Leaf based plant identification system for Android using SURF features in combination with Bag of Words model and supervised learning

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Thi Lan Le
MICA Institute, HUST

Ngoc-Hai Pham
National Institute for Research in Computer Science and Control

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Quang-Khue Nguyen
Faculty of Information Technology
Hanoi University
Hanoi, VietNam
khuenq.hjc@gmail.com

Thi-Lan Le, Ngoc-Hai Pham
International Research Institute MICA – UMI2954
Hanoi University of Science and Technology
Hanoi, VietNam
{Thi-Lan.Le, Ngoc-Hai.Pham}@mica.edu.vn

***Abstract*— Even many works have been proposed for automatic plant identification, there exists very few plant identification applications on the market. To the best of our knowledge, Leafsnap [1] is the first automatic plant identification application. However, this application is dedicated to iOS users and is working with tree species of the Northeastern United States. Today, a huge number of Android users make an interesting market for developing plant identification for Android. The contribution of this paper is two-fold. Firstly, we propose a leaf based plant identification method using SURF features in combination with Bag of Words and supervised learning. This method obtains better results in comparison with other existed methods in the same database. Secondly, we develop a leaf based plant identification system for Android.**

***Keywords—* plant identification; leaf image analysis**

I. INTRODUCTION

Developing a plant identification system for a personal computer with average hardware power is a challenge. However, building a system for plant identification using mobile devices is an even more sophisticated process as these devices have many limitations in terms of size, hardware functionalities, storage, etc. Even many works have been proposed for automatic plant identification, there are few plant identification applications on the market. To the best of our knowledge, Leafsnap [1] is the first automatic plant identification application. However, this application is dedicated to iOS users and is working with tree species of the Northeastern United States. Today, a huge number of Android users makes an interesting market for developing plant identification for Android. The contribution of this paper is two-fold. Firstly, we propose a leaf based plant identification method using SURF features in combination with Bag of Words and supervised learning. This method obtains better results in comparison with other existed methods in the same database. Secondly, we develop a leaf based plant identification system for Android.

II. RELATED WORKS

While working with plant identification based on leaf image, the most crucial part is leaf representation, in which, we need to define and to decide the robust features in order to obtain the best leaf representation. There are two main features used for the plant identification: shape and venation.

Concerning shape descriptors, a huge number of descriptors have been introduced for representing shape of the leaf. The shape descriptors can be implicit or explicit.

Many works attempt to extract the explicit shape descriptors such as leaf diameter because these descriptors are close to taxonomy terms used by botanist. Wu et al. [2] focus on extracting 5 basic geometric features including diameter, physiological length, physiological width, leaf area and leaf perimeter. Based on these geometric features, they also defined 12 digital morphological features used for leaf recognition. For data dimension reduction, they use Principle Component Analysis (PCA) method. Then, a Probabilistic Neural Network (PNN) is implemented for classifying feature vectors. Each feature vector is classified to specific class which has the maximum probability to be the correct class. Lin et al. [3] calculated some basic descriptors (area, perimeter, length, width, convex hull) and some dimension less shape factors (compactness, roundness, elongation, roughness), they also extracted Fourier descriptor and Bezier descriptors. The authors in [4] analyzed all morphological parameters and combined them with Hu invariants.

Along with explicit shape descriptors, others works try to extract the implicit features of shape such as histogram of oriented gradients (HOG) features. In [5], the authors apply HOG to plant identification. Since, HOG is a high dimensional feature, the authors proposed to use maximum margin criterion (MMC) method to reduce dimension of feature vector. In [6], Pham et al. apply also HOG and SVM (Support Vector Machine) to plant identification. The authors have compared HOG with Hu moments and the obtained results show that HOG is more robust than Hu moment for plant identification. Recently, the authors in [7] have proposed a new approach based on shape context.

Contrary to works dedicated to plant identification based on leaf shape, few works [8], [9], [10], [11] proposed for plant identification based on venation even the biologist said that venation is an important factor for leaf identification. The main reason is that it is difficult, sometime impossible to extract and process leaf venation feature effectively. The works belonging to this direction focus on addressing two main issues: venation extraction and venation classification. In [11], the authors proposed an algorithm for leaf venation extraction based on scale-space. The obtained result shows that the proposed method is better than that of the automatic method but not as robust as manual method. However, in order to apply this algorithm for leaf identification based on venation, we needs to do further processing. In [10], the authors presented a venation extraction method for leaf image based on independent component analysis. This work is dedicated to develop an interactive tool which helps botanists to extract the vein system with little user interaction. Therefore, we cannot apply directly this work for plant identification. Concerning venation classification, the authors in [8], [9] proposed a method for classify four types of venation. However this approach works with well-prepared venation image.

Concerning plant identification application for mobile, Leafsnap [1] is the most famous application. With Leafsnap, user can take a photo of plant of the interest, send it to server of Leafsnap, the system will return information of the identified plant. However, this application is dedicated to iOS users and is working with tree species of the Northeastern United States.

III. LEAF BASED PLANT IDENTIFICATION FOR ANDROID

A. System overview

In this section, we describe the working flow and the main components of our system (see. Fig.1.).

Similar to Leafsnap [1], our system is based on client-server. Firstly, the user takes leaf photo by Android mobile. Then, this photo is sent to the server in which this photo will be analyzed in order to identify plant based on leaf photo. The server contains two main modules: leaf/non leaf classification and leaf identification. The identified ID of the plant will be sent to client. The client will analyze and display plant information to users. In the following sections, we will describe in detail two main modules in our system: leaf/non leaf classification module and leaf-based plant identification.

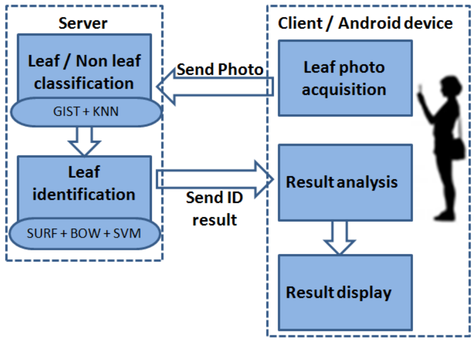

Fig. 1. Leaf based identification system for Android

B. Leaf/non leaf classification

Since the plant identification application is developed for end users. End users may take a photo that does not contain leaf. Therefore, the leaf-based plant identification has to perform leaf/non-leaf classification before leaf identification. In Leafsnap [1], the authors proposed to use GIST with SVM. In this paper, we propose to use GIST as descriptor and kNN as classifier for leaf/non leaf classification that are proved robust for scene classification and object recognition [12], [13]. The GIST extraction step is illustrated in Fig. 2.

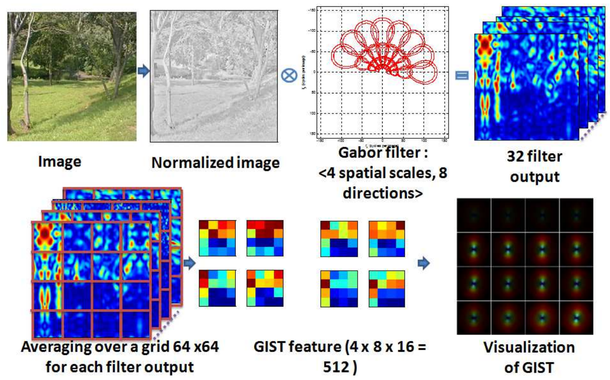

Fig. 2. GIST extraction from image

Firstly, an original image is converted and normalized to gray scale image I(x,y). We then apply a pre-filtering to I(x,y) in order to reduce illumination effects and to prevent some local image regions to dominate the energy spectrum. The filtered image I(x,y) then is decomposed by a set of Gabor filters. A 2-D Gabor filter is defined as follows:

$$h(x,y) = e^{-\frac{1}{2}\left(\frac{x^2}{\delta_x^2}+\frac{y^2}{\delta_y^2}\right)} e^{-j2\pi(u_0x+v_0y)} \qquad (1)$$

As shown in Fig. 2, configurations of Gabor filters contain 4 spatial scales and 8 directions. At each scale (δ_x, δ_y), by passing the image I(x,y) through a Gabor filter *h(x,y)*, we obtain all those components in the image that have their energies concentrated near the spatial frequency point (u_0, v_0). Therefore, the GIST vector is calculated using energy spectrum of 32 responses. To reduce dimensions of feature vector, we calculated averaging over grid of 4x4 on each response. Consequently, the GIST feature vector is reduced to 512 dimensions.

K-Nearest neighbor (K-NN) classifier is selected for classification GIST feature because they are high dimensional descriptors. Given a testing image, we found K cases in the training set that is minimum distance between the feature vectors of the input image and those of the training set. A decision of the label of testing image was based on majority vote of the K label found. In this work, we select Euclidian distance that is usually realized in the context of image retrieval.

C. Leaf based plant identification

The overview of the proposed approach is shown in Fig. 3.

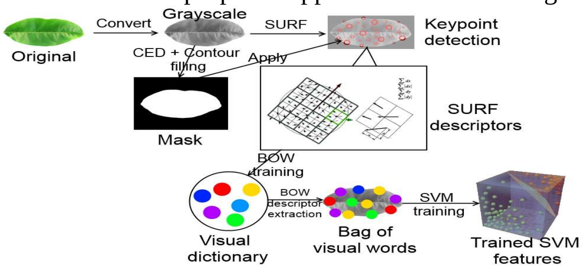

Fig. 3. Plant identification based on SURF, BOW and SVM.

First of all, in preprocessing step, we convert training image to grayscale image and use thresholding technique for producing binary image of the leaf shape. The binary image created after preprocessing step will then be used as a mask in feature extraction step, where we detect and extract the SURF keypoints and descriptors within the scope of the mask. In order to make more descriptive and smaller feature set for training the classifier, we take advantage of Bag-of-word (BOW) model as a dimension reduction method, which clusters all extracted SURF descriptors into different sets, known as feature dictionary, by unsupervised learning technique. The system will then compute BOW descriptor as a histogram, where each bin counts the number of SURF descriptors closest to the respective visual word from the dictionary. Finally, the Support Vector Machine (SVM) classifier will take all BOW descriptors as input data for training and export trained feature vectors to system storage.

SURF detection and extraction

SURF was first introduced in [14] as a more robust feature detection than Scale Invariance Feature Transform (SIFT). The idea of SURF is based on sums of 2D Haar wavelet responses and makes an efficient use of integral images. With an integral image, it uses an integer approximation to the determinant of Hessian blob detector. For features, it uses the sum of the Haar wavelet response around the point of interest with the aid of integral image. SURF has proven to be fast and robust when apply to local feature extraction task. In this paper, we use both SURF keypoint detector and SURF descriptor extractor. The application of SURF keypoint detector with leaf shape mask is illustrated in Fig. 4.

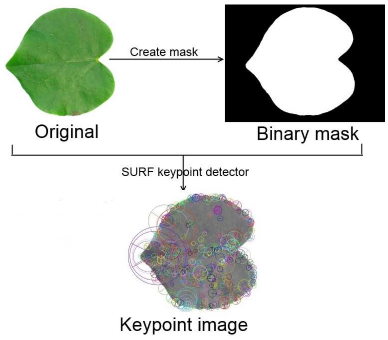

Fig. 4. Detected SURF on leaf image

Bag of Words (BOW) model and SVM

Although SURF descriptors are good enough to describe leaf, we still need a mean to reduce the dimension of detected feature vectors in order to reduce computational expense of matching local features. Therefore, we use Bag-of-Words (BOW) model, originated in natural language processing and information retrieval field [15]. In our work, BOW model is defined by a dictionary of visual words or feature clusters, each represents a cluster of SURF features classified by K-means clustering method over all detected features. Finally, each image is represented by a histogram of visual words. These histograms become feature vector for training SVM.

IV. EXPERIMENT RESULTS

A. Leaf/non leaf classification results

In order to evaluate the performance of leaf/non-leaf classification, we have created two datasets. The leaf dataset contains images extracted from Flavia dataset[2]. The total number of images of two datasets is 1952. These images are divided into training (1472 images) and testing dataset (480 images). With GIST feature and KNN classification method, we obtain 95% of accuracy. This result shows that the proposed method for leaf/non-leaf is reliable enough for deploying in our application.

B. Leaf based plant identification results

We compare our proposed method for leaf-based plant identification with the method based on HOG and SVM [6] and the method based on PNN [16] on the same database (Flavia database [2]). This database consists of 1907 images (1600*1200 pixels) of 32 species. The leaf in this database is taken with simple background (see Fig.5). This dataset is firstly used for evaluating the method proposed in [16]. In order to compare the performance of four methods, we divide this dataset to training and testing set by the same way as explained in [16].

Fig. 5. Flavia database

This means that for each species, we pick 10 images for testing set and the rest belonging to training set. Concerning the plant identification method based on SUFR, BOW and SVM, we choose the dictionary size is 250. Tab. 1 shows the average accuracy obtained for each method.

TABLE I. AVERAGE ACCURACY OF THE THREE METHODS

Method	Average accuracy
Method [16]	84.68%
Method [17]	90.3%
Our method	**95.94%**

The experimental results show that our method obtains the best results in comparison with two other methods on the same database. The reason is that leaf images in this database contain simple background and SURF is detected mostly on the leaf contours.

C. Application for Android

Based on the above results, we have implemented leaf based plant identification for Android. The client and server exchange the information based on socket (see Fig. 6). Fig 7 shows some screenshots of our applications.

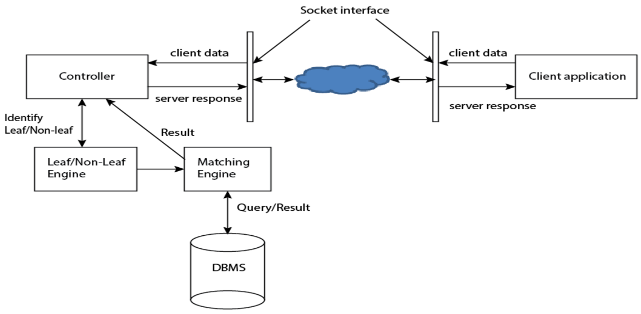

Fig. 6. Information exchange between client and server in our application.

(a) (b) (c)

Fig. 7. Some screen photos of leaf based plant identification application for Android (a) Leaf image captured by users, (b) Identification results including scientific name, common name and other informations of the identified plant (c) Results screen with more images and informations of the identified plant.

V. FUTURE WORK

In this paper, firstly we have presented a new method for leaf based plant identification method using SURF features in combination with Bag of Words and supervised learning. The experimental results prove that this method outperform the existing methods. Secondly, we have developed a leaf based plant identification system for Android based on our research results.

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