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Health and Safety Situation Awareness Model and Emergency Management Based on Multi-Sensor Signal Fusion

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ABSTRACT Disasters that are uncertain and destructive pose severe threats to life and property of miners. One of the major precautions is to set up real-time monitoring of disaster with a number of different sensors. Single sensor which features weak, unstable, and noisy signal is prone to raise misjudgment leading to non-linearly correlated data coming from different sensors. This paper unfolds with a theoretical introduction to the situation awareness of data from sensors in the Internet of Things, covering theories including the Internet of Things, multi-sensor data fusion, and situation awareness. Subsequently, we construct a framework for the situation awareness system based on multi-sensor fusion in the open-pit mine Internet of Things. The data coming from multiple sensors are pre-processed with wavelet transform, data filling, and normalization. In addition, information entropy theory is introduced to weight the data varying with attributes. An RF-SVM-based model is constructed to accomplish data fusion and determine situation levels as well. The output of the RF-SVM-based model is input as an ELM model. The fusion results at the first 10 time points are used to forecast the situation level at next point, so that the proposed disaster forecast approach in this paper is practiced. To test the stationarity and validity of the approach, MATLAB is employed to run a simulation of the data of a given open-pit mine. The results show that the RMSE of the model remains below 0.2 and TSQ is no greater than 1.691 after we run 50 times, 100 times, and 200 times iteration. It convinces that forecast results made by the model are valid, indicating that the multi-sensor signal fusion which is effective and efficient provides support to disaster situation forecast and emergency management in the mine.

INDEX TERMS Internet of Things, multi-sensor fusion, health and safety of miners, signal processing, situation awareness.

I. INTRODUCTION

The disaster in mine areas pose serious threat to the health of mine workers mentally and physically. Thus, the most important is to predict and control effectively the occurrence of disasters and to reduce the harm after disasters. Situation awareness based on multi-sensor fusion has been under consideration of researchers over these years, many of whom

have investigated this field deeply and made attempts to apply theoretical findings into various practical domains. Under the circumstance of Internet of Things (IoT), information fusion can collect more effectively information, monitor real-time the disasters in mine areas, and improve the supervision of IoT by collecting database. Besides, it also helps the construction of working database. In this way, useful

information can be stored in database and be protected. The information can be used as theoretical basis for the analysis of data. Documents relating to the application of situation awareness theory (SA) are teased out as following. Xi *et al.* [1] propose comprehensive network security situation awareness system (CNSSA), a novel instrument for network security situation awareness, when they apply SA into network security. With quantitative analysis on network security, analysts are in the knowledge of network security. An improved dynamic routing algorithm for real-time threats situation awareness is come up with by researches including Mirakhorli and Clelandhuang [2], Gennarelli *et al.* [3] and Lenders *et al.* [4]. In these studies, three-dimensional threats situation awareness forecast on indoor fires is made by constructing a model based on data of multi-source heterogeneous sensors in semantic space. This theoretical finding is applied in the dynamic adjustment of evacuating routes in fires. Webb *et al.* [5] introduce an approach on a visualized situation awareness model and its core algorithm module. In this study, the previous graphs of situation are kept for predicting the future dynamic situation, and this model is applied to supervise situation of the smart power grid. Chen *et al.* [6] construct a conceptual model as well as its system structure for network security situation awareness. In this model, they explore the data supporting the network security situation awareness system in terms of feature extraction, network security evaluation, emergency response and safety warning. This exploration allows current situation awareness of a network as well as forecast on future changes. Yang *et al.* [7] presents an evaluation integrating the internal effectiveness situation awareness in network system and external threat situation awareness, which is a result of taking the impact of internal effectiveness on network security situation into account. There are volumes of theoretical works and application of multi-sensor fusion. According to Chen *et al.* [8], an improved adaptive neural network-based classification system is introduced, which is an integration of Dempster-Shafer evidence theory and improved probabilistic neural network. In their study, classification of data in feature-level fusion is made by improved probabilistic neural network. Furthermore, Dempster-Shafer evidence theory is employed for more accurate results when data are in decision fusion. This finding has been credited as an innovative approach in multi-sensor data fusion. This approach is adopted by Basir and Yuan [9] to diagnose failures in engines. Under the guidance of the Dempster-Shafer evidence theory which is closer to human mind, they construct a model for evaluating the quality of engines, which applies multi-sensor data fusion into engineering. In the study made by Rajendran and Srinivasan [10], information fusion is introduced into structure damage warning methods based on wavelet packet analysis. In light of Dempster-Shafer evidence theory, the wavelet packet energy spectrum (WPES) identified in ambient excitation sees an improvement after it is operated by multi-source information fusion, which then facilitates computing indicators for structure damage warning. Given the heterogeneity

of mass data, researchers including Deng *et al.* [11] and Han *et al.* [12] etc. have investigate into the challenges haunting multi-source heterogeneous data fusion and then point out deep learning should be introduced into the exploration in this regard.

In order to better the management of mine workers' safety and healthy, Jiang *et al.* [13] designs a wireless sensor network-based monitoring system for safety in mines. This system allows a real-time monitoring of the situation of mines as well as the operation of facilities at work. Despite that it makes the safety management system more efficient, it fails to report the overall situation, as the relationship between information of various attribute is unlikely to set given the fact that the system is constructed on the basis of a single sensor. In the study carried out by Wang *et al.* [14] to explore environment monitoring in mines, an approach integrating multi-sensor data information fusion and Controller Area Network (CAN) is introduced, which demonstrates high efficiency in processing mass data. For successful early warning on fire in mine-pits, Amezcua-Sanchez and Adeli [15] employs multi-sensor information fusion to construct an early warning system of mine workers' safety and health. He lists a series of standards for safety-health warning and six stages of mine workers' safety and health. Another leap in this field is made by Liu [16] and Jiang *et al.* [17]. To improve personnel management and roll out plans for emergency responses, they introduce function design and integral design to the emergency management system of mine workers' health after resorting to AI and Critical Chain method, coupled with technologies including J2EE, SOA, GIS and GPS. In this system, there is less damage from sudden disasters in mine-pits, since both ex ante forecasting and responses are at working [18].

Emergency management is to prevent accidents in mine areas or to control failure propagation or reduce damage. But the traditional safety emergency management is weak in information sharing. When the emergency occurs, the ill-informed data on production and law enforcement leads to the unclarity of responsibilities. With the rapid development of IoT and increasingly mature cloud computing technology, it is inevitable to lead to the close connection and coordinated development between big data and cloud computing. Thus, it's necessary to use cloud computing technology to process such huge data of safety emergency management in mine areas. The stereotype situation awareness methods and information fusion might be less applicable when there is various equipment for information collection and the collected data are in continuum or disparity. Accordingly, technologies including SA, multi-sensor fusion and Internet of Things for mines should be leveraged for accurate and complete information which is indefensible to forecasting disasters in mines.

II. MODEL ESTABLISHMENT

Accordingly, an open-pit mine disaster situation awareness and emergency management system based on multi-sensor information fusion is introduced in this study, which is a result

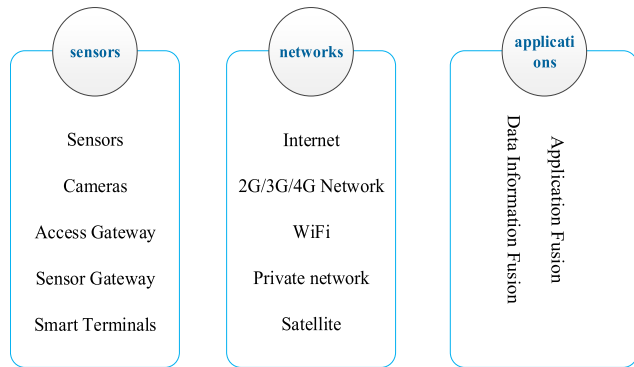


FIGURE 1. Three-layer structure of Internet of things detection.

of SA, multi-sensor fusion and Internet of Things. Major attempts are presented as follows: Section 2 is to explore the theories of Internet of Things, multi-sensor fusion and SA. With the support of these technologies, the framework of situation awareness forecast based on the Internet of things for mines has been proposed. In section 3, data pre-processing of sensors vary with properties is displayed, which involves wavelet noise reduction, data filling and normalization. In the subsequent section, the data are weighted under the guidance of information entropy, and they are inputted into RF-SVM based data fusion. The generated outputs are the safety levels of an open-pit mine. For more precise forecast on open-pit mining, an ELM based open-pit mine disasters situation forecast model is then introduced. In section 5, the models are tested for validity. Specifically, the disaster situation forecast in the open-pit mine made in these models is tested by examining the changes in the mean-square error RMSE and TSQ when iterations are run.

A. INTERNET OF THINGS FOR MINES

Internet of Things, an extension of Internet, has raised opportunities driving major breakthroughs made in information field. This improvement allows effective cooperation between responders, accuracy awareness of disasters and a targeted responding effort deployment when it is introduced to the emergency responses in natural disasters is of remarkable significance [19]. Real-time monitoring and emergency responses in the open-pit mine involve sensor nodes installed at sites with higher safety level, so that real-time data are collected. With Internet of Things, open-pit mine disaster dynamic awareness and emergency responses are thus made [20]. An open-pit mine safety monitoring system based on the sensor, network and application of Internet of Things.

B. PRINCIPLES IN MULTI-SENSOR DATA FUSION

Multi-sensor data fusion is process of combining robust and complete information to provide a consistent description of the observations. Before the combination following given fusion rules, the information is temporally or spatially redundant or complimentary when they are collected from a

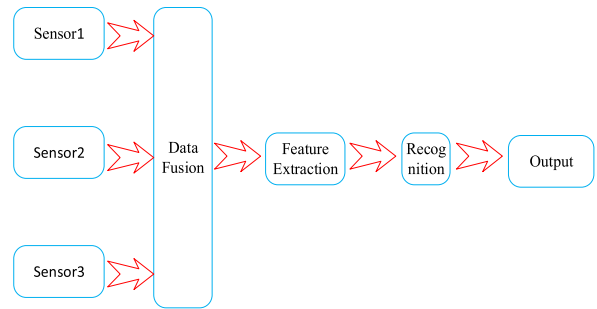


FIGURE 2. Data-level fusion.

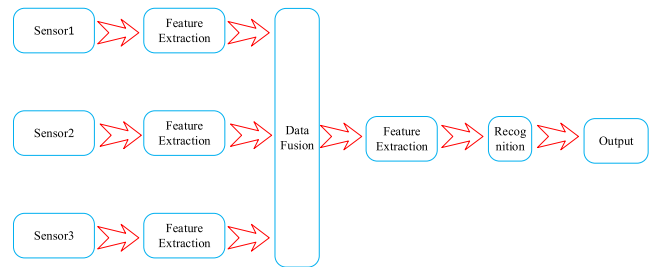


FIGURE 3. Feature-level fusion.

number of different data sources. Multiple sensors are more sensitive to an environment than a single sensor is. Information collected by multi-sensors demand corresponding information processing systems, since the information are not only distinct in terms of time, dimension and content, but also involve mass data. Multi-sensor data fusion usually processes at data level, feature level and decision level [21]–[23].

1) DATA-LEVEL FUSION

Data-level fusion is a low-level information fusion in which data of the same feature are collected and fusion is made in sensors.

In this fusion, despite that details of data are well kept, there are some demerits including amounting resource consumption and high financial cost arising from mass data, as well as a failure in processing complex information.

2) FEATURE-LEVEL FUSION

At feature-level fusion, probability statistics and neural network are employed to combine feature information coming from different sensors.

With this fusion extracting information associating with decision-making, data information is preliminarily filtered and evaluated, so that there is much less workload on data processing. The major features of data information are revealed while fewer resources are consumed.

3) DECISION-LEVEL FUSION

Decision-level fusion, the highest-level fusion, is the process that independent sensor makes decisions by referring to its own information, and then the fusion center provides support to an objective by combining these decisions.

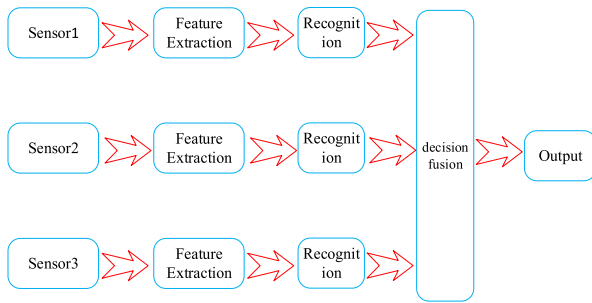


FIGURE 4. Decision-level fusion.

Fusion at decision level is of flexibility, as it is completely immune from interference while trimming redundancy. Nevertheless, it is resource-consumed, since each sensor is required to make decisions. Moreover, it is demanding in combining the decisions.

C. BASIC PRINCIPLE OF SITUATION AWARENESS

Situation awareness (SA), deriving from military sphere, is the perception of environmental elements and events with respect to time or space, and the analysis of the correlation of the elements. Objective groups are fused with the comprehension of their meaning and the projection of their future status. SA is made up of situation perception, situation comprehension and situation forecast [24].

1) SITUATION PERCEPTION

Situation perception is to detect data of key elements that determine the situation of mines. Subsequent forecast depends on the complete coming from sensors, which reveals situations of the open-pit mine.

2) SITUATION COMPREHENSION

Situation comprehension comes after information from sensors is detected. Integrated information is employed to interpret the situation, which provides references to forecast future status of the open-pit mine.

3) SITUATION FORECAST

Situation forecast is made based on decision-level data fusion. Forecasting future events and trend of the mine is made. This is of critical significance to manage emergencies of the mine. Its procedures are presented as follows:

With the above theoretical analysis, we introduce an open-pit mine disaster situation awareness system based on multi-sensor information fusion.

III. PRE-PROCESSING DATA FROM MULTI-SENSORS IN INTERNET OF THINGS FOR MINES

Data form sensors are found to be multi-level, multi-dimensional and heterogeneous. Therefore, before fusion, the data should be filtered to reduce interfering signals including noise, which is the data pre-processing we are doing.

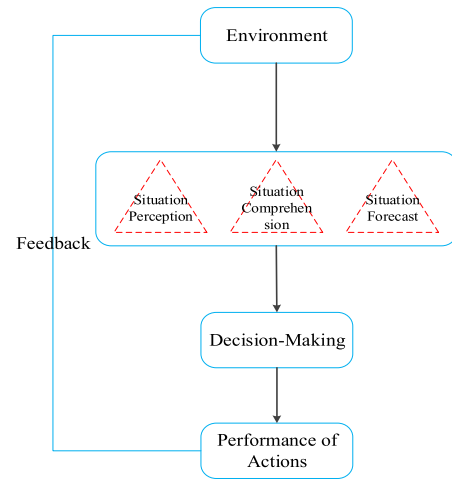


FIGURE 5. Situation awareness procedures.

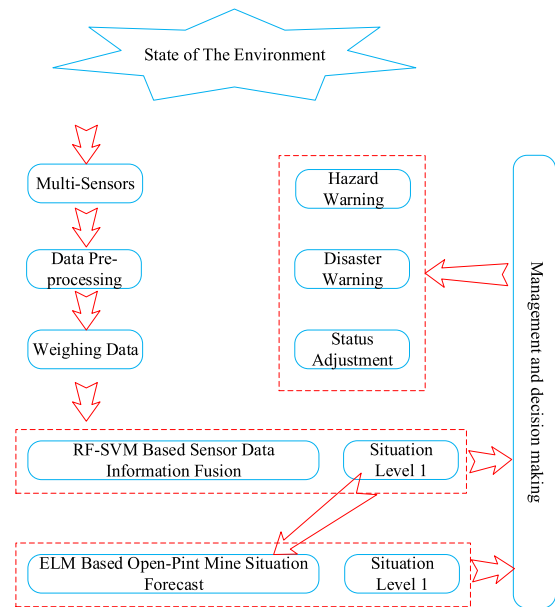


FIGURE 6. Framework for open-pit mine disaster situation forecast system.

A. WAVELET TRANSFORM FOR NOISE REDUCTION

With wavelet transform of useful data and useless noise [25], [26], less noise are left due to the various features data. For the useful data, substantially various wavelet coefficients are found (low-frequency and stationary signals), while for the useless noise, the results are slight (high-frequency signals). Wavelet transform is run in a sequence of raw data decomposition, wavelet transform of the threshold value of high-frequency coefficients, and reconstruction of the decomposed data. For details, please refer to following presentation:

The raw data observed by sensors are treated by wavelet decomposition. The data are decomposed into several levels, with each one corresponding to coefficient w_{jk} ;

An improved threshold value function [27] is adopted calculate the threshold values of wavelet decomposition

coefficient w_{jk} , and estimated coefficient \hat{w}_{ik} is then determined. The improved function is denoted as:

$$\hat{w}_{jk} = \begin{cases} \operatorname{sgn}(w_{jk})(|w_{jk}| - \frac{\lambda}{\exp[a(w_{jk}^2 - \lambda^2)]}), & |w_{jk}| \geq \lambda \\ 0 & |w_{jk}| < \lambda \end{cases} \quad (1)$$

The formula turns into soft-threshold function when $a = 0$; when $a \rightarrow +\infty$, it is for hard threshold. This demonstrates the flexibility the improved function has. In this study, the solution is determined as the threshold function, when $a = 0.2$. The solutions to the above function are the estimated wavelet decomposition coefficients \hat{w}_{jk} . With these coefficients, wavelet reconstruction is then made, and the subsequent results are the data free from noise.

B. DATA FILLING

For the problem of missing data, major responses include deleting, filling and ignoring. In this study, filling is the resort. A regression model is constructed based on the features of data, with regression coefficient being figuring out. This model produces the data for filling. Formula for regression coefficient is denoted as [28]:

$$\hat{\beta} = \frac{\sum_{i=1}^n (y_i - \bar{y})(x_i - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (2)$$

where β is the regression coefficient of Y to X, and $\hat{\beta}$ is its least square estimation. With this coefficient, we are allowed to forecast the missing data:

$$y_i^* = \bar{y} + \hat{\beta}(x_i - \bar{x}) \quad (3)$$

where y_i^* is the predicted filling data. The more acute the features of regression objectives have, the more accurate the filling data are.

C. NORMALIZATION

Sensors installed for the open-pit mine are for temperature, light and compound purposes. They vary with the size, number and dimension of their data. To facilitate subsequent processing, a normalization of data is required. The formula employed in this study is the following [29]:

$$X = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (4)$$

Where X is the result of the data coming from one sensor, with x_{\min} and x_{\max} being the minimal and the maximum.

D. INFORMATION ENTROPY BASED WEIGHT ALLOCATION OF DATA

Different sensor data stand for different attribute during multi-sensor information fusion, for which significance of

different attribute data should be considered before. Distinguished prediction goals may lead to distinguished effect from attribute data.

The weight of data, to a certain extent, shows the level of influence attribute data on decision making: the much the weight is, the higher the influence is. Target at weight allocation of different sensor data, the change of information entropy, after taking data into decision making, was analyzed according to information entropy theory, to realize an information-gain based data weight allocation.

Information entropy is mainly used to measure the uncertainty of events [30], [31]. Higher information entropy refers to higher uncertainty, and more information will be needed to describe the event correspondingly. Following formula was used to calculate information entropy:

$$H = - \sum_{i=1}^n P_i \log_2 P_i(\text{bit}) \quad (5)$$

In this formula, p_i stands for respective probability of decision taking corresponding attribute data into account. During weight allocation, probability of decision which did not take attribute data into account was calculated first, getting the original information entropy. Then was the information entropy after adding attribute data, i.e. conditional information entropy. Weight allocation was determined based on the difference value between original and conditional information entropy: the higher the information entropy is, the more influence the attribute datum has on decision making.

Let attribute data of different sensors as x_1, x_2, \dots, x_n , and let the decision variable as I . The process of data weighting should be as following:

Step 1: Calculation of the original information entropy $H(I)$:

$$H(I) = - \sum_{e_I \in SS(I)} P(I = e_I) \log_2 P_i(I = e_I) \quad (6)$$

$SS(I)$ stands for state space of decision variable I .

Step 2: Calculation of correspondingly conditional information entropy $H(I | x_1), H(I | x_2), \dots, H(I | x_n)$ after taking different attribute data into account, with the following formula:

$$\begin{cases} H(I | x_i = e_{x_i}) \\ = - \sum_{e_I \in SS(I)} P(I = e_I | x_i = e_{x_i}) \log_2 P(I = e_I | x_i = e_{x_i}) \\ H(I | x_i) = - \sum_{e_{x_i} \in SS(x_i)} P(x_i = e_{x_i}) \times H(I | x_i = e_{x_i}) \end{cases} \quad (7)$$

Step 3: Calculation of the difference value between the conditional and original information entropy $\Delta(I, x_1), \Delta(I, x_2), \dots, \Delta(I, x_n)$ with the following formula:

$$\Delta(I, x_i) = H(I | x_i) - H(I) \quad (8)$$

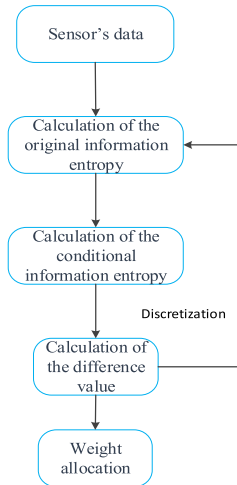


FIGURE 7. Process of weight allocation.

Step 4: Calculation of different attribute data's weight vectors according to difference value of information entropy:

$$W_i = \frac{\Delta(I, x_i)}{\sum_{i=1}^n \Delta(I, x_i)} \quad (9)$$

Only a few observation data of sensors were discretized. Since sensors took continuous observation of the environment and data collected were also continuous observation data, which could be regarded continuous data, these data should be discretized first before calculation. Then comes probability statistics, and further weight allocation of continuous attribute data and discretized attribute data. Based on the above analysis, the weight allocation process of different attribute data of sensors was:

IV. THE MULTI-SENSOR INFORMATION FUSION AND SITUATION FORECAST OF THE MINE NETWORK

For the fusion of multi-sensor data in mine network, in order to make the data fusion at the decision level more instructive, weight allocation of different sensor's data was performed first based on the information entropy theory, whose data were then input as in SVM category [32], [33] to realize information fusion. According to output data after fusion and ELM theory [34]–[36], the situation of open-pit mine in next period was forecasted to provide decision base for mine's emergency management.

A. MULTI-SENSOR INFORMATION FUSION MODEL BASED ON RF-SVM

For effective situation forecast of disasters in open-pit mine, RF-SVM (Regression Forecast – Support Vector Machine) was adopted: to construct a hyperplane which can fulfill class conditions, and take this plane as the decision plane, to ensure correct categorization and the largest difference among different attribute data from different sensors.

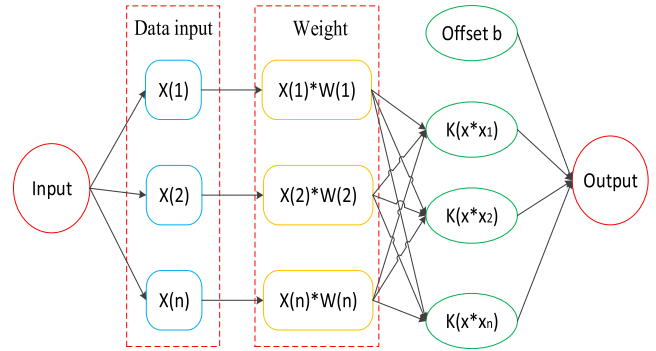


FIGURE 8. RF-SVM model.

Diversity of input values should be considered during data fusion: character data and numerical data. Therefore, input data were all normalized quantized data during RF-SVM, with the flowing quantization formula:

$$x_i = m + (M - m) \times X \quad (10)$$

M , m are the upper and lower area in map section of vector machine respectively, and X are normalized data.

In order to show influence of different attribute data on decision, weight allocation of different attribute data was performed based on information entropy theory through methods mentioned above after data quantization. Improved SVM model was as following:

As shown in Fig. 8, in RF-SVM process, the core idea is regression forecast. The regression function in construction of characteristic space adopted is as following:

$$F = \left\{ f \mid f(x) = w^T \Phi(x) + b, w \in R^n \right\} \quad (11)$$

According to the principle of minimization risk:

$$R[f] \leq R_{emp} + R_{gen} \quad (12)$$

$R[f]$ is the value of expected risk. R_{emp} measures the deviation between $f(x)$ and the sample, which is called empirical risk; R_{gen} measures the complexity of $f(x)$, which is called confidence interval. Based on above principles, structural risk function was introduced:

$$R[f] = C \bullet R_{emp}^e + \frac{1}{2} \|w\|^2 \quad (13)$$

C is a constant, $\|w\|^2$ is describing function. In the formula:

$$R_{emp}^e = \frac{1}{l} \sum_{i=1}^l |y_i - f(x_i)| \quad (14)$$

R_{emp}^e demonstrates the core idea of RF-SVM. The complexity of model and training error were controlled at the same time, to endow model with great generalization ability.

Thus, support vector can be constructed as following:

$$\begin{cases} \min \frac{1}{2}w^T w + C \sum_{i=1}^l \ell + \ell^* \\ s.t. y_i - w^T x_i - b \leq \varepsilon + \ell \\ w^T x_i + b - y_i \leq \varepsilon + \ell^* \\ \ell, \ell^* \geq 0 \end{cases} \quad (15)$$

ℓ, ℓ^* are slack variables. With Lagrangian function and according to duality principle, the final decision function is:

$$f(x) = \text{sgn}((w^*)^T x + b^*) = \text{sgn}\left(\sum_{i=1}^n a_i^* y_i x_i^* + b^*\right) \quad (16)$$

a_i^* is Lagrangian operator, b^* is acquired through constraint condition. Binary classification was extended through second optimized natural extension form. The final decision function is:

$$f(x) = \arg \max[(w_i \bullet x) + b_i] \quad (17)$$

B. ELM BASED OPEN-PIT MINE DISASTER SITUATION PREDICTION MODEL

1) DISASTER SITUATION ELEMENT ACQUISITION IN OPEN-PIT MINE

Main disaster types in open-pit mine: pit slope or dump slide; deformation of the main structure in concentrator’s surface; fissure and collapse of underground mine’s round etc. with analysis above, the disaster prediction of open-pit mine involved mainly following elements: dust concentration, slope stability, and safety distance of the dump [37].

Every step of mining in the open-pit mine will produce amounts of dust, which is characterized by rapid settlement difficulty, long-time floating and large-scale floating under the action of natural wind. Therefore, the detection of dust concentration plays an extremely important part in the open-pit mine monitoring.

The open-pit mine is usually surrounded by slope and dump, which, weathering rain, wind, and solarization, will become loose in its slope structure and have decreased strength, leading to landslide and collapse easily. Thus, monitoring the open-pit mine slope with sensors is a significant element in mine situation prediction. Two indexes were adopted in this paper to observe the slope stability: slant range and displacement of the monitoring point on slope. Related formula [38] is as following:

$$S = \sqrt{D^2 + \Delta H^2} \quad (18)$$

S is the slant range of the monitoring site, while D refers to the horizontal distance, and ΔH means the observed value of the slant range.

$$\begin{cases} X_i = D_i \cdot \cos F_i + X_0 \\ Y_i = D_i \cdot \sin F_i + Y_0 \\ H_i = \Delta h_i + H_0 \end{cases} \quad (19)$$

TABLE 1. Disaster situation element in open-pit mine.

Situation elements	Membership degree		
	Normal	Abnormal	Dangerous
Dust concentration (mg/m3)	<0.2	0.2-0.7	>0.7
Slant range’s change rate at the monitoring site(mm/h)	<0.5	0.5	>0.5
Stability Displacement of the monitoring site(mm)	<20	20-200	>200
Displacement rate of the monitoring site(mm/h)	<5	5-15	>15
Safety distance (m)	>50	50	<50

X_0, Y_0, H_0 refer to coordinates of the monitoring points. Hereby, the displacement of the monitoring site was:

$$\begin{cases} \Delta X = X_i - X_0 \\ \Delta Y = Y_i - Y_0 \\ \Delta H = H_i - H_0 \end{cases} \quad (20)$$

Since dump is mainly used to store waste of industrial exploitation, its site should be as close as possible to the open-pit mine once there is enough safety distance. With the piling of industrial waste, dump will expand horizontally, for which the safety distance of dump needs to be monitored to ensure safety of open-pit mines.

It is reported in Cheskidov V’s research that [39] when there is already a dump in the open-pit mine, the top of the dump would be influenced most by slope construction. Horizontally, with 50-meter safety distance influencing the slop displacement most, larger safety distance means smaller displacement and 250-meter safety distance influence the slope least, with displacement of 0 meters; vertically, the weight of waste in dump will influence the internal structure and horizontal surface of the slope, but no significant influence showed vertically. So, the safety distance of dump in open-pit mine selected in this paper was 250 meters.

With analysis above, the safety situation elements and other related standards of the open-pit mine selected in this paper were as following:

2) FORMATION AND ASSESSMENT OF DISASTER SITUATION AT THE OPEN-PIT MINE

After getting safety situation elements, a comprehensive judgment upon the environment of the open-pit mine should be made according to sensor’s data. Together with RF-SVM data fusion model, the safety level of the open-pit mine for that day was output, based on which comes further judgment of the safety situation. Specific steps are as following:

Step 1: Situation elements acquisition: acquisition of data like dust concentration, slope stability, and safety distance of the dump in the open-pit mine;

Step 2: Data pre-processing: de-noising, filling, normalization, and assignment of data;

Step 3: Data fusion: through RF-SVM, preprocessed data were fused, and current safety level of the open-pit mine was output.

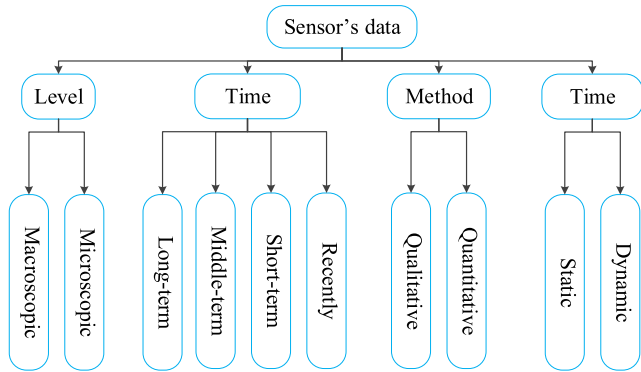


FIGURE 9. Situation prediction classification.

3) DYNAMIC PREDICTION AND EMERGENCY MANAGEMENT OF DISASTER SITUATION IN THE OPEN-PIT MINE

The disaster situation prediction of the open-pit mine is an overall concept targeting at the whole mine, aiming at producing a comprehensive, direct, and accurate understanding towards the overall safety situation of mine through different attribute data from sensors. Situation prediction can be classified into several different types according to different standards, like shown in the following figure 9:

Different prediction methods are used for different data types. Such as the study of disaster occurrence mechanism is used for the short static micro-prediction. Qualitative description is usually used for the study of hazard level. The disaster prediction of the open-pit mine in this paper is a kind of macroscopic, long-term, quantitative, and dynamic prediction.

Situation prediction of the open-pit mine is to use past and current situation vale to predict that in future, which belongs to non-linear time series prediction mathematically. This procedure involves situation values in the past, at present, and in the future, which have clear functional relation as following:

$$\hat{y}(t + d\tau) = f(x(t), x(t - 1), \dots, x(t - (n - 1)\tau)) \quad (21)$$

τ refers to time delay, selection of which influences prediction results significantly: too large τ will lead to $x(t)$ and $x(t + \tau)$ having a random relation; and too small τ will lead to too close value of $x(t)$ and $x(t + \tau)$, which cannot meet the requirement of independence. If there are n independent variables in the formula, the situation prediction will fit the hypersurface in $n+1$ dimension, which means the problem of situation prediction equals to the one of function approximation. Extreme learning machine was adopted to complete prediction in this paper. We only need to set the number of hidden nodes in ELM without requiring the adjustment of weight and hidden units. And ELM can generate the most optimal solution. Therefore, it enjoys advantages of fast learning and effective generation performance. The structure of ELM can output sample data through learning RF-SVM, and regulate input weight and the deviation allocation of the hidden layer, hereby output the disaster situation of the open-pit mine in next period. Its structure was like:

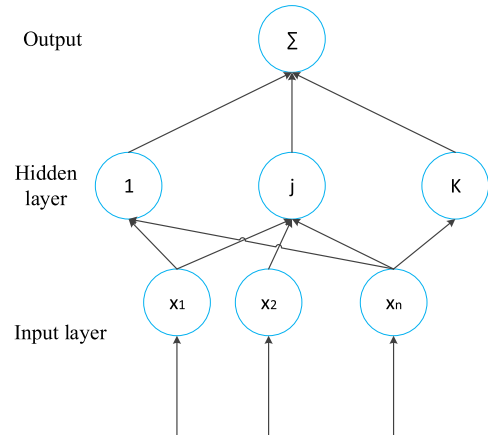


FIGURE 10. ELM model.

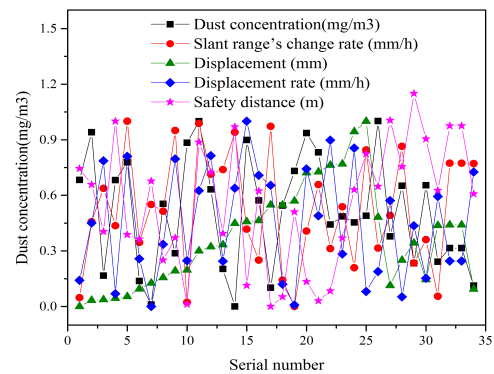


FIGURE 11. Data processing results.

V. SIMULATION ANALYSIS

The monitoring data from March of 2018 to September of 2018 from the monitoring data of an open-pit mine in Luoyang, Henan were selected to examine our model. In order to analyze our situation prediction model, MATALAB was adopted to simulate the model. For stimulating a more real situation in open-pit mines, noisy data were added and part data were missing in data stimulation. Specifically seen below:

A. DATA PRE-PROCESSING

Wavelet noise reduction, missing data filling, and normalization were performed during pre-processing. Processed data were as following:

Since different attribute data influence prediction goal to different extents, attribute data of 5 groups were assigned with values, with weight allocation of: dust concentration 0.1; slant range's change rate, displacement, and displacement rate of stability as 0.2, 0.3, and 0.1 respectively; safety distance 0.3.

B. DATA INFORMATION FUSION

Weight RF-SVM input according to weight allocation results. Take data of 25 randomly selected groups as input, and take 1, 2, and 3 as normal, abnormal, and dangerous respectively as output. Data of 10 randomly selected groups were

TABLE 2. Stimulation data of different attribute sensors in open-pit mines.

NO.	Situation elements					
	Dust concentration (mg/m ³)	Slant range's change rate (mm/h)	Displacement (mm)	Displacement rate (mm/h)	Safety distance (m)	Safety level
1	0.644	0.042	5.905	3.450	45.346	1
2	0.880	0.351	13.573	9.306	40.521	2
3	0.169	0.487	0.002	15.670	26.377	2
4	0.643	0.335	16.037	2.063	59.649	2
5	0.731	0.760	17.975	16.127	25.425	3
6	0.143	0.267	27.194	5.653	24.096	1
7	0.026	0.421	34.353	0.758	41.585	1
8	0.525	0.394	40.939	--	17.771	2
9	0.280	0.722	49.068	15.875	24.486	3
10	0.828	0.023	--	5.444	4.494	1
11	0.935	0.751	73.306	12.631	53.290	3
12	0.597	0.544	78.224	16.210	44.307	3
13	0.202	0.563	80.815	5.408	25.807	2
14	0.016	0.715	106.52	12.866	57.948	3
15	0.842	0.321	108.53	19.732	10.157	3
16	0.542	0.195	109.76	14.197	38.618	3
17	0.109	0.739	128.87	13.170	3.784	2
18	0.517	0.114	128.87	3.042	0.002	1
19	0.688	0.0063	133.61	0.931	32.309	2
20	--	0.313	167.78	14.839	11.293	3
21	0.780	0.502	168.86	10.054	5.526	3
22	0.423	0.242	0.001	17.795	8.460	3
23	0.463	0.412	178.36	6.144	24.423	2
24	0.433	0.164	217.46	16.973	38.971	3
25	0.466	0.643	230.01	2.291	49.773	2
26	0.433	0.164	217.46	16.973	38.971	3
27	0.936	0.244	114.10	4.344	39.957	2
28	0.364	0.377	31.400	11.605	59.899	1
29	0.615	0.658	61.967	1.755	45.931	1
30	0.231	0.183	82.758	9.036	67.979	2
31	0.617	0.278	38.417	3.652	54.305	1
32	0.238	0.048	104.10	12.023	38.762	2
33	0.638	0.576	42.881	4.014	43.249	1
34	0.306	0.589	104.58	5.416	58.225	3
35	0.12	0.588	27.076	14.527	37.768	1

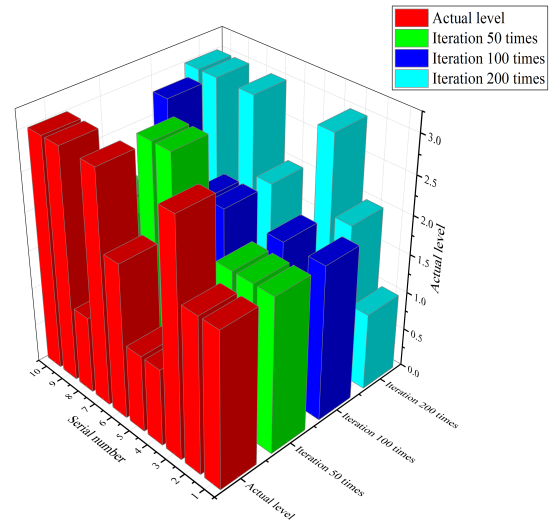


FIGURE 13. Fusion models with different iterations.

examination of the model, iteration of 50 times, 100 times, and 200 times were performed to compare their accuracy respectively. Related results were as following:

This figure indicated that with increase of iteration time, the model's fusion accuracy increased, and reached the peak at 200 iteration times. 90% accuracy was reached even there were only a small amount of data, which evidences well-performed information fusion ability of the RF-SVM model constructed.

C. DISASTER SITUATION PREDICTION IN OPEN-PIT MINE

Take output results of the above model as ELM input to predict disasters in open-pit mine. Situation level output from trained RF-SVM was taken as ELM input data, i.e. to predict the disaster situation in the 11th period according to data in previous 10 periods. Predicted error indexed should be taken during testing of the prediction result. However, the predicted error index cannot be calculated since future event has not happened [40], [41], for which back test and interpolation were utilized in this paper to examine the prediction accuracy, among which back test is to judge the prediction ability of model, and interpolation test is to reflect the retrieval ability of our model.

Extrapolation test and interpolation test are calculated mainly through calculation of mean-square error RMSE and TSQ [42], [43], with formula as following:

$$RMSE = \sqrt{\frac{1}{N} \sum_{n=1}^N (y_n - t_n)^2} \tag{22}$$

$$TSQ = \frac{\frac{1}{N_1} \sum_{n_1=1}^{N_1} (y_{n_1} - t_{n_1})^2}{\frac{1}{N_2} \sum_{n_2=1}^{N_2} (y_{n_2} - t_{n_2})^2} \tag{23}$$

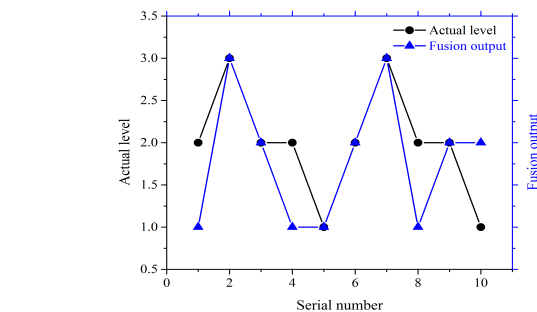


FIGURE 12. RF-SVM training results.

fused through trained RF-SVM network, and compare the fusion results with actual result, shown as following:

Above figure showed that, compared with actual result, the fusion result of left 5 groups' data could only reach 60% accuracy when data selected were relatively small. For further

TABLE 3. Comparison of prediction effect after iteration of different times.

Iteration times	RMSE	TSQ
50	0.020	1.691
100	0.017	1.475
200	0.06	1.091

y_n refers to the actual output value, and T_n to expected output value. The smaller RMSE and TSQ is, the more accurate the prediction is. RMSE and TSQ after iteration of different times were as following:

This table showed that the mean-square error maintained below 0.02, and the largest TSQ value was 1.691, which means this prediction model works well overall. Comparison of RMSE and TSQ values after iteration of different times told us that with increase of iteration times, the accuracy of prediction model will also rise up.

VI. CONCLUSION

In order to ensure the accuracy of signal transmission and reduce the risks posed to the mine workers' safety and health. Information management is an inevitable trend in mining industry. Breaking traditional static and empirical situation prediction, this research of situation awareness and emergency management of disaster in open-pit mines studied three steps of data pre-processing of sensor signal, data information fusion, and data application in support of the advantageous feature of mine's net of things, and discovered a more accurate dynamic prediction model for disaster situation in open-pit mines.

In this study, complete data pre-processing system of multi-sensor with varying property was constructed, and the information entropy theory was utilized to weight data with different attribute; it also studied the information fusion model of multi-sensor's data based on RF-SVM theory and situation prediction model based on ELM theory, to guarantee dynamic, precision, and timeliness of the prediction system; stimulation analysis of model's prediction ability was also performed, and the model's stability was tested both from mean-square RMSE and TSQ values. This model is of vital importance for improvement of emergency management and safety of lives and property in open-pit mines. Innovations of this paper are mainly listed as following:

- 1) It is testified that the model proposed in the paper can effectively reduce the risks posed to mine workers' safety and health by introducing the Internet of Things, signal processing, multi-sensor data fusion to the situation awareness of mine disasters and emergency management, which constructs creatively a basic framework of predicting model of situation awareness based on the Internet of Things.
- 2) Together with RF-SVM and ELM model, this model makes full use of advantage of small-sample data fusion of RF-SVM and extreme learning machine of ELM, realizing a comprehensive fusion and accurate prediction of multi-sensor data with varying property;

- 3) Together with RF-SVM and ELM model, this model makes full use of advantage of small-sample data fusion of RF-SVM and extreme learning machine of ELM, realizing a comprehensive fusion and accurate prediction of multi-sensor data with varying property;
- 4) Back test and interpolation test were adopted during prediction examination to avoid the disadvantage of "unable to calculate predicted error indexes because of things have not happened" effectively. Through analysis of change of mean-square error RMSE and TSQ values after iteration of different times, the validity of disaster situation prediction in open-pit mines was tested.

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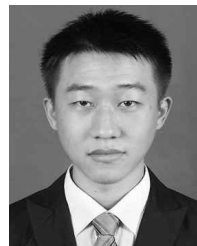
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