Recognizing Plant Species by Normalized Leaf Shapes

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Abstract

In order to recognize plant species from their shapes, contours of their leaves can be used. Leaves can be classified using their structural property that a leaf consists of triangular pieces that protrude around a polygon. However their shapes have variations even though they belong to the same species. Variations of leaf contours can be represented statistically. However there is variation caused by the large deformation of structural elements of leaves. Because tips of leaf veins can bend according to their environment, shapes of pieces can be deformed largely and influence the descriptions of leaves. It is desirable such deformed shapes be modified to the original undeformed shapes of the leaves in order to reduce the variation of the leaf shapes.

A leaf is considered to be composed of a number of overlapping leaflets which have a single apex and have symmetric shapes with respect to their veins basically. In this paper, a method that normalizes shapes of leaves is presented using the symmetry of each leaflet with respect to its vein. Recognition using normalized shapes of leaves shows improved results compared with the method using unnormalized leaves.

1 Introduction

Because there are a lot of plant species, it is helpful to search a database of plant species using the features of their shapes as indices. Leaves of plants have varieties of shapes. Therefore we can use the features of the leaf shapes in order to discriminate plant species.

We can consider that a leaf consists of leaflets that are overlapped by each other. A leaflet has a single apex which is a convex sharp corner and has a symmetric shape with respect to its vein basically. Therefore we can decompose a leaf into a number of triangular pieces that protrude around a polygon. Pieces of plant spices have varieties of shapes. On each piece, there are a number of teeth. In addition to such complexities of leaf contours, they have variations even though they belong to the same species. There are large variations caused by deformation of structural elements of leaves. Tips of leaf veins can be bent according to their environment and this influences shapes of pieces largely.

There are few methods for recognizing plant species which also use contours of leaves. Abassi [1] represents contours of leaves using curvature scale space images. However they use only peaks of curves in the upper part of the scale space images to compare contours of leaves. Such features can represent only global structures and ignore the detailed shapes of leaves. Tsukioka [5] represents leaf contours using critical points of curvature of them. However because of local variations of curvature of them, the method does not work well.

A method for detecting a detailed pattern on a curve is presented using wavelet local extrema[2]. They detect regular sequences of types of wavelet extrema of contour curvatures. However because shapes of teeth of leaves are not so regular, the method does not work well for detection of teeth.

Problems of the previous methods are lack of ability of representing detailed shapes and inefficiency of representing variations of shapes. Because previous methods described above do not assume any structural properties of leaf shapes, it is unclear which parts should be represented more in detail and which parts have small or large variations. The problem caused by deformation of leaf veins cannot be solved if the structural properties of leaves are not clarified.

In order to solve the problems, we have proposed a hierarchical method for representing leaf contours [3]. We represent detailed shapes of leaves in addition to global structures of leaves. We deal with relatively small variation of contours by using statistical method. However it is desirable that statistics are taken after large variations caused by deformation of leaf veins are removed because the variation influences descriptions of leaves largely. We should use the properties of leaf structures in order to remove such variations.

In this paper, we present a method for recognizing plant species from their normalized leaf shapes using their structural properties. We define a normal form of a leaf shape as a form of which veins are straight. We obtain features from normalized forms of leaves for representing and recognizing leaves of plant species. The results of the method show improved performance compared with the method using unnormalized form.

This paper is organized as follows. In section 2, we describe the hierarchical structure of leaf shapes. Section 3 includes subsections about normalization of leaves, representation of global shapes, that of local detailed shapes and that of teeth. We describe a recognition method in section 4 and experimental results are presented in section 5.

2 Shapes of Leaves

Shapes of leaves are classified into two types[6]. One is simple and the other is compound. Compound leaves consist of non-overlapping leaflets (Fig1). Simple leaves have no separate leaflets and we can consider them to be composed of overlapping leaflets (Fig2,3). When a simple leaf consists of a number of leaflets, we call it a lobed leaf. Lobed leaves are classified to pinnately lobed leaves and palmately lobed leaves. Pinnately lobed leaves consist of leaflets that branch along a main vein. Palmately lobed leaves consist of overlapped leaflets that branch from a base. The number of the leaflets that constitute most of the palmately lobed leaves is constant for the same species.

In this paper, we focus on the species that have palmately lobed leaves. Contours of palmately lobed leaves consist of the contours of leaflets that is not hidden by the other leaflets. As a result, we can consider a leaf consists of a number of triangular pieces (or lobes) that protrude around a polygon (Fig.3). We call a sharp convex corner of a leaf contour an apex and a sharp concave corner a pit. Pieces of leaves for plant species have varieties of shapes. In addition to such features, there are teeth on contours.

Therefore we can represent leaves of the plant species by three classes of features which constitute hierarchical representation. The first class is for global structures and shapes. The second class is for local detailed shapes such as shapes of pieces. And shapes of teeth are represented finally.

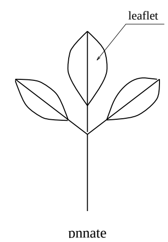


Figure 1: Compound Leaves

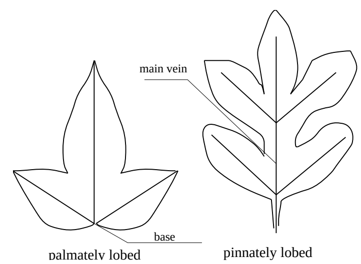


Figure 2: Simple Leaves

3 A Method of Representing Leaves

Because the tips of pieces may bend according to their environment, before describing features of leaves, it is desirable to remove such deformation. From the normalized shape of leaves, we obtain features at each class of the hierarchy. In order to recognize plant species, we represent the features statistically and recognition is done based on a similarity measure which is defined as probability.

3.1 A Method of Detecting Global Structures of Leaves

Before we normalize shapes of leaves, we should detect global structures of leaves because it is necessary to know them in order to obtain an axis of each piece. Because shapes of pieces are triangular, we can detect each piece by an apex and two pits beside it. We can find apexes and pits from the set of critical points of curvature which is calculated from the leaf contour. Because apexes correspond to critical points with high positive values and pits correspond to critical points with high negative values, we can select them based on the critical values.

Contours of leaves are first smoothed enough to remove teeth on them [4] in order to get global shapes of

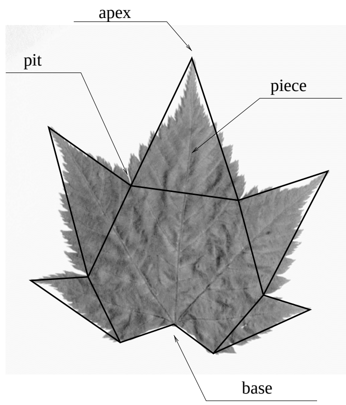


Figure 3: Pieces of a Leaf

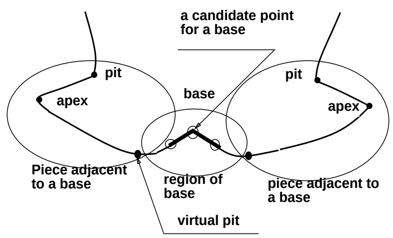


Figure 4: A Bottom of a Leaf

leaves. This can be checked by distances between adjacent zero crossing points of curvature which represent inflection points of the contours. Subsequently, we can detect apexes by selecting critical points with positive value which are larger than some threshold and can detect pits between two adjacent apexes by selecting the points with negative value which are smaller than some threshold.

The region of two piece contours that are adjacent to the base of a leaf is unclear because there are no pits between the base and the apexes of the pieces (Fig.4). We approximate the contour between the apex and the base by two line segments that minimize the difference between the sum of the length of two line segments and arc length between the base and the apex of the piece (Fig.9). We assume a virtual pit of the piece which connects the two line segments (Fig.9,4). The base is found in a region between the two apexes of the pieces by measuring angles formed by three points. One is a candidate point for the base and the other two are the points which have certain distances from this point (Fig.4).

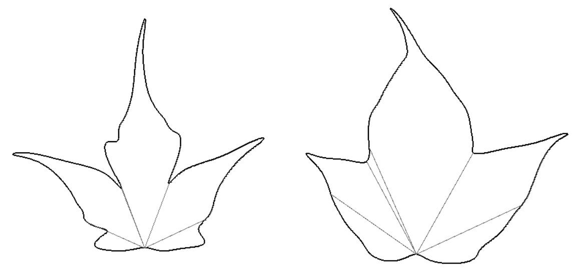


Figure 5: Pairs of Symmetric points

3.1.1 A Method of Normalizing Shapes of Leaves

We can find two points which are symmetric to each other on contours if we assume that lower parts of pieces do not deform so much. One of the candidates for such points is a pit of each piece. Because each leaflet branches from a base, distances from the base to the pair of symmetric points are the same. Therefore we can find a point that is symmetric to the chosen pit by measuring distance from the base(Fig.5). Therefore we can choose a pair of symmetric points for each piece by following procedure.

1. Among two pits of each piece, one which is farther from the base is chosen for a point of the pair.
2. The point which have the same distance from the base as the distance from the base to the chosen pit is selected on the contour of the piece
    - We start to search the symmetric point from the pit which is not chosen to the apex

In Fig.5, lines which connect the base and the chosen pairs are drawn.

Next, we find an axis of each piece. Because contours of pieces are formed by connecting end points of thin veins which branch in parallel from a main vein of each piece, they are basically symmetric (Fig.6). However because of deformation of the axis, the contour becomes asymmetric. The contour shape is unknown in advance and it is difficult to detect veins of a leaf. Therefore we should make an assumption on the deformation of the contour. We can consider that two curves branch from the apex of the piece to the pair of symmetric points obtained in the previous stage. We assume the axis bend in one direction and becomes nearly circular arc. Therefore we can assume every part of each curve stretches or shrinks uniformly. Under this assumption, we can obtain the axis of the piece by following procedure(Fig.7).

Figure 6: Veins of a Leaf

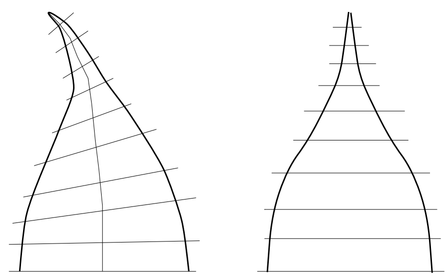


Figure 7: An axis of a piece

1. Each curve is divided into the same number of segments. Let nodes of each curve be $a_1, \ldots, a_n$ and $b_1, \ldots, b_n$.

2. Mid points c_i between a_i and b_i $(i = 1, \cdots, n)$ are computed by $c_i = \frac{a_i + b_i}{2}$. We can assume these points lie on the axis.

3. The segmented axis is obtained by connecting $c_1, \ldots, c_n$.

The obtained axis is straightened to normalize the piece shape. Because the distances from the nodes of the axis to each curve are the same, we can obtain the points on each curve by aligning each segment (c_i, c_{i+1}) along the y-axis and finding points of which distances from the points c_i are $\frac{|a_i - b_i|}{2}$. Therefore the points on each curve can be represented by $\left(\frac{|a_i - b_i|}{2}, \Sigma_{j=2}^{i}|c_j - c_{j-1}|\right)$ and $\left(-\frac{|a_i - b_i|}{2}, \Sigma_{j=2}^{i}|c_j - c_{j-1}|\right)$ where the axis lie on the y-axis. Some of the examples of normalized leaves are shown in Fig. 8. They correspond to contours in Fig. 5.

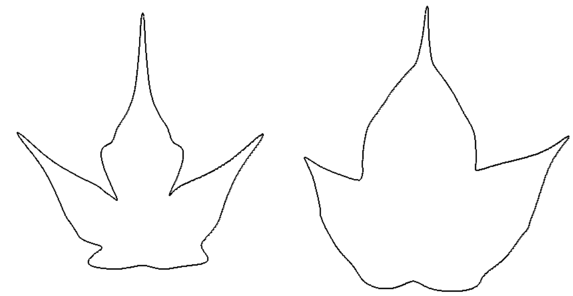


Figure 8: Normalized Shapes of Leaves

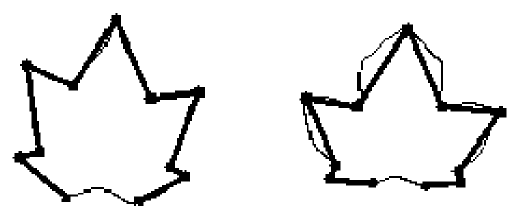


Figure 9: Polygonal Approximation

3.1.2 A Representation of a Global Shape of a Leaf

Using normalized shapes of leaves, we represent the leaf contours hierarchically. Global structures of leaves can be represented by sequences of alternate pits and apexes. We use the changed positions of the apexes for representation. The polygonal approximations that are obtained by the method are shown in Fig. 9.

3.1.3 A Representation of a Shape of a Midmost Piece of a Leaf

For further classification of leaves, we should represent more detailed shapes of leaves. We use only the midmost piece of a leaf, because the hidden part of the contour is small compared to the others and the shape is more stable than the others. Because the curvature of piece contours are low, we approximate the contour using two line segments that minimize a difference between the sum of segment lengths and the arc length between the pit and the apex of the piece. Some of the results are shown in Fig. 10.

Figure 10: Polygonal Approximation of A Mid-Most Piece of A Leaf

Figure 11: Teeth of A Leaf

3.2 A Representation of Features

We represent polygonal approximations that are obtained by the methods by following features.

- The length of each line segment l_i which is divided by the perimeter of the contour of a leaf
- Angle formed by two consecutive line segments θ_i

These features are represented statistically. This means that they are represented by averages and variances of their values.

3.3 A Similarity Measure of Leaves

We define a similarity measure as a probability based on the statistics that are obtained by the method. We assume that the distribution of each feature is normal and independent to each other.

3.4 Detection and Representation of Teeth

A tooth can be represented by an apex and two pits beside it also. In order to detect teeth, contours are smoothed slightly. However because slightly smoothed contours have many triangles created by discreetness of contours, we impose following conditions on critical points that constitute teeth.

- The line that connects two pits should be included inside the contour.
- The height and the base length of the triangles should be larger than some threshold.
- Ratio of the height to the base length of the triangles should be larger than some threshold.

Teeth are detected in order of their sizes and larger teeth which are detected in following stage replaces the smaller one if they include only one tooth because the tips of teeth can be detected in the stage of detecting small teeth. An example is shown in Fig11.

Teeth can be represented by the number, sizes and shapes of triangles that approximate teeth . Each feature is represented statistically except the number of triangles for each leaf. Teeth of each species are represented statistically by regarding these statistical features as features for leaves. A similarity measure is defined in the same manner as that of the global structure.

4 A Recognition Method

Recognition of species of leaves follows the similar process of representing shapes of leaves. Features of global structure and shapes are prior to those of the mid-most pieces for classification. Features of mid-most pieces are prior to those of teeth. First, teeth of leaves are detected and the features are recorded for a sample leaf of unknown species. This stage is done ahead of the other stages because teeth are detected from the contour that is smoothed slightly. Next the contour is smoothed enough and a global structure is detected. Then the shape of the leaf is normalized according to the structure. First, the leaf is classified according to the number of pieces. Second, features for the approximate shape of the leaf are calculated and the leaf is classified according to the value of the similarity measure. If the classification fails, the features for the shape of the mid-most piece are calculated and the leaf is classified according to the value of similarity measure. If it fails again, the similarity measure for the features of teeth which are recorded is used for the classification. If it fails again, we try to append two pieces on the bottom of the leaf or remove from the bottom of the leaf. If it succeeds, the recognition process is repeated.

5 Experimental Results

		1st	2nd	3rd	sum
(a)		0.083	0.000	0.583	0.666
(b)		0.616	0.230	0.000	0.846
(c)		0.462	0.385	0.000	0.847
(d)		1.000	0.000	0.000	1.000
(e)		0.714	0.144	0.000	0.858
(f)		0.846	0.000	0.077	0.923
(g)		0.583	0.000	0.417	1.000

Table 1: Classification Rate for More than 5 Apexes for Unnormalized Form

In this paper, 14 plant species are used for experiments. There are about 10 to 15 testing samples for each species. We choose a sample leaf from the set of leaves as a test leaf to recognize and obtain statistics from the other samples of the set. "1st" in Tables 1,2,5,6 means the first stage of classification based on the approximate shapes of leaves. "2nd" is the second stage of classification according to the shapes of mid-most pieces. "3rd" is the classification based on the teeth. Tables 1,2 shows the classification rate of leaves that have 5 or more than 5 apexes. For the leaves that have relatively many leaves, the effect of normalization is not so large. This indicates the deformation of the pieces are not so large. Table5 and 6 show confusion matrices. Columns of the table show inputs of leaves for each species and rows show the outputs of the system. Because two additional pieces are detected for some testing samples of the species (b), those leaves are first compared to the species (d). However because they are determined that they are not classified to species (d), two pieces at the bottom of them are removed and the procedure is repeated. As a result, they are accepted as the species (b). Only 3 pieces are detected for some testing samples of the species (f) and they are compared with the species of 3 apexes. As a

		1st	2nd	3rd	sum
(a)		0.083	0.000	0.667	0.750
(b)		0.693	0.230	0.000	0.923
(c)		0.615	0.154	0.000	0.769
(d)		1.000	0.000	0.000	1.000
(e)		0.643	0.214	0.000	0.857
(f)		0.692	0.077	0.154	0.923
(g)		0.583	0.000	0.417	1.000

Table 2: Classification Rate for More than 5 Apexes for Normalized Form

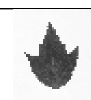
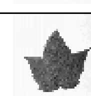
		1st	2nd	3rd	sum
(h)		0.357	0.286	0.071	0.714
(i)		0.308	0.308	0.153	0.769
(j)		0.274	0.181	0.181	0.636
(k)		0.071	0.715	0.000	0.786
(l)		0.083	0.333	0.167	0.583
(m)		0.333	0.133	0.400	0.866
(n)		0.538	0.154	0.000	0.692

Table 3: Classification Rate for 3 Apexes for Unnormalized Form

	(a)	(b)	(c)	(d)	(e)	(f)	(g)
(a)	0.666	0.000	0.000	0.000	0.071	0.000	0.000
(b)	0.167	0.846	0.153	0.000	0.071	0.000	0.000
(c)	0.000	0.000	0.847	0.000	0.000	0.000	0.000
(d)	0.000	0.000	0.000	1.000	0.000	0.000	0.000
(e)	0.167	0.077	0.000	0.000	0.858	0.000	0.000
(f)	0.000	0.077	0.000	0.000	0.000	0.923	0.000
(g)	0.000	0.000	0.000	0.000	0.000	0.000	1.000

Table 5: Confusion Matrix for Species of More than 5 Apexes for Unnormalized Form

	(a)	(b)	(c)	(d)	(e)	(f)	(g)
(a)	0.750	0.000	0.000	0.000	0.000	0.000	0.000
(b)	0.167	0.923	0.231	0.000	0.143	0.000	0.000
(c)	0.000	0.000	0.769	0.000	0.000	0.000	0.000
(d)	0.000	0.000	0.000	1.000	0.000	0.000	0.000
(e)	0.083	0.000	0.000	0.000	0.857	0.000	0.000
(f)	0.000	0.077	0.000	0.000	0.000	0.923	0.000
(g)	0.000	0.000	0.000	0.000	0.000	0.000	1.000

Table 6: Confusion Matrix for Species of More than 5 Apexes for Normalized Form

	(h)	(i)	(j)	(k)	(l)	(m)	(n)
(h)	0.714	0.000	0.091	0.000	0.083	0.000	0.000
(i)	0.214	0.769	0.000	0.000	0.000	0.000	0.000
(j)	0.000	0.000	0.636	0.000	0.083	0.067	0.000
(k)	0.000	0.000	0.000	0.786	0.000	0.000	0.000
(l)	0.000	0.000	0.000	0.000	0.583	0.067	0.000
(m)	0.072	0.231	0.181	0.214	0.251	0.866	0.308
(n)	0.000	0.000	0.000	0.000	0.000	0.000	0.692

Table 7: Confusion Matrix for Species of 3 Apexes for Unnormalized Form

	(h)	(i)	(j)	(k)	(l)	(m)	(n)
(h)	0.856	0.077	0.091	0.000	0.083	0.000	0.000
(i)	0.072	0.769	0.000	0.000	0.000	0.000	0.000
(j)	0.000	0.000	0.818	0.000	0.083	0.000	0.000
(k)	0.000	0.000	0.000	0.786	0.000	0.000	0.000
(l)	0.000	0.000	0.091	0.000	0.750	0.000	0.000
(m)	0.072	0.154	0.000	0.214	0.167	0.933	0.077
(n)	0.000	0.000	0.000	0.000	0.000	0.000	0.923

Table 8: Confusion Matrix for Species of 3 Apexes for Normalized Form

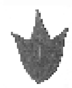
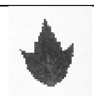
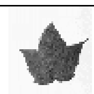
		1st	2nd	3rd	sum
(h)		0.571	0.214	0.071	0.856
(i)		0.230	0.230	0.309	0.769
(j)		0.454	0.182	0.182	0.818
(k)		0.143	0.643	0.000	0.786
(l)		0.500	0.167	0.083	0.750
(m)		0.401	0.266	0.266	0.933
(n)		0.615	0.308	0.000	0.923

Table 4: Classification Rate for 3 Apexes for Normalized Form

result, they are classified to the species (i).

Tables 5,6 show the classification rate of leaves of 3 apexes. In this case, the normalization improves the performance of the classification. Especially, the classification rate at the first stage increases. Table7 and 8 show confusion matrices. Two additional apexes are detected for some leaves of species (h) and (i). They are compared to the species of 5 apexes and they are not accepted as the species of 5 apexes. Addition of two pieces are failed and two pieces are removed and tested. As a result they are accepted as (h) and (i) respectively. Two additional pieces are detected for some leaves of the species (j) and they are classified to the species (b). Some leaves of the species (j) which are unnormalized are classified to the species (g). Two additional pieces are detected for some leaves of the species (m) and they are classified to (f).

6 Discussion

In this paper, we have present a recognition method using normalized shapes of leaves. Examples of the normalized shapes of leaves have shown the effectiveness of this normalization method. Because the tips of pieces usually bend in one direction, the simple assumption we made in order to obtain axes of pieces can produce desirable results. Most of the leaves that have more than 5 apexes do not have effects of normalization. This is because the tips of pieces of such species do not bend largely. The normalization is quite effective for the leaves which have three apexes.

Leaves of some spices have pieces which can bend largely. However because of the height of their pieces, effect of the normalization is small. Leaves of such spices are shown in the sixth row of the table 1,2.

Some leaves are classified to the other species because the number of pieces is different from that of standard leaves of the species. This is because there are large teeth which can be regarded as pieces near the base. Leaves of some species have pieces that are inherently small near the base. Some leaves of such species have a little bit larger pieces. In such cases, more pieces may be detected than expected.

Acknowledgment

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