MOBILE PLANT LEAF IDENTIFICATION USING SMART-PHONES

Bin Wang[1,2]*, Douglas Brown*[2]*, Yongsheng Gao*[2]*, John La Salle*[3]
[1] Key Laboratory of Electronic Business, Nanjing University of Finance and Economics,
Nanjing 210096, China
wangbin@njue.edu.cn
[2] School of Engineering, Griffith University, QLD 4111, Australia
{bin.wang, douglas.brown, yongsheng.gao}@griffith.edu.au
[3] Atlas of Living Australia, CSIRO Ecosystem Sciences, Canberra ACT 2601, Australia
John.Lasalle@csiro.au

ABSTRACT

A novel shape description method is proposed for mobile retrieval of leaf images to aid in plant recognition. In this method, traveling the shape contour, the convexity and concavity properties of the arches of various levels are measured, respectively, to generate a multiscale shape descriptor. Its performance has been tested on two leaf datasets and the experimental results indicated higher recognition accuracies than the state-of-the-art approaches with a speed improvement of more than 170 times. The proposed method has been successfully applied to develop a prototype system of online plant leaf identification working on a consumer mobile platform.

Index Terms—plant identification, shape description, leaf image retrieval, mobile leaf identification

1. INTRODUCTION

Plants play an important role in the cycle of nature. The number of plant species is estimated to be around 400,000, however there still exist many species which are yet unclassified or unknown [6]. Therefore, plant identification is a very important and challenging task. With the rapid progress of information technologies, many works [1], [2], [3], [4] have been dedicated to applying the technologies of pattern recognition and image processing to plant identification. Since leaves are the organ of plants and their shapes vary between different species, the leaf shape provides valuable information for plant identification. In this work, we focus on the shape based leaf identification.

Leaf shape description is the key problem in leaf identification. Up to now, many shape features have been extracted to describe the leaf shape. Wang et al. [1] use the center distance curve, which is generated by calculating the distance between the center of the contour and each contour point, to represent leaf images. Du et al. [5] extract invariant moment features and geometric features including aspect ratio, rectangularity, area ratio of convexity, eccentricity, etc. to describe leaf shape. Wang et al. [6] describe the leaf shape using seven Hu geometric moments and sixteen Zernike moments derived from the binary leaf image. However, due to the large intra-class variations and small inter-class differences of leaf shapes, the above mentioned global features cannot provide powerful discrimination to handle inter-class similarity and intra-class dissimilarity.

Abbasi et al. [7] and Moktarian et al. [8] apply the well-known curvature scale space (CSS) [9] based shape descriptor for Chrysanthemum variety classification. Since this method describes the convex parts of the shape contour based on the assumption that every concavity must be surrounded by two convexities, it has the limitation that it cannot distinguish totally convex shapes. To address this problem, Adamek et al. [10] use the displacement of the contour between two consecutive scale levels instead of curvature to measure the convexity and concavity of the curve. Alajlan et al. [11] propose another multiscale shape descriptor which utilizes the areas of the triangles formed by the boundary points to measure the convexity/concavity of each point at different scales, where the scale is associated with triangle side length. Ling et al. [12] proposed the leading method of inner distance. This method utilizes inner distance rather than Euclidean distance for constructing the shape context descriptors [13] and reported 94.13% recognition rate on the Swedish leaf data set [14]. However, the above methods have an expensive computational cost making them unsuitable for online leaf shape identification.

In this paper, we propose a novel multiscale shape descriptor for mobile leaf identification. The contributions of our work are: (1) a novel multiscale convexity/concavity measurement scheme is proposed for shape description which achieves higher effectiveness and superior efficiency over the benchmark methods on the tested leaf databases; (2) We apply the proposed algorithm to develop a prototype system of online plant leaf identification which works on a consumer mobile platform. This system can conveniently aid recognition and classification of the plant.

2. EXTRACTION OF LEAF SHAPE FEATURES

2.1. Shape Description

A shape contour can be mathematically represented by a coordinate function $C(u) = (x(u), y(u))$, $u \in [0,1)$, where u is the arc length which has been normalized by the perimeter of the contour and denotes the distance traveled from the starting point along the contour in a counter-clockwise direction. Since the shape contour is closed, $C(u)$ is a periodic function and satisfies $C(u \pm 1) = C(u)$. For a contour point $P(u) = (x(u), y(u))$, its arch of size S is defined as $A_u^S = \{P(t) = (x(t), y(t)) \mid u - \frac{S}{2} \le t \le u + \frac{S}{2}\}$, i.e. A_u^S is a piece of curve segment centered on the point $P(u)$. Let $H_u^S(t)$ denote the perpendicular distance from point $P(t)$ to the straight line which connects the point $P(u - \frac{S}{2})$ and the point $P(u + \frac{S}{2})$. $\zeta_u^S(t)$ is defined as a binary function which takes value 1 if the point $P(t)$ falls in the right side of the directed line segment $\overrightarrow{P(u - \frac{S}{2})P(u + \frac{S}{2})}$, and takes 0 otherwise. Then the convexity and concavity measures of the arch A_u^S are defined as

$$f_{\cap}^S(u) = \int_{u-\frac{S}{2}}^{u+\frac{S}{2}} H_u^S(t)\zeta_u^S(t)dt \qquad (1)$$

and

$$f_{\cup}^S(u) = \int_{u-\frac{S}{2}}^{u+\frac{S}{2}} H_u^S(t)(1-\zeta_u^S(t))dt, \qquad (2)$$

respectively. Fig. 1 graphically expresses the means of Eq. 1 and Eq. 2.

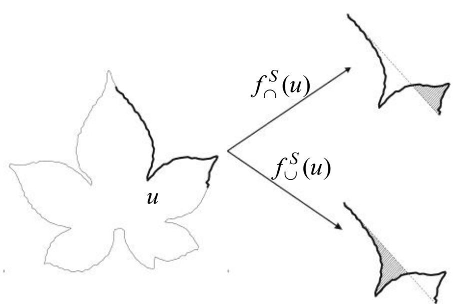

Figure 1. The convexity measure $f_{\cap}^S(u)$ and concavity measure $f_{\cup}^S(u)$ of the arch A_u^S (the bold line represents the arch A_u^S of the contour point $P(u)$).

Fixing the size of A_u^S and varying u from 0 to 1 in the range $[0,1)$, we obtain two 1D functions $f_{\cap}^S(u)$ and $f_{\cup}^S(u)$ which can be regarded as the measures of convexity and concavity properties of the shape contour at a scale level S , respectively. For S at K scale levels, i.e. $S = \frac{1}{2^1}, \frac{1}{2^2}, \ldots, \frac{1}{2^K}$, $2K$ 1-D functions $f_{\cap}^{\frac{1}{2^i}}(u), f_{\cup}^{\frac{1}{2^i}}(u)$, $i = 1,2,\ldots,K$ will be obtained. An example of showing the arches at four scales $S = \frac{1}{2^5}, \frac{1}{2^4}, \frac{1}{2^3}, \frac{1}{2^2}$ is presented in Fig. 2. It can be seen from this figure that the obtained $2K$ 1-D functions operate on multiscale shape information; the functions of smaller scale focus on capturing the shape detail while the functions of larger scales tend to reflect the global properties.

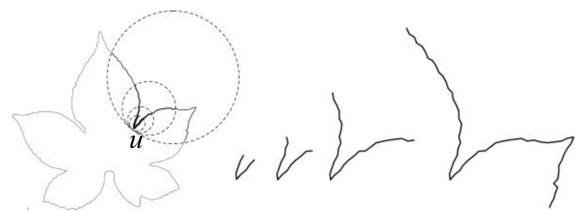

Figure 2. The arches A_u^S of four scale levels $S = \frac{1}{2^5}, \frac{1}{2^4}, \frac{1}{2^3}, \frac{1}{2^2}$ (from left to right).

From the definitions of $f_{\cap}^S(u)$ and $f_{\cup}^S(u)$, they have the intrinsic invariance to the translation of shape contour. However, they are not invariant to rotation and scaling. To achieve scale invariant, for each function, we use its maximum value to normalize it. Since the rotation of the shape contour will change the position of the starting point of the contour, $f_{\cap}^S(u)$ and $f_{\cup}^S(u)$ will become $f_{\cap}^S(u+l)$ and $f_{\cup}^S(u+l)$, respectively, where l is the offset of the start point of the contour, we apply a Fourier transform, retaining the magnitudes of the lowest M order coefficients $|F_{\cap}^S(u)|$, $u = 1,2,\ldots,M$ and $|F_{\cup}^S(u)|$, $u = 1,2,\ldots,M$ to describe the shape. In addition to the Fourier coefficients of $f_{\cap}^S$ and $f_{\cup}^S$, the standard deviations $\sigma_{\cap}^S$ and $\sigma_{\cup}^S$ are taken to further enhance the discrimination power of the shape descriptor.

2.2. Dissimilarity Measure

For shape 1 and shape 2, their shape descriptors are

$\{|F_{1\cap}^{\frac{1}{2^i}}(u)|, |F_{1\cup}^{\frac{1}{2^i}}(u)|, \sigma_{1\cap}^{\frac{1}{2^i}}, \sigma_{1\cup}^{\frac{1}{2^i}}\}$, $i = 1,\ldots,K$, $u = 1,\ldots,M$

and

$\{|F_{2\cap}^{\frac{1}{2^i}}(u)|, |F_{2\cup}^{\frac{1}{2^i}}(u)|, \sigma_{2\cap}^{\frac{1}{2^i}}, \sigma_{2\cup}^{\frac{1}{2^i}}\}$, $i = 1,\ldots,K$, $u = 1,\ldots,M$,

respectively. Let

$$D_{\cap} = \sum_{i=1}^{K}\left(\left|\sigma_{1\cap}^{\frac{1}{2^i}} - \sigma_{2\cap}^{\frac{1}{2^i}}\right| + \sum_{u=1}^{M}\left\| F_{1\cap}^{\frac{1}{2^i}}(u)| - |F_{2\cap}^{\frac{1}{2^i}}(u)\right\|\right)$$

and

$$D_{\cup} = \sum_{i=1}^{K}\left(\left|\sigma_{1\cup}^{\frac{1}{2^i}} - \sigma_{2\cup}^{\frac{1}{2^i}}\right| + \sum_{u=1}^{M}\left\| F_{1\cup}^{\frac{1}{2^i}}(u)| - |F_{2\cup}^{\frac{1}{2^i}}(u)\right\|\right).$$

The dissimilarity D between shape 1 and shape 2 can be measured as

$$D = W * D_{\cap} + D_{\cup}, \qquad (3)$$

where W is the weight parameter.

3. MOBILE LEAF IDENTIFICATION SYSTEM

Modern smart phones embody incredible convenience and performance in an affordable compact low-powered device. These devices possess onboard cameras, GPS receivers and data communication systems. Android OS, having the majority market share for mobile platforms [15], [16] and being open-source, is a good target for application development. The ubiquity of smart phones make them perfect for use as field leaf identification systems, however these devices have less available RAM, storage, network bandwidth and computational power than desktop or server machines which limits the algorithm choices for mobile computer vision applications.

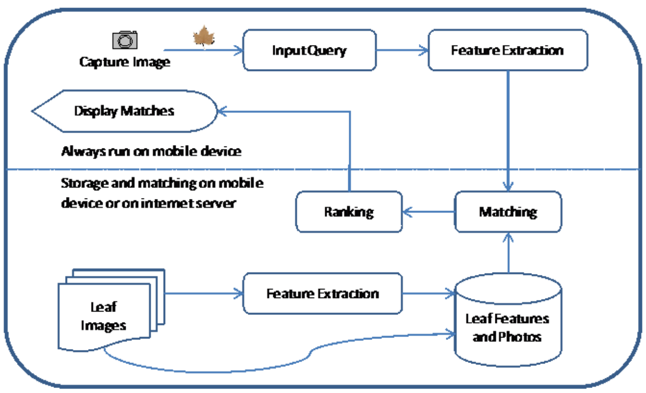

Figure 3. Android mobile application flow diagram

Due to the constraints of the mobile device, which could foreseeably have a sub-600MHz CPU and only 16MB of RAM available to the application [17], it can be tempting to offload some of the processing to a high performance server; however, this requires a reliable internet connection. The other approach is to use fast, efficient algorithms which can run directly on the device, without the need for a network connection or a support server. In our implementation, we provide interfaces to both an online and offline leaf image database. The feature extraction could alternatively be performed at the server for more computationally expensive algorithms. The android mobile application flow diagram is plotted in Fig. 3.

4. EXPERIMENTAL RESULTS

4.1. Performance evaluation and comparison

To evaluate the identification performance of the proposed method, two leaf image datasets are used. One is the widely used Swedish leaf dataset [14], which contains 75 samples each of 15 species of Swedish tree leaves (see Fig. 4). Since it has small number of classes and large number of samples in each class, it is used to test the classification performance. We collected the images for the other dataset. It contains 1200 leaves from 100 plant species (see Fig. 5); we will refer to it as the Leaf100 dataset henceforth. This dataset is used to test the retrieval performance. In all the experiments, the same parameters (K=7, M=7, W=2.2), which are empirically determined for the best performance, are used for the proposed method.

Figure 4. Swedish leaf dataset samples, one image per species.

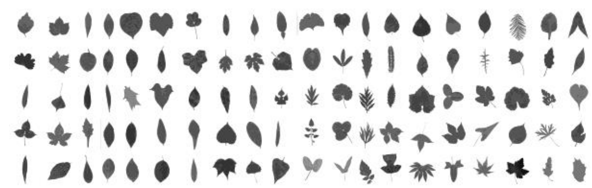

Figure 5. Leaf100 dataset samples, one image per species.

For the Swedish leaf dataset, the same leaf classification protocol and accuracy measurements used in [12] are adopted in our experiment. 25 training samples and 50 testing samples per species are used and the classification rate is calculated using the nearest-neighbor classification rule. The classification rates of the proposed method together with those of the state-of-the-art approaches, including the well-known inner distance (IDSC) [12], multiscale convexity/concavity representation (MCC) [10], Triangle-area representation (TAR) [11] and the classical Fourier descriptor, are presented in Table 1.

Table 1. Classification rates for the Swedish leaf dataset

Algorithm	Classification rate
MCC [10]	94.75%
TAR [11]	95.97%
IDSC [12]	94.13%
Fourier descriptor	87.54%
The proposed	96.05%

The retrieval experiments are conducted on the Leaf100 dataset. The retrieval rate is measured using the well-known "bulls-eye test" [10], [11], [12]. In this measurement, each shape is used in turn as a query and matched with all the shapes in the database. The number of correct matches in the top $2 \times 12 = 24$ matches are counted. Since the maximum number of correct matches for a single shape is 12, the total number of correct matches is $1200 \times 12 = 14400$. The percentage of matched shapes out of 14400 is the retrieval rate of the bulls-eye test. The reported computational time of each shape retrieval is the time to compare the query with all 1200 shapes including the feature extraction time of the query shape. In this section, all the algorithms are implemented in Matlab and run on a PC with Intel Core-2 Duo 2.8 GHz CPU and 2 GB DDR2 RAM under Windows XP. The retrieval results of the proposed method and the benchmark methods are listed in Table 2.

Table 2. Retrieval results for the Leaf100 dataset

Algorithm	Retrieval rate	Retrieval time (s)
MCC [10]	77.10%	2.0×10^{1}
TAR [11]	77.66%	2.3×10^{1}
IDSC [12]	85.64%	1.5×10^{1}
Fourier descriptor	60.12%	4.0×10^{-3}
The proposed	86.86%	8.7×10^{-2}

It can be seen from Table 1 and Table 2 that the proposed method has the best classification and retrieval accuracies and is the second fastest approach among all the competing methods. It is worth mentioning that the proposed method achieves 26.74% higher retrieval accuracy than the fastest approach, i.e. Fourier descriptor, and a high retrieval accuracy is achieved at a speed of over 170 times faster than MCC [10], TAR [11] and IDSC+DP [12]. Therefore, the proposed method is suitable for plant leaf identification on mobile devices.

4.2. Testing on the Mobile platform

Testing was performed on a HTC Pico, 600MHz CPU, 512MB RAM, which is a mid-2011 entry-level device. All code is in Java and the RAM usage is below 10MB. Typical screenshots are shown in Fig. 6.

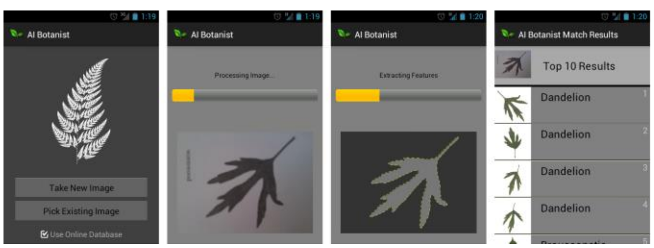

Figure 6. Android mobile application screenshots matching a dandelion leaf.

4.2.1. *Offline leaf recognition*

Using an offline database allows the most reliable and consistent match speed and continues to function without a network connection. Of course it means that all the processes must be done on the device and the entire database must be downloaded initially. For the offline recognition mode of our algorithm, the feature extraction, database search and extraction of the top 10 results takes between 145 - 171ms. The database consists of 300KB of features, and 19MB of images (or 1.5MB if only a single image per class is used for display).

4.2.2. Online leaf recognition

Using an online database can be attractive where the dataset or algorithm is likely to be updated regularly or have large computational and/or memory requirements. It also removes the need to download a local copy of the potentially large database. The disadvantages include the maintenance of the servers, the upload/download delay and bandwidth required to transfer the image and results. In remote areas, where leaf identification applications are likely to be most useful, an internet connection may be unreliable or unavailable.

In our implementation, the online interface involves sending only the feature vector to the server. The feature-extraction is done on the phone itself, drastically reducing bandwidth requirements over transmitting the full image. The server returns a dynamic webpage showing the closest matches to the database which is opened in the device's browser. Clicking on the thumbnail view of a match can redirect to a webpage containing more detailed information about the matched plant.

The feature extraction takes between 112 - 137ms using our method; loading the web page is the limiting factor as it will generally take longer. Of the top 15 available Android leaf identification applications viewed, the majority were expert systems relying on human recognition and categorization of leaf and plant attributes; only two utilized computer vision, both of which relied on transmitting the full image to a server. One claimed less than 5 seconds processing time on a "high powered server" with additional upload times. The propose method is 30 times faster using the limited hardware of the phone itself making the response seem almost instant. This efficiency, together with the high accuracy, detailed in the 4.1 section, makes our algorithm the most attractive for deployment on mobile devices.

5. CONCLUSION

In this work, we have presented a novel shape descriptor for accurate and fast plant leaf identification. An effective multiscale shape descriptor is constructed based on the concave and convex measures of arches of various levels. The performance of the proposed method has been evaluated on the well-known Swedish leaf dataset and our Leaf100 dataset. The experimental results show that the proposed method can achieve higher recognition accuracy than the state-of-the-art methods with an over 170 times faster speed. It has consequently been able to be deployed on a low-powered mobile plant leaf identification system. The deployment on mobile platforms make this kind of application very accessible to government, industry and civilians for use in e.g. assaying plant life for monitoring biodiversity and biosecurity.

6. ACKNOWLEDGMENTS

This research was partially supported by a project funded by the priority academic program development of Jiangsu higher education institutions (PAPD), the key natural science fund for colleges and universities in Jiangsu Province, No. 11KJA520004, and the academic scientific research industrialization projects of Jiangsu province, No. JHB2012-18.

7. REFERENCES

[1] Z. Wang, Z. Chi, and D. Feng, “Shape based leaf image retrieval, ” *IEE Proc. Vis. Image Signal Process., 150 (1),* pp. 34-43, 2003.

[2] J.X. Du, D.S. Huang, X.F. Wang, and X. Gu, “Computer-aided plant species identification (CAPSI) based on leaf shape matching technique, ” *Trans. Inst. Measure. Control, 28 (3),* pp. 275-284 , 2006.

[3] F. Mokhtarian and S. Abbasi, “Matching shapes with self-intersection: application to leaf classification, ” *IEEE Trans. Image Process., 13 (5),* pp. 653-661 , 2004.

[4] C.L. Lee and S.Y. Chen, “Classification for leaf images, ” *Proc. 16th IPPR Conf. Comput. Vision Graphics Image , Process, pp. 355–362, 2003.*

[5] J.X. Du, X.F. Wang and G.J. Zhang, “Leaf shape based plant species recognition, ” *Applied Mathematics and Computation, 185, pp. 883–893, 2007.*

[6] X.F. Wang, D.S. Huang, J.X. Du, H. Xu and L. Heutte, “Classification of plant leaf images with complicated background, ” *Applied Mathematics and Computation, 205, pp. 916–926, 2008.*

[7] S. Abbasi, F. Mokhtarian and J. Kittler. “Reliable classification of chrysanthemum leaves through curvature scale space, ” *ICSSRC97*, pp. 284–295, 1997.

[8] F. Mokhtarian, S. Abbasi and J. Kittler, “Efficient and robust retrieval by shape content through curvature scale space, ”. *Proceedings of the International Workshop Image DataBases and MultiMedia Search, pp. 35 –42, 1996.*

[9] F. Mokhtarian and A.K. Mackworth, “A theory of multiscale curvature based shape representation for planar curves, ” *IEEE Trans. Pattern Anal. Machine Intell., 14, pp. 789-805, 1992.*

[10] T. Adamek and N.E. O'Connor, “A Multiscale representation method for nonrigid shapes with a single closed contour, ” *IEEE Trans. on Circutis and System for Video Technology, 14(5), pp. 742-753, 2004.*

[11] N. Alajlan, I.E. Rube, M.S. Kamel and G. Freeman, “Shape retrieval using triangle-area representation and dynamic space warping, ” *Pattern Recognition, 40, pp. 1912-1920, 2007.*

[12] H. Ling and D.W. Jacobs, “Shape classification using the inner-distance, ” *IEEE Trans. Pattern Anal. Machine Intell., 29, pp. 286-299, 2007.*

[13] S. Belongie, J. Malik and J. Puzicha, “Shape matching and object recognition using shape contexts, ” *IEEE Trans. Pattern Anal. Machine Intell., 24, pp. 509-522, 2002.*

[14] O. Soderkvist, Computer vision classification of leaves from swedish trees. *Master thesis, Linoping Univ., 2001.*

[15] Nielsen, "Nielsen Tops of 2012: Digital." Internet: blog.nielsen.com/nielsenwire/online_mobile/nielsen-tops-of-2012-digital/, Dec. 20, 2012 [Jan. 3, 2013]

[16] Gartner, "Mobile operating system." Internet: en.wikipedia.org/wiki/Mobile_operating_system, Jan. 15, 2013 [Jan 20, 2013]

[17] "Displaying Bitmaps Efficiently." Internet: developer.android.com/training/displaying-bitmaps/, [Jan. 20, 2013]