Knowledge-based Genetic Algorithms Data Fusion and its Application in Mine Mixed-gas Detection

Haigang Li
School of Safety Engineering,China University of Mining &Technology,Xuzhou,China
Email: haigangli@cumt.edu.cn

Deming Wang
School of Safety Engineering,China University of Mining &Technology,Xuzhou,China
Email: wdmcumt@163.com

Yong Zhang
China University of Mining & Technology Xuzhou, 221116, China
Email: zhangyong@126.com

Abstract--- **In Considering that the high concentration of mine gas and hydrogen will disturb the output of electrochemical carbon monoxide sensor, this paper integrates gas sensor array with data fusion Algorithm. The output signals of three sensors are trained by BP neural network to get the mathematical model of information fusion for the analysis of mixed gas of methane, hydrogen and carbon monoxide. The experiments show that the information fusion could correct the crossed sensitivity error, and improve the accuracy of carbon monoxide, therefore achieve quantitative analysis mixed gas of coal mine.**

Index Terms—**Gas Sensor, Information Fusion, Neural Networks, Genetic Algorithm**

I. INTRODUCTION

Mine gas is composed with multiple gas. At present, the phenomenon that electrochemistry sensor used in CO testing exist some sensitivity in H_2 and CH_4 influences testing result seriously. And the fault result is deadly in mine[1,2].

Generally gas (GA) sensor is sensitive to not only measured gas but also other gases, namely ‘Crossed sensitivity’. In application, such parameters that output characteristic, crossed sensitivity, temperature, pressure and humidity in sample have large influence on response characteristic in gas testing system. The gas testing system based on multi-sensor information fusion technology can solve nonlinear problem caused by gas crossed sensitivity, and do sensor’s drifting and noise suppression, that can improve testing precision[3].

At present, the common method to analyze gas is sensor array composed with multi-gas sensor have different sensitivity combined with neural network method[4]. By using gas sensor array, genetic algorithm and neural network, this paper provide multi-gas analysis and testing and give a description on achievement in gas quantitative analysis.

II. GAS SENSOR ARRAY

Through the mechanism of biological olfactory system, it was noted, and the natural smell of other organisms in the process of identification does not know the chemical composition and concentration. Nevertheless, the biological able to almost instantaneously to the odor judge. This provides us with an excellent imitation of examples.

Mixed-gas analysis accomplished by identifying test pattern of gas sensor array output essentially. So, the output of array should represent all gas composition that consist in mixed-gas. And the output of all sensitive elements are linear independence. Therefore, at the moment of gas sensor array composing, the dimension of array and characteristic of gas sensor are need to special consideration[5,6]. In theory, the dimension of gas sensor array is the higher the better. But, more sensors can cause louder noise. In addition to the measured gas sensor sensitivity, in general, are often also affected by the influence of other gas off, the so-called cross-sensitivity, which for the selectivity and accuracy of the sensor is bad. The traditional solution is by finding new sensitive materials, device structure and compensation circuitry to eliminate the profit impact. However, this method is not only complex structure of the device, and the device manufacturing costs increase.

So, in order to produce uncorrelated testing pattern, the characteristic of all gas sensors in array is different. Particularly, the sensibility and stability of test gas still important in gas analysis by using neural network pattern identify.

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Project number: the National Natural Science Foundation of China No. 50927403/E041002
Corresponding author: haigangli@cumt.deu.cn, 13952194041

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Gas test system with gas sensor array is described in Fig.1. Network structure is compartmentalized three layers, namely input layer-x, hidden layer-z, output layer-y. The BP neural network in this paper is single hidden and low dimension, that is easy to simulated in computer. Testing measured gas with gas sensor array composed with CO and H_2 electrochemistry sensors and gas heat catalytic sensor, we get three parameter. After the preliminary treatment, the collecting data are trained in neural network and the key parameters of network are kept, and then the network is established. In the testing phase, we can get the result as long as the measured data import the trained network.

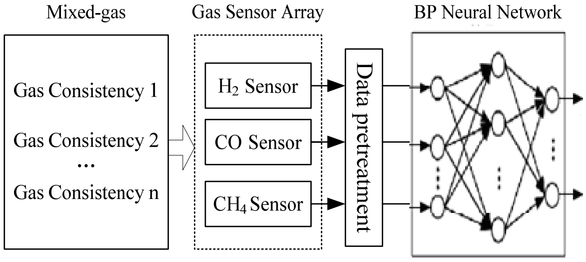


Fig.1. Architecture of Measuring Mixed-gas

III. IMPROVER BP NEURAL NETWORK

Based on GB 12358-90 'common technology need on working environment gas test alarm', error of gas test about this mine disaster relief robot environment detection module should satisfy three conditions: CH_4 less than 0.5% volume fraction, O_2 less than 0.7% volume fraction, CO's relative errorless than 10%.

In application of neural network, BP network or its changed forms are used in most models and it is the key part in feedforward neural network.

A. Knowledge Based Genetic Algorithm

In most optimal searching problems, the distribution of the optimal solutions is unknown, especially for some complex problems such as multi-modal or deceptive problems. The optimal solutions can be distributed in different subspaces. In this proposed algorithm, the traditional Gas with large population, large mutation probability and small selection probability are taken in the initial stage of the evolution so as to make individual expansion in the whole space rapidly and to collect as much data as possible.

Then **RST** is used to analyze the data and to form S_{POS} region, S_{NEG} region, and S_{BON} region by the fitness function thresholds α, β ($0<\alpha<\beta<M$). Determining the subspace for further searching depends on computing correlation between individual variables and their corresponding fitness function. Eigenvector is used to judge the property of the problem, and then different evolution strategies are applied.

Through data analysis by RST, the whole solution space can be divided into multiple subspaces[7]. Multiple population evolution strategy keeps implicit parallelism of the GA, and at the same time, the natural population is also included to supplement the new knowledge. This process embodies the knowledge learning ability of human beings, from rough to fine and from false to true.

The algorithm is shown as A1.

A1 Knowledge-based Genetic Algorithm

```
input: Problem and Parameter of KGA.
output: Optimum results
begin
    Using SGA to solve the problem.
    Saving the data during the process of SGA, including
    each individual and its fitness.
    while not Termination-condition do
        Simplifying the data, Generate upper and lower
        approximation set and boundary according to
        threshold defined.
        Generating the binary relation table between the
        individual and its fitness function.
        Calculating the eigenvector of the problem.
        Judging the type of the problem.
        Generating the evolution subspaces.
        for each subspace do
            Doing SGA evolution calculation in the
            limited subspace.
            Saving the data in the SGA process
        end
    end
end
```

B. BP Network Design

1) Description of the Problem

By training, the network test the concentration of gas. In this problem, sensitive signal of three sensors in seven standard gas sample is defined by input vector matrix P and aim vector is defined by a variable T . Each aim vector including three elements represents concentration of gas. For example, after normalization, the element value of vector corresponding to 100 ppm CO is 100/5000.

2) Network Structure

Firstly, a basic single hidden layer BP neural network is constructed, whose neurons number of input layer equal to the dimension of gas sensor array, and neurons number of output layer equal to measured gas species.

The number of hidden layer has direct relations with specific demand and the number of input or output layer. In application, less hidden layer number is accepted at the beginning. By training the sample, we add hidden layer if unsuccessful until have a reasonable result. But the cost time of this method to determine hidden layer is too long. There are some empirical formula on calculate the number of hidden nodes of three layer BP neural network.

$$k < \sum_{i=1}^{n} C_i^{n_l} \quad (1)$$

Where, k is the number of sample, n_1 is the number of hidden layer, n is the number of input layer.

$$n_1 = \sqrt{n+m} + a \qquad (2)$$

Where, m is the number of output neurons, n is the number of input neurons, a is a constant. By calculating and comparing, the number of hidden layer neurons is determined to six.

The designed tan-sigmoid/purloin network is described in Fig.2.

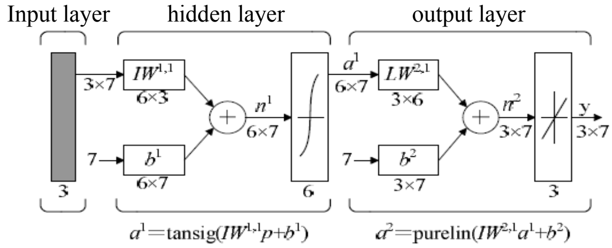


Fig.2. Architecture of BP Neural Network

3) Network Initialization

Establish a single hidden layer network using function newff[8]:

net = newff(minmax(P),[6,1],{'tansig','purelin'}, 'trainbr');

The number of hidden layer neurons is six. To obtain good generalization, training function trainbr is choosen. Then, we initialize network weights and thresholds.

net.LW{2,1}=net.LW{2,1}*0.01;

net.b{2}=net.b{2}*0.01;

4) Network Training Parameter Setting

Network Training Parameter Setting:

net.performFcn='msereg'; %performance function is msereg

net.trainParam.mu_max=200;

net.trainParam.show=200;

net.trainParam.goal=0.01; % the least permiterrors 10^{-2}

net.trainParam.epochs=1000; % setting training step

[net,tr]=train(net,P,T);

While training the network using train function, the training results are shown on Matlab command lines. After training, we compare expected output to simulated output with sim function in order to checkout the network performance.

C. Using KGA to Optimize Neural Network

The weights of the neural network are trained by BP study algorithm in literature[9]. But, the disadvantages are very obvious: the train velocity is slow, and the weights are sometimes local optimization. So we have to train the network for several times to get satisfying result. However, we can optimize the weight of neural network by generic algorithm to solve the problem. So we optimize the weight of the neural network for multi-sensor system by KGA.

1) For a $r-n_{hid}-1$ forward neural network, let the hidden layer function is $\psi(x)$ and the output layer function is $\phi(x)$ personally. If the sample set is $\Omega=\left\{P_i,q_i \middle| 1\le i\le N, P_i\in R^r, q_i\in R\right\}$ $P_i=(p_{i,1},p_{i,2},\cdots p_{i,r})$, the output of the network is

$$\hat{q}_i=\phi\left[\sum_{j=1}^{n_{hid}}V_j\psi\left(\sum_{k=1}^{r}W_{j,k}P_i+b_j\right)+b_0\right]$$

where, W,V are the weights, coded by real number, and one individual is expressed as $X=\left\{W_{j,k},V_j,b_j,b_0\right\}$ $\left(j=1,2,\cdots n_{hid},k=,2,\cdots r\right)$. $W_{j,k}$ is the joint weight between the kth node in the input layer and the jth node in the hidden layer. V_j is the joint weight between the jth node in the hidden layer and output layer. b_j and b_0 are the offset value of hidden node and output node respectively. The structure of the network is 5-15-1 in this paper, thus there are 106 parameters to be optimized.

2) The fitness function is $f=1\Big/\left(\frac{1}{N}\sum_{1}^{N}\left(q_i-\hat{q}_i\right)^2\right)$, which describes the comparability between the output of neural network and the train sample.

3) The parameters of the KGA are set as follows: initial group scale is 200, mutation probability $P_m=0.4$; select proportion $P_s=0.15$. After the evolution space is identified, the group scale is 50, mutation probability $P_m=0.25$ and the select proportion $P_s=0.4$.

VI. MIXED GAS DETECTION TEST

A Test Method

This test equipment coincides with environment detection sensor calibration device. The gas sensor array composed with CO, H_2 electrochemistry sensors and gas heat catalytic sensor. Experiment flow is described in Fig.3.

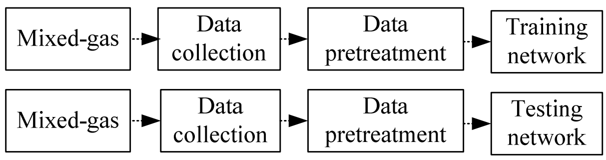


Fig.3. Test Flow of Mixed-gas

The sample gases are the mixed with CO, H_2 and CH_4—background gas is N_2. Measuring response of gas sensor array in eight different consistency, we get twenty four group data, described in table 1.

Table **1** Response of Gas Sensor Array to Mixed-gas

Sample	Mixed-gas (ppm)			Sensor response (mV)		
	CO	H_2	CH_4	CO	H_2	CH_4
1	100	100	2000	963.0	37.8	121.2
2	100	100	5000	108.2	44.3	263.5
3	100	200	2000	119.4	67.5	125.9
4	100	200	5000	130.9	79.2	274.0
5	200	100	2000	153.0	39.5	123.8
6	200	100	5000	164.6	46.2	268.7
7	200	200	2000	175.7	69.4	131.0
8	200	200	5000	187.5	86.5	282.1

B Data Preprocessing

There are several data pretreatment methods, we choose normalization of sensor signal and gas consistency signal. The normalization of sensor signal cause output of every sensor lies between 0 to 1, which make all of vectors in the same magnitude. This method not only decrease the calculate error in stoichiometry identify, but also provide appropriate data to neural network recognition. The normalization of gas consistency can meet the output amplitude of neurons activation function. When forecast or measurement, the output transformed into gas practical consistency by inverse transformation.

Normalized the sensor data in table 1 by using formula as follows:

$$X'_{gas,j} = \frac{X_{gas,j}}{\max X_{gas,j}} \qquad (3)$$

Where, max() represents take the max value of all the test sample.

In addition, due to the expectation output of network lies between 100ppm to 5000ppm, the gas consistency data in table 1 should normalized. The formula as follows:

$$c'_j = \frac{c_j}{\max(c_j)} \qquad (4)$$

Where, $max(cj)$=5000ppm

C Analysis of Experimental Results

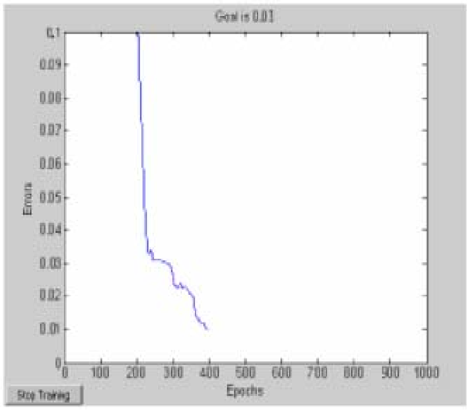
Taking the 1、2、4、5、6、7、8 groups data in table1 as learning sample and the third group data as testing sample, the error curve of BP neural network designed in Fig.4.

The comparison between BP algorithm and KGA method is shown in Fig. 4. In Fig. 4(a), when training arrive at 397 step, the mean square error less than required precision 0.01, is 0.0099996. Fig. 4(b) shows that we can get more satisfying resolution in many subspaces, which reflects that the optimized weight of the Neural Network is not unique. when training arrive at 810 step, the mean square error less than required precision 0.01, is 9.99992e-004. We can see the KGA method has quick convergence, better efficiency and high resolution, especially, when optimization subspaces is confirmed. And on the other hand, the confirmed subspaces enhanced optimization precision and convergence speed.

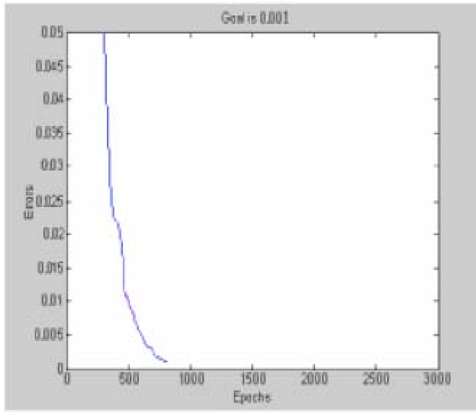
Finally, we analyses sample of mixed-gas using trained network. Take input vector P as the input of network, utilizing sentence y=sim(net,P)and y=y*5000. The component and consistency of convergence BP network output mixed-gas are shown in table 2.

Table **2** Test Results on Mixed-gas

Mixed-gas(ppm)	Test results		
	Single sensor	BP	KGA
CO: 100	184	126	110
H_2: 100	117	113	106
CH_4: 2000	2135	2090	2039



(a)



(b)

Fig.4. Error Curve of BP and KGA

V. CONCLUSION

A knowledge-based genetic algorithm is proposed in this paper. Rough set and granular computing method is introduced to explore knowledge hidden in the data generated in GA evolution process. The knowledge then can be used to guide the evolution orientation. The optimization of forward neural network shows that the proposed algorithm in this paper is good to increase the convergence speed of the genetic algorithm and enhanced optimization precision. It overcomes the deceptive problem to some extent in the genetic algorithm. The proposed algorithm shows the good performance for the multimodal function. Therefore the knowledge-based genetic algorithm is effective.

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Haigang Li JiangSu Province, China. Birthdate: Mar, 1981. is Safety Technology and Engineering Ph.D., graduated from School of Information and Electrical Engineering China University of Mining and Technology.And research interests on Intelligent test and control Instrument, Safety of Mining.

Deming Wang GuiZhou Province, China Birthdate: Aug,1956. Safety Technology and Engineering Ph.D., graduated from China University of Mining and Technology in 1993.And research interests on Safety of Mining

He is a professor of Dept.Safety Engineering China University of Mining and Technology. He hosted 7 national research projects in recent years, to obtain a National Teaching Achievement Award, one National Science and Technology Progress Award, three provincial and ministerial level scientific research and teaching achievement award and 4 second prize, and published 4 monographs And materials.

Yong Zhang ShanDong Provice, Chian. Birthdate: Sep, 1979. is Ph.D., Master Instructor. Lecturer for School of Information and Electrical Engineering China University of Mining & Technology. Research interests include swarm intelligence and multi-robot coordination control.

Dr. Zhang is contributing reviewer for domestic and foreign journals like "International Journal of Electrical Power and Energy Systems" and "Automation Technology". Recently published (employment) of more than 20 academic articles, which were retrieved 14 SCI and Ei.