Warehouse Environment Parameter Monitoring System and Sensor Error Correction Model Based on PSO-BP

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Abstract: The warehouse environment parameter monitoring system is designed to avoid the networking and high cost of traditional monitoring system. A sensor error correction model which combines particle swarm optimization (PSO) with back propagation (BP) neural network algorithm is established to reduce nonlinear characteristics and improve test accuracy of the system. Simulation and experiments indicate that the PSO-BP neural network algorithm has advantages of fast convergence rate and high diagnostic accuracy. The monitoring system can provide higher measurement precision, lower power consume, stable network data communication and fault diagnoses function. The system has been applied to monitoring environment parameter of warehouse, special vehicles and ships, etc.

Key words: parameter portable monitoring system; ZigBee technology; particle swarm optimization-back propagation (PSO-BP); fault diagnosis

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0 Introduction

Warehouse is important for material supply system and responsible for material storage, management and deployment. Monitoring warehouse environment parameters is crucial to the safety and quality of materials in the warehouse. Traditional warehouse environment monitoring system has many disadvantages, such as more field devices, wiring complexity, low reliability and high maintenance costs. The application of wireless sensor network (WSN) helped to realize the remote intelligent management of warehouse[1-2].

WSN is a self-organizing network which is able to take the advantage of ZigBee technology for wireless transmission by many micro-sensors. Different sensors can sense different environmental information: Pressure sensor can sense atmospheric pressure change, temperature and humidity sensor can sense air conditions; accelerometer sensor can sense acceleration change, etc. ZigBee technology is a short-range, low-complexity and low-power wireless communication technology and it is based on IEEE802. 15. 4 standard low-power local area network protocol[3]. Complicated wireless sensor networks can facilitate monitoring environment parameters with the help of remote portable monitoring and automatic control system.

Nonlinear errors are the major problem of sensor system and can directly affect the performance of monitoring system. Many researchers have addressed this issue. Ref. [4] has carried on error compensation with hardware circuit, but complex circuit and compensation effect was poor. Ref. [5] has conducted error compensation by using piecewise interpolation method. This method is simple but it is only applicable to low precision system. Refs. [6—7] proposed a sensor error

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compensation method based on back propagation (BP) neural network. However, this algorithm has the shortcomings of slow speed in local optimization and convergence, so that it is very difficult to be used practically. Particle swarm optimization (PSO) algorithm is a global optimization algorithm based on random population evolution, and it has high search efficiency and strong robustness throughout the solution space without relying on gradient information[8]. Thus, the combination of BP and PSO neural network algorithms seems more potential in nonlinear systems. In this area, intelligent fault diagnosis based on neural network is the focus at present. It concentrates on the following approaches: (1) Constructing observer by using neural network; (2) realizing fault diagnosis through pattern recognition while using neural network as classifier; (3) realizing fault detection by utilizing neural network as a dynamic prediction model; (4) establishing expert system for fault diagnosis based on neural network.

We design an environmental monitoring system to collect information of temperature, humidity, light-intensity, as well as pressure and acceleration state through ZigBee wireless sensor network. Then we develop an error compensation model using PSO-BP neural network to improve detection precision and eliminate nonlinear error which produced in the collection process.

1 Monitoring System Design

The monitoring system mainly composed of three parts: A host computer, a portable monitoring terminal and a wireless monitoring node. The diagram of the system is shown in Fig. 1.

The monitoring terminal is based on a ZigBee network. The monitoring nodes can automatically find and join the ZigBee network through monitoring terminals. Monitoring terminals send acquisition commands to monitoring nodes. Terminal nodes receive the data from coordinator nodes to collect instruction. We use sensing parameters to collect information, and set up the ZigBee network and coordinator node, which communicate

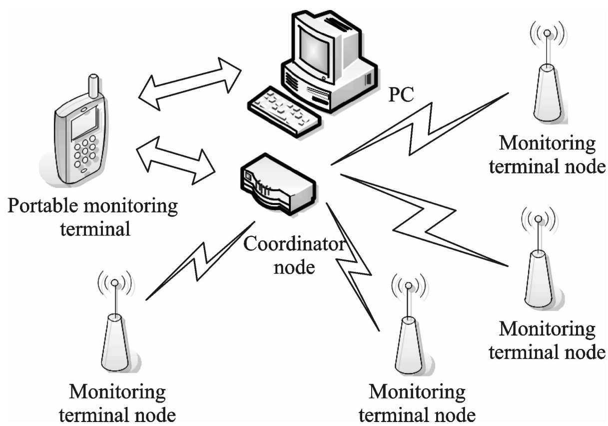

Fig. 1 Monitoring system

with each other. Monitoring terminals send collected data to the host computer for error compensation in order to improve the detection accuracy. Monitoring results is displayed on the OLED screen of the monitoring terminal.

2 Hardware and Software Design

2.1 Hardware design

The hardware of the system mainly includes two parts: Monitoring terminals and monitoring nodes, as shown in Fig. 2. ARM microprocessor is used as the core of monitoring terminals, and ZigBee module as a coordinator node to achieve wireless data transmission. In addition, EEPROM, SD card, Beidou/GPRS, power circuit, JTAG, USB and RS232 module are integrated into the system. It provides the interface for matrix keyboard and OLED screen.

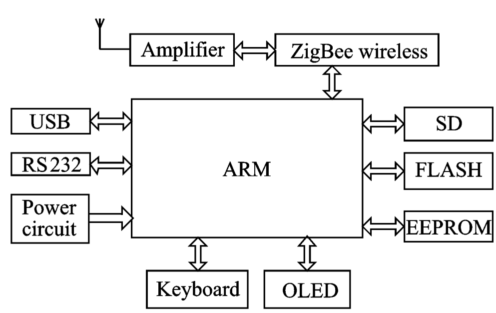

Fig. 2 Hardware of monitoring terminal

The ZigBee core module supports IEEE 802.15.4 ZigBee wireless communication protocol which is worked in the 2.4 GHz frequency band. The module integrats JTAG interface to facilitate program downloading and debugging. RS232 and

USB interface read data through PC serial port[9-10]. The amplifier chip is used to amplify the signal in ZigBee module. The ZigBee module uses temperature and humidity sensor chip to sample temperature and humidity. Acceleration chip is used to sense acceleration which ranges within ±2 g, ±4 g, and ±8 g, with a resolution of 1 mg/LSB on the ±2 g range. The pressure chip is an absolute piezoresistive pressure sensor which recieves information from sensing element and provides a digital signal to the external world[11]. The module holds high measuring precision, small package size and high reliability transmission. The diagram of the module is shown in Fig. 3.

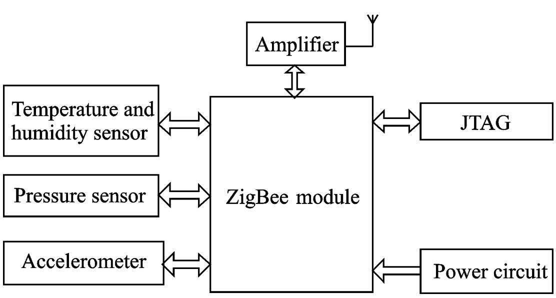

Fig. 3 Wireless monitoring node

2.2 Software design

The software design of the monitoring terminal is divided into two parts: The protocol stack designing based on TI′s ZigBee Pro, which establishes ZigBee wireless network to send and receive data; the data processing part which is responsible for data acquisition, storage, processing, analysis and display functions. The ARM programming software is the Keil development environment which uses C language to realize different functions. Wireless monitoring nodes charge the sensor′s data acquisition and transmission. and this part of the software based on Z-Stack protocol initializes and drives the sensor hardware.

The coordinator establishes the ZigBee network after the microprocessor and the ZigBee module finish initialization. It assigns the address when a monitor node requests to join the network. Then the monitoring terminal which transmits the collecting information acquires and sends commands to the monitoring node in order to run related operations. The monitoring node then enters sleep state automatically in order to reduce power consumption after finishing data transmission.

3 Sensor Error Correction Model Based on PSO-BP

The artificial neural network with error correction is a novel method with advantages of a small number of samples required, and simple algorithm, etc. PSO-BP is used to process nonlinear input-output for the temperature and humidity sensor to improve the measurement accuracy and nonlinear error correction.

3.1 BP neural network

The learning rule of BP neural network (BPNN) adjusts the network weights and thresholds by reversing spread constantly to sum the minimum of squared error of the network. BP neural network includes input layer, hidden layer and output layer. Suppose an arbitrary network has L layers and N nodes, then there are P samples(x_k, d_k) $(k=1,2,L,P)$. The sum of input network in the lth layer of the j neurons is I_{jk}^l and the output is O_{jk}^l. The connection weights between the i neurons in the $(l-1)$th layer and the j neurons in the l the layer are W_{ij} [12-13]

$$I_{jk}^l = \sum_{i=1}^{nk} W_{ij} O_{jk}^l, \qquad O_{jk}^l = f(I_{jk}^l) \tag{1}$$

We define that the expected output of the network is d_k and the squared error of the actual output y_k is the objective function when the network is a BP network[14-15]

$$E_k = \frac{1}{2}\sum_{j=1}^{m}(d_{jk} - y_{jk})^2 \tag{2}$$

The total error of the P sample is defined as

$$E = \frac{1}{2P}\sum_{k=1}^{P} E_k \tag{3}$$

The learning problem of the network is equivalent to the unconstrained optimization problem. The weight is changed by the negative gradient of the error function when adjusting the weight of W to make the total error E very small

$$W_{ij}(t+1)=W_{ij}(t)-\eta\frac{\delta E}{\delta W_{ij}} \tag{4}$$

where t is the number of iterations and η the size of step. Usually, the most common is the three-layer BP neural network. The model diagram of network is shown in Fig. 4.

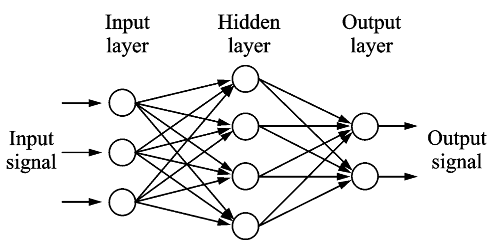

Fig. 4 Model of BPNN

3.2 PSO-BP composite algorithm

The learning process of neural network is the process of optimizing the weights, so the optimization of BP neural network with PSO algorithm optimizes the weight of the neural network. The connect weights of BP neural network as the dimension of the vector particle is each particle′s solution. The weight space is the search space of particle swarm[16]. The fitness function of PSO is the output error of the neural network. The formula is as follows

$$f=\frac{1}{P}\sum_{j=1}^{P}\sum_{k=1}^{m}(d_{jk}-y_{jk})^2 \tag{5}$$

where m is the number of output node; P the number of samples in training set; y_{jk} the actual output of the BP network and d_{jk} the desired output.

PSO algorithm which trains the BP network as the change of information dissemination process boosts the search speed faster and the convergence of the whole algorithm suitable. The basic flow chart of the algorithm is shown in Fig. 5.

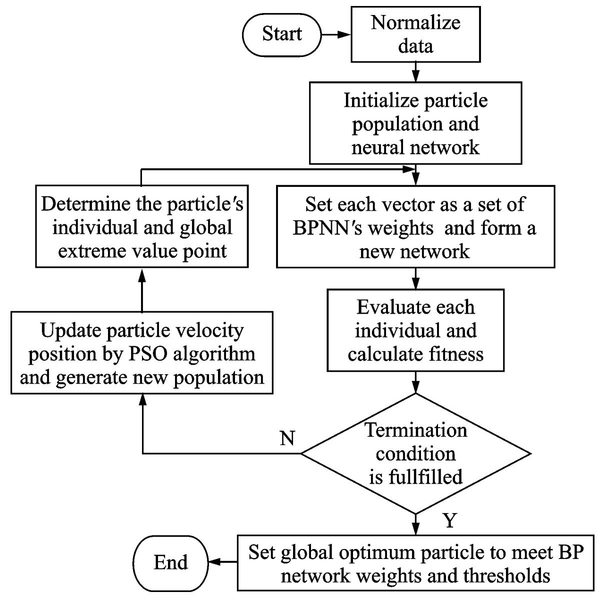

Fig. 5 PSO-BP composite algorithm

3.3 Neural network model construction

The design of a three-layer BP neural network can be achieved in accordance with the nonlinear error correction requirements of the system. $\Delta t(i)$, the output node of BP neural network, is the difference between the digital temperature sensor measurement values $t_1(i)$ and the actual temperature $t_2(i)$. $T(i)$, the standard temperature signal, and $U(i)$, the output voltage of the sensor A/D sampling data, are two input nodes in input layer of the BP neural network[17].

There are the following empirical formulas for the selection of the hidden layer nodes[18]

$$q=2n_{\mathrm{I}}+1 \tag{6}$$

$$q=\sqrt{n_{\mathrm{I}}+n_{\mathrm{O}}}+l \qquad l\in[1,10] \tag{7}$$

where n_{I} is the number of input layer node; n_{O} the number of output layer nodes; and q the number of nodes in the hidden layer.

The transfer function of the sigmoid function in the hidden layer is

$$f_1=\frac{1}{1+e^{-x}} \tag{8}$$

The transfer function in the output layer is taken as a linear function

$$f_2=x \tag{9}$$

The three-layer neural network which is used in this system has two input nodes, five hidden layer nodes and one output node according to the choice of the initial conditions. The temperature sensor′s error analysis of neural network structure model is shown in Fig. 6.

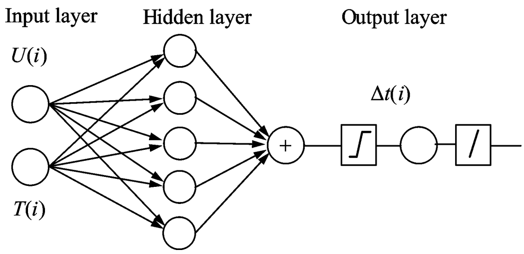

Fig. 6 Temperature sensor's error analysis of neural network structure model

4 Simulation and Analysis

4.1 Experimental data acquisition

The laboratory environment is used as the experimental greenhouse. A total of nine experimental nodes, including one coordinator node and eight terminal nodes, are set up according to the size of the laboratory. The control function of the air conditioner is used to simulate the changes of temperature and humidity in the course of the experiment. The temperature and humidity measurement data from the sensor is used by the control experiment.

The data of the twenty groups are recorded in order to avoid the chance of the experiment result, and the results are prepared for the experiment. The data of temperature are listed for reference in the experiment. The results of the experimental data are shown in Table 1.

Table 1 The Results of experimental data

Number	Thermometer reading/℃	Sensor data/℃	Number	Thermometer reading/℃	Sensor data/℃
1	15.2	15.4	10	20.8	20.9
2	17.3	17.0	11	28.9	29.2
3	18.5	18.6	12	27.1	26.8
4	20.3	20.6	13	25.8	25.9
5	22.7	22.9	14	23.6	23.9
6	25.1	24.8	15	21.5	21.3
7	26.6	26.4	16	19.7	19.6
8	28.5	28.9	17	18.2	18.5
9	30.3	30.0	18	17.3	17.4

4.2 Experimental data normalization

The data collected by the temperature sensor was normalized, and it is the output value from the interval mapping to the [0, 1] interval by linear mapping way, which is as follows

$$z_1^* = \frac{z_0 - z_{\min}}{z_{\max} - z_{\min}} \tag{10}$$

where $z_{\max}$ and $z_{\min}$ are the upper and the lower bounds of the output value, respectively; z_0 is the original value; and z_1^* the normalized value. The normalized values of temperature data are shown in Table 2.

Table 2 Results of experimental data analysis

Experiment number	Normalized value	Experiment number	Normalized value	Experiment number	Normalized value
1	0	7	0.753	13	0.719
2	0.109	8	0.924	14	0.582
3	0.219	9	1	15	0.404
4	0.356	10	0.993	16	0.287
5	0.513	11	0.945	17	0.212
6	0.643	12	0.780	18	0.136

4.3 MATLAB software simulation

Digital temperature sensor nonlinear error compensation of BP model is established through the neural network toolbox of MATLAB software simulation. Selection of parameters mainly include: network layer, implicit layer, number of neurons, learning rate and the desired error. The number of layers of BP network is set as 3. The number of neurons in the hidden layer is 5, and the expected error is selected as the ten levels according to the model. The convergence of the PSO-BP algorithm is shown in Fig. 7.

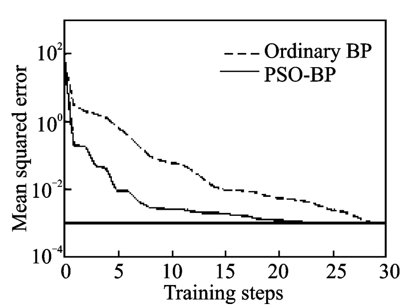

Fig. 7 Convergence curves of PSO-BP and ordinary BP algorithm.

Fig. 7 shows that the detection accuracy of the sensor has been greatly improved with the using of PSO-BP neural network compensation when the error value from the 100 stage convevging to the desired error value of 10^{-3}. The training speed of PSO-BP neural network is faster than the ordinary BP neural network. The ordinary BP neural network uses about 6 times more than the PSO-BP to achieve the same training goal. When dealing with the fault samples, the PSO-BP neural network fault diagnosis rate is 100% and the ordinary BP neural network is 97.6%.

5 Sensor Fault Diagnosis

There are two ways of neural network used in fault diagnosis: One way is to use neural network to approximate any continuous bounded nonlinear function in order to establish a nonlinear mathematical model for the system fault; another way is to use the classification neural network to diagnose faults by classification and learning of fault modes. Sensor fault diagnosis actually includes the following three questions: How to detect whether there is a sensor fault occurring at a certain moment X; how to find the fault sensor when determining a sensor is failure; how to compensate the fault signal and send a correct signal after find fault sensor.

The output of the neural network is used to estimate sensor values. It obtains a value from comparing the sensor actual output values with the estimating output of neural network. If this value is larger than a certain threshold value, sensor fault happens. Then the neural network output value instead of the sensor value outputs into the controller. Namely, the actual output value modified. Neural network needs to be trained before the system is operated. The first thing is to determine the choice of input parameters of neural network. The output measuring sensor of the system is failure at moment X and the main input is the signal before moment X, so the output is the right signal which is more different form the fault signal at moment X. The system alarms and completes the sensor fault detection when the difference is larger than the threshold. The subnet of fault sensor also alarms, but other sensors except fault sensor input are the correct value before the moment X, and the output is correct. The sensor output is the normal signal of the system at the moment of X. So the subnet of the rest which completes the location of fault sensor does not alarm in addition to the subnet of fault sensor alarming. The output of the fault sensor subnet instead of the sensor output completes the compensation of sensor fault.

6 Conclusions

The warehouse environment monitoring system based on ZigBee wireless sensor network and ARM microprocessor is established to realize the remote real-time monitoring of environmental parameters. A new error compensation method by using the combined model of BP neural network and PSO algorithm to deal with the non-linear characteristics of the sensor is presented. This model can not only exert the local quick search with the help of BP neural network, but also avoid the BP neural network being trapped in local minimum value. Using the PSO-BP neural network model can reduce the absolute value of the error, improve prediction accuracy and lower iteration steps. This method compensates the impact of nonlinear error of sensors effectively, and improves the precision of fault diagnosis and forecast of sensor. The PSO-BP neural network can be used effectively to diagnose the fault of warehouse system sensor, and the learning process is simple and practical. Experiments indicate that the monitoring system has the feature of higher measurement precision, lower power consume, stable network data communication and fault diagnoses function.

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