



# Article Multi-Sensor Data Fusion Method Based on Improved Evidence Theory

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Abstract: To achieve autonomous navigation in complex marine environments, unmanned surface vehicles are equipped with a variety of sensors for sensing the surrounding environment and their own state. To address the issue of unsatisfactory multi-sensor information fusion in stochastic uncertain systems with unknown disturbances, an improved evidence theory multi-sensor data fusion method is proposed in this article. First, the affiliation function in fuzzy set theory is introduced as a support function to assign initial evidence for multi-sensor data, and the initial evidence is corrected according to the degree of data bias. Second, a divergence measure is employed to measure the degree of conflict and discrepancy among the evidence, and each piece of evidence is allocated proportional weight based on the conflict allocation principle. Finally, the evidence is synthesized through the evidence combination rule, and the data are weighted and summed to obtain the data fusion results. Since it is difficult to obtain dynamic information from multiple sensors carried by unmanned surface vehicles in practical applications, and considering that the proposed method has universal applicability, practical application experiments using previous research demonstrate that the proposed method has higher fusion accuracy than other existing data fusion methods.

Keywords: multi-sensors; Dempster–Shafer evidence theory; data fusion; divergence measure



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# 1. Introduction

The autonomous navigation of unmanned surface vehicles in complex marine environments requires sensing their own state and the dynamic information of the surrounding environment, based on which they can successfully make collision avoidance strategies to ensure the safety of navigation. The acquisition of this dynamic information relies on a variety of sensors; therefore, the study of the accuracy of the information collected by the sensors is beneficial for guaranteeing the safe navigation of unmanned surface vehicles. A single sensor can only provide partially accurate information and thus cannot exclude ambiguity in the description of the external environment [1,2]. The complementary characteristics of the discrepancies in the performance of each sensor are the principle ability of multi-sensor data-fusion technology to combine information from different sources [3], which is widely used in a variety of fields [4,5], e.g., anomaly diagnosis [6,7], reliability evaluation [8,9], target tracking [10], etc. Data fusion, which extracts key data from each sensor to provide superior estimation and improves the reliability of the system, has attracted the attention of many scholars and has become a national and international research hotspot [11].

To realize the effective fusion of multi-sensor data, a variety of approaches have been proposed. Among them, the adaptive weighting data fusion method, which can determine the weighting factor by solving the optimal solution based on the principle of minimizing the total mean square error, is a relatively simple data fusion method [12]. Zhu et al. [13] proposed a multi-sensor adaptive fusion method based on fuzzy inference and applied

it to the visual inertial measurement unit wheel odometry. Setting the same initial conditions for different aero-propulsion system units cannot solve all faults; to overcome this problem, Li et al. [14] proposed a new shape-constrained neural data-fusion network for the construction of health indicators. To address the problem that the limitation of an unknown distribution of multi-source data leads to the poor stability of simple wavelet neural networks in a multi-source discrete data environment, Yang et al. [15] proposed a decision-fusion method combining Bayesian inference and wavelet neural networks. Other data fusion methods include genetic algorithms [16], particle filtering algorithms [17], the Kalman filtering algorithm [18,19], etc. However, these methods are not capable of resolving uncertain information.

Dempster–Shafer (D–S) evidence theory [20] provides an effective solution to the problem of data fusion uncertainty without prior information, which has led to its widespread study. To overcome the issue that highly contradictory evidence combination results may not be consistent with human intuition, Mi et al. [21] proposed a method to fuse the ordered weighted average operator and the soft likelihood function. To address the issue that some existing methods cannot effectively take into account the relevant preferences of decision makers and individual belief degree characteristics, Wang et al. [22] proposed a dynamic multi-sensor data fusion method based on weighted average operator and evidence theory. To deal with the evidence of higher conflict, Xiao [23] proposed a new measure of reinforcement belief divergence for measuring discrepancies between basic belief assignments. The Dempster combination rule is potentially counter-intuitive in the case of conflicting evidence; to overcome this challenge, Xiao [24] developed a hybrid multi-sensor data fusion approach by combining an evidence credibility measure and prospect theory. Song et al. [25] proposed a temporal evidence adaptive fusion method, which determines the amount of evidence sets based on the temporal fusion results of multiple moments and selects an appropriate fusion method to fuse the evidence based on the maximum power pignometric probability distance to evaluate whether the evidence is contradictory or not. Zhao et al. [26] proposed a new square mean distance measure method to assess the distance between pieces of evidence, which is combined with modified information volume to devise a new method of conflicting information fusion. Zhou et al. [27] proposed a new information fusion method to address the counterintuitive and poor robustness issues that appear in traditional D-S evidence theory for the fusion of highly conflicting evidence. However, these methods fuse the probabilities of sensors' collection of target attributes for target recognition and fault diagnosis, and they cannot fuse the measurements of multi-sensors. To realize the fusion of multi-sensor measurements, a new multi-sensor data fusion method [28] is proposed to convert each measurement into the corresponding evidence according to its accuracy. Wang et al. [29] extended the method of [28] to propose a multiple-attribute fusion algorithm combining improved evidence theory and fuzzy clustering, which uses a fuzzy clustering approach to cluster and group measurements and then uses improved evidence theory for fusion. However, this method requires a large amount of data to achieve the fusion accuracy and is not applicable in the case of a small number of sensors. Therefore, to further improve the accuracy of the method of [28], a modified multi-sensor data fusion method is proposed in this paper. The main contributions of this study are summarized as follows.

- (1) The affiliation function in fuzzy set theory is introduced as the support function to assign initial pieces of evidence for the multi-sensor data, and the initial evidence is corrected according to the degree of the data bias.
- (2) A divergence measure is employed to measure the degree of conflict and discrepancy between the evidence to devise the principle for conflict resolution, and each piece of evidence is allocated proportional weights based on the conflict allocation principle.
- (3) The evidence is synthesized using a more appropriate evidence combination rule to obtain the weights of measurements, and the data are weighted and summed to obtain the multi-sensor data fusion results.

The remainder of the article is organized as follows. Section 2 provides the preparatory knowledge that needs to be used. A modified multi-sensor data fusion method is proposed in Section 3. In Section 4, the proposed method is tested against other data fusion methods using three multi-sensor measurement experiments. The conclusion is given in Section 5.

## 2. Preliminaries

# 2.1. D–S Evidence Theory

D–S evidence theory, as an approach based on Bayesian probability theory in the field of artificial intelligence, is an effective theory for processing uncertain information [30,31]. Due to its effectiveness in modeling imprecision without prior information [32], it is widely used in decision making [33], pattern classification [34] and other fields.

A discriminative framework  $\Theta$  consisting of a finite number of complete and mutually exclusive elements can be expressed as

$$\Theta = \{R_1, R_2, \dots, R_n\} \tag{1}$$

The power set of  $\Theta$ , denoted by  $2^{\Theta}$  [35], can be written as

$$2^{\Theta} = \{\emptyset, \{R_1\}, \dots, \{R_2\}, \{R_1, R_2\}, \dots, \{R_1, R_2, \dots, R_n\}, \dots \Theta\}$$
(2)

where  $\emptyset$  denotes the empty set.

The basic belief assignment *m* maps from  $2^{\Theta}$  to [0, 1] and is given as follows

$$m: 2^{\Theta} \to [0, 1] \tag{3}$$

It satisfies

$$\begin{cases} \sum_{A \subseteq \Theta} m(A) = 1\\ m(\emptyset) = 0 \end{cases}$$
(4)

where  $A \in 2^{\Theta}$  denotes a proposition. If m(A) > 0, then *A* is considered to be the focal element. The belief function can be expressed as

$$Bel(A) = \sum_{B \subset A} m(B)$$
(5)

The plausibility function is described as

$$pl(A) = \sum_{B \cap A = \emptyset} m(B) = 1 - Bel(A)$$
(6)

If there exist two independent basic belief assignments  $m_1$ ,  $m_2$  in  $\Theta$ , the form  $m = m_1 \oplus m_2$ of the Dempster–Shafer combination rule [36] is given as follows

$$m(A) = \begin{cases} \frac{1}{1-K} \sum_{B \cap C=A} m_1(B)m_2(A), & A \neq \emptyset \\ 0, & A = \emptyset \end{cases}$$
(7)

with

$$K = \sum_{B \cap C = \emptyset} m_1(B) m_2(C) \tag{8}$$

where  $B, C \in 2^{\Theta}$ , and K represent the conflict coefficient of  $m_1$  and  $m_2$ . It is worth noting that the Dempster–Shafer combination rule is only feasible when two basic belief assignments satisfy the condition K < 1.

#### 2.2. Belief Divergence Measure

The uncertainty measure of the basic probability assignment is currently also a significant part of the D–S evidence theory that can make it applicable to many fields [37]. Actually, the uncertainty measure of the basic probability assignment is a measure of the conflicting pieces of evidence. Measuring the conflict of evidence in the D–S evidence theory has been an open question, which is crucial to the synthesis of evidence. Several methods have emerged to measure conflicting evidence over recent decades; one of which is the divergence measure, e.g., Jensen–Shannon divergence [38], BRE divergence [39], etc. Based on [32], a divergence measure named Belief Jensen–Shannon (BJS) divergence is employed, which is described below.

Let  $m_1$ ,  $m_2$  be any two mutually exclusive basic belief assignments in the same discriminative framework; the BJS divergence between  $m_1$  and  $m_2$  is given by

$$BJS(m_1, m_2) = H\left(\frac{m_1 + m_2}{2}\right) - \frac{1}{2}H(m_1) - \frac{1}{2}H(m_2) = \frac{1}{2} \left[\sum_i m_1(z_i) \log\left(\frac{2m_1(z_i)}{m_1(z_i) + m_2(z_i)}\right) + \sum_i m_2(z_i) \log\left(\frac{2m_2(z_i)}{m_1(z_i) + m_2(z_i)}\right)\right]$$
(9)

where  $H(m_k) = -\sum_i m_k(z_i) \log m_k(z_i)$  represents the Shannon entropy, while i = 1, 2, ..., n and k = 1, 2.

From (9), it can be seen that if the basic belief assignment is assigned to zero, it causes the fractional values to tend to infinity, making their logarithmic values also tend to infinity. BJS will terminate when it encounters such a situation, so a smaller value can be used instead of zero when the above situation occurs.

Belief Jensen-Shannon divergence exhibits several properties below in practical applications:

- (1)  $BJS(m_1, m_2)$  is mutually symmetric with respect to  $m_1$  and  $m_2$ .
- (2)  $BJS(m_1, m_2)$  is bounded and satisfies  $BJS(m_1, m_2) \in [0, 1]$ .
- (3) The square root  $\sqrt{BJS(m_1, m_2)}$  can verify the triangle inequality.

#### 3. The Proposed Method

Assuming that there exist *n* sensors to measure the target *z*, the measurement obtained by the *j*th sensor is  $z_j(j = 1, 2, ..., n)$ . Inspired by the idea of evidence theory, the overall measurements  $\{z_1, z_2, ..., z_n\}$  are treated as the discriminative framework  $\Theta$ . The basic belief assignment can be regarded as the weight assignment function for each measurement. Each measurement is converted into evidence based on its accuracy when synthesized for all pieces of evidence [28].

The proposed method consists of four main parts: the determination of support function, the basic belief assignment for measurements, the rule of evidence combination, and the conflicting measure and weighting combination. The support function is designed to generate initial evidence, which can reflect the degree of support between the data. The basic belief assignment is arranged to correct the initial evidence and assign more reasonable weights to the data. The conflicting measure and weighting combination is to resolve the highly conflicting contradiction between the pieces of evidence, and the rule of evidence combination is used to fuse the measurements.

#### 3.1. Determination of Support Function

Due to environmental noise, human interference and the limitation of the sensor's own observation accuracy, the measurement of the sensor is the superposition of the true value of the target and disturbances. Obviously, the overall measurements are within the normal deviation and fall within the neighborhood of the true value. Considering the ambiguity of the measurement error of the sensor, the affiliation function is used as a support function for the data and is defined as

$$Y_{ij} = 1 - \frac{2\arctan(|z_i - z_j|)}{\pi}$$
(10)

where  $z_i$  and  $z_j$  represent the measurements of the *i*th and *j*th sensors.

If the support  $Y_{ij}$  is larger, it indicates that the *j*th sensor's measurement is closer to the true value and that the support of the measurement is higher; otherwise, the support is lower. The support matrix of the *j* sensor for target recognition in the discriminative framework  $\Theta$  is written as

$$SUP_{ij} = \begin{bmatrix} Y_{11} & \cdots & Y_{1i} & \cdots & Y_{1n} \\ \vdots & \cdots & \vdots & \vdots & \vdots \\ Y_{i1} & \cdots & Y_{ii} & \cdots & Y_{in} \\ \vdots & \cdots & \vdots & \vdots & \vdots \\ Y_{n1} & \cdots & Y_{ni} & \cdots & Y_{nn} \end{bmatrix}$$
(11)

The support matrix reflects the degree of ambiguity between each datum and the rest, i.e., the degree of support. It is more roughly equivalent to the probability that the measurement is close to the true value and serves as initial evidence to provide initial values for subsequent corrections.

#### 3.2. Basic Belief Assignment for Measurements

In practical applications, the measurement of each sensor is not completely reliable due to the interference from various factors. Abnormal measurement data can reduce the accuracy of data fusion and even lead to incorrect fusion results. To exclude the influence of outliers, the measurement of each sensor needs to be checked for consistency, and the extent to which the measurement of each sensor agrees with the measurements of other sensors is fused into the evidence assignment as the degree of confidence.

To measure the magnitude of the deviation of the different sensor measurements, the distance between measurements  $z_i$  and  $z_j$  is defined as

$$d_{ij} = \left| z_i - z_j \right| \tag{12}$$

where i, j = 1, 2, ..., n. The mean of the sum of the distances between measurement  $z_i$  and other measurements are denoted as

$$d_{i} = \frac{\sum_{j=1}^{n} d_{ij}}{n-1}$$
(13)

where  $d_i$  is the mean value that reflects the degree of discrepancy between the sensor *i* and the other sensors. If  $d_i$  is larger, it means that the discrepancy between the sensor and the other sensors is larger, indicating a higher probability that the sensor measurement is an outlier; otherwise, there is a lower probability that it is an outlier. The mean distance between all measurements is described as

$$\bar{d} = \frac{\sum_{i=1}^{n} d_i}{n} \tag{14}$$

From the above analysis, the measurement  $z_i$  can be converted into evidence. The idea of basic belief assignment is that the affiliation matrix can be regarded as initial evidence, i.e.,  $m_{ij}(z_j) = SUP_{ij}$ , and the degree of discrepancy of each measurement is used to correct it. If  $d_i$  is larger than  $\bar{d}$ , the measurement is considered an outlier and is rejected; otherwise, it is considered a valid value. The basic belief assignment formula is given as follows:

$$\begin{cases} m_{i}(z_{j}) = 0, \quad d_{j} > \alpha \bar{d} \\ \frac{m_{i}(z_{j1})}{m_{i}(z_{j2})} = \frac{d_{j2}}{d_{j1}}, \quad d_{j} \le \alpha \bar{d} \end{cases}$$
(15)

where  $z_{j1}$  and  $z_{j2}$  denote any two valid measurements, and  $\alpha$  is a threshold that satisfies  $\alpha \ge 1$ .

In practice, a set of correction coefficients  $\{\omega_p\}(p = 1, 2, ..., n)$  can be generated from (15), and the correction coefficients are used to normalize and weight each piece of evidence, i.e.,

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$$n_i'(z_j) = \frac{\omega_j m_i(z_j)}{\sum\limits_{p=1}^n \omega_p m_i(z_p)}$$
(16)

where  $z_m$  represents any one measurement.

#### 3.3. Rule of Evidence Combination

There may be high conflict among the evidence generated by (16), and the original Dempster evidence combination rule is used to deal with the high-conflict evidence that may present the paradox, resulting in unreasonable data combination results. The evidence combination rule based on [28] can solve the above problems more effectively and is also more suitable for the fusion of measurements, which is given below.

The probabilities of supporting conflicting evidence are assigned to each measurement in a certain proportion, and the combination formula is given as follows:

$$n(z_j) = \prod_{i=1}^n m'_i(z_j) + b\bar{m}'_i(z_j)$$
(17)

where j = 1, 2, ..., n, m is the mean basic belief assignment of  $z_n$  among all evidence and b is a conflict factor, which is written as

$$b = 1 - \sum_{j=1}^{n} \prod_{i=1}^{n} m'_{i}(z_{j})$$
(18)

where  $m'_i(z_n)$  is expressed as

$$\bar{m}'_i(z_j) = \frac{1}{n} \sum_{i=1}^n m'_i(z_j)$$
(19)

The basic belief assignment  $m(z_j)$  for measurement  $z_j$  in the synthetic evidence is the weights assigned to the measurements. The fusion results can be expressed as

$$Z_0 = \sum_{j=1}^{n} z_j m(z_j)$$
(20)

#### 3.4. Conflicting Measure and Weighting Combination

The processes of conflicting measure and weighting combination are also more important as they are the last part of the proposed method. First, they use BJS divergence to measure the conflict and discrepancy between the pieces of evidence to calculate the evidence's credibility weights. Afterward, the evidence's credibility weights are converted to evidence for evidence combination. Finally, the evidence is adjusted and combined using the final weights of the evidence [32]. The flowchart of conflicting measure and weighting combination is illustrated in Figure 1, whose pseudocode is shown in Algorithm 1.



Figure 1. Flowchart of conflicting measure and weighting combination.

Algorithm 1 Conflicting measure and weighting combination.

Inputs: 
$$m_i, i = 1, 2, ..., n, m_j, j = 1, 2, ..., n$$
  
for  $i = 1 : n$   
for  $j = 1 : n$   
1:  $BJS_{ij} = \frac{1}{2} \left[ \sum_i m_i(z_i) \log \left( \frac{2m_i(z_i)}{m_i(z_i) + m_j(z_i)} \right) + \sum_i m_j(z_i) \log \left( \frac{2m_j(z_i)}{m_i(z_i) + m_j(z_i)} \right) \right]$   
end for  
end for  
2:  $BJ\bar{S}_i = \frac{\sum_{j=1, j \neq i}^n BJS_{ij}}{n-1}$   
3:  $Sim_i = \frac{1}{BJ\bar{S}_i}$   
4:  $Crd_i = \frac{Sim(m_i)}{\sum_{j=1}^n Sim(m_i)}$   
5:  $m_{weight} = \sum_{i=1}^n (Crd_i \times m_i)$   
6:  $\bar{m}_i(z_j) = \frac{1}{n} \sum_{i=1}^n m_i(z_j)$   
7:  $b = 1 - \sum_{j=1}^n \prod_{i=1}^n m_i(z_j)$   
8:  $m(z_j) = \prod_{i=1}^n m_i(z_j) + b\bar{m}_i(z_j)$   
9:  $Z_0 = \sum_{j=1}^n z_j m(z_j)$   
Outputs:  $Z_0$ 

Step 1: The BJS divergence is used to calculate the distance measure of two random  $m_i$  (i = 1, 2, ..., n) and  $m_j$  (j = 1, 2, ..., n). The divergence matrix *DMM* is written as

$$DMM = \begin{bmatrix} 0 & \cdots & BJS_{1i} & \cdots & BJS_{1n} \\ \vdots & \cdots & \vdots & \vdots & \vdots \\ BJS_{i1} & \cdots & 0 & \cdots & BJS_{in} \\ \vdots & \cdots & \vdots & \vdots & \vdots \\ BJS_{n1} & \cdots & BJS_{ni} & \cdots & 0 \end{bmatrix}$$
(21)

Step 2: The mean evidence distance  $BJS_i$  across the evidence  $m_i$  is defined as

$$BJ\bar{S}_i = \frac{\sum_{j=1, j\neq i}^n BJS_{ij}}{n-1}$$
(22)

Step 3: The similarity of the evidence  $m_i$  is described as

$$Sim_i = \frac{1}{B\bar{I}\bar{S}_i} \tag{23}$$

Step 4: The credibility degree of the evidence  $m_i$  obtained from the similarity normalization is given by

$$Crd_i = \frac{Sim(m_i)}{\sum_{j=1}^n Sim(m_i)}$$
(24)

Step 5: According to the weight  $Crd_i$  of the evidence, the synthetic average weight evidence is written as

$$m_{weight} = \sum_{i=1}^{n} \left( Crd_i \times m_i \right)$$
(25)

Step 6: The weight evidence, viewed as ordinary evidence, is fused with other pieces of evidence based on the rule of evidence fusion.

# 4. Experiments

Since the proposed method is universal, the fusion performance of experimental data from other aspects can also reflect the multi-sensor information fusion performance of unmanned surface vehicles. The feasibility and effectiveness of the proposed method and its superiority over other fusion methods were verified by testing all fusion algorithms on the measurement data of two multi-sensor experiments provided by [28] and the measurement data of one multi-sensor experiment provided by [40].

#### 4.1. Experiment 1

The nondestructive measurement for the metallization layer thickness of the vacuum electronic device requires that several measurements be averaged to obtain more accurate results, which will consume a significant amount of time and resources. Therefore, eight data are sampled from fifty iterations of sample thickness measurement data collected by the multi-sensors as experimental data for data fusion, and the average value of 65.57  $\mu$ m from the fifty tests is used as the reference accuracy; the sampling data are shown in Table 1.

According to (11), the initial evidence generated by the support matrix for each measurement of the multi-sensors are

$$m_{ij}(z_j) = \begin{bmatrix} 1 & 0.7856 & \cdots & 0.9365 \\ 0.7857 & 1 & \cdots & 0.8440 \\ \vdots & \vdots & & \vdots \\ 0.9365 & 0.8440 & \cdots & 1 \end{bmatrix}$$

From (13) and (14), the elements consisting of  $d_j$  are calculated as  $d_1 = 0.3386$ ,  $d_2 = 0.3186$ ,  $d_3 = 0.4071$ ,  $d_4 = 0.3729$ ,  $d_5 = 0.8957$ ,  $d_6 = 0.3100$ ,  $d_7 = 0.3471$ ,  $d_8 = 0.3100$ .

The average distance between all measurements is  $\bar{d} = 0.4125$ . The correction factors obtained from (15) are calculated as  $\omega_1 = 0.1362$ ,  $\omega_2 = 0.1448$ ,  $\omega_3 = 0.1133$ ,  $\omega_4 = 0.1237$ ,  $\omega_5 = 0.0515$ ,  $\omega_6 = 0.1488$ ,  $\omega_7 = 0.1329$ ,  $\omega_8 = 0.1488$ .

Table 1. Metallization layer thickness measurements.

Number	Measurement (µm)	Number	Measurement (µm)
1	65.41	5	66.45
2	65.76	6	65.73
3	65.31	7	65.81
4	65.35	8	65.51

The corrected pieces of evidence are shown in Table 2. As can be seen from Table 2, one piece of evidence can be assigned to each measurement of the multi-sensors according to the improved basic belief assignment method, and the probabilities of each piece of evidence corresponding to outliers are assigned to zero, which can exclude the interference of outliers to the data fusion. The divergence matrix *DMM* is constructed as follows:

	0	0.0060	• • •	0.0068 ]	
	0.0060	0		0.0001	
DMM =					
	:	:		:	
	0.0006	0.0034	• • •	0	

**Table 2.** Mass function for each evidence.

<b>Basic Belief</b>	Measurement									
Assignment	$z_1$	$z_2$	$z_3$	$z_4$	$z_5$	$z_6$	<i>z</i> 7	$z_8$		
$m_1(z_1)$	0.1632	0.1363	0.1271	0.1426	0	0.1431	0.1206	0.1670		
$m_2(z_2)$	0.1293	0.1749	0.1000	0.1124	0	0.1763	0.1554	0.1517		
$m_3(z_3)$	0.1591	0.1319	0.1412	0.1503	0	0.1385	0.1168	0.1622		
$m_4(z_4)$	0.1601	0.1331	0.1349	0.1511	0	0.1397	0.1177	0.1634		
$m_5(z_5)$	0.1284	0.1723	0.1004	0.1123	0	0.1734	0.1638	0.1495		
$m_6(z_6)$	0.1311	0.1702	0.1014	0.1140	0	0.1783	0.1512	0.1538		
$m_7(z_7)$	0.1277	0.1734	0.0988	0.1110	0	0.1747	0.1644	0.1499		
$m_8(z_8)$	0.1510	0.1446	0.1172	0.1316	0	0.1517	0.1280	0.1760		

The mean evidence distance  $BJ\bar{S}_i$  across the pieces of evidence can be calculated as  $BJ\bar{S}_1 = 0.0037$ ,  $BJ\bar{S}_2 = 0.0036$ ,  $BJ\bar{S}_3 = 0.0049$ ,  $BJ\bar{S}_4 = 0.0045$ ,  $BJ\bar{S}_5 = 0.0038$ ,  $BJ\bar{S}_6 = 0.0032$ ,  $BJ\bar{S}_7 = 0.0040$ ,  $BJ\bar{S}_8 = 0.0025$ .

The similarity of the evidence is computed as  $Sim_1 = 274$ ,  $Sim_2 = 279$ ,  $Sim_3 = 204$ ,  $Sim_4 = 222$ ,  $Sim_5 = 264$ ,  $Sim_6 = 312$ ,  $Sim_7 = 249$ ,  $Sim_8 = 404$ .

The evidence's credibility degree can be obtained as  $Crd_1 = 0.1241$ ,  $Crd_2 = 0.1263$ ,  $Crd_3 = 0.0925$ ,  $Crd_4 = 0.1007$ ,  $Crd_5 = 0.1195$ ,  $Crd_6 = 0.1414$ ,  $Crd_7 = 0.1126$ ,  $Crd_8 = 0.1830$ .

The synthetic average weight evidence is calculated as  $m_w(z_1) = 0.1433$ ,  $m_w(z_2) = 0.1552$ ,  $m_w(z_3) = 0.1140$ ,  $m_w(z_4) = 0.1271$ ,  $m_w(z_5) = 0$ ,  $m_w(z_6) = 0.1603$ ,  $m_w(z_7) = 0.1401$ ,  $m_w(z_8) = 0.1600$ .

The synthesized evidence is derived as  $m(z_1) = 0.1437$ ,  $m(z_2) = 0.1547$ ,  $m(z_3) = 0.1150$ ,  $m(z_4) = 0.1280$ ,  $m(z_5) = 0$ ,  $m(z_6) = 0.1596$ ,  $m(z_7) = 0.1398$ ,  $m(z_8) = 0.1593$ .

The fusion result obtained from (20) is  $Z_0 = 65.5678$ , and the data fusion results of the proposed method and other comparative methods are displayed in Table 3. It can be seen from Table 3 that the fusion result of the proposed method has higher accuracy compared to other comparative methods. Although the improvement in accuracy of the proposed

method is not so obvious, the fusion result of the proposed method is close to the reference true value, which is already considered a more effective performance improvement effect. There are two reasons why the proposed method is capable of achieving approximate equivalence to the true value. One is because the support relationship of the measurements and the mutual evaluation of the sensors can effectively identify anomalous measurements. The second is due to the use of the Belief Jensen-Shannon divergence to measure the credibility of the evidence, which increases the weights of reliable pieces of evidence and decreases the weights of unreliable evidence, thus mitigating its negative impact on the final fusion result.

Table 3. Comparison of fusion results of all methods.

Method	Fusion Results (µm)	Absolute Error (µm)	<b>Relative Error (%)</b>
Arithmetic mean	65.6663	0.0963	0.1469
Xiong et al. [25]	65.5601	0.0099	0.0151
Proposed method	65.5678	0.0022	0.0034

# 4.2. Experiment 2

The performance of the proposed method continues to be tested using the measurements of a characteristic parameter as an example. Table 4 shows the measurements of 10 sensors with variance obtained from historical data and the true value set to 1.

Table 4. Measurements from 10 sensors.

Number	Measurement	Variance	Number	Measurement	Variance
1	1.000	0.05	6	0.650	0.25
2	0.990	0.07	7	1.010	0.10
3	0.980	0.10	8	1.020	0.10
4	0.970	0.20	9	1.030	0.20
5	0.500	0.30	10	1.500	0.30

The initial evidence generated by the support matrix for each measurement of the multi-sensors are given by

	[ 1	0.9936	•••	0.7048
$m_{ij}(z_j) =$	0.9936	1	• • •	0.6998
	:	:		÷
	0.7048	0.6998	• • •	1

The elements consisting of  $d_j$  are calculated as  $d_1 = 0.1633$ ,  $d_2 = 0.1633$ ,  $d_3 = 0.1656$ ,  $d_4 = 0.1700$ ,  $d_5 = 0.5167$ ,  $d_6 = 0.3833$ ,  $d_7 = 0.1656$ ,  $d_8 = 0.1700$ ,  $d_9 = 0.1767$ ,  $d_{10} = 0.5944$ . The average distance between all measurements is  $\bar{d} = 0.2669$ . The correction factors obtained from (15) are constructed as follows:  $\omega_1 = 0.1276$ ,  $\omega_2 = 0.1276$ ,  $\omega_3 = 0.1259$ ,  $\omega_4 = 0.1226$ ,  $\omega_5 = 0.0403$ ,  $\omega_6 = 0.0544$ ,  $\omega_7 = 0.1259$ ,  $\omega_8 = 0.1226$ ,  $\omega_9 = 0.1180$ ,  $\omega_{10} = 0.0351$ .

The corrected evidences are shown in Table 5. It can be seen from Table 5 that multiple outliers in the measurements are given a weighting of 0, indicating that the proposed method is capable of eliminating the effects of anomalous data, despite the presence of multiple outliers. The divergence matrix is constructed as follows:

$$DMM = \begin{bmatrix} 0 & 0.0051 & \cdots & 0.0309 \\ 0.0051 & 0 & \cdots & 0.0531 \\ \vdots & \vdots & & \vdots \\ 0.0309 & 0.0531 & \cdots & 0 \end{bmatrix}$$

<b>Basic Belief</b>			Μ	Measurement						
Assignment	$z_1$	$z_2$	$z_3$	$z_4$	$z_5$	$z_6$	$z_7$	$z_8$	Z9	$z_{10}$
$m_1(z_1)$	0.1482	0.1484	0.1444	0.1397	0	0	0.1453	0.1406	0.1344	0
$m_2(z_2)$	0.1474	0.1478	0.1454	0.1407	0	0	0.1445	0.1398	0.1337	0
$m_3(z_3)$	0.1469	0.1476	0.1468	0.1420	0	0	0.1440	0.1393	0.1332	0
$m_4(z_4)$	0.1466	0.1477	0.1465	0.1436	0	0	0.1437	0.1390	0.1329	0
$m_5(z_5)$	0.1466	0.1477	0.1467	0.1439	0	0	0.1436	0.1388	0.1326	0
$m_6(z_6)$	0.1466	0.1465	0.1467	0.1439	0	0	0.1436	0.1388	0.1326	0
$m_7(z_7)$	0.1474	0.1460	0.1436	0.1389	0	0	0.1464	0.1417	0.1354	0
$m_8(z_8)$	0.1469	0.1457	0.1431	0.1384	0	0	0.1459	0.1430	0.1367	0
$m_9(z_9)$	0.1467	0.1456	0.1428	0.1382	0	0	0.1456	0.1427	0.1382	0
$m_{10}(z_{10})$	0.1467	0.1484	0.1426	0.1379	0	0	0.1457	0.1430	0.1386	0

Table 5. Mass function for each evidence.

The mean evidence distance  $BJ\bar{S}_i$  across the pieces of evidence can be calculated as  $BJ\bar{S}_1 = 0.000021$ ,  $BJ\bar{S}_2 = 0.000022$ ,  $BJ\bar{S}_3 = 0.000029$ ,  $BJ\bar{S}_4 = 0.000037$ ,  $BJ\bar{S}_5 = 0.000042$ ,  $BJ\bar{S}_6 = 0.000041$ ,  $BJ\bar{S}_7 = 0.000027$ ,  $BJ\bar{S}_8 = 0.000037$ ,  $BJ\bar{S}_9 = 0.000047$ ,  $BJ\bar{S}_{10} = 0.000053$ .

The similarity of the pieces of evidence is computed as  $Sim_1 = 47931$ ,  $Sim_2 = 45264$ ,  $Sim_3 = 34587$ ,  $Sim_4 = 27382$ ,  $Sim_5 = 24074$ ,  $Sim_6 = 24113$ ,  $Sim_7 = 37688$ ,  $Sim_8 = 27081$ ,  $Sim_9 = 21486$ ,  $Sim_{10} = 18975$ .

The evidence's credibility degree can be obtained as  $Crd_1 = 0.1553$ ,  $Crd_2 = 0.1467$ ,  $Crd_3 = 0.1121$ ,  $Crd_4 = 0.0887$ ,  $Crd_5 = 0.0780$ ,  $Crd_6 = 0.0781$ ,  $Crd_7 = 0.1221$ ,  $Crd_8 = 0.0878$ ,  $Crd_9 = 0.0696$ ,  $Crd_{10} = 0.0615$ .

The synthetic average weight evidence is calculated as  $m_w(z_1) = 0.1471$ ,  $m_w(z_2) = 0.1472$ ,  $m_w(z_3) = 0.1449$ ,  $m_w(z_4) = 0.1407$ ,  $m_w(z_5) = 0$ ,  $m_w(z_6) = 0$ ,  $m_w(z_7) = 0.1449$ ,  $m_w(z_8) = 0.1406$ ,  $m_w(z_9) = 0.1346$ ,  $m_w(z_{10}) = 0$ .

The synthesized evidence is derived as  $m(z_1) = 0.1470$ ,  $m(z_2) = 0.1470$ ,  $m(z_3) = 0.1449$ ,  $m(z_4) = 0.1407$ ,  $m(z_5) = 0$ ,  $m(z_6) = 0$ ,  $m(z_7) = 0.1448$ ,  $m(z_8) = 0.1407$ ,  $m(z_9) = 0.1348$ ,  $m(z_{10}) = 0$ .

The fusion result obtained from (20) is 0.9997, and the data fusion result of the proposed method and other methods are displayed in Table 6. It can be seen from Table 6 that the fusion result of the proposed method has higher accuracy compared to other methods, which indicates that the proposed method also performs well in additional experiments and is universal, further validating the effectiveness of the proposed method. The proposed method obtains a high fusion accuracy by fusing less data, which is capable of achieving and engineering acceptable measurement accuracy.

Table 6. Measurement fusion results of all methods.

Method	<b>Fusion Results</b>	Absolute Error	<b>Relative Error (%)</b>
Arithmetic mean	0.9650	0.0350	3.5
Xiong et al. [25]	0.9995	0.0005	0.05
Proposed method	0.9997	0.0003	0.03

#### 4.3. Experiment 3

To further verify the performance of the proposed method, the measurements of the thermostat temperature are tested as an example. The assumed true temperature is 50.50 °C. Any eight data from the thirty data are selected as test data and are shown in Table 7.

Number	Measurement (°C)	Number	Measurement (°C)
1	49.80	5	50.55
2	49.92	6	50.60
3	50.25	7	50.64
4	50.15	8	50.75

Table 7. Metallization layer thickness measurements.

The initial evidence generated by the support matrix for each measurement of the multi-sensors are

	1	0.9240	• • •	0.5163	1
	0.9240	1	• • •	0.5590	
$m_{ij}(z_j) =$	•				
	:	:		:	L
	0.5163	0.5590	•••	1	

From (13) and (14), the elements consisting of  $d_j$  are calculated as  $d_1 = 0.6086$ ,  $d_2 = 0.5057$ ,  $d_3 = 0.3457$ ,  $d_4 = 0.3743$ ,  $d_5 = 0.3457$ ,  $d_6 = 0.3600$ ,  $d_7 = 0.3828$ ,  $d_8 = 0.4771$ . The average distance between all measurements is  $\bar{d} = 0.4250$ . The correction factors

obtained from (15) are calculated as  $\omega_1 = 0.0840$ ,  $\omega_2 = 0.1011$ ,  $\omega_3 = 0.1479$ ,  $\omega_4 = 0.1366$ ,  $\omega_5 = 0.1479$ ,  $\omega_6 = 0.1420$ ,  $\omega_7 = 0.1335$ ,  $\omega_8 = 0.1071$ .

The corrected pieces of evidence are shown in Table 8. As can be seen from Table 8, the proposed method can similarly exclude outliers by assigning evidence to the measurements. The divergence matrix *DMM* is constructed as follows

	F 0	0	• • •	0.0098
DMM =	0	0	• • •	0.0099
	:	÷		:
	0.0098	0.0099		0

Table 8. Mass function for each evidence.

Pasia Poliof Assignment	Measurement								
Dasie Dener Assignment	$z_1$	$z_2$	$z_3$	$z_4$	$z_5$	$z_6$	$z_7$	$z_8$	
$m_1(z_1)$	0	0	0.2360	0.2344	0.1907	0.1769	0.1619	0	
$m_2(z_2)$	0	0	0.2366	0.2347	0.1906	0.1767	0.1615	0	
$m_3(z_3)$	0	0	0.2425	0.2098	0.1975	0.1830	0.1672	0	
$m_4(z_4)$	0	0	0.2365	0.2332	0.1913	0.1772	0.1619	0	
$m_5(z_5)$	0	0	0.1896	0.1629	0.2328	0.2165	0.1982	0	
$m_6(z_6)$	0	0	0.1840	0.1581	0.2268	0.2249	0.2061	0	
$m_7(z_7)$	0	0	0.1817	0.1561	0.2245	0.2228	0.2150	0	
$m_8(z_8)$	0	0	0.1810	0.1556	0.2245	0.2232	0.2157	0	

The mean evidence distance  $BJ\bar{S}_i$  across the pieces of evidence can be calculated as  $BJ\bar{S}_1 = 0.0052$ ,  $BJ\bar{S}_2 = 0.0052$ ,  $BJ\bar{S}_3 = 0.0039$ ,  $BJ\bar{S}_4 = 0.0051$ ,  $BJ\bar{S}_5 = 0.0040$ ,  $BJ\bar{S}_6 = 0.0048$ ,  $BJ\bar{S}_7 = 0.0052$ ,  $BJ\bar{S}_8 = 0.0053$ .

The similarity of the evidence is computed as  $Sim_1 = 194$ ,  $Sim_2 = 191$ ,  $Sim_3 = 257$ ,  $Sim_4 = 196$ ,  $Sim_5 = 247$ ,  $Sim_6 = 210$ ,  $Sim_7 = 193$ ,  $Sim_8 = 189$ .

The evidence's credibility degree can be obtained as  $Crd_1 = 0.1153$ ,  $Crd_2 = 0.1140$ ,  $Crd_3 = 0.1533$ ,  $Crd_4 = 0.1170$ ,  $Crd_5 = 0.1473$ ,  $Crd_6 = 0.1250$ ,  $Crd_7 = 0.1152$ ,  $Crd_8 = 0.1128$ .

The synthetic average weight evidence is calculated as  $m_w(z_1) = 0$ ,  $m_w(z_2) = 0$ ,  $m_w(z_3) = 0.2113$ ,  $m_w(z_4) = 0.1925$ ,  $m_w(z_5) = 0.2102$ ,  $m_w(z_6) = 0.2002$ ,  $m_w(z_7) = 0.1857$ ,  $m_w(z_8) = 0$ .

The synthesized evidence is derived as  $m(z_1) = 0$ ,  $m(z_2) = 0$ ,  $m(z_3) = 0.2110$ ,  $m(z_4) = 0.1930$ ,  $m(z_5) = 0.2098$ ,  $m(z_6) = 0.2002$ ,  $m(z_7) = 0.1859$ ,  $m(z_8) = 0$ .

The fusion result obtained from (20) is  $Z_0 = 50.44$ , the data fusion results of the proposed method and other fusion methods are displayed in Table 9. It can be observed from Table 9 that the fusion result of the proposed method has higher accuracy compared to other fusion methods. The fusion accuracy of the proposed method is not significantly improved compared to other fusion methods, which is due to the fact that the fusion result of the proposed method is closer to the true value, and the discrepancy between the measurements is not significant. However, the universality and superiority of the proposed method over other fusion methods are further verified by this experiment.

Method Fusion Results (µm) Absolute Error (µm) **Relative Error (%)** Arithmetic mean 50.33 0.170.3366 50.42 Xiong et al. [25] 0.080.1584 50.440.06 0.1188 Proposed method

Table 9. Comparison of fusion results of all methods.

## 5. Conclusions

To solve the problem of unsatisfactory accuracy of multi-sensor data fusion for measurements with uncertainty and without prior information, an improved evidence theory multi-sensor data fusion method is proposed. Basic belief assignment in evidence theory is realized by introducing a support function and a mutual support evaluation between sensors. A divergence measure is employed to measure the degree of conflict and discrepancy to weaken the conflict between pieces of evidence; drawing on the idea of evidence combination can obtain effective evidence synthesis results. The experimental results show that the proposed method can obtain high fusion accuracy with relatively few detection data without prior information, which is conducive to engineering implementation and can be used in multi-sensor information fusion for unmanned surface vehicles. Since the proposed method draws on the idea of evidence theory for multi-sensor data fusion, a more accurate measure of mutual evaluation for each sensor and a reasonable conversion of evidence can further improve the fusion performance of the method, which will be the focus of subsequent research. The proposed method can also be explored in combination with machine learning techniques and implemented in real-time with multi-sensor data fusion for unmanned surface vehicles under different weather conditions and water depths, and its performance in practical applications can be evaluated to further improve the accuracy and efficiency of the method. It would be interesting to explore how the proposed method performs with different types of sensors, such as lidar, radar, and sonar, which are commonly used in autonomous navigation systems for unmanned surface vehicles. Furthermore, it would be worthwhile to compare the proposed method with other popular fusion algorithms, such as Kalman filtering, particle filtering, and the smooth variable structure filter, to assess its effectiveness in various scenarios.

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## References

- 1. Wang, Q.; Jin, T.; Mohamed, M.A. A fast and robust fault section location method for power distribution systems considering multisource information. *IEEE Syst. J.* 2022, *16*, 1954–1964. [CrossRef]
- Huang, F.; He, Y.; Deng, X.; Jiang, W. A Novel Discount-Weighted Average Fusion Method Based on Reinforcement Learning For Conflicting Data. IEEE Syst. J. 2022, 1–4. [CrossRef]
- Montanari, A.N.; Oliveira, E.D. A novel analog multisensor design based on fuzzy logic: A magnetic encoder application. *IEEE Trans. Signal Process.* 2017, 17, 7096–7104. [CrossRef]
- 4. Kordestani, M.; Saif, M.; Orchard, M.E.; Razavi-Far, R.; Khorasani, K. Failure prognosis and applications-survey of recent literature. *IEEE Trans. Rel.* 2021, *70*, 728–748. [CrossRef]
- 5. Wen, L.; Li, X.; Gao, L.; Zhang, Y. A newconvolutional neural networkbased data-driven fault diagnosis method. *IEEE Trans. Ind. Electron.* **2018**, *65*, 5990–5998. [CrossRef]
- 6. Gong, W.; Wang, Y.; Zhang, M.; Mihankhah, E.; Chen, H.; Wang, D. A fast anomaly diagnosis approach based on modified CNN and multisensor data fusion. *IEEE Trans. Ind. Electron.* **2021**, *69*, 13636–13646. [CrossRef]
- 7. Zheng, Y.; Luo, Q.; Cui, Y.; Dai, H.; Han, X.; Feng, X. Fault identification and quantitative diagnosis method for series-connected lithium-ion battery packs based on capacity estimation. *IEEE Trans. Ind. Electron.* **2022**, *69*, 3059–3067. [CrossRef]
- 8. Song, Y.; Wang, X.; Zhu, J.; Lei, L. Sensor dynamic reliability evaluation based on evidence theory and intuitionistic fuzzy sets. *Appl. Intell.* **2018**, *48*, 3950–3962. [CrossRef]
- 9. Xiao, F. GIQ: A generalized intelligent quality-based approach for fusing multisource information. *IEEE Trans. Fuzzy Syst.* 2021, 29, 2018–2031. [CrossRef]
- 10. Li, S.; Cheng, Y.; Brown, D.; Tharmarasa, R.; Zhou, G.; Kirubarajan, T. Comprehensive time-offset estimation for multisensor target tracking. *IEEE Trans. Aerosp. Electron. Syst.* **2019**, *56*, 2351–2373. [CrossRef]
- 11. Safari, S.; Shabani, F.; Simon, D. Multirate multisensor data fusion for linear systems using Kalman filters and a neural network. *Aerosp. Sci. Technol.* **2014**, *39*, 465–471. [CrossRef]
- 12. Li, D.; Shen, C.; Dai, X.; Zhu, X.; Luo, J.; Li, X.; Chen, H.; Liang, Z. Research on data fusion of adaptive weighted multi-source sensor. *Comput. Mater. Contin.* 2019, *61*, 1217–1231. [CrossRef]
- 13. Zhu, J.; Tang, Y.; Shao, X.; Xie, Y. Multisensor fusion using fuzzy inference system for a visual-IMU-wheel odometry. *IEEE Trans. Instrum. Meas.* **2021**, *70*, 1–16. [CrossRef]
- 14. Li, Z.; Wu, J.; Yue, X. A shape-constrained neural data fusion network for health index construction and residual life prediction. *IEEE Trans. Neural Netw. Learn. Syst.* **2021**, *32*, 5022–5033. [CrossRef]
- Yang, W.; Chen, B.; Yu, L. Bayesian-Wavelet-Based Multisource Decision Fusion. *IEEE Trans. Instrum. Meas.* 2021, 70, 1–10. [CrossRef]
- 16. Liu, F.; Cai, X.; Shi, B.; Wang, Y. Multisensor data fusion based on genetic algorithm. In *Electronic Imaging and Multimedia Systems*; SPIE: Santa Clara, CA, USA, 1996; Volume 2898, pp. 43–48.
- 17. Xu, C.; Shi, Y.; Wan, J.; Duan, S. Uncertainty-Constrained Belief Propagation for Cooperative Target Tracking. *IEEE Internet Things J.* **2022**, *9*, 19414–19425. [CrossRef]
- 18. Li, C.; Wang, Z.; Song, W.; Zhao, S.; Wang, J.; Shan, J. Resilient Unscented Kalman Filtering Fusion with Dynamic Event-Triggered Scheme: Applications to Multiple Unmanned Aerial Vehicles. *IEEE Trans. Control. Syst. Technol.* **2022**, *31*, 370–381. [CrossRef]
- 19. Liu, X.; Zhou, B.; Huang, P.; Xue, W.; Li, Q.; Zhu, J.; Qiu, L. Kalman filter-based data fusion of Wi-Fi RTT and PDR for indoor localization. *IEEE Sens. J.* 2021, 21, 8479–8490. [CrossRef]
- 20. Yager, R.R. Entailment for measure based belief structures. Inf. Fusion 2019, 47, 111–116. [CrossRef]
- 21. Mi, X.; Lv, T.; Tian, Y.; Kang, B. Multi-sensor data fusion based on soft likelihood functions and OWA aggregation and its application in target recognition system. *ISA Trans.* **2021**, *112*, 137–149. [CrossRef]
- 22. Wang, J.; Yu, Q. A Dynamic multi-sensor data fusion approach based on evidence theory and WOWA operator. *Appl. Intell.* **2020**, 50, 3837–3851. [CrossRef]
- 23. Xiao, F. A new divergence measure for belief functions in D–S evidence theory for multisensor data fusion. *Inf. Sci.* 2020, 514, 462–483. [CrossRef]
- Xiao, F. Evidence combination based on prospect theory for multi-sensor data fusion. ISA Trans. 2020, 106, 253–261. [CrossRef] [PubMed]
- 25. Song, Y.; Zhu, J.; Lei, L.; Wang, X. Self-adaptive combination method for temporal evidence based on negotiation strategy. *Sci. China Inf. Sci.* **2020**, *63*, 1–13. [CrossRef]
- Zhao, K.; Sun, R.; Li, L.; Hou, M.; Yuan, G.; Sun, R. An improved evidence fusion algorithm in multi-sensor systems. *Appl. Intell.* 2021, 51, 7614–7624 [CrossRef]
- 27. Zhou, K.; Lu, N.; Jiang, B. Information Fusion-Based Fault Diagnosis Method Using Synthetic Indicator. *IEEE Sens. J.* 2023, 23, 5124–5133. [CrossRef]
- 28. Xiong, Y.; Ping, Z. Data fusion algorithm inspired by evidence theory. J. Huazhong Univ. Sci. Technol. 2011, 39, 50–54.
- 29. Wang, W.; Yan, Y.; Zhang, R.; Wang, Z.; Fan, Y.; Yang, C. Multi-attribute fusion algorithm based on improved evidence theory and clustering. *Sensors* **2019**, *19*, 4146. [CrossRef]

- 30. Liu, P.; Yu, G.; Wang, Z.; Zhou, B.; Chen, P. Object classification based on enhanced evidence theory: Radar–vision fusion approach for roadside application. *IEEE Trans. Instrum. Meas.* 2022, 71, 1–12. [CrossRef]
- Liu, B.; Deng, Y.; Cheong, K.H. An improved multisource data fusion method based on a novel divergence measure of belief function. *Eng. Appl. Artif. Intell.* 2022, 111, 104834. [CrossRef]
- Xiao, F. Multi-sensor data fusion based on the belief divergence measure of evidences and the belief entropy. *Inf. Fusion* 2019, 46, 23–32. [CrossRef]
- 33. Fu, C.; Chang, W.; Xue, M.; Yang, S. Multiple criteria group decision making with belief distributions and distributed preference relations. *Eur. J. Oper. Res.* 2019, 273, 623–633. [CrossRef]
- 34. Liu, Z.G.; Pan, Q.; Dezert, J.; Martin, A. Combination of classifiers with optimal weight based on evidential reasoning. *IEEE Trans. Fuzzy Syst.* **2018**, *26*, 1217–1230. [CrossRef]
- 35. Gao, X.; Liu, F.; Pan, L.; Deng, Y.; Tsai, S.B. Uncertainty measure based on Tsallis entropy in evidence theory. *Int. J. Intell. Syst.* **2019**, *34*, 3105–3120. [CrossRef]
- Chen, L.; Deng, Y.; Cheong, K.H. Permutation Jensen–Shannon divergence for Random Permutation Set. *Eng. Appl. Artif. Intell.* 2023, 119, 105701. [CrossRef]
- 37. Deng, Y. Uncertainty measure in evidence theory. Sci. China Inf. Sci. 2020, 63, 210201. [CrossRef]
- 38. Lin, J. Divergence measures based on the shannon entropy. IEEE Trans. Inf. Theory 1991, 37, 145–151. [CrossRef]
- Song, Y.; Deng, Y. A new method to measure the divergence in evidential sensor data fusion. Int. J. Distrib. Sens. Netw. 2019, 15, 1550147719841295. [CrossRef]
- 40. Wang, W.Q.; Yang, Y.L.; Yang, C.J. A data fusion algorithm based on evidence theory. Control. Decis. 2013, 28, 1427–1430.

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