

Method of multi-sensor data Association based on large scale

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Abstract. In the multi-sensor fusion system, great difference of detection information accuracy results high uncertainty of heterogeneous information correlation. This paper proposes a multi-sensor data correlation method basing on large scale which combines evidence theory and multi-factor fuzzy integrated decision theory in information correlation. For solving the problem of uncertainty of information correlation and obtaining evidence difficultly, the method first combines uncertain information evidence, and then obtains evidence from multi-factor fuzzy integrated decision membership degree function. The test results that heterogeneous information correlation using this method can conquer uncertainty of evidence combination and reduce the error and miss correlation rate.

1 Introduction

For a single sensor, it is difficult to detect the target correctly because of single detection means, limited data and failure detection probably. Multi-source heterogeneous data fusion can solve the problem. Multi-sensor heterogeneous data correlation is the base of multi-source data fusion.

Now, traditional data correlation algorithm is mainly based on statistics and fuzzy mathematics [1-2]. Weighting method, sequential method, dual-threshold, the nearest-neighbor method, K-NN method, and amended K-NN method are based on statistics. Fuzzy mathematics method, fuzzy dual-threshold method, fuzzy integrated function method and multi-factor fuzzy integrated decision method are based on fuzzy mathematics. Membership degree function of fuzzy mathematics can express fuzzy factors well, which brings high correlation rate[3]. These traditional methods are better for similar sensors data correlation. But there is high error correlation rate and miss correlation rate for uncertain heterogeneous data correlation.

This paper proposes a method of large scale for multi-sensor heterogeneous data correlation. Evidence theory that has preponderance for uncertain data, is used to multi-factor fuzzy integrated decision theory which can obtain evidence well from membership degree function[4]. Improved method step based on evidence theory and fuzzy decision theory is provided in this article. Simulation proves the method can reduce the error and miss correlation rate effectively for heterogeneous data correlation.

2 Related theory

2.1 Multi-factor fuzzy integrated decision data correlation algorithm

1) Determination of the fuzzy factors set

Taking Euclidian distances of target location and orientation angle of two different type of sensor to the factors set, that is fuzzy set $U = \{u_k\} = \{u_1, u_2, \dots, u_n\}$ with $n=2$. Where u_1 is the target location, u_2 is orientation angle, then:

$$\begin{cases} u_1(l) = \left[(x_r(l) - x_a(l))^2 + (y_r(l) - y_a(l))^2 \right]^{1/2} \\ u_2(l) = |\arctan[y_r(l)/x_r(l)] - \arctan[y_a(l)/x_a(l)]| \end{cases} \quad (1)$$

Where $u_1(l)$ is the diameter distance difference of two targets for time l , $u_2(l)$ is the orientation angle difference of two targets for time l , $x_r(l)$ is X location component of sensor 1 for time l , $x_a(l)$ is X location component of sensor 2 for time l , $y_r(l)$ is Y location component of sensor 1 for time l , $y_a(l)$ is Y location component of sensor 2 for time l . The right angle coordinate is used in calculation process.

2) Determination of the fuzzy judgments set

If the associated result of two sensors' data is divided into m Level, the set consisted by these results is called the judgments set, and denoted $V = \{v_l\} = \{v_1, v_2, \dots, v_m\}$, where $v_l, l=1, 2, \dots, m$ is the judgment results of l th level. Any judgment result of two sensors' data is a fuzzy subset of V actually.

We only concern about whether the target data association. Therefore, from the point of view of practical applications and simplifying the process, the judgments set is selected $V = \{v_1, v_2, \dots, v_m\}$ with $m=3$, where v_1

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denotes correlation, v_2 denotes non-correlation, v_3 denotes uncertainty, that is $V = \{\text{correlation, non-correlation, uncertainty}\}$. of course, the judgments set can be easier, that is $V = \{\text{correlation, non-correlation}\}$.

3) Determination of single factor fuzzy judgment matrix

Single factor fuzzy judgment matrix is defined $R = (r_{kl})_{n \times m}$ from U to V in direct product set $U \times V$, where r_{kl} denoted the probability of the l th result of two sensors' data when the k th factor is considered.

According to the characteristics of fuzzy data correlation factors, memberships can be used with normal distribution, Cauchy distribution, middle distribution, etc. The paper selects normal distribution membership function. When $m=2$, the normal distribution membership degree based on the k th factor judgment is:

$$r_{k1} = \exp[-\tau_k(x^2 / \sigma_k^2)]; k=1,2 \quad (2)$$

$$r_{k2} = 1 - \exp[-\tau_k(x^2 / \sigma_k^2)]; k=1,2 \quad (3)$$

Where τ_k is the adjustment coefficient; σ_k^2 is the variance. Therefore, the single factor fuzzy judgment matrix as follows:

$$R = \begin{bmatrix} r_{11} & r_{12} \\ r_{21} & r_{22} \end{bmatrix}$$

4) Criterion of multi-factor fuzzy judgment

The factor weight fuzzy set is $A = (a_1, a_2)$ with $a_1 = 0.7, a_2 = 0.3$ in the paper considering that distance precision is higher than orientation precision of sensor. Factor weight coefficients can be adjusted through a large number of experimental statistics.

Integrated decision of two sensors' data is compound effect of the factor weight fuzzy set A and fuzzy judgment matrix R , which is the composition operation. The fuzzy set B of correlation probability of two sensors' data in V compositing by A and R is following:

$$B = A \cdot R = (b_l) = (b_1, b_2)$$

$b_l (l=1,2)$ is the membership degree of v_l which is an element of judgments set. Composition operation has three kinds of algorithm, which are "weighting average", "subjective factor" and "hybrid". In order to equalize all factors based on weight, "weighting average" is used as follows:

$$b_l = \sum_{k=1}^2 a_k r_{kl}, l=1,2$$

If data correlation probability of two sensors' for level l is judged by the maximum membership degree principle, the result is following:

$$b_l = \max \{b_1, b_2\}$$

However, the reliability is poor by above method. Because so long as the condition is $b_1 > b_2$, the judgment is correlation. The composition operation is simple, but the result is not accurate.

2.2 Evidence theory

D-S evidence theory defined a space Θ which is called frame of discernment. It is composed of mutual exclusive and exhaustive elements. Any proposition A of the problem domain is belonged to powers set 2^Θ . Basic probability assignment function is defined in 2^Θ set: $m: 2^\Theta \rightarrow [0,1]$. m satisfies three conditions, which are:

$$(1) m(\Theta) = 0 ; (2) 0 \leq m(A) \leq 1 ; (3) \sum_{A \subset \Theta} m(A) = 1 \cdot$$

$m(A)$ denotes a true subset which supports proposition A by evidence but not any A . If A is a subset of Θ , and satisfies $m(A) > 0$, it is called focus element of evidence. Interval $[Bel(A), Pl(A)]$ is used to describe event A in evidence theory, where Bel is called belief function and pl is called plausibility function.

D-S evidence theory provides a very useful composition formula. It can compose evidences from multiple evidence sources. The formula is defined as follows (an example for two evidences):

$$m(A) = \frac{1}{1-K} \sum_{A_i \cap B_j = A} M_1(A_i)M_2(B_j) \quad (4)$$

With $k = \sum_{A_i \cap B_j = \Phi} M_1(A_i)M_2(B_j)$. Its value reflects

conflict degree of evidence. The coefficient $1/(1-k)$ is called normalization factor. Its role is to avoid that non-zero probability is assigned to the null set when composing evidences.

3 Improved correlation method based on evidence theory

Frame of discernment for evidence is $\Theta = (\text{correlation, non-correlation, uncertainty})$. The factors set influencing the decision is $U = \{u_1, u_2, \dots, u_n\}$. Supposing that the basic probability of the main two factors influencing data correlation is assigned as following:

$$\begin{aligned} m_1(\text{correlation}) &= 0.6 & m_1(\text{non-correlation}) &= 0.3 \\ m_1(\text{uncertainty}) &= 0.1 \\ m_2(\text{correlation}) &= 0.4 & m_2(\text{non-correlation}) &= 0.5 \\ m_2(\text{uncertainty}) &= 0.1 \end{aligned}$$

The basic probability is obtained by membership degree functions of multi-factor fuzzy integrated decision data association algorithm.

Synthesizing evidence by evidence theory:

Table 1. calculation of evidence synthesis

Assignment m_2	Evidence synthesis calculated values		
	$m_1(\text{correlation})$ 0.6	$m_1(\text{non-correlation})$ 0.3	$m_1(\text{uncertainty})$ 0.1
$m_2(\text{correlation})$ 0.4	0.24	0.12	0.04
$m_2(\text{non-correlation})$ 0.5	0.3	0.15	0.05
$m_2(\text{uncertainty})$ 0.1	0.06	0.03	0.01

$$\begin{aligned} k &= m_1(\text{non-correlation}) \times m_2(\text{correlation}) + \\ & m_1(\text{uncertainty}) \times m_2(\text{correlation}) + m_1(\text{correlation}) \times \\ & m_2(\text{non-correlation}) + m_1(\text{uncertainty}) \times m_2(\text{non-} \end{aligned}$$

$$\text{correlation}) + m_1(\text{correlation}) \times m_2(\text{uncertainty}) + m_1(\text{non-correlation}) \times m_2(\text{uncertainty}) = 0.4$$

Integrated probability after evidence synthesis is assigned:

$$m(\text{correlation}) = 0.6 \quad m(\text{non-correlation}) = 0.375 \\ m(\text{uncertainty}) = 0.025$$

If data correction decision rules are:

Table 2. Data Association guidelines

Decision	Rules
correction	$m(\text{correlation}) > m(\text{non-correlation})$ and $m(\text{correlation}) > m(\text{uncertainty})$
non-correction	$m(\text{non-correlation}) \geq m(\text{correlation})$ and $m(\text{non-correlation}) \geq m(\text{uncertainty})$
Uncertainty	$m(\text{uncertainty}) > m(\text{correlation})$ and $m(\text{uncertainty}) > m(\text{non-correlation})$

By combination rules of evidence, the result is data correction.

4 Simulation analysis

$\Theta = \{A, B, \theta\}$, Initial evidence formed by decision

factor that two weights are 0.7 and 0.3 is:

$$a_1(\text{weight}) = 0.7 \quad m_1(A) = 0.7 \quad m_1(B) = 0.3 \quad m_1(\theta) = 1 - a_1 = 0.3 \\ a_2(\text{weight}) = 0.3 \quad m_2(A) = 0.1 \quad m_2(B) = 0.9 \quad m_2(\theta) = 1 - a_2 = 0.7$$

Evidences are obtained by multi-factor fuzzy integrated decision method. The result using multi-factor fuzzy integrated decision membership degree synthesis data correction algorithm is following

$$\begin{cases} m(A) = a_1 m_1(A) + a_2 m_2(A) = 0.52 \\ m(B) = a_1 m_1(B) + a_2 m_2(B) = 0.48 \\ m(\theta) = m_1(\theta) + m_2(\theta) = 1 \end{cases}$$

After normalization:

$$m(A) = 0.26 \quad m(B) = 0.24 \quad m(\theta) = 0.5$$

The evidences combination result is that

$$\begin{cases} m(A) = m_1 \oplus m_2(A) = 0.23 \\ m(B) = m_1 \oplus m_2(B) = 0.31 \\ m(\theta) = m_1 \oplus m_2(\theta) = 0.46 \end{cases}$$

Data correction algorithm using multi-factor fuzzy integrated decision, although can choose A as the final decision according to new evidences. Obviously, the trust degree difference for A and B is only 0.02, but uncertainty degree is 0.5, that is unreasonable and is not conformity with algorithm rule. Using evidences combination, the trust degree difference for A and B is 0.08, but uncertainty degree reduces to 0.046, and the result is B. Therefore data correction algorithm using evidence theory can reduce uncertainty degree effectively, obtain better reasonable correction result, and reduce error correction rate.

5 Conclusions

Multisource heterogeneous data correction exits high uncertainty degree, but evidence theory can dispose the problem well. It is difficult to obtain evidence, but it is easy to obtain evidences by multi-factor fuzzy integrated decision membership degree function. Therefore, for high uncertainty degree of heterogeneous data correction,

combining evidence theory and multi-factor fuzzy integrated decision can reduce error correction rate and leak correction rate. In addition, evidence theory gets some beneficial progress in disposing evidence conflict, calculation complexity and evidence combination explosion etc. The dependability of evidence theory becomes better in engineering. As a result, it is a useful expand that evidence theory is used to heterogeneous data correction.

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