A Web-based Plant Identification Application Using Multi-Organ Images Query

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Abstract

In this paper, we describe a plant identification system based on various image organs query. The proposed system handles several issues such as preprocessing, feature extraction and description, classification method and fusion techniques. For the preprocessing step, we aims to separate the Region-of-interests (e.g., fruits, flowers, leaves) from complicated backgrounds. The relevant preprocessing techniques for each type of organ are selected based on its characteristics. For the feature extraction and description, we propose to use kernel-based descriptor (KDES). For each type of organ, we proposed to use a suitable type of kernel. Then, we investigate an efficient fusion scheme that combines classification results from different organ types in order to build the retrieved observation list. Finally, we have deployed the proposed system in form of a web application for easy using

Keywords: Plant Identification , Kernel Descriptor, Late Fusion, Segmentation Technique

1. Introduction

Plant identification is a process that aims at matching a given specimen plant to a known taxon. This is a difficult and time consuming task even for the botanist experts. Recently, with the advanced research in computer vision community, a number of studies have been proposed for plant identification based on images. However, most of them dedicated to one sole organ of the plants such as using only leaf and/or flower images. Since 2014, the dataset for multi-organ plant identification is available, aims of the plant identification moves from image-centered to observation-centered [1]. In other words, the plant identification can be defined as an image retrieval problem in which input of each query plant is a set of organ images and outcome is a ranked list of retrieved plants. Our previous works utilizing only leaf images has shown that the Kernel-based descriptors (KDES) are robust ones for leaf representation [2]. In this study, we deploy different KDES(s) that are descriptors at image level for each type of organs. Similar to our previous works, a Support Vector Machine (SVM) is utilized for classification. For the late-fusion techniques, we investigate three fusion schemes: BC (Borda Count), IRP (Inverse Rank Position) and WP (Weighted Probability). The experimental results show that using IRP obtains the highest precision rate. Consequently, we deploy the proposed techniques in form of a web-based application.

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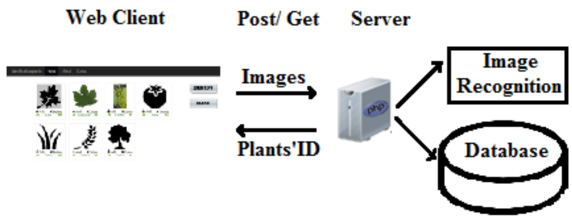

Fig. 1 Architecture of the proposed system

The remaining of the paper is organized as follows. In Section 2, we present details of each step of the proposed system including preprocessing, feature extraction, and fusion techniques. The experimental results on both validation and testing sets are shown in Section 3. Section 4 gives some conclusions and future works.

2. The proposed technique: A plant identification system using multi-organs images

2.1. Overview of the web-based application

Figure 1 shows the architecture of the proposed system. It is based on client-server architecture. The client is a web-based interface. Server-side serves as a PHP dynamic web application that aims to connect an identification program and a database of images. The web-side application will process request (e.g., organ images query) and return the results to the client. The main component of the system is an identification program that is described in next section. Other functions are to display visual results on the screen. The application allows an end-user selecting images

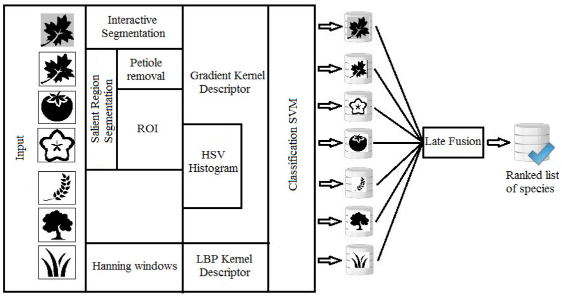

Fig. 2 Overview of the proposed method

of each organ, then the system will automatically identify and display the best matching results.

2.2. Proposed method for plant identification using multi-organ images

1) Overview: The overview of the plant identification scheme is illustrated in Fig. 2. There are four main modules: image preprocessing, feature extractions, classification, and fusion. Function of each module is briefly described below.

– Pre-processing techniques: We propose different pre-processing techniques so that they are suitable to characteristic of each plant organ, concretely:

- Leaf on complicated background images: we deploy an interactive image segmentation method. This method has been presented in our previous work, as shown in [2].
- Leaf scan images: we deploy a salient-based segmentation method and perform removing petiole and leaf normalizations in term of size and direction.
- Flower and fruit images: we utilize algorithms to detect the ROIs that are based on salient characteristics.
- Stem images: in order to eliminate border of image, we use a Hanning filter to emphasize on stem region only.
- Branch and entire images: because those images are natural scenes; we do not apply any pre-processing techniques for branch and entire images

2) Pre-processing techniques: The pre-processing techniques aim to separate the regions-of-interest (ROI) from an image. As shown in Fig. 3, except the leaf scan image, most of remaining images in an observation are captured from natural scenes. In ImageClef 2014 challenge [1], participated teams utilized simple threshold methods (e.g., Otsu threshold) in order to separate leaf regions for leaf scan images. IBM-AU team deployed more complicated techniques (e.g., active contour-based with a pre-determined size of ROI) to make boundary regions for flower, fruit, or leaf on complicated background, so on [1]. In this study, we deploy

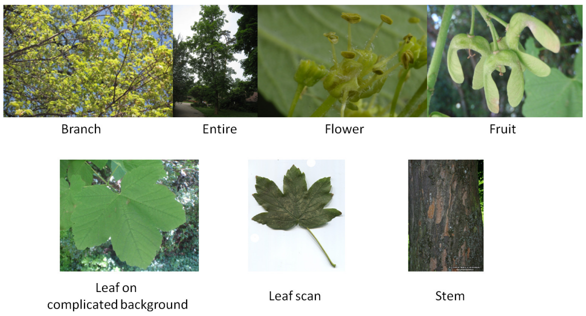

Fig. 3 Seven types of organs. Left-to-right, top-to-bottom: Branch, Entire, Flower, Fruit, Leaf on complicated background, Leaf scan, and Stem images of same plant

appropriated pre-processing techniques for each type of organ images. The detailed techniques are described below:

– For leaf on the complicated background: An interactive segmentation method, as described in [2], is adapted to segment leaf from background regions; Fig. 4 shows some illustrations of the pre-processing techniques applied on the leaf images with the complicated backgrounds. Because it is an interactive technique, it requires user intentions. This procedure takes longer time when we have a large number of images.

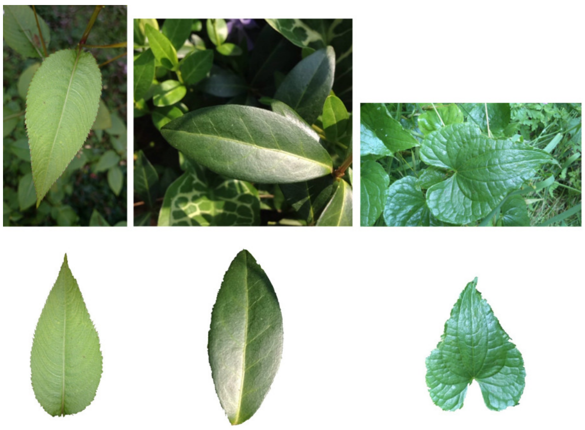

Fig. 4 Upper: original images; Lower: the corresponding segmented leaf.

– Leaf-scan images: We adapt a saliency extraction method as described in [3] and a common segmentation technique (e.g., mean-shift algorithm).

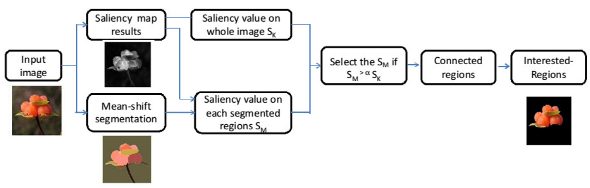

Fig. 5 The pre-processing techniques for selecting the ROIs of leaf-scan, fruit, flower images.

The segmented region is selected based on a condition that its corresponding saliency value is large enough. The connected-region techniques then are applied to connect the selected regions. The main flow works are expressed in Fig. 5. Because leaf-scan images contain only simple background. We obtain stable results with leaf-scan images. Main reasons are that saliency values of leaf regions are more significant from background ones.

– Flower and fruit images: we apply same saliency-segmentation procedure as Leaf-scan image for selecting the ROIs on flower and fruit images. However, main difference from leaf-scan images is that we do not immediately use the results after connecting selected-regions. Because the flower and fruit images are captured in natural scenes; They are difficult to obtain stable and correct results; Instead of that, a boundary boxes are obtained based on top-left; bottom-right points on boundary of the connected-regions; Results of the selected flower and fruit regions are shown in Fig. 6.

Fig. 6 The results of selected ROIs on flower and fruit images

– Stem images: We observe that stem texture spans almost regions on the captured images. Moreover, we take into account texture features for stems images. A simple procedure selecting ROIs on the stem image aims to eliminate boundary effects. To do this, we apply a Hanning window on the stem image. The size and scale of the Hanning window is pre-determined. We then crop stem regions on the filtered image; The crop procedure utilizes a pre-determined pad which is 15 pixels from image border for both dimensions; Fig. 7 shows ROI extracted on a stem image.

3) Feature extraction and description:

Kernel-based descriptor (KDES) has been proposed firstly by Liefeng Bo et al. [4]. In our previous works [2], [7], KDES has been proved to be robust for leaf representation. In this work, we propose to use KDES for all types of the organ images.

Fig. 7 The result of selected ROIs on stem images. Left: original stem image; Right: Filtered image using a Hanning window. ROI is marked in yellow box on the filtered image.

As shown in Fig. 8, KDES descriptor extracts features from of the processed organ images through 3 levels, as listed below. We employ the same process to compute KDES as proposed by Liefeng Bo et al. [5], [4]. However, we make different choices at pixel-level feature for each type of organs:

- Pixel-level feature extraction: At this level, a normalized gradient vector is computed for each pixel of the leaf, leaf scan, flower, fruit, branch, and entire images. Whereas, we use LBP (Local Binary Pattern) for stem image. The main reason is that stem images infer dominant texture features.

- Patch-level feature extraction : For each patch, we compute patch features based on a given definition of match kernel. The gradient match kernel is constructed from three kernels.

- Image-level feature extraction: Given an image, the final representation is built based on features extracted from lower levels using efficient match kernels (EMK).

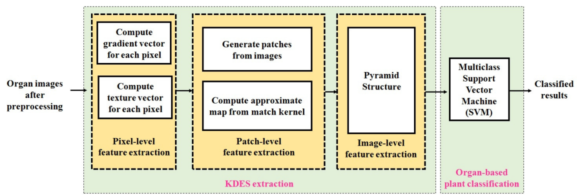

Fig. 8 KDES extraction and organ-based plant identification

For each organ image, we apply multi-class SVM classification. At the end, given an organ image query, we have a list of ranked plants.

*4) Late fusion schemes:*In our work, we investigate three different fusion techniques. They are BC (Borda Count), IRP (Inverse Rank Position) and WP (Weighted Probability) [6]. Definition of each fusion technique is given below:

$$BC(i) = \sum_{j=1}^{n} rank(i, j)\ ,\ \ \mathrm{IR}P(i) = \frac{1}{\sum_{j=1}^{n} \frac{1}{rank(i, j)}}$$

$$\mathrm{W}P(i) = \sum_{j=1}^{n} \mathrm{w}(j) \times rank(i, j)$$

where n is the number of retrieved lists, $rank(i, j)$ is rank of species i in list j^{th}; $w(j)$ is the weight of list j^{th}

3. Experiments and Results

3.1. Database descriptions:

We ultilize the dataset supported by LifeCLEF 2015[1] challenge. Training data of this year consits of 27,907 plant-observations illustrated by 91,759 images while the test data consists of 13,887 plant-observation-queries illustrated by 21,446 images [8]. The number of images for each organ in training and testing set is shown in Table 1. The number of images for each organ in our training and validation set is shown in Table 2. Fig. 9 extracts several sample images from training and testing dataset supported by LifeCLEF 2015.

Firstly, we apply the proposed pre-processing techniques as described in Sec. 3. In order to evaluate performance of the proposed system, we divide the training set into training and validation sets by taking randomly 1/5 observation for validation and the remaining for training. Particularly, for the leaf image (with complicated background), we use interactive segmentation and this is time consuming. In order to reduce user intentions, we deploy a practical implementation that is if the leaf scan set contains images of the leaf of a plant, instead of using images from corresponding leaf (with complicated background) training set, we use images from leaf-scan of training set.

Table 1. Training and testing sets provided by LifeCLEF2015

	Train	Test
Leaf	13367	2690
LeafScan	12605	221
Flower	28225	8327
Fruit	7720	1423
Stem	5476	584
Branch	8130	2088
Entire	16235	6113

Table 2. Training and validation sets used in our experiments

	Train	Test
Leaf	15220	1814
LeafScan	9787	2610
Flower	22945	5280
Fruit	6356	1364
Stem	4485	994
Branch	6542	1588
Entire	13031	3204

[1] http://www.imageclef.org/lifeclef/2015/plant

3.2. Experimental results

This section presents the results on both datasets: validation and testing set. For the testing set, we use the results reported by the organizers of the task (LifeCLEF 2015 organizers).

1) Evaluation results on the validation set

We perform two experiments. In the first experiment, we use KDES for all organs. The second experiments using KDES with LBP kernel for stem. The results at image level and observation level of two experiments are shown in Table 3, Table 4, Table 5, and Table 6, respectively. Besides the score image, we compute the accuracy at rank k.

$$Accuracy = \frac{T}{N}$$

where T is the true recognition and N is the number of queries. One image or observation is correctly recognized if the relevant plant is in the k first plants of the retrieved list. In our experiments, we compute accuracy two different ranks: rank 1 and rank 10.

Table 3. Results at image level of the first experiment on validation set

	Accuracy (%)		
	S_{image}	**Rank 1**	**Rank 10**
Leaf	32.90	24.26	46.36
LeafScan	***62.88***	***78.28***	***92.76***
Flower	20.63	10.95	24.62
Fruit	13.96	6.52	20.46
Stem	13.16	16.6	34.2
Branch	7.18	3.53	9.70
Entire	10.36	6.40	14.61

Table 4. Results at observation level of the first experiment on validation set

Observation	**BC**	**IRP**	**WP**
$Score_{observation}$	21.86	23.31	22.22
Rank 1	22.49	24.22	22.96
Rank 10	37.8	39.28	38.84

Table 5. Results at image level of the second experiment on validation set

	Accuracy (%)		
	$Score_{image}$	**Rank 1**	**Rank 10**
Leaf	32.90	24.26	46.36
LeafScan	62.88	78.28	92.76
Flower	22.55	11.38	38.05

Fruit	13.96	6.52	20.46
Stem	13.16	16.6	34.2
Branch	7.18	3.53	9.70
Entire	11.30	6.62	17.51

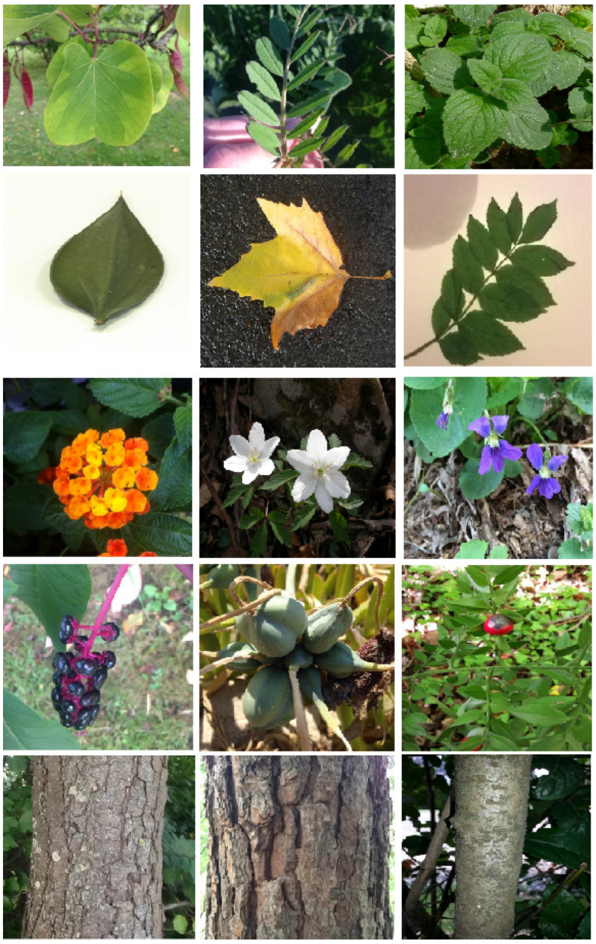

Fig. 9 Several images in the database

Table 6. Results at observation level of the second experiment on validation set

Observation	**BC**	**IRP**	**WP**
$Score_{observation}$	21.75	23.27	22.36
Rank 1	22.31	23.29	22.83
Rank 10	38.75	39.51	39.95

Based on the results of two experiments, we have three observations:

- Firstly, the obtained results have shown that KDES is a good descriptor for Leaf and Leaf Scan images. The score at image level for Leaf Scan is 62.88 % and the accuracy at the rank 1 is 78.28%. The performance of KDES is reduced when applying for Leaf images (with complicated background). The reason is that in Leaf image set, there is a number of compound leaf and we do not apply any specific technique for compound leaf.

- The KDES is not a good choice for the others types of organ. This shows that KDES is relatively good and distinctive feature for classify the classes with high intra similarity such as leaf. Rather than using Kernel-based descriptors, by utilizing global feature such as color histogram can improve slightly the performance for Flower images. For example, we check a combination of HSV histogram and KDES, the accuracy rate improves from 20.63% to 22.55% for flower images; and from 10.36% to 11.3% for Entire images. More robust and local features need to investigate.

- Finally, we can observe performance of different fusion techniques. Results in Table 6 show that IRP and WP obtain better results that BC for both experiments.

Based on the results of two experiments in validation dataset, we decide to submit runs to LifeClef 2015 - multi-organ plant identification task. The characteristic of each run is described as follows:

- Run 1: In this run, we employ KDES for all types of organs and IRP (Inverse Rank Position) for late fusion scheme.

- Run 2: The difference between Run 1 and Run 2 is that for flower and entire images, we combine HSV histogram with KDES by using IRP. We also apply IRP for late fusion scheme.

- Run 3: This run is similar to Run 3. However, instead of using IRP, we employ WP (Weighted Probability).

Runs on test set is shown in Fig. 9 while the score for each type of organs is illustrated in Fig. 10. We can see that Run 2 is slightly better than Run 1 and Run 3. This is consistent with the results obtained in the validation set. From the detailed score for each type of organs, we can see that KDES is relative good in comparison with other descriptors used by others labs/teams. The score obtained with KDES for Leaf Scan is 0.737 while the score of the first place team is 0.766.

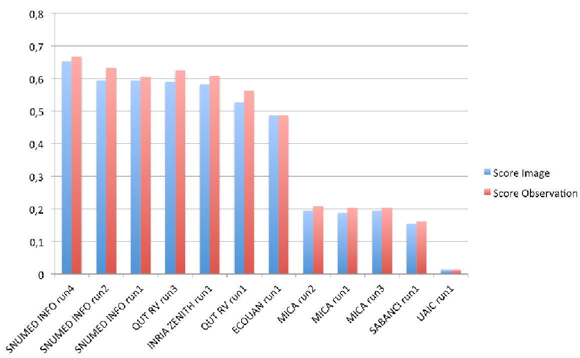

Fig. 10 Score image and score observation of our three runs on test set [8].

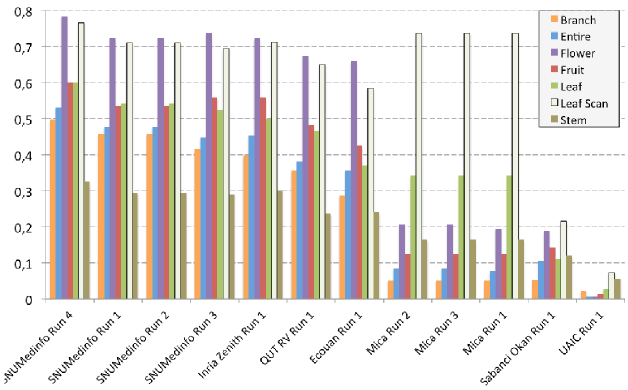

Fig. 11 Detailed scores obtained for each type of plant organs of our three runs on test set. [8]

C. *Interface of the proposed web-based application*

Based on the proposed algorithms, we have built a web-based plant identification using multi-organ image query. The interfaces of application are shown Fig. 11, Fig. 12. In the future, we will evaluate real cases in which end-user captures different organ images from natural scenes. Such evaluation scenarios are more practical and closed to daily activities.

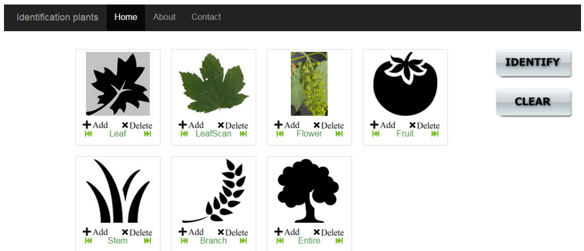

Fig. 12 Main interface of our application

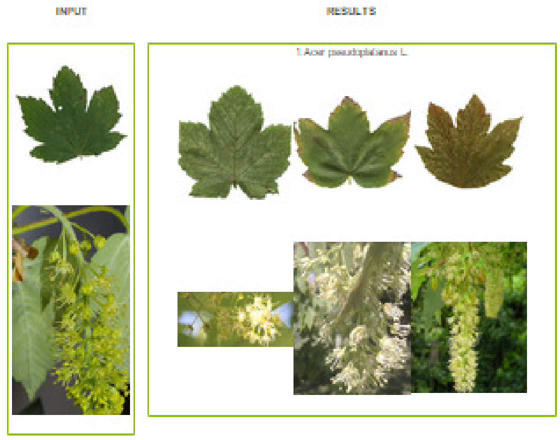

Fig. 13 Interface of query results on a web-client

4. Conclusion

In this paper, we have presented our proposed system for multi-organ plant identification. We have described in detail the proposed system and analyzed the results obtained on both validation and testing set on LifeCLEF 2015 datasets. The obtained results with KDES for LeafScan are promising. However, the results are still limited for the others types of organs and multi-organ plant identification. Based on the proposed algorithms, we build a web-based application for plant identification using multi-organ image query. In the future, we focus on investing descriptors in order to improve performance of other types of organs, beside leafs, particularly, for compound leafs, flowers, fruits.

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References

[1] Herve Goeau, Alexis Joly, Itheri Yahiaoui, Vera Bakic, Anne Verroust-Blondet, Pierre Bonnet, Daniel Barthelemy, Nozha Boujemaa, and Jean-Francois Molino. Pl@ntNet's participation at LifeCLEF 2014 Plant Identification Task.

[2] Le, T. L., Duong, N. D., Nguyen, V. T., Vu, H., Hoang, V. N., Nguyen, T. N.: Complex background leaf-based plant identification method based on interactive segmentation and kernel descriptor. In Proceeding of the 2nd International Workshop on Environment.

[3] R. Achanta, S. Hemami, F. Estrada, and S. Susstrunk Frequency-tuned salient region detection. In the Proc. Of IEEE Conference on Computer Vision and Pattern Recognition, 2009. pp 1597–1604, June 2009.

[4] Liefeng Bo, X Ren, and Dieter Fox. Kernel Descriptors for Visual Recognition. in the Proceeding of NIPS, pages 1–9, 2010.

[5] Liefeng Bo and Cristian Sminchisescu. Efficient Match Kernel between Sets of Features for Visual Recognition, in the Proceeding of NIPS 2009, pages 1–9, 2009.

[6] Jovi, M. (2006). Image Retrieval Based on Similarity Score Introduction : Image Similarity Computation, Pattern Recognition, 461–470.

[7] LE Thi Lan, TRAN Duc-Tuan, HOANG Van-Nam. Fully automatic leaf-based plant identification, application for Vietnamese medicinal plant search, in Proceeding of the fifth symposium on Information and Communication Technology (SoICT 2014) – 2014.

[8] Göeau, Hervé, Alexis Joly and Bonnet Pierre. LifeCLEF Plant Identification Task 2015. CLEF working notes 2015, 2015.