

## **Stratified classification of plant species based on venation state.**

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### **Abstract**

**This paper presents a novel approach for classifying leaf based on its five types of venation: palmate, parallel, pinnate, uninervous and reticulate. This novel approach is called Binary Directional Pattern (BiDirP); it outperforms traditional Edge Orientation Histogram (EOH) because it reduces the influence of outlier data or noise if the summation of distance in histogram method is used. Besides that, BiDirP index is closer to human perspective and easily categorizes leaves into their venation state as simply as matching their BiDirP index based on their BiDirP venation range. This method is less time consuming as it does not require powerful classifiers that train for longer time in order to get better performance. Overall, BiDirP outperforms the EOH by 11.48% in accuracy; for BiDirP, percentage accuracy of venation classification is 96.02% while it is 84.54% for EOH.**

**Keywords:** Leaf recognition, Binary directional pattern, Leaf venatio, Edge orientation histogram, Canny edge detection.

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### **Introduction**

Leaf veins are hierarchical fine lines of different sizes and patterns found on the surface of the leaf [1-3]. They consist of vascular bundles made of two main transport tissues: xylem and phloem. The arrangements of leaf veins configure a unique and intricate pattern called leaf venation [4,5]. Leaf venation is an important feature for botanists and taxonomists to identify and catalogue a plant species. Leaf venation feature can become a more important key when the plant species is differentiated with similar leaf shape and has similar related characteristics [6-8]. For example, the delimitations of the genera *Shorea* and *Hopea* are supported by leaf venation where both of them are from the family Dipterocarpaceae. Besides that, leaf venation features are used to differentiate plant species from the same genus too, like *Xanthoceroideae* and *Lepisanthes* sensu lato which are from the genera *Sapindaceae* [9]. Also, the pattern of leaf veins gives important information to other fields such as hydraulic efficiency [10,11], theoretical modelling [12], phylogenetic relationship among plant species [13] and pharmacological approaches [14].

In this research, we used stratified sampling to cluster the population of plant species into homogeneous subgroup. Herein, we stratified (sub-population) the leaf species by clustering them based on their lobes, shape, apical, basal, margin and venation. However, we presented the clustering method based on their vein order types, which are: parallel,

pinnate, palmate, uninervous and reticulate venations. The advantages of using stratified sampling are: (i) it reduces the search space, lowers computation and requires less memory capacity for finding a leaf species from a large population; (ii) it reduces the variability in enquiry search space which is able to produce more precise recognition; (iii) minimizes execution time and reduces time for recognizing a leaf species in sub-population or smaller homogeneous sub-group; (iv) is more systematic.

There are some research findings on leaf are based on its density, the angle between veinlet, the thickness or diameter of veinlet and the number of veinlet [15]. These measurements can be easily affected by many other factors, for example the thickness or diameter of veinlet and the number of veinlet can be influenced by the age of leaf. The density of leaf venation is influenced by the resolution of image and the venation detection methods, so the extracted features are unstable and unreliable. However, in this research, Binary Directional Pattern (BiDirP) which is based on the botanical knowledge is utilized. This method is more human perspective and able to divide the leaf into sub-group which can reduce the searching space to match the query image with the sample leaf collected in database. The proposed method is also advantageous when it comes to unclear leaf venation.

## Materials and Methods

### Dataset

In this research, we used Flavia dataset to evaluate our algorithm performance. Flavia dataset encompasses 32 plant species with total leaf samples of 1907 which include 5 general venation states namely, pinnate, palmate, reticulate, parallel and uninervous. The leaf samples are either scanned or photographed, which the author did not state clearly in his article [15]. However, the samples are prepared in  $1600 \times 1200$  resolution, which is considered as low for capturing the information of leaf venation, as the colour contrast of leaf vein and leaf tissue is considered not significant. Therefore, it is a challenging task to extract the information of leaf venation network.

### Vein feature extraction

To localize the edge direction efficiently, the lines extracted from pre-processing  $B$  are further divided into smaller segmented line called  $L$ . In this research, every line segment is bounded by two distinct end points with ten continuous pixels linked between start point  $P_{start}$  and end point  $P_{end}$ .  $L$  is a subset of  $B$ ,  $L \subset B$  and  $L$  is a line segment, parameterized as Equation 1. The parameters  $t$  should be a natural number which is a whole number; that is, a positive number but excluded zero, in this situation, the  $t$  value is  $10$ .

$$L = \{u + tu | t > 0, t \in N\} \rightarrow (1)$$

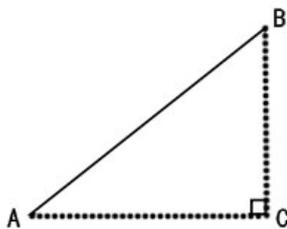


Figure 1. Line segment acting as hypotenuse of right triangle.

The parameter  $u$  represents the starting point;  $P_{start}$  of line segment and  $u + tu$  represents the end point  $P_{end}$  of line segment. The above statement is presented as Equations 2 and 3.

$$P_{start} = u \rightarrow (2)$$

$$P_{end} = u + tu \rightarrow (3)$$

In this case, line segment was assumed as the hypotenuse of a right triangle as presented in Figure 1. The line  $\overline{AB}$  represents the line segment, point A represents the start point of line segment,  $P_{start}$  and  $P_{end}$  denote the end point of the line segment,  $P_{end}$ . However the dash line  $\overline{AC}$  denotes the horizontal distance and the dash line  $\overline{CB}$  represents the vertical distance. The angle of the line segment (angleL) can be

obtained by using Equation 4.

$$\text{angle}L = \tan^{-1} \left( \frac{P_{end}(Y) - P_{start}(Y)}{P_{end}(X) - P_{start}(X)} \right) \rightarrow (4)$$

The directional line segment is basically encoded in eight directions which are  $Angle_i = \{0^\circ, 45^\circ, 90^\circ, 135^\circ, 180^\circ, 225^\circ, 270^\circ, 315^\circ\}$  or equivalent to  $Radian_i, i = \{0, \pi/4, \pi/2, 3\pi/4, \pi, 5\pi/4, 3\pi/4, 7\pi/4\}$ . However, for the line segment which is bent, arbitrary and deviated from being straight line, these are denoted as curve or strands and there are non-directional line segment. In total, the line segment is grouped into nine directional units which are  $0^\circ, 45^\circ, 90^\circ, 135^\circ, 180^\circ, 225^\circ, 270^\circ, 315^\circ, \text{curve}$ . The traditional edge histogram excludes the existence of curve. Leaf venation, especially tertiary venation is in strand condition.

The line segment, which lies along start point  $P_{start}$  and end point  $P_{end}$ , is called directional line segment. Conversely, the non-directional lines do not lie straight but diverge and deviate. Non-directional lines are then grouped into curve unit. Below is an equation to determine whether the line segments are directional lines or non-directional lines.

$$\text{slope} = \frac{P_{end}(Y) - P_{start}(Y)}{P_{end}(X) - P_{start}(X)} \rightarrow (5)$$

$$D = \sum_{i=0}^N |Y_i - [\text{slope} * (X_i - P_{start}(X)) + P_{start}(Y)]| \rightarrow (6)$$

$$\text{lineType}(D) = \begin{cases} \text{directional line, } D < \text{Threshold} \\ \text{non-directional line, } D \geq \text{Threshold} \end{cases}$$

$\rightarrow (7)$

According to Clapham and Nicholson, slope is a statistic which indicates the direction and steepness for a line as presented in Equation 5. Equation 6 computes the total number of each point from line segment that deviated from the straight line with two distinct end points,  $P_{start}$  and  $P_{end}$ . The parameter  $N$  represents the total pixel in line segment and  $i = \{1, 2, 3, \dots, N\}$ . Finally, the total number of deviation,  $D$  determines the categorization of line segment either into directional line or non-directional line, according to Equation 7.

The frequency and number of occurrence of each directional unit is computed as presented in a graphical representation called edge histogram. The edge histogram is well described in the distribution of the venation direction. However, this descriptor is ideal with a complicated statistic representation that cannot be interpreted directly from human perceptible and easily influenced by false edge.

### Converting them into binary pattern

To simplify the Edge Histogram (EOH), we binarized the edge histogram to Binary Edge Histogram (BEH), using thresholding method and finally transformed it into binary directional pattern. In this case, binary directional pattern retains its discriminative power but slightly outperforms the edge histogram as it discards the insignificant outlier or noise.

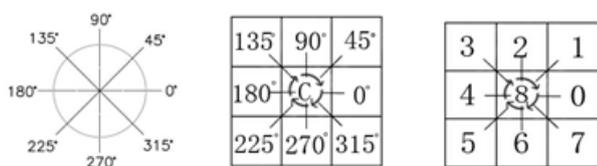
Traditional edge histogram calculates the summation of distance between histogram or uses powerful classifiers to differentiate among them. The former approach may easily be influenced by an outlier data or noise, but with the latter, it takes longer time to learn the dataset. The frequency of each directional unit in edge histogram is equal to 1's if it is greater or equal to a defined threshold (*Threshold*). Conversely, if the

value is less than the defined threshold, the unit directional is equal to 0's. Equation 8 converts the edge histogram to binary edge histogram and Table 1 presents the example of conversion between edge histogram and binary edge histogram.

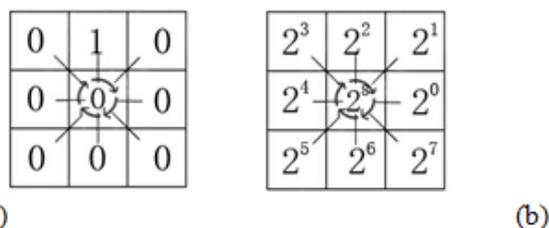
$$H_B(x) = \begin{cases} 0, & x < \text{thres} \\ 1, & x \geq \text{thres} \end{cases} \rightarrow (8)$$

**Table 1.** The example of conversion between edge histogram and binary edge histogram.

Angle code	0	1	2	3	4	5	6	7	8
Directional unit	0	$\pi/4$	$\pi/2$	$3\pi/4$	$\pi$	$5\pi/4$	$3\pi/4$	$7\pi/4$	Non-directional/curve
Angle	337.5 to 22.4	22.5 to 67.4	67.5 to 112.4	112.5 to 157.4	157.5 to 202.4	202.5 to 247.4	247.5 to 292.4	292.5 to 337.4	Non-directional/curve
EOH	11	0	270	0	0	0	0	13	20
Calculation	11<Threshold	0<Threshold	270>Threshold	0<Threshold	0<Threshold	0<Threshold	0<Threshold	13<Threshold	20<Threshold
BEH	0	0	1	0	0	0	0	0	0



**Figure 2.** (a) Angle presented in circle (b) Angle presented in matrix form (c) Angle code presented in matrix form according to its angle or direction.



**Figure 3.** (a) Arrangement of binary edge histogram in  $3 \times 3$  square matrix and called binary edge matrix, MA (b) Binary pattern map in the exponential of two according to direction, MB.

The binary edge histogram is then arranged to  $3 \times 3$  square matrix denoted as DP, according to the directional pattern. In which the centre of the matrix located at  $DP_{22}$  represents the non-directional curve. The left uppermost located at  $DP_{11}$  represents  $3\pi/4$  or  $135^\circ$ . The right uppermost located at  $DP_{13}$  represents the angle of  $\pi/4$  or  $45^\circ$  and so forth. Below is the equation to get the index of Binary Directional Pattern (BiDirP). Figure 2a displays the angle in circle and Figure 2b depicts the  $3 \times 3$  square matrix of angle code according to its direction. Figure 2c represents the range angle in angle code, angle  $\pm 45/2$ . Figure 3a displays the arrangement of binary edge histogram based on the angle code in matrix form as presented in Figure 2. Figure 3b presents the binary pattern

map in the exponential of two according to the angle code presented in Figure 2. The parameter  $D_c$  denotes the total number of column element in matrix and the parameter  $D_r$  denotes the total number of row element in matrix.

### Matching Method

The result of BiDirP is the summation of multiplication of each element in matrix MA and matrix MB. According to the above example in Figures 2 and 3, the index of BiDirP is 4; which means this leaf species possesses parallel venation. Below are the index of BiDirP for other venation types and the calculation of each venation state (Table 2).

**Table 2.** The index of BiDirP for each venation state.

Venation type	Index of BiDirP
Parallel	4
Pinnate	14 or 224
Palmate	14 to 255
Reticulate	>256
Uninervous	0

### Results and Discussion

In this research, we test our novel approach BiDirP with flavia dataset. The average venation classification accuracy for parallel vein using BiDirP and EOH is approximately indifferent at about 95%. BiDirP outperforms EOH with 13.74% for uninervous-veined. For reticulate-veined, BiDirP defeats EOH with 21.83% and achieves 96.98%. The accuracy for discriminate palmate-veined leaves by using EOH is even worse compared to BiDirP. EOH only reaches 61.21% which is 38.34% lower than BiDirP. BiDirP achieves higher classification accuracy which is 91.45 and EOH achieves only

70.59% in pinnate-veined. Uncertain leaf venation either pinnate-veined or reticulate-veined; therefore, both methods are achieved at 100% accuracy. Overall, BiDirP outperforms the EOH by 11.48%, where venation classification percentage for BiDirP is 96.02% and EOH, 84.54%.

## Conclusion

This paper has presented a novel approach for leaf venation classification that outperforms a traditional Edge Orientation Histogram in terms of time usage and accuracy percentage. Our algorithm is tested by Flavia dataset of which the sample plant species comprises five basic different venation states namely pinnate, parallel, reticulate, palmate and uninervous. The Stratified Sampling approach divided the plant species into several venation state groups which reduced the searching space when undergoing plant identification. The suggested novel approach named BiDirP has promising result, as an advanced traditional Edge Orientation Histogram with 11.48% accuracy on leaf venation classification. The other leaf part such as leaf margin, apex, base, shape, lobes and sinuses are suggested using Stratified Sampling approach too, as subdivide them into group before undergo numerical analysis can largely reduce the search space to match plant species.

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