Study on Intelligent Perception Internet of Things Apply in Mine Safety

Liangchen Xu¹, Lin Sun², Daoyuan Wang³* and Jingzhao Li³

¹School of Internet, Anhui University, Hefei 230601, China.
²Shandong Dongshan Xinyi Coal Mine Co., Ltd, Jining 272116, China.
³School of Computer Science and Engineering, Anhui University of Science and Technology, No.168 Taifeng Street, Huainan 232001, China.
*Corresponding author Email: Wdy1227@126.com

Abstract. Due to the complexity, multi-source and heterogeneity of mine safety scene perception information, the mine safety monitoring system has some problems, such as slow perception, communication lag, lack of effective information extraction and intelligent decision-making, a mine safety situation perception self configuration system based on the Internet of things is proposed in this paper, the architecture and perception model of mine safety situation perception system are established, and the embedded neuron is designed mine safety monitoring system based on perceptual node and distributed neural network. The unscented Kalman filter is used to adjust the BP neural network to reconcile and process the multi-sensor parameter information. The simulation results show that the system has good fault tolerance and high precision of intelligent decision-making, which plays an important role in improving mine intelligent level and safety production.

1. Introduction

Mine safety situational perception is mainly to obtain information of mine equipment, environment and personnel. At present, many mines have been built for a long time. Due to the limitation of scientific level and later reconstruction cost at that time, the "stage" upgrading of mine underground safety scene perception technology has resulted in the difficulty of information resource integration due to the difference of technology and data protocol in various information source systems, which is not conducive to the real-time and comprehensive understanding of mine underground environment. In reference [1], YUAN Liang through the construction of mine sensor network ontology, to achieve miners' situational information modeling, and through customized services to help miners prevent mine accidents. The implementation of the model mainly includes situation information acquisition, reasoning, and service provision. The model can effectively help miners reduce the risk of work, but in view of the research level at that time, the model construction is complex, and the emergence of cloud computing and edge computing can make the model more simplified. In reference [2], a distributed wireless sensor network node deployment algorithm is proposed, which improves the deployment scheme of sensor nodes through particle swarm optimization. The algorithm optimizes the network coverage of the target monitoring area and the placement of the sensing nodes, but the traditional particle swarm optimization algorithm is prone to premature convergence, resulting in the solution of the deployment scheme may only be the local optimal scheme. In reference [3], the design of universal signal acquisition system in wireless sensor network is proposed, which effectively improves the efficiency of system identification and transmission of universal signals, but does not solve the problem of misinformation and data optimization of universal signals. Literature [4] points out the
position, role, framework, technical goal and function of cloud computing and platform technology in the construction of the Internet of things in mines; literature [5-7] introduced the application of cloud computing in several scenes in mines, but fails to notice the limitations of the high delay and high delay jitter characteristics of cloud computing on scene perception. Reference [8] showed the application of distributed file system in cloud server, which provides convenience for the storage and transmission of information with large memory requirements such as video and picture in scene perception. Therefore, edge computation with low delay and jitter is chosen to make up for this limitation.

In this paper, the mine safety system scene sensing self configuration system is constructed, the mine safety situation sensing system architecture and sensing model are established, and the mine safety monitoring system based on embedded neuron sensing node and distributed neural network is designed. It provides a technical basis for building a mine safety scene perception system with self configuration of scene perception, multi route of information upload and multi decision.

2. Architecture and Model of Mine Safety Situational Perception System

2.1. Architecture of Mine Safety Situational Perception System

Mine safety situational perception system consists of four layers: perception layer, data transmission layer, data service layer and cloud service layer.

The main function of the sensing layer is to collect underground scene information, which is the information source of edge computing and cloud computing decision-making; the data transmission layer is responsible for uploading the sensing layer information to the edge computing node and cloud, and distributing the decision-making information to the executive mechanism; the data service layer is composed of the edge computing node and blockchain, and the edge computing extends the cloud service to the edge of the network, providing local computing. It has the advantages of low delay, high reliability and low cost, which can realize the local processing of system perception information and pre-processing before going to the cloud; the data of block chain can't be tampered, which is used for privacy protection of data uploaded in mine production; the cloud service layer mainly realizes the integration of perception information of the whole system, improves the intelligent level of the system, and provides the service for the mine Mountain safety production provides more comprehensive, safer and more effective decision-making.

2.2. Mine Safety Situational Perception Model

Although the topographical structure of each mine is different, the regional division basically meets the following categories: conveyor lane, return air lane, chamber, driving area and mining area. According to the needs of scene perception, these categories can be subdivided, for example, the chamber can be divided into machine repair chamber, explosive chamber and rest chamber. When the scene perception deployment is carried out, it must be completed according to the actual situation of the mine. In this paper, according to the actual scene of the mine, each sensing area is divided into a subclass, and the sensing information in each sensing area is divided into different subclass. Among them, the same perceptual information of the whole mine is listed as a subclass. According to the division of the region, the data in the cloud is classified and processed to realize the underground scene information management of the whole mine.

Set the mine Internet of things system as D, and D = {D1, D2, D3, D4, D5}, D1, D2, ..., D5 are respectively five regional categories: conveyor lane, return air lane, chamber, driving area and mining area; Let Di = {P1, P2, ..., PN}, Di ∈ D, i = 1, 2, ..., 5, N is the total number of sensing areas under the mine information physics system, Pj ∈ Di is the set of perceivable area subclass, j = 1, 2, ..., N; Let Pj = {Qj1, Qj2, ..., QjM}, Qji ∈ Pj is the subclass of perceptual information in perceptual area, t = 1, 2, ..., M, M is the total number of perceptual information; Qt = {x1, x2, ..., xa}, xi ∈ Qt is the data uploaded by the sensing device to the sensing information subclass, l = 1, 2, ..., α, α is the number of sensing information Q devices.

Take the mean value and variance of the same kind of data uploaded by a certain sensing area
device:

\[
E(Q_t) = \frac{\sum_{i=1}^{\alpha} x_i}{\alpha} \\
\text{Var}(Q_t) = \frac{\sum_{i=1}^{\alpha} x_i^2}{\alpha}
\]

Set Y as the overall safety state of the mine, \(Y = \{0,1\}\), 0 as failure, 1 as safety, and Y satisfied:

\[
Y = \bigcap_{j=1}^{N} Y_j
\]

In equation (3), \(Y_j\) is the security state of perception region \(j\), \(Y_j = \{0,1\}\). Where \(Y_j\) satisfied:

\[
Y_j = \bigcap_{i=1}^{M} S_t
\]

In equation (4), \(S_t\) is the security state of perceptual information \(Q_t\), \(S_t = \{0,1\}\). Let \(\delta = \{\delta_1, \delta_2, \ldots, \delta_M\}\) and \(\sigma = \{\sigma_1, \sigma_2, \ldots, \sigma_M\}\) be the upper limit of the security value of data value and variance of each kind of perceptual data respectively. When the mean value and variance of perception information meet the requirements of \(E(Q_t) \geq \delta_t\) or \(\text{Var}(Q_t) \geq \sigma_t\), \(S_t = 0\) means that the danger value of the information \(Q_t\), in the perception area is detected, and the danger alarm information of the area \(j\) information \(Q_t\) must be triggered, \(Y_j = 0\), and then \(Y = 0\), which means that the mine has a dangerous area, and the information is displayed through the whole monitoring platform; otherwise, \(S_t = 1\) means that the perception information \(Q_t\) is in the safe value range.

3. Design of Mine Safety Situational Perception Node

Take the mine system as the research object, establish the mine neuron perception system, and the system architecture is shown in Figure 1. Neuron is a unit of the function and structure of the whole mine nervous system, which is used to sense the information of mine environment, equipment and personnel. The sensed mine system information is transmitted to the edge computing platform through the edge communication equipment in the form of data, forming a wireless sensor neural network. After training and learning, the network carries out information processing and decision-making, and then transmits the decision results to the corresponding neuron node layer to realize a complete mine sensing system.

![Figure 1. Framework of mine neuron perception system](image-url)
Figure 2. Hardware architecture of wireless neuron sensing node

The main difference between the wired communication node and the wireless communication node in the hardware architecture is the communication mode, which is different from the communication mode in which the wireless node transmits the electromagnetic wave signal through the antenna. The wired node realizes the information transmission through the optical fiber communication, RS485, can bus and other wired communication modes according to the specified information interaction protocol.

4. Design of Mine Safety Situational Perception Network
Firstly, according to the needs of mine condition monitoring, the neuron nodes are randomly placed. Then, RSSI algorithm is used to determine the location of sink node and estimate its network coverage.

(1) Random arrangement of neuron sensing nodes
As a unit of perceptual neural network, neuron perceptual node is placed statically in the specified space according to the needs of mine condition monitoring.

(2) Location and coverage estimation of converging nodes
Each neuron sensing node determines its own position by positioning algorithm, and the distance between nodes is calculated as follows:

\[ d_{mn} = \sqrt{(x_m - x_n)^2 + (y_m - y_n)^2} \] (5)

The shadow fading model is selected as the signal propagation model of the sink node in the neural perceptual node network \( P_R(d_i) \):

\[ R_k(d_i) = A - 10\beta \lg(d_i) + n_{dB} \] (6)

Where: \( d_i \) is the distance between node i and sink node, A is the transmit power of sink node, \( \beta \) is the path loss, and \( n_{dB} \) is the deviation function.

According to formula (5), the distance between the neuron sensing node and the sink node is calculated. The sink node is located by RSSI algorithm and its transmitting power is known. The distance between the converging node and three or more nearby neuron sensing nodes is calculated, and the position \( \hat{X} = (\hat{x}, \hat{y}) \) of the converging node is estimated by the maximum likelihood estimation method.

After the sink node is located, the communication coverage distance of the sink node is estimated according to the wireless signal propagation model. Taking the converging node \( \hat{X} = (\hat{x}, \hat{y}) \) as the center and the limit distance as the radius, the communication coverage of converging node is obtained.

5. The Simulation Results and Analysis
In the simulation experiment, the coal and methane outburst risk grade prediction of the mine is taken as the research object, and the UFK-BPNN coal and methane outburst risk grade prediction model is established. According to the simulation results, the reliability of the multi-sensor information
decision-making algorithm of the system is further analyzed.

In order to ensure the effectiveness of the experiment, 50 groups of data samples provided by reference [11] are selected, and 8 sensor parameter information input indexes are selected for the designed UFK-BPNN model: methane content, methane pressure, initial velocity of methane emission, permeability coefficient of coal, drilling cuttings amount index, coal seam thickness, mining depth, initial outburst depth, 9 hidden layers are set, with iteration times of 1000 and target accuracy of 0.001. The prediction results of outburst risk grade of coal and methane are shown in Figure 3.

![Comparison of prediction results](image)

**Figure 3.** Prediction results of outburst risk grade of coal and methane

It can be seen from the simulation results that the decision coefficient $R^2$ of UFK-BPNN model is 0.99108, and the sample training effect is good, and the fitting effect is better than PCA-Fisher discriminated analysis model proposed in reference [8].

When UFK-BPNN is used to predict the outburst risk level of coal and methane in the mine, the advantages and disadvantages of different algorithm models under different performance indexes are compared.

| Table 1. Performance comparison of different algorithms |
|---------------------------------------------|---------------|---------|
| algorithm       | training time/ms | accuracy/\% |
| UFK-BPNN        | 10             | 98.2    |
| BPNN            | 761            | 90.4    |
| PCA-Fisher      | /              | 92.9    |

According to the performance comparison of different algorithms provided in Table 1, the training time of UFK-BPNN model is 10ms, which is far less than the traditional BPNN model. The prediction accuracy of UFK-BPNN algorithm is 98.2%, which is higher than PCA Fisher discriminated analysis model proposed in [8]. This shows that the proposed UFK-BPNN model has higher accuracy and lower delay, and verifies the effectiveness and superiority of UFK-BPNN in the mine multi-sensor parameter information decision.
6. Conclusion
In this paper, the edge computing technology is fully used in the design, and the decision task of data processing is transferred from the remote network monitoring center to the edge side of the network to realize the filtering of lengthy data on the edge side of the system, so as to reduce the pressure of mass data analysis and storage on cloud computing, improve the efficiency of data information processing, and effectively improve the decision-making ability of the mine full scene monitoring system. It provides guarantee for coal mine safety production.

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8. References
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