Image Recognition of Navel Orange Pest Based on PSO Constrained Optimization and Coupling Local Regularization

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***Abstract* — An image recognition model (GCMPSO-BP) of one gray level co-occurrence matrix and catfish particle swarm optimization neural network for parameter optimization problem of BP neural network is proposed to improve the image recognition of navel orange pest. First, image features have been extracted with gray level co-occurrence matrix, and then the features have been input into BP neural network for study, BP neural parameters have been optimized through particle swarm optimization algorithm, "catfish" effect has been introduced to get over the local optimal defect of particle swarm optimization algorithm and finally specific image database has been adopted to make simulation test for model performance. The simulation results showed that compared with traditional image recognition model, GCMPSO-BP could attain better image recognition performance, which not only improved the image recognition rate and recognition efficiency of navel orange pest but also solved the problem of parameter optimization for BP neural network.**

Keywords - image recognition; gray level co-occurrence matrix; navel pest recognition; particle swarm optimization; neural network

I. INTRODUCTION

Image recognition refers to that make features extraction for image with adoption of computer and divide image into corresponding category based on certain classification rules to replace the vision of people to make recognition for image, which has been widely applied in remote sensing image processing, image retrieval, object detection in a visual scene, medical image processing and other fields [1].

The essence of navel orange pest image recognition is the classification problem of model recognition, which includes feature extraction and classifier design [2]. Features extraction is the basis of image recognition and the quality of its result directly affects the accuracy rate of following image recognition, in which image texture features are not depending on color and brightness changes and can make accurate description for image spatial information. Gray level co-occurrence matrix is a common method of describing the related features of gray space; therefore, gray level co-occurrence matrix is usually adopted to express the texture features of image [3]. Image classifier includes designing based on distance method and machine learning algorithm; Euclidean distance is with advantages of simple calculation and speed etc, at present, the differences among images are big and the recognition accuracy rate is high, while when the differences among images are small, the accuracy rate of image recognition is low [4]. Machine learning algorithms mainly include neural network and support vector machine etc [5,6], which is a machine learning algorithm specially for small sample and high dimension with excellent generalization capability, but when the sample is bigger, the exercising time is long, which affects the real time of image recognition and restrict the application range [7]. Neural network is with strong nonlinear classification ability, rapid learning speed as well as self-organization and self-adaptive learning ability, especially the BR neural network is widely applied in image recognition [8]. However, BP neural network has inherent defects, for example, algorithm is easily trapped in local minimum, quantity of hidden layer neuron is difficult to confirm and network initial value can't be determined etc, which affects the accuracy rate of image recognition to some extent [8]. For these defects, some scholars have made optimization for BR neural network parameters and attained certain effects [9, 10]. However, this algorithm still can't solve the problem of local optimum, when one particle attains local optimum, the particle swarm will converge quickly at this point and then loss global searching ability [11].

To further improve the accuracy rate of image recognition for navel orange pest, this paper has proposed an image recognition model of one gray level co-occurrence matrix and catfish particle swarm optimization neural network for above problems, optimized BP neural network with catfish particle swarm optimization algorithm to get over the phenomenon of "precocity" and verified the performance of image recognition in this paper through simulation contrast experiment.

II. EXTRACT IMAGE CHARACTERISTICS

A. Gray Level co-occurrence Matrix

Presume one image f has L gray levels, Δx and Δy represents the relative position between two pixels, G represents on gray level co-occurrence matrix and its element g_{ij} is the times of pixels with gray levels of $f(x,y)=i$ and $f(x+\Delta x, y+\Delta y)=j$ in f, $0 \le i, j \le L-1$, g_{ij} calculation formula is:

$$g_{ij} = N\{(x,y) \mid f(x,y)=i \,\&\, f(x+\Delta x, y+\Delta y)=j\} \quad (1)$$

Gray level co-occurrence matrix is:

$$G = \begin{pmatrix} g_{0,0} & \cdots & g_{0,L-1} \\ \vdots & \ddots & \vdots \\ g_{L-1,0} & \cdots & g_{L-1,L-1} \end{pmatrix} \tag{2}$$

In the formula, N is the quantity of pixels meeting requirements, f(x,y) is gray level of pixel at (x,y). Δx , Δy reflects the distance d and direction θ between two points.

B. Feature Vector

Gray level co-occurrence matrix provides the information of image gray direction, spacing and variation range, and corresponding feature value can be calculated based on co-occurrence matrix, use corresponding feature value to characterize the texture information of image. This paper adopted following common statistical feature value to characterize the texture information of people image.

(1) Energy

Energy is the measurement for uniformity of image gray level distribution, which can describe the uniformity of image gray level distribution as well as the fineness degree of texture; the coarse texture is with greater energy than fine texture.

$$Q_1 = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}\left(p_{ij}\right)^2 \tag{3}$$

(2) Contrast.

Image contrast represents the clarity degree of image texture. If the texture of image is deep, and then the contrast is big and the image is clearer, on the contrary, more blurred.

$$Q_2 = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}(i-j)^2 p_{ij} \tag{4}$$

(3) Relativity

Relativity is used to measure the similarity degree of gray level co-occurrence matrix element in row or column direction.

$$Q_3 = \sum_{i=0}^{L-1}\sum_{j=0}^{L-1}\frac{(i-m_r)(j-m_c)p_{ij}}{\sigma_r\sigma_c} \tag{5}$$

(4) Entropy

Entropy represents the density of texture in image. When the texture of image is dense, the entropy value is big; when the texture is sparse, the entropy value is small [9].

$$Q_5 = -\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p_{ij}\log_2 p_{ij} \tag{6}$$

In the formula, $p_{ij} = g_{ij}/n$, n is the sum of elements of G , and $\sum_{i=0}^{L-1}\sum_{j=0}^{L-1} p_{ij} = 1$, the definition of $m_r, m_c, \sigma_r, \sigma_c$ is as following:

$$\begin{cases} m_r = \sum_{i=0}^{L-1} i \sum_{j=0}^{L-1} p_{ij} \\ m_c = \sum_{j=0}^{L-1} j \sum_{i=0}^{L-1} p_{ij} \\ \sigma_r^2 = \sum_{i=0}^{L-1}(i-m_r)^2 \sum_{j=0}^{L-1} p_{ij} \\ \sigma_c^2 = \sum_{j=0}^{L-1}(j-m_c)^2 \sum_{i=0}^{L-1} p_{ij} \end{cases} \tag{7}$$

III. DESIGN OF IMAGE CLASSIFIER

A. BP Neural Network

BP neural network is a feedforward network with the widest application, which consists of input layer, hidden layer and output layer; the hidden layer has many layers and connected by weight matrix between layers, the structure of neural network is as shown in picture 1 [12].

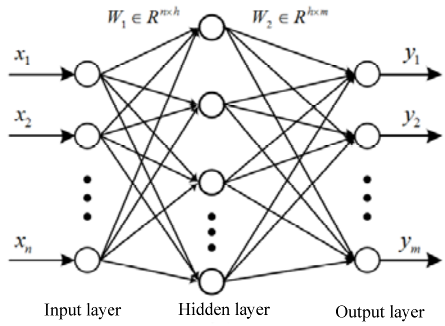


Figure 1. the structure of BP neural network

It can be learned from picture 1, the input vector of BP neural network is $x \in R^n$, $x = (x_1, x_2, \cdots, x_n)^T$ output vector is $y \in R^m$, $y = (y_1, y_2, \cdots, y_m)^T$ hidden layer has h neurons. Presume the connection weight matrix between input layer and hidden layer is W_1 , the weight matrix between hidden layer and output layer is W_2 , and then the output of each neuron is:

$$x'_j = f(\sum_{i=1}^{n} w_{ij}x_i - \theta_j)\,, \quad j = 1,2,\cdots,h-1,h \tag{8}$$

$$y_k = f(\sum_{j=1}^{h} w_{jk}x'_j - \theta'_k)\,, \quad k = 1,2,\cdots,m-1,m \tag{9}$$

DOI 10.5013/ IJSSST.a.17.40.07 ISSN: 1473-804x online, 1473-8031 print

In formula, $f(\cdot)$ is Sigmoid function.

B. Basic Particle Swarm Optimization Algorithm

Presume in one n-dimension target searching space, a population $x=(x_1,x_2,\ldots,x_m)^T$ composed of m particles, in which the position of No. i particle is $x_i=(x_{i,1},x_{i,2},\ldots,x_{i,n})^T$, the flying speed of No. i particle is $v_i=(v_{i,1},v_{i,2},\ldots,v_{i,n})^T$. The position with the best adaption experienced by particle i is $p_i=(p_{i,1},p_{i,2},\ldots,p_{i,n})^T$, the best searched position of the whole particle swarm till today, that is the best global position is $p_g=(p_{g,1},p_{g,2},\ldots,p_{g,n})^T$. After particle finding the above values, it will update its speed and position based on the below two formulas:

$$v_{i,d}^{k+1}=wv_{i,d}^{k}+c_1rand()(p_{i,d}^{k}-x_{i,d}^{k})+c_2rand()(p_{g,d}^{k}-x_{i,d}^{k}) \quad (10)$$

$$x_{i,d}^{k+1}=x_{i,d}^{k}+v_{i,d}^{k} \quad (11)$$

In the formula, c_1 and c_2 are called learning factors; $rand()$ is the random number between $(0,1)$, $v_{i,d}^k$ and $x_{i,d}^k$ are speed and position in No. d-dimension of particle i in No. k; $p_{i,d}^k$ is the individual optimal position in No. d dimension of particle i, $p_{g,d}^k$ is the global optimal position of population in No. d dimension; w is inertia weight factor [13].

C. Catfish Swarm Optimization Algorithm

According to the enlightenment of "catfish effect": when particles gather at local optimal and cause search stagnation, find a "catfish" to simulate particle swarm, change the aggregation state of particle warm at the position of particle swarm and make particle swarm jump out of local extremum point to find global most, which is the basic idea [14] of catfish particle swarm (GCMPSO). GCMPSO adopts deviation threshold as trigger condition, make disturbance for global extremum and local extremum through catfish operator. The speed of particle is updating as following:

$$\begin{aligned} v_{i,d}^{k+1}=&\omega\cdot v_{i,d}^{k}+c_1\cdot rand()\cdot(c_3\cdot rand()\cdot pbest_{i,d}^{k}-x_{i,d}^{k})\\ &+c_2\cdot rand()\cdot(c_4\cdot rand()\cdot gbest_{d}^{k}-x_{i,d}^{k}) \end{aligned} \quad (12)$$

In the formula, c_3 represents the optimal impact strength of catfish to individual, c_4 represents the optimal impact strength of catfish to global; $c_3\cdot rand()$ and $c_4\cdot rand()$ are called as catfish operator, its definition is as following:

$$c_3\cdot rand()=\begin{cases}1, & e_p>e_{0p}\\ c_3\cdot rand(), & e_p\le e_{0p}\end{cases} \quad (13)$$

$$c_4\cdot rand()=\begin{cases}1, & e_g>e_{0g}\\ c_4\cdot rand(), & e_g\le e_{0g}\end{cases} \quad (14)$$

In the formula, e_p represents the deviation of current value and current individual optimal value; e_g represents the deviation of current value and current global optimal value; e_{0p} represents the threshold of deviation of current value and current individual optimal value; e_{0g} represents the threshold of deviation of current global optimal value.

It can be learned from formula (13) and (14) that when the deviation of current value is bigger than deviation threshold, catfish value is 1, at this moment, GCMPSO algorithm is standard PSO algorithm; on the contrary, it is believed that aggregation happened to particle at the moment, jump out of local optimal by introducing catfish operator to impact individual optimal value or global optimal value.

D. Catfish Particle Swarm Algorithm Optimizes BP Neural Network

(1) Initialize BP neural network, set the number of neurons of input layer, hidden layer and output layer, transfer function and learn step etc.

(2) Initialize the speed, population size, inertia weight, learning factor and iteration number etc. of particle swarm and each particle randomly.

(3) Transfer the initial position of particle to BP network as the initial weight value and initial threshold value of BP network. Input sample into network and calculate the output value of network based on forward calculation method of BP network.

(4) Calculate the deviation of BP neural network and return network deviation to particle swarm algorithm as the fitness value of algorithm.

(5) Compare the current fitness value and individual optimal fitness value of each particle, if the current fitness value is better, and then make current fitness as individual optimal fitness value and record the position of particle as individual optimal position.

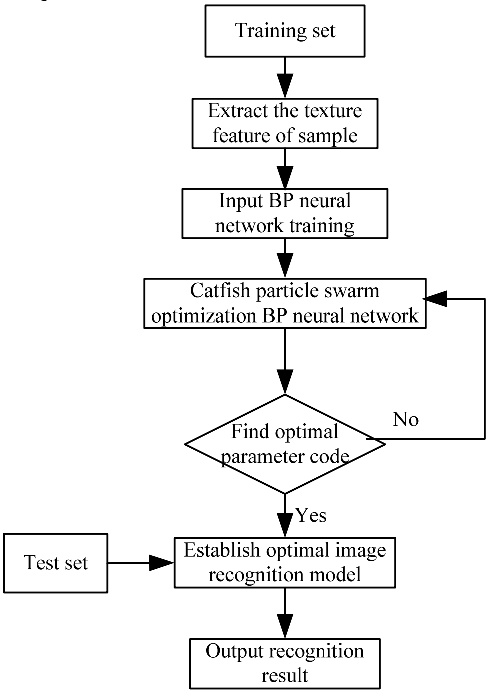
(6) Compare current fitness value and global optimal fitness value of all particles, if the current fitness value is better, and then make current optimal fitness value as global optimal fitness value and record the position of particle as global optimal position.

(7) Determine catfish operator according to formula (13) and (14) and update the speed and position of particle.

(8) If the number iteration exceeds the maximum allowed number of iteration, and then the training is over.

(9) The output global optimal position is the best weight value and best threshold vale of neural network. Or else, return to step (4) and algorithm continues iteration.

The image recognition of gray level co-occurrence matrix and catfish particle swarm optimize neural network is as shown in picture 3.



Picture 2. Image recognition process

IV. SIMULATION EXPERIMENT

A. Source of Image

Make simulation experiment with adoption of ORL navel orange pest image database and Yale navel orange pest image database. ORL image library includes 40 kinds of navel orange pest images, each navel orange pest with 10 images and 400 images in total; part of navel orange pest images in ORL image library are as shown in picture 3.

Picture 3. 4 Navel orange pest images in ORL image library

B. Comparison Model and Performance Evaluation Index

To make the recognition result of image model in this paper with comparability, select particle swarm optimization BP neural network model (PSO-BP) and support vector model (SVM) as comparison model, performance evaluation indexes are recognition rate (%), training time and recognition time (second, ms).

C. Result and Analysis

The results of GCMPSO-BP, PSO-BP and SVM for RL and Yale image recognition are as shown in table 1 and table 2. Analyze the simulation results of table 1 and table 2 and following conclusion can be reached:

(1) The recognition rate of optimizing neural network is higher than SVM model and the training time and recognition time is far higher than SVM model, which explains that adoption of BP neural network can attain image recognition performance.

(2) The recognition rate of GCMPSO-BP is higher than PSO-BP, which proves that the introduction of “catfish” effect into PSO algorithm can get over the local optimal defects in PSO algorithm in a better way, find out better BP neural network parameter, establish better image recognition model, at the same time, the recognition speed is obviously quicker than PSO-BP and improve the efficiency of image recognition.

TABLE 1. RECOGNITION RESULT OF ORL IMAGE DATABASE

Recognition Model	Training Time	Recognition Time	Recognition Rate
SVM	16.7	12.10	91.11
PSO-BP	6.9	4.53	92.75
GCMPSO-BP	5.8	3.44	95.65

TABLE 2. RECOGNITION EFFECT OF YALE IMAGE DATABASE

Recognition Model	Training Time	Recognition Time	Recognition Rate
SVM	20.7	17.35	91.89
PSO-BP	7.8	6.32	93.34
GCMPSO-BP	5.5	4.46	96.38

V. CONCLUSION

BP neural network has shortages in the process of image recognition and propose an image recognition model based on gray level co-occurrence matrix and catfish particle swarm optimization neural network. The simulation results show that compared with other image recognition model, GCMPSO-BP can not only improve the accuracy rate of image recognition, but also attain the optimal recognition efficiency, which is with extensive application prospect in the field of image recognition.

ACKNOWLEDGMENTS

Science and technology support project of Jiangxi province (No.: 20151BBF6-0071).

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