Multiple leaflets-based identification approach for compound leaf species

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ABSTRACT

Leaves of plants can be classified as being either simple or compound according to their shapes. Compound leaves can be seen as a collection of simple leaf-like structures called leaflets. However, most computer vision-based approaches describe these two leaf categories similarly. In this paper, we propose a new description and identification method for compound leaves that takes into account particularities related to the arrangement of their shapes (specifically, their division into leaflets). In fact, we propose a new multiple leaflets-based identification approach. Our main motivation behind this choice is that some compound leaf species may hold variabilities in terms of their leaflets number, size and even shape. Thus, a local description based on a certain number of leaflets may provide greater accuracy. In our approach, we were limited to three leaflets that were automatically extracted from image based on some geometric assumptions inspired from botany. Then, we construct and evaluate our identification scheme based on some classical texture descriptors for local leaflets description and using some state-of-the-art fusion algorithms to combine responses obtained from each leaflet query. Experiments carried out on compound leaves of the Pl@ntLeaves scan database have shown an improvement in classification results with regard to entire image query.

1. INTRODUCTION

New interdisciplinary technologies that integrate computer vision in botanical research are being developed in response to ecological challenges such as global climate change, rapid urban development, destruction of habitats, overexploitation of natural resources, food insecurity, biodiversity crises, etc. In particular, computer vision studies are increasingly focusing on accurate, complete and user-friendly systems for taxonomic identification of plant species (i.e, intended for a wide range of people, not only experts). A number of project-systems have already been built, for instance, Leafsnap in America [15, 19], CLOVER [25] in Asia, Pl@ntNet[4], ReVes [5] and ENVIROFI [1] in Europe, etc, and most of these systems use leaves to identify plant species. In fact, unlike other organs such as flowers, fruits or seeds, leaves are generally easy to collect (available throughout the year) and to scan or photograph (they have an approximately two-dimensional shape). Moreover, they often hold discriminative information that is useful for characterizing plant species.

Existing leaf-based plant identification approaches differ in several aspects: One is the type of feature used. Fundamental features are shape [22, 30, 29] and texture [9, 3, 8] which describe respectively the leaf margins and the vein pattern, the main key indicators of leaf species. Another aspect concerns the way the leaf is viewed: using generic or domain-specific representations. Generic approaches consist in using common computer vision representations such as the Shape Context, the Curvature Scale Space, the Multi-Scale Fractal representation, the Fourier and Wavelet Transforms [8]). These methods have the advantage of being simple and rapid. However, they are not always sufficient to provide accurate identifications mainly due to the high inter-class and low intra-class similarity that occur for some species in terms of certain characteristics. For example, in the case of the Acer Negundo (see Figure 1), the use of contour descriptors may induce errors since some specimens have lobed and/or serrated margins while others have entire margins. For that reason, there has been a recent trend toward using domain-specific or botanical knowledge, particularly about the leaf architecture, in order to enrich the leaf image representation [7, 12, 23, 26]. In fact, the leaf architecture, built and extensively used by botanists, refers to the description and categorization of leaves according to the properties of their structure. This includes several foliar characters that describe, hierarchically, the form and the placement of different elements constituting the leaf struc-

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Figure 1: Intra-variation within the Acer Negundo species: from right to left: lobed, serrated, entire margins.

ture such as venation pattern (see $1^{s}t$ row of Figure 2) [31, 17], marginal configurations (see $2^{n}d$ row of Figure 2) [6], shapes of leaf parts (see $3^{r}d$ row of Figure 2) [14], etc. So far, the use of this information has remained limited to some simple characters (such as the laminar form described by the ratio of the laminar width and height, the apical and basal form expressed respectively by the apex and base angles, etc. [16]). In this paper, we are interested in one of the most important characters that has been less exploited: the leaf arrangement (or type). In fact, leaves of trees are grouped into two basic classes: simple and compound leaves (see Figure 3).

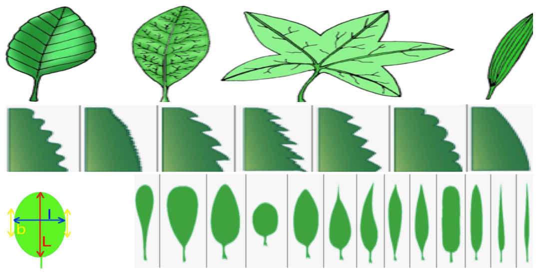


Figure 2: Some botanical leaf characters, from top to bottom: Venation, margin and shape variations

In current leaf image retrieval approaches, simple and compound leaves are described similarly by using global descriptors (for the whole leaf image) [22, 30, 29, 9, 3]. However, compound leaves can be seen as a subdivision of simple leaves. Otherwise, each leaflet has a blade-like structure. For that reason, a local description, whose regions of interest are leaflets, may provide greater accuracy, not only in the case of occlusion or partial damage, but more specifically, when dealing with partial intra-species non-similarity. For instance, the Gleditsia triacanthos species may have different types of leaflets (simple and pinnate) within the same leaf (see Figure 4). Also, the fraxinus angustifolia and the fraxinus ornus species may have a variable number of leaflets (see Figure 5). Furthermore, the Vitex Agnus Cactus species hold leaflets with different sizes (see Figure 6).

In these cases, the whole leaf images are clearly totally different. However, the similarity can be revealed by comparing leaflets separately. From this assertion, in this paper, we propose an image retrieval system for compound leaves based on the combination of response lists derived from each leaflet sub-image query. This involves the following steps:

- First, we automatically detect at most three represen-

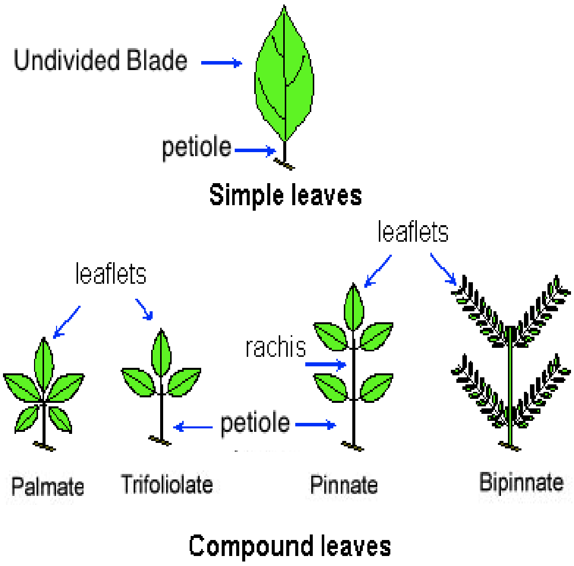


Figure 3: Leaf types: from top to bottom: simple, compound leaves which are divided (from left to right) into: palmate, trifoliate, pinnate and bi-pinnate compound leaves.

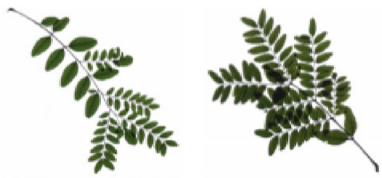
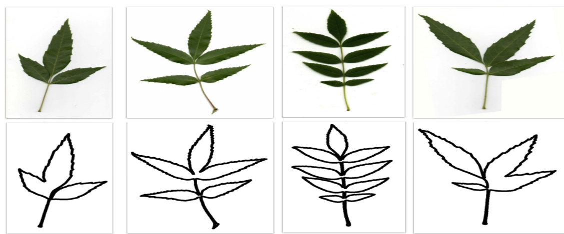
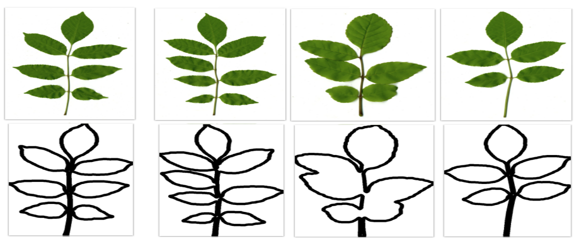


Figure 4: Intra-variation of leaflet types (pinnate and bi-pinnate) in the Gleditsia triacanthos species.



(a) Fraxinus angustifolia



(b) Fraxinus ornus

Figure 5: Intra-variation of leaflet number (color image (up) and contour image (down))

Figure 6: Intra-variation of leaflet size in Vitex Agnus Cactus species

tative leaflets of the image using geometric properties related to their contours.

- Then, we consider sub-images of leaflets as multiple views of the same compound leaf image. In other words, we replace the entire image by its three leaflets in the identification scheme. We index each leaflet sub-image separately. The list of responses includes all the remaining leaflets sub-images other than the two leaflets obtained from the same entire image as the query.

- Finally, we combine the ranking lists obtained from each leaflet query obtained from the same original compound leaf, a posteriori, in order to find the overall responses of the whole image. Different state-of-the-art fusion methods are tested and evaluated with regard to the entire compound leaf image query.

This paper is organized as follows. First, we briefly describe some previous work on parts-based plant identification and specifically those that deal with compound leaves. Next, we describe the steps of our leaflets-based retrieval scheme. Experiments and evaluations are presented in the final section.

2. RELATED WORK

The elementary analysis and description of leaves, or plants in general, based on their parts are traditionally performed by botanists (mainly using qualitative features) in order to identify species. Some recent computer-vision approaches have used this assumption to enhance plant retrieval results. For instance, the authors of [12] have combined different views of plant organs (such as flowers, bark, leaves) using a late fusion process. Analogically, the authors of [23] have used the same principle (that is the late fusion) to parts of simple leaves. They follow the Manual of Leaf Architecture [14] for parts definitions (which divides simple leaves into three parts: the apical, basal and margin parts) and they automatically detect them based on semantic geometric features.

Compound leaf identification based on their parts (leaflets) has also been discussed in two previous studies: In the first one [7], the authors propose a two-stage compound leaf shape modelling. In the first stage, it makes the assumption that compound leaves are reflectively symmetric and that their leaflets have the same size and orientation. In this phase, the leaflets are assimilated to uniform circles arranged, pairwise, on either side of the main axis, and defined by their positions, their radius and distance from the main axis. In the second stage, a joint polygonal model is used to estimate the shape of the leaflets (by estimating the length, width, bilateral width, angles of base and apex of each leaflet. For each stage, an energy function, based on a color dissimilarity map, is minimized. This method has the advantage that it accomplishes both leaf segmentation and recognition using the same model. However, it is limited by the high computational cost and the intervention of the user to initialize the model's parameters. Moreover, the model's assumptions are so strict that they do not correspond to the reality of the processed data (i.e, they are not valid for all types of compound leaves). In fact, leaves are not always axially symmetric even for pinnately compound leaves (see Figure 3)). Furthermore, the leaflets' size may vary (see Figure 6). The second study that has dealt with compound leaves is presented in [2]. It looks for the top 3 leaflets, obtained using the following two hypotheses:(1) First, they are located on either side of the main axis (estimated by a polynomial of order 4). (2) they have the most elliptic shapes (defined by the ratio between the area of the shape and its minimum enclosing ellipse). The final identification stage is based on only one leaflet, selected from the three candidates , based on its similarity distance, computed with the complex network shape descriptor, which should be the lowest with regard to the two others.

The approach, presented in this paper, presents similarities with regard to the two first studies, mentioned above, related to plant organs [23] and simple leaf parts [12]. In fact, we aim to identify compound leaves based on an a late fusion of responses of their parts (leaflets) queries. On the other hand, the proposed method presents several differences from the two last studies [2, 7], described previously, about leaflet-based identification: First, we propose to decompose both pinnately and palmately compound leaf shapes, and even leaflets are not similar or symmetric. Second, we use more than one leaflet in order to cope with intra-variation of leaflets shapes unlike [2]. Third, we choose to retrieve each leaflet separately and to combine the ranking lists obtained, a posteriori unlike the work presented in [7], in which an early fusion is rather used. In fact, the early fusion, which consists in concatenating leaflet representations in a single one, needs an appropriate leaflet representations matching algorithm since leaflets are not selected in the same order from an image to other.

3. AUTOMATIC LEAFLET EXTRACTION

Parts-based shape decomposition is generally important to shape representation and recognition. Several studies have dealt with this problem. They are mainly based on the perceptual rule of decomposing shapes into regions with important concavities [28, 20]. The definition of the best cut that joins minima points is still a challenging issue. Most approaches are based on a recursive procedure or use some optimization criteria, which is a time-consuming task. Domain-specific knowledge related to shapes may be useful to simplify the decomposition process. In our case, we are dealing with shape of compound leaves (either pinnate or palmate). They are, by definition, fully subdivided into leaflets, arranged on either side of the rachis (main stalk) in pinnately compound leaves and centred around the base point (the point that joins the blade to the petiole) in palmately compound leaves (see Figure 3) [14]. From that, we can deduce that the generic perceptual rule can be applied for shapes of compound leaves. In fact, leaflet shapes may be seen as regions separated by extra points with deep concavities. In order to determine the points that limit leaflets, we base our solution on the two following botanical assumptions:

- In compound leaves, concave points may correspond, besides to leaflets endpoints, to other irregularities such as tooth, lobes, petiole bending or even points derived from the aliasing effect. These points should be discarded (only points corresponding to leaflets and rachis terminals should be kept). In order to do so, we first apply a smoothing to the leaf shape. We reject all concave points that are aligned with its two-sided neighbourhood inflexion points (see circled green points in Figure 7). The remaining concave points (see Figure 8) are used to determine leaflets. Notice that inflexion points and concave points are defined respectively as the zeros-crossing and the local maxima with negative value of the curvature function of a contour. In practice, we compute the curvature function as presented in [21].

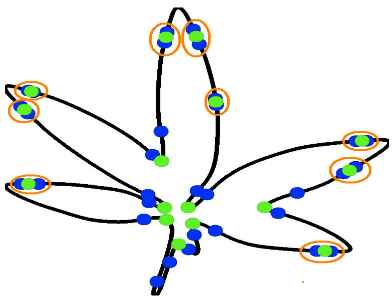


Figure 7: Concave points coloured in green aligned with their two-sided neighbourhood inflexion points coloured in blue are rejected (the ones that are circled in orange colour).

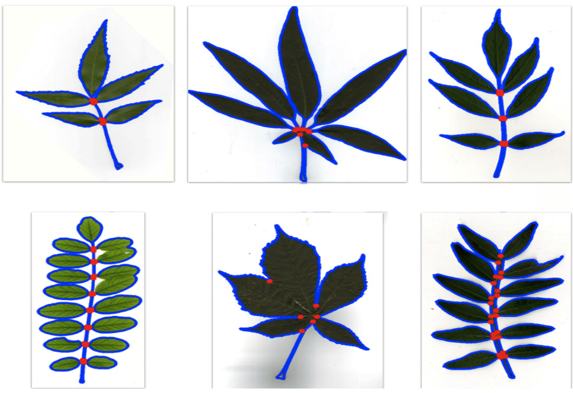


Figure 8: Selection of pertinent compound points (red points).

- leaflets endpoints are generally close. Thus, we sort the list of Euclidean distances between each two consecutive concave points in ascending order and we consider the k-first pairs respectively as the two terminals of the k-first leaflets. In Figure 9, we display the 3-first leaflets of some compound leaves.

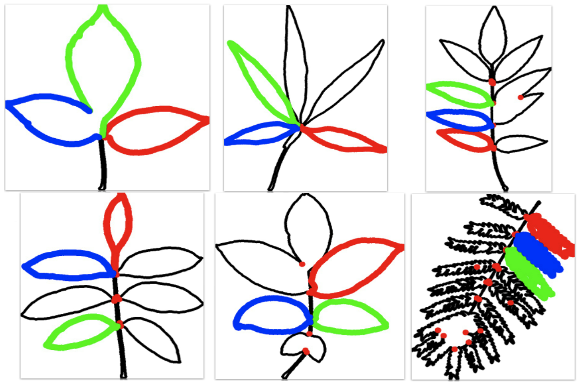


Figure 9: The 3-leaflets selected.

In practice, we only select, at most, three leaflets in order to try to lead to the compromise between information richness, derived from leaflets variations within the same species (see Figures 4 and 6) and leaflets overlapping problem, that may eventually induce false detections if the number of selected leaflets is high (see Figure 10). In fact, since the processed data (the pl@ntLeaves Scan dataset) hold generally partial leaflets overlapping, the first leaflets are often approximately complete (see Figure 10). This simple hypothesis (about the number of selected leaflets) ensure a low computational cost, compared to sophisticated methods such as active polygonal models [7] which also fail to distinguish and delimit overlapped leaflets. Furthermore, trifoliate leaves (see Figure 3) have only three leaflets (see 1st image, 1st column at left in Figure 9). Finally, we judge the relevance of the selected three leaflets, according their size. This is mainly important in the case of approximately totally overlapped leaflets (for example, in the 2nd column of Figure 10, only one leaflet is selected).

4. LEAFLETS TEXTURE DESCRIPTION

We evaluate our multiple leaflets based identification approach by testing some texture descriptors described as following. The local description of leaflets texture allow to outline vein networks which are an important attribute in leaf identification.

- The Fourier histogram (Fourier) proposed in [11] describes the distribution of the spectral power density within the complex frequency plane. This is expressed using two types of histogram defined according to two partitions of the Fourier plane: the first is a disk partition used to differentiate between low, middle and high frequencies, while the second is based on a partition according to different directions of the spectrum.

- The Edge Orientation Histogram (EOH) [10], computes the distribution of edge directions. In a leaf, the edges are composed of two parts: the interior and the exterior contours which correspond respectively to the vein networks and the margins.

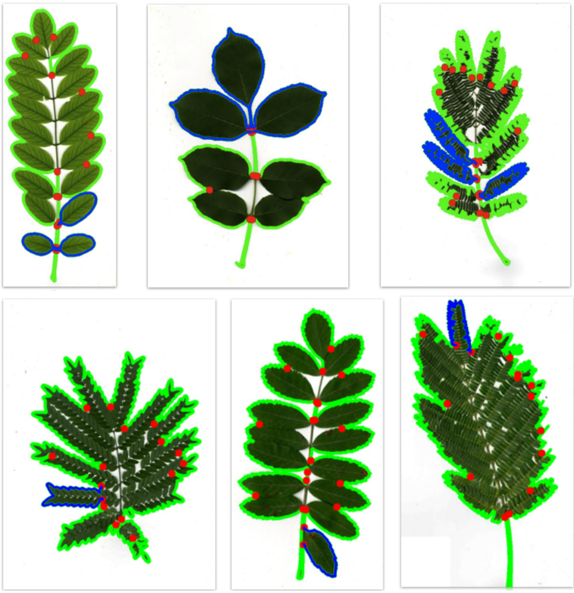


Figure 10: Illustration of the overlapping problem (see the green part of the contour), detected leaves are coloured in blue, only one leaflet is detected for images of the $2^n d$ row, where the remaining leaflets are overlapped.

- The Local Edge Orientation Histogram (LEOH) [23]. Here, instead of accumulating occurrences of gradient orientations in n bins such as in EOH, the LEOH encodes the relative frequency distribution of groups of gradient points contained within a sliding window (blob). All local distributions are combined into a single global histogram.

- A Hough histogram (Hough) [11], is a 2D histogram based on the Hough transform which gives the overall behaviour of pixels in the image along straight lines. Each pixel is represented by the orientation of the gradient and the projection of its position vector onto its tangent vector (i.e the vector orthogonal to the gradient).

5. MULTIPLE LEAFLETS-BASED QUERIES FUSION

The proposed multiple leaflets-based fusion method consists in constructing a single overall ranked list by merging, a posteriori, different lists obtained for different queries of leaflets sub-images.

Let Q be the whole compound leaf image query, and Q_i the leaflet-based queries where $1 \leq i \leq 3$. For the query Q, the visual index is composed of all the remaining images of the database, noted R^n, (where $1 < n < N$ and N is the number of images in the dataset). In the same way, for each leaflet query Q_i, the returned images are denoted by R_i^n and may belong to the set of all the remaining leaflet sub-images, except the other two leaflet sub-images, obtained from the same entire image as the leaflet associated to the query Q_i. For each image, all queries Q_i of leaflet sub-images are indexed separately. In order to show the effectiveness of the leaflets-based fusion, we test three fusion methods:

- The leave out method (LO) [18]
  Responses are inserted in the final ranking list circularly from different leaflets queries lists. The best position of an image among the returned lists is kept.

- The inverse rank position method (IRP) [18]

$$IRP(Q, R^n) = \frac{1}{\sum_1^3 \frac{1}{r_{R_i^n}(Q_i)}}$$

  where $r_{R_i^n}(Q_i)$ is the rank of the partial response R_i^n to the partial query Q_i. The final list is obtained by sorting the IRP values in increasing order.

- The increasing distance method (DistInc) [27]
  The ascending order of the scores, which correspond in our case, to the similarity distance values, defines the order of the final list. In fact, we can concatenate the ranking lists obtained by three leaflet queries into a single one. We sort the resulted list, in ascending order, in terms of similarity distances in order to obtain the overall ranking list.

Finally, once the overall ranking list is obtained after the late fusion of leaflet queries, we apply the knn classifier in order to determine the identity of the query image.

6. EXPERIMENTAL RESULTS

Experiments were carried out on a subset including compound leaves of the Pl@ntLeaves Scan pictures dataset [13]. This subset contains 595 images belonging to 16 plant species characterised mainly by a high intra-species variabilities (mainly in terms of leaflets number, size variations, see Figures 5 and 6). The dataset categorisation (into simple and compound) is performed automatically based on the approach proposed in [24]. We evaluate the effectiveness of our approach using the correct classification rate metric, obtained by the K-NN classifier, for different values of k ($k \in \{5, 10, 20, 25, 30\}$). This metric is adequate to the context of plant species identification because it reflects the user satisfaction, which is achieved when the accurate species is the mostly present in the k first responses.

Recall that the principle of our leaflets-based identification scheme is that each leaflet represents a different view of the entire image (i.e, the entire image is replaced by these views in the identification scheme). For that reason, we can show the robustness of our approach by comparing its classification results with regard to the classical retrieval scheme based on the global representation of the entire image. We perform several test configurations using four texture descriptors: Hough, Fourier, Leoh, Eoh (see Section 4), in the description phase, and three fusion algorithms, in the leaflets-based queries fusion phase: IRP, LO, DistInc (see Section 5). Figure 11 presents results for these different configurations. We can see an enhancement in the classification rates, obtained by all descriptors and fusion algorithms tested, and for different values of k, with regard to the classical retrieval scheme for compound leaves. This prove the effectiveness of our leaflets-based scheme for enhanced compound leaves identification. Also, fusion algorithms IRP and LO perform both the best classification rate values. Figure 12 presents the 6−top images, returned for the leoh descriptor, for both the classical retrieval scheme with the entire image (top) and our leaflets-based approach (bottom) using

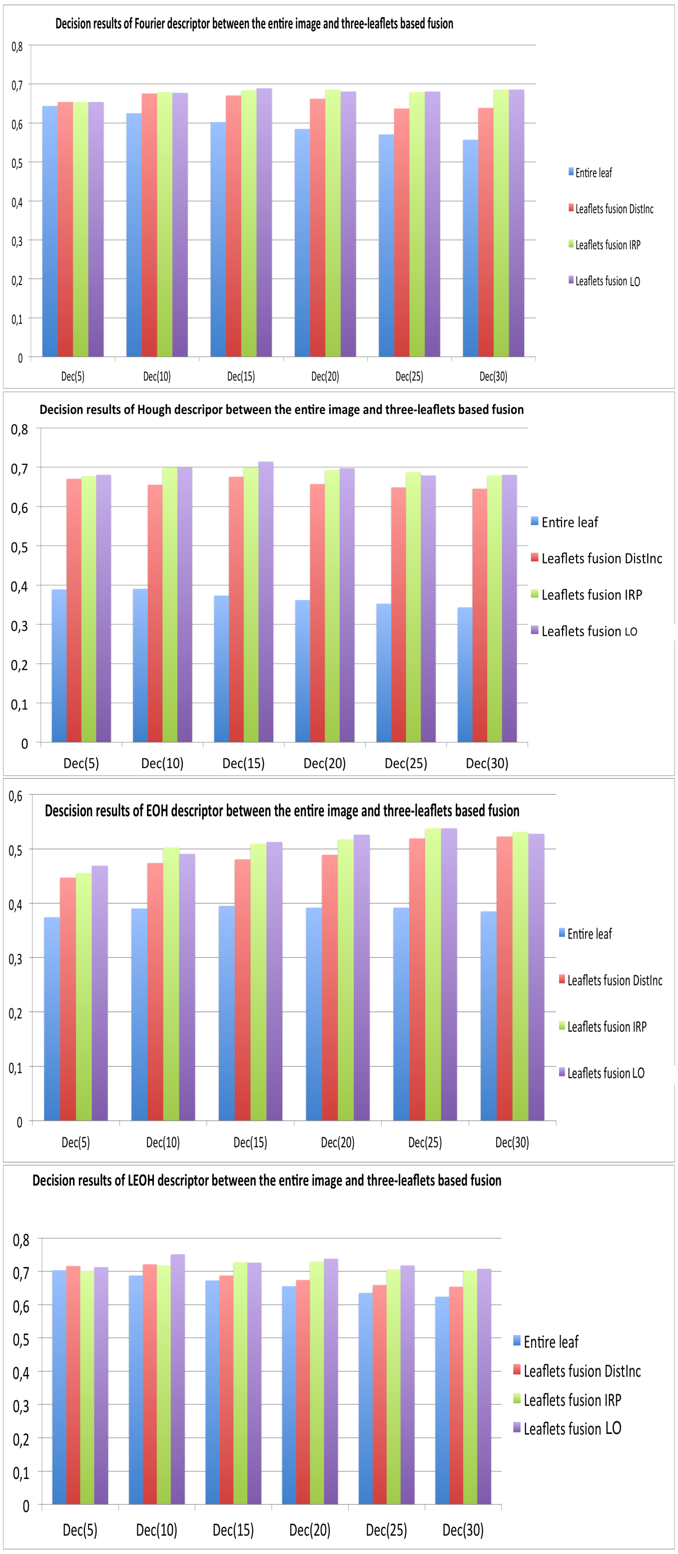


Figure 11: Comparison of the correct classification rates obtained for different values of knn, using 4 texture descriptors, between the classical retrieval scheme (labelled Entire leaf and displayed with the blue bar) and our three leaflets-based identification approach using three fusion techniques: DistInc, IRP and LO.

the IRP fusion algorithm, for a specimen that belongs to the species Fraxinus angustifolia. This species was particularly chosen because it holds variability of leaflets number (see some examples in Figure 5). We can see that all the responses returned for the entire image are wrong (they does not belong to the right species). It seems that the leoh descriptor has provided these responses because of the high global similarity in terms of macro-texture. Nevertheless, when we use our leaflets-based approach, we obtain 5 accurate images from the 6−top ones, although that the three last ones have different leaflets number with regard to the query image which illustrates well the efficiency of our strategy.

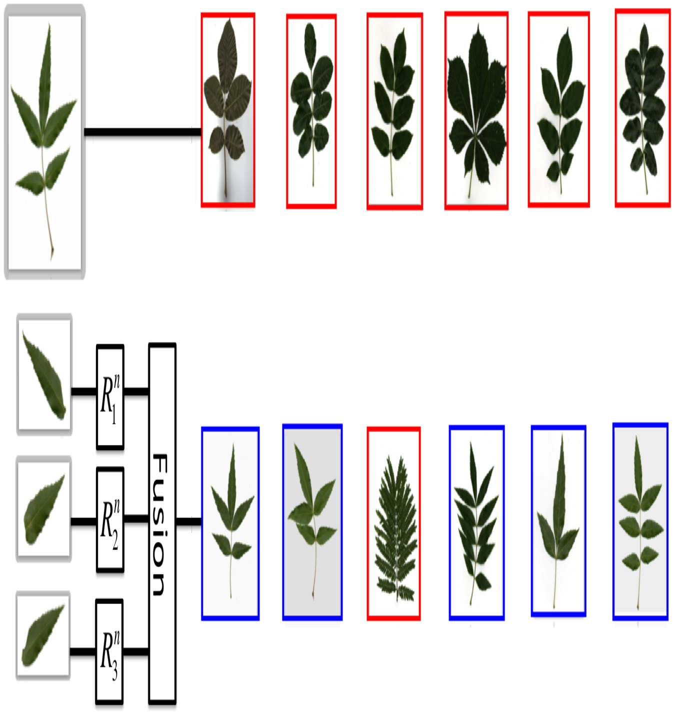


Figure 12: The 6−top images obtained by the classical retrieval scheme based on the entire image (top) and our three-leaflets based scheme (bottom), using the leoh descriptor and the IRP fusion algorithm: false positives are framed by red, the others (which belong to the same species as the query image) are framed by blue.

7. CONCLUSION

In this paper, we propose a new multiple leaflets-based identification approach dedicated to compound leaves. We construct our approach in three phases: (1) The first is the leaflets extraction. This step is established using simple geometric parameters which are defined based on botanical observations. We fix the number of leaflets to three in order to lead to the compromise of information richness derived from leaflets variations within the same species and false leaflet detections induced by leaflets overlapping problem. Our leaflets extraction method has the advantage of being rapid and efficient for different types of compound leaves unlike previous methods (2) The second step is the local description of leaflets. In this step, we test four classical texture descriptors (Hough, Fourier, Leoh, Eoh). (3) The third step is the late fusion of ranking lists obtained by each leaflets queries. We test three state-of-the-art fusion algorithms which are IRP, LO and distInc. Experiments were performed on compound leaves of the Pl@ntLeaves Scan pictures dataset for the different configurations of descriptors and fusion algorithms. They have shown an improvement in the classification rates with different values of the knn classifier, with regard to the classical retrieval scheme obtained by the entire image. Our ongoing work aims at constructing and evaluating the global parts-based leaf identification, defined depending on the leaf type: simple or compound.

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