Shape And Texture Based Plant Leaf Classification

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Abstract. This article presents a novel method for classification of plants using their leaves. Most plant species have unique leaves which differ from each other by characteristics such as the shape, colour, texture and the margin. The method introduced in this study proposes to use two of these features: the shape and the texture. The shape-based method will extract the contour signature from every leaf and then calculate the dissimilarities between them using the Jeffrey-divergence measure. The orientations of edge gradients will be used to analyse the macro-texture of the leaf. The results of these methods will then be combined using an incremental classification algorithm.

Keywords: Plant identification; Shape-based analysis; texture-based analysis; Sobel operator; incremental classification

1 Introduction

The role of plants is one of the most important in the natural circle of life. As they form the bulk of the living organisms able to convert the sun light energy into food, they are indispensable to almost every other form of life. They have interested humans since Greek antiquity and the efforts to classify them is, perhaps, the most ancient activity of Science.

Since the development of a systematic classification of plants by the Swedish botanist Carolus Linnaeus in the 18th century [9], plant classification has been attempted in many different ways. The first person who studied the leaf features in this purpose was L.R. Hicher in 1973.

Since then, with the dramatic development of digital image processing, machine vision and pattern recognition, numerous techniques for plant classification using leaves have been investigated. To contribute to these techniques, this paper proposes to develop a classification system using both shape-based and texture-based analysis.

Section 2 introduces the dataset used in this paper, and the outlines the pre-processing performed.

Section 3 presents the shape-based method which uses the contour signatures of the leaves and calculates the dissimilarities between them using the Jeffrey distance. This method has proven its effectiveness for leaf identification [15, 13, 14, 3, 19].

The texture-based method is presented in Section 4. The most common techniques of texture description are, in general, based on the statistical analysis of the pixels (co-occurence matrices, etc.) [8, 21, 5, 17], and their spectral analysis (Fourier Transform, Wavelet Transform, Gabor filters, etc.)[20, 11, 4, 22, 12, 7, 1].

Although there are numerous techniques for texture classification, few of them have been applied to leaves [6, 10, 18, 2]. The technique implemented by the authors makes use of the Sobel operator to analyse the macro-texture of the leaf.

Finally, Section 5, will present an incremental algorithm used to combine the results of the previous methods using probability density functions.

2 Data Pre-processing

The leaves used in this work were collected in the Royal Botanic Gardens, Kew, UK. The dataset contains 3 to 10 leaves from each of 18 different species.

As the colour of the leaves cannot be used as reliable information, since it varies depending on the period of the year as well as other factors, the data has been transformed into greyscale images. The image background, the paper on which the leaf is mounted, is removed using Otsu's thresholding method [16].

3 Analysis Of The Contour Signature

Two contour signatures are calculated for analysing leaf shapes. For each leaf, first the outline is extracted by selecting from the image the foreground pixels which neighbour a background pixel on at least one of their four main sides (N,S,E,W). Moving in a clockwise direction, for every $\frac{l}{n}^{th}$ contour pixel, where l is the length of the outline and n is the number of points to be sampled, two values, $f(i)$ and $g(i)$ are calculated:

$$f(i) = \sqrt{(cont_x(j) - cent_x)^2 + (cont_y(j) - cent_y)^2} \tag{1}$$

$$g(i) = |\tan(\frac{cont_x(j) - cent_x}{cont_y(j) - cent_y}) - \frac{2i\pi}{n}| \tag{2}$$

Where, $j = \frac{i \times l}{n}$, $cont_x(j)$,$cont_y(j)$ are the x and y co-ordinates respectively for the j^{th} contour pixel, and $cent_x$, $cent_y$ are the x and y co-ordinates of the leaf's centroid.

The first of the resulting signatures f, gives the distances between the contour point and the centre of the leaf. The second, g, is the absolute difference between the angle at the leaf centre between the starting point and the current point, and the corresponding angle on a circle. Together, these two signatures provide a significant amount of information about the leaf's shape.

These signatures are treated like probability density functions (pdfs) by dividing each value by the sum of all the values in the signature. Doing this provides us with scale-invariance. The difference between the signatures for two leaves can then calculated using the Jeffrey-divergence distance measure. For two pdfs, f_a and f_b, the distance between them, $JD(f_a, f_b)$, is calculated as follows:

$$JD(f_a, f_b) = \sum_i \sum_j f_a(i,j) log(\frac{2f_a(i,j)}{f_a(i,j) + f_b(i,j)}) + f_b(i,j) log(\frac{2f_b(i,j)}{f_a(i,j) + f_b(i,j)}) \quad (3)$$

Since the signatures for two leaves may begin at different points on the leaves, the signature must be aligned before they can be compared. This can by using cross-correlation, whereby the amount to offset the second leaf's signature by is calculated as follows:

$$offset = \underset{j=0..(n-1)}{argmin} (\sum_{i=0}^{n} (f_a(i) - f_b(i+j))^2) \quad (4)$$

3.1 Differentiation between lobed and unlobed leaves

Shape-based leaf classification can be improved by differentiating between lobed and unlobed leaves. This can be done by calculating the number of inflection points in the contour distance signature. Each point in the signature is compared to the 3 points either side of it. If the point is either less than all these neighbours, or greater than them, then the point is an inflection point. Once every inflection point has been detected, they are counted and if the total number is above some threshold, the leaf is considered lobed.

Using this method, serrated leaves would be identified as having many lobes. To prevent this, the signature is first smoothed by using a Gaussian filter. The difference between a lobed and a serrated leaf, as well as their contour graphs (normal and smoothed), can be observed in figure 1. The normal graph would give a lot of inflection points for these two leaves and would classify both in the lobed category although only the first one actually is.

3.2 Results

The results of the contour signature method can be seen in table 1. All the leaves in the dataset were compared to all others, and classified as the same species as the closest other leaf. The overall correct classification rate is 69.2%. Whilst some of the species achieved a high recognition rate (with 3 at 100%), many did much worse, with 6 under 50%. Part of reason for this is the high intra-species variation present within some lobed species, and the low inter-species variation between species with ovate leaves. Another cause of errors appears when leaves have overlapping regions, which cause the contours to be incorrectly traced, as shown in figure 2a. Figure 2b shows that petiole (stems) cut that different lengths before imaging the leaves can also cause problems.

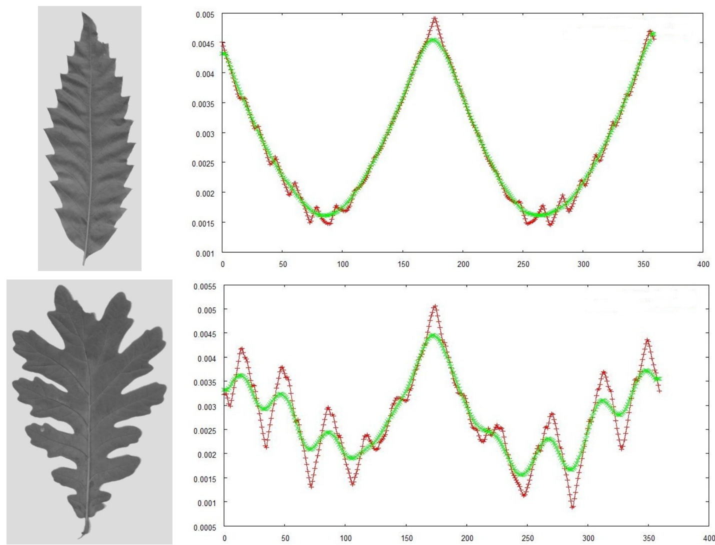


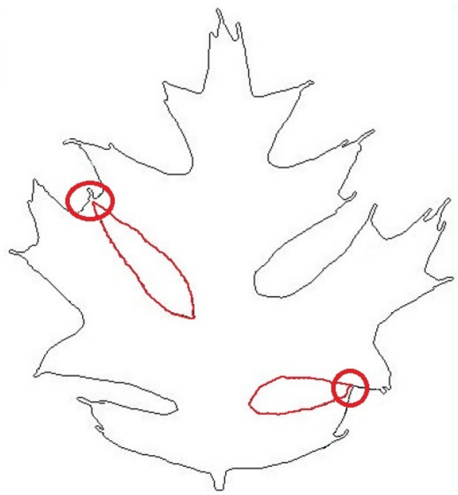
Fig. 1: With the smoothing, the lobed leaf (bottom) is distinguished from the serrated leaf (top)

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
0	0.94	0	0	0	0	0	0	0	0	0.05	0	0	0	0	0	0	0	0
1	0	0.64	0	0	0.08	0.24	0	0.04	0	0	0	0	0	0	0	0	0	0
2	0	0	0.47	0.11	0	0	0.19	0	0	0	0	0	0	0.19	0	0.02	0	0
3	0	0	0	0.56	0	0	0.43	0	0	0	0	0	0	0	0	0	0	0
4	0	0.37	0	0	0.37	0.18	0	0.06	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0.18	0.78	0	0	0.06	0	0	0	0	0	0	0	0	0
6	0	0	0	0.36	0	0	0.64	0	0	0	0	0	0	0	0	0	0	0
7	0	0.22	0	0	0.13	0.19	0	0.38	0.02	0	0	0.02	0	0	0	0	0	0
8	0	0.04	0	0	0.04	0.28	0	0.08	0.40	0	0	0.16	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0.97	0	0	0	0	0	0	0.02	0
10	0	0	0	0	0	0	0	0	0	0	1.00	0	0	0	0	0	0	0
11	0	0.06	0	0	0.07	0.20	0	0.11	0.08	0	0	0.45	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	0.77	0	0.22	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	1.00	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0.11	0	0	0.22	0	0.44	0	0.22	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.00	0	0
16	0	0	0	0	0	0	0	0	0	0.05	0	0	0	0	0.02	0	0.91	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0.22	0	0	0	0.77

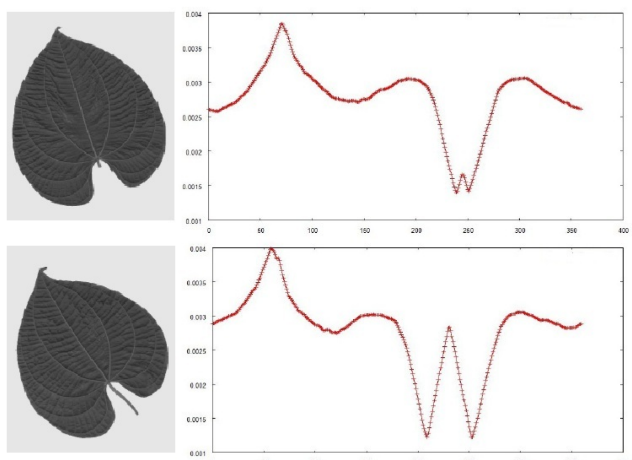
Table 1: The confusion matrix for the contour signatures, including lobe differentiation

4 Texture Analysis Using Sobel

The results for the contour signatures suggest that leaves cannot be adequately classified based on shape alone. The texture is also an important feature of the leaf. Two types of texture can be defined: the micro-texture at the microscopic scale and the macro-texture which is the pattern formed by the venation of the



(a) Overlapping regions



(b) Varied petiole lengths

Fig. 2: The main issues for the contour signature method

leaf. The venation is specific to every leaf, similar to a fingerprint. In this chapter, the concept of macro-texture is quantified using edge gradients.

4.1 Histogram of the gradient intensity

For each image, we calculate a histogram of the gradient orientations, whereby for the angle θ:

$$h(\theta) = \sum_x \sum_y M(x,y) \text{ if } \Theta(x,y) = \theta, 0 \text{ otherwise} \tag{5}$$

Where $M(x,y)$ is the gradient magnitude at pixel (x,y) and $\Theta(x,y)$ is the gradient direction, calculated using the Sobel operator. This histogram provides a description of the relative directions of the main veins. Examples of these histograms for four leaves from the species Quercus Ilex can be seen in figure 3.

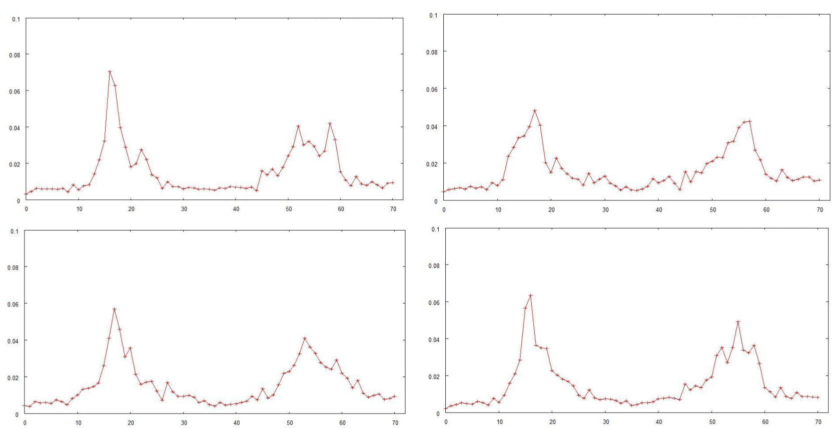


Fig. 3: Sobel direction histograms for four leaves from the same species

The difference between the gradient histograms is again calculated using the Jeffrey-divergence distance measure. The confusion matrix for this method can be seen in table 2. Table 3 shows the correct classification rates for the shape and texture methods. Whilst the Sobel method only achieved a rate of 66.1%, it can be seen that though some species are classified more accurately using the contour method, others do much better using the Sobel method. For instance, the Agrifolia, the 1982 and the 1998-4292 are well recognized by the contour method, due to low intra-species variation, and very badly by the Sobel method, possibly due to uneven lighting in the images. On the other hand, the Ellipsoidalis, the Turneri and the 2005 are better identifyed by the Sobel method, where flatter leaves created less shadowing. It may therefore be possible to greatly improve the overall results by combining the two methods in the correct manner.

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
0	0.27	0.11	0	0	0	0	0	0	0.13	0	0	0	0.13	0	0	0	0.33	0
1	0	0.88	0	0	0.12	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0.77	0.22	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0.25	0.56	0	0	0.18	0	0	0	0	0	0	0	0	0	0	0
4	0	0.37	0	0	0.43	0.12	0	0	0.06	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0.06	0.81	0	0	0.12	0	0	0	0	0	0	0	0	0
6	0	0	0	0.28	0	0	0.72	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0.02	0	0.72	0.25	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0.04	0	0.08	0.76	0	0	0.04	0	0	0	0	0.08	0
9	0	0.03	0	0	0	0	0	0	0	0.32	0	0.11	0.12	0	0.16	0	0.26	0
10	0	0	0	0	0	0.06	0	0.06	0	0	0.75	0	0	0	0	0	0.12	0
11	0	0.03	0	0	0	0	0	0.01	0.02	0.17	0	0.29	0.11	0	0.14	0	0.19	0
12	0	0	0	0	0	0	0	0	0	0	0	0	1.00	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	0.48	0	0.52	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0.11	0	0.88	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0.06	0	0.93	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.00	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.66	0	0.33

Table 2: The confusion matrix for the gradient histograms

5 Incremental Classification

It seems that leaves cannot be sufficiently well classified based on the shape or the texture alone, though good results may be achieved by using both of these features. In order to limit the risks of failure and improve the recognition rate, we will use an incremental classification method. Firstly, the calculation of the inflection points is used to separate the lobed and unlobed leaves. The species which are in the same category as the leaf being analysed are kept and the other species are ignored.

Secondly, a classification using only the contour signature method is performed (the shape of the leaf being the most important feature for classification). Leaves for which the distance between their contour signatures and those of the leaf being classified are greater than some threshold are removed. The same procedure is then performed on the remaining leaves using the texture histograms.

For the final remaining leaves, the distances between both contour signature and the texture histogram are combined, and the leaf is classified as the same species as the closest of these. The results for this are shown in table 4. The overall classification rate is 81.1%, a clear improvement over the separate methods.

6 Conclusion

In this work, an efficient classification framework was proposed to classify a dataset of 18 species of leaves.

Firstly, a classification based on the shape of the leaf is described. Two contour signatures are calculated based on the distance and angle of contour points from the leaf's centre. This operation is done for every leaf of the dataset and the dissimilarties between the graphs are calculated using the Jeffrey distance.

		Contour Score	Sobel Score
1	Agrifolia	0.94	0.27
2	Castaneifolia	0.64	0.88
3	Ellipsoidalis	0.47	0.77
4	Frainetto	0.56	0.56
5	Hispanica	0.37	0.43
6	Ilex	0.78	0.81
7	Robur	0.64	0.72
8	Turneri	0.38	0.72
9	Variabilis	0.40	0.76
10	1982	0.97	0.32
11	1995	1.00	0.75
12	1996	0.45	0.29
13	1998-523	0.77	1.00
14	1998-4292	1.00	0.48
15	2005	0.44	0.88
16	2008	1.00	0.93
17	F184	0.91	1.00
18	Passifloranono	0.77	0.33

Table 3: Results for the two methods

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
0	1.00	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1	0	0.88	0	0	0.12	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0.86	0.13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0.81	0	0	0.18	0	0	0	0	0	0	0	0	0	0	0
4	0	0.37	0	0	0.43	0.18	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0.37	0.56	0	0	0.06	0	0	0	0	0	0	0	0	0
6	0	0	0	0.24	0	0	0.76	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0.02	0	0.75	0.22	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0.04	0	0.16	0.76	0	0	0.04	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0.50	0	0	0	0	0	0	0.50	0
10	0	0	0	0	0	0	0	0	0	0	1.00	0	0	0	0	0	0	0
11	0	0.27	0	0	0	0.06	0	0.07	0.18	0	0	0.40	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0	1.00	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	0	1.00	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0.11	0	0.88	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.00	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.00	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.00

Table 4: The confusion matrix for the final, incremental classification

This classification, called the contour signature method, presents quite good results. Further improvement is made by the separation of the lobed leaves from the unlobed leaves by the calculation of the signature's inflection points.

Secondly, a classification using the Sobel operator is used in order to capture the dissimilarities of the macro-texture of the leaves. A histogram is formed from the orientation and magnitude of the edge gradients. Finally, a method combining the lobe differentiation, the shaped-based and the texture-based method through the use of probability density functions is implemented. The incremental process is intended to extract the most potential from each individual method.

The results show that 10 species out of 18 are successfully classified with a classification rate greater than 85% and 4 with one of more than 75%. The overall classification rate was 81.1%.

The identification of the leaves is a difficult problem because there is often high intra-species variability, and low inter-species variation. Nevertheless, the approach adopted in this work demonstrates the classification of leaves using a combination of relatively simple methods is a valid and promising approach.

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