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Sensor data association using relative positions among targets and bias estimation between separate sensors

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Abstract: Sensor data association is an important problem in modern multi-sensor systems. The purpose to solve this problem is to decide which measurements from the different sensors belong to the same target. The traditional methods for data association usually form the association matrix and find the optimal solution in different ways. These solutions are, however, sensitive to the characteristics of the sensors. A novel method which uses the relative positions among the targets and extracts the relative positions pattern to compare and search for the matching pairs between the separate sensor systems is proposed. An improved algorithm which is suitable for sensor data association using relative positions is also presented. The sensor bias has little influence upon this association algorithm due to the inherent characteristics of the relative positions. Simulation results show that association using relative positions is robust against sensor bias and has an overall improvement.

Key words: sensor network; data association; sensor fusion; bias estimation

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基于目标相对位置的多传感器数据关联及传感器偏差估计

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摘要：多传感器数据关联是现代多传感器系统中的一个重要问题.多传感器数据关联即是确定不同传感器系统观测到的若干测量信号是否来源于同一个目标.传统的数据关联方法通过形成关联矩阵，来求取关联矩阵的最优解，但是容易受到传感器性能的影响.为了降低传感器性能对关联结果的影响，提出了一种新的通过采用比较传感器测量信号之间的相对位置并提取相对位置模式的方法来获得不同传感器系统对应的目标匹配对的方法，并给出了一种改进的适用于传感器目标信号关联的匹配算法.这种方法充分利用了测量信号之间相对位置的内在特性.仿真结果表明传感器偏差对于采用相对位置进行数据关联的方法基本没有影响，并

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且这种方法整体性能上有所提升.

关键词:传感器网络;数据关联;传感器融合;偏差估计

0 Introduction

Multi-sensor data association is a fundamental problem in modern multi-sensor fusion systems[1]. The advantage of fusing information from separate sensor systems is that the systems can achieve better performance than traditional single-sensor systems. The multi-sensor systems can provide more accurate and more comprehensive information by using the redundancy of separate sensors[2]. Data association is to decide which of the measurements from these sensors belong to the same target. The association problem is usually complicated by a lot of problems such as sensor bias, random errors, false alarms and misdetections[3].

Associating sets of observations from different sensor systems is common in the multi-sensor data association problem. The traditional methods to solve the problem of data association consist of several steps[3]. First, valid estimation of the bias, which usually results from sensor coordinate deviation or registration bias between the sensor systems, is needed and this bias needs to be removed in order to eliminate the impact. Then, an assignment matrix based upon the statistical distances among different targets is formed. After that, several algorithms for solving this assignment matrix need to be proposed to minimize assignment cost as an optimal problem. This problem is usually considered as global nearest neighbor GNN problem[4], and many mathematical methods, such as auction algorithm and JVC algorithm, can solve this optimal problem successfully.

Blackman provides many effective methods to solve the sensor data association problem meaningfully[3]. These traditional methods are usually sensitive to sensor bias, random errors, false alarms and misdetections. Stone proposes a heuristic algorithm for data association[5]. Although the algorithm in Ref. [5] is practical since the relative bias estimation method is not based on any association hypothesis, it still requires effective bias estimation before association. Levedahl poses the assignment problem as global nearest pattern (GNP) using a cost function in the presence of bias and random errors, false alarms and misdetections conditions, and compute the maximum likelihood with the bias estimation for every possible association hypothesis[6]. In this way, the relevant parameters of the sensors are successfully introduced into association process but as the number of targets increases, the algorithm complexity grows rapidly. In Ref. [7], Papageorgiou proposes a solution for optimizing the computation complexity and a fast algorithm for GNP. In Ref. [8], Ferry computes the association probability with a prior distribution of sensor bias. However, we cannot get the prior distribution of the sensor bias in reality. In Ref. [9], Shi et al. use the "Fuzzy reference topology" as the target feature in polar coordinates and define a likelihood function between two topologies with three different kinds of sensor biases. In Ref. [10], Du et al. further study the "Fuzzy reference topology" algorithm and propose a fast method for solving this algorithm. This method improves the performance of data association, but is easily affected by the misdetections of the targets and the time complexity of the algorithm is still relatively high.

In this paper, we propose a novel method which takes relative positions among the targets and extracts the relative position pattern to compare and find the matching pairs between the separate sensor systems, instead of using absolute positions to search for the matching pairs. An improved algorithm which is suitable for this method is also presented. By comparing the relative positions and finding the maximum number of possible matching pairs, one matching pair can be found and the relative bias can be estimated. Then through finding other matching pairs by mapping the targets from one sensor to the other sensor using the relative bias, all matching pairs can be obtained and more accurate relative bias between the sensors can be estimated. Computer simulation shows that the algorithm using relative positions is robust against sensor bias errors and has better performance than traditional approaches.

1 Problem formulation

In this section we present the sensor bias model and the definition of association problem, then show the traditional approach to the association problem.

1.1 Sensor bias model

Assume that two separate sensor systems, A and B, observe N objects in the observation space. A detects m of the targets and B detects n of the targets. Each sensor system may also detect some noise clutters due to the false alarm which actually do not exist in observation field and these clutters can affect the association result. The observation space is converted to the two-dimensional Cartesian coordinates. The purpose of sensor data association is to identify the pairs sharing the same origin target, but due to the impact of sensor bias, random noise, misdetections or false alarm, this association problem is difficult. Eliminating these effects has a critical influence on the data association result.

In this frame, each target detected by separate sensor systems can be modeled by Ref.[6]:

$$A_i = \overline{X}_i + G(P) + \bar{x}_A;\ i = 1, \cdots, m,$$

$$B_j = \overline{X}_j + G(Q) + \bar{x}_B;\ j = 1, \cdots, n,$$

where:

A_i location of i_{th} observation from sensor A

B_j location of j_{th} observation from sensor B

$\overline{X}_{i,j}$ actual locations of the targets

$G(v)$ Gaussian noise (mean 0 and covariance matrix v)

P covariance matrices for Gaussian noise in sensor A

Q covariance matrices for Gaussian noise in sensor B

$\bar{x}_A$ bias vector in sensor A

$\bar{x}_B$ bias vector in sensor B

The target states are described by state vectors A_i and B_j, and the measurement noise in separate sensor systems is described as the zero-mean Gaussian vectors with covariance matrix P and Q. Though the sensor bias of each sensor is actually changing slowly, the bias can be considered as a constant vector at the association time. The association problem is to determine the matching pairs of target observations in sensors A and B. The requirement is that all association matching pairs are unique. In other words each target observed by A maps either 0 or 1 target in B.

1.2 Definition of association

Consider two sets $\{\alpha_i\}_{i=1}^m$, $\{\beta_j\}_{j=1}^n$. The expression $\{\alpha_i\}_{i=1}^m$ represents the m targets observed by sensor A, $\{\beta_j\}_{j=1}^n$ represents the n targets observed by sensor B. Define an association hypothesis as an injective function on a subset Dom (α) of $\{\alpha_1, \alpha_2, \cdots, \alpha_m\}$ taking values in $\{\beta_1, \beta_2, \cdots, \beta_n\}$. The expression $j = \alpha(i)$ means that the i_{th} target in sensor A maps the target j_{th} in sensor B while they share the same target source. The expression $i \notin \mathrm{Dom}(\alpha)$ means that i_{th} target from sensor A has no matching pair from sensor B, while $j \notin \mathrm{Im}(\alpha)$ means that j_{th} target from sensor B has no matching pair from sensor A. This situation implies that the target may be a clutter noise or a target which is detected only by one sensor system.

1.3 Traditional approach to the association problem

The traditional approach to the sensor association problem uses the following steps to achieve sensor association[3]. First, the method estimates and corrects the bias, and an association matrix is formed by calculating the statistical distances among the targets. The second step solves the optimal assignment of the association matrix which is usually called global nearest neighbor GNN problem[4]. Some mathematical methods can be used to solve this assignment problem such as auction or JVC algorithms which are used to minimize the assignment cost. Then the corresponding targets from the different sensors can achieve the final association.

2 Data association using relative positions

In this section, we use the relative positions rather than the absolute positions among the targets for association. In the following, we can see that association using relative positions is robust against sensor bias since the bias has little impact during the association process. The complete algorithm using this method is represented and some important issues are also discussed.

Sensor bias correction is required in multiple sensor systems[3]. For the sensor data association problem, it is not meaningful to estimate the bias for individual sensors, but the estimation of the relative bias between the separate sensors is needed[5]. As the traditional approaches use the statistical distances among the targets to measure the similarity between the targets, the relative bias affects the performance of the traditional data association approaches significantly.

2.1 Relative Positions among targets

Assume that there are m targets observed by sensor system A and n targets observed by sensor system B.

Assume that two targets i and j observed by sensor A and their states can be defined as:

$$\mathbf{X}_{Ai} = \mathbf{X}_i + \mathbf{B}_A + \boldsymbol{v}_A,$$
$$\mathbf{X}_{Aj} = \mathbf{X}_j + \mathbf{B}_A + \boldsymbol{v}_A,$$

where $\mathbf{X}_{Ai}=[x_{Ai}, y_{Ai}]^T$ is the measurement state of target i, $\mathbf{X}_{Aj}=[x_{Aj}, y_{Aj}]^T$ is the measurement state of target j. Vector $\mathbf{X}_i=[x_i, y_i]^T$ is the actual state of target i while vector $\mathbf{X}_j=[x_j, y_j]^T$ is the actual state of target j. Vector $\mathbf{B}_A=[b_{Ax}, b_{Ay}]^T$ is the bias of sensor A at the association time and $\boldsymbol{v}_A$ is the Gaussian measurement noise of sensor A with mean 0 and covariance matrix $\begin{bmatrix}\sigma_1^2 & 0\\ 0 & \sigma_1^2\end{bmatrix}$.

Then:

$$\mathbf{X}_{Aij} = \mathbf{X}_{Aj} - \mathbf{X}_{Ai} = \mathbf{X}_j - \mathbf{X}_i + \boldsymbol{v}'_A = \mathbf{X}_{ij} + \boldsymbol{v}'_A.$$

From the equation above, the relative distance between the targets i and j observed by sensor A is determined by $\mathbf{X}_{ij}$ and noise $\boldsymbol{v}'_A$. The noise $\boldsymbol{v}'_A$ is a two-dimensional Gaussian noise with mean 0 and covariance matrix $\begin{bmatrix}2\sigma_1^2 & 0\\ 0 & 2\sigma_1^2\end{bmatrix}$.

For sensor B, assume that the same targets i and j are also observed by sensor B, and their measurement states can be expressed as follows:

$$\mathbf{X}_{Bi} = \mathbf{X}_i + \mathbf{B}_B + \boldsymbol{v}_B,$$
$$\mathbf{X}_{Bj} = \mathbf{X}_j + \mathbf{B}_B + \boldsymbol{v}_B,$$

where vector $\mathbf{B}_B=[b_{Bx}, b_{By}]^T$ is the bias of sensor B at the association time and $\boldsymbol{v}_B$ is the Gaussian measurement noise of sensor B with mean 0 and covariance matrix $\begin{bmatrix}\sigma_2^2 & 0\\ 0 & \sigma_2^2\end{bmatrix}$.

Then:

$$\mathbf{X}_{Bij} = \mathbf{X}_{Bj} - \mathbf{X}_{Bi} = \mathbf{X}_j - \mathbf{X}_i + \boldsymbol{v}'_B = \mathbf{X}_{ij} + \boldsymbol{v}'_B.$$

From the equation above, the relative distance between the same targets i and j observed by sensor B is determined by true distance $\mathbf{X}_{ij}$ and noise $\boldsymbol{v}'_B$. The noise $\boldsymbol{v}'_B$ is a two-dimensional Gaussian noise with mean 0 and covariance matrix $\begin{bmatrix}2\sigma_2^2 & 0\\ 0 & 2\sigma_2^2\end{bmatrix}$.

Compare the relative distances $\mathbf{X}_{Bij}$ and $\mathbf{X}_{Aij}$, and their differences can be calculated as:

$$\mathbf{X}_{Bij} - \mathbf{X}_{Aij} = \boldsymbol{v}'_B - \boldsymbol{v}'_A = \boldsymbol{v}''.$$

From the equation above, the difference between the relative distances of the separate sensor systems meets the Gaussian distribution with mean 0 and covariance matrix $\begin{bmatrix}2\sigma_1^2+2\sigma_2^2 & 0\\ 0 & 2\sigma_1^2+2\sigma_2^2\end{bmatrix}$.

It can be observed through the analysis above that the sensor bias has little impact on the association results by comparing the relative distances among the targets to find matching pairs.

2.2 Relative position between sensors

Assume that the target i observed by sensor A maps the target a observed by sensor B. Then the measurement states of target i and a can be expressed as:

$$\mathbf{X}_{Ai} = \mathbf{X}_i + \mathbf{B}_A + \boldsymbol{v}_A,$$
$$\mathbf{X}_{Ba} = \mathbf{X}_a + \mathbf{B}_B + \boldsymbol{v}_B.$$

Then:

$$\mathbf{X}_{ia} = \mathbf{X}_{Ba} - \mathbf{X}_{Ai} = \mathbf{B}_B - \mathbf{B}_A + \boldsymbol{v}_B - \boldsymbol{v}_A = \mathbf{R}_b + \boldsymbol{v}'''.$$

The vector $\mathbf{R}_b$ is defined as the relative bias between sensors A and B. The residual noise between the targets in sensors A and B is vector $\boldsymbol{v}'''$ which is a two-dimensional Gaussian distribution variable with mean 0 and covariance matrix $\begin{bmatrix} \sigma_1^2+\sigma_2^2 & 0 \\ 0 & \sigma_1^2+\sigma_2^2 \end{bmatrix}$. The relative bias $\mathbf{R}_b = \mathbf{B}_B - \mathbf{B}_A$ between sensors A and B usually needs to be estimated for further processing.

2.3 The complete algorithm for data association using relative positions

The purpose for data association is to map the targets of sensor A to the targets of sensor B. In the area of pattern recognition and intelligent computing, the problem of searching for optimal matching pairs between two point patterns is regarded as point pattern matching, and there are many effective ways to solve this problem. In Ref. [11], Shih-Hsu Chang proposes an effective matching algorithm for fingerprint identification and the algorithm can handle translation, rotation, and scaling differences under noisy or distorted condition, but this method is not very applicable to the sensor data association problem.

Here we propose an improved algorithm which is suitable for the problem of sensor data association and provide a method for calculating parameters in this algorithm. In order to find all the matching pairs, we try to find the maximum number of matching pairs between sensors A and B. In the following steps, we first find one matching pair and estimate the relative bias between the sensors, and then we use this bias estimation to find the other matching pairs.

Assume the sensor system A observes m targets while the sensor system B observes n targets. First we select one target named target i from sensor A and select one target named target a from sensor B. The pairs are thought to be the matching pairs now although they may not be so in fact. Then we can calculate the relative distances between target i and the other $m-1$ targets j in sensor A. For sensor B, we also calculate the relative distances between target a and the other $n-1$ targets b. If the relative distance difference $\| A_{ij} - B_{ab} \| \leqslant \triangle_1$, the targets j and b may be matching pairs. A new matrix CntNum_{ia} is defined here to accumulate the number of matching pairs j and b. Through an iterative progress, the max value $\mathrm{MaxCntNum}_{ia}$ in matrix CntNum_{ia} can be searched. As the matching pairs between sensors A and B are one-to-one mapping pairs, so the maximum number of matching pairs is not greater than $\min\{m, n\}$. The number of matching pairs Matchingpair is defined here and its initial value $\mathrm{Matchingpair}=\min\{m,n\}$. We assume $m \leqslant n$ here. If $\mathrm{MaxCntNum}_{ia} = m-1$, the number of matching pairs between sensors A and B is $m-1$. Then the first matching pair is found. If $\mathrm{MaxCntNum}_{ia} < m-1$, it means that the maximum number of matching pairs is less than $m-1$. So decrease the number of matching pairs and continue iterating.

Then we start to repeat the above process for the other targets observed by sensor A from 1 to m. For $i=c$, if the max value in matrix CntNum_{ia} is less than $m-c$, it means that the number of matching pairs is not greater than $m-c$, so decrease the number of matching pairs and continue iterating. If the max value $\mathrm{MaxCntNum}_{ia} \geqslant m-c$ in matrix $\mathrm{MaxCntNum}_{ia}$, it means that the maximum number of pairs is found, and the first matching pair is found.

After we find the first matching pair and a rough bias estimation, we can find the other matching pairs using the next step.

In the previous step, we have found the first matching pair while the correspondence among other points is still unknown. By adding the relative bias estimation in the previous step, all the targets j in sensor A can be mapped to the target b' in sensor B. If A_j and B_b are matching pairs, then the target b' would be close to the target b in sensor B. By comparing $\|\text{map}(A_j)-B_b\| \leqslant \triangle_2$, some targets closed to map(A_j) can be found while the number of these targets is not necessarily equal to 1. Select the matching pair in which there is only one target in sensor B inside the threshold. Now we can find some matching pairs. Using these matching pairs, we can get more accurate bias estimation. By using this new bias estimation, the remaining targets can be mapped to sensor B and the closest target surrounding the map(A_j) can be thought to be the matching pairs. Until now, all the matching pairs have been found and the most accurate bias estimation can be calculated here which can be used for filtering and state estimation. The algorithm flow chart is showed in Fig. 1.

2.4 Determine $\triangle_1$, $\triangle_2$

In the process above, we use $\triangle_1$ to compare the relative distances between A_{ij} and B_{ij}, from the above analysis:

$$\mathbf{X}_{Bij} - \mathbf{X}_{Aij} = \boldsymbol{v}'_B - \boldsymbol{v}'_A = \boldsymbol{v}''.$$

The difference between the relative distances is vector $\boldsymbol{v}''$ which is a two-dimensional Gaussian

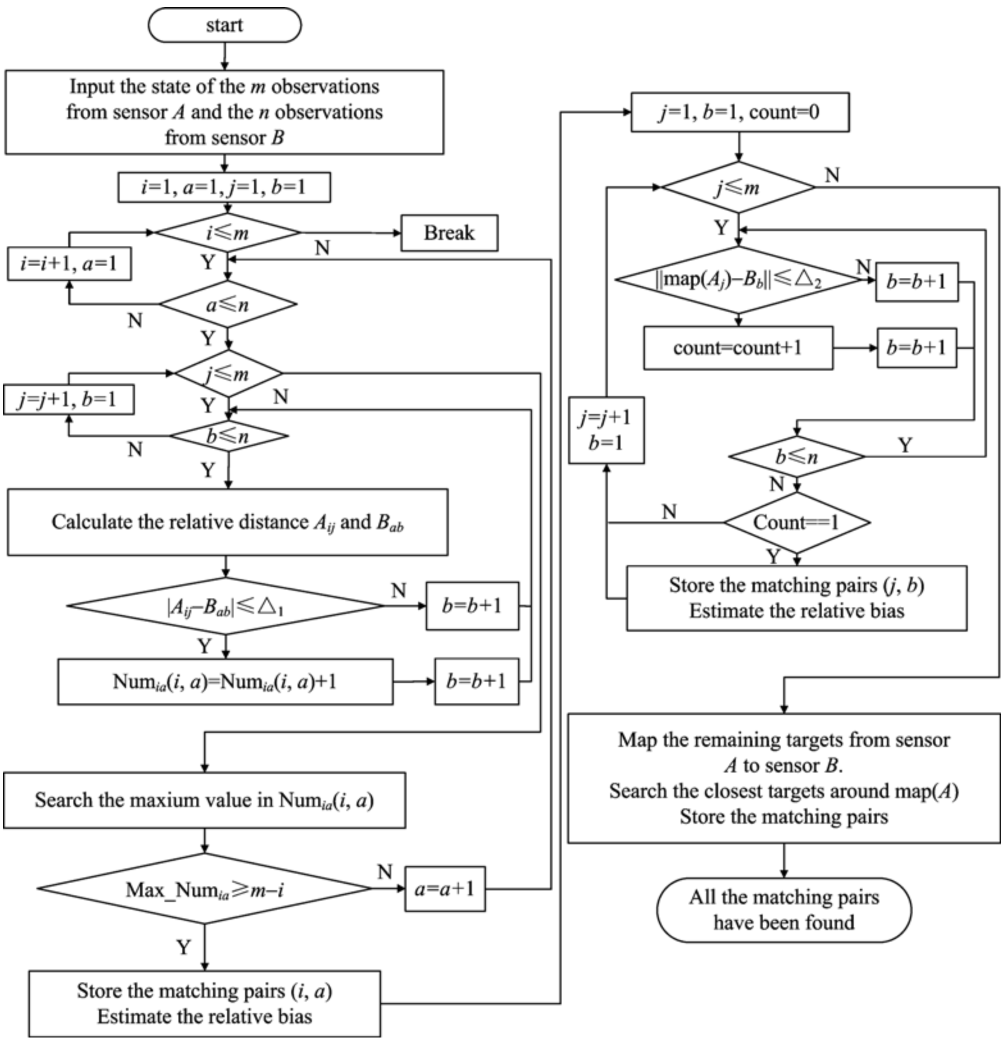

Fig. 1　The algorithm flow chart for sensor data association using relative positions

noise vector with mean 0 and covariance matrix $\begin{bmatrix} 2\sigma_1^2+2\sigma_2^2 & 0 \\ 0 & 2\sigma_1^2+2\sigma_2^2 \end{bmatrix}$. So due to the principle of $3-\sigma$ for Gaussian distribution, select $\triangle_1$ as $3\sqrt{2\sigma_1^2+2\sigma_2^2}$.

In order to find the rest of the matching pairs in step 2, we use the $\triangle_2$ to find the targets in sensor B around the mapping point in sensor A, from the above analysis:

$$\mathbf{X}_{ia} = \mathbf{X}_{Ba} - \mathbf{X}_{Ai} = \boldsymbol{B}_B - \boldsymbol{B}_A + \boldsymbol{v}_B - \boldsymbol{v}_A = \mathbf{R}_b + \boldsymbol{v}'''.$$

The residual noise between the targets in sensors A and B is the vector $\boldsymbol{v}'''$ which is a two-dimensional Gaussian distribution variable with mean 0 and covariance matrix $\begin{bmatrix} \sigma_1^2+\sigma_2^2 & 0 \\ 0 & \sigma_1^2+\sigma_2^2 \end{bmatrix}$. So due to the principle of $3-\sigma$ for Gaussian distribution, select $\triangle_2$ as $3\sqrt{\sigma_1^2+\sigma_2^2}$.

2.5 Relative bias estimation

Relative Bias Estimation is a fundamental problem in this algorithm. The relative bias is used to decide the matching pairs when one matching pair is found. It can also be used in the ensuing steps. An effective method for relative bias estimation is given here by using the method of least squares estimation[12]. As mentioned above, the measurement bias between the points in one matching pair (i, a) can be expressed as follows:

$$\mathbf{X}_{ia} = \mathbf{X}_{Ba} - \mathbf{X}_{Ai} = \mathbf{R}_b + \boldsymbol{v}'''.$$

Assume that there are n matching pairs, the measurement bias between these n matching pairs is:

$$\mathbf{X}_{AB} = H \times \mathbf{R}_b + \boldsymbol{v}_{(2n\times 1)},$$

where $\mathbf{X}_{AB} = [x_{(B1-A1)}, y_{(B1-A1)}, x_{(B2-A2)}, y_{(B2-A2)}, \cdots, x_{(Bn-An)}, y_{(Bn-An)}]^{\mathrm{T}}_{(2n\times 1)}$ means the relative distance vector between these n matching pairs, and $H = \begin{bmatrix} 1 & 0 & 1 & 0 & \cdots & 1 & 0 \\ 0 & 1 & 0 & 1 & \cdots & 0 & 1 \end{bmatrix}^{\mathrm{T}}_{(2\times 2n)}$, and $\boldsymbol{v}_{(2n\times 1)}$ is the noise vector. The expression $\mathbf{R}_b$ is the relative bias between the sensors which needs to be estimated.

The method of least squares estimation is to minimize the value[12]:

$$\varepsilon(\hat{R}) = [\mathbf{X}_{AB} - H \times \hat{R}_b]^{\mathrm{T}}[\mathbf{X}_{AB} - H \times \hat{R}_b].$$

Then take the vector $\varepsilon(\hat{R})$ partial derivatives and set it to zero:

$$\frac{\partial}{\partial \hat{R}_b}\bigg|_{\hat{R}_b=\hat{R}_{bls}} = \frac{\partial}{\partial \hat{R}_b}[\mathbf{X}_{AB} - H \times \hat{R}_b]^{\mathrm{T}}[\mathbf{X}_{AB} - H \times \hat{R}_b] = 0.$$

We obtain the following result for $\hat{R}_{bls}$:

$$\hat{R}_{bls} = (H^{\mathrm{T}} H)^{-1} H^{\mathrm{T}} \mathbf{X}_{AB}.$$

3 Simulation result

In this section, several experiments are used to explore the performance of this algorithm. The Monte Carlo experiment is used to evaluate this algorithm. Here we compare three algorithms: the novel algorithm "relative position data association" (RPDA), the "fuzzy reference topology data association" (FRTDA) using its improved fast algorithm[9-10] and the traditional association approach "GNN" (TGNN)[4]. All the experiment results are verified through the Monte Carlo experiment for 5 000 times.

3.1 Target scenario

All experiments assume a two-dimensional case in a 10 km×10 km square. There are a total 8 targets which are randomly dispersed in the field. Sensor systems A and B are considered. Sensor system A is located in the position [0, 0] and sensor system B is located in the position [6, 0]. The detection probability for both sensor systems A and B is set to 0.99. The false alarm probability is also considered here and it is set to 0.1 for both sensor systems. The measurement random noise is independent and uncorrelated zero-mean Gaussian noise distributed with variances $\sigma_1^2 = 0.01\ \mathrm{km}^2$, and $\sigma_2^2 = 0.02\ \mathrm{km}^2$, respectively. The simulation scenario is similar to real situation.

3.2 Association success ratio for algorithm RPDA

Tab. 1 shows the association success ratio of the novel "Relative Position Data Association" (RPDA) in ten times of the experiments.

Tab. 1　Association success ratio for association using relative positions RPDA (ten times of the experiments)

1	2	3	4	5
0.987 7	0.989 1	0.990 5	0.991 2	0.987 4
6	7	8	9	10
0.988 5	0.990 3	0.989 2	0.988 9	0.989 6

3.3　Association success ratio along with the increase of relative bias

Fig. 2 shows the association success ratio along with the increase in relative bias. The relative bias between the sensor systems grows from 0 to 2 km. Other conditions are consistent with section 3.1. From the figure, the increase in relative sensor bias has little effect on the correct ratio of RPDA and FRTDA. On the contrary, the correct ratio of association using TGNN decreases with the increase of relative sensor bias obviously. To a certain extent, association success ratio of the novel algorithm RPDA is higher than the algorithm FRTDA.

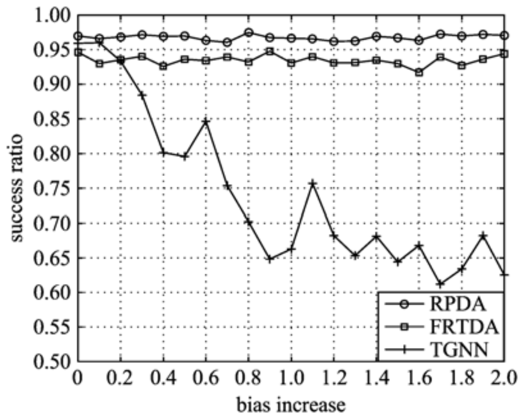

Fig. 2　Association success ratio along with the increase in relative bias

3.4　Association success ratio along with the increase of the number of targets

Fig. 3 shows the association success ratio along with the increase in the number of targets. The total number of the targets in this section increases from 8 to 15. Other conditions are consistent with section 3.1. As can be seen from the figure, the algorithm RPDA has a higher performance compared with the other two algorithms.

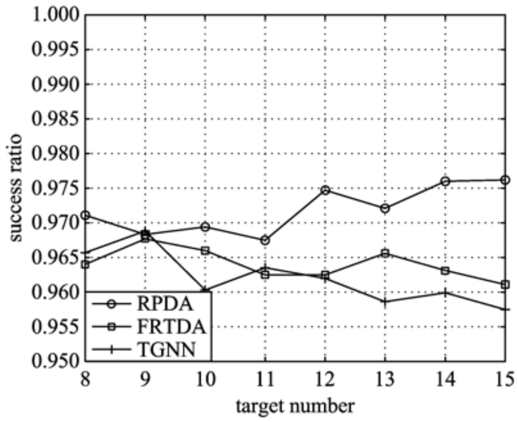

Fig. 3　Association success ratio along with the increase in the number of targets

3.5　Association success ratio along with the increase in sensor probability of detection

Fig. 4 shows the association success ratio along with the increase in the probability of detection of the sensors. The detection probability of the sensors increases from 0.85 to 1. Other conditions are consistent with section 4.1. The association success ratio of the three algorithms all increases with the increase of detection probability. As shown in the figure, the algorithm RPDA has a higher accuracy than the other two algorithms when the detection probability of the sensor increases. The performance of the algorithm FRTDA has no advantage due to its sensitivity to misdetections.

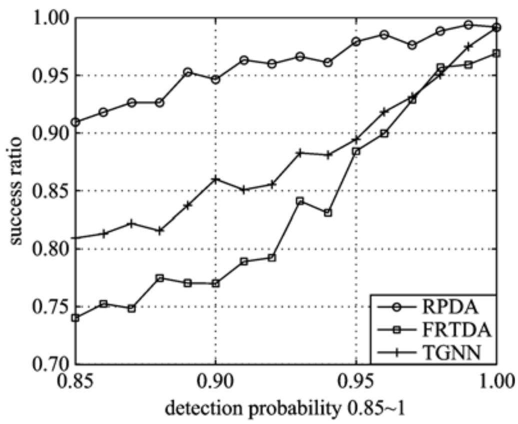

Fig. 4　Association success ratio along with the increase in sensor probability of detection

3.6 Association success ratio along with the increase in the sensor random noise

The Fig. 5 shows the association success ratio along with the increase in the sensor random noise. The random noise variances of the sensors increase from 0 to 0.05. Other conditions are consistent with section 4.1. From the experiment, the random noise has certain influence on the association method RPDA, but when the measurement noise is not very large, the success ratio for association method RPDA nearly stays the same compared with the other methods.

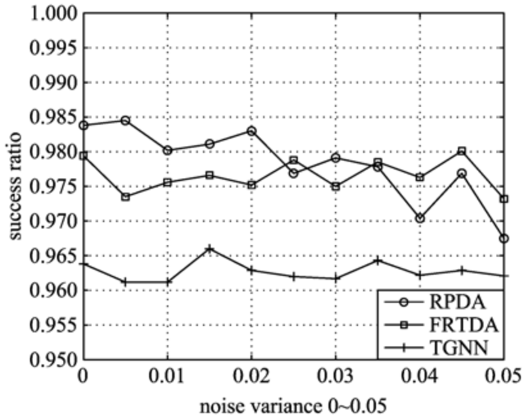

Fig. 5 Association success ratio along with the increase in the sensor random noise

4 Conclusion

The traditional method GNN has been proved to be an effective way for sensor data association, but the performance will gradually decline because of the influence of the sensor bias. In this paper, the method using the relative positions is introduced to achieve a better association result. By using the relative positions among the targets for sensor data association, the bias between the sensors has little effect on the performance of data association, and the simulation experiments show that the method using relative positions has an overall improvement. Some problems still remain to be solved. When the number of targets detected by the sensors is less than two, this method cannot be used as there is only one relative distance between the two targets. Some adaptive methods for the determination of the thresholds still need to be discussed.

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