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Public Opinion Data Fusion Method based on Ontology Semantics

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Abstract

In order to improve the decision-making level for public opinion responses and realize the semantic fusion of multi-level and multi-source heterogeneous public opinion information, an ontology-based public opinion information fusion method is proposed. Firstly, aiming at quick response decision-making, the situation assessment model of public opinion information fusion is studied, and the information fusion system is constructed. The multi-level evaluation model of situation recognition, situation understanding, and situation prediction is formed. Then, the multi-indicator ontology model and method for public opinion decision-making are constructed, and the public opinion data fusion model based on ontology semantics is proposed, which realizes the relevance analysis and semantic fusion of domain knowledge. Finally, a multi-level public opinion data fusion model is constructed, and the construction of the underlying emergency information knowledge base to support the above functions is deeply studied. The simulation results show that the feasibility and efficiency of the situation assessment problem are solved by this method, the time complexity and space complexity of attribute reduction and value reduction are reduced, and the matching efficiency of situation assessment rules is improved.

Keywords: situation assessment; information fusion; ontology semantics; public opinion decision; relevance analysis

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1. Introduction

Internet public opinion is a combination of people's political beliefs, attitudes, opinions, and emotions expressed by the Internet through government management, and it shows various phenomena and problems in society. It is the most active and acute aspect of social conditions and public opinions. It quickly and directly reflects the public opinion situation and development situation at all levels of society. It has more and more influence on society, so it has been attached great importance by the relevant departments of the state [1]. However, the source of network public opinion information is diversified and heterogeneous. Effectively integrating such information to achieve better decision-making is a technical problem that needs to be solved urgently [2].

The evolution of Internet public opinion is intertwined with the spread of lyric topics and the evolution of opinions of netizens on lyricism. With the extensive exchanges and discussions between netizens, the opinions of the public in the network will gradually become unified [3-4]. Once a unified opinion is formed, the public opinion will be disseminated more quickly. The formation of unified opinion arouses the attention of traditional social media. At this time, the public opinion will be further spread [5]. At present, all kinds of scientific research and engineering implementation have entered a data-centric era, and it is no exception for the Internet public opinion management. All kinds of decision analysis in the public opinion management process are based on the basic data of public opinion [6]. In decision-making, people ultimately need the information reflected by data and the impact of information on decision-making. To obtain such meaningful information for decision-making [7], it is necessary to study the true information reflected by the data itself and the semantic relationship between the data [8]. Public opinion information is the embodiment of the real world. The purpose of public opinion information fusion is to integrate heterogeneous data of distributed information sources into semantic processing according to the needs of decision-making objectives [9], so as to prepare for the decision-making and scheme-making of public opinion management.

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In this paper, aiming at the problem of big data fusion in network public opinion decision-making, this paper proposes to study the semantic fusion mechanism of network public opinion big data based on ontology semantic analysis and establish a network public opinion data fusion semantic model. Using the ontology theory method and technology, the heterogeneous problem of network public opinion information is analysed. By constructing various ontology models, the network public opinion fusion algorithm is studied to realize the semantic level fusion of network public opinion information combining the theory of data combination inference and the theory of rule inference, this paper studies how to construct a fusion model of multi-source information in network public opinion decision-making to achieve network public opinion assessment. Applying the idea of ontology modeling, the ontology model of network public opinion response method and plan are studied to solve the problem of information homogeneity and heterogeneity in multi-agent response task planning, that is, to realize multi-agent distributed plan fusion based on semantic fusion. Finally, the basic methods and algorithms of semantic fusion of network public opinion response method and multi-agent planning fusion based on constraints are studied.

2. Semantic Fusion of Public Opinion Information

2.1. Entropy Theory of Multi-Source Data Fusion

The multi-source information is abstracted into multiple input variables, and the fused output is abstracted into output variables. The mathematical model of multi-source data fusion can be symbolically established [10]. Information entropy is the most mature tool for expressing uncertainty. It can be used to describe the state of motion of uncertainty in the process of fusion and transmission. It is used to study the essential principles and processes of uncertainty in multi-source data fusion processing [11]. Shannon used two measures for information: information extraction and mutual information [12]. The information entropy $H(X)$ measures the amount of information of the discrete stochastic process $\{X_n\}$. Shannon proposed a coding theory that for a random process $\{X_n\}$, the sender can encode it into a set of binary sequences, and the receiver can completely reconstruct the original signal $\{X_n\}$ through the set of binary sequences. The mutual information describes the validity of the information transmission: the source $\{X_n\}$ transmits and outputs $\{Y_n\}$ in a noisy channel, and the extent of the original information $\{X_n\}$ can be estimated by observing $\{Y_n\}$. Shannon defined the average mutual information as follows:

$$I(X,Y) = H(X) - H(X) + H(Y) - H(X,Y) \tag{1}$$

Where $H(X)$ is the difference between the self-information and the joint entropy of the two. Another form of average mutual information can be expressed as

$$I(X,Y) = H(X) - H(X \mid Y) = H(Y) - H(X \mid Y) \tag{2}$$

Given a random variable X and its distribution ρ, Shannon's information entropy can be expressed as

$$H(X) = -\sum_{x\in\chi} \rho(x)\log_2 \rho(x) \tag{3}$$

Where χ is the set of values of the random variable X, and $H(X)$ measures the degree of unevenness of the distribution ρ. When $H(X)=0$, the random variable X is a constant, that is, there is no uncertainty in the change in X. When ρ is evenly distributed, $H(X)$ takes the maximum value.

Let x_1 and x_2 be two observation opinion data, and the two public opinion monitoring data can be similar or heterogeneous. Set $x_1 \in R^n$, $x_2 \in R^m$, and the observing system output as $y = R^c$, which can represent continuous state variables or discrete decision variables.

The fusion entropy of the observing system is defined as $H(y \mid x_1, x_2)$, which represents the average uncertainty of the target output y under the joint observation of x_1 and x_2. According to the nature of conditional entropy in information theory, conditional entropy is less than or equal to unconditional entropy, and entropy with more conditions is less than or equal to entropy with less conditions.

2.2. Semantic Mapping Relationship of Data Fusion

Any system can be regarded as a mapping process from space to space. Data fusion system is no exception, no matter which data fusion system can be regarded as the mapping process from external world space to target space [13-14]. In order to further reveal the essence of the data fusion method, this section will discuss the mapping between different data levels involved in the data fusion process. Let the data fusion model be defined as a quintuple $DFU=\{Sw, M, Mf, P, F\}$, where the first four items represent the four data spaces contained in the fusion model. *SW* represents the state data in real world space, M represents the measurement space, Mf represents the fusion space, and P indicates the target space for which fusion judgment is required. F represents a set of mapping relationships between different spaces. Set $F=\{\varphi, \theta, f\}$, where φ represents the mapping from the real world space to the measurement space, that is, the original data vector space of the discrimination target is obtained from the external space through a plurality of data sources. Through processing, the original data is converted into fusion spatial data, that is, mapping θ. Data in the fusion space can be fused at a higher level through the function mapping relation f. Let the real world space Sw composed of n targets be expressed as [15].

$$Sw=\begin{pmatrix} Sw_{11} & \dots & Sw_{1m} \\ \vdots & \ddots & \vdots \\ Sw_{n1} & \dots & Sw_{nm} \end{pmatrix} \tag{4}$$

Where the behavior target vector represents the target included in the world space and is listed as an attribute vector, indicating the attribute possessed by the target. Then, the element Sw_{ij} represents the eigenvalue of the attribute j of the target i in real world space, and m denotes the maximum number of features possessed by a target. When a target does not contain this feature, the value is 0.

The measurement space M set at time t is expressed as

$$M_t=\begin{pmatrix} ms_{11} & \dots & ms_{1m} \\ \vdots & \ddots & \vdots \\ ms_{n1} & \dots & ms_{nm} \end{pmatrix} \tag{5}$$

In the matrix, ms_{ij} represents the j raw data obtained by the information source i at time t. Set the number of information sources as L, and the maximum number of data provided by each information source is k. Therefore, the matrix may contain many 0 elements. The mapping relationship between measurement space and real space is $M=\varphi(Sw)$.

Set the matrix representation form of the fusion space Mf as

$$Mf=\begin{pmatrix} mf_{11} & \dots & mf_{1m} \\ \vdots & \ddots & \vdots \\ mf_{n1} & \dots & mf_{nm} \end{pmatrix} \tag{6}$$

In essence, Mf is formed by processing the original measurement data on the basis of the matrix M_t, that is, there is a mapping relationship $Mf=\theta(M_t)$. In the underlying data level fusion, only the original data is simply pre-processed, and the θ mapping relationship is a 1:1 mapping.

The target space P is composed of fusion results. Set $P=(fu_1, fu_2, \cdots, fu_n)^{\mathrm{T}}$, and fu_i is the final fusion measure of target i. There is a mapping relationship to obtain $P=f(\sum_{i=0}^{n} Mf_i)$, where n is the number of data measurements.

3. Multi-Source Heterogeneous Information Fusion Method in Public Opinion Situation Assessment

3.1. Method of Public Opinion Situation Assessment

Situation assessment is an important research content in information fusion. It emphasizes the relationship between entities, events, entities, and events [16]. The goal of situational awareness is to obtain information factors in the environment and provide support for situational understanding and analysis. The purpose of situation assessment technology in situation information fusion is to understand the meaning of acquisition factors, and the function of situation prediction is to understand and predict the events and situations that will happen [17]. On this basis, the decision-making and actions that have been made come back to influence the current situation, and thus it is a cyclical process. The situational model is shown in Figure 1, where Level1, Level2, and Level3 represent environmental element perception, current situational understanding, and future situational prediction, respectively.

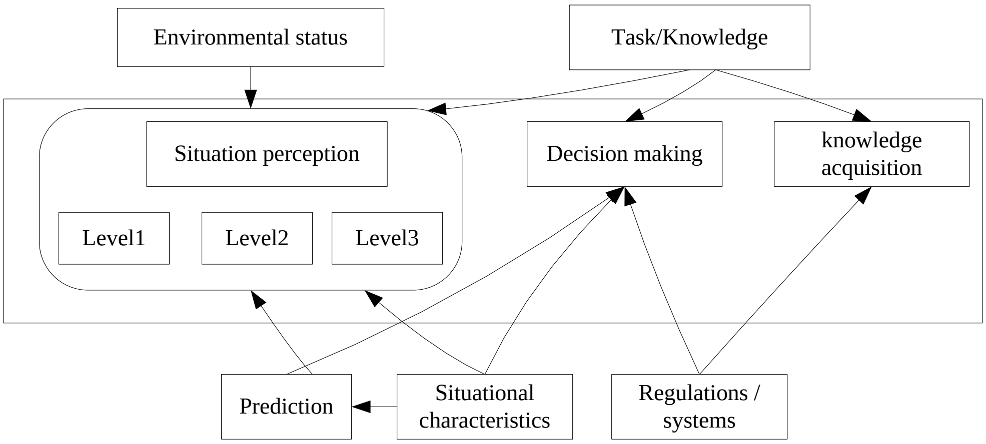

Figure 1. Situation assessment model diagram

As shown in Figure 1, the situation assessment is public opinion information that detects and perceives an event that has occurred in the current public opinion environment and information about the event that is occurring. It analyses and understands the relationship between what has occurred and what is happening. It also anticipates the events and actions to be taken, as well as the process of taking decisions on the current situation.

3.2. Problem Description of Public Opinion Assessment Decision

Based on the above analysis, a description model of the emergency situation assessment decision problem is established, and the following definitions are given for the main concepts [18]. The source of public opinion is the sender of the public opinion information received after the occurrence of a network event. There are many types of lyric information sources, such as various online media, personal microblogs, and WeChat. The public opinion identification framework is a detailed description of the facts of lyrics. If a public opinion occurs, the degree of public opinion transmission is judged. The public opinion view involves different descriptions of the same entity by different information sources, that is, basic associations with different information sources, forming a representation of the same disaster entity. Related elements can be set to time, location, esoteric entity object, etc. [19].

Accept the input of the underlying basic data fusion, that is, the fusion object belongs to the feature set and decision level information. The public opinion information fusion planning problem can be defined as a six-tuple, $FUS = \{Re, Op, De, Ob, Ru, Fu\}$, where Re is the fusion information source; Op is the disaster situation view set, and the feature vector is extracted from it to form the decision feature set De; Ob is a recognition target set, that is, an identification frame set, $T = \{\sigma_1, \sigma_2, \cdots, \sigma_n\}$; and σ is an identification frame. Let A be the basic proposition set, where $A \subseteq \sigma$. Ru is a fusion rule set, including an association set Re of features and propositions and an association rule set De between each recognition framework. Fu represents the fusion function, where $Fu : De \times Ru \to Ob$.

It is assumed that the fusion system accepts information transmitted by n information sources at a certain level. The public opinion environment inputs the information set S at the current time t and the first k-1 time, which can be expressed as $S = \{I_1, I_2, \cdots, I_n\}$. I_i represents the entire set of information entered by input unit i. $I_i = \{I_{i(t-k+1)}, I_{i(t-k+2)}, \cdots, I_{i(t)}\}$ represents the set of state information of the unit I_i at the current time t and the previous k-1 time. Described based on this hierarchical rule, if an input source also receives a lower level of information input, it can represent $I_{i(t-k+j)} = \{I_{i1}^{(j)}, I_{i2}^{(j)}, \cdots, I_{in}^{(j)}\}$, that is, the set of state information of the input unit I_i at the j time.

The feature level fusion result is $De = \{I_1 \cup I_2, \cdots, I_i \cup I_j \cup I_k, Re_1, Re_2, \cdots, Re_m\}$, which indicates an integrated scenario description of the emergency object in the disaster that needs to be evaluated. Finally, the global situational decision is made based on the integrated scenario description: $DDS = \{T_i, F\}$.

3.3. Decision-Related Potential State Analysis under Data Fusion Angle

Through the application of granular computing, the granulating processing of multi-source heterogeneous public opinion data is carried out, and the uncertainty of decision information, decision rules, decision tasks, decision information, and expression forms of preference information are analysed.

In the granulating process of public opinion data, ontology semantics and granular computing are related to the general process of the decision system. In the analysis process, the general decision system can be composed of D, F, V, f, denoted by S and recorded as $S = (D, F, V, f)$. In data fusion, it can be transformed into ontology integration for semantic representation [20]. D, F, V is a finite set of multiple types of data in the decision process, and f is a related inference function that can correspond to an axiom function for the ontology. In the granulation process of data, all kinds of multi-source heterogeneous big data in D need to be granulated. F is a collection of attributes of big data, and $F = M \cup N$, $M \cap N = \varnothing$. The elements in M are called conditional attributes, and the elements in N are called decision attributes. These defined attributes can be used for concepts in ontology. M and N can map the mapping relationship in cost ontology [21]. V is called the range of attributes, and its elements are called attribute values, which can be used to represent instances in ontology modeling [22]. The decision-making system is decomposed by using the granular computing method, so that the decision-making in the decision-making system can be transformed into subsystems, which is convenient for large data fusion modeling based on the granulation mechanism.

In decision rules, for a decision system $S = (D, F, V, f)$, due to $F = M \cup N$ and $M \cap N = \varnothing$, the elements in M and N are conditional attributes and decision attributes respectively, so the decision system is also recorded as $S = (D, M \cup N, V, f)$. Further decompose $S = (D, M \cup N, V, f)$ according to the decision rule, set $M = \{m_1, m_2, \cdots, m_n\}, N = \{n_1, n_2, \cdots, n_m\}$, and take two sets of attribute values $V(v_1, v_2, \cdots, v_n)$ and $V(q_1, q_2, \cdots, q_n)$. A decision rule with $S = (D, M \cup N, V, f)$ can be defined as

$$\alpha \to \beta = (n_1, v_1) \wedge (n_2, v_2) \wedge, \cdots, \wedge (n_m, v_m) \to (m_1, q_1), (m_2, q_2), \cdots, \wedge (m_n, q_n) \tag{7}$$

For the decision system $S = (D, F, V, f)$ defined above, let $\alpha \to \beta$ be the S decision rule. When the decision system S driven by big data is very large, it is necessary to decompose S into several subsystems [23]. The decision corresponding to the decision rule $\alpha \to \beta$ is equivalently converted to a certain subsystem, so that multi-granularity decision system decomposition and transformation can be realized, as well as cross-granular reasoning and data fusion [24]. When further decomposing the conditions and decision attributes in the decision system $S = (D, M \cup N, V, f)$, set $u_1, u_2, \cdots, u_n \in M \cup N$, and attributes $u_1, u_2, \cdots, u_n$ can have conditional attributes or decision attributes. For n attribute values $q_1, q_2, \cdots, q_n \in V$, we can set

$$\phi = (u_1, q_1) \wedge (u_2, q_2) \wedge, \cdots, \wedge (u_m, q_m) \tag{8}$$

Then, ϕ is the corresponding grain on S. When the attribute $u_1, u_2, \cdots, u_n$ is fixed, the grain $|\phi|$ changes as the property value $q_1, q_2, \cdots, q_n$ changes, so that a collection of particles can be obtained.

$$L = \{|\phi|, |\phi| \neq \varnothing, \phi = (u_1, q_1) \wedge (u_2, q_2) \wedge, \cdots, \wedge (u_m, q_m), q_1, q_2, \cdots, q_n \in V\} \tag{9}$$

Where L is the set of granules associated with attributes $u_1, u_2, \cdots, u_n$, and multiple different decision making subsystems can form a collection of granules of multiple different spaces. For any decision rule $S = (D, M \cup N, V, f)$ of the decision system $\alpha \to \beta$, its corresponding decision can be equivalently converted to a certain partitioning system S_i.

It can be seen from the above problems that the collection of public opinion information involves a multi-intelligence acquisition system, which has the characteristics of multi-agent multi-level coordination. This paper proposes a scheme based on semantic fusion. The fusion processing mainly includes three-level processing tasks: real-time input of the underlying data, sorting according to the unified structure form and then analyzing the correlation of the data to form the lyrics of the local information homogeneous description, and constructing a lyric view. A variety of feature information is extracted from the public opinion view as evidence, and the fusion strategy is selected according to the knowledge base. The multi-feature fusion is used to judge the situation of the situation, and the final decision of the global environment is obtained. The decision fusion process is shown in Figure 2.

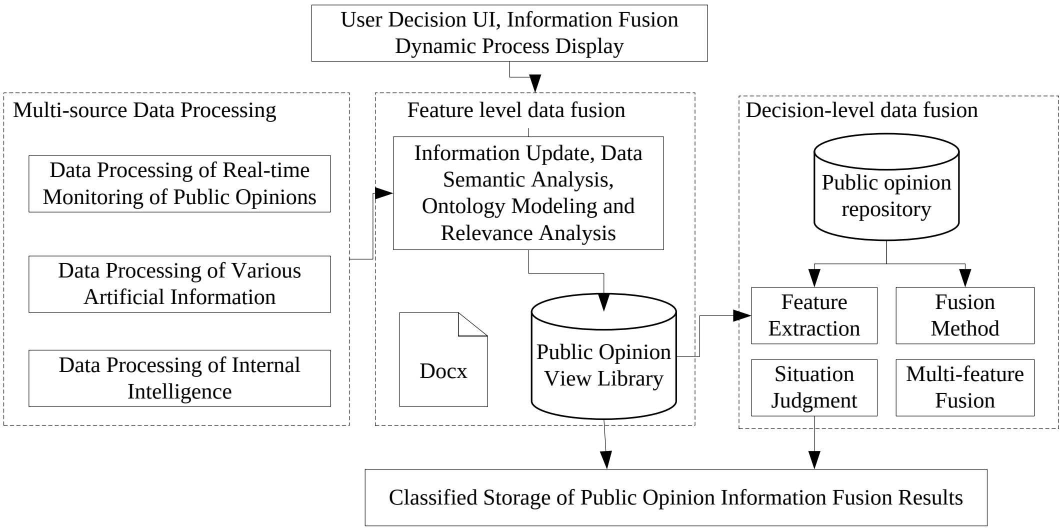

Figure 2. Fusion planning processing flow

4. Experimental Analysis

The polarity evolution of the network sentiment field refers to the overall tendency expressed in the different stages of development of the network, reflecting the unity of the dynamic and periodic characteristics of the network. In order to more clearly explain the formation mechanism of the network sentiment field, the characteristics of the dynamics of the polarity, and the evolution of the cycle in the different stages of development of the network, we introduce the case of reality and reveal the movement trend of real data. We also confirm the formation process and periodic evolution mode of the network sentiment field.

In order to reflect the fusion performance of the proposed algorithm, a simplified example is used to identify the case as a simulation example. Assuming five lyrics are identified to participate in the fusion calculation, the monitoring data can be recorded. Assume that the target set is $Object = (O_1, O_2, O_3, O_4, O_5)$, and the normalized mean square deviation ε of the five public opinion recognition parameters are 0.021, 0.012, 0.032, 0.121, and 0.009, respectively. The variance is used to make 200 measurements to calculate the characteristic parameters. The target fusion set attribute measurements are shown in Table 1, and the six sub-criteria are shown in Table 2. Their fusion process and running speeds are shown in Figure 3.

Table 1. Target recognition set data

	S_1	S_2	S_3	S_4	S_5
O_1	[0.12,0.24]	[0.23,0.16]	[0.14,0.36]	[0.31,0.41]	[0.38,0.15]
O_2	[0.61,0.98]	[0.33,0.65]	[0.76,0.56]	[0.88,0.92]	[0.42,0.51]
O_3	[0.36,0.76]	[0.87,0.89]	[0.65,0.76]	[0.69,0.86]	[0.43,0.89]
O_4	[0.25,0.13]	[0.44,0.32]	[0.52,0.13]	[0.66,0.76]	[0.55,0.66]
O_5	[0.53,0.68]	[0.39,0.71]	[0.66,0.41]	[0.49,0.38]	[0.33,0.72]

It is clearly evident from Tables 1 and 2 that our proposed the public opinion has the highest recognition degree to the target, and it is necessary to give Q_i a higher weight in order to obtain a high recognition of the target. However, as can be seen from Table 2, for each expected monitoring index ε_3, the degree of satisfaction is different, and the satisfaction degree of the certainty criterion S_2 is the worst, which is because the recognition of the target is very vague. As a result, the overall degree of certainty is low, so there is a great possibility of deviation in the fusion of single criteria, because the selection of single criteria is too one-sided.

Table 2. Criteria measure

	ε_1	ε_2	ε_3	ε_4	ε_5
S_1	0.3356	0.2432	0.3221	0.9213	0.5643
S_2	0.1211	0.2543	0.3132	0.8765	0.3456
S_3	0.9232	0.9212	0.3452	0.6789	0.5675
S_4	0.9121	0.3211	0.5764	0.9123	0.3456
S_5	0.3211	0.3212	0.5686	0.8654	0.5673

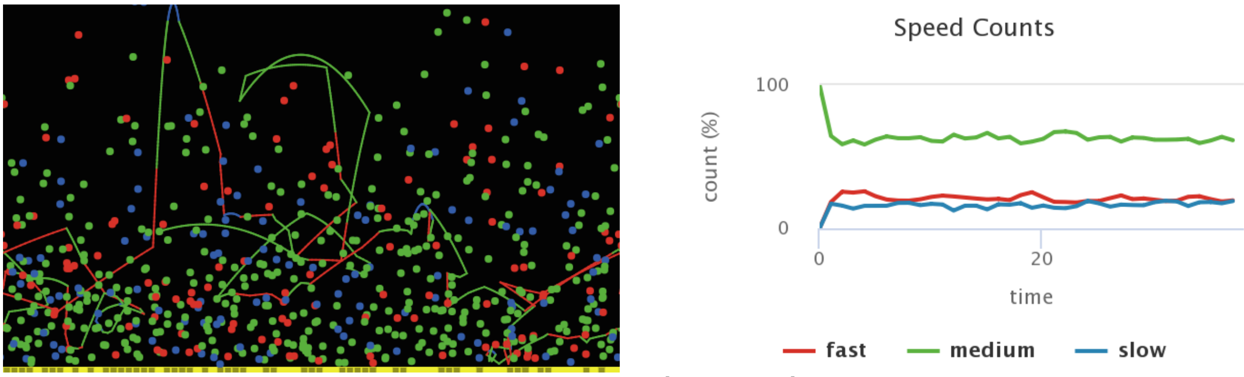

Figure 3. Fusion process and running speed

Several experiments were conducted to change the route of public opinion transmission and monitoring. As shown in Figure 4, different criteria have different degrees of advantages. The fusion results of single criteria are greatly affected by the evaluation indicators and monitoring status, showing large fluctuations. The fusion results under multi-criteria are more stable, and the stability of fusion results based on multi-criteria decision-making is the best.

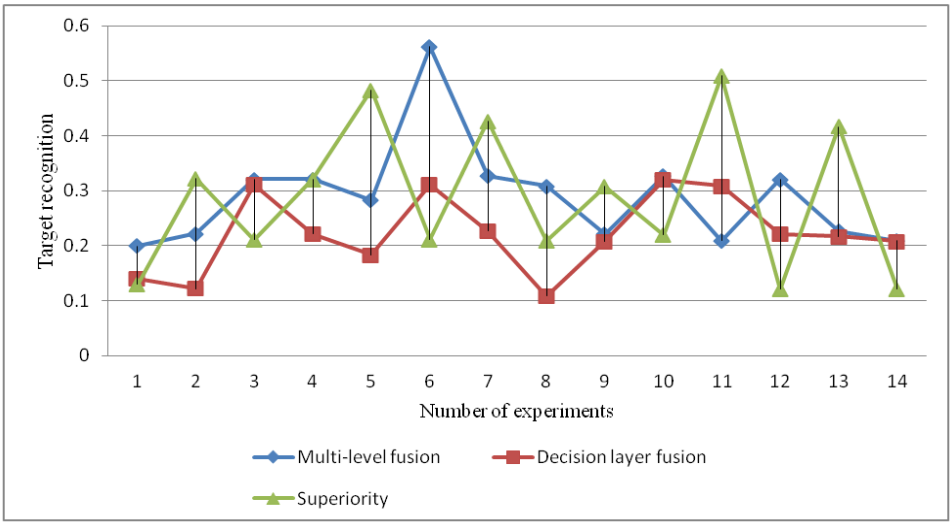

Figure 4. Multiple test results

In order to demonstrate the fusion performance of the proposed method, the multi-objective optimization is compared with the traditional multi-criteria decision-making method, and the target recognition accuracy under different criteria is observed. The recognition error rate of 1,000 trials is the observation index. As shown in Figure 5, our proposed simulation results show that with the increase in the number of evaluation indicators, the error rate of multi-source public opinion target recognition fusion is reduced, and the proposed method has the lowest error rate and the highest robustness.

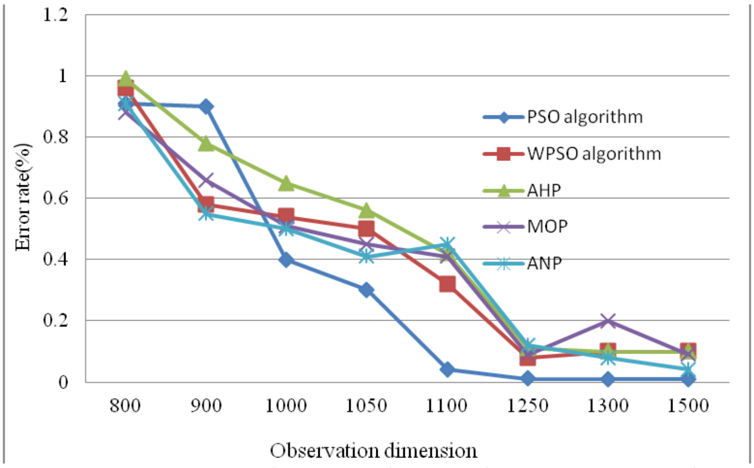

Figure 5. Schematic diagram of anti-risk performance of multi-criteria decision fusion

5. Conclusions

The fusion method of public opinion information is essentially a category of emergency decision theory and method. The main research area of this paper is to study how to effectively deal with multi-source heterogeneous information related to public opinion to support the formulation of emergency decision-making tasks. In practice, in the face of a sudden outbreak of large-scale public opinion transmission and in the case of coping with relatively scarce knowledge and extremely urgent response time, the fusion of existing multi-source information is an effective way to improve the decision-making level of public opinion response. From the three aspects of decision-making tasks, decision-making rules, and expressions of preference information, the paper analyses the key factors of the decision-making process driven by big data, the hierarchical relationship between decision-making tasks, and the formation mechanism of uncertain decision-making information particles. Starting from the semantic fusion of heterogeneous big data, this paper explores the intrinsic relationship between "granular computing" and "ontology", and it studies the global semantic consistency and semantic relevance description framework based on multi-granularity pattern discovery fusion. It also analyses the heterogeneous big data multi-granularity semantics. Based on the data-level fusion ontology of granular computing and ontology-related data for decision-making data-level fusion, a heterogeneous data element semantic fusion method suitable for different decision-making applications is proposed. The specific research contents include the formal description method of big data multi-granular ontology, the hierarchical design of big data multi-granular ontology, and the big data multi-granularity semantic fusion model. The simulation demonstration of distributed and multi-agent information source fusion lacks an in-depth analysis of the architecture of its implementation, and further research on the system design in the fusion process is needed.

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References

1. S. Jesse, M. Chi, A. Belianinov, C. Beekman, S. V. Kalinin, A. Y. Borisevich, et al., “Big Data Analytics for Scanning Transmission Electron Microscopy Ptychography,” *Scientific Reports*, Vol. 26348, No. 1, pp. 1-10, January 2016
2. F. Zhang, H. F. Xue, and D. S. Xu, “Big Data Cleaning Algorithms in Cloud Computing,” *International Journal of Online Engineering*, Vol. 9, No. 3, pp. 77-81, March 2013
3. X. L. Dong, E. Gabrilovich, G. Heitz, W. Horn, K. Murphy, S. Sun, et al., “From Data Fusion to Knowledge Fusion,” *The VLDB Endowment*, Vol. 7, No. 1, pp. 881-892, January 2014
4. P. Mihir, D. Towsley, D. Englund, and S. Guha, “Percolation Thresholds for Photonic Quantum Computing,” *Nature Communications*, Vol. 6, No. 3, pp. 6-10, March 2019
5. N. Anstead and B. O'Loughlin, “Social Media Analysis and Public Opinion: The 2010 UK General Election,” *Journal of Computer-Mediated Communication*, Vol. 20, No. 2, pp. 204-220, March 2015
6. F. Herrera, E. Herrera-Viedma, and L. Martinez, “A Fusion Approach for Managing Multi-Granularity Linguistic Term Sets in Decision Making,” *Fuzzy Sets and Systems*, Vol. 114, No. 1, pp. 43-588, January 2000
7. J. Bolstad, “Dynamics of European Integration: Public Opinion in the Core and Periphery,” *European Union Politics*, Vol. 16, No. 1, pp. 23-44, January 2015
8. F. Zhang, H. F. Xue, and J. -C. Zhang, “Multi-Source Big Data Dynamic Compressive Sensing and Optimization Method for

Water Resources based on IoT," *Sustainable Computing*: *Informatics and Systems*, Vol. 20, No. 6, pp. 210-219, July 2018
9. K. H. Liu, Z. G. Chen, J. Wu, Y. Tan, L. Wang, Y. Yan, et al., "Big Medical Data Decision-Making Intelligent System Exploiting Fuzzy Inference Logic for Prostate Cancer in Developing Countries," *IEEE ACCESS*, Vol. 7, No. 1, pp. 2348-2363, January 2019
10. Z. Wang, J. Marko, L. Shi, J. Lee, Y. Iwasa, and S. Boccaletti, "Exploiting a Cognitive Bias Promotes Cooperation in Social Dilemma Experiments," *Nature Communications*, Vol. 9, No. 1, pp. 2954- 2959, January 2018
11. J. D. Clinton and J. A. Grissom, "Public Information, Public Learning, and Public Opinion: Democratic Accountability in Education Policy," *Journal of Public Policy*, Vol. 35, No. 3, pp. 355-385, March 2015
12. C. Sandra and A. Nielsen, "Shaping of Infant B Cell Receptor Repertoires by Environmental Factors and Infectious Disease," *Science Translational Medicine*, Vol. 11, No. 8, pp. 142-154, August 2019
13. F. Herrera and L. Martinez, "A Model based on Linguistic 2-Tuples for Dealing with Multigranular Hierarchical Linguistic Contexts in Multi-Expert Decision-Making," *IEEE Transactions on Systems*, *Man*, *and Cybernetics*, Vol. 31, No. 2, pp. 227-234, March 2001
14. B. V. Dasarathy, "A Special Issue on Agent-based Information Fusion," *Information Fusion*, Vol. 11, No. 3, pp. 215-219, 2010
15. R. Kontchakov, M. Rodr ǵuez-Muro, and M. Zakharyaschev, "Ontology-based Data Access with Databases: A Short Course," *Lecture Notes in Computer Science*, Vol. 2, No. 2, pp. 194-229, March 2013
16. S. Jiang, Y. Zheng, V. Babovic, Y. Tian, and F. Han, "A Computer Vision-based Approach to Fusing Spatiotemporal Data for Hydrological Modeling," *Journal of Hydrology*, Vol. 567, No. 1, pp. 25-40, January 2018
17. V. G. Donkal and K. Gyanendra, "A Multimodal Fusion based Framework to Reinforce IDS for Securing Big Data Environment using Spark," *Journal of Information Security and Applications*, Vol. 43, No. 1, pp. 1-12, January 2018
18. Z. L. Huang and X. W. Pu, "Modeling Real-Time Human Mobility based on Mobile Phone and Transportation Data Fusion," *Transportation Research Part C-Emerging Technologies*, Vol. 96, No. 11, pp. 251-269, December 2018
19. P. Gong, Y. Cao, B. Cai, and K. Li, "Multi-Information Location Data Fusion System of Railway Signal based on Cloud Computing," *Future Generation Computer Systems-The International Journal of eScience*, Vol. 88, No. 11, pp. 594-598, December 2018
20. T. B. Isabel, A. D. Javier, and I. Lan, "Big Data for Transportation and Mobility: Recent Advances, Trends and Challenges," *LET Intelligent Transport Systems*, Vol. 12, No. 8, pp. 742-755, September 2018
21. Y. Yang, X. H. Zheng, and Z. Wen, "Privacy-Preserving Fusion of IoT and Big Data for e-Health," *Future Generation Computer Systems-The International Journal of eScience*, Vol. 86, No. 9, pp. 1437-1455, September 2018
22. G. C. Sun and V. G. Steven, "Big Data and Internet of Things-Fusion for Different Services and its Impacts," *Future Generation Computer Systems-The International Journal of eScience*, Vol. 86, No. 9, pp. 1368-1370, September 2018
23. Y. Wang and P. W. Xin, "Position Synchronization for Track Geometry Inspection Data via Big-Data Fusion and Incremental Learning," *Transportation Research Part C-Emerging Technologies*, Vol. 93, No. 8, pp. 544-565, September 2018
24. F. Alamdar, M. alantari, and A. Rajabifard, "Towards Multi-Agency Sensor Information Integration for Disaster Management," *Computers, Environment and Urban Systems*, Vol. 56, No. 1, pp. 68-85, January 2016

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