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LEAF RECOGNITION SYSTEM BASED ON MORPHOLOGICAL AND DISCRETE WAVELET TRANSFORM WITH PROBABILISTIC NEURAL NETWORK

Özkan Arslan [*]

[*] Electronics and Communication Engineering, Tekirdağ Namık Kemal University, Tekirdağ, Turkey

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ABSTRACT

In this study, it is aimed to classify leaf species by using morphological and wavelet features with probabilistic neural networks. The morphological features of the leaf images as eccentricity, form factor, the ratio of the secondary axis to the main axis, the ratio of the convex shell to the perimeter, rectangularity, extent and solidity is used. The mean, standard deviation, energy and entropy which are calculated by wavelet coefficients in two level sub-bands are used as features. The effects of the features used in this study on the success of classification were investigated. The radial based probabilistic neural network is used for the classification process. The results obtained from the study showed that 92.5% of the leaf species by using the morphological features were correctly classified. In case of the entropy features obtained by the wavelet transform are added to these morphological features, 97.5% of the leaves species are correctly classified. All experimental results show that the use of entropy features obtained by the discrete wavelet transform with the morphological features in the leaves species image classification provides higher accuracy classification compared with other feature combinations.

KEYWORDS: leaf recognition, morphological, wavelet transform, entropy, probabilistic neural network.

1. INTRODUCTION

In the world, the existence of 310,000-450,000 plant varieties is known with the emergence of new species. Besides nature and environmental protection, the value of the studies on plant species significantly increases due to their intensive use in the field of medicine and industry [1]. In recent years, studies on the protection of plants and the continuation of the species belonged to have a great importance. Nowadays, plant classification is mostly done by traditional methods. An automatic leaf type recognition system is very useful in classifying and understanding plant species. Recognition of plant species by machine learning will increase quality and speed in industrial processes.

In recent years, image recognition has become one of the important areas of digital image processing. Image recognition is usually carried out in three steps, including image preprocessing, feature extraction from the image, and classification that allows these features to be classed or categorized into images. There are various methods of classification of leaf images, containing statistical methods using histograms and gray levels of pixels, model-based such as the Markov chain or wavelet-based signal processing methods [2]. Uluturk et al. proposed a method of dividing the leaves into two parts and they used 10 morphological features for two part of leaves. Then, all features were used as input in a Probabilistic Neural Network (PNN) and 92.5% accuracy rate was obtained [3]. In another leaf recognition study, Hossain et al. [4] used shape features which are area, perimeter and eccentricity with PNN structure. The leaf type recognition accuracy rate of this method was found to be 91.4%. Kadir et al. [5] proposed method that uses the color, shape and texture features of the leaves image. All features used as input in a PNN and accuracy rate were obtained as 95%.

In this study, the features used for leaf recognition are mainly examined in two parts. These are morphological features of the leaf image and wavelet transform-based features derived from the wavelet coefficients in the different sub-bands of the leaf image [6].

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2. MATERIALS AND METHODS

The leaf species classification system based on image processing developed in this study consists of five main sections as seen in Figure 1. As can be seen from Figure 1, the image of the leaf type is subjected to filtering pre-processing in order to de-noising. Then, the leaf image is segmented and the center of the leaf is located. The segmented leaf image is bisection from the center. The morphological and wavelet transform based features are extracted from the right and left parts of the bisection image. These extracted features are used in the training and testing of artificial neural network classifier and the performance of the system is measured.

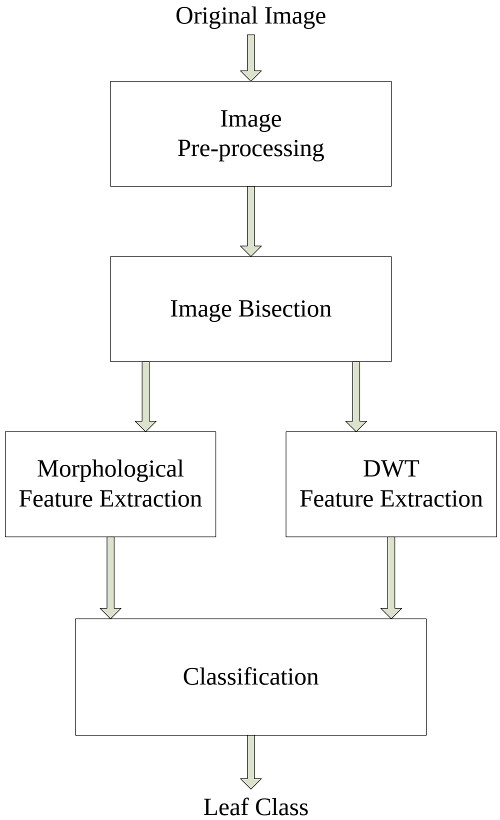

Figure 1 The block diagram of the leaf image recognition

2.1 Image Pre-Processing

The first stage of preprocessing is the conversion from RGB to gray. Then, the median filter was used to smoothing the image. A white leaf image was obtained on a black background with the conversion to a binary image. The image background was then discarded and the leaf region of interest in the image was obtained as shown in Figure 2 [3].

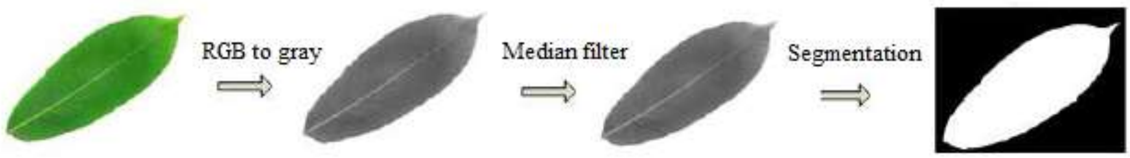

Figure 2 The pre-processing steps

2.2 Image Bisection

In order to extract the features based on morphological and wavelet transform, segmented leaf images are divided into two by orienting them at an angle from the center point. Thus, the leaves can be split into two parts evenly perpendicular to the horizontal axis. The rectification and bisection process are shown in Figure 3.

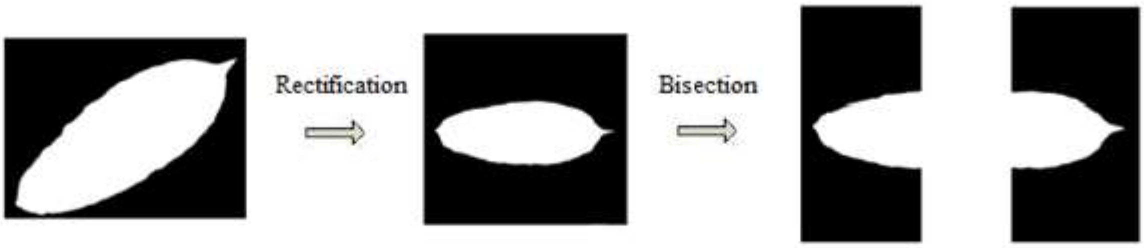

Figure 3 Rectification and bisection the image

2.3 Morphological Feature Extraction

Morphological features obtained from the geometric properties of the image were used in the classification of leaf images. These morphological features:

1. ***Eccentricity:*** The ratio of the length of the main inertia axis of the segmented image to the length of the secondary inertia axis. The value varies between 0 and 1.

2. ***Form factor:*** It refers to the ratio of interest to the image perimeter.

3. ***The ratio of the secondary axis to the main axis:*** This feature, which is the inverse of the height aspect, refers to the ratio of the secondary axis to the main axis.

4. ***The ratio of the convex shell to the perimeter:*** The ratio of the convex shell circumference to the perimeter of the leaf.

5. ***Rectangularity:*** The ratio of the area of the leaf region to the product of the main and secondary axis lengths.

6. ***Extent:*** A numeric value that refers to the ratio of pixels in a given region to pixels within the total surrounding rectangle.

7. ***Solidity:*** The ratio of the interest area to the area of the convex shell.

2.4 Feature Extraction Based on Discrete Wavelet Transform

The Discrete Wavelet Transform (DWT) is a special form of wavelet transformation that facilitates computability at time and frequency and enables a sign to be shown as a single piece. The discrete wavelet transform is expressed as follows:

$$W(j,k) = \sum_j \sum_k x(k) 2^{-j/2} \psi(2^{-j/2} n - k) \qquad (1)$$

where ψ is a time function with finite energy and it is called the main wavelet [7].

The Discrete Wavelet Transform is based on the principle of calculating the detail and approximation coefficients by high pass and low pass filtering indicated by Equations 2 and 3.

$$y_h[k] = \sum_n x[n] g[2k - n] \qquad (2)$$

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$y_l[k] = \sum_n x[n]h[2k-n]$ (3)

where $y_h[k]$ and $y_l[k]$ are denote high pass g and low pass h filters, respectively.

In the 2-dimensional wavelet transform, scaling and wavelet functions are extracted from one-dimensional wavelet transform as in Equations 4-7 [8].

$\varphi_{LL}(x,y) = \varphi(x)\varphi(y)$ (4)

$\phi_{LH}(x,y) = \phi(x)\varphi(y)$ (5)

$\psi_{HL}(x,y) = \psi(x)\varphi(y)$ (6)

$\psi_{HH}(x,y) = \psi(x)\psi(y)$ (7)

Figure 4 shows two levels decomposition of an image using wavelet transformation. The image is primarily divided into 4 regions by passing through low and high pass filters. $I_{LL}^{(2)}$ (A2) refers to the approximation sub-images of the original image decomposed by wavelet transform, $I_{LH}^{(2)}$ (V2), $I_{HL}^{(2)}$ (H2), and $I_{HH}^{(2)}$ (D2), vertical, horizontal and diagonal detail sub-images of the original image, respectively. This process continues at each level through the approximation sub-bands.

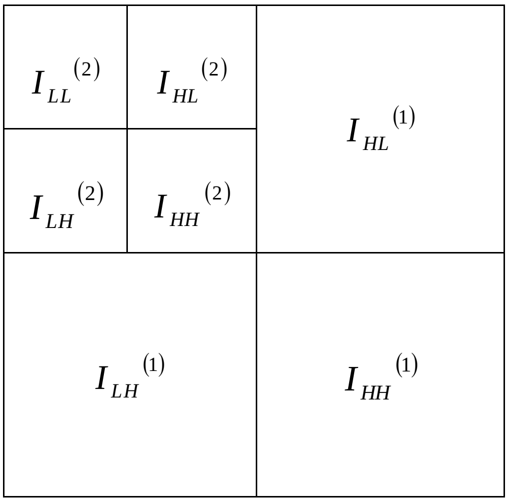

Figure 4 Two level wavelet decomposition in the image

In this study, which is performed in order to classify leaf images, the images were decomposed into 7 sub-bands consisting of approximation and detail coefficients by decomposing 2 levels with the db4 wavelet function which is successful in image classification in a similar study. In Equations 8-11, features such as energy, entropy, standard deviation, and mean to be used in the classification by using the approximation and detail coefficients for each sub-band were extracted [9]. At the end of the feature extraction process with DWT, a total of 56 features were extracted, 28 for each leaf image region (left and right).

$Mean_s^{(i)} = \frac{1}{N^2}\sum_{x,y=1}^{N} d(x,y)$ (8)

$SD_s^{(i)} = \left\{\frac{1}{N^2}\sum_{i,j=1}^{N}\left(d(x,y) - Mean_s^{(i)}\right)^2\right\}^{1/2}$ (9)

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$$Entropy_s^{(i)} = \frac{1}{N}\sum_{i,j=1}^{N}|d(x,y)|^p \quad 1 \le p < 2 \qquad (10)$$

$$Energy_s^{(i)} = \sum_{i,j=1}^{N} d^2(x,y) \qquad (11)$$

where i represents DWT level, s denotes LL, HL, LH and HH sub-bands. $d(x,y)$ and N represent wavelet coefficients and the size of each sub-band, respectively.
The features extracted using the db4 wavelet function is combined with the morphological features to find the features that increase the success of the classification. In this study, radial based probabilistic neural network (PNN) was used as the classifier.

2.5 Probabilistic Neural Network

Probabilistic neural networks (PNN) are commonly used in automatic pattern recognition, probability of membership in class and estimation of similarity ratio [10-12]. PNN is one of the most suitable classifiers for leaf recognition. It produces stable results by learning quickly. It also offers a convenient structure for training and testing. For these reasons, probabilistic artificial neural network was used in the development of leaf recognition system. In the formation of the probabilistic neural network, 7 morphological features as input vectors, as well as the features obtained from wavelet transform were added to measure the success of classification. These features were used in both the training and testing stages. The spread value of radial-based functions is an important parameter of the PNN [3]. Figure 5 shows the basic structure of PNN. As can be seen from the Figure 5, the PNN consists of three parts: input layer, hidden layer and class layer. The results from the classes are evaluated by a decision rule and the output is determined.

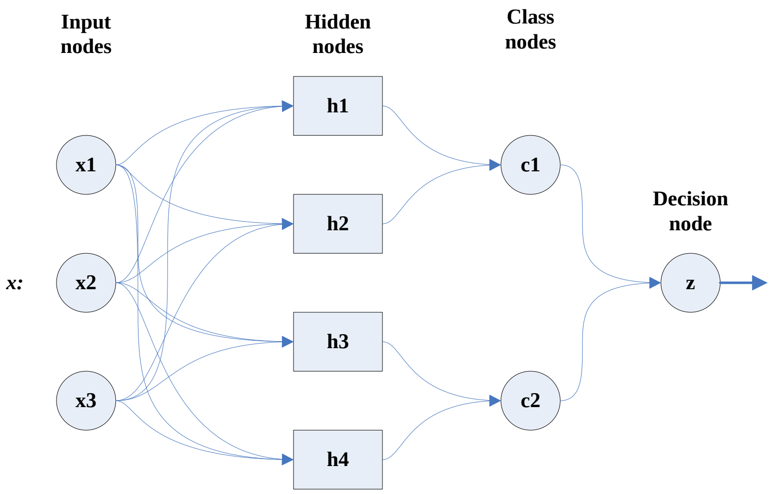

Figure 5 Basic structure of PNN

3. EXPERIMENTAL RESULTS

In the experiments, Flavia [13] dataset which contains 32 species of leaves was used. Morphological and Wavelet features were used as an input to probabilistic neural network (PNN). PNN was trained with 1120 leaf images from 32 different plant species and 160 leaf images were used for testing. Experimental results vary with the influence of various parameters. These parameters are the number of leaf species that need to be recognized, the features extracted from the leaves and the spread value of the radial-based functions, which is the parameter of the probabilistic neural network. In this study, the spread value was taken as 0.02.

As the number of leaf species increases, the performance of recognition of the probabilistic neural network decreases. The reason for this is that the need for more leaves species recognition makes it difficult to train the neural network. Since the artificial neural network is expected to recognize the leaf species more accurately, it is more likely that the recognition result will be wrong. The larger the result set, the lower the probability that the

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given answer belongs to the correct class. Excessive or inadequate number of features decreases the success rate. The use of less than required features causes the amount of data required to distinguish the leaves from one another. The use of more than necessary features causes the leaf species to be mixed with each other due to the increase in the amount of data used in the learning process. Table 1 shows the success of leaves species classification by using morphological features and wavelet sub-band features determined by db4 wavelet function using discrete wavelet transform.

Table 1. Classification accuracy rates in terms of different features

Features	**Classification Rate (%)**
Morphological	92.50
Mean, Standard Deviation, Entropy, Energy	87.50
Morphological + Mean (DWT)	83.75
Morphological + Standard Deviation (DWT)	80.00
Morphological + Energy (DWT)	89.37
Morphological + Entropy (DWT)	97.50
Morphological + Energy (DWT) + Entropy(DWT)	94.37

As given in Table 1, in the classification of the leaf images, the morphological features and the mean, standard deviation, energy and entropy features which are based on discrete wavelet transform were determined from the left and right regions of the leaves image.
Experimental results show that the entropy features obtained from the second level horizontal (H2) and vertical (V2) detail wavelet coefficients of the image decomposed by wavelet transform increase the success rate in the classification of images. The classification rate is 92.5% when only morphological features were used, and the classification accuracy rate is 97.5% when the entropy is added to these morphological features. In addition, the mean and energy features calculated from the wavelet approximation coefficients, which was used together with the morphological features, negatively affected the accuracy rate of the classification.

4. CONCLUSION

In this study, it is aimed to classify leaf species by using morphological and wavelet features with probabilistic neural networks. The effects of the features used in this study on the success of classification were investigated. The results obtained from the study showed that 92.5% of the leaf species by using the morphological features were correctly classified. When the entropy features obtained by the wavelet transform are added to these morphological features, 97.5% of the leaf species are correctly classified. Six leaves species which cannot be found with morphological features can be found correctly by using entropy features. In addition, all of the features obtained from the approximation coefficients in the sub-band have a negative effect on the classification success. Similarly, the wavelet transforms did not show any positive or negative contribution to the success of classification in the horizontal, vertical and diagonal detail coefficients of the 1st level. Also, the use of energy features in classification of leaf types has a negative effect on the correct classification of images. All experimental results show that the use of entropy features obtained by the discrete wavelet transform with the morphological features in the leaves species image classification provides higher accuracy classification.

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