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Leaf Identification Using Fourier Descriptors and Other Shape Features

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Abstract

Leaf identification is a challenging research. So far, many approaches have been proposed. In this paper, an approach that combines Fourier descriptors with other shape features was investigated to identify 100 hundred kinds of leaves. The result shows that the combination of Fourier descriptors and several other shape features can be used to identify leaves with the accuracy rate of 88%. This result indicates that this approach is a promising way for identifying leaves.

Keywords: Fourier descriptor, leaf identification, shape features

1 Introduction

So far, many researchers have proposed various approaches in identifying leaves in order to develop a system that can help ordinary people to identify plants based on a leaf. The features used in the identification systems can be classified into shape or morphological features, texture features, margin features, vein features and color features. Some researchers combined some of those feature types. For example, Herdiyeni et al. [3] used shape/morphological, texture, and texture features for identifying 30 species of medicinal plants. Kadir et al. [4] applied shape, texture, vein, and color features in identifying 50 kinds of plants. Mallah et al. [7] integrated the shape, texture and margin features in classifying 100 kinds of plants.

Various shape features were used in the leaf identification systems. Hu geometric moments and Zernike orthogonal moments were used by Wang et al. [12]. Hu geometric moments were also used by Zulkifli [14]. Kulkarni [5] combined features extracted by using pseudo Zernike moments and other features. Meanwhile, aspect ratio, compactness, centroid and vertical and horizontal projections were used by Lee and Chen [6]. However, combining shape features (and other non-shape features) is a challenge because fusion of features does not always give a good accuracy rate.

Various classifiers were involved in the leaf identification systems. Probabilistic neural network (PNN) was used in [3]. General Regression Neural Network (GRNN) was applied in [14] and Radial Basis Probabilistic Neural Networks (RBPNN) was tested in [5]. Meanwhile, Linear Discriminant Analysis (LDA) was used by Shabanzade et al. [11]. Each classifier has the advantages and disadvantages. For example, PNN is fast to identify a leaf, but it needs a lot of training samples. So, the selection of a classifier is also a challenge.

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The purpose of this research was to explore Fourier descriptors and other shape/morphological features to capture the shape of leaves so it could be used to identify a leaf with high accuracy without any other information such as its color, vein and texture. Other information would be used to increase the higher accuracy in other researches. The Fourier descriptors were chosen based on their good performance in several applications: protein classification [1], vehicular shape-based objects [13] and fingerprint classification [9]. However, some other shape/morphology features were explored to support Fourier descriptors in order to get high accuracy in identifying leaves.

2 Materials and Methods

2.1 Fourier Descriptors

Fourier descriptors (FD) are usually used for representing the shape of an object by using Fourier transform. Those descriptors have been introduced by Cosgriff in 1960 [8]. The descriptors are calculated based on the contour of the object. If $\mathbf{x}$ is the vector of all x values in the boundary object containing N pixels and $\mathbf{y}$ is the vector of all y values in the boundary object containing N pixels, a complex number of pair of x and y can be written as follows:

$$\mathbf{z} = \mathbf{x} + j\mathbf{y} \tag{1}$$

Then, the Fourier descriptors of z can be calculated by using the following formula:

$$Z[k] = \frac{1}{N} \sum_{m=0}^{N-1} z[m]\, e^{-j2\pi mk/N}, \quad (k = 0, ..., N-1) \tag{2}$$

In practice, Fast Fourier Transform (FFT) is used for calculating $Z[k]$.
Some properties in the Fourier descriptors are as follows:

- $Z'[k] = SZ[k]$ for scaling;
- $Z'[k] = Z[k] + z_0\delta[k]$ for translation (So, it influences the DC component Z[0] of the FD);
- $Z'[k] = Z[k]\, e^{j\phi}$ for rotation;
- $Z'[k] = Z[k]\, e^{-j2\pi mk/N\phi}$ for shifting the starting point in the boundary from 0 to m.

To normalize the Fourier descriptors (FD) from all those properties, some actions are done by using the following pseudo-code:

$(1) G \leftarrow FD$

$(2) G \leftarrow G/|FD(0)|$

$(3) G \leftarrow |G|$

In this case, the step 2 is used for normalizing the descriptors from scaling, translation and moving the starting point, by dividing with the DC component. Meanwhile, the step 3 is used for normalizing the descriptor from rotation by taking the magnitude of the complex numbers.

Figure 1. A leaf and its convex hull.

2.2 Other Shape/Morphology Features

Other shape/morphology features that can be used in leaf identification systems are aspect factor, roundness factor, irregularity factor [8], solidity [10]and convexity [10]. How to calculate all these features is shown in Eq.(1)-(7). Two of them involve convex hull of the leaf. Figure 1 shows an example of leaf convex hull.

$$aspect\ ratio = \frac{width\ of\ leaf}{length\ of\ leaf} \tag{3}$$

$$roundness\ factor = \frac{4\pi A}{p^2},\ where\ A = leaf\ area\ and\ p = leaf\ perimeter \tag{4}$$

$$irregularity = \frac{radius\ of\ the\ maximum\ circle\ enclosing\ the\ leaf}{radius\ of\ the\ minimum\ circle\ can\ be\ contained\ in\ the\ leaf} \tag{5}$$

$$solidity = \frac{area\ of\ the\ leaf}{area\ of\ the\ convex\ hull} \tag{6}$$

$$convexity = \frac{perimeter\ of\ the\ leaf\ convex\ hull}{leaf\ perimeter} \tag{7}$$

2.3 Bayes Classifier

Bayes Classifier follows Bayes rule as shown in Eq.(8) [2].

$$P\left(\omega_i \left| x \right.\right) = \frac{p\left(x \left| \omega_i \right.\right) P\left(\omega_i\right)}{p\left(x\right)},\ p\left(x\right) = \sum_{i=1}^{c} p\left(x \left| \omega_i \right.\right) P\left(\omega_i\right) \tag{8}$$

In the above formula, $p\left(x\right)$is a priori probability of class ω_i; $P\left(\omega_i \left| x \right.\right)$is a posteriori probability density function (pdf) of x_i; $p\left(x \left| \omega_i \right.\right)$ is the class conditional pdf of x given ω_i where $i = 1, 2, ..., c$ and c is number of classes. The data in each class is distributed to the Gaussian distribution $N\left(m_i, S_i\right)$, where $m_i$is the mean of the class ω_i and $S_i$is the covariance matrix of the class ω_i. Then, x is assigned to the class ω_i if it fulfills Eq.(9).

$$P\left(\omega_i \left| x \right.\right) > P\left(\omega_j \left| x \right.\right),\ \forall j \neq i \tag{9}$$

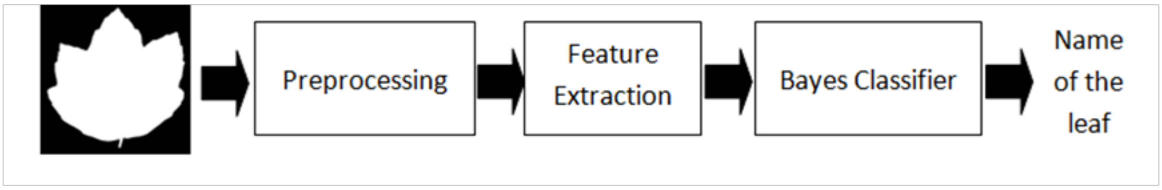

Figure 2. Identification process of a leaf.

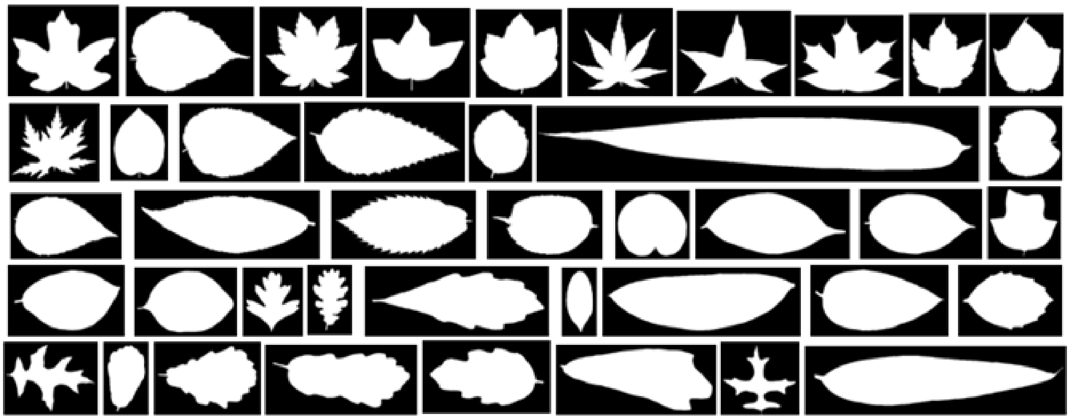

Figure 3. Samples of the dataset.

3 Proposed System

The block diagram of the proposed system is illustrated in Fig.(2). The image of leaf was preprocessed so the part of the leaf can be separated from its background by using Canny operator. After that, features of the leaf were extracted. Then, the features were processed by using the Bayes classifiers. In this case, some precalculated features of some leaves were used for decision making in identifying the leaf.

4 Experiment Results

To test the system, a dataset containing 100 plants [7] was used. Some of them are shown in Fig.(3). The dataset contains 16 samples of each leaf. 20% of the samples was used as testing leaves and the rest (80%) was used as reference leaves. So far, the dataset contains leaves with black and white colors. Therefore, only shape/morphology and margin features can be calculated. In this case, only shape/morphology features were tested.

The accuracy rate was calculated as follows:

$$Performance = \frac{Number\ of\ relevant\ images}{Total\ number\ of\ query}$$

Testing based on the above formula shows that the system can gave 88.03% of accuracy rate.

5 Conclusion

The proposed leaf identification system gave 88.03% of accuracy rate. Actually, this accuracy is lower than the original result by Mallah et al. [7], that included margin and texture features. However, this result is good enough in capturing the shape of leaves. So, by adding the margin features and other features, it is possible to increase the accuracy of the system. Therefore, some experiments will be conducted for improving the performance.

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