Learning-Based Leaf Image Recognition Frameworks

Jou-Ken Hsiao, Li-Wei Kang, Ching-Long Chang and Chih-Yang Lin

Abstract Automatic plant identification via computer vision techniques has been greatly important for a number of professionals, such as environmental protectors, land managers, and foresters. In this chapter, we propose two learning-based leaf image recognition frameworks for automatic plant identification and conduct a comparative study between them with existing approaches. First, we propose to learn sparse representation for leaf image recognition. In order to model leaf images, we learn an over-complete dictionary for sparsely representing the training images of each leaf species. Each dictionary is learned using a set of descriptors extracted from the training images in such a way that each descriptor is represented by linear combination of a small number of dictionary atoms. Second, we also propose a general bag-of-words (BoW) model-based recognition system for leaf images, mainly used for comparison. We experimentally compare the two learning-based approaches and show unique characteristics of our sparse representation-based framework. As a result, efficient leaf recognition can be achieved on public leaf image dataset based on the two proposed methods. We also show that the proposed sparse representation-based framework can outperform our BoW-based one and state-of-the-art approaches, conducted on the same dataset.

Keywords Plant identification · Leaf image recognition · Dictionary learning · Bag-of-words (BoW) · Sparse representation

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J.-K. Hsiao · L.-W. Kang (✉) · C.-L. Chang
Department of Computer Science and Information Engineering,
National Yunlin University of Science and Technology, Yunlin, Taiwan
e-mail: lwkang@yuntech.edu.tw

L.-W. Kang
Graduate School of Engineering Science and Technology-Doctoral Program,
National Yunlin University of Science and Technology, Yunlin, Taiwan

C.-Y. Lin
Department of Computer Science and Information Engineering, Asia University,
Taichung, Taiwan

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1 Introduction

Recently, with global warming, rapid urban development, biodiversity loss, and environmental damage, there has been great demand for applying advanced computer vision techniques to broaden botanical knowledge. Automatic plant identification technique is one of them, which is of great importance for a number of professionals, such as environmental protectors, land managers, foresters, agronomists, and amateur gardeners [1].

Plant identification is a fairly difficult task even for experienced botanists, considering the huge number of species existing in the world [2], as examples shown in Fig. 1. The task is generally based on the observation of the morphological characteristics of a plant, such as stems, roots, flowers, and leaves. Most important information about the taxonomic identity for a plant is usually contained in its leaves [2], as examples shown in Fig. 2. Therefore, similar to most existing image-based plant identification [1–15] or retrieval [16–18] approaches, the proposed framework focuses on the recognition of leaf images which can be further applied to plant identification.

To achieve leaf image recognition, the first step is to extract feature(s) from leaf images to be recognized. Similar to feature extraction from general images, a leaf image can be characterized by extracting its color [13, 17], texture [1, 2, 13, 17],

Fig. 1 Examples of number of plant species

Fig. 2 Examples of number of leaf species

and shape [1–18] features. Nevertheless, the color of a leaf may vary with the seasons and climatic conditions, while most species of leaves have similar colors. Hence, only shape and texture features are shown to be applicable in leaf image recognition or retrieval in the literature.

On the other hand, to achieve recognition of leaf images, it is usually required to train a classifier in advance using some training leaf images. Most recently developed plant identification frameworks rely on content-based image retrieval techniques (usually with *k*-nearest neighbor, i.e., *k*-NN, classification) [1–8], while several ones are based on neural network-based classification [9, 10]. Moreover, a novel classification method, called move median centers (MMC) hypersphere classifier was proposed in [11], and another similar one called moving center hypersphere (MCH) classifier was also proposed in [12].

In this chapter, we propose two learning-based leaf image recognition frameworks for automatic plant identification and conduct a comparative study between them with existing approaches. First, we propose to formulate leaf image recognition as a sparse representation problem. Sparse representation (or sparse coding) techniques have been shown to be efficient in solving several computer vision problems, such as face recognition, action recognition, image denoising and enhancement [19–28]. For the proposed sparse representation-based leaf recognition method, in the learning stage, we learn a dictionary for sparely representing the training leaf images in each plant species. In the recognition stage, we calculate the sparse representations of a test image with respect to each learned dictionary of species to find the leaf category with the largest correlation between them.

Moreover, we also present a general bag-of-words (BoW) model-based recognition system for leaf images, mainly used for comparison. BoW model has been also widely applied in the applications of image recognition, classification, and retrieval [29–32]. In the learning stage of our BoW-based framework, we train a codebook consisting of a number of representative codewords for representing the training leaf images in each plant species. Then, we train a support vector machine (SVM) [33] classifier for leaf image classification. In the recognition stage of our BoW-based framework, we quantitatively represent each test leaf image based on the trained codebook, followed by recognizing the image with the trained SVM classifier.

The main contribution of this work is three-fold: (i) to the best of our knowledge, we are among the first to propose a sparse representation framework for leaf image recognition; (ii) the proposed framework is adapted to newly added leaf species without retraining classifiers and suitable to be highly parallelized as well as integrated with any leaf image descriptors/features; and (iii) benefited from the property of sparse representation, the proposed method would be robust to inaccurate feature extraction of leaf images, while providing more compact and richer representation for leaf images.

The rest of this chapter is organized as follows. In Sect. 2, we briefly review the concepts of sparse representation and dictionary learning techniques, which form the basis of our sparse representation framework for leaf image recognition. Section 3 presents the proposed leaf image recognition framework via sparse representation. Section 4 introduces the proposed BoW model-based recognition system for leaf images, used for comparison. In Sect. 5, experimental results are demonstrated. Finally, Sect. 6 concludes this chapter.

2 Sparse Representation and Dictionary Learning

As an example shown in Fig. 3, sparse coding (SC) [27, 28] is a technique of finding a sparse representation for a signal by solving a small number of nonzero or significant coefficients corresponding to the atoms in a dictionary. To learn a dictionary for sparsely representing each signal, such as a feature vector or an image patch extracted from an image, we collect a set of training exemplars, y_j, j = 1, 2, …, P, to learn a dictionary D sparsifying y_j by solving the following optimization problem [25, 26]:

$$\min_{D,\, x_j} \frac{1}{P} \sum_{j=1}^{P} \left(\frac{1}{2} \left\| y_j - Dx_j \right\|_2^2 + \lambda \left\| x_j \right\|_1 \right), \tag{1}$$

where x_j denotes the sparse coefficient vector of y_j with respect to D and λ is a regularization parameter. Equation (1) can be efficiently solved by performing a dictionary learning algorithm, such as the online dictionary learning [25] or K-singular value decomposition (K-SVD) [26] algorithms.

After obtaining the dictionary D, for each signal Q_j to be sparsely represented with respect to D, its sparse coefficient θ_j can be obtained by solving the following optimization problem [25, 26]:

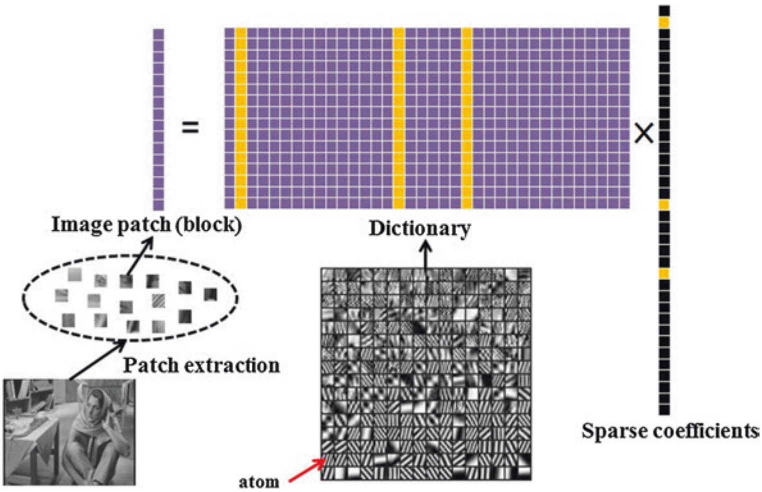


Fig. 3 An example of illustrating the sparse representation of image patches (blocks) based on a given dictionary

$$\min_{\theta_j}\left(\frac{1}{2}\left\|Q_j - D\theta_j\right\|_2^2 + \lambda\left\|\theta_j\right\|_1\right). \tag{2}$$

That is, θ_j is a sparse coefficient vector for sparsely representing Q_j with respect to D, and Q_j can be approximately recovered via $D\theta_j$.

In this study, we propose to apply dictionary learning to learn a dictionary for representing each category of leaf images. Then, the recognition of an input leaf image can be achieved by analyzing the correlation between the input image and each leaf class, derived from calculating the sparse representation of the input image with respect to the learned dictionary of each class. The detailed method of our first leaf image recognition framework (sparse representation-based) will be elaborated in Sect. 3.

3 Proposed Leaf Image Recognition Framework via Sparse Representation

In this section, we first introduce the problem formulation of our first framework in this chapter, followed by presenting the proposed leaf image recognition framework via sparse representation (or sparse coding), consisting of the learning and recognition stages.

3.1 Problem Formulation of Our First Framework

In our first framework of this study, we consider total C species of leaves, where we learn the dictionary D_i for sparsely representing the i-th class of leaf images, i = 1, 2, …, C. To recognize a test leaf image I, we formulate the problem as a sparse representation problem and solving it by calculating the histogram h_i^I derived from the sparse representation of I with respect to each D_i, and identify the one with the largest correlation between h_i^I and D_i, i = 1, 2, …, C. The detailed method shall be elaborated below.

3.2 Learning Stage of Proposed First Framework

As illustrated in Fig. 4, in the learning stage of the proposed first framework, for each class L_i (the *i*th class) of leaf images, we select a number of training images to learn a dictionary D_i for representing this class. We extract a set of P_i descriptors (or feature vectors) $\left\{y_{ij} \in R^n\right\}_{j=1}^{P_i}$ from all training images in each L_i, $i = 1, 2, \ldots, C$, where any shape, texture, or hybrid image features can be used here, such as scale-invariant feature transform (SIFT) [34]. For learning the dictionary $D_i \in R^{n\times m}$ for compactly representing L_i, we apply dictionary learning to minimize [25]:

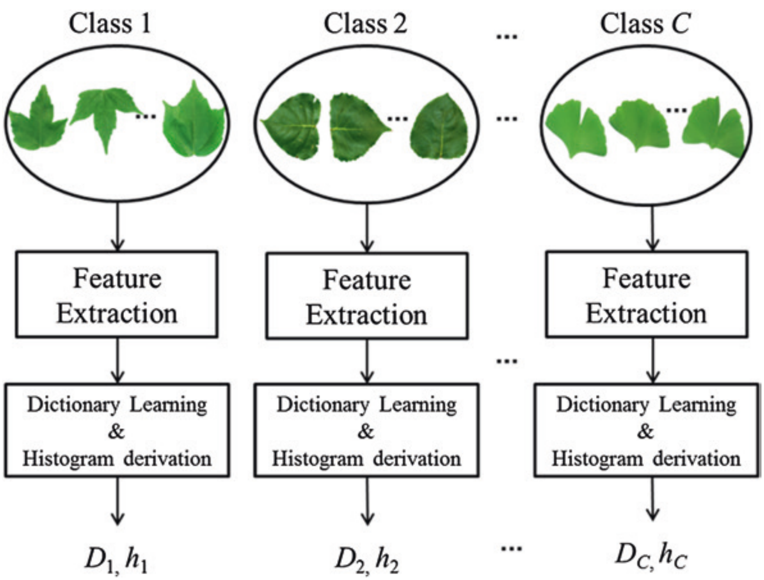


Fig. 4 The learning stage of the proposed first leaf image recognition framework via sparse representation

$$\min_{D_i \in R^{n \times m},\, x_{ij} \in R^m} \frac{1}{P_i} \sum_{j=1}^{P_i} \left(\frac{1}{2} \left\| y_{ij} - D_i x_{ij} \right\|_2^2 + \lambda \left\| x_{ij} \right\|_1 \right), \tag{3}$$

where x_{ij} denotes the sparse coefficients of y_{ij} with respect to D_i and λ is a regularization parameter. After obtaining D_i, we calculate the histogram h_i associated with the sparse coefficients $\left\{x_{ij} \in R^m\right\}_{j=1}^{P_i}$ of $\left\{y_{ij}\right\}_{j=1}^{P_i}$ as:

$$h_i = \frac{1}{P_i} \sum_{j=1}^{P_i} x_{ij}. \tag{4}$$

As an example, for the ith class, the learning stage is summarized in Fig. 5. Then, for each class L_i, we store its dictionary D_i and histogram h_i for leaf image recognition task described in Sect. 3.3.

3.3 Recognition Stage of Proposed First Framework

As illustrated in Fig. 6, for a test leaf image I to be recognized, we first extract its set of descriptors (image feature vectors) $\left\{Q_j \in R^n\right\}_{j=1}^{q}$ and the corresponding

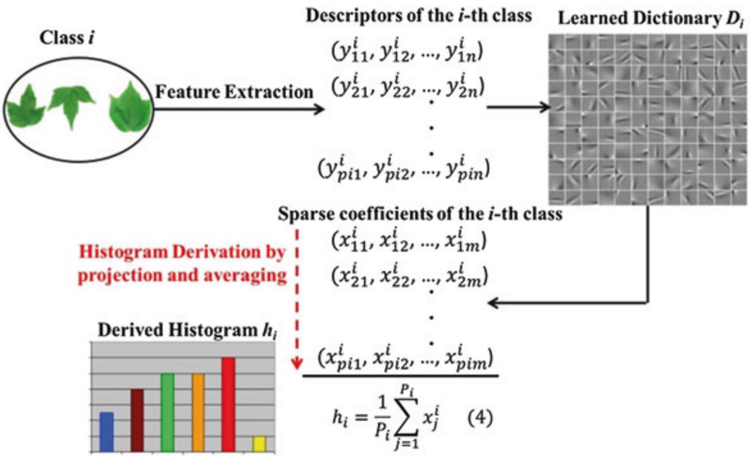
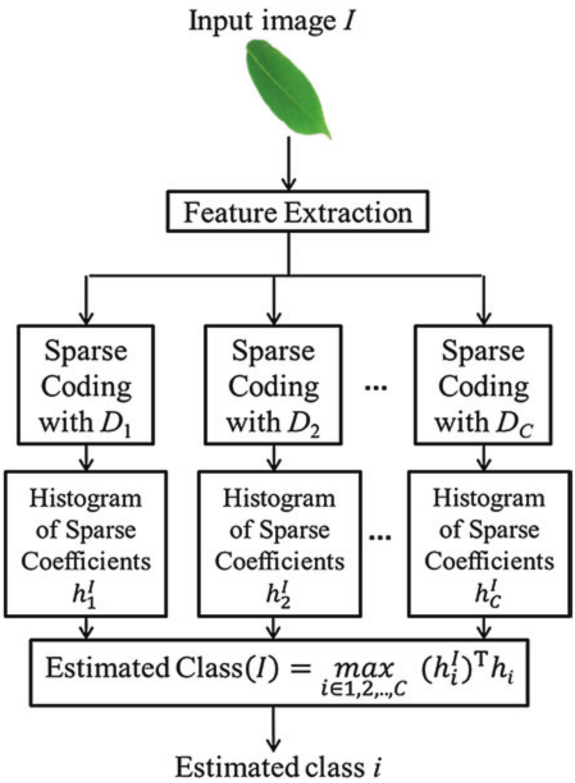


Fig. 5 Summarization of the learning stage of the proposed leaf image recognition framework via sparse representation

Fig. 6 The recognition stage of the proposed leaf image recognition framework via sparse representation



sparse coefficients $\{\theta_{ji} \in R^m\}_{j=1}^q$ with respect to D_i, $i = 1, 2, \ldots, C$, to find the sparse representation of I with respect to each class L_i as:

$$(\theta_{ji})^* = \arg\min_{\theta_{ji} \in R^m} \left(\frac{1}{2} \|Q_j - D_i\theta_{ji}\|_2^2 + \lambda \|\theta_{ji}\|_1 \right), \tag{5}$$

where $(\theta_{ji})^*$ denotes the solution minimizing (5). We then calculate the histogram h_i^I of I associated with its sparse coefficients $\{\theta_{ji}\}_{j=1}^q$ with respect to each D_i as:

$$h_i^I = \frac{1}{q} \sum_{j=1}^{q} \theta_{ji}. \tag{6}$$

Then, the class that the image I belongs to can be decided as:

$$\text{Estimated class}(I) = \arg \underset{i \in 1,2,\ldots,C}{\max} = \left(h_i^I\right)^{\mathrm{T}} h_i. \tag{7}$$

That is, the class associated with the maximum correlation derived from (7) with the input image will be decided to be the class that the input image belongs to.

4 Proposed BoW Model-Based Leaf Image Recognition Framework Used for Comparison

To evaluate the performance of the proposed first framework via sparse representation, we present another framework based on well-known bag-of-words (BoW) image model. As illustrated in Fig. 7, in the learning stage of our BoW-based framework, we first extract a set of descriptors (or feature vectors) from all training leaf images of C classes for training a codebook consisting of K representative codewords. Based on the BoW image model [29], we apply the

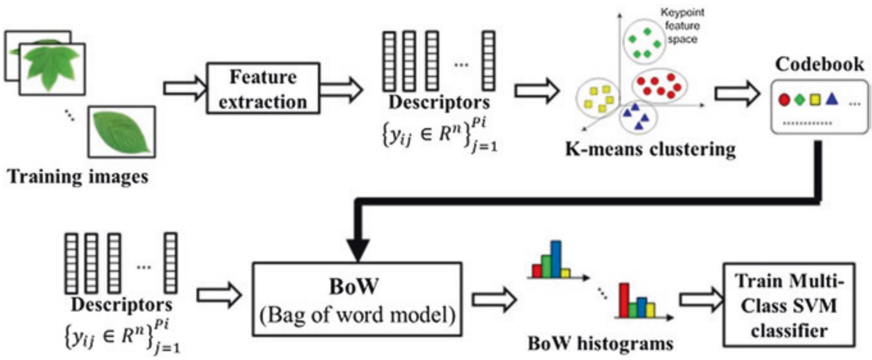


Fig. 7 An illustrated example of the learning stage in the proposed BoW-based leaf image recognition framework

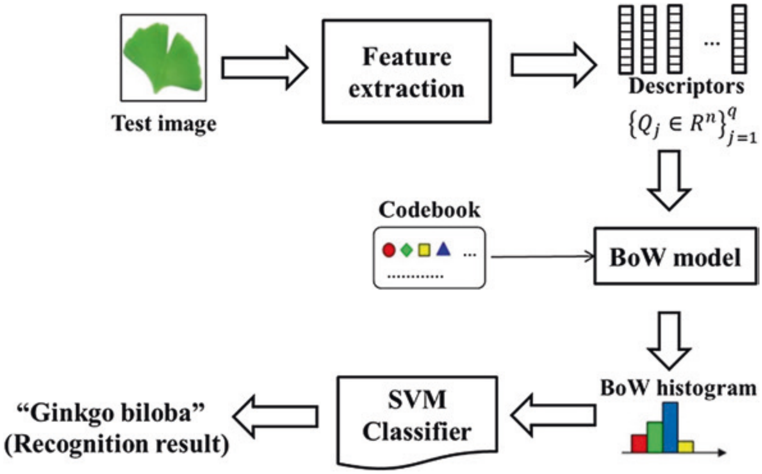


Fig. 8 An illustrated example of the recognition stage in the proposed BoW-based leaf image recognition framework

K-means clustering algorithm [35] to cluster all of the descriptors into K clusters with a cluster center for each cluster to form a codebook of K codewords. After obtaining the codebook, we quantize each training descriptor into its closest codeword in the codebook. Then, for each training image, we calculate a BoW histogram by counting the frequencies that each codeword is used. That is, each training image has been converted into a histogram. Then, we train a SVM classifier with C classes of leaf images.

As illustrated in Fig. 8, in the recognition stage of our BoW-based framework, for each test leaf image to be recognized, we first extract a set of descriptors and quantize each descriptor to its closest codeword in the codebook. Then, we can obtain the BoW histogram of this image. Finally, based on the trained SVM classifier, recognition of the image can be achieved. Comparisons between the proposed sparse representation-based approach and the proposed BoW-based approach in detail will be presented in Sect. 5.

5 Experimental Results

5.1 Experiment Settings

In this work, the two proposed recognition methods were implemented in MATLAB® R2013a (64 bits version) on a personal computer equipped with Intel® Core™ i5-2410M processor and 4 GB DDR2 memory. Moreover, the Matlab implementation of the employed K-SVD dictionary learning tool is available online from [26], while the Matlab interface implementation of the employed SVM classifier is also available online from [33].

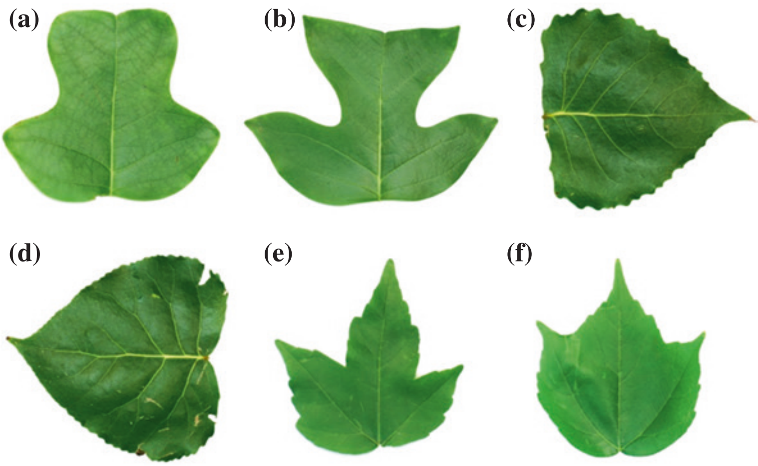


Fig. 9 Examples of leaf images in the dataset released by Wu et al. [9]: **a**, **b** Liriodendron chinense (Hemsl.) Sarg. (Chinese tulip tree); **c**, **d** Populus x canadensis Moench (Canadian poplar); and **e**, **f** Acer buergerianum Miq. (trident maple)

To evaluate the performances of the proposed leaf image recognition frameworks via sparse coding (denoted by Proposed-SC) and BoW (denoted by Proposed-BoW), respectively, we used the leaf image dataset, "*Flavia* leaf image dataset," released by Wu et al. [9] which has been a popular leaf image dataset for research purpose. The dataset consists of 32 classes of leaf images ($C = 32$), where each class contains 40–60 images, as illustrated in Fig. 9.

In the learning stage of our framework via SC, we randomly selected 30 images per class for dictionary learning, while the rest images were used for testing. For simplicity, the feature used was SIFT [34] with length $n = 128$ for each descriptor (or feature vector), which can be replaced by any shape, texture, or hybrid features. Moreover, for each learned dictionary D_i, we evaluated the four sizes (number of atoms) of 128, 256, 512, and 1,024 atoms ($m = 128, 256, 512, 1{,}024$), respectively. The sparsity and the number of training iterations used in the employed K-SVD dictionary learning algorithm [26] are empirically set to 12 and 100, respectively, to achieve the best tradeoff between recognition performance and computational complexity based on our experiments.

On the other hand, to fairly compare the proposed SC-based framework and our BoW-based framework described in Sect. 4, the evaluated codebook sizes for BoW are also set to 128, 256, 512, and 1,024, respectively, obtained by using the K-Means clustering algorithm [35] with 100 iterations based on the same training images and the SIFT feature [34]. The comparison of recognition performances between Proposed-SC and Proposed-BoW is shown in Fig. 10, where each data point was obtained by averaging the results of five runs.

Moreover, we also compare our method with the probabilistic neural network-based approach proposed in [9] (denoted by PNN), move median centers

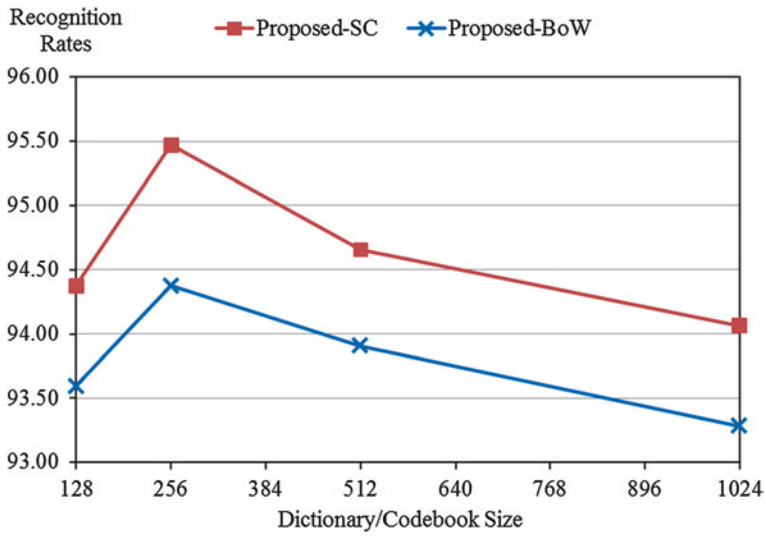


Fig. 10 Performance comparisons between Proposed-SC and Proposed-BoW methods

(MMC)-based approach proposed in [11] (denoted by MMC), hybrid feature with PNN-based approach proposed in [13] (denoted by HPNN), and combinatorial shape feature-based approach proposed in [14] (denoted by CShape), conducted on the same leaf image dataset.

6 Results

Table 1 lists the recognition rates obtained by PNN [9], MMC [11], Proposed-BoW, and Proposed-SC, respectively. In Table 1, the recognition rates obtained by Wu et al. [9] and Du et al. [11] were reported in [9], while those of Proposed-BoW and Proposed-SC were their respective best ones from Fig. 10 (the dictionary/codebook size is set to 256).

It can be observed from Fig. 10 that the proposed method via SC outperforms the proposed method via BoW used for comparison conducted on the evaluated

Table 1 Recognition rates of leaf images

Method	Rate (%)
PNN [9]	90.31
MMC [11]	91
HPNN [13]	93.75
CShape [14]	94.62
Proposed-BoW	94.38
Proposed-SC	95.47

dataset [9]. Compared with the BoW-based approach, the main advantage of our SC-based approach is that it is not required to re-train classifiers with newly leaf image class added, while in the BoW-based approach, both the codebook and the SVM classifier are required to be re-trained.

It can be also observed from Table 1 that both the proposed methods via SC and BoW outperform (or are comparable with) the four existing approaches used for comparisons (PNN [9], MMC [11], HPNN [13], and CShape [14]). Moreover, our methods only used 960 training images, while the PNN method [9] used 1,800 training images for neural network training. On the other hand, only single feature (SIFT [34]) is currently used in our methods to achieve these performances. More complex leaf image features may be properly integrated with our frameworks to achieve better performances.

In addition, to investigate some erroneous recognition cases, we illustrate an example in Fig. 11, where the two leaf images (Figs. 11a, b) of different species are identified as the same class. The main reason should be that only single feature was employed in this study without enough distinguishability. To cope this problem, hybrid features (e.g., integration of several shape and texture features) would be a solution.

6.1 Discussions

In this section, we discuss the main reason that the proposed sparse coding-based approach can outperform the proposed BoW-based approach, in terms of the inherent respective properties of the two image models. In the BoW-based framework, as depicted in Fig. 12a, each input image descriptor will be quantized into its closest codeword in the pre-trained codebook, which can be viewed as a special case of sparse representation, i.e., extremely sparse. That is, using the terminology of sparse coding, only one atom (with corresponding nonzero/significant coefficient of value "1") in the pre-learned dictionary is used to represent the input

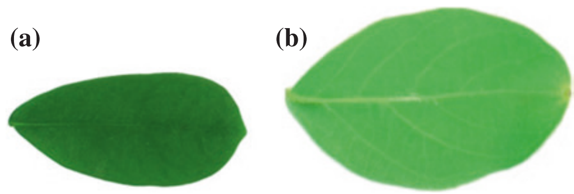


Fig. 11 An illustrated example of erroneous recognition: **a** the leaf species of Indigofera tinctoria L; and **b** the leaf species of Lagerstroemia indica (L.) Pers

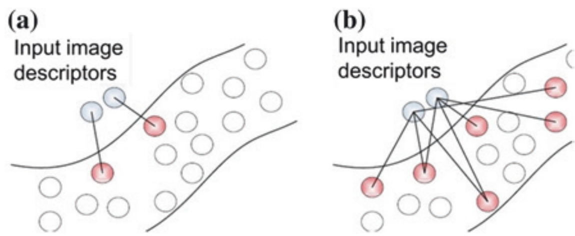


Fig. 12 An illustrated example of: **a** BoW-based; and **b** sparse coding-based frameworks

descriptor. On the other hand, as depicted in Fig. 12b, each input image descriptor will be represented by a few numbers of atoms (with corresponding nonzero/significant coefficients) in the pre-learned dictionary. Therefore, the sparse coding-based framework can provide richer representation for each image descriptor than the BoW-based framework, resulting in better recognition performance. To further achieve better performance with sparse coding, more constraints (e.g., locality [36] or group sparsity [37] conditions) may be incorporate into the regulation term to ensure that similar input image descriptors will have similar sparse representations based on a given dictionary.

7 Conclusions

In this chapter, we have proposed two leaf image recognition frameworks via sparse representation and BoW image model, respectively, and conducted the comparative studies between them. By learning dictionary for sparsely representing each species of leaf images, accurate recognition can be achieved. Besides better recognition performance obtained by our sparse representation-based framework, several unique characteristics benefited from the sparse coding theory include: (i) the proposed framework is adapted to newly added leaf species without retraining classifiers and suitable to be highly parallelized as well as integrated with any leaf image descriptors/features; and (ii) the proposed method would be robust to inaccurate feature extraction of leaf images, while providing more compact and richer representation for leaf images. For future works, we will integrate more advanced image features with our sparse representation-based framework and implement our system as a mobile application to achieve mobile visual search (e.g., [7, 8], as illustrated in Fig. 13). The proposed framework via sparse coding can be also extended to the applications of recognizing other types of images/videos.

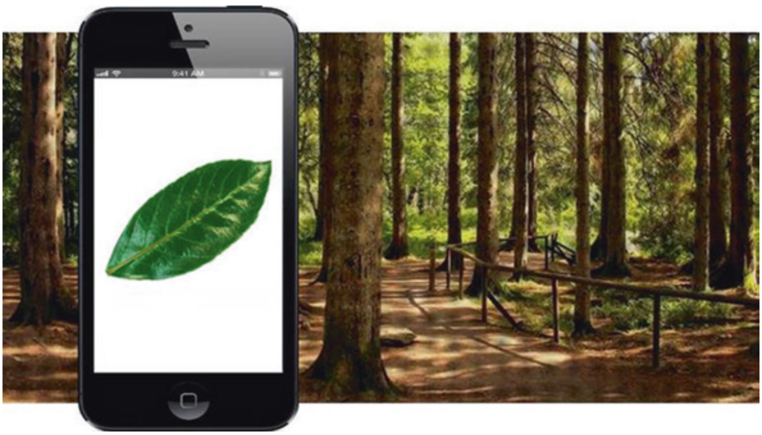


Fig. 13 An example of mobile visual leaf image recognition/retrieval applications

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