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Feature extraction algorithm based on dual-scale decomposition and local binary descriptors for plant leaf recognition

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ABSTRACT

Plant leaf recognition is very important and necessary to agricultural information and ecological protection. Unfortunately, the robustness and discriminability of the existing methods are insufficient. This paper describes a novel plant leaf recognition method. In order to extract distinctive features from plant leaf images and reduce the probability of disruption by occlusion, clutter, or noise, a novel feature extraction algorithm based on dual-scale decomposition and local binary descriptors is proposed. The dual-scale decomposition consists of two phases. In the first phase, a plant leaf image is decomposed into several subbands with an adaptive lifting wavelet scheme. In the second phase, each subband is filtered using a group of variable-scale Gaussian filters. Local binary descriptors are extracted from the filtered subbands to capture both shape and texture characteristics, and then the histograms of the local binary descriptors at different scales and different subbands are determined and regarded as features. In order to improve the robustness and discriminability of plant leaf recognition further, a fuzzy *k*-nearest neighbors' classifier is introduced for matching. Experimental results show that the proposed approach yields a better performance in terms of the classification accuracies compared with the state of the art methods. It is also shown that this method is relatively robust to noise, occlusion and smoothing.

1. Introduction

Plant recognition is very important and necessary to agricultural information, ecological protection, and automatic plant recognition systems. Many classification technologies, such as morphologic anatomy, cell biology, molecule biology, and phytochemistry, have been used. These technologies are based on the biological characteristics or phytochemistry properties of plants, and need a complicated processing course, and so, they are not suitable for on-line applications. Recently, plant recognition based on leaf images has attracted some attention [1]. It can extract plant features directly from living plants, and is suitable for on-line applications.

Popular works on plant leaf recognition focused on shape features [2–11]. They developed edge detectors or used the existing edge detection methods to extract the contour of a leaf, which was matched directly or represented in other formats such as curvature scale space or deformable templates for matching. Kumar et al. [7] extracted curvature features from the binarized leaf images, and selected a nearest neighbor classifier with histogram intersection as the distance metric for classification. Based on this method, they presented a mobile application for identifying plant species using automatic visual recognition. Ling and Jacobs [8,9] proposed a shape classification method called Inner Distance Shape Context. They sampled points along the boundary of a shape, and built a 2D histogram descriptor at each point. This histogram represents the distance and angle from each point to all other points, along a path restricted to lie entirely inside the leaf shape. Belhumeur et al. [10] combined Inner Distance Shape Context with a nearest neighbor classifier, and designed a computer vision system for identifying plant species. Hu et al. [11] presented a novel contour-based shape descriptor, named Multiscale Distance Matrix. In their method, given n sample points $p_1, p_2, \ldots, p_n$ on the contour of a shape with certain order, an $n \times n$ distance matrix D can be constructed, where D_{ij} denotes the Euclidean distance between point p_i and point p_j. For each column of matrix D, it was shifted up circularly so that the first element becomes zero, and then elements of each row were sorted by their values in ascending order. The Multiscale Distance Matrix was obtained by eliminating the redundant elements from the resultant matrix, followed by rotation and scaling normalization operations. Since the Multiscale Distance Matrix descriptor is with relatively high dimensions, they applied dimensionality reduction methods including the Decomposed Newton's Method [12] and Maximum Margin Criterion [13]

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Fig. 1. The textures in some plant leaves.

to the descriptor for improving its efficiency and effectiveness, and then used Euclidean distance and the nearest neighbor rule for classification.

These methods yield a good identification performance for the plants which have significantly different leaf contours, but are often sensitive to the quality of the contour resulting from a segmentation process. Moreover, they extracted features only from the boundaries of leaves, and neglected other useful characteristics in the leaf images. In practice, there are many different plant species with similar leaf contours, and the same kind of plant species possesses leaves with different shapes. Hence, their discriminability is not strong enough for all plant recognition applications.

In order to alleviate the drawbacks as mentioned above, Rejeb et al. [14] present a plant retrieval system using multiple leaf images from a plant, they used a hierarchical representation derived from domain knowledge and multiple key-based local features within a likelihood ratio framework, and then the results were collated into a single ranked list to suggest the most relevant species along with additional representative images. Du et al. [15] combined the morphology features of leaf contours including aspect ratio, rectangularity, eccentricity etc. with the region-based features i.e. invariant moments. A move median centers hypersphere classifier was used for classification. Zhang et al. [16] extended manifold learning [17] to plant leaf recognition. They utilized locally linear embedding algorithm [18] to detect the low-dimensional nonlinear manifold embedded in the high-dimensional Euclidean space constructed by plant leaf images. A modified maximizing margin criterion was used for classification. Although these methods have reported promising recognition performances, their robustness and discriminability are also insufficient. Thus, how to improve the robustness and discriminability of plant leaf matching remains a challenging problem.

As shown in Fig. 1, besides leaf contours, texture is another kind of the most clear and significant characteristics in plant leaf images. A wide variety of methods [19,20] have been applied to the extraction of the vein networks from leaf images, although arguably with limited success thus far [1]. By using synthetic or manually extracted vein images, Park et al. [21] used the pattern of end points and branch points to classify each vein structure as one of the main venation types. Meanwhile, a number of texture analysis techniques have also been applied to leaf texture classification. Casanova et al. [22] used an array of Gabor filters to decompose a leaf image, and calculated the energies for the responses of all applied filters as features. Cope et al. [23] proposed a method based on the co-occurrences of different scale Gabor filters. Liu et al. [24] presented a method based on wavelet transforms and support vector machine. These methods achieved reasonable results, and their classification accuracies are generally lower than the state of the art shape-based methods for the plants which have significantly different leaf contours [1], whereas, from these methods, it can be observed that the pattern of texture in a leaf is useful for leaf identification [1]. Motivated by this observation, this paper addresses the issue to improve the robustness and discriminability of plant leaf matching by combining textures with leaf contours in plant leaf recognition.

Sweldens [25] proposed a lifting scheme for wavelet transform, known as the second generation wavelet transformation, which inherits the multiresolution representations of the classical wavelet transforms. It has many advantages over the classical wavelet transforms such as very low computational cost, in situ operation, and easy hardware implementation [26]. Unlike the classical wavelet transforms which are constructed by the dyadic translations and dilatations of one particular function called mother wavelet, the lifting scheme presents a means for decomposing wavelet transform into prediction and update stages. One may adapt prediction or update stage filters to local signal properties and build the desired adaptive wavelet transform. In recent years, several adaptive wavelet lifting approaches have been developed to highlight the concerned signal features for different applications [27–29]. In our early work [30], an adaptive lifting wavelet scheme was developed as well, which offers special consideration for image textures. Moreover, it can balance extracting the useful information with filtering distortions from images. As a result, it yields a prominent performance in palmprint recognition.

This paper describes a novel plant leaf recognition method based on dual-scale image decomposition and local binary descriptors. The dual-scale image decomposition is implemented with our adaptive lifting wavelet scheme [30] and a group of variable-scale Gaussian filters. In which, a plant leaf image is decomposed into several subbands with our adaptive lifting wavelet scheme, and then, each subband is convoluted with the group of variable-scale Gaussian filters. From the resultant images, local binary descriptors are extracted to capture both shape and texture characteristics. The histograms of the local binary descriptors at different scales and different subbands are calculated and regarded as the features. In order to improve the robustness and discriminability of plant leaf recognition further, we design a fuzzy k-nearest neighbors' classifier for matching. Experimental results show the superiority of this approach compared with the recent plant leaf recognition approaches.

The outline of this paper is as follows. Section 2 will provide a brief introduction of our adaptive lifting wavelet scheme. The proposed method is described in Section 3 and the experimental results are presented in Section 4. In Section 5, the concluding remarks are provided.

2. Our adaptive lifting wavelet scheme

The lifting wavelet scheme proposed by Sweldens [25] provides a simple yet flexible method for building new, possibly nonlinear, wavelets from existing ones. It comprises a given wavelet transform, followed by an update and a prediction step such as depicted in Fig. 2(a).

The original signal $S:\mathbb{Z}^d \to \mathbb{R}$ is first split into an approximation signal x and a detail signal y by a particular wavelet transform or simple polyphase decomposition. The update map U acting on y is used to modify x, resulting in a new approximation signal x', i.e.

$$x' = x + U(y) \tag{1}$$

Subsequently, the prediction map P acting on x' is used to modify y, yielding a new detail signal y', i.e.

$$y' = y - P(x') \tag{2}$$