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Safety prerequisite for coal mine using Wireless Sensor Technique and Artificial Intelligence Technology

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Abstract— Coal mines are the great source of goods 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[2]. By using these techniques we can easily detect diverse parameters, which can reduce human and material losses. In Coal mine we usually found pivotal parameters which include Dust, Temperature, Wind Speed (WindS), various poisons Gases. So before the mining we should also look for the safety prerequisites for the miners. Here in this paper we have taken some referential data and by utilizing that we have tried to increase the effectiveness of the proposed approach.

Keywords- wireless sensor networks, information fusion, Self-Organizing Map, coal mine security, Artificial Intelligence.

1. INTRODUCTION

This is the case study taken into consideration from the Dhanbad coal mines, as well as the various references which are undersigned below.

In coal mine the frequent occurrences of accidents are a very important problem for all over the country. In accidents, thousands of miners die or hurt[2]. These accidents are mostly occurs due to unawareness about the problem scenarios. Hence to provide the better facility we use the technological advances in micro-electro-mechanical systems and wireless communications have motivated the development of WSN and AI in recent years [1]. WSN is a class of wireless 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,[2][4] 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

To implement the WSN approach we have to mount some sensors in a well equipped manner so that analyzing security state by collecting diversity data. We can effectively mount the WSN technique along with the Modern AI technique in underground coal mine in a feasible and efficient manner. But it is still remains as a tuff 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.[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.

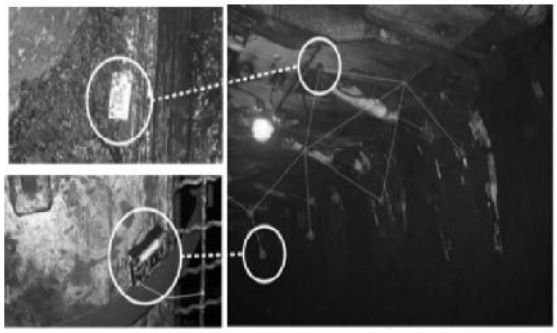

Figure 1. WSN Deployed in a Coal Mine

3. Classifying Information Fusion

Information fusion [5] 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

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It is the first layer which is associated with the row data[3]. It 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

It is the second category, which consist of 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 times. So by using this we can asily 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 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.

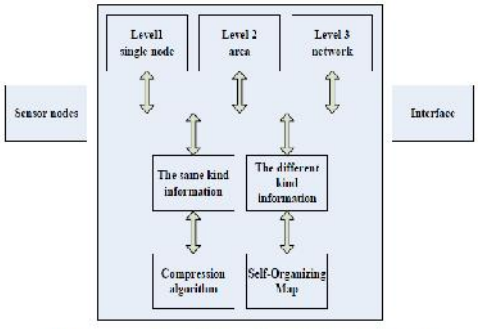

Figure 2. SOM based Information Fusion Model

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 kind of Artificial Neural Network (ANN) with grouping capacity and it gives the new thought to us to assess the entire condition. The point we take it as one mixture technique in our model. A self-sorting out guide is a simulated neural system calculation utilized for bunching, representation, and reflection. It is a structure made of two layers, see Figure 3 Formally, the SOM can be portrayed as a nonlinear mapping of high-dimensional info information onto the components of a customary low-dimensional cluster in view of their likeness in a requested manner [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 neighbouring neurons on the map learn to recognize neighbouring 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.

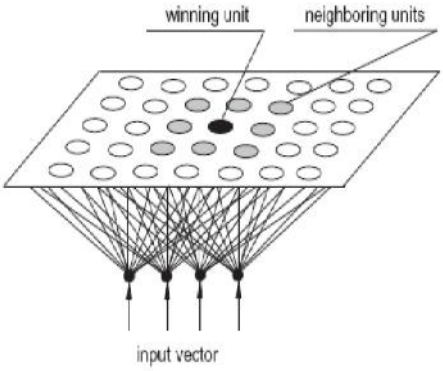

Figure 3. The Self-Organizing Map Structure

4.2. Self-Organizing Map (SOM) Algorithm

In the event that we will examine the SOM design, it is a rectangular element outline a hexagonal layer topology function, which figures the neuron positions for layers whose neurons are masterminded in a N-dimensional hexagonal example. Out of which,We picked the hexagonal structure since it gives every unit all the more neighboring associations, permitting better collaboration with the adjoining units.

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The preparation calculation proposed by Kohonen for shaping a component guide is condensed as takes after. Every unit has its own particular model vector, being a nearby stockpiling for one specific sort of information vector that has been acquainted with the framework.

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

Where represents the input pattern, is the total number of unit, and indicates the Euclidean norm. ()jxtN.
(3) Weights Updating: adjust the weights of the winner and its neighbours, using the following rule:

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

5. Experiments

5.1. Related Parameter

The essential parameters are temperature, wind speed, gas thickness, carbon monoxide thickness and tidy thickness. By the sheltered rule of coal mine, when the temperature achieves some degree, the coal is select to be oxidized effortlessly significantly more to blaze suddenly. In the meantime, it is conceivable to frame fire because of gas smoldering. The wind speed specifically has consequences for the ventilation volume and it is exceptionally conceivable to include the likelihood of bringing on the unconstrained fire. Furthermore, the wind speed additionally has some effect on the spread warmth and enhances the hazardous degree on unconstrained fire of coal layer. The gas is basically made of firedamp, which is combustible, hazardous and lighter than air. While it achieves some thickness and once there is electric start, it is extremely conceivable to detonate with the assistance of internal air. Thus, these parameter should be observed ongoing. Table 1 demonstrates the example information gathered by WSN in coal mine.

5.2Experiment 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.

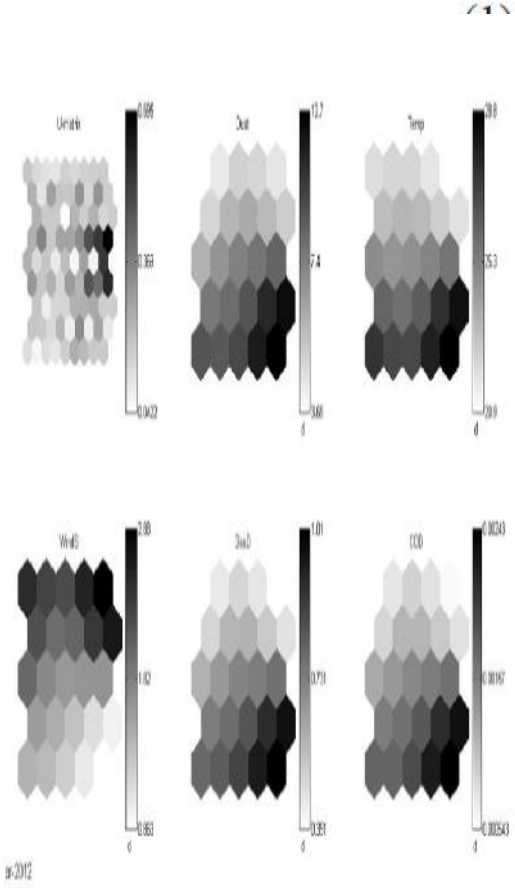

Figure 5. Relationship among all Parameters

5.2.2 Clustering Result:

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

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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

5. 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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