LEAF CLASSIFICATION BASED ON A QUADRATIC CURVED AXIS

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ABSTRACT

We introduce a new reference axis for leaf classification. The new reference axis, called a Mid-Leaf axis, is based on a quadratic curve that lies on the middle of a leaf. This curve is derived from three basic landmark points: an apex, a centroid, and a petiole. After mapping to a new plane based on this curve, leaf shape features are invariant under translation, rotation, scaling, and bending. We propose the leaf shape features based on partitioning the morphological features and the tangent's direction angle of the leaf contour. Using the ImageCLEF2012 database (Scan-type only), our experimental results show that the proposed method outperforms the state-of-the-arts for leaf classification in the accuracy metric.

***Index Terms*—** Leaf classification, Leaf retrieval, Plant identification

1. INTRODUCTION

Plants have been used for food and medical treatments throughout the history of mankind. Modern medicine uses many plant-derived compounds as the testing basis for drugs. On the other hand, traditional medicine has relied heavily on thousand species of indigenous herbs and plants for a long time. With threats of not-yet-curable diseases, emerging illness, virus evolution, and drug resistance, our hope may rest on the existing plants. To know these plants in the wild, we need an intelligent mobile tool that integrates knowledge on botany and herbal medicine with computer vision. Leaf classification algorithm is an important part of this tool. The goal of this research is to design a leaf classification algorithm that is suitable for a mobile device to help identify plants in the field.

Most leaf classification algorithms usually map the shapes of individual leaves into certain representations or descriptors. In order to handle variations of input leaves, the algorithms need to convert input leaf images into some forms of reliable representations. These representations should be invariant with respect to scaling, translation, and rotation. Moreover, they have to cope with various kinds of deformation of input leaves in nature. In order to handle these problems, the shape-to-descriptor conversions may need to be aligned with a frame of reference, a landmark, or some self-relationship features.

Most automatic leaf classification approaches capture morphological and geometrical features that can be used to differentiate one plant species from the others. Morphological features do not contain many details—i.e., aspect ratio, rectangularity, circularity, eccentricity, and invariant moments. Du et al. [1] extracted 9 morphological features based on leaf shape. However, these features could not distinguish between two species with some different details. Hence later approaches used these morphological features in addition to their geometrical features to improve classification accuracy.

The most popular geometrical feature is the leaf contour. Neto et al. [2] used the Elliptic Fourier function to represent a chain code of the leaf contour. Ling and Jacob [3] proposed the Inner Distance for representing an object contour. The inner-distance is defined as the length of the shortest path between landmark points within the shape silhouette. Hu et al. [4] introduced the Multiscale Distance Matrix, which is generated by co-relationship between two contour points with a fixed distance. Mouine et al. [5] presented the Multiscale Triangular Representation by exploiting area, side length, and relative angles, these being created from triangular points on the leaf contour. Laga et al. [6] applied the Elastic Riemannian Metric to the leaf contour in order to handle leaf deformation. Wang et al. [7] created features from the arch of two contour points, called the Multiscale Arch-Height. Recently, Cao et al. [8] introduced the Multiscale R-angle by measuring the angle between the intersections of the contour with a fixed radius circle. Some leaf classification methods [9,10] combined morphological and geometrical features for better accuracy.

Unlike most previous methods, which tried to find self-relationship among contour points, the proposed method relies on contour mapping with a new reference axis. The new axis is based on a quadratic curve that lies at the leaf's center, between the apex to the petiole. The leaf contour in the new plane is invariant from translation, rotation, and scaling. Moreover, it maps bent leaves into straight leaves, thus reducing deformation to some degree and increasing reliable features for better leaf classification accuracy.

2. THE PROPOSED METHOD

In this section, we explain the processing steps used in our proposed method. First, an input color image is converted to a grayscale image; the images are from the Scan-Type of ImageCLEF2012 database [11]. Due to the images' clear backgrounds, a leaf can be simply segmented from its background using Otsu's thresholding. Then the leaf contour and its centroid are obtained. The six required processes are explained as follows.

2.1. Quadratic Curve Estimation

To handle translation, rotation, and scaling problems, a reference axis is required. From our observation, a primary vein (midvein or midrib) is an ideal reference axis. However, some leaves lack a midrib such as those with parallel or rotated vein patterns. Hence midrib detection may not be possible for all cases. Instead of detecting midrib, we propose a new curved axis as a reference, which is estimated from three landmark points of a leaf: an apex, a centroid, and an end of petiole. Because, these three points may not be linearly aligned, so the reference curve is approximated by a 2nd-order polynomial function, defined by

$$y = ax^2 + bx + c \,, \tag{1}$$

where (x, y) represents points on the curved axis and a, b, c are the coefficients of the 2nd -order polynomial function.

To detect the apex and the end of petiole, we have noticed that two points as far apart as possible on the leaf contour often indicate the apex and the end of petiole. Though not always true, the above assumption suffices to provide a reference axis if the two furthest apart points are the same for each leaf class. Instead of calculating the distance between every two points on the contour and finding the maximum, we perform the convex hull of the segmented leaf image. Finally, at the boundary of convex hull, the furthest apart points can be selected with reduced computational complexity and they must be identified as either the end of petiole or the apex.

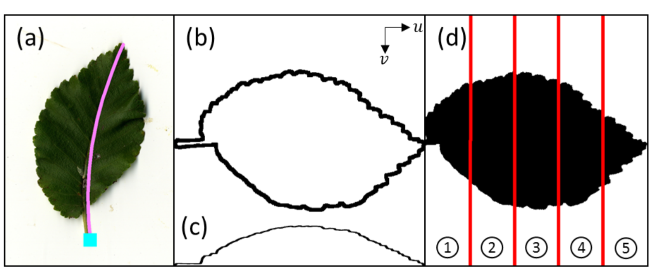
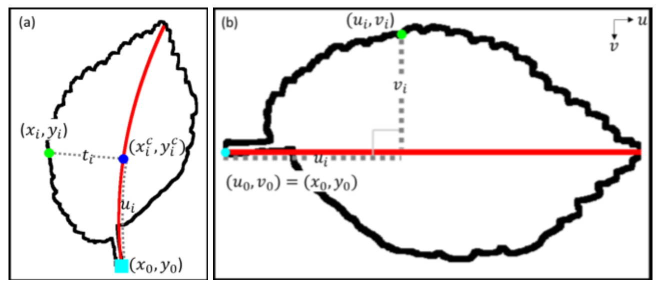


Figure 1 The proposed method: (a) Quadratic curve, (b) Leaf contour projection aligned with the Mid-Leaf axis, (c) Leaf projection for petiole removal (d) Leaf partitioning.

In general, the petiole is thinner and longer than the apex. Hence the ratio of the petiole's segmented area to the background should be less than that of the apex's to the background. Each detected point is defined as a center point at a side of 100×100 pixels square window then we calculate the corresponding segmented area. The point with the lower ratio is chosen as the end of petiole while the other is the apex. We then construct a straight line between the apex and the centroid and another straight line between the centroid and the end of petiole. All points on the two straight lines are used in the 2nd-order polynomial regression to obtain the reference curved axis. Figure 1(a) shows a quadratic curve plotted on an input leaf with the square representing the detected end of petiole.

2.2. Alignment of the Contour Projection with the Quadratic Curve

To translational and rotational invariant, the leaf contour must be mapped onto a new 2-dimensional plane. Our goal is to project a point (x,y) on the leaf contour onto a point (u,v) in a new reliable plane using the estimated quadratic curve as the reference axis, as shown in Figure 1(b).



(a) Original plane (b) New plane

Figure 2 Demonstration of the proposed contour mapping based on the reference curve onto the new plane with the Mid-Leaf axis

From Figure 2, assuming that the end of petiole (x_0, y_0) has been obtained from the previous process, we can arrange the points (x_i, y_i) in consecutive order along the leaf contour, where $i = 0,1,2,\ldots,N\text{-}1$, and N is the total number of pixels on the leaf contour. Considering a point (x_i, y_i), the distance t_i is defined as the Euclidean distance from a point (x_i, y_i) to a point (x_i^c, y_i^c) on the curved axis. Suppose the point (x_i^c, y_i^c) gives the minimum distance t_i to the point (x_i, y_i). We select two points as a mapping couple, $\{(x_i,y_i),(x_i^c,y_i^c)\} \in S_{MC}$, where S_{MC} is the mapping set. The minimum distance t_i is defined as

$$t_i = \min_{(x^c, y^c) \in S_{CA}} \{ \sqrt{(x_i - x^c)^2 + (y_i - y^c)^2} \} \,, \tag{2}$$

where S_{CA} is the set of points on the quadratic curve. To map the leaf contour to the new plane, the quadratic curve is mapped onto a linear axis, called the Mid-Leaf axis, and the leaf contour is mapped onto new locations corresponding to the relationship as follows:

$$(x_i, y_i) \rightarrow (u_i, v_i) \,, \tag{3}$$

where $(x_0, y_0) \rightarrow (u_0, v_0)$ is a starting point, u_i is the distance (pixels) from (x_0, y_0) to (x_i^c, y_i^c) along the quadratic curve, and $v_i = s_i \cdot t_i$ where $s_i = \text{-}1$ if (x_i, y_i) stay on left side of the curved axis, $s_i = 1$ otherwise.

All points on the leaf contour must be mapped onto the new plane as shown in Figure 2(b). If a point on the curve has no corresponding point on the leaf contour (no mapping couple), the corresponding point will be interpolated from the neighboring points on the contour. Clearly, the proposed mapping is nonlinear and not one-to-one. In conclusion, the quadratic curve is mapped onto the new straight axis called the Mid-Leaf Axis, and all points on the leaf contour are projected onto the new plane by minimum distance condition. Note that the proposed mapping should reduce leaf deformation/variations to some degree such as in twisted leaves from the same species.

2.3. Mid-Leaf Axis Normalization

The previous process is translational and rotational invariant but not yet scaling invariant. To make it scaling invariant, the length of the Mid-Leaf Axis is normalized. However, this Mid-Leaf axis's length depends on the size of the input leaf. For the proposed method, the length of the Mid-Leaf Axis is linearly scaled to a fixed 512 points. If the Mid-Leaf axis is greater than 512, the leaf contour points are down-sampled by averaging the redundant points. If the Mid-Leaf axis is less than 512, the leaf contour points are up-sampled by linear interpolation. Our proposed method is now invariant against translation, rotation, and scaling.

2.4. Leaf Contour Feature Extraction

At this point, the leaf contour has been aligned with and normalized to the Mid-Leaf axis. Reliable features could then be extracted from leaf contour. We have noticed that the tangent's direction of the leaf contour could be used as a distinctive feature for leaf classification. Hence a tangent's angle θ_i is formed by a tangent vector at the i^{th} point on the leaf contour and the Mid-Leaf axis. However, the value of $\tan(\theta_i)$ ranges from zero to ± infinity, which is very difficult to handle in practice. Hence $\sin(\theta_i)$ or $\cos(\theta_i)$, whose values range from zero to ± 1, can be used instead. In this work, we adopt an approach from [8]—in which the R-angle was represented by an absolute sine term and a quadrant separation term—and apply it to the tangent's angle of the leaf contour; the sine term of the tangent's angle is obtained by calculating horizontal and vertical displacement inside a controlled window $2w$ at an estimated point along the leaf contour. At the i^{th} estimated point, the $(i–w)^{th}$ point and the $(i+w)^{th}$ point are used to calculate the absolute sine of the tangent's direction angle d_i and the quadrant selection q_i, as shown

$$d_i = |\sin(\theta_i)| = \frac{|y_{i+w} - y_{i-w}|}{\sqrt{(x_{i+w} - x_{i-w})^2 + (y_{i+w} - y_{i-w})^2}}, \quad (4)$$

$$q_i = \begin{cases} 1 & \text{if} \quad (y_{i+w} - y_{i-w}) \geq 0 \\ -1 & \text{if} \quad (y_{i+w} - y_{i-w}) < 0 \end{cases}, \quad (5)$$

where (x_{i-w}, y_{i-w}) and (x_{i+w}, y_{i+w}) are the coordinates of the $(i–w)^{th}$ and $(i+w)^{th}$ points, respectively. Clearly, the parameter d_i represents the vertical projection of the tangent's angle. The parameter q_i represents the quadrant selection, which extends tangent's direction information d_i for representing left turn (convex) or right turn (concave) at the evaluated point i.

To capture various details of the leaf contour, multiple window sizes are used for estimating the tangent's angle for multi-resolution representations. Figure 3 shows two window sizes, w=3 and w=5. The small window seems to capture edge details such as the leaf margin (saw-tooth shape). On the other hand, the large window seems to smoothen the leaf contour and reduce noise. Our proposed method utilizes window sizes of w = 3 and 9.

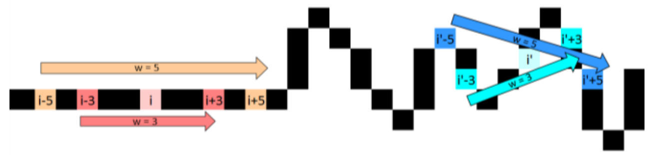


Figure 3 Demonstration of the Tangent's Direction Angle with Different Window sizes; i.e. w = 3 and w = 5.

To form a feature vector, we use sample points on the leaf contour, with the number of sampling points depending on the contour's length. We then control the number of points in a feature vector by uniformly extracting features from the i^{th} locations on the contour by a normalized number L— L=1024 for our experiment.

The feature vector **d** is obtained by taking absolute sine of the tangent's direction angle while the feature vector **q** is obtained by the quadrant selection. To reduce redundancy and make the feature vectors more compact, we apply Fast Fourier Transform (FFT) to the **d** and **q** vectors and use the magnitudes of the resulting FFT as the final feature vectors for leaf classification. The final feature vectors are then defined as

$$|\mathbf{D}| = |F\{\mathbf{d}\}| = |F\{\{d_i\}_{i=1}^{L}\}|, \text{ where } \mathbf{d} = \{d_i\}_{i=1}^{L}, \quad (6)$$

$$|\mathbf{Q}| = |F\{\mathbf{q}\}| = |F\{\{q_i\}_{i=1}^{L}\}|, \text{ where } \mathbf{q} = \{q_i\}_{i=1}^{L}, \quad (7)$$

where **D** is the Fourier coefficients of the absolute sine of the tangent's direction angle, **Q** is the Fourier coefficients of the quadrant selection, $F\{\cdot\}$ represents the Fourier transform operation, and |**D**| is the magnitude of **D**.

2.5. Partitioning Morphological Feature Extraction

The proposed method also adopts morphological features. Morphological features are reliable global features that have been used for leaf classification/retrieval in the past [1,9,10]. The proposed method uses morphological features by extracting them from leaf partitions and the whole leaf. The leaf partitions are sectioned along the Mid-Leaf axis, making them translational, rotational, and scaling invariant.

To extract reliable morphological features from leaf partitions and to reduce variations of the morphological features, we need to remove the petiole. We could perform this petiole removal process after we obtain the image from Mid-Leaf axis normalization. We projected vertical value of the leaf contour as shown in Figure 1(c). The detected petiole should be on the left of this leaf contour projection. Then the small vertical value is eliminated from the leaf contour, as shown in Figure 1(d) before the whole leaf is uniformly split into P parts. In our experiments, we have found that using P=5 yields the best classification result.

Morphological features are then extracted from whole leaf and each leaf partition. We adopt most of the morphological features from [1] such as Eccentricity, Rectangularity, Area convexity, Perimeter convexity, Circularity, Perimeter ratio, and 7th moments of Hu. Moreover, we also include the Average Margin Distance from [9] to our morphological features. We then use Principal Component Analysis (PCA) to transform these morphological features. All PCA coefficients are used in a morphological feature vector **M** in our leaf classification method with no dimensional reduction.

2.6. Pattern Matching with Dissimilarity Measure

In order to perform leaf pattern classification, we perform a 1-to-1 matching using dissimilarity measure. Each plant class is represented by the leaf's class model obtained from averaging all feature vectors of leaf images within the same class from the training set. The input feature vector, extracted from the input image, is matched with feature vectors from each class model. All features are normalized in the range of 0 to 1. The dissimilarity score between the input leaf image I and the leaf's class model C can be computed by

$$DS(I,C) = w_M\left\|\mathbf{M}_I - \mathbf{M}_C\right\| + w_D\left\||\mathbf{D}_I| - |\mathbf{D}_C|\right\| + w_Q\left\||\mathbf{Q}_I| - |\mathbf{Q}_C|\right\|, \quad (8)$$

where $\| \|$ is the L2-norm, w_M, w_D, and w_Q are the weights of the morphological feature vector **M**, |**D**| is the Fourier Transform's magnitude of the absolute sine of the tangent's direction angle, and |**Q**| is the Fourier transform's magnitude of the quadrant selection. For our experiments, the weights w_M, w_D, and w_Q are set to 0.2, 1.0 and 0.7, respectively.

3. EXPERIMENTAL RESULTS & CONCLUSION

To test the proposed method, we used the ImageCLEF 2012 database [11] as a benchmark. This database consists of three types of leaf images: scan, scan-like, and photograph. In this experiment, we used only scan type because leaf images are appropriate for basic segmentation scheme. The scan type of the ImageCLEF 2012 database contained 6630 images from 115 plant species. Each plant species had different number of samples ranging from 2 to 259 images. The scan type images were divided into two sets: a training set (4870 Images) and a testing set (1760 Images). The average classification score, defined in [11], was used as our evaluation metric. All parameters were obtained via exhaustive searches for the best result.

Table 1. Accuracy comparison for testing various methods using ImageCLEF2012 database (Scan type only)

Methods	Score (%)
Proposed Method: Morphological Feature **M** *Only*	52.77
Proposed Method: Contour Feature **D**, **Q** *Only*	53.53
Multiscale Triangular Representation [5]	54.0
Multiscale Arch Height (MARCH) [6]	54.8
Shape, Texture, and Color Features [10]	58
Multiscale R-Angle [8]	61.2
Proposed Method: Combined Features **M**, **D**, **Q**	**64.97**
Proposed Method: Combined Features **M**, **D**, **Q** *with Manually Marked Mid-Leaf Axis*	**65.64**

Table 2. Average execution time per an input image

Process	Seconds
Preprocessing and Quadratic Curve Estimation	0.092
Contour Projection Aligned with Quadratic Curve	0.353
Leaf Contour Feature Extraction	0.196
Partitioning Morphological Feature Extraction	0.734
Overall Feature Extraction Time	1.375
Pattern Matching with Dissimilarity Measure	0.003

Table 1 compares accuracies of our proposed methods that employ different testing features to those of the state-of-the-arts. Almost all the proposed methods employ automatic reference curve estimation except the last one in which the reference curves are manually marked. The proposed method using combined features with automatic reference curve estimation outperforms the state-of-the-arts for the CLEF2012 database (scan-type only).

The experimental results demonstrate how leaf's shape could be transformed to reliable features. We found that the reference curve might not be estimated properly in some leaf types whose longest length is not from the tip to the petiole. However, if leaves in the same species yield similar reference curves, which might not be exactly at the primary vein, these reference curves are good enough for robust projection. Hence the extracted features are still reliable for classification. The classification accuracies of the manually marked curve and the automatically estimated curve are slightly different, approximately less than 1 percent.

The computational time of each process per an input image—measured on a 3.2 GHz Intel i5-4460 with 8G of Memory and MATLAB programming—is reported in Table 2. Note that the proposed algorithm has not been optimized in this proof-of-concept experiment.

With the new reference axis, leaves are more distinguishable by the combination of the leaf contour feature and the whole/partitioning morphological features. These proposed features are stable to translation, rotation, scaling, and bending. Moreover, the accuracy of the proposed method could be improved by adding new features such as leaf's texture and color [10]. In the near future, we will add an advanced preprocessing process to handle scan-like/photograph images. The computational complexity needs be optimized for practical mobile applications.

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