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Plant Recognition Based on Intersecting Cortical Model

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Abstract*—plant recognition recently becomes more and more attractive in computer vision and pattern recognition. Although some researchers have proposed several methods, their accuracy is not satisfactory. Therefore, a novel method of plant recognition based on leaf image is proposed in the paper. Both shape and texture features are employed in the proposed method. Texture feature is extracted by intersecting cortical model, and shape feature is obtained by the representation of center distance sequence. Support vector machine is employed for the classifier. The leaf image is preprocessed to get better quality for extracting features, and then entropy sequence and center distance sequence are obtained by intersecting cortical model and center distance transform, respectively. Redundant data of entropy sequence vector and center distance are reduced by principal component analysis. Finally, feature vector is imported into the classifier for classification. In order to evaluate the performance, several existing methods are used to compare with the proposed method and three leaf image datasets are taken as test samples. The experimental result shows the proposed method gets the better accuracy of recognition than other methods.

***Keywords*—plant recognition; ICM; feature extraction; leaf image, classification;**

I. I. INTRODUCTION

PLANTS play a very important role in the life, they can not only provide the daily necessities such as food, medicine and industry crop, but also play a irreplaceable role in the ecological balance. Hence, it is important to recognize and protect the diversity of plants.

Leaf can be collected in several months of a year, whereas the flowers and fruits may remain in a shorter specific period. It is the reason that many botanists and plant specialist would better like to use the characteristics of leaf to recognize plant species recognition. Plant recognition is generally based on the observation of the morphological characteristics of leaf, but it will be a tricky task for experienced botanists to identify the plants because of the huge number of species existing in the world. In this case, it is helpful and significant for developing a quick and efficient plant recognition systembased on computer to identify the plant species.

With the development of image processing and pattern recognition, it is available to apply them to recognize plant automatically. Many studies in the past decades have shown that leaf contains rich information (e.g. color, shape, texture) for recognition. The shape is the general feature of leaf. As the color of a leaf may vary with the climatic and seasons conditions, and most plants have similar color (e.g. green), so color is not commonly used in classification.

In the past decades, many researchers occupied themselves with plant recognition [1-11]. Most of the existing methods generally employ the shape feature. In fact, texture feature also plays a part in plant recognition based on leaf image.

The intersecting Cortical Model (ICM), which was introduced by J.M. Kinser [12], is a simplified model of the Pulse-Coupled Neural Network (PCNN) of Eckhorn [13]. The ICM is also a powerful tool for image processing. As it is a simpler version of PCNN, it is faster than the full PCNN model, so ICM is more suitable for calculating on computer. Because ICM inherited the biological characters of PCNN it is suitable for image processing. Hence, it is widely used in image segmentation, feature extraction, image denoising, image retrieval, and so on [14-17].

Although some artificial neural networks has been applied into plant recognition, it is usually used as the classifier. As far ICM is not applied into feature extraction of leaf image.

In the paper, we propose a new method for plant recognition based on leaf image using ICM and SVM. In the proposed method, entropy sequence from ICM represents the texture feature of leaf. Shape feature of leaf also is employed in the form of center distance sequence. Principal Component Analysis (PCA) is employed to reduce redundant data of feature vector. Support Vector Machine (SVM) is taken as the classifier.

The rest of paper is organized as follows. Some basic theories used in the paper are introduced in Section II. The principle of extracting the features is explained in Section III. The scheme of our method of plant recognition is designed in

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Section IV. Finally the experimental results are provided in Section V and the paper is summarized in section VI.

II. II. RELATED THEORIES

A. ICM

The Intersecting Cortical Model (ICM) is based on several visual cortex models [12]. This model is provided for the purpose of attempting to minimize the cost of calculation but maintain the effectiveness of the cortical model when applied to images. Its foundation is based on the common elements of several biological models.

The important contribution of the ICM is to quickly and effectively refine information from the image and there is little concern as to the deviation from any single biological model. So this model at least has two advantages. One is to make an efficient and quick algorithm because of reducing the costs of computation and another is to have a good performance in consideration of originating from several biological models.

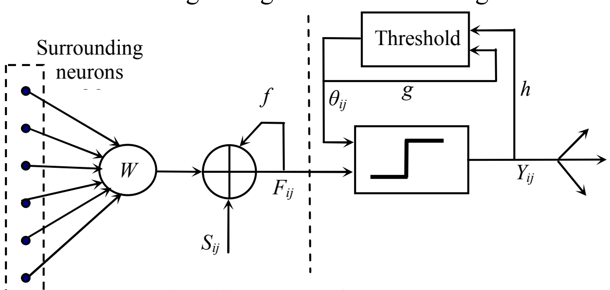

Fig.1. the structure of ICM neuron

The ICM consists of two coupled oscillators, shown in fig.1, a small number of connections and a nonlinear function. The model is described mathematically by the following three equations [14]:

$$F_{ij}[n+1] = f F_{ij}[n] + S_{ij} + W\{Y\}_{ij} \qquad (1)$$

$$Y_{ij}[n+1] = \begin{cases} 1 & if \;\; F_{ij}[n+1] > \theta_{ij}[n] \\ 0 & Otherwise \end{cases} \qquad (2)$$

$$\theta_{ij}[n+1] = g\, \theta_{ij}[n] + h\, Y_{ij}[n+1] \qquad (3)$$

The coupled oscillator's states of all the neurons are represented by a 2D array F (the internal neuron states; initially, $S_{ij}=0$, for $\forall\, i, j$) and the threshold oscillators of all the neurons by a 2D array θ (initially $\theta_{ij}=0$, for $\forall\, i, j$). Thus, the ij^{th} neuron has state F_{ij} and threshold θ_{ij}. They are computed from formula (1) and (3), separately.

In those equations, S_{ij} is the stimulus (the input image, scaled so that the largest pixel value is 1.0), and Y_{ij} is the firing state of the neuron (Y is the output image). f, g and h are scalars, and n stands for the iteration number. The connections between the neurons are described by the function W {} and for now these are still the $1/r$ type of connections. The scalars f and g are decay constants and thus less than 1.0 and $g < f$ is required to ensure that the threshold eventually falls below the state and the neuron pulses. The scalar h is a large value the dramatically increases the threshold when the neuron fires. These firings are computed from formula (2). The output of the ICM is the binary images $Y[n]$. As these images are obtained after a number of n neural pulse iterations, the images are called pulse images, too [16]. These parameters of ICM are usually set by experience.

Because the ICM consists of just three simple equations, and each neuron has two oscillators (the neuron potential and the neuron threshold) and each neuron has a nonlinear operation, when stimulated, each neuron is capable of producing a spike sequence, and groups of locally connected neurons have the ability to synchronize pulsing activity. When stimulated by an image, these collectives can represent inherent segments of the stimulating image. Thus, the ICM will become a powerful step in the processing of extracting feature. In addition, the ICM could, as soon as possible, avoid the bad influence of local error information on the result of recognition for the reason that what the ICM processes is the whole stimulant image.

B. SVM

SVM is one kind of supervised learning models with associated learning algorithms that analyze data and recognize patterns [18]. It is widely used for classification and regression analysis. The principle of SVM is to employ mathematical algorithms to construct a hyperplane or set of hyperplanes in a high- or infinite-dimensional space according to the training data. In fact, SVM uses the training data to build a model that assigns new data into one category or the other. A good separation is achieved by the hyperplane that has the largest distance to the nearest training data point of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier. SVM is employed as the classifier in the paper.

C. PCA

PCA is an important tool for data analysis. The principle of PCA is to uses orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables which are called principal components. Usually, the number of principal components is less than the number of original variables.

The principle of PCA is explained in mathematics. Suppose that there is a data Matrix X with M rows and N columns. Each row $X_{(m)}$ represents a different repetition of the experiment, and each column $X^{(n)}$ represents a variable for experimental observation. Through the orthogonal linear transformation The component $Z_1 = \sum a_n X^{(n)}$ is obtained, when a_n can be determined with the constraint condition $\sum (a_n)^2=1$ and the max variance of Z_1, this component is called the first principal component. Similarly, the first principal component can be obtain by the second greatest variance, and so on. The whole data can be described approximately by some principal components. Hence PCA can be used to reduce the dimension of data.

III. III . FEATURE EXTRACTTION

Feature extraction is a crucial step for plant recognition. In our method two features are employed. One feature is entropy sequence extracted by ICM, and the other is center distance sequence. The definition of center distance and entropy sequence will be introduced in this section.

A. Entropy Sequence

When ICM works, it will create a set of pulse images from an input image. Generally speaking, various traits can be got from the pulse images. But we will take the entropy sequence of the output as the feature vector in this paper, because this entropy sequence has such advantages as invariance to rotation, scale, translation. These characteristics are very useful in the image recognition. And the entropy sequence could be produced easily from these pulse images. The entropy sequence (*EnS*), proposed by Ma[19], is defined by the equation:

$$EnS[n] = -p_1[n]\log_2 p_1[n] - p_0[n]\log_2 p_0[n], \quad (4)$$

where $p_1[n]$ and $p_0[n]$ represent the probability when $Y_{ij}[n] = 1$ and $Y_{ij}[n] = 0$ in the output $Y[n]$ separately.

J.M. Kinser has pointed out that these pulse patterns are dependent upon the image texture [20]. In other words, these pulse patterns are unique to the original images in theory. Thus, the entropy sequence got from these images is unique to the stimulant image. So it is feasible to use the ICM to extract texture feature of leaf.

B. Center Distance Sequence

Suppose that there is a contour(***C***) of the leaf shown in fig.2, and the point $C(x, y)$ lies on ***C***. Point $C(x_c, y_c)$ is the centroid of the region ***C***. The center distance is defined by

$$D(x, y) = \sqrt{(x - x_c)^2 + (y - y_c)^2} \ . \quad (5)$$

Hence, $D(x, y)$ represents the Euclidean distance between the point $C(x, y)$ and the centroid $C(x_c, y_c)$.

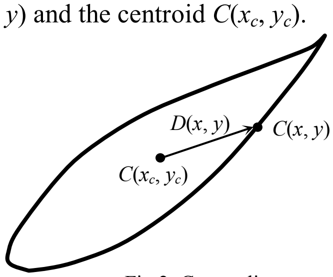

Fig.2. Center distance

For digital image, the length of contour ***C*** is limited. Suppose M is the length of contour ***C***. The center distance sequence(*CDS*) is defined as

$$CDS = \{D(x_i, y_i) \mid 0 < i < M - 1\}. \quad (6)$$

In other words, The center distance sequence is the set of the distances between all the point $C(x_i, y_j)$ and the centroid $C(x_c, y_c)$. Therefore, *CDS* describes the shape information of leaf.

IV. IV. The Proposed Method of Plant Recognition

The scheme of our method is shown in fig.3. It can be divided into three steps: image preprocessing, feature extraction, and classification.

A. Image preprocessing

Firstly the leaf image is preprocessed to improve image quality. Image preprocess contains the following step:

1) 1) Image segmentation: If the leaf image has some background information, first of all background should be deleted. Because most the leaf image datasets are built By virtue of optical scanner, the background is simple and easy to be removed by a method of adaptive threshold segmentation.

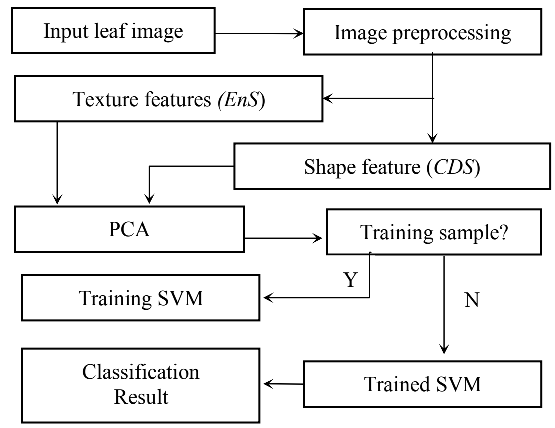

Fig.3. Flow diagram of proposed method

2) 2) Image smoothing: In order to reduce the effect of noises, it is necessary to smooth the edge. The median filter is employed to remove noises.

3) 3) Image enhancement: Sometimes it is essential to enhance the contrast and texture. In our method, histogram equalization and linear stretching are adopted in the method.

B. Feature Extraction

Because the definitions of *EnS* and *CDS* are explained in section III, their implementations are introduced in this section.

4) 1) Entropy Sequence: EnS is obtained by ICM, where the parameters of ICM are $f = 0.9$, $g = 0.8$ and $h = 20$, respectively.

5) 2) Center Distance Sequence: According to the definition of *CDS*. It is sensitive to rotation and scale. Rotation invariance and scale invariance are important for feature vector. In order to assure that *CDS* is invariant for scale, the amplitude and the length are respectively normalized for *CDS*.

Because the rotation of leaf will lead to the phase shift of *CDS*, the good method is to realign them according to standard position e.g. leaf apex or leaf base.

C. Classification

Although *CDS* and *EnS* are obtained, these feature data generally contain much redundant information. After *CDS* and *EnS* are simply concatenated, it is necessary to reduce the redundant data with the help of PCA before the classification.

SVM with an RBF kernel must be trained by training samples before classification. For the dataset, training samples and should be independent of test samples. Furthermore, test samples should be superior in number to training samples. When SVM are trained, it can be used to classify the different kinds of features.

V. V. Experimental Results

Some experiments are carried on in this section to prove that the proposed method is feasible and efficient.

A. Datasets

Two popular leaf image datasets are employed in the paper. One dataset is from Intelligent Computing Lab of Institute of Intelligent Machines (IIM), Chinese Academy of Sciences (CAS). It is called by ICL dataset in the paper. This dataset can be downloaded in the website [21].

ICL dataset contains 220 kinds of plants (total 17032 leaf images). It is divided into two parts in the paper. One part, called ICL1, contains the pros leaves of 187 kinds of plants. The other part called ICL2 contains the cons leaves of 207 kinds of plants.

The other dataset is the famous Flavia dataset, which can be download in the website [22]. This dataset has 1907 samples of 32 species, most of them are common plants in the Yangtze Delta, China.

B. Quality of features

Extracting high-quality feature is the key for success of plant recognition. 12 images from 12 kinds of plants, shown in fig.4 are used to prove that entropy sequence and center distance sequence are efficient features.

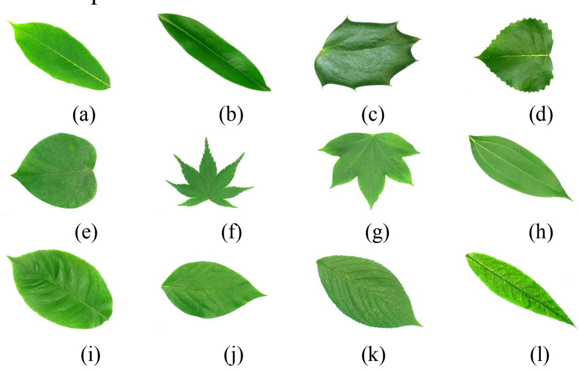

Fig.4 12 images from different plants

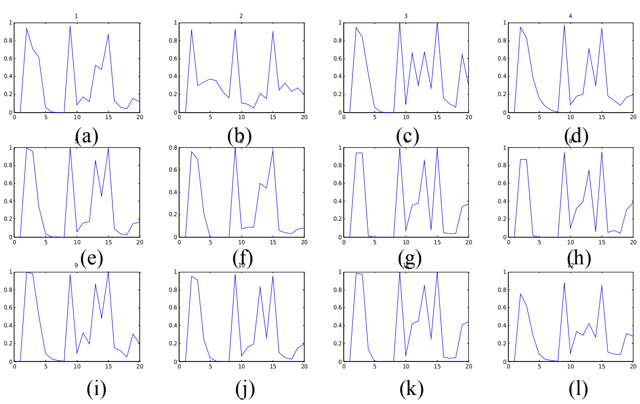

Fig.5. entropy sequences of different plants

Fig.5 shows the entropy sequences are corresponding to fig.4. Fig.6 shows the center distance sequences are corresponding to fig.4.

From fig.4 and fig.5, we can find that entropy sequence and center distance sequence are recognizable, because each kind of plant has different entropy sequence and center distance sequence.

10 images of the same plant, shown in fig.7, are chosen to show the uniformity of features. Fig.8 and Fig.9 show that for the same plant, it has very similar the entropy sequence and center distance sequence.

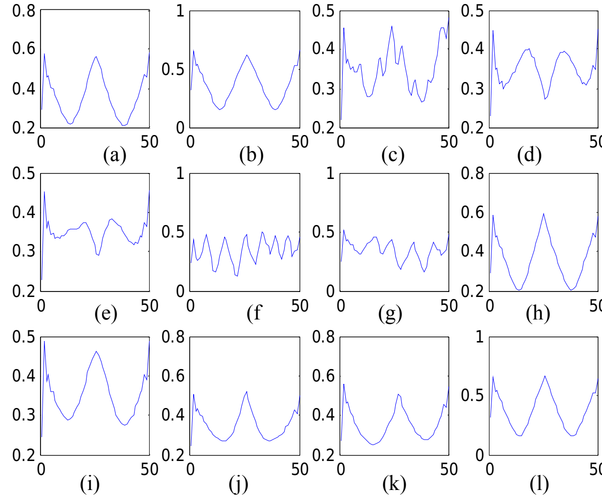

Fig.6. center distance sequence of different plants

Fig.7. test image for robustness

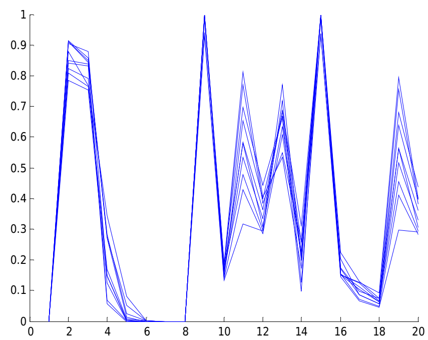

Fig.8. entropy sequence of the same plant

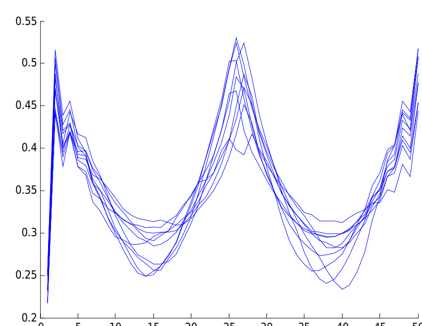

Fig.9. center distance sequence of the same plant

C. Comparison with the existing methods

For plant recognition, the objective evaluation criterion is the accuracy of recognition, which is defined by

$$Accuracy = \frac{Num\,(R)}{Num\,(T)} \times 100\,\%\,, \qquad (7)$$

where, $Num(T)$ is the total number of the testing sample(not contain the training sample) and $Num(R)$ is the number of obtaining right recognition. In order to evaluate the performance of our method, some typical methods are compared with the proposed method.

Because many existing methods use Flavia dataset to test and verify the performance of methods of plant recognition, this dataset is also employed to compare the existing methods with the proposed method in the paper.

For Flavia dataset, 761images are used for training SVM (the training samples are less than half of the whole samples). And the rest of images are used to test the rate of recognition. The experimental results of plant recognition are listed in table 1 and shown in fig.10. In the paper, five methods are employed, the method of ANN comes from Ref.[1], the method of PNN comes from Ref.[4], the method of PNN with HLF (PNN-HLF)comes from Ref.[1], the method of Fourier descriptor (FLD) comes from Ref.[5], and the method of Zernike moment(ZRM) comes from Ref.[23]. Our method is denoted by the method of ICM.

TABLE I. TABLE 1. EXPERIMENTAL RESULTS

Methods	Accuracy
PNN	90%
PNN+HLF	92.5%
FLD	94%
ANN	93.3%
Zernike moment[23]	93.44%
Proposed method	97.82%

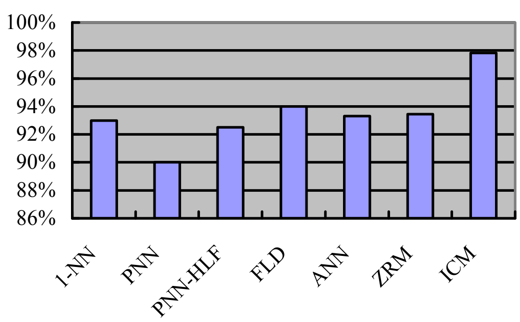

Fig.10. the accuracy of different methods

Experimental results show the accuracy of our method is up to 97.82%. It is higher than other methods.

Because ICL dataset contains numerous plants for recognition, it also used to test the performance of the proposed method. In ICL1, 3264 images are used for training samples, and the rest of 4283 images is used for test samples. The accuracy of our method is up to 95.87%. In ICL2, 3826 images are taken as training sample and the rest of 4063 images are used as testing sample, the accuracy of our method is 94.21%. In addition, Ref.[5] employs this dataset its accuracy is 84.62%. Ref.[10] only use on part of ICL less than ICL1, their accuracy is up to 93.53%. In all, the proposed method is efficient and its accuracy is superior to other methods whatever in ICL dataset or in Flavia dataset.

VI. VI. CONCLUSION

In this paper, we propose a new method of plant recognition based on leaf image using ICM and SVM. In the proposed method, two features (*EQS* and *CDS*) of leaf have been adopted. PCA are employed to reduce the redundant data. SVM is taken as the classifier. Two popular leaf image datasets (ICL dataset and Flavia dataset) are used to validate the performance of the proposed method. Experimental results show that our method is better than other methods.

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