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Cloud Bayesian Network Based Data Processing in Battlefield Sensor Networks

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***Abstract*—The application of battlefield sensor networks needs a simple but efficient method to fuse the data and information from multi-sources and generate a cognitive result for commanders. However, it is still a challenge to convert the sensor data into fuzzy concepts so that people can understand easily. In this paper we present a new data processing model named Cloud Bayesian Network (CBN), which is inspired by fuzzy Bayesian Network but has more advantages. Based on CBN, we illustrate some important techniques in this algorithm and apply the model to a case study for data processing in battlefield sensor networks. Finally, we evaluate the performance of proposed model by comparing it with other models and verify its effectiveness.**

Keywords—cloud model; bayesian network; data processing; battlefield sensor networks; data fuzzification; data fusion

I. INTRODUCTION

Advances in sensor networks have led to the blossom of battlefield information and data. Common goals in battlefield sensor networks application is to construct the situation with the help of observations and support the decision of commanders. However, the assistance by data from sensor networks is challenging. On one hand, battlefield situation is constructed by merging the information from distributed sensor networks, it's difficult to manage information in a simple but high-quality manner. On the other hand, the purpose of constructing situation is to provide commanders with them, thus, the generated information by data fusion should be easy to understand and cognitive. Nowadays, there is a growing need for such versatile architectures and frameworks capable of fusing data from sensor networks [1]. At the core of nonlinear techniques is Bayesian Network (BN), which models the relationships of data nodes based on probability reasoning. BN has been widely used in data processing because of its simplicity but complete mathematical basis and strong ability to represent knowledge [2].

Despite the strong reasoning and data fusion ability of BN, the data and information from sensor networks still cannot construct a cognitive situation picture. Because the concepts in human mind are always fuzzy, like fast, slow, while the data from sensor networks are accurate and consistent. It is difficult for human to understand the situation with accurate data in huge volume. A data fuzzification method should be included into BN to solve this problem. A traditional one is using fuzzy set theory to make fuzzy classification of data and obtain the membership of them [3]. However, owing to the accuracy of membership function values, the fuzziness that whether a continuous observation belongs to a fuzzy set is strangled, which leads to an incomplete fuzzy evaluation and is inconsistent with the essence of fuzzy set. Therefore, it is inappropriate to use the accurate membership functions to represent fuzziness [4].

In this paper, we introduce a new fuzzification model named membership cloud model to alternate the membership functions and discretize data from sensor networks. One of the novelty of cloud model is its simplicity. In contrast with membership function, the cloud model uses a random number rather than an accurate number to represent the membership. Besides, cloud model doesn't require to establish the membership function, but builds the fuzzification model by numerical characteristics, which is simpler and more efficient. Then, the cloud model is combined with BN to process the data. As a reasoning model to fuse information, BN is employed after data fuzzification and designed to construct the situation assessment result for commanders. BN provides great ability to conduct probability reasoning. It can transfer the fuzzy information of data from the bottom to the top, which ensures the result to remain fuzziness and all of the information of data. Embedding cloud model into BN, the proposed algorithm not only employs the advantage of cloud model in knowledge representation, but also combines BN's inferring capability.

This paper proposed a data processing architecture for distributed sensor networks in battlefield. The model can obtain the multi-source data provided by sensor networks and perform the data fuzzification by cloud model. BN is then designed to fuse the information by reasoning, which helps to construct the situation. The remainder of this paper is organized as follows: Section 2 introduces the new data fuzzification method, cloud model. Section 3 describes how to fuse the data from sensor networks. Section 4 presents the case study and Section 5 gives the conclusions.

II. DATA FUZZIFICATION METHOD

After obtaining the observations from battlefield sensor networks, it is proposed to conduct data fuzzification by cloud model. Cloud model develops from fuzzy set theory but solves the problems that fuzzy set theory doesn't. The membership function value in fuzzy set theory is an accurate number, which shows the correlation degree between the input and the fuzzy set. However, it is definite that using an accurate number to represent fuzziness is impossible and impractical. Therefore, to develop the fuzziness and randomness of membership function, cloud model is proposed [5].

Definition 1.

Suppose that U is a set of accurate values, named the universe of discourse, over which a qualitative concept or a fuzzy set $\tilde{A}$ is defined. Let each number x in U be a random instantiation of fuzzy set $\tilde{A}$ and $\mu_{\tilde{A}}(x)$ represents the membership of x belonging to $\tilde{A}$, which is a random number with a steady tendency, then the distribution of x over U is called a cloud and $drop(x, \mu_{\tilde{A}}(x))$ represents a cloud drop.

From the definition of cloud model, membership in universe of discourse is not a fixed number, but a probability distribution. And this accords with a large number of random phenomenon in human society and nature. Because most of the data are approximated by normal distribution [6], we choose normal cloud model to conduct data fuzzification.

Normal cloud model is the most widely used cloud model, it can use the three numerical characteristics to describe any fuzzy concept, which can be written as $C(Ex, En, He)$. Expectation Ex is the information center of a fuzzy concept, which represents the most typical value of the qualitative concept. Entropy En is the scope of fuzzy concept and shows its uncertainty. Hyperentropy He represents the randomness of membership of different random instantiation in a fuzzy set, it is also the uncertain degree of En. Figure 1 shows a normal cloud model with $Ex=0$, $En=6$, $He = 0.6$ and 1500 drops.

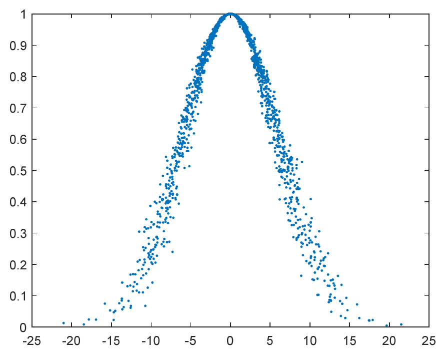

FIGURE I. NORMAL CLOUD MODEL

In cloud model, the transformation between sensor data and fuzzy concept is achieved by a generator of forward cloud. The construction of forward cloud generator is described as following [7].

Input: fuzzy concept $\tilde{A}$ and its numerical characteristics (Expectation Ex, Entropy En, Hyperentropy He), quantitative value x from sensor.

Output: certainty degree $\mu(x)$ of x.

1) Randomly generate a number En' subject to normal distribution with expectation En and standard deviation He.

2) Calculate certainty degree $\mu(x)=e^{-\frac{(x-Ex)^2}{2(En')^2}}$.

3) Output the cloud drop $drop(x, \mu(x))$.

If there are several fuzzy concepts, a set of clouds named cloud group need to be constructed with each one corresponding to a fuzzy concept. The definition of cloud group is as follows [8].

Definition 2.

Given a universe of discourse U, and $U_1, U_2, \cdots, U_k$ is a division of that, if the division satisfies the following three conditions, it can be called a cloud group. The three conditions are: (1) $\bigcup_{i=1}^{k} U_i = U$; (2) $\bigcap_{i=1}^{k} U_i = \varnothing$; (3) As for $\forall x_i \in U_i$ and $\forall x_j \in U_j$, if $i < j$, then $x_i < x_j$.

Based on the cloud group, we can design the corresponding cloud generators, and calculate certainty degree of an accurate sensor observation value belonging to different fuzzy concepts, which completes the discretization of sensor data.

III. BAYESIAN NETWORK BASED DATA FUSION MODEL

In this part we illustrate the data inference process of Bayesian Network. We use it as a data fusion model to construct the battlefield situation. As a directed acyclic graph, Bayesian Network (BN) has the ability to represent conditional and causal relation between nodes. Information can be transferred from the observation nodes to target nodes. And in fact, this process of information transmission is a way to fuse data. The information of data is fused in a form of probability reasoning. Thus, the target node contains the whole information of the observation data and it can be used to represent the situation constructed by sensor data. The essence of Bayesian reasoning is to calculate the posterior probability distribution under the condition of known observations, which is marked by $p(x | e)$.

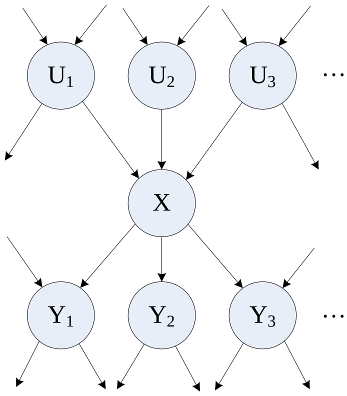

FIGURE II. REASONING PROCESS OF BN

Figure 2 shows the reasoning process of BN. Suppose that an unobserved node is X, its parent nodes collection is $U=\{U_1,U_2,\cdots,U_n\}$, child nodes collection is $Y=\{Y_1,Y_2,\cdots,Y_n\}$, e is the set of evidence nodes, and e_X^+ is the evidence nodes which connect with X through its parent nodes, e_X^- is the evidence nodes collection which connects with X through its child nodes. The posterior probability distribution of X can be represented by [9]:

$$p(x|e)=p(x|e_X^+,e_X^-)=\frac{p(e_X^+,e_X^-|x)p(x)}{p(e_X^+,e_X^-)}=$$
$$\frac{p(e_X^+|x)p(e_X^-|x)p(x)}{p(e_X^+,e_X^-)}=\frac{p(x|e_X^+)p(e_X^-|x)p(e_X^+)}{p(e_X^+,e_X^-)}=$$
$$\alpha\, p(x|e_X^+)p(e_X^-|x)=\alpha\pi(x)\lambda(x) \tag{1}$$

α is a normalization constant. $\pi(x)$ and $\lambda(x)$ are the information transferred by parent nodes and child nodes respectively.

Then, the information that updated by parent nodes collection marked with $\pi(x)$ is:

$$\pi(x)=\sum_{u_1,\cdots u_n} p(x|u_1,\cdots u_n)\prod_{i=1}^{n}\pi_x(u_i)\,. \tag{2}$$

The information that propagated from child nodes collection written as $\lambda(x)$ is:

$$\lambda(x)=\prod_{j=1}^{m}\lambda_{Y_j}(x)\,. \tag{3}$$

Synthesize the whole information that is transferred to X through its parent nodes collection and child nodes collection, the posterior probability of X under the condition of observed evidence is:

$$p(x|e)=\alpha\pi(x)\lambda(x)=$$
$$\alpha[\sum_{u_1,\cdots u_n} p(x|u_1,\cdots u_n)\prod_{i=1}^{n}\pi_x(u_i)][\prod_{j=1}^{m}\lambda_{Y_j}(x)] \tag{4}$$

Now we can calculate each node' posterior probability distribution.

IV. DESIGN OF DATA PROCESSING ARCHITECTURE

In this section, we combine the cloud model with Bayesian Network and propose a data processing model named Cloud Bayesian Network (CBN). The data processing model aims at fusing the data generated from distributed sensor networks in battlefield and providing the commander with the fusion result. The whole processing model consists of data acquisition, data fuzzification and data fusion. In the first stage, it is necessary to extract the relevant data from sensors and construct their relationship. Once the data that we are interested in are obtained, they can be conducted by fuzzification process. The final process is to fuse the information and data by BN, which can form a situation supported by sensor data. Now we will give a detailed illustration to several critical stages in the data processing architecture.

A. *Model of Sensor Networks in Battlefield*

Figure 3 shows the topology of distributed sensor networks in battlefield [10]. Let $\boldsymbol{s}=\{s_1,\cdots,s_n\}$ be a finite set of n sensors in battlefield. Sensors obtains different data, such as from environment, from radars and so on. The gathered data are then fused in fusion node. And the fusion result gives the decisions assisted by all of multi-source observations in set s.

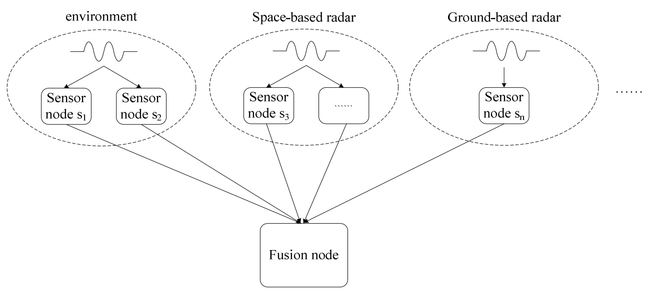

FIGURE III. MODEL OF DISTRIBUTED SENSOR NETWORKS IN BATTLEFIELD

B. *Extracting Data from Sensor Networks*

Data extracting is to find the data that we may use and determine their relations. Figure 4 shows the relationship of data extracted from sensor networks. From Figure 4 we can see that the data obtained from sensor networks are divided into three types: the sensor data representing battlefield environment, the sensor data relevant to deployment and the data indicating combat capability. Based on such relationship network we can turn it into a Bayesian Network and fuse the information from the bottom to the top. The top node is the fusion result and represents the battlefield situation.

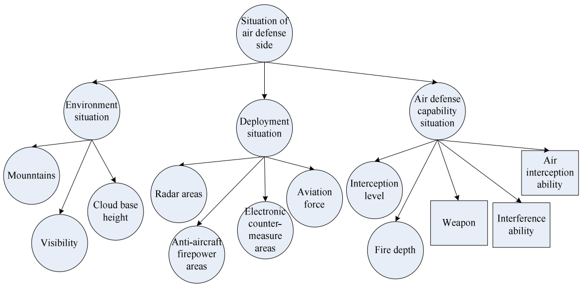

FIGURE IV. RELATIONSHIP OF DATA EXTRACTED FROM SENSOR NETWORKS.

C. *Designing Cloud Groups*

In Figure 4, the nodes marked by circle are continuous observations. The nodes in square are discrete observations, they can be input into BN and fused directly. The continuous observations have to be processed by fuzzification, which assisted by cloud model. Now we should construct the cloud group for continuous nodes in Figure 4. Suppose that the universe of discourse is divided based on the meaning of the data generated by sensors. We construct a cloud group for each node with three cloud models C_1、C_2、C_3, each of which corresponds to a fuzzy concept {many, medium, few}. Suppose the range of value of a node has an upper limit of $H_{\max}$ and a minimum of $H_{\min}$, then the universe of discourse is marked as $[H_{\min}, H_{\max}]$. We design C_1 and C_3 as half-down normal cloud and half-rise normal cloud respectively. Therefore, the divisions of universe of discourse are $[H_{\min}, \frac{H_{\max}+3H_{\min}}{4}]$, $[\frac{H_{\max}+3H_{\min}}{4}, \frac{H_{\min}+3H_{\max}}{4}]$ and $[\frac{H_{\min}+3H_{\max}}{4}, H_{\max}]$. The center of each division is the most typical value to represent its corresponding fuzzy concept, also named as its expectation. Besides, in a normal cloud, because the contribution of domain $[Ex-3En, Ex+3En]$ to the fuzzy concept reaches up to 99.74%, the entropy of a cloud is usually designed as one-sixth of width of each division. What's more, the hyperentropy of cloud is an order of magnitude smaller than the entropy, and it can be set as one-sixtieth of width of each division. In conclusion, the cloud group of a node is $C_1(H_{\min}, \frac{H_{\max}-H_{\min}}{12}, \frac{H_{\max}-H_{\min}}{120})$,

$C_1(\frac{H_{\max}+H_{\min}}{2}, \frac{H_{\max}-H_{\min}}{12}, \frac{H_{\max}-H_{\min}}{120})$ and

$C_1(H_{\max}, \frac{H_{\max}-H_{\min}}{12}, \frac{H_{\max}-H_{\min}}{120})$. After constructing cloud groups of all nodes, we can generate Figure 5 to represent them.

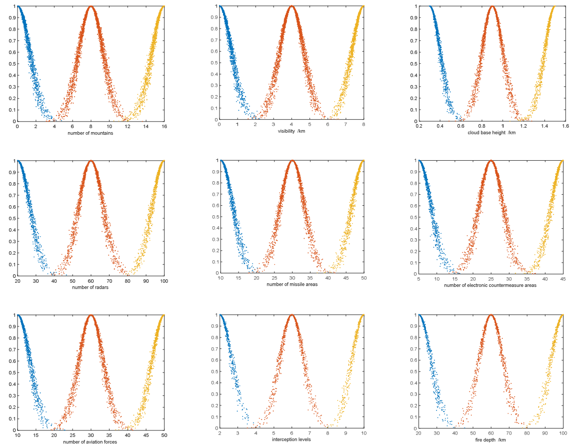

FIGURE V. CLOUD GROUPS OF CONTINUOUS NODES

D. *Constructing Cloud Generator*

The step following cloud group designing is to construct cloud generators, which are based on cloud groups. For simplicity, three states are designated for all continuous nodes. The numerical characteristics can be generated as $(Ex_1, Ex_2, Ex_3, En, He)$, based on which we can build the cloud generators (Table.1). Now we can convert the continuous observations into fuzzy concepts and calculate certainty degrees.

TABLE I. NUMERICAL CHARACTERISTICS OF CLOUD GENERATORS

Entity	Mountain	Visibility	Cloud base height
Numerical characteristics	(0, 8, 16, 4/3, 2/15)	(0, 4, 8, 2/3, 1/15)	(0.3, 0.9, 1.5, 0.1, 0.01)
Entity	Radar	Missile area	Electronic countermeasure area
Numerical characteristics	(20, 60, 100, 20/3, 2/3)	(10, 30, 50, 10/3, 1/3)	(5, 25, 45, 10/3, 1/3)
Entity	Aviation force	Interception level	Fire depth
Numerical characteristics	(10, 30, 50, 10/3, 1/3)	(2, 6, 10, 2/3, 1/15)	(20, 60, 100, 20/3, 2/3)

E. *Probability Conversion*

After conducting data fuzzification, we can obtain the certainty degrees of data belonging to fuzzy concepts. However, the certainty degrees can not be input directly into BN to fuse. They have to be converted into probabilities. We introduce a formula to transform the certainty degree into probability in Equation (5).

$$P(C_i) = \frac{\mu_i^{1/\alpha}}{\sum_{j=1}^{k} \mu_j^{1/\alpha}} \tag{5}$$

where C_i means the i th fuzzy concept, μ_i is the certainty degree of input belonging to C_i, α represents the consistency between probability and certainty degree, which is set as 1 in this paper. Based on Equation 5, we can get the visual probability of the continuous observations and input them into BN to finish data fusion.

V. Simulations and Comparisons

A. Case Study

In the case study, we present the application of proposed Cloud Bayesian Network model in battlefield data process. The proposed model can be used in the situation that contains information and data of battlefield sensor networks in huge volume.

To show how the algorithm works, it suffices to use several observations with continuous and discrete states, which are shown in Table.2.

Input all the continuous value into the corresponding cloud generator and calculate their certainty degrees. The certainty degrees are the symbol that how much the input belongs to the fuzzy concepts. We give the certainty degrees in Table. 3. After transforming the certainty degrees into probabilities by Equation 5, we can get the visual evidence shown in Table. 4.

TABLE II. OBSERVATIONS OF SITUATION IN BATTLEFIELD

Observations	Mountains	Visibility	Cloud base height	Radar areas	Missile areas	Electronic countermeasure areas
Air defense	4	6km	1.2km	40	20	20
Observations	Aviation force	Interception level	Fire depth	Weapon	Interference ability	Air interception ability
Air defense	40	5	40km	Conventional	Medium	Medium

TABLE III. CERTAINTY DEGREES

Entity	Mountains			visibility		
Fuzzy sets	little	medium	many	weak	medium	strong
Air defense side	0.0174	0.0402	4.453e-30	1.2372e-15	0.0146	0.0026
Entity	Cloud base height			Radar		
Fuzzy sets	low	medium	high	few	medium	many
Air defense side	6.032e-20	0.0149	0.087	0.0633	0.0024	4.447e-11
Entity	Missile area			Electronic countermeasure area		
Fuzzy sets	few	medium	many	few	medium	many
Air defense side	0.0092	0.0099	4.747e-14	4.186e-4	0.4218	1.881e-11
Entity	Aviation force			Interception level		
Fuzzy sets	few	medium	many	few	medium	many
Air defense side	1.771e-23	0.0198	0.0359	1.007e-4	0.396	2.425e-11
Entity	Fire depth					
Fuzzy sets	short	medium	long			
Air defense side	0.0200	0.0104	4.780e-16			

TABLE IV. VISUAL PROBABILITIES

Entity	Mountains			visibility		
Fuzzy sets	little	medium	many	weak	medium	strong
Air defense side	0.303	0.697	0	0	0.849	0.151
Entity	Cloud base height			Radar		
Fuzzy sets	low	medium	high	few	medium	many
Air defense side	0	0.146	0.854	0.963	0.037	0
Entity	Missile area			Electronic countermeasure area		
Fuzzy sets	few	medium	many	few	medium	many
Air defense side	0.482	0.518	0	0	1	0
Entity	Aviation force			Interception level		
Fuzzy sets	few	medium	many	few	medium	many
Air defense side	0	0.355	0.645	0	1	0
Entity	Fire depth					
Fuzzy sets	short	medium	long			
Air defense side	0.658	0.342	0			

Table.4 shows the visual probabilities of continuous nodes, we can input all the evidence into BN and generate the data fusion result, as is shown in Figure 6. This simulation is supported by GeNIe2.0.

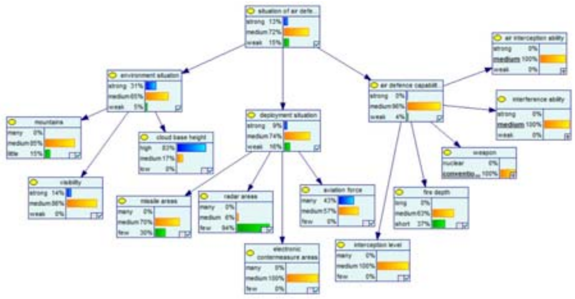

FIGURE VI. ASSESSING RESULT OF AIR DEFENSE SIDE

In Figure 6, the top node represents the battlefield situation. There are three attributes in the top node. Each of them shows the situation that air defense side is in. As is seen, air defense side is most likely in the attribute of medium situation, whose probability is 72%. The probability of situation low is larger than the one of situation strong. And it means that the air defense side has more entities in low situation than in strong situation. Based on the above data fusion result, the commander can be assisted to make a decision, that is, to make up for the weakness.

B. Comparisons with Fuzzy Bayesian Network

The Cloud Bayesian Network (CBN) model is inspired and developed based on Fuzzy Bayesian Network (FBN). Therefore, the comparison between these two models can show us the differences. Using FBN to complete data fusion needs designing the membership functions and calculating the membership values. Then we input them into BN to complete the data fusion. Figure 7 shows the data fusion result by fuzzy Bayesian Network and Figure 8 is the comparison between them. The results fused by two models are generally the same. In CBN model the situation in weak attribute is more likely than in the strong one. However, in FBN model the situation has the same probability to be in strong and weak attribute. Comparing the results to observations in Table 2, which shows that there are more observations in weak situation, we can conclude that the CBN model represents the reality better.

The reason why CBN model performed well on this problem is that it can represent the fuzziness of data well. The data obtained from battlefield sensor networks are mostly accurate. The CBN can transform the data into fuzzy concepts by calculating their certainty degrees. And the most important is the certainty degree is not a constant value like the membership but a random number obeying a certain distribution. Therefore, the CBN model can express fuzziness of sensor data better. And in this extent, it can be verified that CBN is more effective than FBN model.

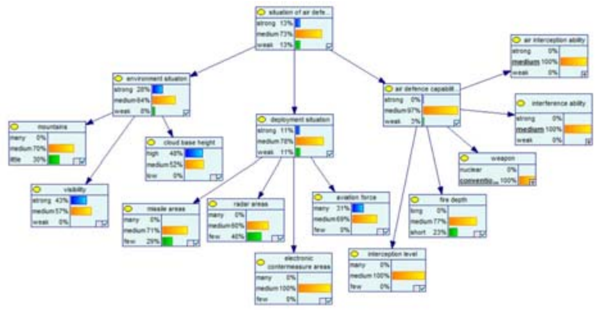

FIGURE VII. DATA FUSION BY FUZZY BN

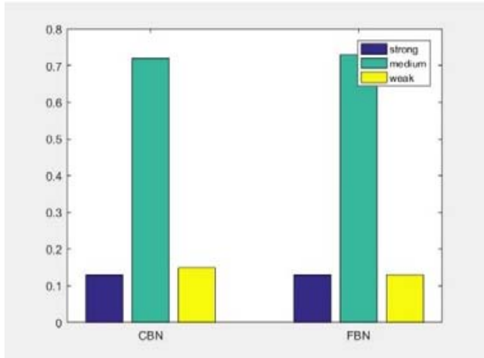

FIGURE VIII. COMPARISON BETWEEN TWO MODELS

VI. CONCLUSIONS

A large number of accurate observations and information existing in battlefield sensor networks escalate the challenge in data fuzzification and data fusion. Traditional data fuzzification method uses fuzzy set theory, which is on the basis of designing membership functions. However, it is obviously inappropriate to use accurate membership value to represent fuzziness. Thus, we propose cloud model to conduct data fuzzification and replace the membership constant value with membership random value. Based on cloud model, we design the cloud group and cloud generator, which calculates the certainty degree. Then we employ Bayesian Network to fuse the data and generate the fusion result which contains the total information of sensor data. Finally, we evaluate the performance of CBN model by comparing it with fuzzy Bayesian Network. In the same situation, the data fusion result conducted by CBN is more suitable to the reality.

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