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Application of multi-sensor fuzzy information fusion algorithm in industrial safety monitoring system

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ABSTRACT

Chemical enterprises are characterized by many casualties and frequent serious accidents. In order to reduce the likelihood of such accidents and ensure safe production effectively, a new safety assessment method based on multi-sensor technology and fuzzy information fusion algorithm is proposed based on theory of fuzzy systems. The important parameters such as dust concentration, temperature and smoke concentration are monitored by various sensors in chemical enterprises, and information obtained by multiple sensors are fuzzified and optimized through the compositional operation and decision rules of a data fusion center, so as to fully utilize the information obtained from each monitoring point and obtain accurate estimations of the environmental safety state. In this paper, an example is presented to illustrate that the multi-sensor fuzzy information fusion algorithm increases the confidence level of industrial safety monitoring and improves the performance of the safety monitoring system.

1. Introduction

Safe production is of great significance to chemical enterprises. A safe production environment prevents major accidents and ensures the safety of workers. At the same time, safety accidents seriously hinder the development of industrial enterprises and reduce economic benefits. Therefore, real-time multi-point monitoring of industrial enterprise environments is needed to ensure the safety of workers. The technological characteristics of modern chemical enterprises include advanced technological process, large material flow, high dust concentration, high reaction pressure and temperature, fast rotating machinery, strict control of production parameters and numerous personnel. If the main technological conditions are not controlled, accidents may occur. Many links in the production process of factories and enterprises involve a large number of flammable and explosive dangerous goods, such as gasoline, toxic gases, liquids, dust, etc. However, these materials are necessary for factory production and require manual testing during the production process. Therefore, there are enormous potential safety hazards in the production process of factory products, and the requirements for the surrounding environment are extremely strict; this includes environmental temperature, ventilation conditions, anti-static measures, etc. Improper management or operation of any link is likely to cause huge potential dangers. In traditional control methods, a large number of sensors are used to monitor and control these parameters. The information collected by each sensor is usually processed separately, which not only increases the processing workload, but also ignores the interrelationship of sensory information sources and loses features obtainable through the organic combination of information. People describe variables in a qualitative way and cannot assess the safety conditions of industrial enterprises accurately. Compared to single sensor signal sources, multi-sensor signals allow more reliable outcome prediction (Gokulachandran, 2015).

Fuzzy theory can handle many vague concepts in industrial production, thus providing a means to improve the objectivity of evaluation. Fuzzy comprehensive evaluation uses the principle of fuzzy linear transformations and maximum membership to formulate a reasonable comprehensive evaluation by considering various factors related to the evaluated aspects. Finally, an optimal evaluation result is given. In multi-source information fusion, the principle of fuzzy comprehensive evaluation can be introduced to deal with the information fusion problem through fuzzy information and fuzzy reasoning. Fuzzy data fusion based on fuzzy system theory synthesizes different types of information obtained from each monitoring point, makes full use of the information obtained from each such point, combines all kinds of detection data in space and time according to some optimization criteria, and produces consistent interpretations and descriptions of the observed environment, so as to obtain more accurate and reliable results (Liu et al., 2008). Therefore, in order to achieve more specific and accurate

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industrial safety monitoring, multi-sensor information fusion techniques have been put forward. Soft computing techniques combined with classical methods like Kalman filtering (Painuli et al., 2014), Bayesian estimators (Baraldi et al., 2017), and Logistic regression (Beruvides et al., 2013) have been applied for achieving fusion. Bayes' decision theory and D-S evidence theory are commonly used in traditional data fusion algorithms, but both have their shortcomings. Data fusion methods based on neural networks, proposed in many studies, also have some shortcomings, such as limited samples, black box structure and the selection of initialization parameter weights (Tong et al., 2002). Due to the nonlinear and stochastic nature of the features extracted from sensor signals, a new multi-sensor information fusion system schema for online remaining useful life prediction of machining tools has been proposed (Wu et al., 2018). However, the proposed method's ability in dealing with different kinds of more complex operating conditions requires improvement. In recent years, a fuzzy set theory-based theoretical system has been initially formed in the field of multi-sensor information fusion, which provides new ideas for information fusion.

In this paper, the technology of fuzzy data fusion is applied to industrial safety monitoring. Under the structure of fuzzy comprehensive evaluation technology and extracted feature fusion, a fuzzy data fusion algorithm is proposed. Multi-sensor information fusion is used to synthesize information from multiple sensors or sources, and finally form a comprehensive safety decision analysis for industrial enterprises. To a certain extent, this increases the confidence level of the system's detection capacity and improves monitoring performance, which is significantly superior to traditional industrial safety monitoring methods.

2. Methodology

2.1. Structure of data fusion system

In the proposed method, the input from each sensor needs to be subjected to a transformation in order to obtain an independent attribute decision. Then, the attribute decision from each sensor is fused sequentially. The global decision process of the fusion center is based on the independent decision of each sensor. Fig. 1 shows the structure of the data fusion system based on fuzzy comprehensive decision-making. In the system structure, a local sensor extracts the features according to the detection results, reaches a local decision, and sends the local decision results to the fusion center. Based on the local decision of each sensor, the fusion center formulates a global decision.

Information fusion can deal with the uncertainty and incompleteness of information effectively. The object of fusion is information obtained from multiple sources, and the core of an information fusion system is the fusion algorithm. Multi-sensor information fusion is an automated information processing technology and a key feature of intelligent systems. In multi-sensor systems, information is diverse, complex and occurs in large amounts. For example, because of the complex industrial and mining environment of chemical enterprises, if only a single sensor is used to acquire data, it is likely that the sensor itself will lead to erroneous decision-making. However, after the processing and analysis of all fuzzy information, the final insight obtained using information processing will be closer to the actual situation. Therefore, decision-making based on multi-sensor information after fusion processing will be more comprehensive, and the system will behave in a hierarchical manner according to the different fusion levels, so as to avoid erroneous single sensor reporting. This will improve the overall performance of the monitoring system of chemical enterprises effectively.

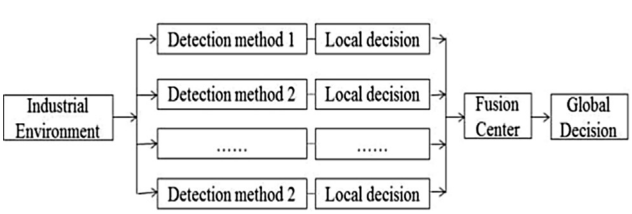

Fig. 1. Structure diagram of data fusion based on fuzzy assessment.

2.2. Multi-sensor fuzzy information fusion algorithm

Fuzzy comprehensive evaluation is a method to formulate a comprehensive evaluation of things affected by many factors using fuzzy set theory. The membership of the set elements can be expanded from 0 or 1 to any value in the interval of [0, 1], which is suitable for describing and dealing with uncertainty.

Based on data fusion theory, it is assumed that there are m sensors in an industrial environment monitoring system, and all the sensors are taken as a factor set V in the fusion system, where $V = (v_1, v_2, \ldots, v_m)$. The decision results of the environmental monitoring system are divided into n levels, which are the decision sets U in the fusion system, where $U = (u_1, u_2, \ldots, u_n)$. In fuzzy control theory, the fuzzy relation matrix $R = \{r_{ij}\}_{\mathrm{m}\times\mathrm{n}}$ can be constructed by assessing each factor in the factor set V according to the grade index of the decision set. In Eq. (1), r_{ij} denotes the possibility of inferring the state of j ($j \in [1, \mathrm{n}]$) in a decision set from a single factor I ($i \in [1, m]$), i.e., the degree of membership of v to u. Under the soft decision fusion structure, the decision result of each sensor is the confidence measure of each level in the decision set, that is to say, for the i-th sensor v_i, the decision result is formed as $r_i = (r_{i1}, r_{i2}, r_{i3}, \ldots, r_{in})$. After normalization, the input vectors of the fusion center are obtained, and the $m \times n$ matrix R can be formulated, which is called the decision matrix (i.e. the fuzzy relation matrix in fuzzy control theory) (Sun et al., 2009).

$$R = \begin{Bmatrix} r_{i1} & r_{i2}\cdots & r_{i1} \\ \vdots & \vdots\ \vdots & \vdots \\ r_{m1} & r_{m2}\cdots & r_{mn} \end{Bmatrix} \tag{1}$$

Each sensor in the fusion system has a different degree of significanc, called the sensor weight, which is a fuzzy subset of V, i.e. the sensor weight vector $A = (a_1, a_2, \ldots, a_m)$ (where A is a fuzzy vector), with $a_i = u(v_i)$, $i = (1, 2, 3, \ldots, m)$ and $\sum_{i=1}^{m} a_i = 1$, $a_i \geq 0$. Matrix B, obtained by the fuzzy transformation, is the possible degree of industrial safety. The decision process can be regarded as a compositional operation on the fuzzy vector A and the fuzzy relation matrix R, which is based on the generalized fuzzy operation, i.e. the result is marked as B in the form of common matrix multiplication.

$$B = A\cdot R = (a_1, a_2, \cdots, a_m)\cdot \begin{Bmatrix} r_{i1} & r_{i2}\cdots & r_{i1} \\ \vdots & \vdots\ \vdots & \vdots \\ r_{m1} & r_{m2}\cdots & r_{mn} \end{Bmatrix} = (b_1, b_2, \cdots, b_m) \tag{2}$$

$$b = \sum\nolimits_{i=1}^{m} a_i r_{ij}$$

$$A \in F(U), \quad (i = 1, 2, \cdots, n),\ u \in U \tag{3}$$

If there exists an i_0 that maximizes $A = \max\{A_{21}, A_2, \cdots, A_n\}$, then u belongs to A_{i_0}.

The flow chart of the fuzzy information fusion diagnostic algorithm is shown in Fig. 2. First, the enterprise status data are collected and fuzzified. Then, the relationship matrix is established, the weight vector and the relationship matrix of each sensor are obtained for multiplication, and the diagnostic membership result matrix is obtained. Finally, the final decision result is obtained according to the safe decision requirements.

3. Results and analysis

In order to make a comprehensive evaluation of the safety situation of a chemical industry workshop and realize the effective industrial early warning safety system, in this paper we consider a chemical industry in Chongqing as an example to analyze the test data. The

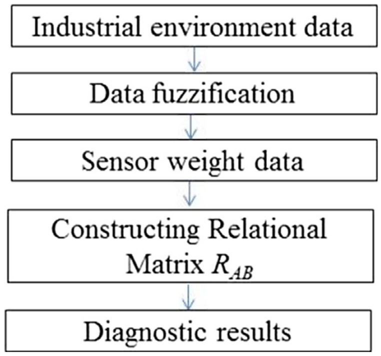

Fig. 2. Flow of fuzzy information fusion diagnosis algorithms.

Table 1
Data collected by each sensor.

Times	Dust Concentration/mg·m^{-3}	Temperature/°C	Smoke Concentration/mg·m^{-3}
t_1	2.08	31.2	0.115
t_2	4.06	40.8	0.128
t_3	4.87	42.9	0.411

monitoring system requires a large number of sensors to monitor the environmental parameters of the factory. Commonly measured parameters are dust concentration, temperature, smoke concentration and pressure intensity. Here, only the first three monitoring signals are tested and analyzed to assess the industrial safety situation. According to their safety status classification, industrial enterprises in China can be divided into three levels: safe, dangerous and very dangerous. Based on this monitoring system, the $V = \{v_1, v_2, v_3\}$ = {dust sensor, temperature sensor, smoke sensor}, $U = \{u_1, u_2, u_3\}$ = {safe, dangerous, very dangerous}. The weight distribution is obtained according to the following calculation process: $A = (a_1, a_2, a_3) = (0.230, 0.648, 0.122)$. Three groups of representative data at different times were selected for test analysis according to the measured data. The sample data are shown in Table 1.

Experts determined the weights of the three sensor indicators according to the assignment of the importance of each indicator factor in the questionnaire.

The expert decision matrix V was as follows:

	$V \to V_i$	V_1	V_2	V_3
$V =$	V_1	1	1/3	2
	V_2	3	1	5
	V_3	1/2	1/5	1

The weights were obtained by summation, and then normalization was applied on the columns.

$$B = \begin{bmatrix} \frac{1}{1+3+1/2} & \frac{1/3}{1/3+1+1/5} & \frac{2}{2+5+1} \\ \frac{3}{1+3+1/2} & \frac{1}{1/3+1+1/5} & \frac{5}{2+5+1} \\ \frac{1/2}{1+3+1/2} & \frac{1/5}{1/3+1+1/5} & \frac{1}{2+5+1} \end{bmatrix} = \begin{bmatrix} 0.222 & 0.217 & 0.250 \\ 0.667 & 0.652 & 0.625 \\ 0.111 & 0.130 & 0.125 \end{bmatrix} \tag{4}$$

After the summing the rows, normalization was carried out to calculate the weight value:

$$\begin{bmatrix} 0.689 \\ 1.944 \\ 0.366 \end{bmatrix}$$

Table 2
Average random consistency indicator of decision matrix after 1000 repeated calculations.

Order	1	2	3	4	5	6	7	8	9	10	11	12
RI	0	0	0.52	0.89	1.12	1.26	1.36	1.41	1.46	1.49	1.52	1.54

$$W = \begin{pmatrix} \frac{0.689}{0.689+1.944+0.366} \\ \frac{1.944}{0.689+1.944+0.366} \\ \frac{0.366}{0.689+1.944+0.366} \end{pmatrix} = \begin{pmatrix} 0.230 \\ 0.648 \\ 0.122 \end{pmatrix} \tag{5}$$

By calculating the eigenvalues, the following results were obtained:

$$VW = \begin{bmatrix} 1 & 1/3 & 2 \\ 3 & 1 & 5 \\ 1/2 & 1/5 & 1 \end{bmatrix} \begin{bmatrix} 0.230 \\ 0.648 \\ 0.122 \end{bmatrix} = \begin{bmatrix} 0.690 \\ 1.948 \\ 0.367 \end{bmatrix} \tag{6}$$

$$\lambda_{max} = \frac{1}{3}\left(\frac{0.690}{0.230} + \frac{1.948}{0.648} + \frac{0.367}{0.122}\right) = 3.001 \tag{7}$$

The consistency test index *C.I.* was

$$C.\,I. = \frac{\lambda_{\max} - n}{n-1} = \frac{3.001 - 3}{3-1} = 5 \times 10^{-4} \ll 0.1 \tag{8}$$

From the above, it is clear that $C.I. \ll 0.10$, which shows that the decision matrix is consistent and acceptable. The average random consistency indicator of the decision matris for 1–12 order is shown in Table 2. Since $RI = 0.52$, as obtained from the table 2, then:

$$\mathrm{CR} = \frac{C.\,I.}{RI} = \frac{5 \times 10^{-4}}{0.52} = 9.62 \times 10^{-4} \ll 0.1 \tag{9}$$

From Eq. (5), the weights of the indicators are shown in Table 3.

$A = (a_1, a_2, a_3) = (0.230, 0.648, 0.122)$ was obtained from the above calculation process for weight assignment. First, the data of each sensor are judged locally, and the results are normalized to determine the monitoring status of each sensor. Then, the decision matrix is constructed using the normalized results and the compositional operation is carried out. Finally, the principle of maximum membership is used for comprehensive evaluation.

The Cauchy distribution was used to determine the degree of membership, Let r_{ij}, where ($i = 1, 2, 3$; $j = 1, 2, 3$) is the degree of membership, and i denotes sensors v_1, v_2 and v_3, , while j denotes that the results of sensor recognition are normal, moderate or dangerous. Then, we have:

$$r_{i1}(x) = \begin{cases} 1, x_i \le a_{i1} \\ \frac{1}{1+\alpha(x_i - a_{i1})^{\beta}}, x_i > a_{i1} \end{cases} \quad (\alpha > 0, \beta > 0) \tag{10}$$

$$r_{i2}(\mathrm{x}) = \frac{1}{1+\alpha(x_i - a_{i2})^{\beta}} \quad (\alpha > 0, \beta > 0) \tag{11}$$

$$r_{i3}(x) = \begin{cases} 0, x_i \le a_{i3} \\ \frac{1}{1+\alpha(x_i - a_{i3})^{\beta} x_i > a_{i3}} \end{cases} \quad (\alpha > 0, \beta > 0) \tag{12}$$

In the above equation, let $\alpha = 1$, $\beta = 2$, $\mathrm{x_i}$ is the actual value measured by the sensor, while a_{i1}, a_{i2}, and a_{i3} are the standard values of the normal, moderate and dangerous states of the enterprise sensors readings, in the enterprise. Based on expert advice, for dust $a_{i1} = 3.0$, $a_{i2} = 4.0$, $a_{i3} = 5.0$; for temperature, $a_{i1} = 35.0$, $a_{i2} = 40.0$, $a_{i3} = 45.0$;

Table 3
The weights of the indicators.

Indicators	V_1	V_2	V_3
The weight	0.230	0.648	0.122

and for smoke, $a_{i1} = 0.1$, $a_{i2} = 0.2$, $a_{i3} = 0.3$;

At time t_1, when the reading of the dust sensor $x_1 = 2.08$:

$$r_{11} = 1,\ r_{12} = \frac{1}{1 + (2.08 - 4.0)^2} = 0.213,\ r_{13} = 0$$

After normalization, we obtain:

$$r_{11}^{'} = \frac{1}{1 + 0.213 + 0} = 0.824$$

$$r_{12}^{'} = \frac{0.213}{1 + 0.213 + 0} = 0.176$$

$$r_{13}^{'} = \frac{0}{1 + 0.213 + 0} = 0$$

When the data of temperature sensor $x_2 = 31.2$,

$$r_{21} = 1$$

$$r_{22} = \frac{1}{1 + (31.2 - 40.0)^2} = 0.013$$

$$r_{23} = 0$$

After normalization, $r_{21}^{'} = \frac{1}{1 + 0.013 + 0} = 0.987$

$$r_{22}^{'} = \frac{0.013}{1 + 0.013 + 0} = 0.013$$

$$r_{23}^{'} = \frac{0}{1 + 0.013 + 0} = 0$$

When the data of smoke sensor $x_3 = 0.115$,

$$r_{31} = \frac{1}{1 + (0.115 - 0.1)^2} = 1.000$$

$$r_{32} = \frac{1}{1 + (0.115 - 0.2)^2} = 0.993$$

$$r_{33} = 0$$

After normalization, $r_{31}^{'} = \frac{1}{1 + 0.993 + 0} = 0.502$

$$r_{32}^{'} = \frac{0.993}{1 + 0.993 + 0} = 0.498$$

$$r_{33}^{'} = \frac{0}{1 + 0.993 + 0} = 0$$

Similarly, for t_2, when the date of dust concentration is $x_1 = 4.06$

$r_{11} = 0.471$, $r_{12} = 0.996$, $r_{13} = 0$

After normalization, $r_{11}^{'} = 0.321$, $r_{12}^{'} = 0.679$, $r_{13}^{'} = 0$

$x_2 = 40.8$, $r_{21} = 0.029$, $r_{22} = 0.610$, $r_{23} = 0$

After normalization, $r_{21}^{'} = 0.045$, $r_{22}^{'} = 0.955$, $r_{23}^{'} = 0$

When the reading of the smoke sensor is $x_2 = 0.128$, $r_{31} = 0.128$, $r_{32} = 0.127$, $r_{33} = 0$

After normalization, $r_{31}^{'} = 0.502$, $r_{32}^{'} = 0.498$, $r_{33}^{'} = 0$

The membership values of each sensor at time t_3 are calculated similarly. In fusion decision-making, the optimal result is obtained by applying the principle of maximum membership degree to formulate decisions (Fu et al., 2008). According to the result of compositional operation, the decision rule of the maximum membership method is that the decision result should have the maximum membership degree. The membership degree of the decision result must be greater than a threshold parameter ε, where $0.5 \le \varepsilon \le 1$ (usually 0.5); the difference between the membership degree of the decision result and that of other decisions must be greater than a certain value (here 0.1).

According to the above rules, the monitoring results of each sensor at time t_1, t_2 and t_3 was obtained, as shown in Tables 4–6.

Next, the normalized results are formed into a decision matrix, which is combined with the sensor vector.

For t_1:

Table 4
Recognition results of sensors at time t_1.

Sensor	State			
	Normal	Moderate	Danger	Result
Dust Concentration Sensor	0.824	0.176	0	Normal
Temperature sensor	0.987	0.013	0	Normal
Smoke Concentration Sensor	0.502	0.498	0	Unknown

Table 5
Recognition results of sensors at time t_2.

Sensor	State			
	Normal	Moderate	Danger	Result
Dust Concentration Sensor	0.321	0.697	0	Slight
Temperature sensor	0.045	0.955	0	Slight
Smoke Concentration Sensor	0.502	0.498	0	Unknown

Table 6
Recognition results of sensors at time t_3.

Sensor	State			
	Normal	Moderate	Danger	Result
Dust Concentration Sensor	0.281	0.719	0	Slight
Temperature sensor	0.131	0.869	0	Slight
Smoke Concentration Sensor	0.485	0.509	0.006	Unknown

Table 7
Recognition results of sensors at time t_1.

Sensor	State			
	Normal	Moderate	Danger	Result
Dust Concentration Sensor	0.824	0.176	0	Normal
Temperature sensor	0.987	0.013	0	Normal
Smoke Concentration Sensor	0.502	0.498	0	Unknown
Fusion results	0.890	0.110	0	Normal

Table 8
Recognition results of sensors at time t_2.

Sensor	State			
	Normal	Moderate	Danger	Result
Dust Concentration Sensor	0.321	0.697	0	Slight
Temperature sensor	0.045	0.955	0	Slight
Smoke Concentration Sensor	0.502	0.498	0	Unknown
Fusion results	0.164	0.836	0	Slight

Table 9
Recognition results of sensors at time t_3.

Sensor	State			
	Normal	Moderate	Danger	Result
Dust Concentration Sensor	0.281	0.719	0	Slight
Temperature sensor	0.131	0.869	0	Slight
Smoke Concentration Sensor	0.485	0.509	0.006	Unknown
Fusion results	0.209	0.791	0	Slight

$$\text{Decision Matrix } R = \begin{bmatrix} r'_{11} & r'_{12} & r'_{13} \\ r'_{21} & r'_{22} & r'_{23} \\ r'_{31} & r'_{32} & r'_{33} \end{bmatrix} = \begin{bmatrix} 0.824 & 0.176 & 0 \\ 0.987 & 0.013 & 0 \\ 0.502 & 0.498 & 0 \end{bmatrix}$$

$$\text{Result } B = A^{\circ}R = (a_1, a_2, a_3)^{\circ} \begin{bmatrix} r'_{11} & r'_{12} & r'_{13} \\ r'_{21} & r'_{22} & r'_{23} \\ r'_{31} & r'_{32} & r'_{33} \end{bmatrix}$$

$$= (0.230, 0.648, 0.122)^{\circ} \begin{bmatrix} 0.824 & 0.176 & 0 \\ 0.987 & 0.013 & 0 \\ 0.502 & 0.498 & 0 \end{bmatrix} = (0.890, 0.110, 0)$$

Similarly, for t_2:

$$\text{Result } B = A^{\circ}R = (a_1, a_2, a_3)^{\circ} \begin{bmatrix} r'_{11} & r'_{12} & r'_{13} \\ r'_{21} & r'_{22} & r'_{23} \\ r'_{31} & r'_{32} & r'_{33} \end{bmatrix}$$

$$= (0.230, 0.648, 0.122)^{\circ} \begin{bmatrix} 0.321 & 0.697 & 0 \\ 0.045 & 0.955 & 0 \\ 0.502 & 0.498 & 0 \end{bmatrix} = (0.164, 0.836, 0)$$

Similarly, for t_3:

$$\text{Result} B = A^{\circ}R = (a_1, a_2, a_3)^{\circ} \begin{bmatrix} r'_{11} & r'_{12} & r'_{13} \\ r'_{21} & r'_{22} & r'_{23} \\ r'_{31} & r'_{32} & r'_{33} \end{bmatrix}$$

$$= (0.230, 0.648, 0.122)^{\circ} \begin{bmatrix} 0.281 & 0.719 & 0 \\ 0.131 & 0.869 & 0 \\ 0.485 & 0.509 & 0.006 \end{bmatrix} = (0.209, 0.791, 0)$$

Finally, the principle of maximum membership degree is applied to synthesize the results and obtain a comprehensive assessment of the security state. The result of the assessment is shown in Tables 7–9.

The above three tables show the individual monitoring results of each sensor (including the dust, temperature and smoke sensors) and the results of sensor data after fusion. From the above Tables 7–9, it is evident that when the sensors are examined independently, the monitoring results of some sensors are unknown; that is, if a single sensor's readings are not indicative of a normal or dangerous state, then it is impossible to realize early warning or a false alarm may be caused, which bears its own hidden dangers and is not conducive to industrial production safety (Zhong, 2009).

Multi-sensor information fusion technology allows the fusion and processing of information collected by sensors from multiple observation points, which can overcome the one-sidedness and incompleteness of information collected by a single sensor effectively, thus improving the system's assessment and decision-making ability. The exploration of information fusion algorithms is endless. It is a theoretical subject that needs to be studied deeply to obtain efficient and fast algorithms and achieve accurate and efficient information fusion.

In summary, multi-sensor data fusion based on fuzzy comprehensive evaluation can improve the feasibility of industrial safety early warning systems, and allows reliable determination of the safety degree in-dustrial envirionments. This improves the performance of industrial safety early warning systems, so that they can alarm users correspondingly under various unsafe conditions.

4. Conclusions

The application of fuzzy set theory in multi-sensor information fusion can help multi-sensor decision-making systems perform fuzzy reasoning and enhances their decision-making confidence.

Safety prediction in the chemical industry is realized using fuzzy comprehensive evaluation and information fusion. A safety early warning model of a chemical plant based on fuzzy data fusion is proposed. The redundancy and complementarity of multi-source information are fully utilized. The information collected at each monitoring point can be judged more accurately after data fusion in the fusion center, so as to enhance monitoring reliability and improve the detection performance of the system, which provides a realistic basis for industrial safety.

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References

Baraldi, P., Maio, F.D., Al-Dahidi, S., Zio, E., Mangili, F., 2017. Prediction of industrial equipment remaining useful life by fuzzy similarity and belief function theory. Expert Syst. Appl. 83, 226–241.
Beruvides, G., Quiza, R., Toro, R.D., 2013. Sensoring systems and signal analysis to monitor tool wear in microdrilling operations on a sintered tungsten–copper composite material. Sens. Actuators Phys. 199 (199), 165–175.
Fu, H., Gao, T., Liu, Y., 2008. Application of multi-sensor fuzzy information fusion in mine safety. Transducer Microsyst. Technol. 27 (5), 114–120 (in Chinese).
Gokulachandran, J., Mohandas, K., 2015. Comparative study of two soft computing techniques for the prediction of remaining useful life of cutting tools. J. Intell. Manuf. 26, 255–268.
Liu, J., Ren, Y., Gao, Y., 2008. Application of fuzzy data fusion in safety detection system of mine. J. Henan Polytech. Univ. (Natural Sci.) 27 (3), 268–271 (in Chinese).
Painuli, S., Elangovan, M., Sugumaran, V., 2014. Tool condition monitoring using K-star algorithm. Expert Syst. Appl. 41, 2638–2643.
Sun, H.G., Zhang, Y., Cao, Y., Yan, X., 2009. Application of fuzzy data fusion in multi-sensor environment monitoring. Ind. Mine Autom. 8, 22–24 (In Chinese).
Tong, S.H., Shen, Y., Liu, Z.Y., 2002. Fuzzy model and algorithms for data fusion. J. Harbin Inst. Technol. 34 (1), 7–18.
Wu, J., Su, Y.H., Cheng, Y.W., Shao, X.Y., Deng, C., Liu, C., 2018. Multi-sensor information fusion for remaining useful life prediction of machining tools by adaptive network based fuzzy inference system. Appl. Soft Comput. 68, 13–23 (in Chinese).
Zhong, M., 2009. Research on early-warning of gas in coal mine based on fuzzy data fusion. Xi'an Univ. Sci. Technol. 32–50 (In Chinese).