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Importance of Wireless Sensor Network and Artificial Intelligence for Safety Prerequisite in Mines

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Abstract

Coal mines are the great source of good for which we are highly dependent. It plays a vital role for the development of growth of nation. Here in this paper we are focusing over the safety prerequisite for the coal mines. As we know that now a day's Wireless sensor networks (WSN) and the Modern Artificial Intelligence technique are good at security monitoring in coal mine. It is able to rapidly detect diverse parameters, which can reduce human and material losses. The Coal mine pivotal parameters include Dust Density (Dust), Temperature (Temp), Wind Speed (WindS), Gas Density (GasD) and Carbonic Oxide Density (COD). It is the most vital area of modern society which requires a proper safety prerequisite for mining. 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, Artificial Intelligence.

1. Introduction

Frequently-happened coal mine accidents are a very important problem for all over the country especially 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 and AI 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. Similarly the AI also plays a vital role to sense the things intelligently and process it according to the logic. Here we somehow use the AI techniques to resolve the burdens of WSN.

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.

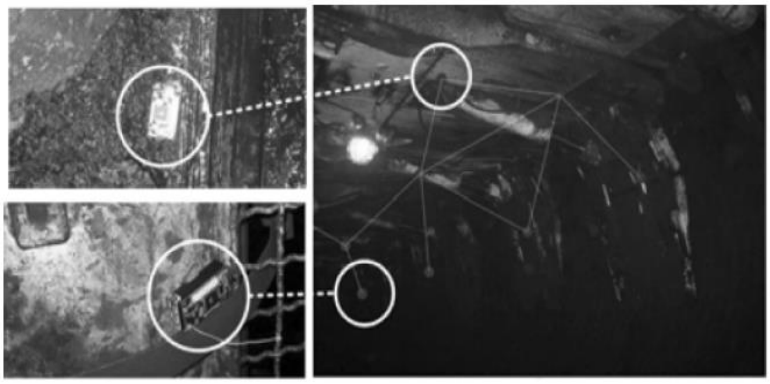

Figure 1. WSN Deployed in a Coal Mine

Environment monitoring in underground tunnels, which are usually long and narrow, with lengths of tens of kilometres 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.

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. 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.

3.2. 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. So by using this we can easily find the subsequent solution.
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. 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). 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, If information is enough much and distance is enough far, compression algorithm works, or else, raw information will be sent to destination directly 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.

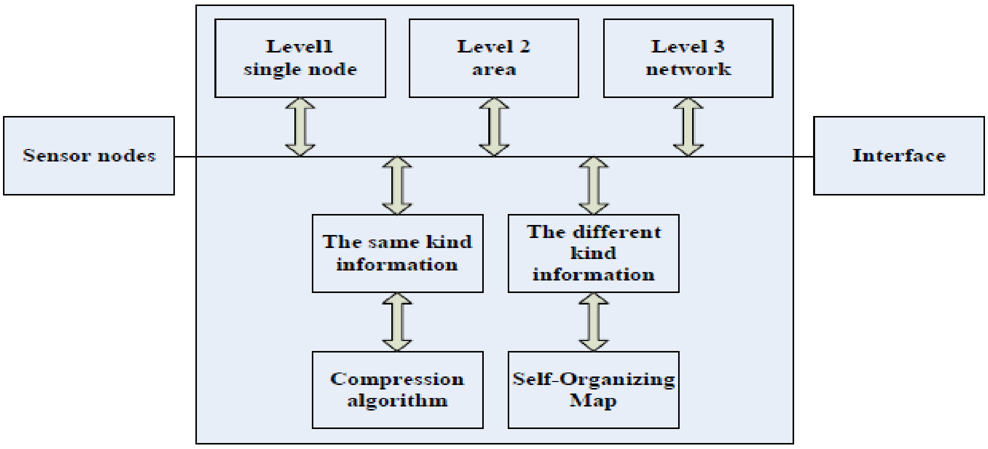

Figure 2. SOM based Information Fusion Model

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.

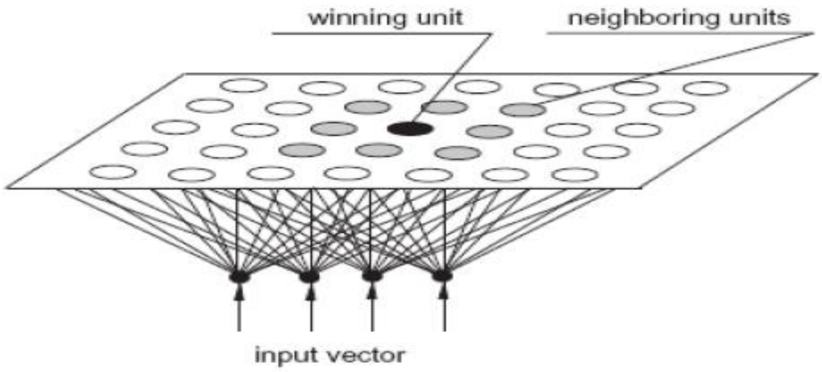

Figure 3. The Self-Organizing Map Structure

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 has its own prototype vector, being a local storage for one particular kind of input vector that has been introduced to the system. j jw

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

(2)Winner Finding: find the winning unitat time, using the minimum-distance Euclidean criterion

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

whererepresents the input pattern, is the total number of unit, andindicates the Euclidean norm. ()jxtN.

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

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

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.

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Table 1. Sample Data

No.	Dust ($g\ m^{-3}$)	Temp(°C)	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

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.

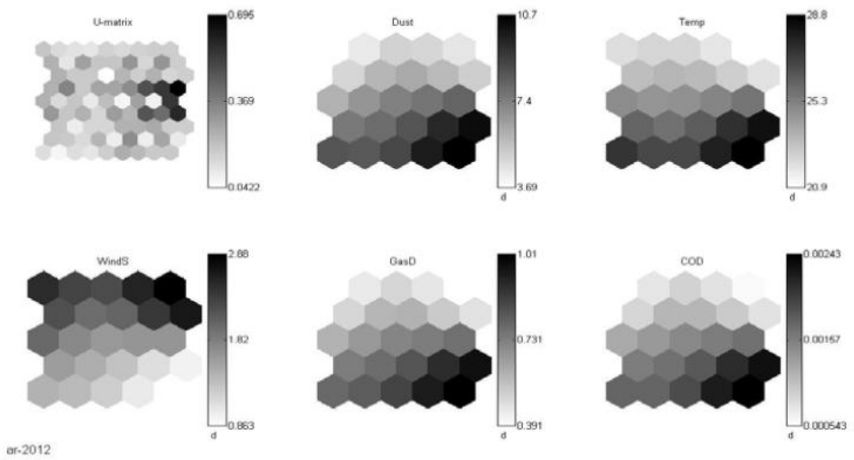

Figure 5. Relationship among all Parameters

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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