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Hybrid Odor Detection System for Search and Rescue Robot Based on PSO

Jin Shang[a], Jian Ding[a], Weifeng Su[a], Yuanzhi Wang[b*]

[a]Control Technology Institute, Wuxi Institute of Technology, Wuxi, 214121, People’s Republic of China
[b]School of Computer and Information, Anqing Normal University, Anqing, 246011, People’s Republic of China
computer2015@vip.qq.com

Aiming at the problem of the search and rescue robots' perception of various gases in chemical engineering sites, a hybrid odor detection system for search and rescue robots based on particle swarm optimization was proposed. In order to improve the stability and prediction accuracy of the system, a method of using particle swarm (PSO) to optimize the weighting coefficients of the integrated neural network is proposed, that is, using the global search ability of PSO and introducing an improved PSO algorithm to optimize the weights and thresholds of the BP neural network on the basis of the original BP neural network, and the optimized network is used in the detection system, thus reducing the detection error of the system. The system analyzed the response signals of the 4 gas mixtures of the sensor array, the experimental results show that the neural network algorithm based on particle swarm optimization is applied to the training of gas mixture quantitative identification, the convergence speed is faster and the detection accuracy is higher than that of BP neural network algorithm.

1. Introduction

With the continuous expansion of modern chemical industry, a large number of toxic and harmful gases, such as C_2H_4, H_2S, NO_2 and C_2H_2, have been produced in the production process. When accidents occur in chemical sites, because of the existence of these harmful gases, human rescue activities are limited (Yamazoe and Miura, 1995; Li et al., 2018). It is becoming more and more meaningful for search and rescue robots to carry out environmental detection and rescue work instead of people entering chemical sites. The detection of harmful gases provides an important basis for the evaluation and strategy formulation of rescue information (Branca et al., 2003). Therefore, the accurate detection of toxic and harmful gases has become a key technology of the search and Rescue Robot Perception system. At the same time, the detection of the above gases has a guiding significance to improve the atmospheric environment.
Gases in chemical sites are mixed, and there is interference between gases. Traditional sensor gas detection is based on the principal component characteristics of a single gas. But when a variety of harmful gases are mixed, the main component characteristics of the gas will be weakened or lost, resulting in the detection cannot be completed normally (Jaradat and Langari, 2009; Sung et al., 2014). At present, the detection methods of mixed gases mainly include compensation or compensation algorithm, differential absorption spectrum, pattern recognition of array sensors, quantitative detection algorithm and so on (Radi et al., 2016; Sanaeifar et al, 2016; Rudnitskaya and Legin, 2008; Pizzileo et al., 2012). Although these methods can detect the main components of mixed gases to a certain extent, they do not consider the requirements of on-line detection of mixed gases, and also do not consider the impact of such variables as temperature and humidity, which leads to these methods cannot be applied to the chemical field rescue robot to detect mixed gases. In view of this defect, the gas sensor array and pattern recognition technology are combined to build a hybrid gas detection system, which can well solve the gas sensor cross-sensitivity problem.

2. Detection principle and system composition

Fig. 1 is the structure diagram of the detection system, which consists of sensor array, signal conditioning circuit, signal acquisition system and pattern recognition. Sensor array is the detection link of the system. It is

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composed of many different types of sensors for different gas types to be detected, and it outputs the response signal to the sensitive gas. The signal conditioning circuit converts the analog signal output from the sensor array to the digital signal used for control; The signal acquisition system collects and further processes the signals of each channel adjusted in the signal conditioning section, and finally obtains the mixed gas component information and the concentration information after the pattern recognition link is identified.

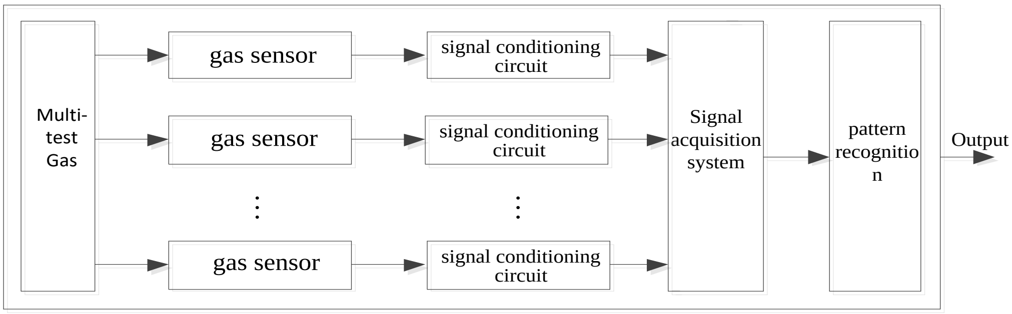

Figure 1: Detection system schematic

3. Detection algorithm principle

3.1 BP neural network algorithm

BP neural network is a kind of multi-layer feedforward neural network. The main characteristics of the network are signal forward transmission and error back propagation. In forward transmission, the input signal is processed layer by layer from the input layer to the hidden layer until the output layer. The neuron state of each layer only affects the neuron state of the next layer (Wang et al., 2012; Hu et al., 2013; Liang et al., 2011; Sun et al., 2012). If the output layer cannot get the desired output, it will turn to back propagation, and adjust the weights and thresholds of the network according to the prediction error, so that the BP neural network prediction output is constantly close to the desired output. The learning process of BP algorithm is based on gradient descent method to modify the weights (weights and thresholds) of network connection, so that the sum of squares of network errors is minimized, that is

$$\omega_{ij}(i+1) = \omega_{ij}(i) - \mu \frac{\partial E}{\partial \omega_{ij}} \qquad (\mu > 0) \tag{1}$$

Among them, E is the total error of the network. Error reduction is carried out in the direction of negative gradient, and it is easy to fall into the dilemma of local minimum. In order to make the deviation between the actual output of each unit and the target value less than the specified value, it is necessary to constantly adjust the connection weight. When the number of training samples is too large or the relationship between input and output is complex, the convergence speed of the network will become very slow (Kim and Kim, 2005). In addition, BP algorithm has other limitations, so this paper uses the improved PSO algorithm to optimize the BP neural network.

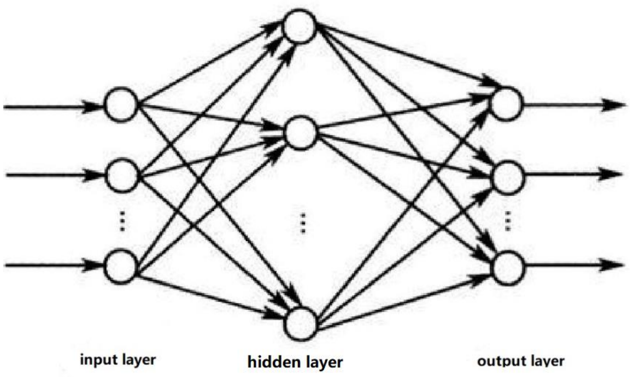

Figure 2: BP neural network structure diagram

3.2 PSO algorithm

The basic idea of PSO algorithm is that the potential solution of each optimization problem is a particle in the search space, all particles have an adaptive value determined by an optimized function, and each particle has a velocity vector to determine its flight direction and distance, then the particles search in the solution space following the current optimal particle (Kim, 2006; Zuppa et al., 2004; Kennedy and Eberhart, 1995; Chen and Qian, 2009). PSO is initialized into a group of random particles, and then the optimal solution is found by iteration. In each iteration, the particle updates itself by tracking two extremes: one is the optimal solution currently found by the particle itself, called the individual extreme P_{best}, and the other is the optimal solution currently found by the entire population, namely the global extreme G_{best}. After finding these two optimal values, each particle updates its speed and position according to the following formula.

$$V_{ij}(t+1)=\omega(t)V_{ij}(t)+c_1*rand()*(P_{ij}(t)-X_{ij}(t))+c_2*rand()*(P_{gj}(t)-X_{ij}(t)) \tag{2}$$

$$X_{ij}(t+1)=X_{ij}(t)+V_{ij}(t+1) \tag{3}$$

$$\omega(t)=\omega_{\max}-t(\omega_{\max}-\omega_{\min})/t_{\max} \tag{4}$$

Among them, $j\epsilon[1,2,\dots,d]$, c_1 and c_2 are learning rates, i.e. acceleration constants, *rand()* is a random function of the range [0,1]; t is the number of iterations, t_{max} is the maximum number of iterations, ω_{max} is the maximum weight, ω_{min} is the minimum weight.

3.3 BP network algorithm based on PSO optimization

Because all the ideas of the neural network are embodied in the weights, PSO is used to optimize the weights of the neural network, which can improve the performance of the neural network (Vukovic and Miljkovic, 2013; Hinton and Salakhutdinov, 2006; Lorwongtragool et al., 2014; Leung et al., 2003). In this paper, PSO is used to replace the gradient descent method in traditional BP algorithm, which avoids the shortcomings of the gradient descent method, such as easy to fall into local minimum and slow convergence speed. The flow chart of the algorithm is shown in Figure 3.

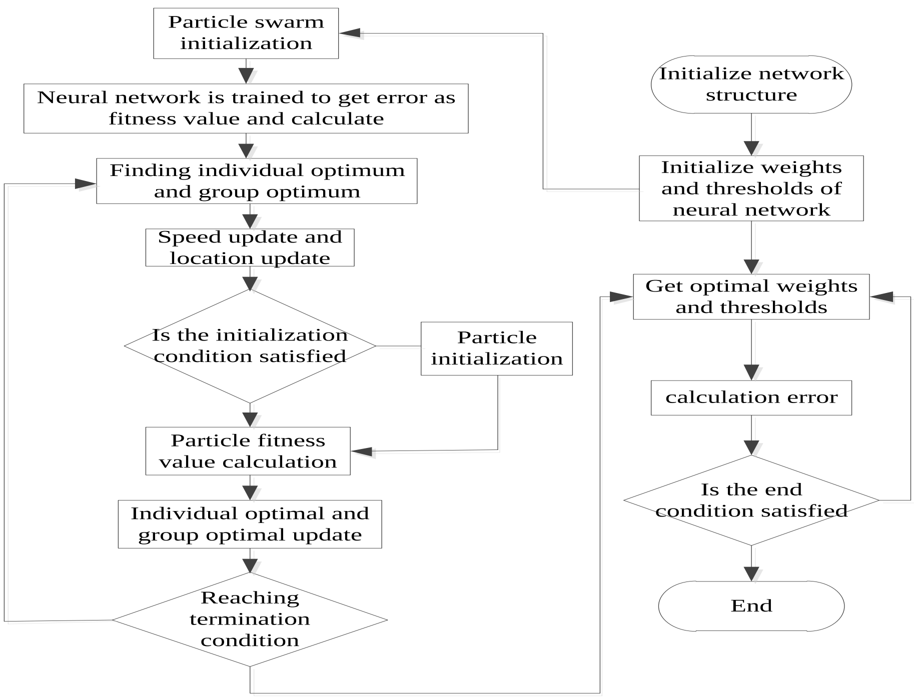

Figure 3: Algorithm flow chart

4. Experimental data processing and analysis

4.1 Data preprocessing

(1) Elimination of Fault Data Since both reading and recording processes may produce errors considered, the standard deviation is calculated according to Bessel formula using 3σ criterion

$$s=\sigma[\frac{1}{n-1}\sum v_i^2]^{1/2} \tag{5}$$

Several sets of data can be eliminated by calculation. 208groups of experimental data were randomly selected from the actual known correct data as the training samples of the neural network, and 12 groups of data as the test samples to detect the accuracy of the network.
(2) Normalization Normalization is a commonly used method in data analysis and processing, that is, the dimensioned expression is transformed into a dimensioned expression, which becomes a pure quantity, thus unifies the sample data into the same dimension. Neural network uses normalization method to make the input variables with different physical meanings and dimensions can be used equally, to prevent the output data from being swallowed smaller values, and ultimately to improve the learning and training speed of the network. The normalization of input data is done in this paper.

$$x^{'}=\frac{x-x_{\max}}{x_{\max}-x_{\min}} \tag{6}$$

Among them, x_{max} is the maximum of the sample and x_{min} is the minimum of the sample.
At the output layer, the actual load is re replaced.

$$x=(x_{\max}-x_{\min})x^{'}+x_{\min} \tag{7}$$

Among them, $x_{max}$is the maximum of the sample and x_{min} is the minimum of the sample.

4.2 Adjustment of BP network structure parameters

In the research, sensor array signals originate from actual experimental tests. During the experiment, four gas sensors were used to form a sensor array. The temperature and humidity of four different volume fractions of C_2H_4, H_2S, NO_2 and C_2H_2 were measured. 220 sets of sensor array signals and corresponding VOC gas components and concentrations were obtained. When constructing BP neural network, the input layer node is set to 6, and the output layer node is set to 4 as the input variables of the sensor array.
For the design of hidden layer, the choice of hidden layer number and the determination of neuron unit number in each hidden layer should be considered. Any continuous function in a closed interval can be approximated arbitrarily by a BP network with a hidden layer, so a three-layer BP network can map arbitrary n-dimensional inputs to m-dimensional outputs. According to the complexity of the problem, multiple hidden layers can also be designed. When each node adopts S-type function, one hidden layer can realize arbitrary decision classification problem, and two hidden layers can represent arbitrary output function of input graph. For the BP network used for classification, formula (8) and formula (9) are use to find out:

$$K<\sum_{i=0}^{n}C_{n_1}^{i} \tag{8}$$

Among them, K is the number of samples, n_1 is the number of hidden layer units, and n is the number of input units. When $i>n_1$, $C_{n_1}^{i}=0$.

$$\mathrm{n}_1=\sqrt{n+m}+a \tag{9}$$

Among them, *m* is the number of output units, n is the number of input units, and *a* is constant between 1 and 10. For the purpose of this paper, the number of input units $n=6$, the number of output units *m=4*. According to the above formula, the number of hidden layer units n_1 is between [4, 14], and the number of hidden layer neurons is 12.
The sample input matrix is the sensitivity of the sensor array to the VOC mixture gas, and the sample output matrix is the type and concentration of the corresponding VOC mixture gas. The 220 groups of sample data were normalized and 208 groups of sample data were randomly selected as input samples to train BP neural

network and PSO-BP neural network respectively. After training, the network parameters were saved and the network was established. The remaining 12 groups of data were input into the trained network as test samples. To detect the accuracy of neural network prediction, the test results are shown in Tables 1 and 2 respectively.

Table 1: test results of PSO-BP

sample	C_2H_4 actual	measured	H_2S actual	measured	NO_2 actual	measured	C_2H_2 actual	measured
1	5	4.89	5	4.82	100	96.55	10	9.55
2	8	7.79	2	2.15	5	4.87	5	4.81
3	20	19.25	100	97.18	5	4.85	10	9.61
4	10	9.66	20	19.58	15	12.85	30	29.01
5	5	4.88	50	48.75	100	96.26	70	64.18
6	10	9.52	50	48.52	100	95.88	60	58.25
7	10	9.75	40	38.99	100	95.15	50	48.02
8	10	9.78	10	10.24	50	48.27	150	144.98
9	10	10.27	10	9.67	10	9.66	200	192.62
10	5	4.85	10	10.27	20	18.82	160	153.05
11	5	5.12	10	9.72	50	48.57	200	194.13
12	5	4.83	5	4.88	50	47.92	200	193.37

Comparing the data of Table 1 and Table 2, it is easy to find that PSO-BP neural network has smaller prediction error than BP neural network under the same training sample, the average relative error of PSO-BP neural network is less than 5%, and the convergence of PSO-BP neural network is obviously better than BP neural network, it can effectively avoid entering the local optimal solution in training and improve the stability of the prediction system.

Table 2: Comparison between BP and PSO-BP

Algorithm	BP				PSO-BP			
Gas	C_2H_4	H_2S	NO_2	C_2H_2	C_2H_4	H_2S	NO_2	C_2H_2
Maximum relative error	0.067	0.092	0.126	0.102	0.048	0.075	0.1433	0.0831
Minimum relative error	0.026	0.029	0.039	0.422	0.022	0.021	0.026	0.029
Mean relative error	0.038	0.046	0.605	0.616	0.029	0.031	0.047	0.04

5. Conclusions

The hybrid odor detection system for search and rescue robot is studied in this paper. Aiming at the slow convergence speed and poor fault tolerance of BP neural network, PSO is introduced into BP neural network, and the BP neural network is optimized by PSO. The performance of BP neural network and the prediction precision of mixed odor detection system are improved. From the experimental results, we can draw the following conclusions: using sensor array to detect multi-component gases can eliminate the influence of gas cross-response, absorb more mixture gas composition information and concentration information, and integrate the detection system of neural network and sensor array technology to detect multi-component gases has achieved good results. In the detection range, the system can better accomplish the task of detecting related gases.

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