

<http://ansinet.com/itj>

ITJ

ISSN 1812-5638

# INFORMATION TECHNOLOGY JOURNAL

**ANSI***net*

Asian Network for Scientific Information  
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

## A Recognition Method of Red Jujube Disease Based on Portable Microscope and Pso-bp Neural Network

Jianghe Yao, Tiecheng Bai and Gang Wu

College of Information Engineering, Tarim University, Xinjiang, Alar, 843300, China

---

**Abstract:** A recognition method of red jujube disease based on portable microscope and particle swarm neural network is put forward in order to achieve early detection of disease. First, grayscale processing, median filtering and threshold segmentation are used to deal with microscopic image, then, eight eigenvectors are extracted based on R, G, B color space, finally, red jujube leaf disease recognition model is established based on BP neural network which is optimized using particle swarm algorithm. The experimental results show that this method can realize early identification of jujube leaf disease comparing with the ordinary digital camera and the identification accuracy reached 90%.

**Key words:** Portable microscope, particle swarm algorithm, BP neural network, disease recognition model

---

### INTRODUCTION

Red jujube belongs to one of the endemic species of China. Southern Xinjiang is high-quality jujube production base because of the natural condition is superior. But, annual output falls by more than 30% as a result of plant diseases and insect pests which seriously affects the yield and quality of the red jujube. Early and accurate identification is priority of prevention and control of plant diseases and insect pests.

Along with the development of computer vision technology, image processing and pattern recognition technology, these advanced techniques can detect plant diseases and insect pests rapidly

instantly and with no destruction so that appropriate remedial measures can be taken to improve the economic benefit. A lot of research about the detection and identification of crops diseases and insect pests were completed. Watson automatic digital image recognition system is developed which selected the 35 species of common lepidoptera insect image to identify, the recognition accuracy can reach 83% in the case of poor image quality (Watson *et al.*, 2004). Murakami used gray level co-occurrence matrix to identify thrips of cucumber leaf, classification accuracy reached 98% (Murakami *et al.*, 2005). Shariff used a digital camera to obtain 6 kinds of common images of rice pests, developed a classification recognition method based on fuzzy logic and insect quantity counting algorithm (Shariff *et al.*, 2006). R.P Ydipati used the machine vision and neural network technology for statistics and

classification of citrus diseases (Pydipati *et al.*, 2005). A new method for recognizing grape leaf disease by using computer image processing and Support Vector Machine (SVM) was studied by Tian Youwen to improve recognition accuracy and efficiency (Tian *et al.*, 2007). An adaptive segmentation method of crop disease images was proposed based on fuzzy C-mean clustering algorithm (FCM) by Mao Hanping. The mean segmentation errors = 5% (Mao *et al.*, 2008). Diseased areas were emphasized using wavelet transformation and texture matrix by Chen Bingqi, of which the binary image was obtained by threshold processing, then the right rate of the detecting with the algorithm is above 90% (Chen *et al.*, 2009). The design of a real-time detection system for agriculture field pests was developed by Qiu Daoyin (Qiu *et al.*, 2007).

But early recognition of disease can be difficult by digital camera. In order to solve this problem, this study proposes an early identification method of jujube leaf diseases by using a portable microscopic image acquisition device and PSO-BP neural network.

### MICROSCOPIC IMAGE ACQUISITION

**Physical hardware is shown in Fig. 1:** According to the characteristics of the red jujube leaf, the design of microscopic image acquisition device consists of embedded processor, CCD camera, optical microscope, light source, stents, cargo trays and USB storage devices and so on. It can enlarge 40 or 100 times and can obtain disease spot site earlier than ordinary digital camera.



Fig. 1: Physical hardware

**MICROSCOPIC IMAGE PROCESSING**

Before jujube leaf disease image recognition, image gray, the image enhancement, image segmentation and feature extraction are used to process the image color.

**Image gray:** Gray processing mainly includes the maximum value method, average method and weighted average method. This study chooses the weighted average method through experiment contrast.

Weighted average method is that R, G, B are endowed with different weights according to the importance or other indicators and R, G, B value are the weighted average value. That is,

$$R = G = B = (WR + WG + WB) / 3 \tag{1}$$

Among them, WR, WG, WB respectively represent weight value of R, G, B. Experiments show when WR = 0.30, WG = 0.59, WB = 0.11, reasonable gray image can be obtained.

Gray processing effect is shown in Fig. 2.

**Image enhancement processing:** In order to reduce the influence of noise, the image needs to be enhanced. The common processing methods include neighborhood averaging method and median filtering method.

Experiment results show that the median filtering method can overcome image detail fuzzy phenomenon caused by the linear filtering the, better protect the edges of the image and can better filter pulse noise interference, particles and empty. So the study uses the median filtering method to strengthen the disease image of red jujube.

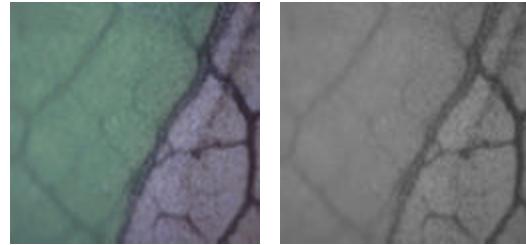


Fig. 2: Gray processing effect

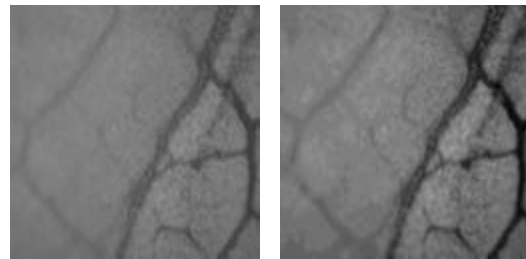


Fig. 3: Treatment effect of median filtering

Treatment effect of median filtering is shown in Fig. 3.

**Image segmentation:** To extract characteristics of red jujube disease, first, these areas need to be separated and extracted. This study uses the iterative method to realize threshold segmentation of image.

Iterative method is based on the idea of approaching. It assumes a threshold in the initial conditions and the hypothesis threshold are constantly updated in the iterative arithmetic of image to get the best threshold value. The initial threshold generally takes average gray level and the specific algorithm steps are as follows:

- **Step 1:** Calculating maximum gray scale image Zmax and minimum gray value Zmin, the initial threshold  $T_0 = (Z_{max} + Z_{min}) / 2$
- **Step 2:** Image is divided into two parts (target and background) according to threshold  $T_k$ , Calculate the average gray value of two parts: the average gray value of target  $Z_{nb}$  and the average gray value of background  $Z_{bj}$ :

$$Z_{nb} = \frac{\sum_{z(i,j) < T_k} Z(i,j) * N(i,j)}{\sum_{z(i,j) < T_k} N(i,j)} \tag{2}$$

$$Z_{bj} = \frac{\sum_{z(i,j) > T_k} Z(i,j) * N(i,j)}{\sum_{z(i,j) > T_k} N(i,j)} \tag{3}$$

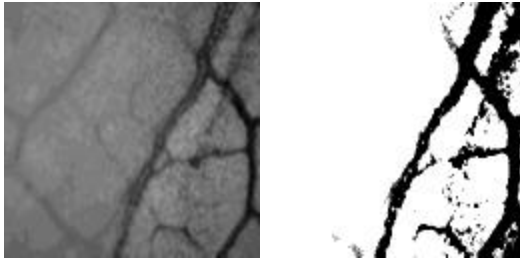


Fig. 4: The effect of threshold segmentation

Among them,  $Z(i, j)$ — $(i, j)$  grey  $N(i, j)$ — $(i, j)$  value, weight  $N(i, j)$ —1.0) coefficient and.

- **Step 3:** To calculate a new threshold

$$T(k+1) = \frac{(Z_{mb} + Z_{bj})}{2} \quad (4)$$

- **Step 4:** if  $T_k = T(k+1)$ , end, otherwise  $k = k+1$ , go to step 2

The effect of threshold segmentation is shown in Fig. 4 according to the above algorithm.

**Extract color feature:** In order to excavate the color information of red jujube image, eight color features are defined quantitatively to describe the color of red jujube diseases. Include: mean of red, standard deviation of red, mean of green, standard deviation of green, mean of blue, standard deviation of blue, mean of lightness, standard deviation of lightness. The calculating formula of color features are as follows:

$$\bar{R} = \frac{1}{n} \sum_{i=1}^n R_i \quad (5)$$

$$S_R = \frac{1}{n} \sqrt{\sum_{i=1}^n (R_i - \bar{R}) * (R_i - \bar{R})} \quad (6)$$

$$\bar{G} = \frac{1}{n} \sum_{i=1}^n G_i \quad (7)$$

$$S_G = \frac{1}{n} \sqrt{\sum_{i=1}^n (G_i - \bar{G}) * (G_i - \bar{G})} \quad (8)$$

$$\bar{B} = \frac{1}{n} \sum_{i=1}^n B_i \quad (9)$$

$$S_B = \frac{1}{n} \sqrt{\sum_{i=1}^n (B_i - \bar{B}) * (B_i - \bar{B})} \quad (10)$$

$$\bar{L} = \frac{1}{n} \sum_{i=1}^n L_i \quad (11)$$

$$S_L = \frac{1}{n} \sqrt{\sum_{i=1}^n (L_i - \bar{L}) * (L_i - \bar{L})} \quad (12)$$

Among them:

- $R$ —the mean of red component
- $S_R$ —the standard deviation of red component
- $G$ —the mean of green component
- $S_G$ —the standard deviation of green component
- $B$ —the mean of blue component
- $S_B$ —the standard deviation of blue component
- $L$ —the mean of mixed component
- $S_L$ —the standard deviation of mixed component
- $N$ —pixel points of red jujube leaf in the image

### ESTABLISH RECOGNITION MODEL

#### Improvement of particle swarm optimization algorithm:

PSO algorithm is improved from the following two aspects. First, PSO algorithm easily appears premature convergence, low search precision and low late efficiency of superposition (Shourian *et al.*, 2008). Improved algorithm process is shown in Fig. 5.

Through using genetic algorithm variation thought, it is initialized with a certain probability after renew particle. Sec, inertial weight  $w$  reflected the degree that the current speed of the particle inherited the original level, a large inertia weights for global search and a smaller inertia weights for local search (Luitel *et al.*, 2010; Ling *et al.*, 2008). In order to better balance Global search and local search capability and linear decrease inertia weight  $w(k)$  instead of  $w$  using the following Eq:

$$w(k) = w_{start} - (w_{start} - w_{end})(T_{max} - k) / T_{max} \quad (13)$$

There:  $w_{start}$  represented initial inertial weight;  $w_{end}$  represented inertial weight of the maximum iteration times;  $k$  represented the current iteration times;  $T_{max}$  represented the maximum iteration times. In this instance,  $w_{start} = 0.9$ ;  $w_{end} = 0.4$ . Early in the iteration, the bigger inertial weight keeps strong global search capability, while later in the iteration, the smaller inertial weight improves the searching for optimal solution in the local region.

The best individual fitness value that the improved PSO algorithm get is 0.0065. The results show that the improved PSO algorithm can jump out of local minimum values, get better BP neural network weights and threshold. Fig. 6 shows the testing results of the improved PSO.

Weights and threshold of BP neural network is optimized by the improved particle swarm algorithm, Three layers BP neural network is constructed, the

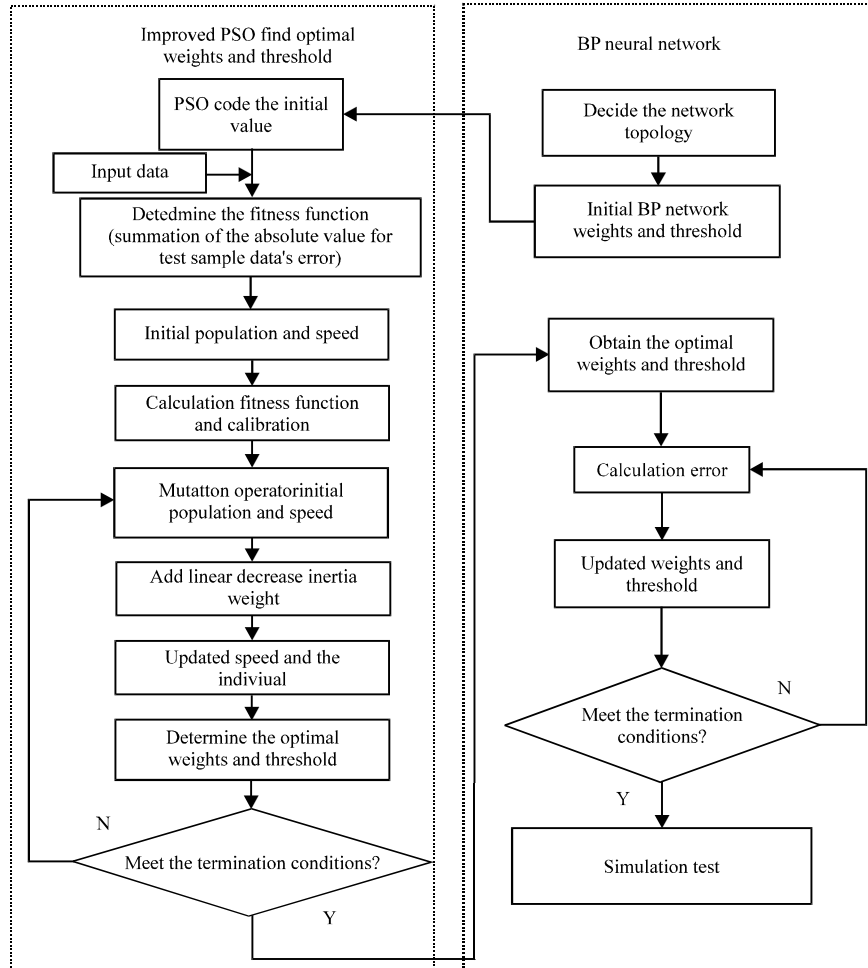


Fig. 5: Improved PSO algorithm to optimize the BP neural network weights and thresholds flow chart

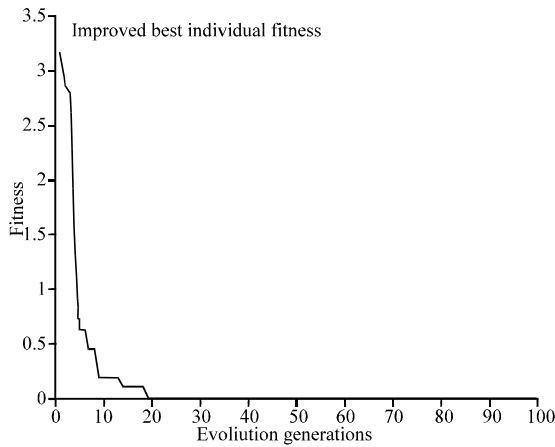


Fig. 6: Testing results of the improved PSO

input unit number is 8, output unit number is 2, hidden layer is 9 neurons, target error is 0.01.

Table 1: Comparison of precision

Improved BP	Model accuracy(%)
BP	73.6
PSO-BP	90.8

The identification accuracy of disease using standard BP to establish model and PSO-BP to establish model is shown in Table 1.

The Table 1 shows that the PSO algorithm can improve the precision of the model, it can reach more than 90%.

### CONCLUSION

Recognition model based on microscopic image acquisition device and PSO - BP neural network can not only realize the early detection but also the PSO algorithm can improve the precision of the model. To employ computer vision provides the following reference for further researches:

- It is difficult how to use computer vision technology to detect early disease and cross infection among a variety of diseases
- The combination of image processing technology and hyper spectral technology is expected to improve the accuracy of disease detection

#### **ACKNOWLEDGMENTS**

The authors would like to thank for the support by Natural Science Foundation of China under the Grant No. 61362026 and Youth innovation fund project of xinjiang production and construction corps of China under the Grant No. 2013CB020. The authors thank for the support by the principal fund of Tarim University under the Grant No. TDZKSS201207.

#### **REFERENCES**

- Chen, B.Q., X.M. Guo and X.H. Li, 2009. Image diagnosis algorithm of diseased wheat. *Trans. Chin. Soc. Agric. Mach.*, 40: 190-195.
- Ling, S.H., H. Iu, F.H.F. Leung and K.Y. Chan, 2008. Improved hybrid particle swarm optimized wavelet neural network for modeling the development of fluid dispensing for electronic packaging. *Ind. Electr. IEEE Trans.*, 55: 3447-3460.
- Luitel, B. and G.K. Venayagamoorthy, 2010. Particle swarm optimization with quantum infusion for system identification. *Eng. Appl. Artif. Intell.*, 23: 635-649.
- Mao, H.P., Y.C. Zhang and B. Hu, 2008. Segmentation of crop disease leaf images using fuzzy C-means clustering algorithm. *Trans. Chin. Soc. Agric. Eng.*, 9: 136-140.
- Murakami, S., K. Homma and T. Koike, 2005. Detection of small pests on vegetable leaves using GLCM. *Am. Soc. Agric. Biol. Eng. Ann. Int. Meeting*, 9: 15-18.
- Pydipati, R., T.F. Burks and W.S. Lee, 2005. Statistical and neural network classifiers for citrus disease detection using machine vision. *Trans. Am. Soc. Agric. Eng.*, 48: 2007-2014.
- Qiu, D.Y., H.T. Zhang, X.Y. Liu and Y.N. Liu, 2007. Design of detection system for agriculture field pests based on machine vision. *Tran. Chin. Soc. Agric. Mach.*, 38: 120-122.
- Shariff, A.R.M., Y.Y. Aik, W.T. Hong, S. Mansor and R. Mispan, 2006. Automated identification and counting of pests in the paddy field using image analysis. *Proceedings of the 4th world congress conference on Computers in Agriculture and Natural Resources*, July 23-25, 2006, Orlando Florida, pp: 759-764.
- Shourian, M., S.J. Mousavi and A. Tahershamsi, 2008. Basin-wide water resources planning by integrating PSO algorithm and MODSIM. *Water Resour. Manage.*, 22: 1347-1366.
- Tian, Y.W., T.L. Li, C.H. Li, Z.L. Piao, G.K. Sun and B. Wang, 2007. Method for recognition of grape disease based on support vector machine. *Trans. Chin. Soc. Agric. Eng.*, 6: 175-179.
- Watson, A.T., M.A. O'Neill and I.J. Kitching, 2004. Automated identification of live moths (macrolepidoptera) using Digital Automated Identification System (DAISY). *Systematics Biodiversity*, 1: 287-300.