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An Application of Wireless Sensor Networks in Underground Coal Mine

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Abstract

Wireless sensor networks (WSN) are good at security monitoring in coal mine. It is able to rapidly detect diverse parameters, which can reduce human and material losses. And it is an important application that has commercial potential. Coal mine pivotal parameters include Dust Density (Dust), Temperature (Temp), Wind Speed (WindS), Gas Density (GasD) and Carbonic Oxide Density (COD). The data collected by the sensors are sent to the sink node to be processed with information fusion technology. This work presents a strategy for the classification of coal mine status based on sensed data by WSN and the use of unsupervised neural network-the Self-Organizing Map (SOM). The SOM application classifies the coal mine environment into four clusters. An experiment confirms the effectiveness of the proposed approach.

Keywords: *wireless sensor networks, information fusion, Self-Organizing Map, coal mine security*

1. Introduction

Frequently-happened coal mine accidents are a very important problem for China to solve in near future. In accidents, thousands of miners die or hurt, due to unawareness of the abnormal methane concentration, temperature or strain under coal mines. These will be avoided if a monitor system can be developed to measure multi-parameters at many locations under the mine in real-time [1]. It reports that among Chinese state-owned collieries, 56% of the mines have been jeopardized by spontaneous combustion, and accounts for 90–94% of the total coal mine fires [2].

The technological advances in micro-electro-mechanical systems and wireless communications have motivated the development of WSN in recent years. WSN is a class of wireless ad hoc networks in which sensor nodes collect, process and communicate information acquired from the physical environment to an external base station (BS), hence allowing for monitoring and controlling various physical parameters, which is becoming a critical part of the information infrastructure in industrial control, environmental monitoring and human life rescue operations, and have been widely studied and deployed in real-life operations. Especially in light of coal mine disasters in recent years, governmental supports in

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this area have given unprecedented attentions to the research, development and deployments of WSN to serve data communication purposes in mining tunnels. Commonly, WSN has constraints regarding power resources and computational capacity.

As we all know, sensor nodes in WSN have limited resources, limited power, limited memory and computational ability. At the same time, various sensor nodes often detect common phenomena, there is likely to be some redundancy in the data. Information fusion techniques can help to conserve the scarce energy resources and prolong the lifetime of WSN. It also can reduce the amount of data traffic, filter noisy measurements, and make predictions and draw accurate inferences about a monitored entity.

The rest of the paper is organized as follows. Section 2 discusses the information fusion, including three fusion classes. We introduce the Self-Organizing Map in Section 3. Section 4 presents experiments. Followed by the conclusion is in Section 5.

2. Related Work

WSN is a promising method for analyzing security state by collecting diversity data. However, how to apply WSN into underground coal mine in a feasible and efficient manner still remains as a problem. There is already some existing works focus on this, which aims to enable computers to better serve people by automatically monitoring and interacting with physical environments. We refer to M. Li as the typical earlier works on this topic [3].A prototype system with 27 Mica2 motes is implemented and deployed in the D. L. Coal mine as illustrated in Figure 1. The system is distributed on a tunnel wall about 8 meters wide and 4 meters high. These motes are preconfigured with their location coordinates and manually placed at surveyed points with an interval of 3 meters.

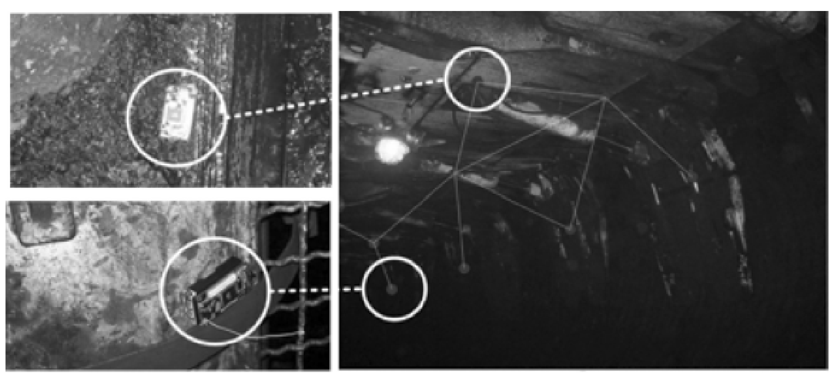

Figure 1. WSN Deployed in a Coal Mine

Environment monitoring in underground tunnels, which are usually long and narrow, with lengths of tens of kilometers and widths of several meters, has been a crucial task to ensure safe working conditions in coal mines. Utilizing wires to connect data requires a large number of wire deployments, which is difficult because of poor working conditions and high maintenance costs underground. In addition, the wired communication methods make the system less scalable. In this situation, the utilization of a WSN to implement the monitoring system benefits from rapid and flexible deployment. Sensors can be deployed on the walls, poles and floors, miners carry mobile sensor. A collapse may change the system structure and break the original WSN structure, but WSN can reconstruct the network dynamically. Efficient and robust communication and routing mechanisms are required in coal mine tunnels.

Query handling is an everlasting job running over the deployed WSN in the coal mine. The WSN collect thousands of data, so it is necessary to utilize information fusion to increase the efficiency of query handling, which enables us to answer fusion accurately and efficiently [4]. Based on sensor data collection through the network, information fusion can be utilized to increase efficiency of answering all kinds of queries. Moreover, to reduce power cost, we introduce information fusion strategy which also is employed to reduce the instant traffic.

However, it is generally difficult to understand the multivariate data in a coal mine as a whole. It can be meaningful to obtain and exact different information from the classification of multivariate data. In other words, it is applicable to divide the whole environment condition into several characteristic patterns. In fact, SOM has been frequently used as a powerful and effective data analysis tool for detection of data characteristics. The application of SOM has been reported in diverse research fields such as ecology [5, 6], geomorphology [7], hydrology [8, 9] and meteorology [10].

3. Classifying Information Fusion

Information fusion [11] derived from military application. With the rapid development of micro-electronic technology, signal monitoring and processing technology, computer technology, communication technology and control technology, its applications have been expanded to many fields such as goal recognition, robot technology and intelligence vehicles, medicine, industry projects, remote sensing [12] and so on.

3.1. In View of Information Level

Generally, application analysis and design for information fusion are held at different levels. Therefore, information fusion is divided into three levels, that is, raw data level fusion, feature level fusion, and decision level fusion.

Applications of raw data level fusion are generally image enhancement, image classification and image compress, which can be advantageous to manually understand images, or provide better input images for feature level fusion. Feature level fusion means that extract all kinds of characters of data and transfer them to another attributes which is advantageous to processing. Decision level fusion is the highest level, which is validated by that the fused result can be used to provide decision for mankind.

3.2. In View of Information Type

Under this method, three types of information fusion as follows: temporal fusion, spatial fusion and spatial-temporal fusion.

1) Temporal fusion: the single sensor fuses the test values about the monitored object in different time.
2) Spatial fusion: at the same time, information collected by different sensors is fused.
3) Spatial-temporal fusion: in period of time, information collected by different sensors is fused continuously.

3.3. In View of Range

WSN may be designed with different objectives. In a nutshell, information fusion can be defined as the combination of multiple sources to obtain improved information (cheaper, greater quality, or greater relevance).

In coal mine monitoring scenarios, we mainly need to handle extern information queries, including fusion queries, like Min, Max and Count, as well as range queries. Information fusion aims to provide accurate and efficient query processing with small in-network communication overhead since the underground environment is not friendly for wireless communication. And the sensor nodes are normally battery powered and changing batteries is often very difficult in an underground coal mine.

From this point, information undoubtedly can be divided into three types: the single information about a concrete place (acquired by one single sensor), new information about certain area, and the complete information about the whole network.

The single node oriented, we consider whether compressed data or not according to amount of information and the distance to destination. If information is enough much and distance is enough far, compression algorithm works, or else, raw information will be sent to destination directly. Owing to allowing lost or not in the process of compressing, loss compression and lossless compression algorithm adopted.

The area oriented, it is necessary to consider whether information acquired by user is from homogenous or not. If it is, fusion algorithm can introduce average with weights attained by estimation of nodes' reliabilities such as Bayesian theory statistic method or D-S evidence method and so on; otherwise, SOM works.

The whole network oriented, similarly as area oriented, there are also distinctions between homogenous information and heterogeneous information; correspondingly, different fusion methods are adopted. Data clustering, which is one of the most studied applications of SOM, classification is another commonly performed data analysis. Figure 2 shows the SOM based information fusion model.

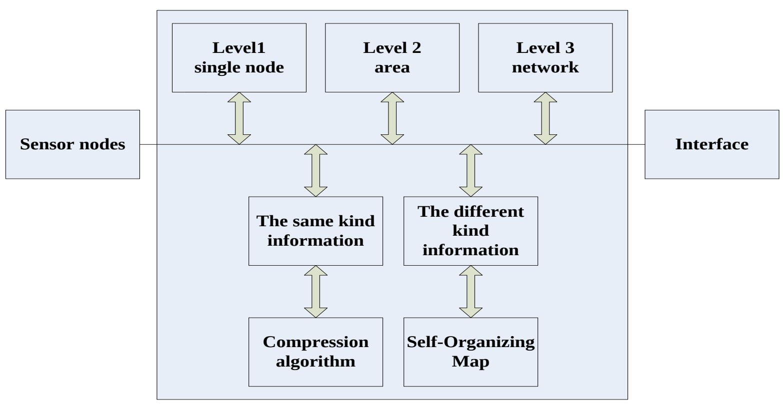

Figure 2. SOM based Information Fusion Model

4. Self-Organizing Map

SOM [13, 14] is a type of Artificial Neural Network (ANN) with clustering function and it provides the new idea for us to evaluate the whole condition. It is the point that we take it as one infusion method in our model.

4.1. Self-Organizing Map Architecture

SOM [13, 14] is a type of Artificial Neural Network (ANN) with clustering function and it provides the new idea for us to evaluate the whole condition. It is the point that we take it as one infusion method in our model. A self-organizing map is an artificial neural network algorithm used for clustering, visualization, and abstraction. It is a structure made of two layers, see Figure 3 Formally, the SOM can be described as a nonlinear mapping of high-dimensional input data onto the elements of a regular low-dimensional array based on their similarity in an ordered fashion [15].The weights of the output units are adapted so that the output space preserves the order of entries in the input space. SOM differs from other competitive structures in the sense that neighboring neurons on the map learn to recognize neighboring sections of the input space. They therefore learn both the distribution (as do competitive layers) and the topology of the vectors of the input space.

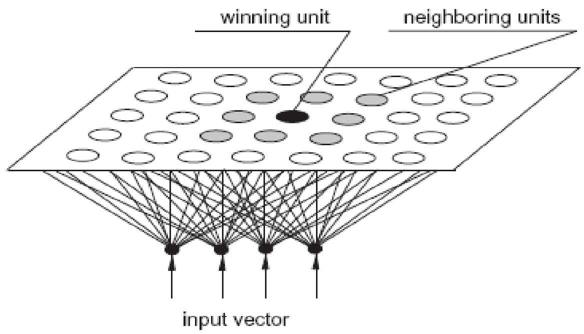

Figure 3. The Self-Organizing Map Structure

The classification of a pattern consists in determining the output neuron of the competitive layer that best represents the input pattern; the neuron that represents the classification is called the winning neuron. During the learning process, the weights between the winning neuron and the input layer are adjusted with the Kohonen training algorithm [15].

4.2. Self-Organizing Map (SOM) Algorithm

The selected SOM architecture is a rectangular feature map with a hexagonal layer topology function, which calculates the neuron positions for layers whose neurons are arranged in a N-dimensional hexagonal pattern. We chose the hexagonal structure because it gives each unit more neighboring connections, allowing better interaction with the adjacent units.

The training algorithm proposed by Kohonen for forming a feature map is summarized as follows. Each unit j has its own prototype vector w_j, being a local storage for one particular kind of input vector that has been introduced to the system.

(1) Initialization: choose random values for the initial weights $w_j(0)$;

(2)Winner Finding: find the winning unit j^* at time t, using the minimum-distance Euclidean criterion

$$j^* = \underset{j}{\operatorname{argmin}} \left\| x_j(t) - w_j \right\|, \; j = 1, ..., N \tag{1}$$

where $x_j(t)$ represents the input pattern, N is the total number of unit, and $\|.\|$ indicates the Euclidean norm.

(3) Weights Updating: adjust the weights of the winner and its neighbors, using the following rule:

$$w_j(t+1) = w_j(t) + \alpha N_{j^*}(t)(x_j(t) - w_j(t)) \tag{2}$$

where α is a positive constant and $N_{j^*}(t)$ is the topological neighborhood function of the winner unit j^* at time t. The neighborhood function is traditionally implemented as a Gaussian (bell-shaped) function:

$$N_{j^*}(t) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(j^*-j)^2/2\sigma^2} \tag{3}$$

with σ a parameter indicating the width of the function, and thus the radius in which the neighbors of the winning unit are allowed to update their prototype vectors significantly. It should be emphasized that the success of the map formation is critically dependent on how the values of the main parameters (*i.e.*, α and $N_{j^*}(t)$), initial values of weight vectors, and the number of iterations are prespecified.

5. Experiments

5.1. Related Parameter

The important parameters are temperature, wind speed, gas density, carbon monoxide density and dust density. By the safe principle of coal mine, when the temperature reaches some degree, the coal is apt to be oxidized easily even more to burn spontaneously. At the same time, it is possible to form fire due to gas burning. The wind speed directly has effects on the ventilation volume and it is very possible to add the probability of causing the spontaneous fire. In addition, the wind speed also has some impact on the spread heat and improves the dangerous degree on spontaneous fire of coal layer. The gas is mainly made of firedamp, which is flammable, explosive and lighter than air. While it reaches some denseness and once there is electric spark, it is very possible to explode with the help of inner air. So, these parameter need to be monitored real time. Table 1 shows the sample data collected by WSN in coal mine.

Table 1. Sample Data

No.	Dust (g m^{-3})	Temp(℃	WindS(m s^{-1})	GasD(%)	COD(%)
1	2.12	21.5	2.87	0.25	0.00018
2	3.65	19.5	3.35	0.19	0.0002
3	3.14	18.0	3.50	0.31	0.00045
4	3.87	22.0	2.56	0.36	0.0005
5	4.03	23.1	2.01	0.45	0.0007
6	5.35	22.7	2.32	0.49	0.0008
7	4.89	22.2	2.21	0.53	0.0009
8	5.87	23.8	2.48	0.57	0.00085
9	6.17	25.9	1.98	0.65	0.0014
10	7.32	24.3	1.55	0.70	0.0013
11	6.87	25.2	1.63	0.73	0.0016
12	7.91	24.0	1.75	0.71	0.0015
13	8.07	26.1	1.50	0.85	0.0020
14	9.13	27.9	1.48	0.82	0.0019
15	8.63	27.4	1.35	0.89	0.00195
16	9.87	26.5	1.14	0.90	0.0023
17	10.05	30.7	0.56	1.01	0.0024
18	12.30	28.9	0.87	1.05	0.0025
19	11.28	29.6	0.96	1.08	0.00245
20	10.87	28.5	0.48	1.03	0.00251

We divide these data into several clusters with SOM methods. The flowchart of Figure 4 outlines the procedure.

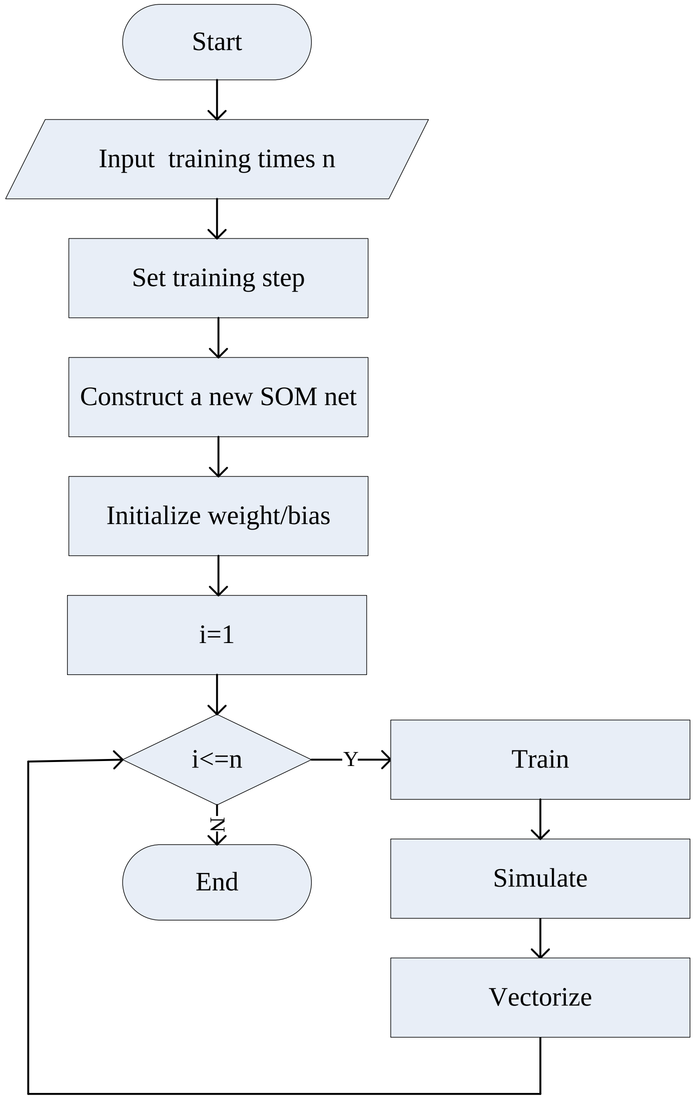

Figure 4. Flow Diagram of the SOM

5.2. Experiment Result and Analyze

5.2.1. Parameter Relationship: Comparison between the component planes can indicate informative and qualitative relationships between parameters of concern [16]. Figure 5 shows the relationships between parameter. For example, the component planes of Dust and GasD reveal that the two parameters have a strong correlation as seen by the similar increase in shade from the upper right part to the lower left. The component planes of GasD and COD are also strongly positively correlated; however, no clear correlation with any other parameter is emergent for WindS.

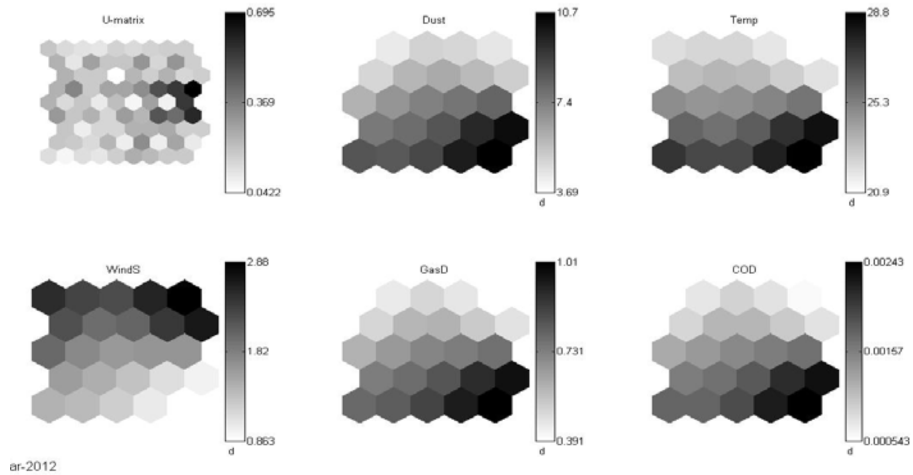

Figure 5. Relationship among all Parameters

5.2.2. Clustering Result: As explained in the previous Section 4.1, we choose 20 records; Clustering results are shown in Table 2.

Table 2. Clustering Result

training step	clustering result
1000	30 39 40 34 28 36 37 31 18 22 17 21 11 15 14 2 5 4 4 8
5000	30 39 40 29 25 36 33 24 15 26 18 22 13 3 5 12 1 1 1 6
10000	38 40 40 34 36 28 30 23 21 20 18 20 14 12 8 5 1 2 2 3

Table 3. The Classified Data into Respective Clusters

Cluster class	Sample data number
Cluster 1	14,15,17,18,19,20
Cluster 2	9,11,13,16
Cluster 3	4,5,8,10,12
Cluster 4	1,2,3,6,7

6. Conclusions

Coal mine accidents all over the world have made human and material losses. In the coal mine, real-time monitoring the parameters like Dust Density(Dust), Temperature(Temp),Wind Speed(WindS), Gas Density(GasD) and Carbonic Oxide Density(COD) directly influences safe production of coal mine and system reliabilities. This paper presents an information fusion model based on SOM, which can make high-dimensional data to a low-dimensional one. This model allows us to divide coal mine status into four clusters: safe, general safe, abnormal, and dangerous. It is useful to reduce the occurrence rate of coal mine accidents and improving the efficiency of environment monitoring.

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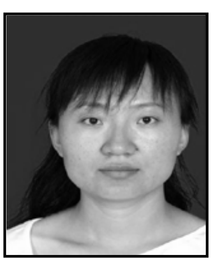

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