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Detection of Insects-contaminated Wheat Based on PSO-BP Network

^{1,2}Shi Weiya, ¹Jiao Keke, ^{1,2} Liang Yitao, ^{1,2} Wang Feng and ^{1,2}Zhang Dexian

¹School of Information Science and Technology, Henan University of Technology

²Grain Information Processing and Control Key Laboratory of Ministry of Education,
Zhengzhou, 450001, China

Abstract: Based on biophoton analytical technology, the ultraweak photons emitted from the normal and insects-contaminated wheat are measured separately. Nine parameters of wheat self-illuminating characteristic are used as wheat feature vector. The study proposed using the PSO-BP algorithm (Particle Swarm optimization-BP neural network) as the classification algorithm. The algorithm is trained to distinguish the normal and insects-contaminated wheat. The experimental results show that the recognition precision can reach to 90%. The model can provide a new thought for the detecting the wheat pests.

Key words: Biophoton analytical technology, stored grain insects, PSO-BP, recognition

INTRODUCTION

The wheat is the main grain stocks of each country. The grain insects are very hazard during the storage of grain, especial the hidden insect, such as maize weevil, Olivier and so on. Because these insects are concealed in the grain, it is time-consuming that the detection is difficult (Shen, 1995). The grain insects not only influent the grain stock, but also the level and quality of grain.

At present, the researches of detecting the hidden insects are paid great attention at home and abroad. The traditional stored-grain insects detection technology consists of screening, trap catching (Hagstrum *et al.*, 1998), computer vision recognition (Ridgway *et al.*, 2002), electronic nose (Zhang and Wang, 2007) and so on. However, these methods have one or more weakness. For example, some methods have the strong subjectivity, destructiveness and inaccuracy. In addition, these methods only detect the pest outside the wheat and can do nothing about the hidden insects. Recently, many new advanced methods appear in succession, such as Nuclear Magnetic Resonance spectroscopy (NMR) (Chambers *et al.*, 1984), X-ray detection (Karunakaran *et al.*, 2004), the Near-Infrared Reflectance spectroscopy (NIR) (Pierna *et al.*, 2012). For these methods, NMR and X-ray detection are unusefulness for the reason of radioactivity and high costs, NIR has the weakness of inconvenient operation and costs are also high. Therefore, it is necessary to explore some rapid, nondestructive and effective detection method.

Bioluminescence emission is the common phenomenon of life, which exists in the animals, plants

and microbial systems. It is metabolic process of lives and comes from the state transition from high energy state to lower energy state (Gu, 2007). With the development of Optoelectronic detection technique, the research of ultraweak photon emissions is increasingly active. In the agriculture, there are researches about seed resistance (Inagaki *et al.*, 2007), the fresh degree and relation with the ultraweak photon emission (Li *et al.*, 2004). It is relatively absence about the research of detecting hidden insect in the grain. The research is still at a tentative stage.

The study combines Biophoton Analytical Technology (BPAT) with the detection of wheat insect, innovatively proposes a detection model for hidden insect in the wheat. The model firstly uses the ultraweak photon detection machine to measure the spontaneous photon emitted from the normal and insects-contaminated wheat. Then, the feature can be gotten from the measuring photon datum. The BP neural network is used as the classification algorithm. The PSO-BP algorithm (Particle Swarm optimization-BP neural network) is introduced to optimize the weight and bias of the network. The model can classify the normal and insects-contaminated, which can acquire the recognition rates of 90%.

PSO-BP ALGORITHM (PARTICLE SWARM OPTIMIZATION-BP NEURAL NETWORK)

BP neural network: Back Propagation (BP), an abbreviation for "backward propagation of errors", is a traditional algorithm of artificial neural networks. The

Corresponding Author: Shi Wei-Ya, School of Information Science and Technology, Henan University of Technology, Henan, Zhengzhou, 450001, China

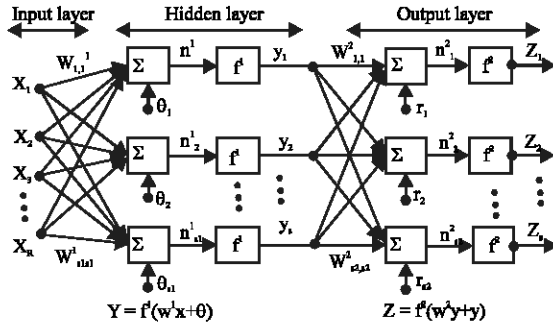


Fig. 1: Typical topology of BP neural network

neural network is widely applied in many fields, such as signal processing, pattern recognition, adaptive control and so on (Dong, 2007). The network generally consists of input layer, hidden layer and output layer. The Fig. 1 gives a typical network topology. In the network, the input layer is in charge of receiving the outside information, which in turn transfers to the hidden layer. The hidden layer acts as the interior information processing and alternation. The output layer gives the finally processed result. The whole algorithm is composed of forward propagation and the back propagation. When the real output result is inconformity with the expected result, the back propagation of error begins. The values of weight and bias are repeatedly revised until the error is less than predefined value.

In Fig. 1, x is the input of neuron, y is the output of hidden layer, z is the output of the output layer and f is the transfer function. Each layer has its own weight matrix $\bar{w}$ and its threshold vector θ, γ .

However, the BP neural network has the shortcoming, which has the slow converge and easily trapped in the local optimum. In addition, its initial weight and bias value are random so that the optimal value cannot be necessarily gotten after a number of experiments.

Algorithm of particle swarm optimization: Particle swarm optimization is intelligence optimization algorithm based on the animal behavior, which has the global search ability. It is firstly proposed by electrical engineer Eberhart and social psychologist Kennedy in 1995 (Ji *et al.*, 2009). The algorithm optimizes a problem by iteratively improving a candidate solution with regard to a given criterion. It is easily realized and can achieve the effectively searching.

PSO optimizes a problem by having a population of candidate solutions, called particles and moving these particles in the search-space by simple mathematical formula according to the particle's position and velocity. In the PSO, the movement of each particle is influenced by

its local position and moves toward the global best known positions in the search-space. At last, the swarm is expected to move toward the best solutions (Wang *et al.*, 2013).

Assuming that there are m particle in D -dimension space, m is the group size. The positional information of the i th particle can be expressed as $X_i = [X_{i1}, X_{i2}, \dots, X_{in}]$ and its velocity information is $V_i = [V_{i1}, V_{i2}, \dots, V_{in}]$. The fitness value is firstly computed. The optimal value of each particle is $P_i = (P_{i1}, P_{i2}, \dots, P_{in})$ and the optimal value of whole group is $P_g = (P_{g1}, P_{g2}, \dots, P_{gD})$. The position and velocity is updated using the following formula:

$$v_{id}^{t+1} = wv_{id}^t + c_1r_1(p_{id} - x_{id}^t) + c_2r_2(p_{gd} - x_{id}^t) \quad (1)$$

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1} \quad (2)$$

where, t is the iterations and v_i^{t+1} denotes the velocity of the i th particle in $t+1$ time. r_1, r_2 is random number between $[0, 1]$, c_1, c_2 is the learning factor, which is located in $[0, 2]$. The velocity is restricted to $[V_{min}, V_{max}]$ and weight w indicates how much the velocity of particle can be hold. PSO-BP algorithm: Considering the weakness of BP algorithm, the study proposes that the weight and bias value of BP network is optimized using Particle Swarm optimization. Then, the BP algorithm is used to explore the optimum classifying result in the solution space. The mixed algorithm is called PSO-BP algorithm. The procedure of the algorithm can be outlined as follows:

- Step 1:** The parameter of PSO is initialized. The position of particle X_i is randomly given in $[X_{min}, X_{max}]$ and the velocity of the particle is set in $[V_{min}, V_{max}]$. The fitness value of each particle and the whole group is then computed. In the computation, the energy function E is given as follows:

$$E = \frac{1}{M} \sum_{p=1}^M \sum_{i=1}^n (y_i - o_i)^2 \quad (3)$$

It can be also used by the error of output layer:

$$F = K \sum_{i=1}^n |y_i - o_i| \quad (4)$$

In the above equation, n is the number of neuron in output layer, y_i is the expected value and o_i is the real value of i th neuron. K is coefficient and M is the number of samples

- Step 2:** The position and velocity of the particle are updated. The Eq. 1 and 2 are separately used to

update the velocity and the position. In each iteration, the fitness of each particle and whole group is also updated

- **Step 3:** To decide if the end condition is satisfied, If not satisfied, the step 2 is repeated, otherwise, the optimal weight and bias of BP neural network is gotten

The algorithm of PSO-BP combines the local searching ability of BP with the global search characteristic of PSO, which can effectively avoid the network trapped in local optimum.

MATERIALS AND METHODS

AK58, which is reaped in June, 2012, is chosen as wheat varieties in the experiment. The maize weevil is fostered as the insect in the wheat. The infestation time of duration lasts for 24-28 days. The weight of wheat is about (5.00 ± 0.02) g in each measure. There are 50 groups to be measured in the experiment.

BPCL-ZL-TGC ultraweak photon measuring instruments is used as the measuring apparatus. In the measuring procedure, the normal and insects-contaminated wheat are separately measured after some preprocessing in the darkroom for 30 min. The temperature of darkroom is 25°C. The preprocessing procedure aims to get rid of the disturbance of ambient light.

The time interval of measures is 1s and duration is 1800s. The indoor temperature is (28 ± 2) , the measuring temperature is (27.5 ± 0.5) and indoor humidity is $(45 \pm 5)\%$. The normal and insects-contaminated wheat are respectively measured 25 groups, which have 50 groups in total. There are 30 training samples, where 15 groups are separately chosen from the normal and insects-contaminated wheat. The other samples are used as the testing samples.

FEATURE EXTRACTION AND DATA PROCESSING

The statistical feature is extracted from the measured ultraweak photon. The following characteristics can be used to depict the measuring signal:

- Position feature reflects the central tendency of data, which denotes the extent of data closed to or gathered to the center. It consists of mode, median and mean
- Dispersion feature is the dispersion degree of data distribution, which reflects the tendency of each data away from the center. It includes quartile deviation, mean deviation variance and Dispersion coefficient

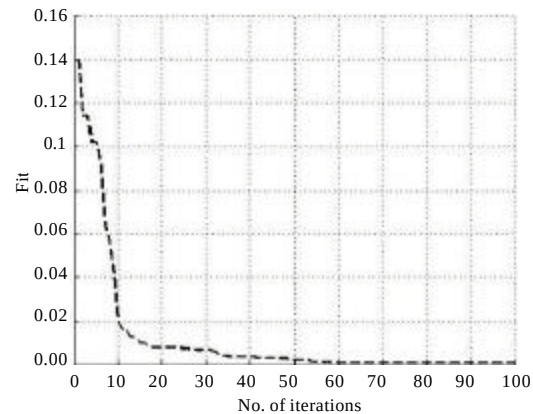


Fig. 2: Fitting curve of PSO

Table 1: Comparative results between different algorithms

Algorithm	Iterations	Time (s)	Accuracy (%)
KNN	-	0.004	55.00
BP (traingda)	3188	11.63	85.00
BP (traingdx)	333	2.31	85.00
BP (trainlm)	16	0.84	85.00
PSO-BP (F)	268	3.25	90.00
PSO-BP (E)	281	3.36	90.00

- Morphological feature is the distribution feature, which reflects the deviation degree of data. It is composed by skewness and kurtosis

There is in all 9 features considering these distribution characteristics. As a result, there are 9 input nodes for the BP neural network. The number of nodes in output layer depends on the classifying result. There are two categories: The normal and insects-contaminated wheat. The number of nodes in hidden layer can be decided using the Fibonacci method.

$$N = n + 0.618(n - m) \quad (5)$$

where, N, n and m are the node numbers of hidden layer, input layer and output layer, respectively. There are 13 nodes in hidden layer, which can fulfil the required precision.

The input features are firstly normalized in $[-1, 1]$. The tan-sigmoid and purelin function are chosen as the transferring function. The learning parameter of PSO is given as following: $C_1 = 2$, $C_2 = 1.8$. The iteration epoch is 100.

After the network reached to convergence, the 20 groups of testing samples are used to give the final classification using the trained PSO-BP network. To give contrastive analysis, we classify the sample using the traditional KNN algorithm, the BP algorithm (having different learning function). The Table 1 gives the result of different algorithm. The Fig. 2 gives the fitting curve of

PSO. From the result, it can be found the proposed PSO-BP gives the better recognition rate.

It can be found that the traditional KNN gives the worst recognition rate, which hardly distinguishes the normal wheat with the insects-contaminated wheat. In contrast, the BP algorithm has better recognition accuracy. Nevertheless, it has the possibilities of trapped in the local optimum. The PSO-BP can give the best recognition result in the three algorithms.

CONCLUSION

The study creatively puts forward a method about the detection of hidden insects in the wheat. The Bioluminescence emission is measured, which forms the feature vectors. The PSO-BP is used as the classifying algorithm. The method can effectively distinguish the normal and insects-contaminated, where the operation is simple and easily realized. In the future, the feature extraction and the classifying algorithm will be the focus of the research.

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