences) datasets.

2. Materials

We have used three different leaf datasets to test our algorithm. These datasets include Flavia, ICL and our own dataset. Our dataset consists of leaves of 14 different seasonal fruit trees that grow in particular regions of Asia. Some fruit trees like apple and apricot grow at higher places and in cold regions like Azad Kashmir (Kotli – a small district of Azad Kashmir, Pakistan) and Murree (Pakistan). We collected leaves from the 3–4 different trees during the month of September (year 2012 and year 2013). Fig grows in warm and plain regions like Punjab (Pakistan). We collected leaves from three different fig trees located in Rawalpindi (Pakistan) during the month of July (2012 and 2013). Leaves of oranges were collected from four different trees located in Rawalpindi (Pakistan) during winter season. These trees belong to different areas and produce fruit in different seasons. We collected these leaves over two years (year 2012 and year 2013). These leaves were collected from different parts of the tree, from different heights and also of different sizes. Criteria for selecting a leaf were that it should be green in colour and it should not be ruptured. Table 1 shows the names of the trees and the number of their sample images. We intend to publish this dataset for future references.

Two different digital cameras, DSLR A100 and DSC TX7, were used to capture the images of the leaves. DSLR A100 uses a 10.2 MP CCD sensor and DSC TX7 uses 10MP CCD sensor.

A leaf without stalk was placed on a white sheet and imaged with the camera. All images were in RGB format. Out of 2525 sample images, 817 images were selected randomly as the training data and of the remaining 1708 were used as test images. Figure 1 shows sample images of 14 types of leaves.

There are some publicly available leaf image datasets such as the Flavia dataset (Wu et al., 2007), the Smithsonian Leaf dataset (Belhumeur et al., 2008), Swedish Leaf dataset (Soderkvist, 2001), CLEF dataset (Goëau et al., 2013) provided by the CLEF and ICL dataset. Among these, we tested our algorithm on Flavia and ICL datasets to verify its effectiveness. Flavia dataset consists of 32 different classes and ICL dataset consists of 20 different types of plants.

3. Methods

The algorithm has three distinct stages i) pre-processing ii) feature extraction and iii) classification, as shown in Fig. 2. In the pre-processing stage, the leaf is segmented from the background using colour segmentation and then it is normalised. Feature extraction follows: the extracted features include different types of morphological features, Fourier descriptors (FD) and a newly proposed feature called shape-defining feature (SDF). These features become the input vector of the artificial neural network (ANN) in the classification stage. ANN with back propagation classifies the leaf based on the extracted features.

3.1. *Pre-processing*

Pre-processing involves two subtasks i.e. leaf segmentation and image normalisation.

3.1.1. *Leaf segmentation*

The input RGB image (I_c (X, Y)) is converted into greyscale image (I_g (X, Y)) using the Equation (1) (Gitelson, Kaufman, Stark, & Rundquist, 2002; Lamm, Slaughter, & Giles, 2002).

$$I_g = \frac{2*G - B - R}{G + B + R} \quad (1)$$

where R, G and B represent the red, green and blue colours respectively of pixel intensities of the input image.

The greyscale image (I_g (X, Y)) is converted into binary image (I_b (X, Y)) using the global thresholding technique (Gonzalez & Woods, 2008) in which we select the valley in between the two peaks and use it as a threshold.