Transactions of the Institute of Measurement and Control

http://tim.sagepub.com/

Computer-Aided Plant Species Identification (CAPSI) Based on Leaf Shape Matching Technique

Ji-Xiang Du, De-Shuang Huang, Xiao-Feng Wang and Xiao Gu

Transactions of the Institute of Measurement and Control 2006 28: 275

DOI: 10.1191/0142331206tim176oa

Transactions of the Institute of Measurement and Control 28, 3 (2006) pp. 275–284

Computer-aided plant species identification (CAPSI) based on leaf shape matching technique

Ji-Xiang Du[1,2], De-Shuang Huang[1], Xiao-Feng Wang[1] and Xiao Gu[1]

[1]Intelligent Computing Lab, Hefei Institute of Intelligent Machines, Chinese Academy of Sciences, Hefei, Anhui 230031, China
[2]Department of Automation, University of Science and Technology of China

In this paper, an efficient computer-aided plant species identification (CAPSI) approach is proposed, which is based on plant leaf images using a shape matching technique. Firstly, a Douglas–Peucker approximation algorithm is adopted to the original leaf shapes and a new shape representation is used to form the sequence of invariant attributes. Then a modified dynamic programming (MDP) algorithm for shape matching is proposed for the plant leaf recognition. Finally, the superiority of our proposed method over traditional approaches to plant species identification is demonstrated by experiment. The experimental result showed that our proposed algorithm for leaf shape matching is very suitable for the recognition of not only intact but also partial, distorted and overlapped plant leaves due to its robustness.

Key words: dynamic programming; leaf-image database; plant species identification; shape matching.

1. Introduction

Plant species identification is a process in which each individual plant should be correctly assigned to a descending series of groups of related plants, as judged by

Address for correspondence: De-Shuang Huang, Intelligent Computing Lab, Hefei Institute of Intelligent Machines, Chinese Academy of Sciences, Hefei, Anhui 230031, China. E-mail: dshuang@iim.ac.cn

 10.1191/0142331206tim176oa

common characteristics. It is important and essential to correctly and quickly recognize and identify the plant species in collecting and preserving genetic resources, the discovery of new species, plant resource surveys and plant species database management, etc. So far, although many plant taxonomy methods, such as molecular biological approaches, are becoming popular, this time-consuming and troublesome task has mainly been carried out by botanists. However, currently, automatic plant recognition from colour images is one of most difficult tasks in computer vision because of a lack of proper models or representations for the plants; and there are a great number of biological variations that different species of plants can take on. In addition, imprecise image pre-processing techniques, such as edge detection, will cause some features to discriminate different species possibly missed (Du *et al.*, 2004). Thus, because of these difficulties, research and development in computer-aided plant species identification (CAPSI) from colour images is still in its infancy.

Plant leaves are approximately two-dimensional in nature and the shape of plant leaf is one of the most important features for characterizing various plants species. Therefore, it is necessary for us to develop an easy and automatic method that can correctly discriminate and recognize leaf shapes of different species. Some research work has been done on this problem.

Rui *et al.* (1996) proposed a modified Fourier Descriptor (MFD) method to achieve translation, scaling and rotation invariance by considering the distance between the FD magnitude and the phase angle separately so as to decrease the discrimination noises. Abbasi *et al.* (1997) and Mokhtarian *et al.* (1996) proposed a curvature scale space (CSS) image to represent leaf shapes for Chrysanthemum variety classification. Mokhtarian and Abbasi (2004) improved the CSS method and applied it to leaf classification with self-intersection. Wang *et al.* (2002, 2003) descibed a method which combines different features based on a centroid–contour distance curve, and adopted a fuzzy integral for leaf image retrieval.

From the above cases, it is shown that shape features are extremely powerful in recognizing plant species through the leaf. In particular, what must be pointed out is that most of the existing plant recognition methods are based on both the global shape feature and the intact plant leaves. However, for the non-intact leaves largely existing in practice, such as the deformed, partial and overlapped leaves, the global shape features are not efficient and these methods are not applicable. So in our work, we propose a modified dynamic programming (MDP) matching algorithm for leaf recognition.

This paper is organized as follows: In section 2, the polygonal approximation and representation of leaf shape is described and discussed. In section 3, the MDP algorithm for shape matching is presented. The experimental results are reported in section 4. Finally, section 5 concludes the whole paper and gives related conclusions.

2. Shape polygonal approximation and invariant attributes sequence representation

An extracted leaf contour often exhibits too many resolvable points, thus it is not suited to be directly applied to shape matching and the shape representation should be compressed. In this paper, we adopted an accelerated Douglas–Peucker approxima-

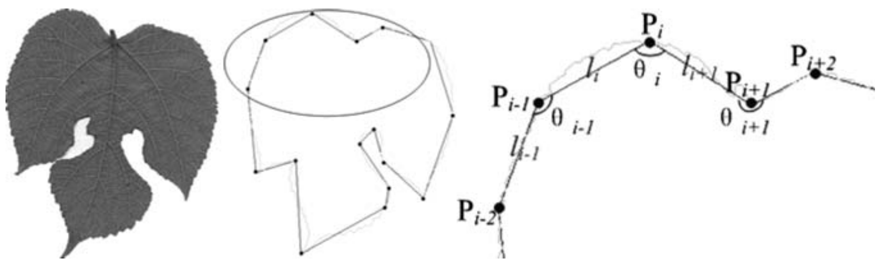

Figure 1 A polygonal representation of contour

tion algorithm (Hershberger and Snoeyink, 1992), a pure geometrical algorithm, to obtain a smooth contour on a smaller number of vertices, which is a better method due to the simplicity and shorter computational time. After performing the polygonal approximation of the contour, a leaf shape can be represented as a sequence of vertices (as shown in Figure 1). The number of the points of this representation is largely smaller than that of the original contours, but it is not invariant to rotation, scale and translation.

Furthermore, to gain the invariant features, another representation method, referred to as the sequence of invariant attributes, is used to represent the shape. Each shape can be represented as a sequence of features or attributes:

$$Q = \{Q_1, Q_2, Q_3, \cdots, Q_n\} \tag{1}$$

For each vertex P_i, selecting two neighbour vertexes P_k and $P_l (i \neq k \neq l)$, a triangle will be formed if these three vertexes are not collinear. For such a triangle, four attributes are defined as $\Delta_{i,k,l} = (\rho, \theta, A, C)$. ρ is the length ratio of two corresponding line segments; θ is the relative angle; A is the area ratio between the current triangle and the triangle $\Delta_{i,i-1,\ i+1}$; and C is the convexity of the corresponding vertex P_i. Thus these four attributes are invariant to rotation, scale and translation.

$$\rho = \frac{l_i}{l_{i-1}} = \frac{|P_i P_{i-1}|}{|P_{i-1} P_{i-2}|} \tag{2}$$

$$\theta = \arccos \frac{|P_i P_{i-1}|^2 + |P_{i-2} P_{i-1}|^2 - |P_{i-2} P_i|^2}{2|P_{i-2} P_{i-1}||P_i P_{i-1}|} \tag{3}$$

$$A = \frac{|P_i P_{i+1}| \sin(\theta_i)}{|P_{i-1} P_{i-2}| \sin(\theta_{i-1})} \tag{4}$$

$$C = \begin{cases} 1 & P_i is \quad convex \\ -1 & P_i is \quad concave \end{cases} \tag{5}$$

For each vertex P_i, the the $\Delta_{i,k,l}$ must satisfy the following conditions:

$$1 \leq |i-k| \leq R_{\max}, 1 \leq |i-l| \leq R_{\max}, i \neq k \neq l \tag{6}$$

where $R_{\max}$ is the maximal number of selected neighbour vertices (in our work $R_{\max} = 2$). Then each of Q_1 is represented:

$$Q_i = (\Delta_{i,i-R_{\max},i-R_{\max}+1}, \cdots, \Delta_{i,i-1,i+1}, \cdots, \Delta_{i,i+R_{\max}-1,i+R_{\max}}) \tag{7}$$

3. The MDP algorithm for shape matching

3.1 Similarity between primitives

In our study, the feature elements are a sequence of invariant attributes; thus the similarity between each attribute of primitives is simply defined as the Euclidean distance:

$$S_C = 0.5{*}\left(1 + \frac{C(I_i)}{C(M_j)}\right) \tag{8}$$

$$S_\theta = 1 - \sin(0.5{*}|\theta(I_i) - \theta(M_j)|) \tag{9}$$

$$S_\rho = 1 - \frac{|\rho(I_i) - \rho(M_j)|}{\max(\rho(I_i), \rho(M_j))} \tag{10}$$

$$S_A = 1 - \frac{|A(I_i) - A(M_j)|}{\max(A(I_i), A(M_j))} \tag{11}$$

where $I = \{I_1, I_2, \cdots, I_n\}$ is the input shape and $M = \{M_1, M_2, \cdots, M_m\}$ is the model shape.

Finally, the combined similarity measure is defined as the weighted sum:

$$S(i,j) = \frac{\sum_{Q_i} S_C \left[\frac{w_\theta S_\theta + w_\rho S_\theta S_\rho + w_A S_\theta S_\rho S_A}{w_\theta + w_\rho + w_A}\right]}{R_{\max}(2R_{\max} - 1)} \tag{12}$$

3.2 Global matching

The goal of a global matching is to find the best-matched pair between the input shape and the reference shapes. Assume that the null symbol λ is to serve as defining the deletion and insertion operations using $a \rightarrow \lambda$ and $\lambda \rightarrow a$, respectively, where in our case, a denotes an attribute node and λ is interpreted as a gap element. Thus, $a \rightarrow \lambda$ means that the second curve is interrupted and a gap element λ is inserted to match with a. We define the cost for both operations, making the insertion of a into one sequence equivalent to its deletion from the other. Thus, the penalty of magnitudes, w_1 and w_2, for both deletion and insertion operations are assigned. If there is no deletion or insertion operation, a penalty w_0 is assigned. So the cost of global matching, GD, can be computed as follows:

$$GD = \min\{D1, D2, D3\} + S(i, j) \tag{13}$$

where

$$\begin{aligned} D1 &= D(i-1, j-1) + w_0 \\ D2 &= D(i-1, j) + w_1 \\ D3 &= D(i, j-1) + w_2 \end{aligned} \tag{14}$$

3.3 Local matching

The cost of interrupting a contour and inserting $k(k \geq 1)$ connected gap elements into the contour, which are matched with k consecutive segments on the other curve, is defined as w_4*log$(k) + w_5$. Thus, we assign a penalty of magnitude w_5 for each single interruption, which is discounted by w_4 for every individual element insertion or deletion. This predefined quantity competes with the lowest cost (or best reward) that can be achieved by k substitutions. A match of k segments, whose cost is higher (less negative) than w_4*log$(k) + w_5$, is considered poor and, in this case, the interruption and gap insertion are preferred. This operation makes it possible to match a gap with a long sequence of segments as required when the curves are partially occluded. On the other hand, the isolated gaps are discouraged due to the high interruption cost. The cost of local matching, LD, can be computed as follows:

$$LD = \min\{D4, D5, D6\} + S(i, j) \tag{15}$$

where

$$\begin{aligned} D4 &= \min_{1 \leq k \leq M-1} [D(k, j-1) + w_3] \\ D5 &= \min_{1 \leq k \leq j-1} [D(i, k) + w_4 {*} \log(k) + w_5] \\ D6 &= \min_{1 \leq k \leq i-1} [D(k, j-1) + w_4 {*} \log(k) + w_5] \end{aligned} \tag{16}$$

Note that to find the minimal value for $D5$, it is not necessary to compare all its k possible values. It is sufficient to keep one index k_0 for each i, such that

$$D5 = D(i, k_0) + w_4 {*} \log(k_0) + w_5 \tag{17}$$

The initial value of k_0 is 1 and after entry $D(i, k)$ has been evaluated, the value of k_0 should be set to k_1 if

$$D(i, k_1) \leq D(i, k_0) + w_4 * \log(k_0) + w_5 \tag{18}$$

A similar argument is applied to the computation of $D4$, $D6$.

It is better to use both the global and local information in assessing the similarity measure between two shapes. The similarity measure between the input shape and the reference shape can be defined as a function of LD and GD. So in our study

$$D = f(GD, LD) = \min(w_G * GD, w_L * LD) \tag{19}$$

where w_G, w_L are the weight of the cost of global and local matching.

Since the shapes for many objects are often closed, the corresponding shape matching should allow the minimum distance path to the wrap-around side of the distance table, accommodating for any cyclic shifts in the signals being matched. In our proposed method, a wrap-around operation was used in initialization (as shown in Equation 20) and local matching. For the calculation of $D(1, j)$ and $D4$, $D(M, j-1)$ is ignored, considering efficient implementation. The omission of this term, however, does not reduce the effectiveness of the algorithm, as the wrap-around case in the final path will not occur more than once for each shape.

$$\begin{aligned} &D(i, j) = S(1, 1) \\ &D(i, 1) = D(i-1, 1) + w_1 + S(i, 1) \\ &D(1, j) = \min[D(M-1, j-1), D(1, j-1) + w_2] + S(1, j) \end{aligned} \tag{20}$$

4. Experimental results and discussions

In our experiments, we used the following plant leaf database, which consists of intact, blurred, partial, deformed and overlapped leaf images of 25 plant species and constructed by our lab. There are 2170 images in our database. A subset of this database is shown in Figure 2.

The experiment is designed to illustrate the superiority of our approach for plant species identification over traditional methods such as Fourier descriptors (MFD; Rui *et al.*, 1996), Hu invariant moment (HM; Chen, 1993), contour moment (CM; Gurta and Srinath, 1987) and the curvature scale space (CSS) image method (Abbasi *et al.* 1997; Mokhtarian *et al.*, 1996) as well as geometrical features (GF; Du *et al.*, 2004).

In the first experiment (Exp1), for each plant species, there are 20 intact leaf images randomly selected from our leaves database as the model images. In addition, there are at least 20 intact leaf images selected from the remaining leaves as input samples. To recognize the class of one input leaf, it is compared with all model images, and the K nearest neighbours are selected. Each of the K nearest neighbours votes in favour of its class, and the class that gets the most votes is regarded as the class of the tested leaf. In our experiment, we set $K = 4$. Then the performance comparison between the GA and the five competitors was implemented, and the results were shown in Table 1.

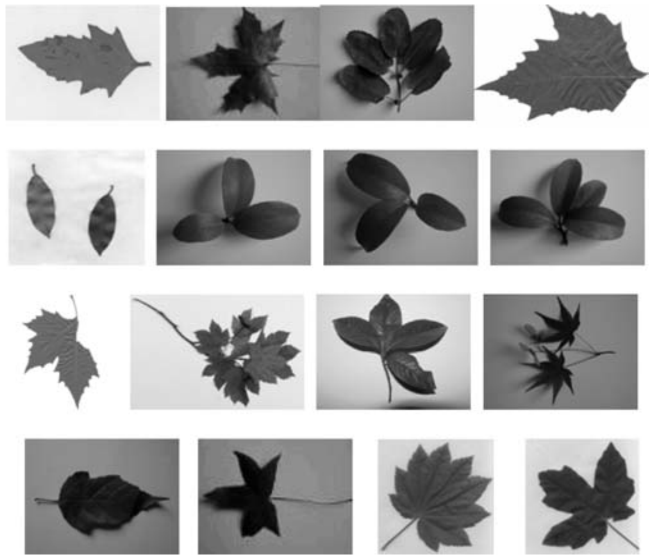

Figure 2 A subset of leaf images database

From Table 1, it can be clearly seen that theses methods are efficient for the recognition of intact leaves, and specifically the MDP and GF methods achieved the best performance. However, note that the MDP algorithm will consume much more time.

To test the capability of recognizing the blurred leaves with the MDP method, each test image used in the above experiment had artificially added Gaussian white noises with zeros-mean and five different variances. The test results were shown in Table 2. In this experiment, only the GF, CSS and MFD comparators are compared. From Table 2, it can be seen that the MDP has better performance in noise toleration and recognition capability than the GF, CSS and MFD method. For the CSS method, the curvature of leaf shape needed to be computed, which is very sensitive to noise. The GF and MFD methods are based on the global features of leaf shape. However the shapes extracted from the noisy leaf images may be deformed or partial.

Next, we will test the capability of recognizing the partial plant leaf. The model samples are the same as above, but for each contour of the input samples of every

Table 1 The performance comparison for different methods

Methods	Average recognition rate (%)
MDP	92.3
GF	92.1
HM	83.4
CM	75.6
CSS	86.1
MFD	89.2

Table 2 The comparison for the recognition results of different noisy levels

Square root of noise variance	Average recognition rate (%)			
	MDP	MFD	CSS	GF
$\sigma = 0$	92.3	89.2	86.1	92.1
$\sigma = 10$	91.1	88.3	85.4	91.3
$\sigma = 20$	90.0	86.7	83.2	89.6
$\sigma = 30$	88.1	84.2	80.6	87.2
$\sigma = 40$	86.6	81.8	75.9	84.6
$\sigma = 50$	84.3	76.8	70.4	80.8

species used in the above experiment, a successive subcontour is randomly extracted to form a partial shape, and the IR (intact rate) is defined as:

$$IR = \frac{P_{Sub\_C}}{P_C} * 100 \tag{21}$$

where P_{Sub_C} is the perimeter of the subcontour.

This experiment was repeated 10 times, and the averaged result is shown in Figure 3. For the MDP method, it is shown that when the shape of leaf can maintain the whole contour information over 50%, the average recognition rate is greater than 70%, but if using the GF, MFD or CSS method to recognize the partial leaves, the accuracy is very low. When the IR is over 90, the correct recognition rate can be accepted. So, the MDP method is a better choice for recognizing partial leaves than other methods.

In additional, the study on leaf image retrieval schemes is also an important stage for developing a (CAPSI). By using such a leaf retrieval method, a number of top-matched leaves together with the whole plant images can be found, which will help to further refine the identification. So in our work, we also use the MDP method for plant leaf retrieval.

In this experiment, there are 50 leaf images randomly selected from our image database as the query images, and each query can retrieve the 20 most similar images

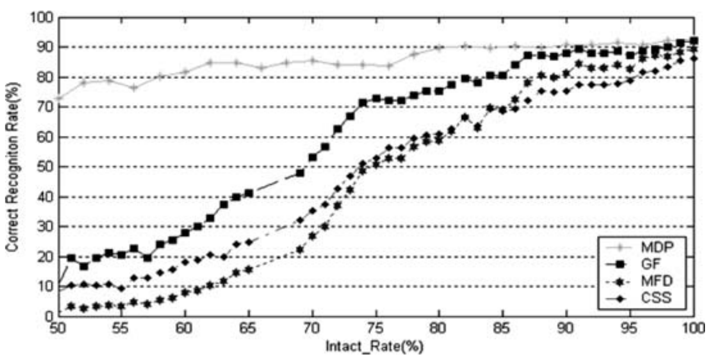

Figure 3 The curves for the correct recognition rates versus IRs

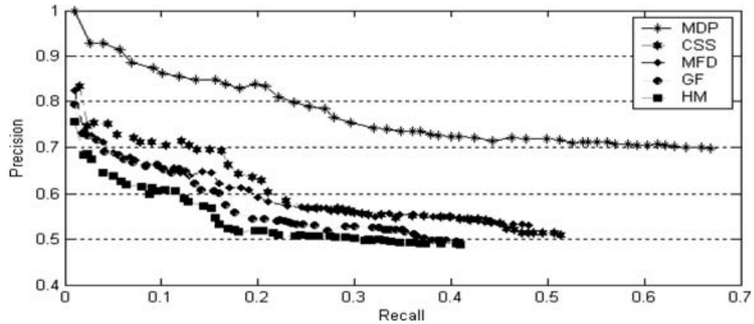

Figure 4 The precision–recall diagram for the leaf image database

from the images database. To evaluate the effectiveness of retrieval for each method, we computed two parameters: precision and recall. The precision is the percentage of similar shapes retrieved with respect to the total number of retrieved shapes, and the recall is the percentage of similarity shapes retrieved with respect to the total number of similar shapes in the database. We present a precision–recall plot for each method. Each method in such a plot is represented by a curve. Each query retrieves the 50 best matches and each point in our plots is the average over 50 queries. The precision and recall values are computed from the 1st to the 50th point and, therefore, each plot contains exactly 50 points. A method is better than another if it achieves better precision and recall.

Figure 4 illustrates the precision recall diagram for the selected queries on the leaf data set. Our proposed MDP method performs much better than the other four methods. Note that our method is the only method with the precision close to 1 for smaller answer sets (*ie*, most of its answers are correct). Figure 5 illustrates a typical query and its 10 best matches retrieved by our method. The results indicate that our method performs better than its competitors on the plant leaf images with moderate amounts of noise and shape details.

5. Conclusions

In this paper, an CAPSI based on a shape matching technique was proposed and performed. First, an accelerated Douglas–Peucker approximation algorithm is

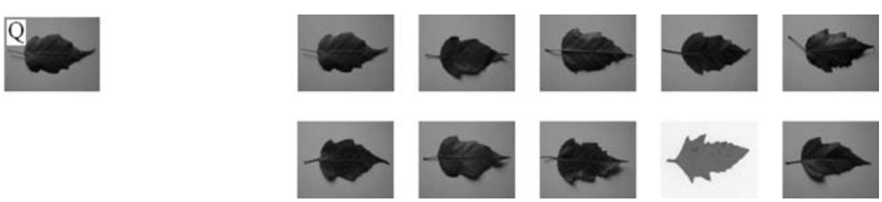

Figure 5 Example of a leaf query and its 10 retrieved results by the MDP method

adopted to the leaf shape approximation, then a shape representation of invariant attributes sequence is used and the proposed modified dynamic programming algorithm for leaf shape matching is presented. The experimental results demonstrated that our proposed method is effective and efficient for the recognition of plant leaves. For recognition of intact leaves, the recognition accuracy of the MDP is over 92% and it performed better than other methods at recognizing blurred leaf images. To classify partial leaves, the experimental results showed that the MDP algorithm is more efficient and robust with respect to other methods. For the retrieval of leaves, our method also performs better than its competitors. So the MDP method is much suitable for the recognition and retrieval of plant leaf images due to its robustness. In future works, we need to combine other features (such as textures or color features) with shape features to recognize and identify living plants and to achieve a more robust and efficient results for practical applications through machine vision and pattern recognition technology.

Acknowledgement

This work was supported by the National Science Foundation of China (Nos. 60472111 and 60405002).

References

Abbasi, S., Mokhtarian, F. and **Kittler, J.** 1997: Reliable classification of chrysanthemum leaves through curvature scale space. *ICSSTCV97*, 284–95.

Chen, C.C. 1993: Improved moment invariants for shape discrimination. *Pattern Recognition* 26, 683–86.

Du, J.X., Wang, X.F. and **Huang, D.S.** 2004: Automatic plant leaves recognition system based on image processing techniques. Technical Report, Institute of Intelligent Machines, Chinese Academy of Sciences.

Gurta, L. and **Srinath, M.D.** 1987: Contour sequence moments for the classification of closed planar shapes. *Pattern Recognition* 20, 267–71.

Hershberger, J. and **Snoeyink, J.** 1992: Speeding up the Douglas–Peucker line simplification algorithm. *Proceedings of the Fifth International Symposium on Spatial Data Handling*, Vol. 1, 134–43.

Mokhtarian, F. and **Abbasi, S.** 2004: Matching shapes with self-intersection: application to leaf classification. *IEEE Transactions on Image Processing* 13, 653–61.

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

Rui, Y., She, A.C. and **Huang, T.S.** 1996: Modified Fourier descriptors for shape representation – a practical approach. *First International Workshop on Image Databases and Multi Media Search*, Amsterdam.

Wang, Z., Chi, Z. and **Feng, D.** 2002: Fuzzy integral for leaf image retrieval. *Proceedings of Fuzzy Systems* 1, 372–77.

Wang, Z., Chi, Z. and **Feng, D.** 2003: Shape based leaf image retrieval. *Image Signal Process* 150, 34–43.