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A Data-Driven Dynamic Data Fusion Method Based on Visibility Graph and Evidence Theory

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ABSTRACT Dynamic data fusion on time series plays an important role in real applications like target identification. The existing credibility decay models (CDM) may be too subjective for parameters setting and do not make full use of time series information. To address these issues, a new method based on visibility graph and Dempster–Shafer evidence theory are presented in this paper. With the assist of a visibility graph averaging aggregation operator (VGA), a structure revision basic belief assignment (SRBBA) which contains past time information can be obtained. Through this way, the judgment to past data credibility is data-driven without the interference of subjective factors and more reasonable because more time information is considered. Besides, a series of identification applications, including numerical simulation, sensitivity analysis, and practical Iris class identifying are executed to illustrate the efficiency of the proposed method. These applications can show that the proposed method has promising aspects in time series data fusion.

INDEX TERMS Time series, data fusion, visibility graph, Dempster-Shafer evidence theory, target recognition.

I. INTRODUCTION

Dempster-Shafer evidence theory (D-S theory) [1], [2] is efficient in dealing with uncertainty problem in data fusion process because of the combination rule of basic belief assignment (BBA) or belief functions [3]–[5]. Such an operator in D-S theory can extract useful information from fuzzy BBAs [6]–[8]. Nowadays, the D-S theory has been widely used to handle uncertainty in target identification problems [9]–[13].

Normally, the data fusion problem in D-S theory can be classified into the static [14], [15] and dynamical fusion two categories [16]. In a static fusion process, all of data is combined simultaneously without considering time [17]. Many evidential fault diagnosis [18]–[20] and decision making methods [21] are based on this kind of static fusion frame. These researches obviously ignore the factor of time in conflict management process [22], [23]. Smets details the difference between two categories [16] and points out that the dynamic data fusion can results in two situations, one is called the dynamical belief revision and the other is belief updating. Based on the work about dynamical belief revision in [16], Song *et al.* [24] defines a credibility decay model (CDM) which considers the influence of time to some extent.

However, existing dynamic belief revision methods such as CDM, cannot fully use the information conserved in time series because CDM overly relies on the newest evidence. There is no appropriate way in CDM to build the relationship of the time interval and past information's credibility. When a time interval is too long, the credibility unreasonably becomes too low, which makes the fusion result overly relies on the latest data. Recently, an improved method is proposed and tries to use the ordered weighted averaging aggregation (OWA) operator to eliminate the effect of inappropriate time intervals [25]. But it may be too subjective because of parameters setting in that improved OWA method. The OWA method also ignores most past information which is only seen as a series of abstract time nodes. Besides, to cater to the Markovian requirement, features on time series are neglect to some extent in both above methods. Past researches on time series [26]–[28] inspire that time series data fusion means not only the most recent data are more reliable, but also all past time information should be well-considered [29], [30]. In this paper, time series data fusion problem is considered from quantitative and structural two aspects. The proposed method also tries to

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overcome the shortages in the CDM and achieve the data-driven goal.

Specifically, in the proposed method, D-S theory is used to make data fusion with the assist of a time series aggregation operator, the visibility graph averaging aggregation (VGA) operator [31], [32]. VGA is a kind of time series analysis technique [33], [34] and it can aggregate time series values in a graph view based on the visibility algorithm [35], which can convert a time series into a graph or network. The final aggregated result from VGA by means of the influence of nodes in a graph through taking the degree distribution into consideration. What should be emphasized is that in [35] and [31], Lacasa el al. and Chen et al. elaborately explained that the visibility algorithm and the VGA can well conserve time series information, respectively, especially in the structure or geometry aspect.

In the proposed method, VGA operator is first used to conserve structure information for past time series and generate a kind of unique BBA which well conserves past time information. Such BBAs are named the structure revision basic belief assignment (SRBBA) in this paper. Then by measuring the difference between the newest BBA and the SRBBA, more reasonable credibility for old data and better fusion result can be obtained. Finally, decisions may be further supported or revised with the change of time, which is totally different from traditional a single decision making [36].

The paper is arranged as follows. Section II introduces some preliminaries about D-S theory, CDM, the visibility graph theory. Section III presents the proposed data fusion method. Following that, applications about target recognition in Section IV illustrate the performance of the proposed method. Finally, a brief summary is given in Section V.

II. PRELIMINARIES

This section introduces some preliminary works including D-S theory, CDM, and the visibility theory.

A. D-S THEORY

The Dempster-Shafer evidence theory is widely used in handling uncertainty problem like risk management [37]–[40] and uncertainty modeling [41], [42] since it is proposed. This theory first supposes that the frame of discernment (FOD) as a finite nonempty set Θ with mutually exclusive and exhaustive hypotheses [43]. The power set of Θ is 2^{Θ}, containing all subsets of Θ.

Let $\Theta = \{H_1, H_2, \cdots, H_n\}$ be a frame of discernment. Assume a proposition A $\in 2^{\Theta}$. The basic belief assignment (BBA) of A, denoted by m(A), is a belief function defined as

$$m(A) \rightarrow [0, 1] \tag{1}$$

and satisfies the following conditions:

$$m(\emptyset) = 0 \quad \sum_{A\subseteq\Theta} m(A) = 1 \tag{2}$$

$A = \Theta$ and $m(A) = 1$ means that there is no knowledge about the frame of discernment, and such a situation is called the vacuous belief function (VBF).

D-S theory is efficient to deal with uncertainty because BBAs from different sources can be combined together to express their mutual belief over the FOD in terms of belief constraints [44]–[46]. Let m_1 and m_2 be two BBAs on Θ, and assume B, C are the subset of Θ. The Dempster combination rule for the proposition A in these two BBAs, denoted by $(m_1 \oplus m_2)(A)$, is defined as:

$$(m_1 \oplus m_2)(A) = \begin{cases} 0, & A = \emptyset \\ \dfrac{\sum_{B\cap C=A} m_1(B)m_2(C)}{1 - \sum_{B\cap C=\emptyset} m_1(B)m_2(C)}, & A \neq \emptyset \end{cases} \tag{3}$$

Data fusion happens in constant combinations [47], [48]. Note that conflict management [49], [50] is important during continuous combination [51]–[53]. One useful way to reduce conflict is that modify the belief function by reliability or credibility discount before combination. Let m be the BBA on the frame of discernment Θ with a reliability of α, then a BBA could be discounted as:

$$m^{\alpha}(A) = \begin{cases} \alpha m(A), & A \neq \Theta \\ 1 - \alpha + \alpha m(A), & A = \Theta \end{cases} \tag{4}$$

BBA can be transformed to a pignistic probability [54] to make decisions. The map from BBA to a kind of probability function is called the pignistic transformation. Assume the frame of discernment is $\Theta = \{A_1, A_2, \ldots, A_n\}$, the pignistic probability function is defined as follows [55]:

$$BetP(A) = \sum_{\mathcal{H}\subseteq\Theta} \frac{|A \cap \mathcal{H}|}{|\mathcal{H}|} \frac{m(\mathcal{H})}{1 - m(\emptyset)}, \quad \forall A \subseteq \Theta \tag{5}$$

where $m(\emptyset) \neq 1$ and $|A|$ is the cardinality of set A.

To measure the difference between two BBAs, Jousselme *et al.* [56] proposed a measure of performance for the distance between two belief functions. Let m_1 and m_2 be two BBAs on the same FOD Θ. The distance between m_1 and m_2 is defined as:

$$d_{BBA}(m_1, m_2) = \sqrt{\frac{1}{2}(\vec{m}_1 - \vec{m}_2)^T \underline{\underline{D}} (\vec{m}_1 - \vec{m}_2)} \tag{6}$$

where $\underline{\underline{D}}$ is an $2^N \times 2^N$ matrix whose elements are

$$\underline{\underline{D}}(A, B) = \frac{|A \cap B|}{|A \cup B|}(A, B \in \Theta).$$

Note that $\frac{1}{2}$ is needed to normalize and to guarantee that $0 \leq d_{BBA}(m_1, m_2) \leq 1$.

B. THE CREDIBILITY DECAY MODEL

The whole data fusion process is static or dynamic [57]. The dynamic one leads to an update or a revision of the belief function [16]. Song *et al.* [24] further defined a model for dynamic belief revision. Assume evidences $e_1, e_2, \ldots, e_n$ are collected at n sequent time nodes $t_1, t_2, \ldots, t_n$. On the FOD, the corresponding BBAs are $m_1, m_2, \ldots, m_n$.

Smets [16] states that the BBA computed at a given time by the combination rule should be sufficient for future combinations, which means past BBAs are fully summarized by present fusion BBA. So the Markovian requirement is needed. Let $f_n(m_1, m_2, \ldots, m_n)$ be the final result of n evidences dynamic combination. f_n is qualified as Markovian (see [16], [24]) iff there is a function g can be defined as follows:

$$f_n(m_1, m_2, \ldots, m_n) = g(g(\ldots g(g(m_1, m_2), m_3), \ldots), m_n) \tag{7}$$

Markovian requirement improves the computational efficiency of BBAs' combinations for there is no need to compute repeatedly.

With the increase of time, the influence of past belief functions should decrease. So there is a credibility, denoted by α, used to discount past BBA every time. Let $\alpha_{i-1} = \alpha(dt) = \alpha(t_i - t_{i-1})$, for $i = 2, 3, \ldots, n$. Function g can combine two BBAs being defined as [24]:

$$f_n(m_1, m_2, \ldots, m_n) = g(g(\ldots g(m_1^{\alpha_1}, m_2)^{\alpha_2}, \ldots)^{\alpha_{n-1}}, m_n) \tag{8}$$

Let m_j be a BPA on the FOD collected at time t_j, the dynamic credibility α at time node $t_i(t_i > t_j)$ is defined as [24]:

$$\alpha_{i,j} = e^{-\lambda(t_i - t_j)} \tag{9}$$

According to past researches [16], [24], let $\lambda = 0.15$.

C. THE VISIBILITY GRAPH

The visibility graph method was first proposed to convert a time series into a graph [35]. Furthermore, the structure of the time series is conserved in the graph topology: periodic series convert into regular graphs, random series into random graphs, and fractal series into scale-free graphs [35].

In the visibility graph, time series values are often plotted as vertical bars. According to the visibility criteria [35], two values (t_a, y_a) and (t_b, y_b) have a visibility if there is a value (t_c, y_c) placed between them fulfills:

$$y_c < y_b + (y_a - y_b)\frac{t_b - t_c}{t_b - t_a} \tag{10}$$

The associated graph (FIGURE 1) extracted from a time series has the following properties:

1) **Connected**: every node can be seen by its nearest neighbors (left and right) at least.
2) **Undirected**: the algorithm defines no direction for the links.
3) **Invariant under affine transformations of the series data**: the visibility criterion is invariant under rescaling of both horizontal and vertical axes, and under horizontal and vertical translations.

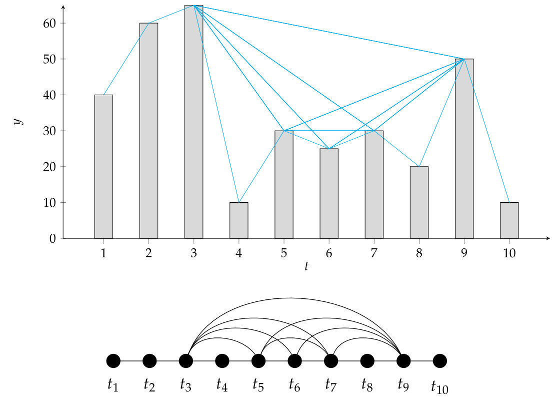


FIGURE 1. The vertical bars represent a group of time series data values. According to the visibility algorithm, if a bar can be seen from the top of considered one, two bars will be linked, and the corresponding vertices will be linked in the associated graph directly.

D. THE VGA OPERATOR

The visibility graph averaging aggregation operator [31] is first proposed based on visibility algorithm as a way to aggregate a series of data with the consideration the influence of time. The weights in the aggregation is obtained according to the importance of the data in the visibility graph as follows:

$$w_i = \frac{d_i}{\sum_{i=1}^{n} d_i} \tag{11}$$

where $w_i \in [0, 1]$, $\sum_i^n w_i = 1$ and d_i is the node degree in the graph which is converted from a time series.

The main calculating process of VGA is detailed as follows:

1) Convert time series data to the related graph by visibility algorithm.
2) Calculate the weights which represents the importance of data at different time node.
3) Aggregate the final result as follows:

$$F_{VGA}(a_1, a_2, \ldots, a_n) = w_1 a_1 + w_2 a_2 + \cdots + w_n a_n \tag{12}$$

where a_i is the ith value in the time series, and w_i is the weight of value ith.

It is evident that in the visibility graph, the degrees of the first and last nodes both equal to 1 and they cannot see each other without linking to nodes between them when the total nodes number is larger than 2.

III. THE PROPOSED METHOD

A. METHOD

In this section, a new time series data fusion method called structure revision credibility decay model (SRCDM) and based on visibility graph is proposed. The model considers the dynamic belief revision problem from quantitative fusion and structure revision two aspects by using D-S combination rule and VGA operator, respectively. The SRCDM method is detailed as follows and shown in FIGURE 2.

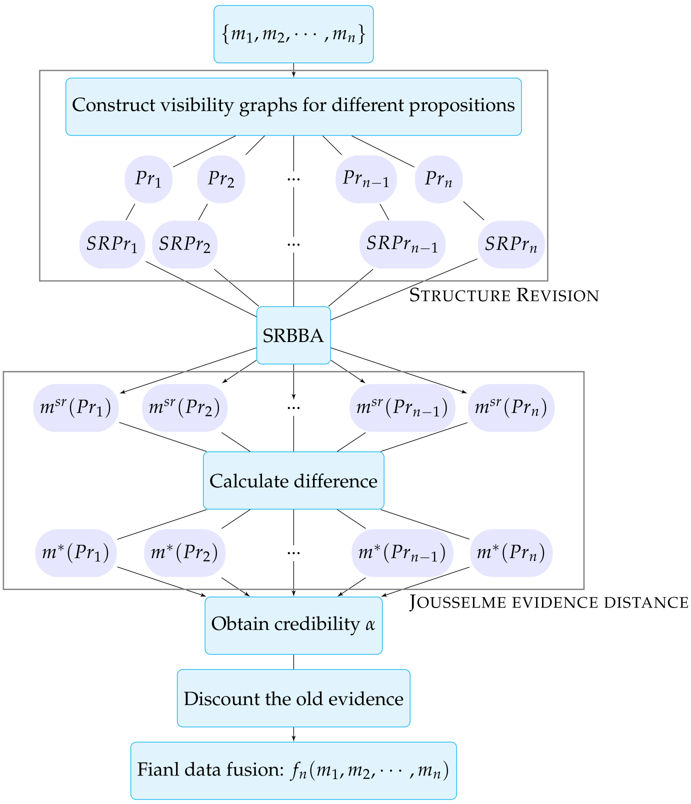


FIGURE 2. **The whole process for the proposed SRCDM method.**

Based on the existing FOD $\Theta = \{H_1, H_2, \cdots, H_m\}$, with the continuous update of the time series $t_1, t_2, \cdots, t_n$, there is a group of BBAs $m_1, m_2, \cdots, m_n$ on the Θ.

Under the FOD, CDM [24] pays too much attention to the time interval in the whole belief function updating process. OWA model [25] only considers the relation, more exactly, position of the newest evidence. Since both of them discard most past time information, the proposed method intends to consider time series values are used from two aspect.

First, from a the structure view, the basic belief assignment on the discernment frame changes with the information source at every time node. To capture the relationship between high and low values, and then help us make decisions on the quality or reliability to the next coming evidence, at time node n the aggregated structure revision proposition (SRPr) of a proposition $A \in 2^{\Theta}$ is defined as follows.

$$\begin{aligned} SRPr(A) &= F_{VGA}\left(m(a_1), m(a_2), \ldots, (a_n)\right) \\ &= w_1 m(a_1) + w_2 m(a_2) + \cdots + w_n m(a_n) \end{aligned} \tag{13}$$

where $a_1, a_2, \cdots, a_n$ is the same proposition A on different time nodes $t_1, t_2, \cdots, t_n$. When the visibility graph is constructed by only two BBAs, the VGA operator becomes the simple average and the structure revision propositions then can be calculated by calculating the mean values. Note that there is no need to take the VBF into consideration.

At time node n, A is a proposition belonging to proposition subsets $A_1, A_2, \cdots, A_{2^m-1}$ (except $\emptyset$) on FOD Θ. The structure revision basic belief assignment (SRBBA) can be obtained by normalizing the aggregated structure revision proposition on all propositions. Let $m^{sr}(A)$ denotes the SRBBA, then we can define it as follows.

$$m^{sr}(A) = \frac{SRPr(A)}{\sum_{i=1}^{2^m-1} SRPr(Pr_i)}, \quad Pr \in 2^{\Theta} \tag{14}$$

Past researches show that the visibility algorithm can conserve some properties about structure information of time series [31], [35] . Besides, VGA only uses the natural property of the node degree in the constructed graph. So SRBBA is believed containing some time information which should not be ignored.

Second, from the quantitative fusion view, the combination rule of D-S theory provides a useful way to express the mutual belief of different BBAs. However, this fusion operator mostly focuses on quantitative analysis without including past information. SRBBA is proposed in this paper distributing importance to all evidence bodies by visibility criteria in visibility algorithm and it can help quantitative analysis by measuring the reliability of past fusion result at a new time node.

At time node n, assume the past fusion BBA is m^*, and SRBBA is m^{sr}. The credibility of old fusion BBA, which is

TABLE 1. Data from sensors.

Time	m(A)	m(B)	m(C)	m(AB)	m(AC)	m(BC)	m(Θ)
t_1 =1s	0.3	0	0	0.5	0	0.2	0
t_2 =3s	0	0.25	0	0.15	0.4	0.2	0
t_3 =4s	0.6	0.2	0	0.1	0.1	0	0
t_4 =6s	0.55	0.15	0	0.1	0.1	0	0.1
t_5 =10s	0.75	0	0	0.15	0.1	0	0
t_6 =30s	0.25	0.65	0	0	0	0	0.1
t =40s (VBF)	0	0	0	0	0	0	1
t_7 =50s	0.6	0.3	0	0	0	0	0.1
t_8 =80s	0.7	0.2	0	0.1	0	0	0
t_9 =110s	0.6	0.2	0	0	0.2	0	0
t_{10} =140s	0.65	0.1	0.15	0	0	0.1	0

TABLE 2. SRBBA at time t_5 = 10s.

$m^{sr}(A)$	$m^{sr}(B)$	$m^{sr}(C)$	$m^{sr}(AB)$	$m^{sr}(AC)$	$m^{sr}(BC)$	$m^{sr}(\Theta)$
0.4112	0.1410	0	0.1762	0.1836	0.0587	0.0294

denoted by α_n, is defined as follow.

$$\begin{aligned}\alpha_n &= 1 - d_{BBA}(m^*, m^{sr})\\ &= 1 - \sqrt{\frac{1}{2}\left(\vec{m}^* - \vec{m}^{sr}\right)^T \underline{\underline{D}}\left(\vec{m}^* - \vec{m}^{sr}\right)}\end{aligned} \tag{15}$$

Note that at time node 1, $m^* = m^{sr}$ and $\alpha_1 = 1$.

Let $f_n(m_1, m_2, \ldots, m_n; A)$ and $g(g(\cdot), m_n; A)$ represent the whole and once fusion result (BBA) for proposition A, respectively, and assume $A \in 2^{\Theta}$, so the final data fusion result of proposition A at time n can be calculated as follows.

$$\begin{aligned}f_n(m_1, m_2, \ldots, m_n; A) &= g((m^*)^{\alpha_n}, m_n; A)\\ &= (m^*)^{\alpha_n} \oplus m_n(A)\end{aligned} \tag{16}$$

At current time node n, the whole fusion process can be rewritten as follows.

$$\begin{aligned}f_n(m_1, m_2, \ldots, m_n) = g(g(\ldots(g(g(VBF^{\alpha_1}, m_1)^{\alpha_2},\\ m_2)^{\alpha_3}, \ldots)^{\alpha_{n-1}}, m_{n-1})^{\alpha_n}, m_n)\end{aligned} \tag{17}$$

B. EXAMPLE ILLUSTRATION

TABLE 1 shows a group of time series values with corresponding belief function information. Let take $t_5 = 10s$ as an example to illustrate the proposed method.

Step 1 Convert time series values into graph for all propositions. And using VGA to aggregate SRPr of A.

$$\begin{aligned}SRPr(A) &= F_{VGA}(0.3, 0, 0.6, 0.55, 0.75)\\ &= \frac{2}{12} \times 0.3 + \frac{2}{12} \times 0 + \frac{4}{12} \times 0.6\\ &\quad + \frac{2}{12} \times 0.55 + \frac{2}{12} \times 0.75\\ &\approx 0.467\\ SRPr(B) &= F_{VGA}(0, 0.25, 0.2, 0.15, 0)\\ &= \frac{1}{10} \times 0 + \frac{3}{10} \times 0.25 + \frac{2}{10} \times 0.2\\ &\quad + \frac{3}{10} \times 0.15 + \frac{1}{10} \times 0\\ &= 0.160\\ SRPr(C) &= F_{VGA}(0, 0, 0, 0, 0)\\ &= 0\\ SRPr(AB) &= F_{VGA}(0.5, 0.15, 0.1, 0.1, 0.15)\\ &= \frac{1}{5} \times 0.5 + \frac{1}{5} \times 0.15 + \frac{1}{5} \times 0.1\\ &\quad + \frac{1}{5} \times 0.1 + \frac{1}{5} \times 0.15\\ &= 0.200\\ SRPr(AC) &= F_{VGA}(0, 0.4, 0.1, 0.1, 0.1)\\ &= \frac{1}{12} \times 0 + \frac{4}{12} \times 0.4 + \frac{7}{12} \times 0.1\\ &\approx 0.208\\ SRPr(BC) &= F_{VGA}(0.2, 0.2, 0, 0, 0)\\ &= \frac{1}{12} \times 0.2 + \frac{4}{12} \times 0.2 + \frac{7}{12} \times 0\\ &\approx 0.067\\ SRPr(ABC) &= F_{VGA}(0, 0, 0, 0.1, 0)\\ &= \frac{1}{3} \times 0.1 + \frac{2}{3} \times 0\\ &\approx 0.033\end{aligned}$$

Step 2 Calculate SRBBA, and the result is shown in Table 2.

Step 3 At time $t_5 = 10s$, there are

$$\vec{m}_4^* = (0.786, 0.109, 0.002, 0.036, 0.037, 0, 0.030)$$
$$\vec{m}_5^{sr} = (0.411, 0.1410, 0, 0.176, 0.184, 0.059, 0.030)$$

The credibility to old BBAs can be calculated as follows.

$$\begin{aligned}\alpha_5 &= 1 - d_{BBA}(m_4^*, m_5^{sr})\\ &= 1 - \sqrt{\frac{1}{2}\left(\vec{m}^* - \vec{m}^{sr}\right)^T \underline{\underline{D}}\left(\vec{m}^* - \vec{m}^{sr}\right)}\\ &= 0.7662\end{aligned}$$

TABLE 3. A comparison for the pignistic probability of target A among three methods.

Model	t_1	t_2	t_3	t_4	t_5	t_6	t_7	t_8	t_9	t_{10}
SRCDM	0.6500	0.5109	0.7739	0.8326	0.9480	0.5188	0.6559	0.8252	0.8642	0.8249
CDM	0.6500	0.4882	0.7589	0.8252	0.9254	0.2949	0.6285	0.7009	0.7014	0.6514
OWAM	0.6500	0.5798	0.7872	0.8015	0.9169	0.4000	0.6163	0.7268	0.9141	0.8771

TABLE 4. A comparison for the success rate based on different baselines. When the value of pignistic probability is larger than the baseline, the success rate in the whole identification process is counted once.

Success rate %	$\kappa = 0.5$	$\kappa = 0.6$	$\kappa = 0.7$	$\kappa = 0.8$	$\kappa = 0.9$
SRCDM	100	80	60	50	10
CDM	80	80	50	20	10
OWAM	80	80	60	40	20

So the final fusion result is

$$\begin{aligned} & f_5(m_1, \cdots, m_5) \\ & = ([\{A\}, 0.910], [\{B\}, 0.013], [\{C\}, 0.00], \\ & \quad [\{AB\}, 0.046], [\{AC\}, 0.031], [\{BC\}, 0], [\{\Theta\}, 0]) \end{aligned}$$

Note that at next time node $t_6 = 30s$, $m_5^* = f_5(m_1, \cdots, m_5)$.

IV. APPLICATION

In this section, applications in target identification can further illustrate the performance of the proposed SRCDM. To verify the rationality, some artificial time series dataset from literature [16], [24] is used (shown in TABLE 1, 5) and two other well developed models, called the credibility decay model (CDM) [24] and the ordered weighted averaging model (OWAM) are also introduced to compare the proposed SRCDM [25]. Finally, a sensitivity analysis and a famous dataset, Iris, are also adopted in verify the feasibility of SRCDM in practice.

A. NUMERICAL SIMULATIONK

The first dataset is used to compare the performances of three models. There are three targets with the right one A, then we have the frame of discernment $\Theta = \{A, B, C\}$. Sensors can continuously transform the received information about the target into BBAs and at time node $t_1 = 1s$, the collected belief function is $(\mathcal{E}_1, m_1) = (\{A\} : 0.3, \{AB\} : 0.5, \{BC\} : 0.2)$. Then the BBAs collected sequentially at different time nodes are shown in TABLE 1. Note that in special situations just like $t_6 = 30s$ and $t = 40s$, the performance of sensors is not so good.

The data collected at t_6 is interference information which is also considered in fusion process but at $t = 40s$ is vacuous information which is ignored in the proposed SRCDM method. Data fusion happens at every time node when a new BBA is obtained. For each fusion process, the result can be transformed to the pignistic probability so that the right target can be identified. FIGURE 3 further shows the whole data fusion process for target identification from $t_1 = 1s$ to $t_1 = 140s$.

In FIGURE 3, it is evident that SRCDM has better performance than CDM and in most cases, SRCDM holds higher belief or pignistic probability values than OWAM to the right target A. Besides, performances at time 6 further illustrate that SRCDM have better robustness when bad information, or inference comes.

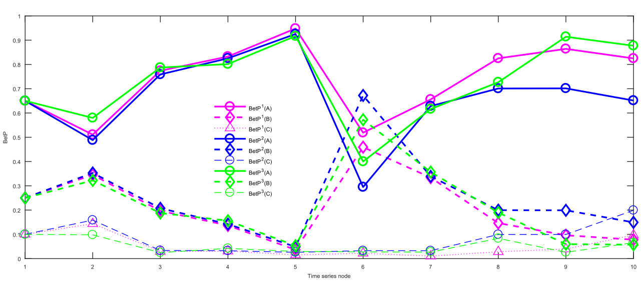
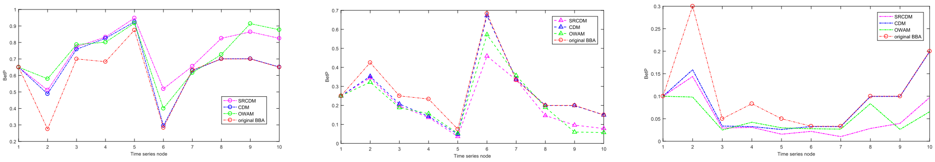


FIGURE 3. A decision making comparison for three models. Note that at node 6, only SRCDM is right.

TABLE 3 presents the fusion results in the pignistic probability form for target A at different time. It shows that SRCDM always intends to hold higher belief that target A is than other two models.

If we set different baselines (κ) for the final decision making, then the corresponding success rates, meaning that a model can identify A successfully, are calculated and shown in TABLE 4.

It seems that using CDM can also get right target in most situations from FIGURE 3. However, further study in FIGURE 4 finds that from t_6 to t_{10}, the CDM is almost ineffective because the value of time interval is too big, and the credibility to old fusion data is inevitably small, which causing the old data makes no sense in data fusion



(a) BetP(A) (b) BetP(B) (c) BetP(C)

FIGURE 4. Three models' performance comparison for different targets.

TABLE 5. Data from sensors with changed target.

t_i	m(A)	m(B)	m(C)	m(AB)	m(AC)	m(BC)	m(Θ)
t_1 =1s	0.4	0.1	0.1	0.2	0.2	0	0
t_2 =5s	0.6	0.2	0.1	0	0.05	0.05	0
t_3 =8s	0.65	0.15	0	0	0	0.2	0
t_4 =12s	0.15	0.65	0	0.2	0	0	0
t_5 =15s	0.2	0.6	0.1	0	0.05	0.05	0
t_6 =20s	0.1	0.4	0.1	0.2	0.2	0	0
t_7 =25s	0.3	0.4	0.1	0.2	0	0	0
t_8 =35s	0.2	0.5	0	0	0	0.3	0

process. CDM works in this case only because the original data source is sound. The coincidence of the red line and the blue line in FIGURE 4 clearly illustrates this situation. Besides, another shortage of CDM is exposed, the unit of time between two data is hard to determine. Start from $t_7 = 50s$, there is a datum coming every thirty seconds or half minute. CDM is ambiguous because the numerical value of time interval may be 30 or 0.5 and there is no other information to help judge which one is better (Past researches [16], [24] always preferred to choose second as time unit without explanation). However, the proposed method can eliminate such a problem because of the property of the visibility algorithm.

Although the OWAM also eliminates the time interval and semantic ambiguity problem in CDM and performs only a little worse than SRCDM, there are still some underlying problems in OWAM. For example, the OWAM is based on OWA operator which including many parameters. OWAM cannot generate these parameters by itself, that is, if there is no prior knowledge or experience about the parameters setting, OWAM may not maintain a good performance in specific situations. On the contrary, the proposed SRCDM is parameter free. The visibility algorithm can help generate a series of proper weights and determine the importance of new and old evidences.

B. SENSITIVITY ANALYSIS

In the whole target identification process, a big difference between the dynamic data fusion and the static one is that the target may change. That is also why the credibility to old fusion data is necessary.

Usually, the expense of better robustness is worse flexibility. So an analysis on the trade-off between real target change and interference is necessary.

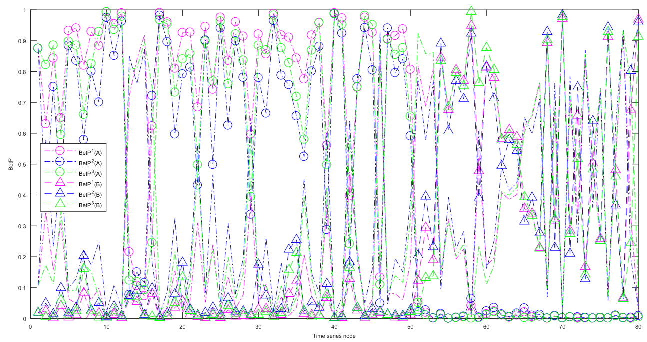


FIGURE 5. The fusion results of Iris dataset from t_1 to t_{80}. Superscript 1, 2, 3 represents the SRCDM, CDM, OWAM, respectively.

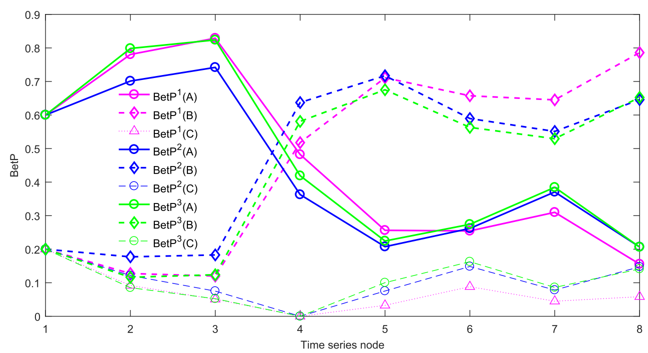


FIGURE 6. Performances of three models in target change situation. Superscript 1, 2, 3 represents the SRCDM, CDM, OWAM, respectively.

Based on data in TABLE 5. The performances of three models are shown in FIGURE 6, it clearly illustrate that SRCDM is better in both robustness and flexibility than other two models.

From $t_1 = 1s$ to $t_3 = 8s$, SRCDM gives more belief to proposition A. At $t_4 = 12s$, conflict data comes but it is

TABLE 6. Statistics results for Iris dataset.

Time	Target	Model	Average BetP	Maximum BetP	Success Rate %		
					κ=0.5	κ=0.7	κ=0.9
From t_1 to t_{50}	Se	SRCDM	0.8016	0.9923	0.9000	0.7800	0.5400
		OWAM	0.7515	0.9930	0.8200	0.7400	0.3000
		CDM	0.6895	0.9867	0.7800	0.6400	0.2000
From t_{51} to t_{80}	Ve	SRCDM	0.5532	0.9714	0.5667	0.3333	0.1333
		OWAM	0.5327	0.9941	0.5333	0.3667	0.1667
		CDM	0.5505	0.9827	0.5333	0.4000	0.1667

hard to determine the target proposition is changed or not. With more supporting data for proposition B coming at $t_4, t_5, \cdots, t_8$, SRCDM soon changes the most possible target to B. At t_5, the pignistic probability of proposition B from the proposed method almost equals to that from CDM and even for the original target, proposition A, SRCDM holds more belief than CDM.

C. CASE STUDY

To verify the performances of the proposed model in practical situations. The Iris dataset is adopted. There are three classes in this dataset named Setosa (Se), Versicolour (Ve) and Virginica (Vi), respectively. Each class has four attributes called Sepal length (SL), Sepal width (SW), Petal length (PL) and Petal width (PW).

First, we can simulate the data sending process. At the sending end, the sender starts transmitting data at time node 1 $t_1 = 0s$ with a random transmit time interval between 5 and 50 seconds. From t_1 to t_{50}, the sender would like to transmit information about class Setosa. To prevent such a target (Se) being detected by an interceptor, the sender chooses to transmit some interference or totally wrong information which can be generated by class Virginica in every transmission. That is, if interception happens, the interceptor will obtain three right BBAs and a wrong BBA. Then, from t_{51} to t_{80}, the sender actually changes his transmission target to Versicolour, and the protection measures are similar to above.

Second, we can simulate the sensors intercepting process. Assume that the sensors have known that there are three targets. We can build the discernment frame as $\theta = \{Se, Ve, Vi\}$. Data intercepted from sensors is then transformed to BBA according to the triangle fuzzy number method proposed in literature [58]. At every time node, sensors generate four BBAs because they receive four attributes' data. Then these four BBAs are combined simultaneously by Dempster combination rule according to Equation (3). Considering that the sensors are not fully reliable, the random variables between 0.5 and 1 is given to represent the reliability.

Third, the dynamic data fusion process can be simulated and shown in FIGURE 5 and the results are shown in TABLE 6. From the average pignistic probability and success rates, it is evident that the proposed SRCDM has the best performance among these three models.

D. DISCUSSION

The proposed method do not view time series simply from time interval like CDM. Since the combination rule in D-S theory can well make data fusion in quantitative aspect, and the VGA operator derived from visibility algorithm is good at conserving time information, especially in structure aspect, it is reasonable to combine these two methods together to solve the time series data fusion problem. Because the property of invariant under affine transformations of the series data, the ambiguity caused by time interval unit is eliminated.

Another benefit of the SRCDM is parameters free. Due to the structural and quantitative analysis of the time series values, past time information can be comparatively fully used. Note that to make full use of past information, the Markovian requirement in the proposed method is not fully satisfied, however, SRCDM only needs to conserve past collected BBAs to aggregate SRBBA for credibility, so past BBAs are not repeatedly computed in fact.

V. CONCLUSION

How to make data fusion dynamically is still an open issue. To overcome the shortcomings of existing credibility decay models, a data-driven method based on visibility graph and D-S theory is presented from both the structural and quantitative consideration. The visibility graph can transform time series information to a related graph and the VGA operator can aggregate a result on the time series. Then the credibility can be obtained by measuring the difference or distance between the old belief function and the aggregated BBA which inherits the information from the past time. After a series of applications in target recognition including numerical simulation, sensitivity analysis, and practical Iris dataset, it is explicit that the proposed SRCDM method can do better than CDM and OWAM and adapt to various situations as well. Besides, these applications further illustrate that the proposed method has the promising aspects in time series data fusion field, but on the other hand, the problem of chasing higher accuracy will never stop and there is still some prior knowledge we should have to determine the FOD in D-S theory. Based on these issues, future work may include improving the data fusion success rate and recognition without prior knowledge on target number.

REFERENCES

[1] A. P. Dempster, "Upper and lower probabilities induced by a multivalued mapping," in *Classic Works of the Dempster-Shafer Theory of Belief Functions*. Berlin, Germany: Springer, 2008, pp. 57–72.

[2] G. Shafer, *A Mathematical Theory of Evidence*, vol. 42. Princeton, NJ, USA: Princeton Univ. Press, 1976.

[3] L. Yin, X. Deng, and Y. Deng, "The negation of a basic probability assignment," *IEEE Trans. Fuzzy Syst.*, vol. 27, no. 1, pp. 135–143, Jan. 2019.

[4] R. R. Yager and N. Alajlan, "Maxitive belief structures and imprecise possibility distributions," *IEEE Trans. Fuzzy Syst.*, vol. 25, no. 4, pp. 768–774, Aug. 2017.

[5] Y. Li and Y. Deng, "Generalized ordered propositions fusion based on belief entropy," *Int. J. Comput. Commun. Control*, vol. 13, no. 5, pp. 792–807, Oct. 2018.

[6] C. K. Murphy, "Combining belief functions when evidence conflicts," *J. Decis. Support Syst.*, vol. 29, no. 1, pp. 1–9, Jul. 2000.

[7] D. Yong, S. WenKang, Z. ZhenFu, and L. Qi, "Combining belief functions based on distance of evidence," *Decis. Support Syst.*, vol. 38, pp. 489–493, Dec. 2004.

[8] E. Lefevre, O. Colot, and P. Vannoorenberghe, "Belief function combination and conflict management," *Inf. Fusion*, vol. 3, no. 2, pp. 149–162, Jun. 2002.

[9] Y. Zhang, Y. Liu, Z. Zhang, H.-C. Chao, J. Zhang, and Q. Liu, "A weighted evidence combination approach for target identification in wireless sensor networks," *IEEE Access*, vol. 5, pp. 21585–21596, 2017.

[10] M. Lachaize, S. Le Hégarat-Mascle, E. Aldea, A. Maitrot, and R. Reynaud, "Evidential framework for error correcting output code classification," *Eng. Appl. Artif. Intell.*, vol. 73, pp. 10–21, Aug. 2018.

[11] Z.-G. Su, T. Denoeux, Y.-S. Hao, and M. Zhao, "Evidential K-NN classification with enhanced performance via optimizing a class of parametric conjunctive t-rules," *Knowl. Based Syst.*, vol. 142, pp. 7–16, Feb. 2018.

[12] X. Xu, J. Zheng, J.-B. Yang, D.-L. Xu, and Y.-W. Chen, "Data classification using evidence reasoning rule," *Knowl. Based Syst.*, vol. 116, pp. 144–151, Jan. 2017.

[13] Y. Han and Y. Deng, "An evidential fractal analytic hierarchy process target recognition method," *Defence Sci. J.*, vol. 68, no. 4, pp. 367–373, Jun. 2018.

[14] H. Zhang and Y. Deng, "Engine fault diagnosis based on sensor data fusion considering information quality and evidence theory," *Adv. Mech. Eng.*, vol. 10, no. 10, pp. 1–10, Nov. 2018. doi: 10.1177/1687814018809184.

[15] P. Dutta, "An uncertainty measure and fusion rule for conflict evidences of big data via Dempster–Shafer theory," *Int. J. Image Data Fusion*, vol. 9, no. 2, pp. 152–169, 2018. doi: 10.1080/19479832.2017.1391336.

[16] P. Smets, "Analyzing the combination of conflicting belief functions," *Inf. Fusion*, vol. 8, no. 4, pp. 387–412, Oct. 2007.

[17] F. Xiao, "Multi-sensor data fusion based on the belief divergence measure of evidences and the belief entropy," *Inf. Fusion*, vol. 46, pp. 23–32, Mar. 2019.

[18] Z. Li and L. Chen, "A novel evidential FMEA method by integrating fuzzy belief structure and grey relational projection method," *Eng. Appl. Artif. Intell.*, vol. 77, pp. 136–147, Jan. 2019.

[19] A. Janghorbani and M. H. Moradi, "Fuzzy evidential network and its application as medical prognosis and diagnosis models," *J. Biomed. Inform.*, vol. 72, pp. 96–107, Aug. 2017.

[20] L. Chen, L. Diao, and J. Sang, "Weighted evidence combination rule based on evidence distance and uncertainty measure: An application in fault diagnosis," *Math. Problems Eng.*, vol. 2018, Jan. 2018, Art. no. 5858272.

[21] F. Xiao, "A novel multi-criteria decision making method for assessing health-care waste treatment technologies based on D numbers," *Eng. Appl. Artif. Intell.*, vol. 71, pp. 216–225, May 2018.

[22] X. Su, L. Li, H. Qian, S. Mahadevan, and Y. Deng, "A new rule to combine dependent bodies of evidence," in *Soft Computing*. 2019. doi: 10.1007/s00500-019-03804-y.

[23] F. Xiao, "An improved method for combining conflicting evidences based on the similarity measure and belief function entropy," *Int. J. Fuzzy Syst.*, vol. 20, no. 4, pp. 1256–1266, Apr. 2018.

[24] Y. Song, X. Wang, L. Lei, and Y. Xing, "Credibility decay model in temporal evidence combination," *Inf. Process. Lett.*, vol. 115, no. 2, pp. 248–252, Feb. 2015.

[25] G. Liu and F. Xiao, "Time series data fusion based on evidence theory and OWA operator," *Sensors*, vol. 19, no. 5, p. 1171, 2019.

[26] S. Liu, X. Gao, W. Fang, Q. Sun, S. Feng, X. Liu, and S. Guo, "Modeling the complex network of multidimensional information time series to characterize the volatility pattern evolution," *IEEE Access*, vol. 6, pp. 29088–29097, 2018.

[27] W. Jiang, B. Wei, J. Zhan, C. Xie, and D. Zhou, "A visibility graph power averaging aggregation operator: A methodology based on network analysis," *Comput. Ind. Eng.*, vol. 101, pp. 260–268, Nov. 2016.

[28] S. Mao and Y. Fu, "Time series forecasting based on complex network analysis," *IEEE Access*, vol. 7, pp. 40220–40229, 2019. doi: 10.1109/ACCESS.2019.2906268.

[29] R. Zhang, B. Ashuri, and Y. Deng, "A novel method for forecasting time series based on fuzzy logic and visibility graph," *Adv. Data Anal. Classification*, vol. 11, no. 4, pp. 759–783, 2017.

[30] P. Xu, R. Zhang, and Y. Deng, "A novel visibility graph transformation of time series into weighted networks," *Chaos, Solitons Fractals*, vol. 117, pp. 201–208, Dec. 2018.

[31] S. Chen, Y. Hu, S. Mahadevan, and Y. Deng, "A visibility graph averaging aggregation operator," *Phys. A, Stat. Mech. Appl.*, vol. 403, pp. 1–12, Jun. 2014.

[32] H. Harb, A. Makhoul, R. Couturier, and S. Tawbi, "Comparison of different data aggregation techniques in distributed sensor networks," *IEEE Access*, vol. 5, pp. 4250–4263, 2017.

[33] K. Yunus, T. Thiringer, and P. Chen, "Arima-based frequency-decomposed modeling of wind speed time series," *IEEE Trans. Power Syst.*, vol. 31, no. 4, pp. 2546–2556, Jul. 2016.

[34] Z. Wu and N. E. Huang, "Ensemble empirical mode decomposition: A noise-assisted data analysis method," *Adv. Adapt. Data Anal.*, vol. 1, no. 1, pp. 1–41, 2008.

[35] L. Lacasa, B. Luque, F. Ballesteros, J. Luque, and J. C. Nuño, "From time series to complex networks: The visibility graph," *Proc. Nat. Acad. Sci. USA*, vol. 105, no. 13, pp. 4972–4975, 2008.

[36] F. Xiao, "A hybrid fuzzy soft sets decision making method in medical diagnosis," *IEEE Access*, vol. 6, pp. 25300–25312, 2018.

[37] Y. Tang, D. Zhou, and F. T. S. Chan, "Amwrpn: Ambiguity measure weighted risk priority number model for failure mode and effects analysis," *IEEE access*, vol. 6, pp. 27103–27110, 2018.

[38] M. Behrouz and S. Alimohammadi, "Uncertainty analysis of flood control measures including epistemic and aleatory uncertainties: Probability theory and evidence theory," *J. Hydrolog. Eng.*, vol. 23, no. 8, May 2018, Art. no. 04018033.

[39] B. Wu, X. Yan, Y. Wang, and C. G. Soares, "An evidential reasoning-based CREAM to human reliability analysis in maritime accident process," *Risk Anal.*, vol. 37, no. 10, pp. 1936–1957, Oct. 2017.

[40] Z. Wang and F. Xiao, "An improved multisensor data fusion method and its application in fault diagnosis," *IEEE Access*, vol. 7, pp. 3928–3937, 2018.

[41] Y. Han and Y. Deng, "A novel matrix game with payoffs of maxitive belief structure," *Int. J. Intell. Syst.*, vol. 34, no. 4, pp. 690–706, Apr. 2019.

[42] L. Fei and Y. Deng, "A new divergence measure for basic probability assignment and its applications in extremely uncertain environments," *Int. J. Intell. Syst.*, vol. 34, no. 4, pp. 584–600, Apr. 2019.

[43] Y. Li and F. Xiao, "Bayesian update with information quality under the framework of evidence theory," *Entropy*, vol. 21, no. 1, p. 5, 2019.

[44] Y. Dong, J. Zhang, Z. Li, Y. Hu, and Y. Deng, "Combination of evidential sensor reports with distance function and belief entropy in fault diagnosis," *Int. J. Comput. Commun. Control*, vol. 14, no. 3, pp. 329–343, May 2019.

[45] X. Deng, W. Jiang, and Z. Wang, "Zero-sum polymatrix games with link uncertainty: A Dempster-Shafer theory solution," *Appl. Math. Comput.*, vol. 340, pp. 101–112, Jan. 2019.

[46] X. Wang and Y. Song, "Uncertainty measure in evidence theory with its applications," *Appl. Intell.*, vol. 48, no. 7, pp. 1672–1688, Aug. 2017.

[47] H. Seiti and A. Hafezalkotob, "Developing pessimistic–optimistic risk-based methods for multi-sensor fusion: An interval-valued evidence theory approach," *Appl. Soft Comput.*, vol. 72, pp. 609–623, Nov. 2018. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1568494618305118

[48] H. Xu and Y. Deng, "Dependent evidence combination based on shearman coefficient and pearson coefficient," *IEEE Access*, vol. 6, pp. 11634–11640, 2017.

[49] Y. Wang, K. Zhang, and Y. Deng, "Base belief function: An efficient method of conflict management," in *Journal of Ambient Intelligence and Humanized Computing*. Berlin, Germany: Springer, 2018. doi: 10.1007/s12652-018-1099-2.

[50] F. Xiao, "A multiple-criteria decision-making method based on D numbers and belief entropy," *Int. J. Fuzzy Syst.*, vol. 21, no. 4, pp. 1144–1153, Jun. 2019.

[51] W. Zhang and Y. Deng, "Combining conflicting evidence using the DEMATEL method," in *Soft Computing*. 2018. doi: 10.1007/s00500-018-3455-8.

[52] J.-B. Yang and D.-L. Xu, "Evidential reasoning rule for evidence combination," *Artif. Intell.*, vol. 205, pp. 1–29, Dec. 2013. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0004370213000945

[53] F. Shi, X. Su, H. Qian, N. Yang, and W. Han, "Research on the fusion of dependent evidence based on rank correlation coefficient," *Sensors*, vol. 17, no. 10, pp. 2362–2377, Oct. 2017.

[54] Z. He and W. Jiang, "An evidential dynamical model to predict the interference effect of categorization on decision making results," *Knowl. Based Syst.*, vol. 150, pp. 139–149, Jun. 2018.

[55] P. Smets and R. Kennes, "The transferable belief model," *Artif. Intell.*, vol. 66, no. 2, pp. 191–234, Apr. 1994.

[56] A.-L. Jousselme, D. Grenier, and É. Bossé, "A new distance between two bodies of evidence," *Inf. Fusion*, vol. 2, no. 2, pp. 91–101, 2001.

[57] A. Mardani, M. Nilashi, E. K. Zavadskas, S. R. Awang, H. Zare, and N. M. Jamal, "Decision making methods based on fuzzy aggregation operators: Three decades review from 1986 to 2017," *Int. J. Inf. Technol. Decis. Making*, vol. 17, no. 2, pp. 391–466, 2018.

[58] T. Ma and F. Xiao, "An improved method to transform triangular fuzzy number into basic belief assignment in evidence theory," *IEEE Access*, vol. 7, pp. 25308–25322, 2019.

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