Application of Evidence Conflict Recognition in Coal Spontaneous Combustion Warning

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Abstract
Aiming at the problem of false alarm and combining spontaneous combustion indices in coal mine, we introduce the K-L information distance function to describe the conflict character with evidence. By this method, we can identify the evidence conflict systematically. Simulation results show that: we can improve the application constraint of D-S theory combination rule by means of the effective conflict recognition based on the K-L distance. On one hand we can get optimal convergence results on the normal conflict evidence combination, on the other hand we can get valuable information from analyzing highly conflicting feature; we can identify the cause of the fire and by means of the consistency determination of multiple indicator feature conflict improve the accuracy and timeliness of safety warning in coal mine.
Key words: DEMPSTER-SHAFTER EVIDENCE FUSION, INFORMATION DISTANCE, CONFLICT IDENTIFICATION, FIRE WARNING

1. Introduction

Mine fire is one of the five nature disasters of coal mine, which will not only cause the direct economic costs such as the coal resources loss and engineering equipment damage, but the more serious thing is its huge threat to the life safety of miners. The reason is that the underground fire caused by exogenous fire (open fire, blasting, welding, etc.) and internal caused fire (spontaneous combustion) will produce the large amount of toxic gas such as CO, CO2, which will poison workers. Besides, the open fire is prone to cause the serious accidents such as gas and coal dust explosion, what' s worse, the renewable combustion source caused by wind pressure and wind currents will expand or cause secondary disasters. Therefore, early prediction and effective control of mine fire is the key research content of coal mine safety warning system. With the development of coal mine informatization technology, it is widely applied that to monitor CO gas using wireless sensor used as fire warning indicator[1]. However, when the study confirms the possible occurrence of original CO in coal seam, prediction of spontaneous combustion relying on CO will give a false alarm, which hampers safe production of mine [2-4]. At the same time, due to the disturbance of complex underground environment and all kinds of uncertain factors, taking CO as the independent monitoring indicators may triggers false alarm and causes danger.

Actually, the multi-sensor data fusion is a kind of functional stimulation which focuses on dealing with complex issues through the human brain, it is also a method and technique which comprehensively utilize various information. In itself, it is a decision-making process[5]. Mine disaster monitoring is a multi-sensor system, the information provided by the various information sources have different characteristics [6] :time-variant or time-varying, real-time and non-real-time, ambiguous or determined, precise or incomplete, reliable or unreliable, mutually supportive or complementary, or it may be contradictory or conflicting. Huang and Miu[7] have realized establishing the information management system of information sharing and data fusion for the development of mine safety monitoring in China. Zhang [8] have brought the concept of information fusion to the condition monitoring in coal enterprises, which provides system framework of safety production information fusion in coal enterprises. Yan and Tu [9]aim at the gas disaster in mine, collect the sampling signal data of gas, temperature, wind speed and others through the multi-sensor data fusion method, extract their feature amount and make the data fusion , to achieve real-time monitoring and predictive control of the mine gas ,provide a strong guarantee for the mine safety. However, due to particularity of production environment, production process and production layout in the coal industries, it frequently generates a lot of complex relationships and redundant data information which bring difficulties to the useful information extraction and system control. Thus, the multi-source information fusion technology has become the essential part in the study of coal mine safety monitoring.

In the basic platform of multi-sensor application of coal mine informatization, introduce D-S evidence theory in multi-source information fusion and gather the information of several feature indicator of mire fire; Under the condition of confirming the value of conflict information, introduce K-L information distance functions replacing traditional D - S conflict coefficient K and define the degree of K-L evidence conflict to determine the conflict characteristics. Combined with the characteristics of mine fire, early fire prediction and recognition of development situation are to be made. It is aimed to take reasonable technical means for the timely prevention and effective control, and provide reliable technical methods and decision-making basis for coal mine safety pre-warning system.

2. D-S Evidence Theory and Evidence Conflict

2.1 Preliminary of D-S evidence theory

D-S theory assumes a nonempty set Θ, used to describe all elements of mutual exclusion and exhaustion, and $\Theta=\{A_1, A_2 \cdots, A_N\}$ is called recognition framework. A collection with the element being N, includes 2^N mutex subsets, is marked as Θ. In D-S theory, Mass is represented by the degree of belief in support of proposition.

According to definition 1 [10] assume set Θ as the recognition frame of D-S theory, the complete and mutually exclusive proposition composing power set function $m: 2^\Theta \to [0,1]$, and satisfying

$$m(\phi)=0, \qquad \sum_{A\subset\Theta} m(A)=1$$

Then, m (A) is called the BPA of A under the frame of Θ, denoting the evidence degree of trust and support for A. When $m(A)\neq 0$, then A is called the focal element (namely, evidence's focus on A) of BPA.

According to definition 2[10], Support or belief function (namely Bel function) represents the policymaker's total trust on proposition A, which is defined as:

$$Bel(A)=\sum_{B\subseteq A} m(B), \qquad A\subseteq\Theta, B\neq\varphi \qquad (1)$$

Belief function is applied to a collection and all its subsets, and Bel is based on global confidence.

Combination rules of D-S theory:

Assume the BPA assignment function of evidence M_1, M_2 in the same recognition frame is m_1, m_2,

And the focal element is $(A_1,...,A_k) and (B_1,...B_l)$,for :

$$K = \sum_{A_{i1} \cap B_{j2} = \varphi} m_1(A_i) m_2(B_j) \quad (2)$$

In this form, K is conflict coefficient, representing the degree of contradiction between combined evidence in Dempster combination.

The combination results of evidence:

$$m(C) = m_1 \oplus m_2 = m_1(A) + m_2(B)$$
$$= \frac{1}{1\text{-}K} \sum_{A_{i1} \cap B_{j2} = C} m_1(A_i) m_2(B_j) \qquad \forall C \subset \Theta, C \neq \varphi \quad (3)$$

$m(C)$ is new evidence assignment produced after orthogonal combination of m_1, m_2; $C = A_{i1} \cap B_{j2}$, namely, when $A_{i1} \subseteq B_{j2}$, $C_i = A_{i1}$, which represents the same information part between evidences of some element ; therefore, when $A_{i1} \cap B_{j2} = \Phi$, the element information is not uniform, expressed as conflict. ⊕ represents orthogonal sum, and (1-K)is normalizing factor after eliminating conflict interference. When there exist n evidences,

$$m(A) = m_1 \oplus m_2 \oplus \cdots \oplus m_n$$
$$= \frac{1}{1\text{-}K} \sum_{A_{i1} \cap A_{i2} \cap \cdots \cap A_{in} = A} m_1(A_i) m_2(A_i) \cdots m_n(A_i) \qquad \forall A \subset \Theta, A \neq \Phi \quad (4)$$

$$K = \sum_{A_{i1} \cap A_{i2} \cap \cdots \cap A_{in} = \varphi} m_1(A_i) m_2(A_i) \cdots m_n(A_i)$$

2.2 The proposal of evidence conflict

1984, Zadch [10] verified the disadvantages of an the normalization factor with examples, and pointed out the application rules of Dempster combination rules under the evidence conflict. Zhang Suodi[11-13] constructs the three more complex paradoxes in the application of Dempster combination rules on the basis of Zadch , and got the example verification in a lot of evidence conflict research[14,15].

For conflict coefficient K : when K = 1, it is believed evidence m1 and m2 conflict completely, and the combination rules of Dempster lose efficacy; When K = 0, evidence information is exactly consistent, and the combination utilizing Dempster can achieve the quick focus.; when K→1, conflict of high degree exists between evidences, and paradox is possible to appear in the combination result; when 0<K<1, the two evidence parts are compatible. Therefore, when K≠0, any evidence combination will make effects on combination results of different degree due to the existence of conflict.

It can be seen that problems mentioned above include system combination error and low efficiency possibly caused by the practical application of D-S combination theory in characteristic conflict of evidence. In order to solve them, this paper introduces the distributive difference between K - L information distance expression evidences. It tries to provide a feasible solution for evidence theory combination under conflict characteristics from the full view of from independent evidence to the evidence system.

3. K-L Information Distance Expression in Evidence Conflict

In practical application, due to the existence of conflicts and interference, it is necessary to judge and distribute equitably the conflicts existing between all evidences, and to make quarantine treatment for the conflicts with high degree of conflict characteristics. Conflict coefficient K in D - S evidence theory is gained by pairwise orthogonal, which can well describe the information contradictory situation between the two evidences. However, the position of a single evidence in conflict characteristics system cannot be expressed concretely, which brings about the practical limits for the conflict characteristic identification in the multiple evidence combination theory. K-L information distance expresses the degree of conflict between evidences, and it gains conflict characteristics of the whole combination system by matrix combination.

3.1 Definition of K-L information distance

K - L information distance was put forward by statisticians Kullback and Leibler in the middle of the 20th century, and it is used to judge the degree of closeness of two probability distributions[16,17].

According to definition 3[17], assume under the same recognition framework $\Theta = \{A, B, C, \varphi\}$, the assignment function of evidence is φ, and then the function distance from M2 to M1 is as the following:

$$m(A),\ m(B) \quad and \quad m(C) \quad (5)$$

According to D-S evidence theory, $m(\varphi) = 0$ under the complete framework $\sum_{\bullet \subset \Theta} m_i(\bullet) = 1$, the number of focal elements of evidence M1,M2 is the same, namely $\underset{BPA}{I}(m_1{:}m_2)$ according to the discrete version of BPA function, the form (5) is expressed as I_i

According to definition three, when $I_{i,j}$, and only when $I_{i,j}$, H. The longer of K-L information distance, the greater of probability assignment function, and the smaller conversely; when the two evidence is identical entirely, I=0. Therefore, K-L information distance has the same meaning with the D-S conflict coefficient K. It reflects the degree of conflict between evidences through describing the distribution discrepancy of BPA function.

3.2 K-L information distance identification for evidence conflict characteristics

Assume multiple evidences of uniform distribution (at random) in the limited time and space H_i for I_i $I_1 \in (1.728, 7.476)$ in general, $I_2 \in (4.601, 11.433)$ $I_3 \in (0.340, 1.345)$ $\overline{I}_1 = 3.171$ denotes the information distance from evidence j to evidence i, and constructs K-L information distance matrix:

$\overline{I}_3 = 0.611$

From the information distance matrix, the information distance sum from all the evidence to the number evidence i in the designated area is

$$\overline{I}_3 = 0.611 \tag{6}$$

Obviously, when I_1, H_1 I_i represents the general discrepancy degree of number i evidence to all the evidence distribution function in the whole combination system. In monitoring system of n evidences, the reliable information evidence not only need support from adjacent evidences, but also keeps reasonable differences with other evidences in steady state of the system, therefore the total information distance is smaller; possibly due to the local variation, the total information distance of some evidences which are consistent with the adjacent evidences and have great discrepancy with the surrounding evidences will become bigger condescendingly; possibly because of the situation mutation or test failure, the total information distance of those evidences which have distinct difference with other evidences is the biggest. Therefore, the comprehensive analyses of total information distance for any evidence to all the evidence can describe the position of evidence i in conflict situation of the whole system.

According to definition 4, in order to show the effect degree of each evidence in the conflict of the integrated system, through the proportion of each distribution discrepancy in the whole discrepancy, it defines distributional difference ration H_2 as I_3

In the form (7), H_3 is termed as the evidence conflict degree based on K-L information distance (abbreviated as K-L evidence conflict degree).

The greater the distributional differences of number i evidence and other evidences, the bigger the "contribution" of information distance H_3 in the total difference of the system, and the more distinct of the described conflict characteristics. Therefore, K-L conflict degree H_i can not only show the conflict characteristics between independent evidence i and other evidences, and also presents its influence status in the total conflict of the whole conflict system.

4. Simulated Experiment

Coal mine environment is complex, and the fire cause is mainly because of spontaneous combustion and open fire of coal seam, and fires of different causes have different index characteristics in different periods [1,18] :

Spontaneous combustion is predictable objective fire, which generally goes through the incubation period, the self-heating period and combustion period. (1) the incubation period is a smooth, slow oxidation process of the coal with self-ignition orientation; (2) the coal oxidation rate is increasing, when coal temperature exceeds the critical temperature (Tc) of self-heat, the temperature rise sharply, and coal oxidation process accelerates, CO gas begins to appear;(3) when the coal temperature rises to critical ignition temperature (Tb), oxidation process intensifies, leading to spontaneous combustion, tend to produce fire, smoke and CO gas.

According to the experimental analysis result of the characteristics of gaseous product oxidized by spontaneous combustion of coal made by the key laboratory of coal mine safety in Liao Ning Province[13]: (1) the emergence of the representative gas CO, marked the coal sample has entered the stage of slow oxidation (i.e., the incubation period); (2) the relationship between the CO concentration and coal temperature obtained in the process of temperature rise and oxidization shows that when the coal temperature surpasses certain temperature, the increase range of CO concentration will rise higher in the process of oxidation; (3) the oxygen concentration in the oxidation and spontaneous combustion process of coal reverse falls as the coal temperature becomes high. when the coal temperature exceeds 100 °C oxidation reaction begins to accelerate, and O2 concentration declines obviously. when the coal temperature exceeds 200 °C, oxidation further accelerates, and O2 consumes faster.

In conclusion, on the basis that with CO gas being the representative gas of the spontaneous combustion of coal seam and the open fire, theory and experiment confirmed that the characteristic index of O2, T and flame is helpful. Secondly, when it is confirmed that in the coal seam CO gas monitoring is beyond the standard caused by the release of native CO [2-4], but it does not meet the other index characteristics of spontaneous combustion and fire other index, using multiple index information gathering can effectively eliminate false alarm of fire. At the same time, using multi-source information fusion method can improve accuracy of early warning, and reduce the false alarm due to the equipment failure and other complicated factors.

According to the related description of the simulated experiment parameters in this paper,: in the real coal mine monitoring system, due to the complexity of mine environment (such as the influence of water source on coal temperature, the influence of ventilation on the oxygen concentration), the application limitation of multi-source sensor equipment, the limit from the information platform on the sharing and gathering of ability of mass dynamic data information, and the uncertainty of the monitoring points and so on, great difficulties exists in the selection of the real (original) monitoring data . Therefore, this article simulated to collect the multi-source information of multiple indicators of coal mine fire, using data mining method aside from original data layer to directly introduce characteristic index. Besides, taking feature conflict judgment as the research object, identify the source by analyzing the identification of characteristics of fire indicators.

In a target monitoring system with limited space and time, assume the identification framework $\Theta = \{A, B, C, \varphi\}$ ={fire, non-fire, uncertainty, φ }. Assume the system collection consists of the three groups of evidences monitored by three multi sensor, and the structure is formed by the feature parameters of four system including CO, O2, T and flame. The values of its BPA function including *m(A), m(B), m(C)* are shown in Table 1, $m(\varphi) = 0$ and satisfying $\sum_{\bullet \subset \Theta} m_i(\bullet) = 1$.

Table 1. Analog data (fire) of coal mine safety monitoring system

	Evidence Group 1				Evidence Group 2				Evidence Group 3			
CO	m11	(A)=0.80	(B)=0.10	(C)=0.10	m21	(A)=0.80	(B)=0.10	(C)=0.10	m31	(A)=0.80	(B)=0.10	(C)=0.10
	m12	(A)=0.75	(B)=0.15	(C)=0.10	m22	(A)=0.75	(B)=0.15	(C)=0.10	m32	(A)=0.75	(B)=0.15	(C)=0.10
	m13	(A)=0.70	(B)=0.10	(C)=0.20	m23	(A)=0.70	(B)=0.10	(C)=0.20	m33	(A)=0.70	(B)=0.10	(C)=0.20
T	m14	(A)=0.60	(B)=0.20	(C)=0.20	m24	(A)=0.10	(B)=0.80	(C)=0.10	m34	(A)=0.80	(B)=0.10	(C)=0.10
	m15	(A)=0.65	(B)=0.25	(C)=0.10	m25	(A)=0.15	(B)=0.70	(C)=0.15	m35	(A)=0.75	(B)=0.10	(C)=0.15
	m16	(A)=0.55	(B)=0.15	(C)=0.30	m26	(A)=0.20	(B)=0.75	(C)=0.05	m36	(A)=0.70	(B)=0.15	(C)=0.15
O2	m17	(A)=0.50	(B)=0.20	(C)=0.30	m27	(A)=0.10	(B)=0.20	(C)=0.70	m37	(A)=0.60	(B)=0.20	(C)=0.20
	m18	(A)=0.55	(B)=0.25	(C)=0.20	m28	(A)=0.20	(B)=0.25	(C)=0.55	m38	(A)=0.55	(B)=0.20	(C)=0.25
	m19	(A)=0.55	(B)=0.30	(C)=0.15	m29	(A)=0.15	(B)=0.30	(C)=0.55	m39	(A)=0.65	(B)=0.15	(C)=0.20
flame	m1a	(A)=0.20	(B)=0.60	(C)=0.20	m2a	(A)=0.10	(B)=0.80	(C)=0.10	m3a	(A)=0.75	(B)=0.10	(C)=0.15
	m1b	(A)=0.10	(B)=0.70	(C)=0.20	m2b	(A)=0.05	(B)=0.85	(C)=0.10	m3b	(A)=0.90	(B)=0.05	(C)=0.05
	m1c	(A)=0.25	(B)=0.50	(C)=0.25	m2c	(A)=0.15	(B)=0.65	(C)=0.20	m3c	(A)=0.80	(B)=0.10	(C)=0.10

Construct K-L information distance matrix, and $I_{BPA}(m_1{:}m_2)$, I_i and H_i calculated from form (6)-(8) are shown in Table 2.

Table 2. Much evidence fusion K-L information distance and the degree of evidence conflict by four index

	CO			O2			T			Flame		
	1	2	3	4	5	6	7	8	9	a	b	c
I1	3.787	3.066	2.939	1.914	2.308	2.349	2.066	1.728	1.825	4.938	7.476	3.661
H1	0.100	0.081	0.077	0.050	0.061	0.062	0.054	0.045	0.048	0.130	0.196	0.096
I2	11.433	9.969	9.629	6.326	4.973	6.035	9.647	6.713	6.620	6.326	7.412	4.601
H2	0.127	0.111	0.107	0.071	0.055	0.067	0.108	0.075	0.074	0.071	0.083	0.051
I3	0.427	0.420	0.496	0.427	0.340	0.373	0.898	1.345	0.572	0.340	1.260	0.427
H3	0.058	0.057	0.068	0.058	0.046	0.051	0.123	0.184	0.078	0.046	0.172	0.058

In Table 2, $I_{i,j}$ represents K-L information distance of from number j evidence to number i evidence, and I_i represents the sum of information distance of from all evidences to number i evidence in the system, and I_i represents the conflict feature degree of evidence i, through calculating the proportion of total gap of the system of K-L information distance I_i . By comparative analysis of the evidence conflict degree of K-L information distance representation of three groups of evidences calculated from Table 2, it can be seen:

(1) Three groups of evidences $I_1 \in (1.728, 7.476)$, $I_2 \in (4.601, 11.433)$, $I_3 \in (0.340, 1.345)$, by calculating K-L information distance, characteristic difference mean value of three groups of parameters are gained: evidence group1 $\overline{I}_1 = 3.171$ exists distinct feature conflict; evidence group2 $\overline{I}_2 = 7.474$ belongs to feature conflict of high degree; evidence group2 $\overline{I}_3 = 0.611$ belongs to feature conflict of low degree.

(2) Evidence group1 confirms conflict. Four mon-

itoring indicators CO and O2, T and flame information feature I_1 exists significant inconsistency, and direct information fusion cannot made; the conflict impact of four indicators exists imbalances gained from each sensor monitoring parameters of position evidence conflict degree I_1 in the total feature conflict, which is embodied that the high-lighting of the flame index is more obvious than the other three indicators in the system.

(3) Evidence group2 confirms highly conflict. four monitoring indexes CO and O2, T and flame information feature I_1 exists highly inconsistency, and direct information fusion cannot made; the conflict impact of four indicators exists imbalances gained from each sensor monitoring parameters of position evidence conflict degree I_3 in the total feature conflict, which is embodied that the conflict high-lighting of the CO index compared with the other three indicators in the system.

(4) Evidence group3 confirms low conflict. four monitoring indexes CO and O2, T and flame information feature I_3 exists show consistency, and information fusion can be made; evidence conflict degree H_3 is more balanced, proving that the monitoring system operates normally; mb is singular point, and timely faculty maintenance on sensor b should be made.

Because of the good function of information gathering of D - S evidence theory with a certain evidence feature conflict scope, D - S information fusion to evidence group3 with low conflict is to be made. Substitute the data into form (2) - (4), fusion results are obtained as shown in table 3.

Table 3. D-S information fusion results of evidence for 3 groups by four index

D-S	Conflict feature	Bel fusion result
m31, m32,…, m39 m3a, m3b, m3c	K3=0.2	m3(A)= 0.999999998 m3 (B)= 3.30357E-10 m3 (C)= 1.65179E-09 m3 (Θ)= 0

In Table3, m3(A)= 0.999999998→1, which means, in the case of the existing monitoring parameters, fire situation of the mine sensors (1-9 ,No.a-c)monitoring area can be determined with the probability of 0.999999998.

If feature conflicts exist between four indicators of Evidence group1 and evidence group2, it cannot be judged to be fire occurrence; And in the case that monitoring CO exceeds standards, simple warning will bring potential safety hazard, therefore, the further analysis of the feature should be done to determine CO source. The early features of spontaneous combustion of coal seam is mainly composed of three indicators including CO and O2 and T, therefore when monitoring information meets the indicator consistency, it can be judged as the spontaneous combustion period.

Table 4 shows K-L information distance and feature conflict degree of three indicators of evidence group1 and evidence group2 through calculation.

Table 4. Much evidence fusion K-L information distance and the degree of evidence conflict by three index

	CO			O2			T		
	1	2	3	4	5	6	7	8	9
I1	0.849	0.590	0.558	0.352	0.584	0.743	0.812	0.494	0.676
H1	0.150	0.104	0.099	0.062	0.103	0.131	0.144	0.087	0.119
I2	6.891	6.021	5.673	6.249	4.847	5.735	6.820	4.643	4.802
H2	0.133	0.116	0.110	0.121	0.094	0.111	0.132	0.090	0.093

By the analysis of K-L information distance and evidence conflict degree of three indicators of two groups in Table4, it can be seen:

(1) In evidence group1, $I_{1i} \prec 1$, belongs to low-degree conflict, which means monitoring parameter features present consistency in the whole system and data fusion can be done based on D-S evidence theory; in evidence group2, $I_{2i} \in (4,7)$, belongs to high-degree conflict, which means monitoring parameter features share inconsistency.

(2) K-L Conflict degree H1i and H2i of evidences of two groups is even relatively, and singular value does not appear, which means each sensor of monitoring system operates normally.

According to analysis made above, D-S information gathering of evidence group1 with the three indicators presenting the consistency, the fusion results are shown in Table5.

Table 5. D-S information fusion results of evidence for 1 group by three index

D-S	Conflict feature	Bel fusion result
m11, m12,…, m19	K1=0.450017	m1 (A)= 0.99998 m1 (B)= 1.23841E-05 m1 (C)= 7.9258E-06 m1 (Θ)= 0

In Table 5, m1(A)= 0.99998→1, which means in the case of the existing monitoring parameters, it is shown that coal seam of mine monitoring group1 area is at spontaneous combustion period with help of the probability of 0.999999998.

When there is no conflict between evidences, using D - S evidence theory to make information fusion of multi-source sensors monitoring data can obtain good convergence effect. As a result, the uniformity of the three monitoring indicator feature of evidence group1 identify fire as spontaneous combustion of coal seam, timely fire preventive treatment of spontaneous combustion should be made; for Evidence groups2, significant conflict exists in the monitoring information of item3 and item4, which does not conform to the feature condition of fire and the spontaneous combustion of coal seam. In the absence of other relevant supporting information, (such as blasting, open flames, etc.) it can be judged as native CO, timely anti-poison safety service should be done; Evidence consistent characteristics of three groups of four indicators can be determined for the fire, should be quick to fire accident handling, to ensure the safety of property. The uniformity of the four monitoring indicator feature of evidence group3 can determine the occurrence of fire, so rapid fire accident treatment should be made to guarantee safety of life and property.

5. Conclusion

Coal mine environment is complex, and the a variety of factors can cause the mine fire, so different fires (predictive period, ignition period and combustion period) corresponding treatment measures should be taken. If taking mine CO monitoring as the only index, the false alarm will occur because of lacking the combination with other fire characteristic information for effective decision. Besides, under the condition that the native CO release of coal seam, false alarm caused by coal natural ignition will occur. In this paper, on the basis of a large number of remote sensing technology application platform, combined with a number of indicators the mine fire and coal seam spontaneous combustion forecast, making data fusion of multi-source information could improve the early warning accuracy using the D - S evidence theory; besides, it introduces K - L information distance, to make identification method research of system feature conflict, and define the feature conflict degree to achieve system consistency analysis on the information feature. According to the simulated calculation results, the effect of absolute convergence under the condition of four indicators of fire and three indicators of coal seam spontaneous combustion are share consistency, and under the condition of inconsistency of indicator feature, CO identification is to be made. Thus, according to the characteristics of real-time monitoring of multi-source information, it effectively determine the occurrence of fire, spontaneous combustion and primary CO release, so that the managers could adopt targeted preventive measures and timely treatment to provide a reliable basis in the prediction of different situations.

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A Direct Method for Estimating Net Radiation from HJ-1B Cloud-Free Data

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Abstract

A simple scheme is proposed to estimate instantaneous net radiation over the Heihe River watershed under clear sky conditions using HJ-1B data. We developed an algorithm that primarily use remote sensing information and eliminates the dependency on measured data from ground