Approach Based on Improved Interval D-S Theory for Target Identification

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Abstract. In traditional multi-sensor based target identification, problems of sensor reliability and identification confidences would generate significant influence on practical implications. Therefore, a new identification algorithm based on Improved Interval Dempster-Shafer Theory (IIDST) is proposed in this paper. Specifically, this algorithm models reliability of sensors and identification outputs from sensors as interval values, and then combines practical interval outputs through interval evidence combination rules. Finally, the capability of the IIDST algorithm is evaluated via theoretical simulations with results demonstrating the effectively of the proposed algorithm.

Introduction

The data fusion technology is an effective solution for dealing with the uncertain information from multi-sensors. Until now, a large number of techniques for data fusion have already been reported, including probability theory [1], fuzzy sets theory [2], Dempster-Shafer (D-S) theory [3, 4] and etc. Considering the effectivity of disposing missing information and uncertainty, the D-S theory is a promising choice to solve the problem of target identification.

The D-S theory was initially proposed by Dempster, who tried to utilise the upper and lower probabilities to represent the practical uncertainty [3]. Shafer expanded this theory to process uncertain information [4]. Afterwards, the D-S theory becomes popular in many areas [5, 6]. Wang proposed a fingerprints and face multi-biometrics features recognition method based on D-S evidence theory [7]. Zhu et al. utilized an improved D-S theory based on an improved particle swarm optimization (PSO) for data fusion, in which the evidence weight value can be obtained by an improved PSO [8]. However, the previous studies mainly focused on the expansions and applications of the D-S theory. Considering the conflicting evidence is interval, these methods are helpless. Chang and Kashyap presented a geometric model based method for dealing with interval conflicting evidence [9]. Liu et al. proposed an interval D-S theory (IDST) algorithm, which is modified for dealing with the target identification problem caused by the achieved reliability of multi-sensors and the measurement uncertainty of the target features [10]. But this method is powerless when the achieved reliability confidences of multi sensors themselves are interval.

In this paper, an improved interval D-S theory (IIDST) is proposed. This algorithm, which models reliability of sensors and identification outputs from sensors as interval values, can process the interval and scalar identification confidences of the target from multi-sensors with considering the reliability of multi-sensors.

Problem Formulation

In this paper, the problems of target identification can be classified into two categories: (1) Due to the presence of measurement errors of equipments and different kinds of interferences, the measured feature parameters of targets always have warps compared to their true values, and the decision-making based on these measurements is uncertainty. It is noticeable that the word
“uncertainty” indicates identification credibility degrees of the measured targets, and these degrees can be represented as interval values; (2) distinct sensors themselves have distinctive reliability confidences for data fusion, which can also be described as interval credibility. The identification problem is modelled as below:

Supposing that there exist \( m \) targets \( T_j (j = 1, 2, ..., m) \) and \( n \) sensors \( S_i (i = 1, 2, ..., n) \), the interval identification confidence of the \( j \)th target \( T_j \) from the \( i \)th sensor \( S_i \) is \( b_{ij} \), and the interval reliability confidence of the \( i \)th sensor \( S_i \) itself is \( p_i \). The actual interval identification confidence \( \hat{b}_{ij} \) of the \( j \)th target \( T_j \) from the \( i \)th sensor \( S_i \) is calculated as

\[
\hat{b}_{ij} = p_i b_{ij} = \left[p_{ij}^L, p_{ij}^U\right] \left[b_{ij}^L, b_{ij}^U\right] = \left[p_{ij}^L b_{ij}^L, p_{ij}^U b_{ij}^U\right]
\]

(1)

where \( 0 \leq p_{ij}^L \leq p_{ij}^U \leq 1 \) and \( 0 \leq b_{ij}^L \leq b_{ij}^U \leq 1 \). The superscripts \( L \) and \( U \) represent the lower limit and upper limit respectively. The actual interval identification confidences \( \hat{B} \) of all targets from each sensor are depicted as below

\[
\hat{B} = \left\{ \hat{b}_1 = \left[p_{11}^L b_{11}^L, p_{11}^U b_{11}^U\right], ..., \left[p_{1m}^L b_{1m}^L, p_{1m}^U b_{1m}^U\right] \right\}, \hat{b}_2 = \left[p_{21}^L b_{21}^L, p_{21}^U b_{21}^U\right], ..., \left[p_{2m}^L b_{2m}^L, p_{2m}^U b_{2m}^U\right] \right\} \\
\vdots \quad \vdots \\
\hat{b}_n = \left[p_{n1}^L b_{n1}^L, p_{n1}^U b_{n1}^U\right], ..., \left[p_{nm}^L b_{nm}^L, p_{nm}^U b_{nm}^U\right] \right\}
\]

(2)

where \( \hat{b}_i (i = 1, 2, ..., n) \), each element of which is interval, denotes the actual interval identification confidences of all \( m \) targets from the \( i \)th sensor.

**Improved Interval D-S Theory Algorithm**

The IIDST algorithm is put forward based on the IDST algorithm [10, 11], and the difference lies in the fact that the IIDST algorithm considers and models the effect of each sensor’s reliability as interval value. The implementation of the IIDST algorithm also includes three steps: normalization, combination and reconstruction.

Supposing that there are \( m \) targets \( T_j (j = 1, 2, ..., m) \) and \( n \) sensors \( S_i (i = 1, 2, ..., n) \). The actual interval identification confidences of each target from all sensors are given in (2). Compared with the specific realization of the IDST algorithm [10, 11], the main difference of the IIDST algorithm is reflected in the first step, namely normalization, which is described detailedly as below:

**Normalization:** Normalize the upper and lower bound of the actual interval confidences of each target from all sensors separately. The normalization of actual interval confidences \( \hat{b}_i^L \) and \( \hat{b}_i^U \) from the \( i \)th sensor is computed as below

\[
\hat{b}_i^L = \left[\hat{b}_{1i}^L, \hat{b}_{2i}^L, ..., \hat{b}_{mi}^L\right]
\]

(3)

where \( \hat{b}_{ij}^L = \frac{p_{ij}^L b_{ij}^L}{\sum_{j=1}^{m} p_{ij}^L b_{ij}^L} \), and \( \sum_{j=1}^{m} \hat{b}_{ij}^L = 1 \)

\[
\hat{b}_i^U = \left[\hat{b}_{1i}^U, \hat{b}_{2i}^U, ..., \hat{b}_{mi}^U\right]
\]

(4)
where \( \hat{b}_{ij}^U = \frac{p_{ij}^U p_{ij}^L}{\sum_{j=1}^m p_{ij}^U p_{ij}^L} \), and \( \sum_{j=1}^m \hat{b}_{ij}^U = 1 \)

So (2) can be re-described as (5) and (6), which have the same expression as that in [10, 11].

\[
\hat{b}_i^L = [\hat{b}_{i1}^L, \hat{b}_{i2}^L, \ldots, \hat{b}_{im}^L]
\]

\[
\hat{b}_i^U = [\hat{b}_{i1}^U, \hat{b}_{i2}^U, \ldots, \hat{b}_{im}^U]
\]

(5)

\[
\hat{b}_i^L = [\hat{b}_{n1}^L, \hat{b}_{n2}^L, \ldots, \hat{b}_{nm}^L]
\]

\[
\hat{b}_i^U = [\hat{b}_{n1}^U, \hat{b}_{n2}^U, \ldots, \hat{b}_{nm}^U]
\]

(6)

where \( \hat{b}_i^L \) denotes the normalized lower identification confidences and \( \hat{b}_i^U \) represents the normalized upper identification confidences. It is noticed that each element of \( \hat{b}_i^L \) and \( \hat{b}_i^U \) are scalar.

The particular realization of combination and reconstruction step, as well as the decision-making rule, can be seen in [10, 11].

Simulations

Two experiments are given to demonstrate and analyse the identification performance of the IIDST algorithm in this section. Assume that four types of warships are observed by two sensors (an electronic support measure (ESM) system and an optical imagery reconnaissance (OIR) system) in two periods.

Performance Evaluation of Experiment 1

Table 1. Interval identification confidences from two sensors and interval reliability confidences of each sensor in two measurement periods.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Warship Type</th>
<th>t₁</th>
<th>t₂</th>
<th>t₃</th>
<th>t₄</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>ICₐⁿ</td>
<td>RCₐⁿ</td>
<td>ICₐⁿ</td>
<td>RCₐⁿ</td>
</tr>
<tr>
<td>b₁₁(·)</td>
<td></td>
<td>[0.35,0.45]</td>
<td>[0.40,0.45]</td>
<td>[0.65,0.75]</td>
<td>[0.60,0.65]</td>
</tr>
<tr>
<td>b₁₂(·)</td>
<td></td>
<td>[0.55,0.70]</td>
<td>[0.80,0.90]</td>
<td>[0.25,0.35]</td>
<td>[0.45,0.50]</td>
</tr>
<tr>
<td>b₂₁(·)</td>
<td></td>
<td>[0.75,0.85]</td>
<td>[0.70,0.85]</td>
<td>[0.25,0.30]</td>
<td>[0.50,0.65]</td>
</tr>
<tr>
<td>b₂₂(·)</td>
<td></td>
<td>[0.65,0.75]</td>
<td>[0.70,0.85]</td>
<td>[0.20,0.35]</td>
<td>[0.70,0.75]</td>
</tr>
</tbody>
</table>

This section is utilised to examine whether the IIDST algorithm can solve the interval identification confidences from two sensors in two measurement periods with considering the interval reliability confidences of each sensor itself. The confidences are listed in Table 1, where \( b_{ij} \) represent confidences from the ESM system in the \( i \)th measurement period while \( b_{ij} \) describing confidences from the OIR system in the \( j \)th measurement period, \( IC_{int} \) denote the identification confidence intervals of each target from each sensor and \( RC_{int} \) describe the reliability confidence intervals of each sensor.
By applying the decision-making rule in [10, 11], it can be concluded that \( t_1 \) represents the identification result, which is obvious to be seen in Figure 1. From Figure 1, it can also get that the IIDST algorithm can deal with the interval identification confidences from two sensors with considering the interval reliability confidences of each sensor.

![Figure 1. Identification performance of the IIDST algorithm for experiment 1.](image)

**Performance Evaluation of Experiment 2**

This section is used to examine whether the IIDST algorithm can deal with the scalar-value identification confidences from two sensors in two measurement periods with considering the interval reliability confidences of each sensor. The confidences are listed in Table 2, where \( IC_{Sca} \) denote the identification confidence scalar-values of each target from each sensor and \( RC_{Int} \) describe the reliability confidence intervals of each sensor.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Warship Type</th>
<th>( t_1 )</th>
<th>( t_2 )</th>
<th>( t_3 )</th>
<th>( t_4 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( b_{11} )</td>
<td>[0.35, 0.35]</td>
<td>[0.70, 0.75]</td>
<td>[0.40, 0.40]</td>
<td>[0.65, 0.75]</td>
<td>[0.15, 0.15]</td>
</tr>
<tr>
<td>( b_{12} )</td>
<td>[0.55, 0.55]</td>
<td>[0.80, 0.90]</td>
<td>[0.25, 0.25]</td>
<td>[0.45, 0.50]</td>
<td>[0.30, 0.30]</td>
</tr>
<tr>
<td>( b_{21} )</td>
<td>[0.75, 0.75]</td>
<td>[0.70, 0.85]</td>
<td>[0.25, 0.25]</td>
<td>[0.50, 0.65]</td>
<td>[0.10, 0.10]</td>
</tr>
<tr>
<td>( b_{22} )</td>
<td>[0.65, 0.65]</td>
<td>[0.70, 0.85]</td>
<td>[0.20, 0.20]</td>
<td>[0.70, 0.75]</td>
<td>[0.25, 0.25]</td>
</tr>
</tbody>
</table>

![Figure 2. Identification performance of the IIDST algorithm for experiment 2.](image)
The identification performance is shown in Figure 2, it is also obvious to conclude that \( t_i \)
represents the identification result. From Figure 2, we can see that the IIDST algorithm can
successfully process the scalar-value identification confidences from two sensors and interval
reliability confidences of each sensor in two measurement periods.

Conclusions

In this paper, we proposed a new identification algorithm based on IIDST, which models reliability of
sensors themselves and identification outputs from sensors as interval values, and these intervals can
be further processed by using interval evidence combination rules. Simulation results demonstrate
that the proposed IIDST algorithm can process the interval identification confidences from sensors
with considering the achieved reliability of multi sensors themselves.

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