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Comparative Study on Different PCNN Models in Plant Leaf Classification*

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Abstract— Plant classification is an important area of botany research. Plant classification based on image processing is also currently one of the hot spots in the research. Pulse coupled neural network(PCNN) has good performance in image processing, especially in the feature extraction. There are a lot of improved models. In this paper, three kinds of important improved PCNN models such as pulse-coupled neural network and intersecting cortical model, spiking cortical model and two-output pulse coupled neural network are applied to plant leaf classification based on image processing so that the network model suitable for leaf classification is selected. We have improved the extraction method of entropy sequence features, and then conducted a comparative experiment. Experimental results show that each model has its own characteristics. However, due to its complete functions, the standard pulse-coupled neural network has slightly better feature extraction ability, followed by intersecting cortical model, spiking cortical model and dual-output pulsed coupled neural network.

Index Terms— PCNN, feature extraction, pulse image, leaf classification.

I. Introduction

Plant identification has closely relation to human life. The traditional plant identification approaches are sophisticated to operation and difficult to popularization. Along with the rapid growth of computer image processing and pattern recognition technology, it has become possible to identify plant species automatically through image processing. In recent years, more and more researchers have paid their attentions on computer automatic recognition technology based on plant images.

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In 1990s, inspired by the cat's visual system, Eckhorn constructed a simplified neural network model which is named as the Pulse Coupled Neural Network (PCNN) [1, 2]. Compared with the neural network of BP, Kohonen and others, PCNN has the ability of extracting some valid information from complex background without training. And it is more consistent with the physiological basis of human visual nervous system in signal form and processing mechanism. PCNN is widely applied in image segmentation, smoothing, noise reduction and other image processing fields [3].

In order to utilize the PCNN model to digital image processing, pattern recognition and many other fields, researchers put forward some improved models, such as SCM[4], ICM[5] and DPCNN[6], according to practical application. And the PCNN model is applied to plant leaf image recognition [7-9]. This paper is mainly to research the performance of PCNN model and its improved models in plant leaf classification, and the purpose is to choose a better network model for leaf classification. And the leaf classification block diagram of this paper is shown in Fig.1

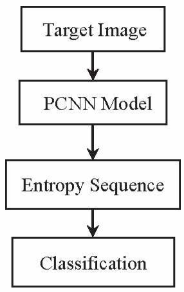

Fig. 1. the block diagram of leaf classification

The reminder of this paper is organized as follows. The standard PCNN and its improved PCNN models are stated in Section 2. In Section 3, the feature extraction method based on PCNN for image classification is

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illustrated, in which the entropy sequence characteristics is stated and improved. Section 4 consists of the experimental results and analysis. And the conclusion is given in the final section.

II. PCNN Models

This section mainly describes the standard PCNN and its three common improved models.

A. Standard PCNN Model

The standard PCNN model, formed by connecting pulse coupled neurons transversely, is a feedback network. The neuron concludes three parts: the dendritic tree, linking modulation and pulse generator. Linking modulation is a dual channel nonlinear modulation region. It includes link channel and feedback channel.

The expression of the PCNN model is as follows:

$$F_{ij}[n] = e^{-\alpha_F} F_{ij}[n-1] + V_F \sum_{kl} W_{ijkl} Y_{ki}[n-1] + S_{ij} \tag{1}$$

$$L_{ij}[n] = e^{-\alpha_L} L_{ij}[n-1] + V_L \sum_{kl} M_{ijkl} Y_{ki}[n-1] \tag{2}$$

$$U_{ij}[n] = F_{ij}[n](1 + \beta L_{ij}[n]) \tag{3}$$

$$Y_{ij}[n] = \begin{cases} 1 \ , \ U_{ij}[n] > E_{ij}[n] \\ 0 \ , \ otherwise \end{cases} \tag{4}$$

$$E_{ij}[n+1] = e^{-\alpha_E} E_{ij}[n] + V_E Y_{ij}[n] \tag{5}$$

Among the above expressions, ij and kl stand for the (i,j) and (k,l) neurons respectively. n is the iteration number of the image, and S_{ij} denotes the external excitation of the neuron. V_F, V_L and V_E defines the normalizing constants, and α_F, α_L and α_E are the attenuation coefficients. M and W express the connection matrix of feedback input F and coupling connection L (in general $M = L$). β is the connection coefficient and Y_{ij} is the output signal. When PCNN is iterated, E (dynamic threshold) $<$ U (internal activity item), Y_{ij} $= 1$, otherwise it is 0.

When PCNN is utilized to image processing, the pixels in the image correspond to the PCNN neurons one by one. Each neuron is located at the center of the N order weight matrix (generally $N = 3$). Every neuron of PCNN is a dynamic neuron with dynamic pulse distribution characteristics. The ignition cycle of each neuron in PCNN is different during the iteration, and its dynamic threshold attenuates according to the corresponding period in a period of time. Only when the dynamic threshold E is less than the internal activity item U, the PCNN can distribute the pulse dynamically.

B. ICM Model

Intersecting Cortical Model (ICM) is a simplified model of PCNN. Compared to PCNN model, it has no connection input. The same as PCNN model, the ICM model has invariance of rotation, scale, translation and so on. It also has good robustness in noise environment and it is suitable for image feature extraction.

The mathematical expressions of the ICM model are as follows.

$$F_{ij}[n] = f F_{ij}[n-1] + \sum_{kl} W_{ijkl} Y_{ki}[n-1] + S_{ij} \tag{6}$$

$$E_{ij}[n] = g E_{ij}[n-1] + h Y_{ij}[n]) \tag{7}$$

$$Y_{ij}[n] = \begin{cases} 1 \ , \ F_{ij}[n] > E_{ij}[n-1] \\ 0 \ , \ otherwise \end{cases} \tag{8}$$

In formula (6)-(8), S is an external excitation. f and g, which can determine the attenuation rate of F and E, stand for the attenuation coefficients of F and E respectively. The superimposed threshold of neurons is controlled by the threshold adjusted value h. If $E < F$, neurons are excited and the output pulses is produced. By comparison, it is found that ICM is a simplified version of PCNN. When $\beta = 0$ (PCNN), ICM equates to PCNN. And f, g and h in ICM replace $e_F^{-\alpha}$, $e_E^{-\alpha}$ and V_E in PCNN respectively. It is obvious that ICM retains the main characteristics of PCNN and it is simpler to operate than PCNN.

C. SCM Model

Spiking Cortical Model (SCM) is also a simplified PCNN model. It was proposed by Zhan Kun et al. after an intensive study of PCNN model. And its mathematical description is as follows.

$$F_{ij}[n] = f F_{ij}[n-1] + S_{ij} \sum_{kl} W_{ijkl} Y_{ki}[n-1] + S_{ij} \tag{9}$$

$$E_{ij}[n] = g E_{ij}[n-1] + h Y_{ij}[n]) \tag{10}$$

$$Y_{ij}[n] = \begin{cases} 1 \ , \ F_{ij}[n] > E_{ij}[n-1] \\ 0 \ , \ otherwise \end{cases} \tag{11}$$

In above formula, f, g and h have the same meanings as that in ICM model. And the main difference between SCM model and ICM model is the input part. When the activity threshold E is less than the feedback input F, neuron in the SCM is fired to produce the output pulse.

D. DPCNN Model

Dual-output Pulse Coupled Neural Network (DPCNN) is also an improved PCNN model. Although the features extracted by PCNN can effectively represent the texture of the image, it still has some limitations. And the limitations mainly include the following three aspects.

1) there is only one pulse generator, and there is no compensation mechanism for neuron excitation.

2) the influence of peripheral neurons on the current neurons does not take the influence of input excitation itself into account.

3) its external incentive has been in an unchanged state.

For this reason, DPCNN model improves the standard PCNN model. Firstly, DPCNN has two pulse generators; Secondly, it can be found external excitation controls the local stimulation from the peripheral neurons to the current neurons in the DPCNN; Finally, it is shown that the external excitation of the neurons in the DPCNN changes with the current output value.

The mathematical expression of the DPCNN model is shown as follows.

$$F_{ij}[n] = fF_{ij}[n-1] + S_{ij}(V_F \sum_{kl} M_{ijkl} Y^U_{kl}[n-1] + \gamma) \tag{12}$$

$$Y^F_{ij}[n] = \begin{cases} 1 \ , & F_{ij}[n] > T_{ij}[n] \\ 0 \ , & otherwise \end{cases} \tag{13}$$

$$U_{ij}[n] = F_{ij}[n] + V_U S_{ij}[n] \sum_{kl} W_{ijkl} Y^F_{kl}[n] \tag{14}$$

$$Y^U_{ij}[n] = \begin{cases} 1 \ , & U_{ij}[n] > T_{ij}[n] \\ 0 \ , & otherwise \end{cases} \tag{15}$$

$$T_{ij}[n+1] = gT_{ij}[n] + V_E Y^U_{ij}[n] \tag{16}$$

$$S_{ij}[n+1] = (1 - Y^U_{ij}[n] + Y^F_{ij}[n])S_{ij}[n] + (Y^U_{ij}[n] - Y^F_{ij}[n])A_{ij} \tag{17}$$

Among the above expression, f and g are attenuation coefficients ($f < 1, g < 1$) . V represents a normalized constant, and S denotes an external incentive. M and W both stand for the connection weights between neurons and adjacent neurons. A is the correction value. And γ is a constant, which is used to determine the external input excitation intensity. Y^F represents the output value of the feedback. Y^U is the compensated output value obtained by comparing activity threshold E and internal activity item U.

From the DPCNN model and its mathematical expressions, it can be found that every neuron in the DPCNN model can be regarded as an active neuron. Firstly, F_{ij} changes when affected by the external excitation and neighborhood neuron compensation output. Once $F_{ij} > U_{ij}$, the neuron produces feedback output pulse. Secondly, the value of the internal activity item U_{ij} is changed by the common effect of the feedback output from the neighborhood neurons, the feedback input and the external excitation. And the compensation output pulse is generated when $U > E$. Finally, the activity threshold E and the external excitation value S are updated.

III. Feature extraction based on PCNN

A. Entropy sequence characteristics

When processing the image, a set of pulse images will be created from the input image by PCNN, and part of the pulse image is shown in Fig.2. These pulse images depend on the texture of the target image, which is very helpful for the representation of target images. After proposing the input image by PCNN for n iterations, a set of binary images will be produced. These binary images contain lots of information about the input image, but taking the binary image of these outputs as feature directly will cause data redundancy.

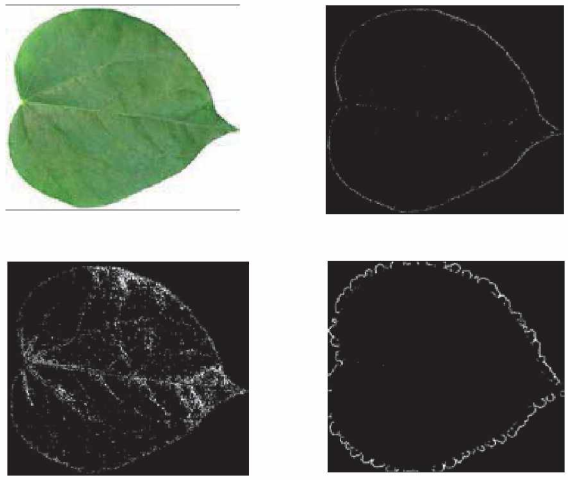

Fig. 2. source image and parts of pulse images

For this purpose, Ma Yide et al. put forward the entropy sequence characteristic (Ens) [10, 11]. It is generated by calculating the entropy of images generated during iteration. The mathematical description is as follows.

$$Ens[n] = Entropy(Y[n]) \tag{18}$$

In formula(18), $Entropy(\cdot)$ represents the entropy of the image, and n is the number of iterations. The entropy sequence characteristics of the leaf image is shown in Fig.3.

B. The improvement of entropy sequence characteristics

As an effective feature of leaf texture description, entropy sequence can also get a good result when classifying and identifying leaves as feature vectors. Through in-depth research on the extraction method of entropy sequence features, it can be found that the input pattern, weight matrix and other aspects affect the characteristics of entropy sequence. Exactly, the description of leaf texture by traditional entropy sequence features has not reached our expectation.

Through our analysis, it can be concluded that the traditional entropy sequence features do not guarantee

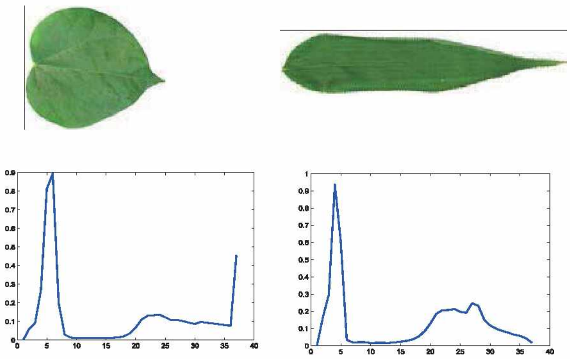

Fig. 3. entropy sequence characteristics

all the effects on the input, that is to say, there is no guarantee to make all the input points ignite, and the traditional entropy sequence is repeated, that is, several input points have been ignited more than once.

According to some experiments, we improve the entropy sequence features extraction approach with the PCNN model in the aspects of the input aproach, the weight matrix and no repeated input and all input.

Specific improvements are made as follows.

1) Ensuring that all neurons are fully ignited and each neuron is ignited once. This method can control the iteration number of the network. That is, the automatic stop function of the network is able to be reached.

2) Considering the characteristics of leaf images, the complementary image of the original image is used as the input of the neural network, which can greatly improve the quality of the extraction features.

3) The size of the weight matrix is related to the quality of the extracted feature. Experiments show that the weight matrix of size 5×5 is effective. And it can not only improve the quality of the extracted feature, but also control the speed of computation.

IV. Experimental results and analysis

A. test dataset

In recent years, the technology of plant recognition based on images has developed rapidly. Many researchers have set up serious of leaf sample libraries of different numbers. In this section, we only introduce three leaf databases used in this paper.

There are 1907 leaf image samples in the Flavia leaf library, which are divided into 32 categories, each concludes approximately 50-73 leaf images. And most of these samples are from the Yangtze River Delta region of China. All the petioles of the leaves in the Flavia library are removed, which is very useful to the image feature extraction. So the Flavia library is very popular with the researchers in experiments.

The ICL leaf library is provided by the Hefei Institute of intelligence of the Chinese Academy of Sciences. There are 16851 leaf slice images in total, which are divided into 220 types, each has about 26-1078 leaf images.

There are 4221 leaf images in the LZU leaf sample library, including the leaves of 30 kinds of plants, each of which has about 53-184 leaf images. And all the plant leaves are obtained from the Lanzhou University campus.

B. Models comparison

In order to further verify the experiment, we carried out experiments on the PCNN and its three related models in the Flavia, ICL, and LZU leaf database respectively, which is also able to verify the effect the improvement of entropy sequence. For making the experimental results more convincing, the feature input vector uses the entropy sequence features, and LIBSVM is used as a classifier, and the number test samples is approximately 1:1 in each class of training. The experiment is carried out 15 times randomly for each group, and the maximum value of the experiment is taken as the final recognition rate, which is shown in Figs. 4-6.

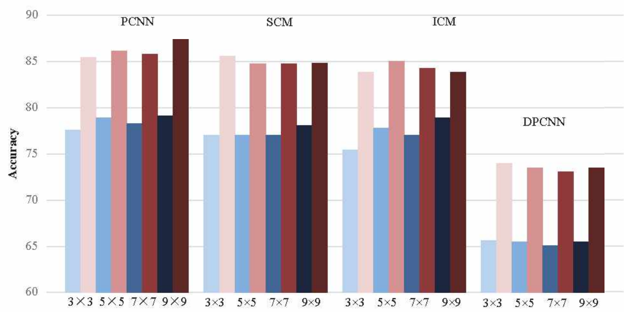

Fig. 4. comparison between a set of PCNN models in Flavia

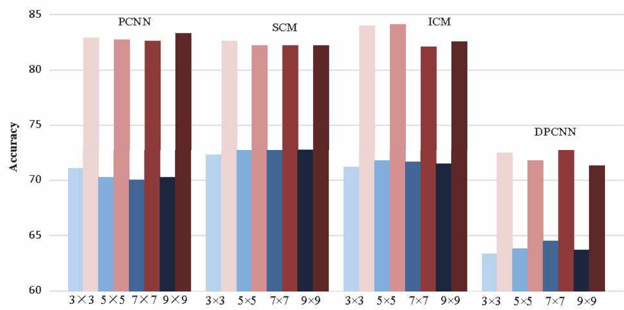

Fig. 5. comparison between a set of PCNN models in ICL

In Figs.4-6, the blue series is direct input, and the red series stands for the reverse input. It can be seen from the figures that reversing the image and inputting it to the neural network can significantly improve the recognition rate of the leaf. The reason is that the pixel values of leaves are larger and the threshold index

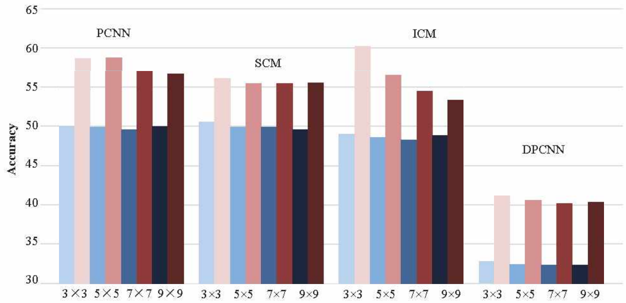

Fig. 6. comparison between a set of PCNN models in LZU

decrease faster, which is not conducive to capturing the texture characteristics of leaves. If reversing the input, the brightness of pixels is reduced. The network is more delicate in dealing with the regions with low pixel, and that is conducive to feature extraction.

In Figs.4-6, the abscissa of 3×3, 5×5, 7×7, and 9×9 represent the weight matrices of 3, 5, 7 and 9 respectively. From this, we can see that the bigger weight matrix is not the better, and it achieves good results at 3×3 and 5×5.

For the same test dataset, each model has its own characteristics and is not absolutely dominant. But from the three datasets, it is obvious the performance of standard PCNN is superior, followed is ICM model and SCM model. DPCNN has poor performance under this experimental condition, the reason is the fact that the premise of our experiment is that each neuron fires only once. This makes the advantages of the dual output PCNN model difficult to play, resulting in the worst recognition rate.

According to the different database data, we can see that the adaptability of the model is still weak. That is to say, the quality of input image also affects the accuracy of plant identification to a great extent.

V. Conclusion

Plant leaf classification is one of the hot topics in current research. This paper refers to three widely used PCNN improvement models and compares the performance of these four kinds of neural networks in plant leaf classification. We improves the method of entropy sequence feature extraction, which advances the recognition rate of the leaf to a certain extent.

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