Combining Leaf Salient Points and Leaf Contour Descriptions for Plant Species Recognition

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Abstract. Manual Plant identification done by experts is tedious and time consuming. This process needs to be automatic and easy to handle by the different stakeholders. In this paper, we propose an original method for plant species recognition, based on the leaf observation. We consider two sources of information: the leaf margin and the leaf salient points. For the leaf shape description, we investigate the shape context descriptor and two multiscale triangular approaches: the well-known triangle area representation (TAR) and the triangle side length representation (TSL). We propose then their combination with a shape-context based descriptor that represents the spatial correlation between the leaf salient points and the leaf margin. Experiments are carried out on three public leaf datasets. Results show that our approach achieves a high retrieval accuracy and outperforms state-of-art methods.

Keywords: plant species recognition, leaf retrieval, shape representation, local descriptors, shape context.

1 Introduction

Automatic plant identification is a challenging task especially when we consider the huge number of plant species existing in the world. A plant identification tool will enable botanists, as well as non-expert stakeholders, to identify a plant in a timely manner. Leaves are often the basis for identifying plants since they are easily observed. Leaf images are usually acquired using either a flat-bed scanner (scan images) or a digital camera (scan-like images). In the later case, leaves must be photographed against a light, untextured background. Plant leaves are present for several months and contain clues about the taxonomic identity of the plant. This is why most plant identification tools based on Content-Based Image Retrieval techniques work on leaf image databases [4, 16]. Leaves can be characterized by their color, shape and texture. The leaf color is not sufficiently discriminant to be used alone in a plant identification task. This feature may vary with seasons and geographical locations. Thus, shape and texture are the most relevant features of the leaf.
Apart from Nam et al. [19], where the shape features computed from the leaf margin are enriched with venation features, most approaches are based on the

description of the leaf margin (see [5] for a review).
Some approaches extract morphological characters commonly used in botany [4, 6]. Shape feature extraction techniques [15] have been adapted to the particular case of leaves, as for example, the Curvature Scale Space [4, 17] and Fourier-based descriptors [20, 26].
Multiscale schemes based on triangles [2, 7, 10, 21, 22] obtained promising results on 2D shape databases such as MPEG7 and Kimia and should be adapted for plant species identification. These methods represent the triangles by their areas at each scale. Shen et al. [10] showed that the triangle area representation (TAR) is affine-invariant. El Rube et al. [7] suggested computing TAR at multiscale wavelet levels (MTAR) to reduce the noise effect on the shape boundary. More recently, Alajlan et al. [1, 2] made the triangle normalization locally for each scale and used a dynamic space warping matching to compute the optimal correspondence between two shapes.
An alternate method of shape representation is to use the shape context descriptor introduced by Belongie et al. [3]. Inner shape context [14] techniques have proven their efficiency for leaf image retrieval. To describe the boundary of a shape accurately and obtain good retrieval results, a regular sampling of the contour points is computed. Xie et al. [24] introduced the skeletal context, which uses a medial axis transform to produce an optimal sampling of the shape contour with a smaller number of points. In [18], the points that vote in the shape context (voting points) and the points where the shape context histograms are computed (computing points), are separated into two different sets. This scheme is used to represent, with the $SC2$ descriptor, spatial relationships between the salient points and the leaf margin in the context of leaf retrieval.
We believe that both contour and local interest points descriptions are useful for leaf species identification. We propose an approach that combines two types of descriptors. The first one is the $SC2$ descriptor introduced in [18]. The second descriptor extracts shape features from contour points. Our approach is presented in Section 2. The results are reported and discussed in Section 3.

2 Our approach

Our overall approach is based on the combination of $SC2$ with a more accurate description of the leaf margin. Two different types of shape descriptors representing the leaf boundary are presented and evaluated. They are both based on the computation of spatial relationships between a set of sampling points uniformly distributed over the leaf boundary (see Section 2.2). The matching and fusion methods used in our approach are described in Sections 2.3 and 2.4.

2.1 Salient points description

Given a leaf image and a salient point p computed on this image, we consider the vectors obtained by connecting p to the boundary points of the shape. We compute a coarse histogram where each vector $\boldsymbol{v}$ joining p and a contour point, represented by a radius r and an angle θ, contributes to the bin k using the log-polar quantization introduced in [3]:

$$h_p(k) = \#\{q \in \{\text{contour points}\} : (q-p) \in \text{bin}(k)\}$$

To approximate salient points of the leaf, Harris points are computed.
This description corresponds to the $SC2$ scenario of [18]. It represents the salient points, in the context defined by the leaf margin (cf. Figure 1(b)).
In the rest of the paper, this descriptor is denoted as $SC2$.

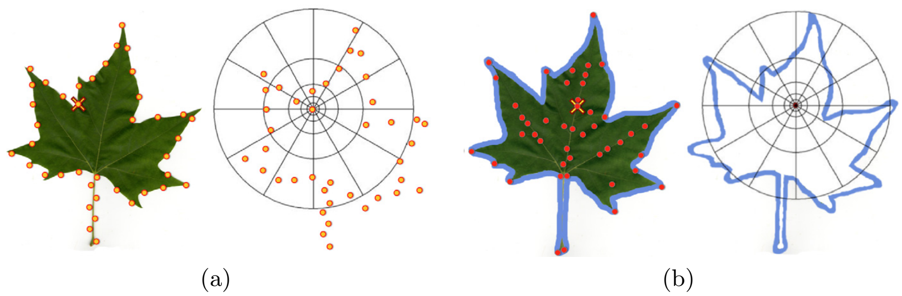


Fig. 1. Detected points on the leaves in $SC0$ and $SC2$ (a) Sample points on the leaf margin used in $SC0$ (b) Salient points in red and contour points in blue, used in $SC2$.

2.2 Leaf margin description

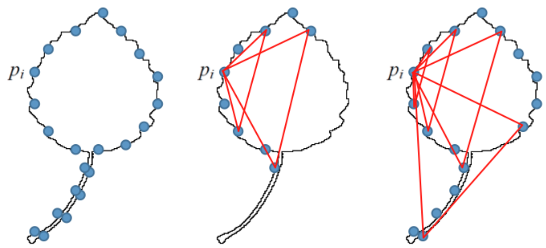
Two different types of shape-based description of the leaf margin are considered here. The fist one is based on the shape context descriptor and the second one is a multiscale triangular description of the shape boundary.

2.2.1 Shape context descriptor

The leaf margin is represented by the shape context histograms of [3] associated to a set of N points regularly sampled on the shape boundary (cf. Figure 1(a)). This corresponds to the $SC0$ scenario of [18]. We will use $SC0$ to denote this descriptor in what follows.

2.2.2 Multiscale triangular representation of the shape

The shape contour is represented by a set of triangular representation associated to a sequence of N sample points $p_1, ...p_N$ uniformly distributed over the contour and numbered in a clockwise order. More precisely, each boundary point p_i is associated with N_s triangles $T_i^1, ..., T_i^{N_s}$, T_i^k being the triangle defined by the contour points $p_{i-d(k)}$, p_i and $p_{i+d(k)}$, $1 \leq k \leq N_s$. N_s is both the number of triangles and the number of scales and $d(k)$ is the distance between the triangle points at scale k, expressed in the number of boundary points, with $1 \leq k \leq N_s$ and d being an increasing function such that $d(N_s) \leq N/2$. The choice of N_s



(a) (b) (c)

Fig. 2. Multiscale triangular representation. (a) N boundary points of the leaf. Here $N = 22$. (b) N_s boundary points are selected on each side of p_i. p_i is represented by two triangles ($N_s = 2$ with $d(1) = 2$ and $d(2) = 4$) (c) p_i is represented by four triangles and logarithmic distance between triangle points ($N_s = 4$ with $d(1) = 1$, $d(2) = 2$, $d(3) = 4$ and $d(4) = 8$)

depends on whether we are seeking to capture local or global information. The distance $d(k)$ may be either uniform or logarithmic. (cf. Figure 2).
Two representations are associated to each p_i:
$\mathrm{TAR}(p_i) = (\mathrm{TAR}(T_i^1), ..., \mathrm{TAR}(T_i^{N_s}))$ and $\mathrm{TSL}(p_i) = (\mathrm{TSL}(T_i^1), ..., \mathrm{TSL}(T_i^{N_s}))$, where TAR is the triangle area representation and TSL the triangle side lengths representation described below. The shape is then described by N feature vectors $\mathcal{T}(p_i); 1 \leq i \leq N$, $\mathcal{T}$ being either TAR, TSL triangle representation. TAR and TSL are both invariant to translation and rotation of the shape. By normalizing the description locally, we also obtain a scale invariant description of the shape.

Triangle area representation(TAR)
For each triangle T, $\mathrm{TAR}(T) = \mathcal{A}(T)$, where $\mathcal{A}(T)$ is the signed area of T. TAR is affine-invariant, robust to noise and provides information about local concavities or convexities at a given boundary point as the signed area is computed. A normalization is made locally with respect to the maximum area in each scale as in [2]. However, the TAR used in this paper is different from the original TAR:
- Here, only a set of N points sampled on the contour is used.
- The number of scales is a parameter (N_s) while in [2] $\frac{M}{2} - 1$ scales are systematically used, where M is the number of points in the contour.
- The matching process is different. A dynamic space wrapping is used in [2] to compare global signatures of the shapes at each scale. Here, the feature associated to a contour point takes into account all the selected scales and then a similarity measure based on a locality sensitive hashing is used to find similar points.

Triangle side lengths representation (TSL)
Considering the following property of similar triangles -"all three pairs of corresponding side lengths are in the same proportion"-, we define the TSL representation that uses the side lengths instead of the area, to represent a triangle.

Let L_{1k}, L_{2k} and L_{3k} be the three side lengths sorted in ascending order ($L_{1k} \leq L_{2k} \leq L_{3k}$) of triangle T_i^k formed by the points $p_{i-d(k)}$, p_i and $p_{i+d(k)}$, $k \in \{1, ..., N_s\}$ of the shape contour. Let $M_k = L_{1k}/L_{3k}$ and $N_k = L_{2k}/L_{3k}$.
Then $\text{TSL}(T_i^k) = (M_k, N_k)$.
The three side lengths of T_i^k are proportional to M_k, N_k and 1; this is also the case for any triangle similar to T_i^k. Thus similar triangles have an equal TSL representation and TSL is invariant under scale, translation, rotation and reflection around the contour points (see figure 3).

2.3 Matching method

The feature matching process is the same for $SC0$, $SC2$, TAR and TSL. It is done by an approximate similarity search technique based on a Locality Sensitive Hashing (LSH) method [11]. We use the distance L_2 to compute the similarity between two feature vectors. The principle of this algorithm is to project all the features in an L dimensional space and to use hash functions to reduce the search and the cost time. At query time, the features $F_1, F_2, ..., F_N$ of the query image are mapped onto the hash tables and the k-nearest neighbours of each feature F_i are searched for in the buckets associated to F_i. These N lists of candidate feature matches are used as input for a voting system to rank images according to the number of matched features.

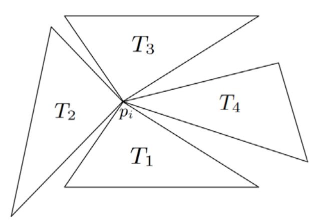


Fig. 3. Four triangles having the same TSL representation. T_2 is a result of a rotation of T_1 around p_i while T3 is the mirror image of T1 w.r.t. a horizontal line. Note that the vertex angle p_i of T_4 is different from the vertex angle p_i of the other triangles.

2.4 Fusion method

All the descriptors are computed independently. Let BD be either $SC0$, TAR or TSL. The combination of BD with $SC2$ is done by a late fusion on the feature similarity ranking lists corresponding to the image queries.
For each leaf query image Q, BD and $SC2$ return a list of images belonging to the same database but ordered differently: a same image may be present in both lists, but at a different rank. We then use the Leave Out algorithm (LO) [12] on the lists composed of the 30 first results to obtain the final list.

3 Results

Our descriptors have been tested on three leaf datasets: the Flavia dataset [23], the ImageCLEF dataset in 2011 [8] and in 2012 [9]. In all the experiments, a leaf image contains a single leaf on a uniform background. A preprocessing step is required to isolate the leaf area. First, we apply the Otsu threshold method to remove the background and keep only the mask corresponding to the leaf. A closed contour is then extracted from the leaf mask.

3.1 The Flavia dataset

The Flavia dataset is composed of 1907 scans of leaves belonging to 32 species. Several methods were tested in [13] on Flavia. To compare our approach with them, we used the evaluation metrics presented in [13]: the Mean Average Precision (MAP) and the recall/precision curves. In this experiment, we used: 400 boundary points and 10 scales ($N = 400$, $N_s = 10$) for both TAR and TSL, 100 contour points for $SC0$ and 100 salient points for $SC2$.

The results are reported in Figure 4. Analysing the individual performance of

	Method	MAP
Methods in [14]	D2	42.82
	MSDM	47.91
	GEDT	48.01
	REM	57.21
Individual descriptors	SC2	**58.70**
	SC0	53.42
	TAR	50.52
	TSL	**65.57**
Descriptors combination	SC2+SC0	**57.28**
	SC2+TAR	**62.17**
	SC2+TSL	**68.48**

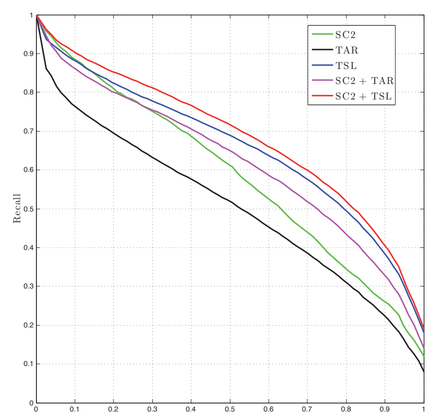


Fig. 4. Results on the Flavia dataset. Left: Mean Average precision (MAP). Right: Recall/Precision curves.

the presented descriptors, we observe that $SC2$ improves slightly the state-of-art methods and the TSL descriptor significantly outperforms other methods. The combination of the $SC2$ with the shape based approaches is promising when the triangular methods are used. Recall/precision curves presented in Figure 4 confirm that the combinations of $SC2$ and the triangular methods improve the individual scores. Despite the noteworthy similarity of the shapes of many species, our approach shows a high capability to discriminate between species.

3.2 Comparison with ImageCLEF 2011 results

The ImageCLEF 2011 leaf dataset [8] contains three categories of images: scans of leaves acquired using a flat-bed scanner; scan-like leaf images acquired using a digital camera and free natural photos. For each category, the images are divided into a training set and a testing set. The goal of the task is to find the correct tree species of each test image. The identification score is quite different from the classic classification rate (cf. [8] for more details). We focus on scans and scan-like images. The first category contains 2349 images for training and 721 test images. For the scan-like category, 717 images are used for training and 180 images for testing.
Table 1 shows the identification scores of our descriptors compared to other submitted runs of ImageCLEF 2011. If we compare the performances of our individual descriptors scores, we observe that TSL is the best on both scan and scan-like images. The combination of $SC2$ and one of the three shape descriptors, outperforms state-of-art scores. $SC2+TSL$ remarkably increases the identification score of scans. On the other hand, the combination of $SC2$ and TSL decreases slightly the score of the TSL descriptor. This is due to the fact that scan-like images may contain noise (shadows, dead leaves, uneven lighting, etc.) that may lead to incorrect salient points detection.

run_id	Scans	Scan-like
inria_imedia_plantnet_run1	**0.685**	0.464
LIRIS_run1	0.539	**0.543**
Sabanci-okan-run1	**0.682**	0.476
inria_imedia_plantnet_run2	0.477	**0.554**
DFH+GP [25]	**0.778**	**0.725**
$SC2$	0.676	0.677
$SC0$	0.654	0.706
TAR	0.721	0.636
TSL	**0.802**	**0.757**
$SC2+SC0$	**0.785**	0.705
$SC2+TAR$	**0.805**	0.698
$SC2+TSL$	**0.839**	**0.753**

Table 1. Normalized classification scores of the scan and scan-like images on the ImageCLEF 2011 dataset using the evaluation metric of [8]

3.3 Comparison with ImageCLEF 2012 results

The formula used to rank the runs in the ImageCLEF 2012 plant identification task is nearly the same as in 2011 (see [9] for details). The scan dataset contains 4870 images for training and 1760 test images. The scan-like category contains 1819 images for training and 907 images for testing.
The results are reported in Table 2. The performances of individual descriptors on scans are similar. However, TSL has the best individual score on scan-like images. All the combinations of $SC2$ and the shape descriptors are equal or

higher than the previous score. Note that $SC2+TSL$ has the best performance if we average the identification scores on scans and scan-like images.

	Scans	Scan-like
Top 3 Scores	0.58	0.59
	0.49	0.55
	0.47	0.54
$SC0$	0.52	**0.59**
$SC2$	0.51	0.42
TAR	0.52	0.51
TSL	0.52	**0.61**
$SC2+SC0$	**0.58**	**0.61**
$SC2+TAR$	**0.61**	**0.59**
$SC2+TSL$	**0.60**	**0.64**

Table 2. Normalized classification scores of the scan and scan-like images using the evaluation metric of [9] (ImageCLEF 2012)

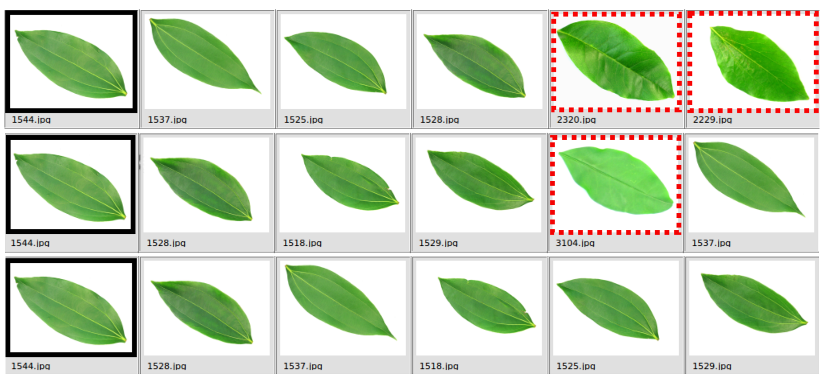


Fig. 5. Retrieval tests showing the first five returned images. The descriptors used are: TSL (Top), $SC2$ (Middle) and $SC2+TSL$ (Bottom). The query image is framed by a solid line. Irrelevant returned images are framed by a dashed red line.

3.4 SC2+TSL description

Figure 5 illustrates the complementarity of $SC2$ and TSL. In fact, like most of shape-based approaches, a classic case of failure is when shapes from different classes are very similar. When we deal with botanical data, this case occurs when two leaves have nearly the same shape but they belong to different species. In this case, another source of information is required to discriminate between leaves. This additional information can be either venation or texture. These two features are represented by the salient points included in the $SC2$ descriptor. If we take a close look to the three retrieval tests shown in Figure 5, we note that a shape-based approach as TSL, is not discriminant enough when the shapes are very similar. $SC2$ gives a better retrieval result compared to TSL. This can be explained by the fact that $SC2$ includes internal informations of the leaf. The combination of these two descriptors is more accurate and all the first five returned images are relevant.

4 Conclusion

We have presented a novel approach for plant species recognition. It merges two sources of information provided by the leaf: the salient points and the margin. The combination of $SC2$ and a shape descriptor generally improves the retrieval results. In particular, $SC2+TSL$ has achieved high identification rates on scans of leaves. Experiments have also shown that TSL gives better identification scores than TAR. This may be due to the fact that using side lengths to represent a triangle is more accurate than using the area, in the context of leaf shape representation for plant species identification. In fact, the TSL description takes into account the property of similar triangles.
In our future work, we want to develop a specific detector of the leaf salient points, instead of using Harris detector.

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