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A Particle Swarm Optimization Algorithm for Neural Networks in Recognition of Maize Leaf Diseases

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Abstract: The neural networks have significance on recognition of crops disease diagnosis, but it has disadvantage of slow convergent speed and shortcoming of local optimum. In order to identify the maize leaf diseases by using machine vision more accurately, we propose an improved particle swarm optimization algorithm for neural networks. With the algorithm, the neural network property is improved. It reasonably confirms threshold and connection weight of neural network, and improves capability of solving problems in the image recognition. At last, an example of the emulation shows that neural network model based on recognizes significantly better than without optimization. Model accuracy has been improved to a certain extent to meet the actual needs of maize leaf diseases recognition. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Neural network optimization, Particle swarm optimization, Opposition-based learning, Maize leaf diseases.

1. Introduction

Maize is an important grain, fodder and economic crop in China which plays a decisive role in the development of national economy. Grey speck disease, brown spot and leaf blight are important leaf diseases in the warm and humid maize areas in china, and they have become more and more serious for recent years [1-3]. The maize disease is one of the major factors influencing maize yield. The traditional identification method is observing with naked eyes by plant protection expert and seasoned farmers which is a time consuming and costly process [4-5]. In recent years, with the development of the image processing and pattern recognition technology, Automatic recognition by computer has been an active topic in the field of disease recognition.

A fuzzy neural network initiated by Helly has solved the recognition of leaf disease by the several steps of segmentation, feature extraction and pattern classification. Pydipati has transformed the color from RGB space to HSI, which improves speed of image processing and robustness of feature extraction, then distinguishes diseased and normal leaves by artificial neural network. Using color as a characteristic space, Tian-youwen et al puts forward the statistical pattern recognition based on general neural network. By dimensional histogram statistic method, Cui-yanli et al get parameters and then put them in example set for neural network training. Ma-xiaodan et al have establishes a multi-layer feed forward neural network used computer digital image processing and artificial neural network to identify the area of diseased spots of soybean laminate. But traditional neural network has the weaknesses such as slow convergent speed, easy getting into local minimum and low rate of correct motion pattern recognition.

Particle swarm optimization (PSO) is an evolutionary computation technique developed by Kennedy and Eberhart in 1995, inspired by social behavior of bird flocking or fish schooling. It is a sort of optimizing method based on iterating and it can be used to solve many kinds of optimization problem. However, it is easily trapped into the local optimization when solving high-dimension functions. In this paper, an improved PSO algorithm is applied to solve the problem, and the improved methods is used in basic PSO which are based on Opposition-Based Learning, making the improved PSO high efficiency in searching for the best solution in the global area. We present the main contributions as follows [10, 11].

A modified PSO is given in this paper. Initialization approach of PSO algorithm is modified by Opposition-Based learning to reduce the possibility that the search for particle swarm falls into the local optima so as to obtain a more optimal solution. To achieve high convergence speed, when the population trap into the local optimum, The corresponding mutation particle will generate and the more compatible particle will be obtain to continuously optimize.

The improved particle swarm algorithm is constructed to solve the optimization problem that traditional neural network has low rate of correct motion pattern recognition, and slow convergence rule of the network. The algorithm is used for optimize neural network structure, weight and threshold to make it have less iterations, faster convergence speed, and be easy to obtain effective and global optimal solution. Then the different leaf disease can be accurately identified and classified.

By image processing technology, the main characteristics of the image are distilled effectively. To make the texture more obvious, the data filtering based on the neighbor information is used to remove the image noise. With the methods of histogram equalization, median filtering and image segmentation, the image enhancement and de-noising is realized. A color feature extraction method based on HSI (hue-saturation-intensity) color components is proposed. Then by extracting the texture characters and shape characters, a base for feature extraction and recognition has been built.

Experiments show that the recognition accuracy and efficiency of this method are improved compared with other feature extraction methods.

The surplus of the paper is concluded in the following part. And section 2 represents the review on the PSO. Section 3 presents our proposed algorithm. Section 4 gives the results of experiments. At length, the concluded remarks are provided in the following Section 5.

2. Swarm Optimization Algorithm

PSO is a global optimization algorithm, which is a newly rising evolutionary computation technique based on swarm intelligence, PSO possesses the better convergent speed and computational precision compares with the traditional algorithms, it can effectively search out the global optimal solution in the space of solution [7-9]. PSO seeks and traversals the optimal particle in solution space. Here suppose the spatial dimension of situation is D and the particle swarm number is S. So particles i is expressed by the formula:

$$X_i(x_{i1}, x_{i2}, \cdots, x_{id})(i = 1,2,\cdots,S; d = 1,2,\cdots,D) \quad (1)$$

Running speed of i is expressed by V_i in the formula:

$$V_i(v_{i1}, v_{i2}, \cdots, v_{id}), \quad (2)$$

The optimum point of i is expressed by the formula:

$$P_i(p_{i1}, p_{i2}, \cdots, p_{id}), \quad (3)$$

Global advantage of the number of particles is expressed by the formula:

$$Pg(p_{g1}, p_{g2}, \cdots, p_{gd}), \quad (4)$$

Position and speed of all the Particle swarm is shift by using iteration method. The iterative rule is expressed by the formula:

$$v_{id}^{k+1} = \omega_i v_{id}^{k} + c_1 r_1 (p_{id}^{k} - x_{id}^{k}) + c_2 r_2 (p_{gd}^{k} - x_{id}^{k}), \quad (5)$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1}, \quad (6)$$

The value of k is related to the number of iterations and c_1,c_2 is related to the accelerated factor. Using the alterable parameter r_1,r_2 to adjust the speed and give expression to the randomicity of movement. The motion inertia is expressed by the parameter ωi. The following factors determine the real-time speed and position:

1) The last speed and location;
2) The trend to approach to optimal location;
3) Members of particle swarm timely adjust the speed and location for information exchange.

Through this way, the optimal solution in solution space can be fast located by PSO to improve the neural network.

3. Neural Network Based on Improved PSO

3.1. Neural Network

The neural network was first proposed in 1986 by Rumelhart and McCelland which is composed of three neuron layers: input layer, hidden layer and output layer to simulate the real structure of the human brain [12]. It may also be regarded as a nonlinear function that regards the input and output values as independent and dependent variables between which the function mapping relationship is reflected. Neural network is suitable for solving non-linear problems based on its good performances on distributed storage and error toleration. However the traditional neural network approaches have some drawbacks such as low convergence speed and local minimal point. The improved particle swarm algorithm is constructed to overcome the shortcomings mentioned [13].

Traditional neural network has low rate of correct motion pattern recognition, and slow convergence rule of the network [14-17]. We introduce PSO to improve the algorithm. The algorithm can find the global optimum of the optimization problems with a faster speed and local minimum can be avoided.

3.2. Opposition-Based Learning

The shortcoming of the standard PSO algorithm is the loss of the population diversity when the global optimal point is apart from particle swarm. In order to relieve the negative impact, the diversity is introduced by randomization. An improved PSO algorithm is based on Opposition-Based Learning. The principle is as the following [18].

When searching the optimum solution x, the usual method is to begin from initial point χ which is determined randomly or according to the experience and obtains the global solution. To resolve the complex problem such as initialization of the weights of the neural network, the method adopted is determined by random samples. A problem to solve is when the random initial weights are apart from the optimal solution, calculating for optimization and searching is a CPU intensive work and convergence is difficult. So in theory, initial feasible solution can be investigated from at all positions and directions of the random point. Supposes that the comparative direction is beneficial for searching and the definition of point is given below firstly [19-22]:

Definition 1: Suppose $x \in [a,b]$ is a real numbers, and its opposite point χ is defined as $\chi = a + b - x$.

Similarly, opposite point in a multidimensional space is defined as follows:

Definition 2: Suppose that $P(x_1, x_2, \cdots, x_n)$ is a point in n dimensional space, $x_1, x_2, \cdots, x_n \in R$ and $x_i \in [a_i, b_i], \forall i \in \{1,2,\cdots,n\}$, the opposite point of P is defined a $P(\chi_1, \chi_2, \cdots, \chi_n)$, in which $\chi_i = a_i + b_i + x_i, i \in \{1,2 \cdots n\}$.

The method of Opposition-Based Learning is provided below: Suppose the function to be optimized is $f(x)$ and the fitness function is $g(\cdot)$ which is used to evaluate the quality of candidate solution. $x \in [a,b]$ is a random initial point and x is the opposite point of x. In the iterative optimization, the values of x and χ are first calculated. Then by comparing the fitness function of the two points to determine the larger one. If $g(f(x)) > g(f(\chi))$, values of x is regarded as the retention value, otherwise, χ.

For example, when optimizating a function of one variable defined on the interval $[a_1, b_1]$ as shown in Fig. 1, the method is: through repeated iteration to evaluate the candidate solution and its opposite solution to find the optimal solution. Initial the x point firstly and obtain its opposite point x_0. Then calculate the distance of d and d0 with the optimum solution respectively. If $d_0 < d$ binary search the space of x, otherwise of x_0. Iterate on till the distance with the optimum solution is less than the predefined thresholds.

Opposition-Based Learning is introduced in order to enhance the performance procedure is provided as following.

Step 1: By using random generation method, the initial uniformly random distributed population is $X = \{Xi, Vi \mid i = 1,2,\cdots N\}$.

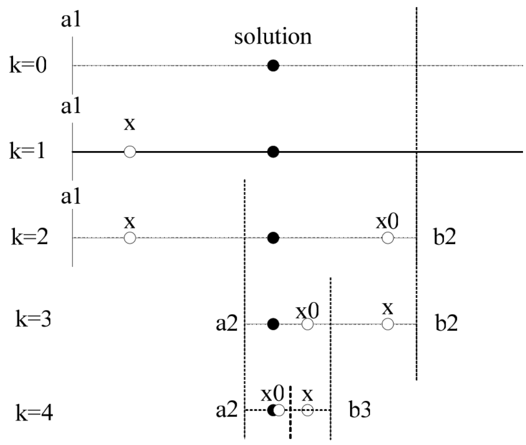

Fig. 1. Adopt Opposition-Based learning to optimize single variable.

Step 2: for each particle in population X, constitute the opposite population from the calculation of the opposite particle $OX = \{OX_i, OV_i \mid i = 1,2,\cdots N\}$ whose position and velocity are described as

$$ox_{id} = L_d + U_d - X_{id} \text{ and } ov_{id} = V_d^{\min} + V_d^{\max} - v_{id}.$$

Step 3: according to the fitness, choose n particles as initial population $X^0 = \{X_i^0, V_i^0 \mid i = 1,2,\cdots N\}$ from X and OX.

In order to search out the global optimal solution in a higher dimensional space, we introduce the mutation model to obtain 2 particles by expansion and contraction. Fitness degree values among the 3 particles are compared and the best is retain for r the next iterative.

For example shown as the Fig. 2 below, a particle expansion is from A (1, 1, 1) to B (2, 2, 2).

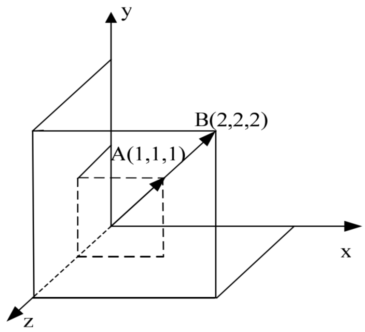

Fig. 2. Simple definition of expand variation.

Its position changes as the formula:

$$x(i+1) = x(i) + a * x(i)\,, \tag{7}$$

3.3. Particle Swarm Optimization

Based on PSO algorithm, parameter t is used as the adaptability function. The formula is the expression:

$$t = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{m}(y^{d}{}_{j.i} - y_{j.i})^{2}\,, \tag{8}$$

The sum of example is denoted by N. The meaning of $y^{d}{}_{j.i}$ is the predict value from samples i and node j. Let $y_{j.i}$ denote the actual value related the predict one. The number of the nodes is denoted by m. the normal steps to establish neural network can be summarized as follow.

Step1: To design and train the structure of neural network by the training documents cluster; to determine the initial parameters;

Step2: To determine the particle swarm initial value based on the neural network which is constructed in Step1;

Step3: By initializing a random particle swarm, updating the velocity and position of particles in accordance with the fitness of particles, searches the optimal coordinates through iterative searching.

Step4: The scheme stops iterative computing when the iterative number is correct. The global optimal solution and the network structure are obtained. If scheme condition is not satisfied, go to Step3.

4. Experimental Results

4.1. Acquisition and Processing

Diseased leaves of leaf blight, gray leaf spot, and brown spot are collected from experimental station of Hebei agricultural university in 2013. The collected images are saved as jpg file.

Image preprocessing schemes include gray processing, histogram equalization and Image segmentation. Then from the open and close operations, Fig. 3 and Fig. 4 show the preprocessing effects.

Fig. 3. Median filtering before (left) and after (right).

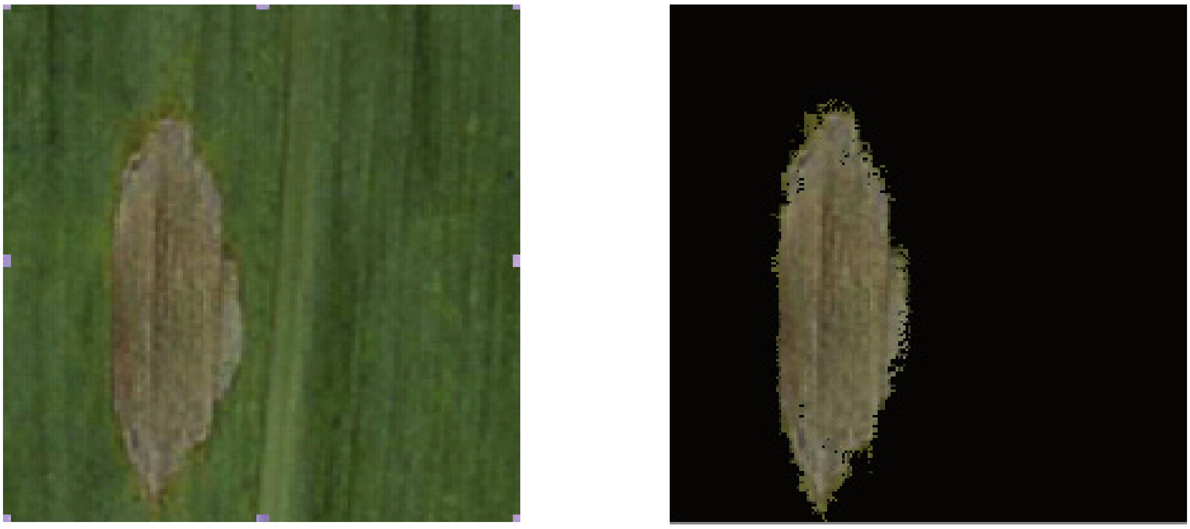

Fig. 4. Image segmentation before (left) and after (right).

4.2. Feature Extraction

Shape features extraction.

There are three characteristic parameters in shape features of maize disease spots which respectively are lesion area, geometrical center and minimum exterior rectangle. Considering the feature of gray leaf spot and leaf blight, we also add the parameters of rectangle degree, roundness degree and figure complexity for feature extraction [23-24].

1) Lesion area.

After image segmentation, the area parameter is the number of pixels of disease part, which is expressed as A0.we put forward an algorithm of area computation by means of the formula in which f (x, y) is two-dimensional digital image of leaf lesions:

$$A_0 = \sum_{i=1}^{N} f(x, y), \tag{9}$$

2) Geometrical center.

The centroid of 2D shape of leaf lesions is regarded as geometrical center. Suppose that there is an only one leaf lesion in image region R which has high connectivity and integrity. We put forward a coordinate algorithm of geometrical center expression by means of the formula in which R is the diseased spots:

$$\begin{cases} \bar{x} = \dfrac{1}{A_0} \sum\limits_{(x,y)\in R} x \\ \bar{y} = \dfrac{1}{A_0} \sum\limits_{(x,y)\in R} y \end{cases} \tag{10}$$

3) Minimum exterior rectangle.

Using the four vertex coordinates of encircle rectangle, this parameters is represented as

$$(X_{\min}, Y_{\min})\ (X_{\max}, Y_{\min})\ (X_{\max}, Y_{\max})\ (X_{\min}, Y_{\max}),$$

among which X_{min}, X_{max}, Y_{min}, Y_{max} denote respectively maximum and minimum of ordinates and abscissas.

4) Rectangle degree.

Rectangle degree means that the ratio of lesion area and minimum exterior rectangle which is expressed Rt. We put forward an algorithm of rectangle degree by means of the formula:

$$R_t = A_0 / A_{cir} \tag{11}$$

The area of lesion is expressed as A_0 and the area of minimum exterior rectangle is expressed as A_{cir}. Thus it can be seen that $R_t \in [0,1]$.

If value of R_t is approaching to 1, the spot shape can be regarded more similar to rectangle, if approaching to π/4, the shape can be a circular. Other values indicate that the spot is mainly irregular in shape.

5) Roundness degree.

Roundness degree means that the similarity between the circular and the spot shape. We put forward an algorithm of roundness degree by means of the formula:

$$C = 4\pi A_0 / L^2 \tag{12}$$

In the formula given above, the circumference of disease spot is expressed by L respectively. Thus it can be seen that $C \in [0,1]$. If value of C is approaching to 1, the spot shape can be regarded more similar to circular.

6) Figure complexity.

This parametric reflects the discreteness of the spot shape which is expressed as S. We put forward an algorithm of figure complexity by means of the formula:

$$S = L^2 / A_0, \tag{13}$$

where L and A0 denote respectively the circumference and area of disease spot. The larger the value of circumference is, the stronger the discreteness and image complexity will be.

The parameters given above are all based on that the shape of disease spot is independent and non-overlapping. But the actual circumstances are not so simple. So it might be necessary to extract the other features of disease spot, including the local color feature and local texture feature to express the contents of an image.

Color features extraction

Compared with other background objects, color features are more stable and specific. It is an important procedure in disease image processing. The widely used color model includes RGB and HSI. HSI color space can give better discrimination according to the properties of plant disease image. The key reason is that the image character based on RGB color space has too more dimensions and high complexity in algorithm. It also affected greatly by the intensity of light resource. So the HSI color space is introduced to extract the color feature. Its main advantage is stable structure and less dimensions. So the image is converted from RGB model to HSI one by the formula [25-26]:

$$\begin{cases} \theta = \arccos\{\dfrac{\frac{1}{2}[(R-G)+(R-B)]}{[(R-G)2+(R-G)(G-B)]^{1/2}}\} \\ S = 1 - \dfrac{3}{(R+G+B)}[\min(R,G,G)] \\ I = \dfrac{1}{3}(R+G+B) \\ H = \begin{cases} \theta, G \geq B \\ 360-\theta, G < B \end{cases} \end{cases} \tag{14}$$

The results of study show that abundant information of the source image is included in the lower order moments and middle order moments of color moment. The most remarkable characteristic of three components in RGB is the B component about maize leaf diseases.

So the feature extraction key steps are: firstly, by dimension reduction, the color images are transformed from RGB space to HSI space; secondly the H component is extracted; then the first, second and third order accuracy of B and H is extracted as the color feature of maize leaf diseases.

Texture features extraction

Texture feature is a significant factor in maize leaf diseases and is a key factor in segmentation. The features are associated with the species of the diseases. According to the different texture information in different directions, we use a gray-primitive co-matrix to describe the feature more exactly. Let N be the grey step in leaf diseases image. The gray level concurrence matrix is expressed by the formula:

$$M_{(\theta,d)}(i,j) = \frac{\{[(x_1,y_1),(x_2,y_2)] \in S \mid f(x_1,y_1)=i \wedge f(x_2,y_2)=j\}}{S}, \tag{15}$$

In the formula, denote the gray level concurrence matrix by $M_{(\theta,d)}$, in which θ represents the direction and d represents the spatial distances between pixels. So the meaning is the probability of coexisted pixels in one diseased spots which respectively has the gray level of i and j. Denote the coordinates of a pair of pixel by(x_1,y_1) and (x_2,y_2). Thus, the pixel number is expressed as $f(x_1,y_1)$ and $f(x_2,y_2)$. The total number of coexisted pixels which satisfies the conditions is denoted by S. The following parameters are selected for texture features expression through a number of experiments.

1) $E(\theta,d)$.

It represents the energy of the matrix which can be represented by the formula:

$$E(\theta,d) = \sum_i^n \sum_j^n M_{(\theta,d)}(i,j)^2, \tag{16}$$

In the formula, $M_{(\theta,d)}$ represents the gray level concurrence matrix, I and j represent the gray value of pixel pair in diseased spots. $E(\theta,d)$ has a higher value if there is most energy around the diagonal.

2) $H(\theta,d)$.

It represents the entropy of gray level concurrence matrix which can be represented by the formula:

$$H(\theta,d) = -\sum_i^n \sum_j^n M_{(\theta,d)}(i,j) \log 2M_{(\theta,d)}(i,j), \tag{17}$$

The value of $H(\theta,d)$ directly proportional to image information quantum. $H(\theta,d)$ has a higher value if image texture distribution is equilibrium.

3) $I(\theta,d)$.

It represents the moment of inertia of gray level concurrence matrix which can be represented by the formula:

$$I(\theta,d) = \sum_i^n \sum_j^n (i-j)^2 M_{(\theta,d)}(i,j), \tag{18}$$

The value of $I(\theta,d)$ is related to the image clarity of texture. $I(\theta,d)$ is very small if the center of matrix is near main diagonal which also reflects the image texture is roughness and obscure.

4) $C(\theta,d)$.

It represents the correlation of inertia of gray level concurrence matrix which can be represented by the formula:

$$C(\theta,d) = \frac{\sum_i^n \sum_j^n i^* j^* M_{(\theta,d)}(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}, \tag{19}$$

The value of $I(\theta,d)$ is related to the similarity of row and column elements. In the formula, μ_x

represents the mean of each column sum in gray level concurrence matrix. μ_y represents the mean of each row sum. σ_x represents the variance of each column sum and σ_y the each row sum [27].

We summed these parameters as metadata for extracting texture feature. Denote the distance between neighboring pixels as d and its value is taken as 1. The matrix direction respectively comes from four directions of coordinate system which is $0,\pi/4,\pi/2,3\pi/4$.So the model of gray level concurrence matrix structure can be constructed. Then the mean value and standard deviation of $E(\theta,d)$, $H(\theta,d)$, $I(\theta,d)$, $C(\theta,d)$ is figured out as the eight parameters to act as the image texture features of leaf diseases.

4.3. Recognition of Diseases

The design of a typical three-layer structure neural network is constructed by sigmod.

The shape features of maize disease spots image consists of 6 attributes as follow: lesion area, geometrical center, minimum exterior rectangle, rectangle degree, roundness degree, figure complexity.

The color features consists of 6 attributes as follow: the first, second and third moment of B and H components.

The texture features consists of 8 attributes as follow: the respective mean value and standard deviation of $E(\theta,d)$, $H(\theta,d)$, $I(\theta,d)$, $C(\theta,d)$.

All of these attributes are used as the inputs of artificial neural network. It contains 20 neurons in total. The output neurons are composed of three major leaf disease of maize: leaf blight, maize brow spot and grey speck disease.

The number of the hidden layer nodes is 19 combining Kolmogorov algorithms. After training the network based on the method of genetic algorithm the optimized weight and threshold are obtained.

The traditional neural network and the optimization methods are trained respectively and finally the suggestibility is compared.

Choose training samples and confirm learning speed as 0.01. A total of 400 effective samples are collected for neural network training which is composed of 175 grey speck disease images, 105 brown spot and 120 leaf blight. Experimental result show that the neural network model convergences at 22 and the optimization neural network at 10. The simulation results show that this algorithm can find the optimal solution more rapidly. A comparison is presented as Fig. 5 and Fig. 6 below.

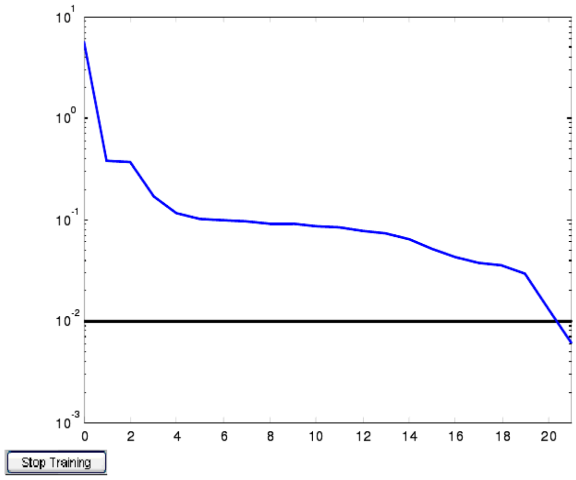

Fig. 5. Traditional neural network convergence.

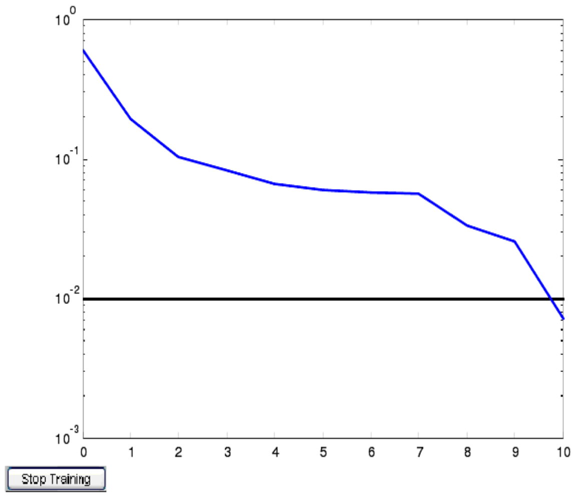

Fig. 6. Optimization neural network convergence.

Test of the neural network is based on 60 images of maize disease respectively. The recognition result is compared below.

Table 1. The maize leaf disease image recognition results.

Maize leaf diseases	Grey speck disease	Brown spot	Leaf blight	Recognition rate
Total numbers of images	60	60	60	————
The recognition rate of traditional optimization network %	86.7	88.3	88.3	87.8
Optimization of optimization network identification rate %	91.7	93.3	95.0	93.3

The result shows that the identification rate of optimization network is 93.3 %. As contrast, at the same time, the traditional neural network is 87.8 %. Conclusions were summarized that the recognition rate is more pronouncedly improved.

Analyses were achieved by multiple regression analysis and through calculating the relevant coefficient, the Incidence degree between prediction value and the real value is shown as Fig. 7.

The predict value of optimization network is represented by the four spots. The predict value is expressed by abscissa and neural network output the ordinate. The actual value is expressed by the dashed line and the fitting value is the solid line. Comparing the simulation results with the real data, we can find that they are similar whose fitting degree R is 0.997.

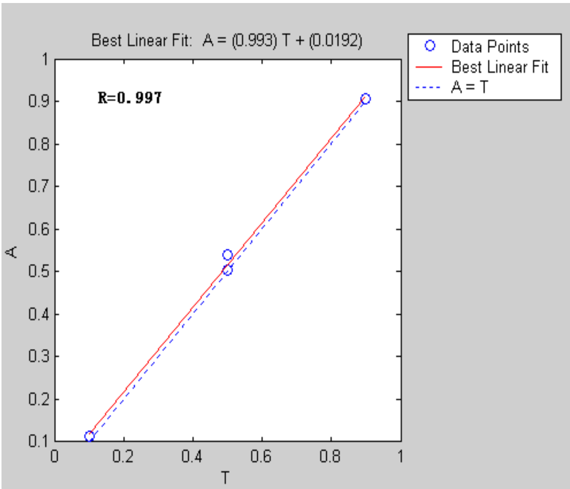

Fig. 7. The optimization of network statistics.

5. Conclusions

In this section, we propose an improved PSO algorithm for neural networks and applied it for the recognition and diagnosis of main maize leaf diseases. The algorithm is based on Opposition-Based Learning and makes the PSO high efficiency in searching for the best solution in the global area to improve neural network predictive model.

Research on neural network in image recognition continues at a rapid pace. This survey provides an introduction to the main concepts of an improved PSO algorithm for neural networks and applied it to the diagnosis of maize disease. The simulation result shows the effectiveness of the method. However, the new optimal methods of neural network can obtain preferable purpose too, such as simulate anneal algorithm, Genetic algorithm et al. At present, the technique of disease detection based on image processing is still a new field of application. It show great potential and form one of the dominant research directions in both agricultural field and the field of image processing.

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