# 分布式多传感器多目标跟踪方法综述(中文/English)

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**摘要**：多传感器多目标跟踪是信息融合领域的热点问题，其通过融合多个局部传感器数据，提高目标跟踪精度和稳定性。多传感器多目标跟踪按融合体系可分为分布式、集中式、混合式3类，其中分布式融合结构对网络通信带宽要求低、可靠性和稳定性强，广泛应用于军事、民用领域。该文聚焦分布式多传感器多目标跟踪涉及的目标跟踪、传感器配准、航迹关联、数据融合4项关键技术，主要分析了各关键技术的理论原理与适用条件，重点介绍了不完整测量条件下的空间配准与航迹关联，并给出仿真结果。最后，该文总结了现有分布式多传感器多目标跟踪关键技术存在的问题，并指出了其未来发展趋势。

**关键词**：分布式多传感器多目标跟踪；目标跟踪；传感器配准；航迹关联；数据融合

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# Review of the Method for Distributed Multi-sensor Multi-target Tracking (in English)

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**Abstract**: Multi-sensor multi-target tracking is a popular topic in the field of information fusion. It improves the accuracy and stability of target tracking by fusing multiple local sensor information. By the fusion system, the multi-sensor multi-target tracking is grouped into distributed fusion, centralized fusion, and hybrid fusion. Distributed fusion is widely applied in the military and civilian fields with the advantages of strong reliability, high stability, and low requirements on network communication bandwidth. Key techniques of distributed multi-sensor multi-target tracking include multi-target tracking, sensor registration, track-to-track association, and data fusion. This paper reviews the theoretical basis and applicable conditions of these key techniques, highlights the incomplete measurement spatial registration algorithm and track association algorithm, and provides the simulation results. Finally, the weaknesses of the key techniques of distributed multi-sensor multi-target tracking are summarized, and the future development trends of these key techniques are surveyed.

**Key words**: Distributed Multi-sensor Multi-target Tracking (DMMT); Multi-target tracking; Sensor registration; Track-to-track association; Data fusion

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## 1 引言

大数据时代，随着传感器监测场景越加复杂，单传感器监测系统已经不能满足人们的要求。为了解决复杂场景下的多目标跟踪问题，将单传感器多目标跟踪扩展为多传感器多目标跟踪势在必行。多传感器目标跟踪系统采用信息融合方式实现对目标的有效跟踪，是一种多传感器信息融合系统。作为现代传感器系统的核心关键技术，多传感器目标跟踪与信息融合技术在军事指挥和工业控制中已得到广泛应用[1,2]。在军事领域，目标跟踪与信息融合广泛应用于天地一体化组网探测。其中，由蜂群无人机、无人车、无人船等构成的立体组网跟踪系统能对隐身目标进行有效探测。目前，美国、欧洲、俄罗斯等国已经拥有多个军用组网跟踪系统，如美国的多平台多传感器目标跟踪处理系统INCA[3]，北约的指挥控制信息系统NATOCCIS[4]，俄罗斯的贝加尔战术系统BANKAA等[5]。近年来，我国也在加快战略防御系统的研究，将目标跟踪与信息融合列为国防科技的重点项目。在工业领域，目标跟踪与信息融合也广泛应用于自动驾驶、气象监控、生物医学等[6–9]。因此，目标跟踪与信息融合是有效、可靠、实用的信息处理工具，推动了社会的发展与进步[10,11]。

多传感器目标跟踪技术又称多传感器融合技术，其按体系结构可分为集中式、分布式和混合式3类[12–14]。其中，集中式信息融合系统是将各传感器获取的原始量测信息送入中央处理器进行时空配准、数据关联、跟踪等处理，这种融合方式信息量损失小、数据融合精度高，能达到最优意义上的融合[15–23]。但是集中式融合对数据质量要求较高，需要较大通信带宽，会加重融合中心负担，导致数据处理实时性差。分布式信息融合系统的每个传感器都有各自的数据处理中心，可以独自对获得的量测数据进行处理。各局部传感器将处理压缩后的数据送入融合中心，并在融合中心进行组合与推理，最终实现信息融合。与集中式融合相比，分布式融合对信道容量要求低、容错性强、易于扩展[24–27]。混合式信息融合模型要求各传感器向融合中心同时发送原始的量测和经过处理后形成的局部目标航迹，兼顾了集中式和分布式的优点，但混合式融合方式的结构比前两种融合方式复杂，增加了通信和计算上的代价[28–30]。由于分布式融合结构简单、易于实现且应用广泛，因此本文主要对分布式多传感器多目标跟踪(Distributed Multi-sensor Multi-target Tracking, DMMT)体系中的目标跟踪、传感器配准、航迹关联、数据融合等关键技术及其相互关系进行归纳总结。整体框架如图1所示，图中的数据融合仅代表信息融合的最终阶段。

客观上讲，信息技术、网络技术等领域的突破推动了分布式多传感器多目标跟踪技术的发展，从相关研究的兴起到今天，该技术始终是国内外研究人员的重点研究课题，相关成果不断涌现。但是分布式多传感器多目标跟踪是一个庞大的体系架构，其包含诸多关键技术且比较分散，大量研究往往基于某种特定场景或针对特定关键技术展开，缺乏较为系统的梳理与总结。本文总结了国内外相关研究机构和院校在分布式多传感器多目标跟踪关键技术领域的研究进展，同时结合仿真实验，分析了典型空间配准技术与航迹关联技术的理论原理与应用条件；归纳了现有关键技术中存在的不足，并指出其未来发展趋势，为该领域今后的研究课题提供一定参考。

## 2 目标跟踪技术研究进展

目标跟踪作为多源信息融合的重要研究内容，是实现传感器组网探测的重要途径。目标跟踪的本质是利用各传感器获得的带噪声量测数据，对目标的状态和个数进行估计的过程。本节主要对单传感器目标跟踪涉及的理论原理与研究方法进行详细总结。

### 2.1 贝叶斯滤波原理

分布式传感器通过目标跟踪产生各自的目标航迹。目标跟踪按目标探测个数分为单目标跟踪和多目标跟踪，它们都基于贝叶斯框架进行递归滤波。贝叶斯递归建立在目标的状态模型和观测模型基础上，且主要包括预测和更新两个步骤[31]。

在贝叶斯递推的预测步骤中，利用状态转移概率密度$f_{k|k-1}(x_k|x_{k-1})$对上一时刻的后验概率密度函数$f_{k-1|k-1}(x_{k-1}|Z_{k-1})$递推，获得目标状态的先验概率密度函数$f_{k|k-1}(x_k|Z_{k-1})$。在更新步骤中，通过引入当前时刻的测量值$z_k$，对目标状态的先验概率密度进行更新，从而得到后验概率密度函数$f_{k|k}(x_k|Z_k)$。后验概率密度函数$f_{k|k}(x_k|Z_k)$封装了

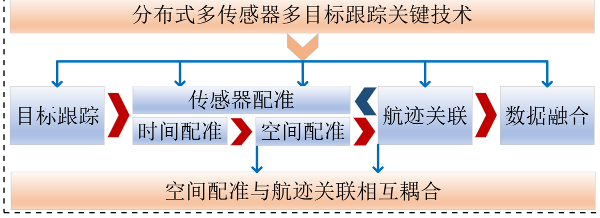



图 1 分布式多传感器多目标跟踪流程图

Fig. 1 Flowchart of distributed multi-sensor multi-target tracking

目标状态$x_k$的所有信息，同时包含了量测集合$Z_k$及状态先验分布的信息。该时刻的状态可利用最小均方差估计(Minimum Mean Squared Error, MMSE)或最大后验估计(Maximum A Posteriori, MAP)得到[1]。贝叶斯滤波适用于线性和非线性系统，线性系统状态的最小均方误差估计可由卡尔曼滤波方程给出。对于非线性系统，由于后验概率密度函数$f_{k|k}(x_k|Z_k)$的闭式解非常困难，所以产生了许多非线性系统次优滤波算法，如扩展卡尔曼滤波(Extended Kalman Filter, EKF)[32]、无迹卡尔曼滤波(Unscented Kalman Filter, UKF)[33]、容积卡尔曼滤波(Cubature Kalman filter, CKF)[34]、粒子滤波(Particle Filter, PF)等[35]。

### 2.2 单传感器目标跟踪方法

单目标跟踪场景下，目标测量数据比较简单，使用常见的单目标滤波算法就能解决其问题。相较于单目标跟踪，多目标跟踪方法更加复杂，一般分为数据关联类多目标跟踪方法和随机有限集类多目标跟踪方法。

数据关联类多目标跟踪方法最初是Sittler在20世纪60年代提出，主要用于建立量测与目标的对应关系，此后Bar-Shalom等人[36,37]将数据关联和卡尔曼滤波相结合，加快了多目标跟踪技术的发展。具有代表意义的关联类跟踪算法有联合概率数据关联(Joint Probability Data Association, JPDA)算法[38–40]、联合综合概率数据关联(Joint Integrated Probability Data Association, JIPDA)算法[41]、最近邻数据关联(Nearest Neighbor, NN)算法[42,43]、多假设跟踪(Multiple Hypothesis Tracking, MHT)算法等[44,45]，这些算法在面对多目标跟踪任务时，通过数据关联，将多目标跟踪问题转化为单目标跟踪进行解决。

1994年，Mahler等人利用有限集统计学(Finite Set Statistics, FISST)提出了处理多目标跟踪问题的最优多传感器多目标贝叶斯滤波器，在不进行数据关联的条件下，完成对目标状态的估计。由于采用随机有限集进行贝叶斯递归时会涉及复杂积分运算而无法用于工程实践，为了解决这一问题，Mahler[46,47]提出了概率假设密度(Probability Hypothesis Density, PHD)滤波器。由于PHD只传递一阶矩，不能对多目标的数目进行有效估计，之后Mahler[47]又提出了势均衡概率假设密度(Cardinalized Probability Hypothesis Density, CPHD)滤波器，该滤波器不仅传递后验概率密度的一阶矩，同时还传递势分布。针对轨迹集合，文献[48]提出了基于最小化KL散度的轨迹概率假设密度(Trajectory Probability Hypothesis Density, TPHD)滤波器和轨迹势均衡概率假设密度(Trajectory Cardinalized Probability Hypothesis Density, TCPHD)滤波器，它们均是通过递归传播泊松多轨迹密度对存活轨迹进行推理实现多目标跟踪。此后，Vo等人[49,50]提出了多目标多伯努利(Multi-target Multi-Bernoulli, MeMBer)滤波器，它直接用多伯努利分布来逼近多目标后验密度，对当前时刻多目标状态和个数进行估计。由于上述随机有限集类(Random Finite Set, RFS)多目标跟踪算法无法为目标分配航迹，因此文献[51,52]提出了广义标签多伯努利(Generalized Labeled Multi-Bernoulli, GLMB)滤波器，它通过在滤波过程中引入标签使得随机集算法也能输出目标航迹信息。为了提升GLMB滤波器计算效率，Reuter等人[53]提出了标签多伯努利(Labeled Multi-Bernoulli, LMB)滤波器，它不仅继承了多伯努利滤波器在状态估计方面的优点，还提高了目标航迹标签估计的准确性。基于多目标共轭先验这一特性，文献[54]又提出了泊松多伯努利混合(Poisson Multi-Bernoulli Mixture, PMBM)滤波器，并证明了$\delta$-GLMB滤波器是PMBM带有标签的特例。目前，以上介绍的多目标跟踪算法已经得到广泛应用，其跟踪精度直接影响到后续多传感信息融合性能。表1给出了典型的单传感器多目标跟踪方法及其性能对比。

## 3 分布式传感器配准技术研究进展

在分布式多传感器多目标跟踪过程中，需要把来自多个传感器的数据转换到相同的时空参照系中。由于不同传感器传输速率及采样周期不同，而且存

**表 1 典型的多目标跟踪方法性能对比**

**Tab. 1 Performance comparison of different multi-target tracking methods**

| 多目标跟踪类型 | 跟踪方法 | 跟踪精度 | 运算量 |
|---|---|---|---|
| 数据关联类 | GNN | 低 | 低 |
| | JPDA | 中等 | 中等 |
| | JIPDA | 中等 | 中等 |
| | MHT | 高 | 高 |
| 随机有限集类 | PHD | 低 | 低 |
| | CPHD | 中等 | 中等 |
| | TPHD | 中等 | 低 |
| | TCPHD | 中等 | 中等 |
| | MeMBer | 中等 | 中等 |
| | PMBM | 高 | 中等 |
| | GLMB | 高 | 高 |
| | LMB | 高 | 中等 |

在传感器系统偏差和量测误差，直接进行转换会降低数据融合精度，因此在对多传感器数据处理时需要进行传感器时空配准[55]。由于时间配准与空间配准对融合结构不敏感，故本文列出的配准方法稍加变化同样适用于集中式融合系统。

### 3.1 分布式传感器时间配准

时间配准就是将各传感器对同一目标的异步量测信息配准到同一时刻。典型的时间配准方法有最小二乘法[56–58]、内插外推法、曲线插值法、曲线拟合法[59,60]以及卡尔曼滤波类方法[61,62]。最小二乘法最早由Blair教授提出，它通过将多个数据压缩成一个新的量测数据以达到数据对齐，但这种方法只适用于匀速运动目标，对非匀速运动目标会产生模型失配，导致配准效果不理想。内插外推法通过内插外推方式实现时间对齐，该方法一般将高精度观测数据向低精度观测数据推算以实现多类传感器的时间同步。最小二乘法与内插外推法模型相对简单，因此应用广泛。

曲线插值与曲线拟合适用于非均匀采样场景。其中，曲线插值方法是在内插外推法的基础上采用曲线替代直线进行插值，曲线拟合法则是直接通过量测数据拟合形成一条光滑曲线，然后进行重采样获取对应时刻数据。这两种方法性能基本相同，计算量都会随着选择参与计算的节点数的增加而呈指数增长。卡尔曼滤波类方法可以调整目标运动模型，在目标运动状态复杂时，相比于其他时间配准方法，配准精度会明显提高。图2与表2给出了常见的时间配准方法及其性能对比。

### 3.2 分布式传感器空间配准

空间配准是利用多传感器对空间公共目标的探测信息对传感器的系统偏差进行估计和补偿的过程，它可以提高信息融合精度[63]。

图3中传感器A、传感器B分别对同一参考目标T进行测量，获得相应的量测$\mathrm{T_A}$和$\mathrm{T_B}$。由于配准误差($\Delta r_{\mathrm{A}}$,$\Delta\theta_{\mathrm{A}}$)和($\Delta r_{\mathrm{B}}$,$\Delta\theta_{\mathrm{B}}$)与姿态角累积误差$\Delta\varphi$的存在，量测$\mathrm{T_A}$和$\mathrm{T_B}$相距目标真值存在一定偏差。这种偏差不仅影响后续参数估计精度，严重时甚至会误判为两个目标，导致虚假目标的出现。故在分布式传感器信息融合过程中，首先需要对各个传感器的偏差进行修正。

常见的空间配准算法按目标类型可分为合作目标空间配准与非合作目标空间配准[64]。两类配准算法的区别体现在是否已知目标的位置。若已获知目标的精确位置，可采用合作目标空间配准算法实现传感器的精确配准。若无法提前获知目标的准确位置，则采用非合作目标空间配准算法。通常，基于合作目标的配准算法适用于传感器出厂校准，而基于非合作目标的配准算法则适用于系统偏差变化及一些无法安置校准源的场合。但在实际工程应用中往往难以获得目标的准确位置，因此本文主要对非合作目标空间配准方法进行综述。

非合作目标的空间配准算法又可以分为离线空间配准算法和在线空间配准算法两类。离线配准算法认为传感器系统偏差在一段时间内保持不变，将其建模为固定值并对其进行估计，离线空间配准算法主要包括最小二乘法(Least Squares, LS)[65–67]、广义最小二乘法(General Least Squares, GLS)[68]、

表 2 多传感器时间配准方法性能对比

Tab. 2 Comparison of multi-sensor time registration methods

| 配准类型 | 配准方法 | 配准精度 | 计算量 | 目标运动状态 |
|---|---|---|---|---|
| 插值类 | 内插外推 | 较低 | 低 | 匀速 |
| | 曲线插值 | 中等 | 较高 | 匀速\非匀速 |
| | 曲线拟合 | 中等 | 较高 | 匀速\非匀速 |
| 参数估计类 | 最小二乘 | 中等 | 中等 | 匀速 |
| | 卡尔曼滤波 | 较高 | 较高 | 匀速\非匀速 |

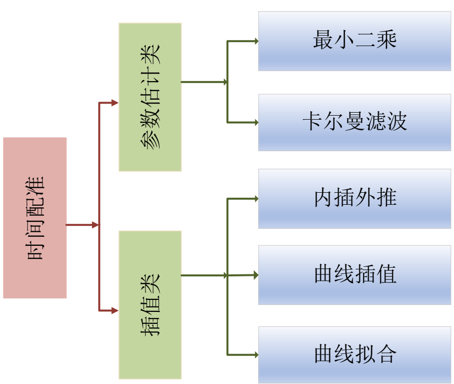



图 2 时间配准方法

Fig. 2 Time registration methods

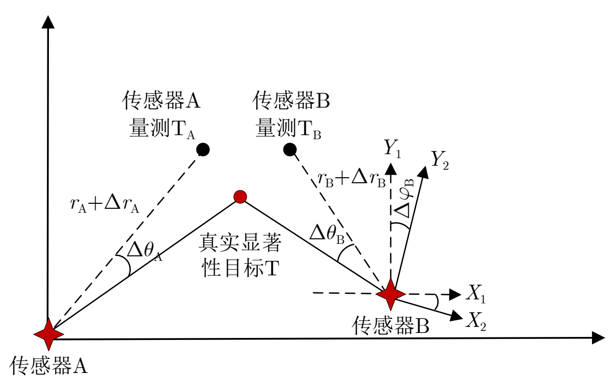



图 3 空间配准几何示意图

Fig. 3 Illustration of spatial registration

实时质量控制法(Real Time Quality Control, RTQC)[69]、精确极大似然估计法(Exact Maximum Likelihood, EML)[70,71]和极大似然配准法(Maximum Likelihood Registration, MLR)[72,73]等。其中，RTQC和LS算法忽略了传感器量测噪声的影响，所以只有当量测噪声很小时，算法的性能才比较好。GLS算法虽考虑了量测噪声的影响，但由于其和LS算法一样，只能以两两配对的方式对系统偏差进行估计，故而性能难以达到最优。EML算法则利用传感器在系统平面中的量测值，运用极大似然法则对目标的位置和传感器的偏差同时进行估计，其对坐标转换过程中的系统偏差的正余弦结果进行了近似，建立了偏差与量测之间线性化模型，并采用迭代的方法获得系统偏差估计。MLR则改进了这种近似方法，基于泰勒展开的方法建立了偏差与量测之间线性化模型，获得了接近克拉默-拉奥下界的偏差估计结果。

另一方面，在线配准算法则认为系统偏差为渐变值，可采用卡尔曼滤波(KF)类方法获得偏差的实时估计。在线配准算法主要包括基于卡尔曼滤波方法、基于扩展卡尔曼滤波方法以及基于无迹卡尔曼滤波方法。文献[74,75]利用卡尔曼滤波来估计传感器的系统偏差，该方法只适用于同一平台内的多传感器信息融合系统，它同时要求传感器的测量误差和姿态误差较小且不随时间变化，对于非线性问题无法很好解决。文献[76]提出了基于扩展卡尔曼滤波的配准算法，扩展卡尔曼滤波是对非线性函数的泰勒展开式进行线性化截断，从而将非线性问题线性化。由于截断了高阶展开项，该方法存在着滤波发散的问题。对于非线性系统模型，文献[77,78]提出了基于无迹卡尔曼滤波的传感器误差配准算法，并对这种算法进行了系统的介绍和应用。由于无迹卡尔曼滤波不需要对非线性系统进行线性化，避免了线性化的近似过程，也避免了雅可比矩阵的计算，在精度和收敛速度上都要优于扩展卡尔曼滤波，因而这种配准算法可以更好地应用于非线性系统的偏差估计。此外，对于低检测概率与高密度杂波环境下的空间配准问题，文献[79–81]提出基于随机有限集(RFS)的空间配准方法，该方法可以同时对多目标进行跟踪和配准。表3给出了常见的多传感器非合作目标空间配准方法分类。

在完整测量中，传感器可以获得目标的完整三维位置信息(距离$R$、俯仰角$\theta$、方位角$\varphi$)，而在不完整测量中，无法获得完整的三维信息。一般来说，提供不完整测量的传感器包括被动传感器(电子支援措施、红外等)和部分主动传感器(测距雷达、超声波等)，这些传感器只能分别提供角度和距离信息。为了解决MLR方法对不完整量测数据配准模型失配的问题[72]，北航ATR实验团队[82]提出了一种基于残留偏差估计的离线空间配准方法(Residual Bias Estimation Registration, RBER)。该方法将所有量测值分为完整量测与非完整量测两部分，首先在公共坐标系下对完整量测进行最大似然估计，求出目标位置估计$\hat{x}_k^{\mathrm{c}}$，然后基于序贯滤波技术用非完整量测数据对$\hat{x}_k^{\mathrm{c}}$进行序贯更新得到更新后的目标位置估计$\hat{x}_k^{\mathrm{all}}$，再将$\hat{x}_k^{\mathrm{all}}$转换到量测坐标系，并在量测坐标系下对所有量测进行最大似然估计，最后通过迭代得到待估参数$\rho$，并利用显著性目标的量测信息消除传感器的系统偏差，更具体的公式及描述见参考文献[82]。

WGS84坐标系下的不完整测量场景如图4所示。其中，传感器1、传感器2和传感器3都获得完整量测(例如：距离$R$、俯仰角$\theta$、方位角$\varphi$)，而传感器4仅获得不完整量测(例如：俯仰角$\theta$、方位角$\varphi$)，其中，非合作目标2是显著性目标，用于空间配准。

图5是配准前后显著性目标在WGS84坐标系下

**表 3 多传感器非合作目标空间配准方法分类**

**Tab. 3 Classification of multi-sensor spatial registration methods based on non-cooperative targets**

| 配准方法 | 实时性 | 是否能估计目标位置 | 参与传感器个数 | 传感器类型 |
|---|---|---|---|---|
| RTQC | 离线 | 否 | 两个 | 同类 |
| LS | 离线 | 否 | 两个 | 同类 |
| GLS | 离线 | 否 | 两个 | 同类 |
| EML | 离线 | 是 | 两个 | 同类 |
| KF | 在线 | 是 | 多个 | 同类 |
| RFS | 在线 | 是 | 多个 | 同类 |
| MLR | 离线 | 是 | 多个 | 同类\异类 |
| RBER | 离线 | 是 | 多个 | 同类\异类 |

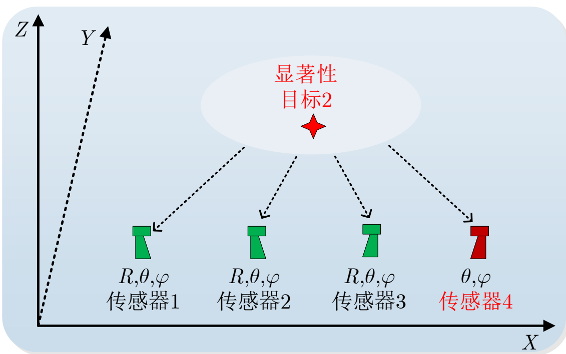
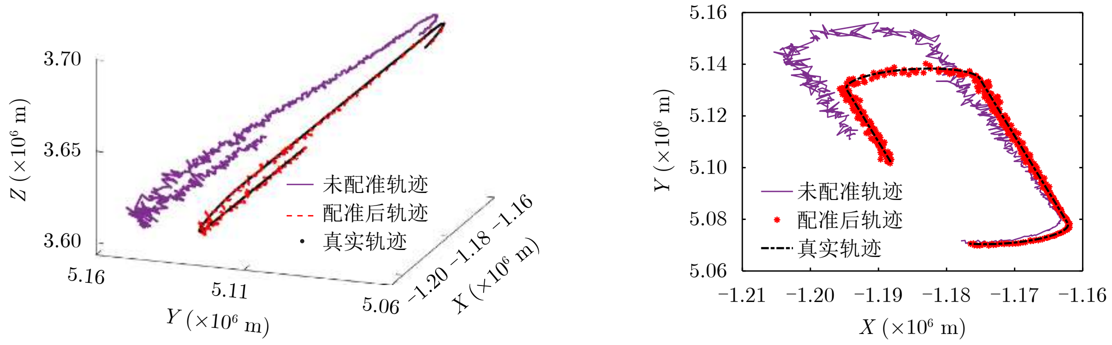



图 4 空间配准场景

Fig. 4 Scene of spatial registration




(a) 三维位置
(a) Result of three-dimensional position

(b) 二维位置
(b) Result of two-dimensional position

图 5 WGS84坐标系下配准前后显著性目标位置[82]

Fig. 5 Registration results before and after registration in the WGS84 coordinate system[82]

的位置。可以看出，配准前直接利用原始数据进行目标状态估计的结果偏离目标真值。经RBER算法配准后，有效地消除了系统偏差对目标状态估计的影响，目标状态估计抖动结果逼近真值。因此，在进行多传感器信息融合前，有必要对各个传感器进行空间配准。

## 4 分布式传感器航迹关联技术研究进展

在分布式多传感器多目标跟踪系统中，每个信源具有独立的信息处理系统，能独立对周围环境目标跟踪，生成对应的目标航迹。由于传感器间的探测区域存在重叠，来自不同系统的航迹可能代表同一目标。因此，如何找出同一目标对应的航迹就是分布式数据融合系统中的航迹关联问题。此外，在分布式传感器航迹关联之前需要将各个传感器探测的目标位置转化到公共坐标系，故这里的航迹主要指目标的三维航迹。

### 4.1 分布式传感器航迹关联

航迹关联算法主要分为两类，一类是基于统计类的方法，一类是基于模糊数学的方法。基于统计的方法最早的研究应该归功于Kanyuck和Singer[83]提出的加权距离检验法，其采用卡方分布检测两个估计是否属于同一个目标。该方法假设两个估计独立，Bar-Shalom[84]进一步对此结果进行了修正，通过引入两个估计协方差阵交叉项，给出了相关条件下的加权距离检验方法。为了解决航迹交叉、分叉等场景下出现错、漏关联的问题，何友教授等人[85,86]借用雷达信号中序贯检测的思想，提出了独立序贯航迹关联方法，该方法引入航迹的历史信息来提升航迹关联性能。此外，借用双门限信号检测的思想，文献[87]提出双门限航迹关联算法，该算法通过增加卡方分布门限检测的关联样本数来增强对复杂环境的适应能力。

基于模糊数学处理的方法采用不确定模型描述航迹之间的关系，通过建立航迹的隶属度函数、置信测度来判断航迹之间的隶属度或置信度，进而获取航迹关系[88,89]。典型基于模糊数学的方法有模糊双门限航迹关联、模糊综合评判航迹关联等。当然，除了主流的航迹关联方法外，也有文献将机器学习用于航迹关联，如文献[90]提出基于直方统计特征的多特征组合航迹关联方法，其利用物体运动特征，提取航迹间的速度差分布直方图，并将这些特征组合，最后基于机器学习的方法进行航迹关联。图6给出了典型的航迹关联方法及分类。

在广域多传感器场景中，随着目标与传感器数量的增加，航迹关联中的分配问题从2-D分配变成S-D分配。S-D分配是一种N-P难问题，最优解的获得除了进行全局搜索，当前并无更好的策略。经典的分配方法分别采用拉格朗日松弛法和序贯m-best算法寻求该问题的次优解，在保证运算代价的基础上，取得了较好的效果。其中，拉格朗日松弛法就

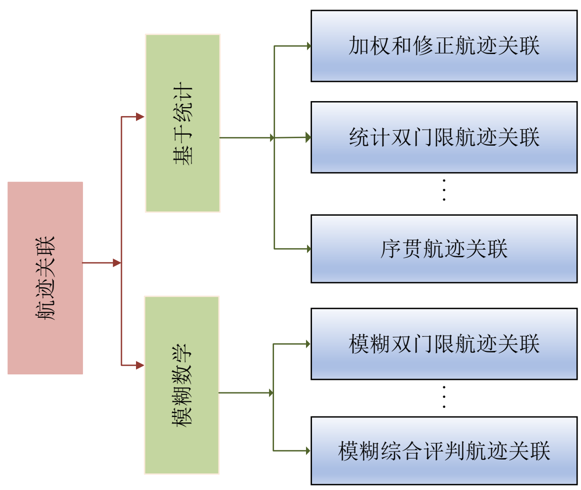



图 6 典型的航迹关联方法及分类

Fig. 6 Classification of track-to-track association methods

是在原始的目标函数中加入拉格朗日乘子来移除一组约束，依次降低高维分配维度。这个方法的关键是选择恰当的拉格朗日乘子来迫使该优化问题满足移除的约束[91]。序贯m-best算法是按照设定的顺序依次进行2D分配得到m个最优分配结果，再将m个最优分配结果进行下一次的迭代分配[92,93]。

针对多传感器探测目标数目不一致场景，文献[89]提出了模糊度函数的方法，根据目标状态估计建立航迹间的模糊因素集，但是其参数设置复杂，需要大量的仿真调整参数，导致计算量大。为此，文献[82]提出一种基于新目标密度的序贯m-best航迹关联算法(Sequential M-Best Track Association algorithm based on the New Target Density, SMBTANTD)，通过迭代的方式每次引入来自下一个传感器的航迹并将这些航迹与先前的结果关联。同时引入新目标密度的概念，将下一个传感器所测得的目标定义为新目标，在计算量较小的条件下有效解决了多传感器测量目标数目不一致的代价分配问题。

在多传感器探测目标数目不一致的场景下，我们对3种典型航迹关联算法的性能进行了对比分析。公共坐标系下的航迹关联场景如图7所示，传感器1、传感器3和传感器4探测到目标1, 2, 3，传感器2只能探测到目标1, 2。

表4和图8是图7场景下正确航迹关联率的两种不同表现形式，与基于传统广义似然加权(Generalized Likelihood)和模糊函数(Fuzzy function)算法相比，基于新目标密度的序贯m-best航迹关联方法(SMBTANTD)在计算量较小的条件下关联正确率得到较大提升。

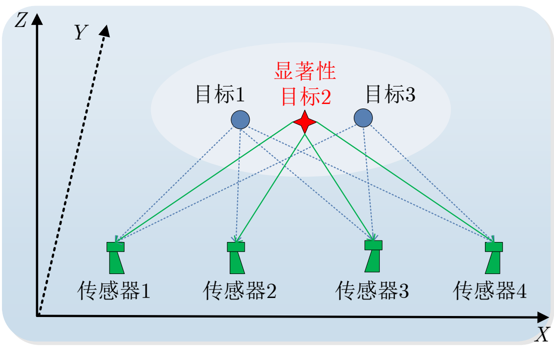



图 7 航迹关联场景

Fig. 7 Scene of track-to-track association

**表 4 航迹关联性能对比**

**Tab. 4 Comparison of multi-sensor track-to-track association methods**

| 航迹关联方法 | 航迹关联正确率(%) | 时间开销(s) |
|---|---|---|
| SMBTANTD[82] | 99.6 | 3.4 |
| Generalized Likelihood[15] | 97.4 | 2.8 |
| Fuzzy function[89] | 96.7 | 8.1 |

## 4.2 分布式传感器空间配准与航迹关联关系

空间配准和航迹关联是多传感器信息融合中的重要组成部分，空间配准和航迹关联的质量直接影响到后续融合的性能[94]。但是空间配准与航迹关联互为前提条件，目前很少有研究能同时考虑航迹关联和传感器空间配准。在大多数空间配准算法中，假设航迹关联问题已经得到解决。同样，在航迹关联算法中，默认完成了空间配准。在实际应用中，航迹关联和空间配准往往是耦合的。事实上，错误的航迹关联导致不精确的空间配准，而错误的空间配准会干扰数据获取，导致航迹关联混乱[95,96]。

对于航迹关联与空间配准之间的耦合问题，现有解决方法主要分为两类。第1类是对航迹关联和系统误差进行联合估计，其中，文献[97]提出了一种联合处理传感器关联、配准和融合的方法，该方法将期望最大化(Expectation Maximization, EM)算法与KF结合，通过E步和M步交替迭代获得参数估计结果。文献[98]则提出了一种基于稳健迭代的联合航迹关联与系统误差估计算法，该算法本质思想是将错误关联结果视为系统误差估计中的野值，它能较好地适应系统误差较大、虚警漏警较高的工作环境。除此之外，文献[99]将系统误差环境下的航迹关联问题建模为全局最近邻模式(Global Nearest Pattern, GNP)数据关联问题，该方法代价函数包括两个观测集之间的偏差，为分配问题提供了最大似然解。第2类是以系统误差不敏感的目标特征为基础来设计航迹关联算法。其中，文献[100]

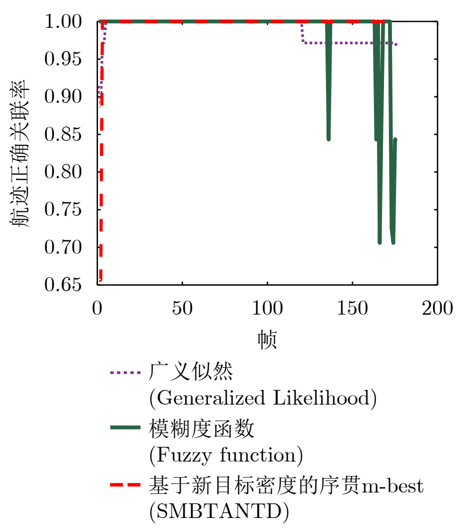



图 8 航迹关联正确率[82]

Fig. 8 Accuracy of track association[82]

利用目标的拓扑特征构建关联费用矩阵，然后基于线性分配算法对费用矩阵求解关联关系。

为了解决航迹关联与空间配准之间的耦合问题，文献[82]提出了一种基于显著性目标的交替迭代解耦算法，如图9所示。首先，通过目标特征属性(雷达散射截面、高分辨距离像、微动、海拔等)选择单个稳定强的显著性目标。然后，采用合适的滤波器(如卡尔曼滤波器)对空间配准后的多传感器多目标量测分别进行滤波跟踪，得到各个传感器对应的目标航迹。最后，对不同传感器不同目标航迹进行关联，本次航迹关联率较高的目标可作为下一次空间配准的显著性目标。通过重复这一过程，可以提高空间配准和航迹关联的精度。

## 5 分布式传感器数据融合技术研究进展

分布式多传感器多目标跟踪又称分布式多传感器数据融合[15]。在该系统中，各局部传感器首先基于单传感器多目标跟踪算法，形成各自目标航迹，接着各传感器将目标航迹送入融合中心完成时空配准与航迹关联，然后融合中心基于某种融合准则对来自同一目标的航迹进行估计融合，最终形成稳定、高精度的全局航迹。第2—4节分别是目标跟踪、传感器配准、航迹关联的归纳总结，本节主要对分布

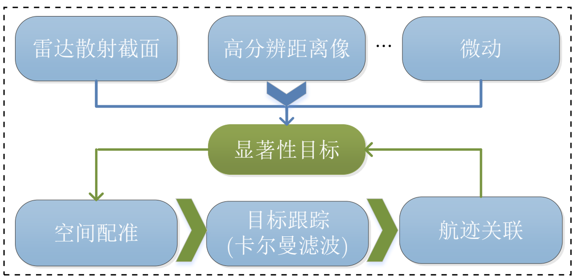



图 9 航迹关联与空间配准关系[82]

Fig. 9 Relationship of track-track association and spatial registration[82]

式多传感器多目标跟踪系统涉及的估计融合准则以及基于估计融合准则的分布式多传感器目标跟踪方法进行综述总结。

### 5.1 分布式传感器估计融合准则

传感器估计融合，或者说是针对估计问题的融合，是传统估计理论与数据融合理论的有机结合，即在估计未知量的过程中，如何有效利用多个数据集包含的有用信息来提高目标状态的估计精度。图10给出了高斯随机变量的估计融合过程，它直观地反应出在各传感器无偏估计的条件下，多传感器融合后的目标状态估计精度明显高于单个传感器所得的目标状态估计精度。

分布式多传感器航迹融合是估计融合最主要的应用领域之一。航迹融合是指基于一定的融合规则，对多传感器提供的航迹信息进行最优组合得到更加精确的目标状态信息。如表5所示，分布式航迹估计融合算法包括简单凸组合融合算法、Bar-Shalom-Campo融合算法、最大后验概率状态估计融合等。简单凸组合融合算法是传感器局部估计误差不相关条件的最优融合估计，它的融合结果与中心式融合相同[101,102]。Bar-Shalom-Campo融合算法考虑到局部传感器估计由于共同的过程噪声引起的相关性，它是最大似然(Maximum Likelihood, ML)意义下的最优估计，将融合后得到估计的不确定性减少到原来的70%，若假设局部传感器估计独立，则会减少到50%[103,104]。一般情况下很难获取数据的相关信息，为了解决这一问题，Uhlmann[105]提出了协方差交叉(Covariance Intersection, CI)融合算法。然而CI融合受限于高斯输入，为了满足任意概率密度函数融合，Hurley[106]以贝叶斯理论为基础提出了适用于任意概率密度函数的广义协方差交叉(Generalized Covariance Intersection, GCI)融合。为了充分利用局部估计信息，美国Chang教授等人[107]提出了基于最大后验概率(MAP)估计融合方法，它

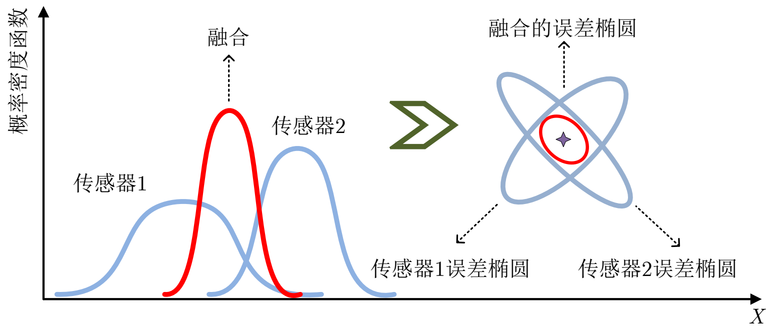



图 10 分布式多传感器估计融合

Fig. 10 Distributed multi-sensor estimation fusion

把各传感器局部估计作为先验信息来计算全局航迹估计。

依据全局信息是否会反馈到局部估计器，将航迹融合分为不带反馈最优分布式融合与带反馈的最优分布式融合[108,109]。四川大学朱允民教授团队[110]已经证明反馈并不能改善全局航迹的跟踪性能，但是它可以减小局部估计的误差协方差阵。针对局部传感器目标状态空间不同(其中一个在笛卡尔坐标系，另一个在极坐标系)，存在非线性转换的航迹融合问题，Bar-Shalom等人[111–113]推导了此情况下的线性最小均方根误差(Linear Minimum Mean Squared Error, LMMSE)估计方法及其互相关计算方法。

近年来，平均共识融合引起了国内外学者的广泛关注，平均共识融合分为算数平均融合(Arithmetic Average, AA)与几何平均融合(Geometric Average, GA)两类。文献[114]指出，与AA融合相比，GA融合具有更好的虚警抑制能力。但是，AA融合以其鲁棒性强、计算效率高且有较强的抗局部故障和漏检能力得到国内外学者的青睐。为此，西北工业大学李天成教授团队[115–117]对AA融合与GA融合的性能进行了详细对比与综述，并将AA融合推广到分布式多传感器多目标检测与跟踪领域。

由于单类传感器在作为独立系统部署时存在特定的弱点，因此对两个或多个异类传感器获得的航迹信息有效融合是非常有利的。针对异类传感器航迹融合，首先根据目标在空间的位置信息是否有缺失分为完整量测和不完整量测。量测的完整与否将影响量测结果能否直接转入笛卡尔坐标系。如三坐标雷达可同时获得目标在测量坐标系下的俯仰、方位及斜距信息，其量测可称为完整量测，经过目标跟踪后可以得到笛卡尔坐标系下完整目标状态估计。一些无源传感器只能获得目标在测量坐标系下的角度信息，其量测则不完整，因此，异类传感器航迹融合常指利用量测坐标系下的不完整量测信息，对笛卡尔坐标系下完整目标状态估计进行更新，这一过程通常可采用非线性滤波的方式实现[118,119]。典型的非线性滤波方法如扩展卡尔曼滤波融合(EKF)、无迹卡尔曼滤波融合(UKF)、粒子滤波融合(PF)等[120–122]。

### 5.2 基于估计融合的分布式多传感器目标跟踪

分布式多传感器多目标跟踪建立在单传感器多目标跟踪的基础上，它需要同时考虑多目标跟踪方法与融合准则两个因素，跟踪方法与融合准则的不同都会对分布式多传感器多目标跟踪的性能产生不同的影响。如表6所示，与单传感多目标跟踪框架

**表 5 多传感器估计融合方法对比**

**Tab. 5 Comparison of multi-sensor estimation fusion methods**

| 估计融合方法 | 是否考虑航迹相关 | 计算量 | 融合精度 | 传感器类型 |
|---|---|---|---|---|
| 简单凸组合融合 | 否 | 低 | 低 | 同类 |
| Bar-Shalom-Campo融合 | 是 | 较高 | 较高 | 同类 |
| 基于MAP | 是 | 较高 | 较高 | 同类 |
| CI融合 | 是 | 较高 | 较高 | 同类 |
| GCI融合 | 是 | 较高 | 较高 | 同类/异类 |
| AA融合 | 是 | 较高 | 较高 | 同类/异类 |
| 基于EKF融合 | 否 | 较高 | 较高 | 同类/异类 |
| 基于UKF融合 | 否 | 较高 | 较高 | 同类/异类 |
| 基于PF融合 | 否 | 高 | 高 | 同类/异类 |

**表 6 典型的多传感器多目标跟踪方法性能对比**

**Tab. 6 Performance comparison of multi-sensor multi-target tracking methods**

| 多目标跟踪类型 | 融合准则 | 跟踪方法 | 运算量 | 跟踪精度 |
|---|---|---|---|---|
| 数据关联类 | CI融合 | JPDA | 中等 | 中等 |
| | 简单凸组合融合 | MHT | 高 | 中等 |
| 随机有限集类 | GCI/GA融合 | PHD | 低 | 低 |
| | | CPHD | 中等 | 中等 |
| | | MeMBer | 中等 | 中等 |
| | | GLMB | 高 | 高 |
| | | LMB | 中等 | 高 |
| | AA融合 | PHD | 低 | 低 |
| | | CPHD | 中等 | 中等 |
| | | MeMBer | 中等 | 中等 |
| | | GLMB | 高 | 高 |
| | | LMB | 中等 | 高 |

类似，分布式多传感器多目标跟踪也分为数据关联和随机有限集两大类。基于关联类的分布式多传感器多目标跟踪方法研究较早，其中具有代表意义的有分布式联合数据关联跟踪(Distributed Multi-Sensor multiple Cheap Joint Probability Data Association, DMS-CJPDA)[123]、分布式多传感器多假设跟踪(Distributed Multi-Sensor Multiple Hypothesis Tracking, DMS-MHT)[124,125]等。

随着适用于任意概率密度的GCI融合的提出，基于随机有限集的分布式多传感器多目标跟踪取得了较大的进展。2013年，Üney等人[126]将随机有限集与GCI融合准则结合，建立一种一致性的分布式多传感器多目标跟踪方法。该方法推导出了用于融合计算的指数混合密度(Exponential Mixture Densities, EMD)的显式公式，实现了基于GCI融合准则的分布式PHD滤波算法。同期，Battistelli

等人[127]提出了一种分布式CPHD滤波方法，该方法通过结合网络共识理论得到了基于GCI融合准则的分布式CPHD滤波数值解，也增强了分布式传感器融合的网络延展性。与PHD, CPHD滤波器相比，多伯努利(Multi-Bernoulli, MB)滤波器能更好地平衡算法性能与计算量之间的关系，具有鲁棒性强、性能稳定等优点。同时，针对多传感器网络节点间量测相关性未知等问题，文献[128]提出了基于GCI准则的MB分布式滤波器融合算法(GCI-MB)，并给出了GCI-MB融合的后验分布解析表达式，为分布式融合提供了先决条件。由于上述方法均无法为多目标分配航迹，因此，2018年，Fantacci等人[129]在不同传感器间共享相同标号空间假设的基础上，首次提出了标号多目标分布式融合方法，并且给出了基于GCI融合准则的GLMB和LMB的闭式表达。但是，该方法并没有进一步解释不同传感器间共享相同标号空间的内在含义，同时也没有对该假设的成立条件进行实际验证。此后，李溯琪等人[130]在标号随机有限集理论框架下，建立了滤波器间标号不一致问题的数学模型，并定量分析了标号不一致对GCI融合性能的影响，得出了GCI融合对滤波器间标号不一致现象敏感的结论。在此结论分析基础上，2018年，李溯琪等人[131]又提出了基于免标号的稳健GCI融合算法，并将其推广至分布式GLMB滤波器、LMB滤波器。

GCI融合也称GA融合是平均共识融合方法的一种，另一种平均共识融合方法是AA融合，这两种融合方法都可以有效避免公共信息的重复计算，且都属于近似次优的分布式融合方法。与GCI分布式融合对应，西北工业大学李天成等人[115,116]将AA融合推广到分布式多传感器PHD, MeMBer滤波器。与此同时，电子科技大学高林等人[132,133]则将AA融合推广到分布式多传感器CPHD, GLMB, LMB滤波器。综上所述，与基于关联类的分布式多传感器多目标跟踪理论相比，基于随机有限集的分布式多传感器多目标跟踪技术是当今信息融合领域的研究热点，但其理论研究还存在诸多问题，有待进一步解决与完善。

## 6 分布式多传感器多目标跟踪技术存在的问题及发展方向

目前，分布式多传感器多目标跟踪已经取得了一定的成果，并广泛应用于军事、民用领域，但是在目标跟踪、空间配准、航迹关联、航迹融合等关键技术方面仍存在诸多难点。

(1) 在多目标跟踪方面，复杂场景下动态未知杂波的存在对弱目标探测和跟踪构成了严峻的挑战，动态杂波会降低目标检测效果，产生大量虚假量测，导致目标跟踪性能下降。所以检测跟踪一体化以及自适应杂波动态估计在多目标跟踪领域具有重要研究意义。

(2) 在空间配准方面，由于系统偏差可能随时间发生变化，虽然已经有基于滤波类的在线空间配准算法，但是在目标机动条件下，在线空间配准算法由于目标运动模型失配导致配准精度相对较低。此外，基于非合作目标空间配准需要寻找相对稳定的公共显著性目标，但实际场景下显著性目标提取相对困难，所以复杂场景下的高精度、实时空间配准具有重要研究意义。

(3) 在航迹关联方面，现有的航迹关联算法关联阈值随场景变化而变化，难以设定。其次，含有残留偏差的航迹无法进行有效关联，虽然有一些基于航迹形状特征的抗偏差关联算法，但是在异类航迹关联场景下某些传感器(红外、电子支援措施等)无法直接得到目标的航迹形状信息。这时，如何进行有效航迹关联也是需要解决的问题。

(4) 在航迹融合方面，由于残留偏差的影响，不同传感器对目标跟踪产生的误差远小于待融合局部航迹之间的位置估计差。此种情况下的融合估计值将被视为不合理，这就需要设定检测门限对每条航迹的残留偏差进行实时评估，然而门限的设定通常是比较困难的。所以对融合航迹的实时质量评估也是未来航迹融合的重要发展方向。

## 7 结语

分布式多传感器多目标跟踪由于其系统生命力强、易于扩展等优点在各个领域得到越来越广泛的应用。本文在分布式多传感器多目标跟踪框架下，分别对目标跟踪、传感器配准、航迹关联和数据融合涉及的关键算法进行了梳理，并分析了这些算法的优缺点及其适用条件。针对信息不完整量测场景下的空间配准问题，重点介绍了基于残留偏差的空间配准方法，对于多传感器探测目标数目不一致的关联场景，重点介绍了基于新目标密度的航迹关联算法。最后分析了复杂场景下分布式多传感器多目标跟踪关键技术存在的难点及发展方向，为该领域未来的研究提供了一定的参考。

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# Review of the Method for Distributed Multi-sensor Multi-target Tracking

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**Abstract**: Multi-sensor multi-target tracking is a popular topic in the field of information fusion. It improves the accuracy and stability of target tracking by fusing multiple local sensor information. By the fusion system, the multi-sensor multi-target tracking is grouped into distributed fusion, centralized fusion, and hybrid fusion. Distributed fusion is widely applied in the military and civilian fields with the advantages of strong reliability, high stability, and low requirements on network communication bandwidth. Key techniques of distributed multi-sensor multi-target tracking include multi-target tracking, sensor registration, track-to-track association, and data fusion. This paper reviews the theoretical basis and applicable conditions of these key techniques, highlights the incomplete measurement spatial registration algorithm and track association algorithm, and provides the simulation results. Finally, the weaknesses of the key techniques of distributed multi-sensor multi-target tracking are summarized, and the future development trends of these key techniques are surveyed.

**Key words**: Distributed Multi-sensor Multi-target Tracking (DMMT); Multi-target tracking; Sensor registration; Track-to-track association; Data fusion

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## 1 Introduction

In the era of big data and increasingly complex sensor-monitored environments, single-sensor monitoring systems no longer suffice. Transitioning from single-sensor to multi-sensor multi-target tracking is imperative to tackle multi-target tracking challenges in intricate settings. This multi-sensor target tracking system achieves effective target monitoring through information fusion, representing a vital technology in modern sensor systems. These technologies are widely deployed in military command and industrial control[1,2]. In military applications, target tracking and information fusion are crucial in unified network detection. For example, a 3D network tracking system integrating swarm drones, unmanned vehicles, and ships can effectively detect stealth targets. Currently, countries including the United States, Europe, and Russia possess diverse military network tracking systems, such as the U.S. multi-platform multi-sensor target tracking processing system[3], NATO's Command and Control Information System[4], and Russia's Baikal tactical system[5]. In recent years, China has intensified its research into strategic defense systems, emphasizing target tracking and information fusion as pivotal defense technology initiatives. In industrial realms, target tracking and information fusion are extensively applied in autonomous driving, meteorological monitoring, and biomedical fields[6–9]. Consequently, target tracking and information fusion emerge as potent, dependable, and practical tools for information processing, propelling societal advancement and growth[10,11].

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Multi-sensor target tracking technology, also referred to as multi-sensor fusion technology, is categorized into three structural types: centralized, distributed, and hybrid[12–14]. In a centralized information fusion system, raw measurement data from individual sensors are transmitted to a central processor for essential tasks, such as spatiotemporal registration, data association, and tracking. This approach minimizes data loss, ensures high precision in data fusion, and achieves optimal information integration[15–23]. However, centralized fusion requires high-quality data and significant communication bandwidth and can result in delays in real-time data processing. By contrast, a distributed information fusion system allows each sensor to operate with its own data processing center, autonomously managing the acquired measurement data. The processed and condensed data from each sensor are then transmitted to a fusion center for integration and inference, resulting in comprehensive information fusion. Distributed fusion requires less channel capacity, boasts robust fault tolerance, and is more readily scalable than centralized fusion[24–27]. In a hybrid information fusion model, sensors transmit raw measurements and locally processed target tracks to the fusion center simultaneously. This hybrid approach leverages the strengths of centralized and distributed methods. However, the hybrid fusion method features a more intricate structure than its predecessors, resulting in heightened communication and computational costs[28–30]. This study primarily focuses on summarizing and organizing key technologies, such as target tracking, sensor registration, trajectory association, and data fusion, along with their interdependencies within the framework of Distributed Multi-sensor Multi-target Tracking (DMMT) given its straightforward implementation, ease of use, and wide-ranging applicability. The overarching framework, depicted in Fig. 1, highlights that data fusion represents the conclusive phase in the information fusion process.

In practical terms, advancements in information technology and network technology have remarkably accelerated the development of DMMT technology. Since its inception, this field has remained a primary focus for researchers worldwide, leading to a continuous stream of notable achievements. However, DMMT represents a complex system with various dispersed key technologies. Research efforts are often concentrated on specific scenarios or individual key technologies, lacking comprehensive organization and summarization. This article consolidates the progress made by domestic and international research institutions and universities in the key technologies of DMMT. Through the integration of simulation experiments, it delves into the theoretical principles and application conditions of prominent spatial registration and trajectory association technologies. This work offers valuable insights for upcoming research endeavors in this domain by identifying the deficiencies in current key technologies and outlining future developmental trajectories.

## 2 Research Progress of Target Tracking

Target tracking is a key area of research in multi-source information fusion, playing a crucial role in enabling sensor network detection. In essence, target tracking involves estimating the

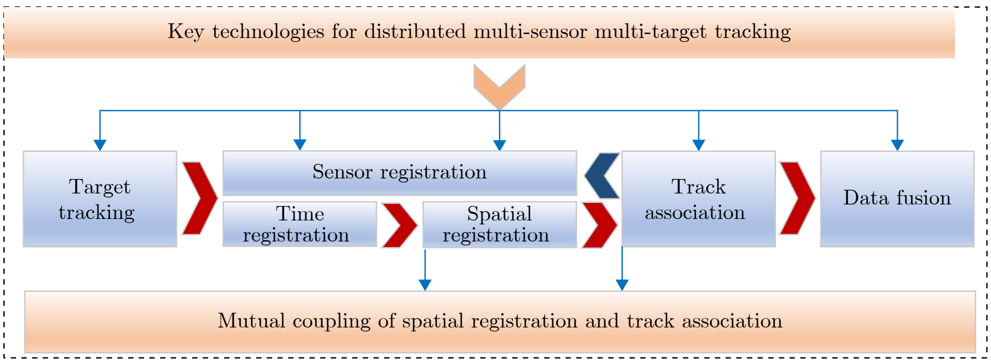


Fig. 1 Flowchart of distributed multi-sensor multi-target tracking

state and quantity of targets using noisy measurement data from multiple sensors. This section provides a comprehensive summary of the theoretical principles and research methods associated with single-sensor target tracking.

### 2.1 Bayesian filtering

Distributed sensors generate individual target trajectories through target tracking, which is categorized into single-target tracking and multi-target tracking based on the number of targets detected. Both categories use recursive filtering within a Bayesian framework. Bayesian recursion relies on the target's state and observation models, encompassing prediction and update steps[31].

In the predictive phase of Bayesian recursion, the prior probability density function $f_{k-1|k-1} \cdot (x_{k-1}|Z_{k-1})$ from the previous time step is iteratively updated using the state transition probability density $f_{k|k-1}(x_k|x_{k-1})$ to derive the prior probability density function $f_{k|k-1}(x_k|Z_{k-1})$ for the target state. During the updating phase, the prior probability density function of the target state is adjusted with the inclusion of the current measurement $z_k$, resulting in the posterior probability density function $f_{k|k}(x_k|Z_k)$, which consolidates all details concerning the target state $x_k$, encompassing the measurement set $Z_k$ and information on the prior state distribution. The state at that instant can be determined through Minimum Mean Square Error (MMSE) or Maximum A Posteriori (MAP) estimation[1]. While Bayesian filtering is suitable for linear and nonlinear systems, the state estimation of linear systems can be facilitated by the Kalman filter equations. Conversely, for nonlinear systems, obtaining a closed-form solution for the posterior probability density function $f_{k|k}(x_k|Z_k)$ is challenging. This difficulty has led to the development of several suboptimal filtering methods for nonlinear systems, such as the Extended Kalman Filter (EKF)[32], Unscented Kalman Filter (UKF)[33], Cubature Kalman Filter (CKF)[34], and Particle Filter (PF)[35].

### 2.2 Single-target tracking method

Data association-based multi-target tracking methods were initially proposed by Sittler in the 1960s, primarily to establish correspondences between measurements and targets. Subsequently, Bar-Shalom *et al.*[36,37] merged data association with KF, accelerating the advancement of multi-target tracking technology. Noteworthy data association tracking algorithms include the Joint Probability Data Association (JPDA) algorithm[38–40], Joint Integrated Probability Data Association (JIPDA) algorithm[41], Nearest Neighbor (NN) data association algorithm[42,43], and Multiple Hypothesis Tracking (MHT) algorithm[44,45]. In multi-target tracking tasks, these algorithms resolve the problem by transforming it into a series of single-target tracking problems through data association.

In 1994, Mahler *et al.* introduced the optimal Bayesian filter for multi-target tracking using Finite Set Statistics (FISST). This method enables the estimation of target states without the need for data association. However, the complexity of the integral operations involved in Bayesian recursion using Fandom Finite Sets (RFS) made it impractical for engineering applications. Mahler proposed the Probability Hypothesis Density (PHD) filter to overcome these challenges[46,47]. The PHD filter, while conveying only the first moment, was insufficient for effectively estimating the number of multiple targets. Subsequently, Mahler developed the Cardinalized Probability Hypothesis Density (CPHD) filter, which conveys the first moment and potential distributions of the posterior probability density[47]. For trajectory sets, a publication[48] introduced the Trajectory Probability Hypothesis Density (TPHD) filter and Trajectory Cardinalized Probability Hypothesis Density (TCPHD) filter based on minimizing Kullback-Leibler divergence. These filters recursively propagate Poisson multi-trajectory densities to infer surviving trajectories, enabling multi-target tracking. Subsequently, Vo and his colleagues[49,50] proposed the Multi-target Multi-Bernoulli (MeMBer) filter, which approximates the multi-target posterior density directly using a multi-Bernoulli distribution to estimate the current time multi-target states and their numbers. A publication[51,52] introduced the Generalized

Labeled Multi-Bernoulli (GLMB) filter, given that the previous RFS multi-target tracking algorithms failed to assign trajectories to targets. By introducing labels during the filtering process, this filter allows random set algorithms to provide target trajectory information. Reuter *et al.*[53] introduced the LMB filter, which inherits the advantages of the multi-Bernoulli filter in state estimation while improving the accuracy of target trajectory label estimation to enhance the computational efficiency of the GLMB filter. Leveraging the characteristic of multi-target conjugate priors, a publication[54] introduced the Poisson Multi-Bernoulli Mixture (PMBM) filter, demonstrating that the $\delta$-GLMB filter is a labeled variant of the PMBM. These sophisticated multi-target tracking algorithms have been widely applied, with their tracking accuracy directly influencing the performance of subsequent multi-sensor information fusion. Tab. 1 presents a comparison of typical single-sensor multi-target tracking methods and their performance.

## 3 Research Progress on Distributed Sensor Registration

In the process of DMMT, data from multiple sensors must be transformed into the same spatiotemporal reference frame. However, due to variations in transmission rates, sampling periods, sensor system biases, and measurement errors, direct transformation can reduce data fusion accuracy. Therefore, sensor spatiotemporal registration is required when processing data from multiple sensors[55]. Since temporal and spatial registration are independent of fusion structures, the registration methods listed in this study are equally applicable to centralized fusion systems.

**Tab. 1 Performance comparison of different multi-target tracking methods**

| Types of multiple target tracking | Tracking methods | Tracking accuracy | Computational complexity |
|---|---|---|---|
| Data association | GNN | Low | Low |
| | JPDA | Medium | Medium |
| | JIPDA | Medium | Medium |
| | MHT | High | High |
| Random finite set | PHD | Low | Low |
| | CPHD | Medium | Medium |
| | TPHD | Medium | Low |
| | TCPHD | Medium | Medium |
| | MeMBer | Medium | Medium |
| | PMBM | High | Medium |
| | GLMB | High | High |
| | LMB | High | Medium |

### 3.1 Distributed sensor time registration

Time Registration involves synchronizing asynchronous measurement data from different sensors to a common time point for the same target. Common methods for time registration include least squares techniques[56–58], interpolation, curve interpolation, curve fitting methods[59,60], and Kalman filter-based approaches[61,62]. The least squares method, first introduced by Professor Blair, combines multiple data points into a new measurement point to align data. However, the least squares method is suitable only for uniformly moving targets and may lead to alignment issues for targets with non-uniform motion. Interpolation and extrapolation methods achieve time alignment by interpolating and extrapolating data, often by extending high-precision observations to low-precision ones for synchronizing data from different sensor types. These approaches, such as least squares and interpolation, are widely used due to their simplicity in modeling.

Curve interpolation and curve fitting are well-suited for non-uniform sampling scenarios. In curve interpolation, curves are used instead of straight lines for interpolation, based on the interpolation and extrapolation methods. In curve fitting, a smooth curve is directly generated by fitting the measurement data, and then resampling is performed to obtain corresponding data at specific time points. Both methods exhibit similar performance, with their computational complexity exponentially increasing as the number of nodes involved in calculations rises. Kalman filter-based approaches can adjust target motion models. When the target motion states are complex, these approaches significantly improve registration accuracy compared with other time registration methods. Fig. 2 and Tab. 2 present common time registration methods and their performance comparisons.

### 3.2 Distributed sensor spatial registration

Spatial registration involves estimating and

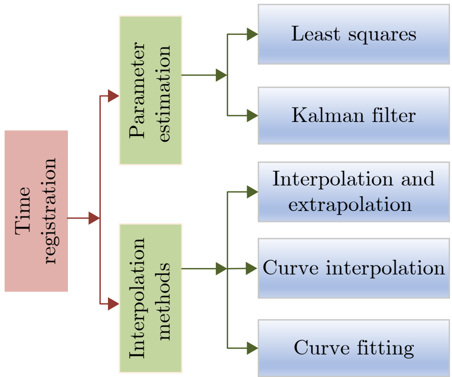


Fig. 2 Time registration methods

compensating for system biases of sensors by utilizing detection information of common targets from multiple sensors. The goal is to improve the accuracy of information fusion[63].

In Fig. 3, sensors A and B measure the same reference target T, obtaining measurements $T_A$ and $T_B$, respectively. The measurements $T_A$ and $T_B$ deviate from the actual target values due to registration errors($\Delta r_A$,$\Delta\theta_A$) and ($\Delta r_B$,$\Delta\theta_B$), as well as the accumulation of attitude angle errors $\Delta\varphi$. These discrepancies not only affect the precision of subsequent parameter estimations but can also lead to misinterpretations as separate targets, resulting in the creation of false targets. Therefore, in the context of distributed sensor information fusion, initially correcting the biases of each sensor is crucial.

Common spatial registration algorithms can be classified into cooperative target spatial registration and non-cooperative target spatial registration based on the type of target[64]. The key difference between these two types of registration algorithms lies in the availability of target position information. Cooperative target spatial registration algorithms are suitable when the precise target location is known in advance, enabling accurate sensor registration. By contrast, non-cooperative target spatial registration algorithms are used when the exact target position is not directly available. Typically, cooperative target-based registration algorithms are more suitable for initial sensor calibration at the factory, whereas non-cooperative target-based registration algorithms are useful in scenarios where system biases fluctuate and calibration sources cannot be conveniently deployed. However, obtaining the precise target position is often challenging in practical engineering applications. Thus, this study focuses predominantly on non-cooperative target spatial registration methods.

Non-cooperative target spatial registration algorithms can be further categorized into offline spatial registration algorithms and online spatial registration algorithms. Offline registration algorithms assume that sensor system biases remain constant over a period, modeling them as fixed values for estimation. Offline spatial registration algorithms mainly include Least Squares (LS)[65−67], Generalized Least Squares (GLS)[68], Real-Time Quality Control (RTQC)[69], Exact Maximum Likelihood (EML)[70,71], and Maximum Likelihood Registration (MLR)[72,73]. RTQC and LS algorithms disregard the influence of sensor measurement noise, making them effective only when measurement noise is minimal. While GLS considers the impact of measurement noise, similar to LS, it can only estimate system biases in a pairwise manner, making it challenging to achieve optimal performance. The EML algorithm uses measurements from sensors in the system plane and applies the maximum likelihood principle to simultaneously estimate the target's position and sensor biases. It approximates the sine and cosine results of system biases during the coordinate transformation process and establishes a linearized model that links biases to measurements. This model iteratively obtains an estimation of system biases. MLR improves this approximation method by using Taylor expansion to linearize the

**Tab. 2 Comparison of multi-sensor time registration methods**

| Registration types | Registration methods | Registration accuracy | Computational complexity | Target motion state |
|---|---|---|---|---|
| Interpolation class | Interpolation and extrapolation | Lower | Lower | Uniform |
| | Curve interpolation | Medium | Higher | Uniform \ Non-uniform |
| | Curve fitting | Medium | Higher | Uniform \ Non-uniform |
| Parameter estimation | Least squares | Medium | Medium | Uniform |
| | Kalman filter | Higher | Higher | Uniform \ Non-uniform |

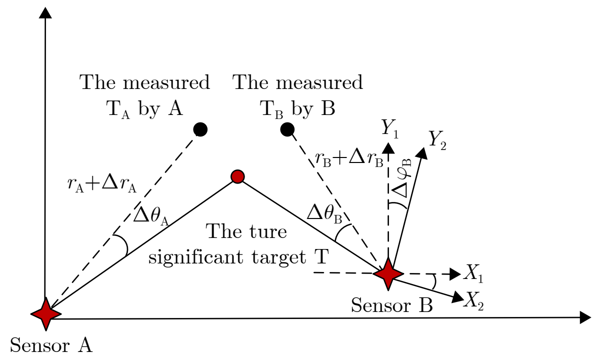


Fig. 3 Illustration of spatial registration

relationship between biases and measurements. This improvement enables MLR to achieve bias estimates close to the Cramér-Rao lower bound.

On the contrary, online registration algorithms consider system biases as varying values and can provide real-time estimates of biases using KF-based methods. Online registration algorithms mainly include methods based on KF, EKF, and UKF. Refs. [74,75] used KF to estimate sensor system biases. This method is only suitable for multi-sensor information fusion systems within the same platform, assuming small measurement and attitude errors that do not change over time. It struggles to effectively address nonlinear problems. Ref. [76] introduced a registration algorithm based on EKF, which linearizes the Taylor expansion of the nonlinear function to address nonlinear problems. However, due to truncating higher-order expansion terms, this approach can lead to filter divergence.

For nonlinear system models, Refs. [77,78] proposed a sensor error registration algorithm based on UKF, providing a comprehensive introduction and application of this method. UKF does not require linearizing nonlinear systems, avoiding the approximation process of linearization and the computation of Jacobian matrices. As a result, it outperforms EKF in terms of accuracy and convergence speed. Therefore, this registration algorithm is better suited for estimating biases in nonlinear systems. Moreover, for spatial registration issues in low detection probability and high clutter environments, Refs. [79–81] introduced a spatial registration method based on RFS, capable of simultaneously tracking and registering multiple targets. Tab. 3 categorizes common non-cooperative target spatial registration methods for multi-sensor systems.

In complete measurements, sensors measure the target's complete 3D position information (range $R$, elevation angle $\theta$, and azimuth angle $\varphi$). In incomplete measurements, the full 3D information cannot be obtained. Sensors providing incomplete measurements typically include passive sensors (*e.g.*, electronic support measure and infrared) and some active sensors (*e.g.*, radar and ultrasound), which only offer angle and range information separately. To address model mismatch in the MLR method with incomplete measurement data[72], the Beihang ATR experimental team[82] introduced an offline spatial registration method called Residual Bias Estimation Registration (RBER). This method categorizes all measurements into complete and incomplete sets. Initially, in a common coordinate system, maximum likelihood estimation is applied to the complete measurements to estimate the target position $\hat{x}_k^{\mathrm{c}}$. Subsequently, using sequential filtering techniques $\hat{x}_k^{\mathrm{c}}$ is sequentially updated with incomplete measurement data to derive an updated target position estimate $\hat{x}_k^{\mathrm{all}}$. $\hat{x}_k^{\mathrm{all}}$ is then converted into the measurement coordinate system for maximum likelihood estimation of all measurements. Through iteration, the parameter $\rho$ to be estimated is determined, leveraging significant target

**Tab. 3 Classification of multi-sensor spatial registration methods based on non-cooperative targets**

| Registration methods | Real-time | Can the target position be estimated? | Number of sensors | Sensor type |
|---|---|---|---|---|
| RTQC | Offline | No | Two | Homogeneous |
| LS | Offline | No | Two | Homogeneous |
| GLS | Offline | No | Two | Homogeneous |
| EML | Offline | Yes | Two | Homogeneous |
| KF | Online | Yes | Multiple | Homogeneous |
| RFS | Online | Yes | Multiple | Homogeneous |
| MLR | Offline | Yes | Multiple | Homogeneous \ Heterogeneous |
| RBER | Offline | Yes | Multiple | Homogeneous \ Heterogeneous |

measurement information to eliminate sensor system biases. Detailed formulas and descriptions are presented in Ref. [82].

In the incomplete measurement scenario depicted in Fig. 4 under the WGS84 coordinate system, sensors 1, 2, and 3 gather complete measurements (*e.g.*, range $R$, elevation angle $\theta$, and azimuth angle $\varphi$), whereas sensor 4 solely captures incomplete measurements (*e.g.*, elevation angle $\theta$ and azimuth angle $\varphi$). In this context, non-cooperative target 2 acts as a crucial target for spatial registration purposes.

In Fig. 5, the positions before and after the registration of significant targets in the WGS84 coordinate system are displayed. Prior to registration, direct target state estimation using raw data deviates from the actual target values. Post RBER algorithm registration, systematic biases' impact on target state estimation is effectively eradicated, leading to target state estimation results closely approximating the actual values.

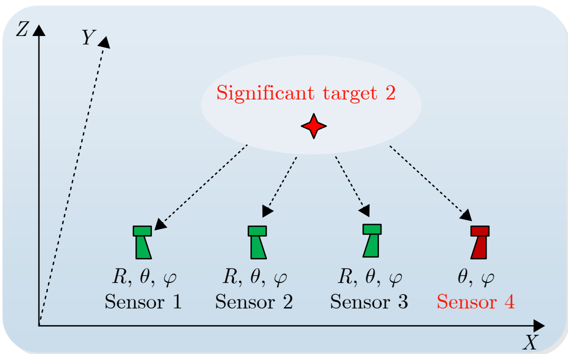


Fig. 4 Scene of spatial registration

Thus, before engaging in multi-sensor information fusion.

## 4 Research Progress of Track Association for Distributed Sensors

In a distributed multi-target tracking system with multiple sensors, each sensor node operates independently with its information processing system to track nearby targets and create their respective paths. Trajectories from different systems could represent the same target, given that the sensors' detection areas overlap. Therefore, the challenge in distributed data fusion systems lies in associating trajectories with the correct target. Prior to associating trajectories from distributed sensors, target positions detected by each sensor must be converted into a shared coordinate system. Here, trajectories mainly refer to the 3D paths followed by the targets.

### 4.1 Track association for distributed sensors

Track association algorithms can be categorized into two: Statistical methods and fuzzy mathematics-based methods. The earliest research on statistical methods can be attributed to the weighted distance test proposed by Kanyuck and Singer[83], which uses a chi-square distribution to determine whether two estimates correspond to the same target. This method assumes that the two estimates are independent. Bar-Shalom[84] further refined this approach by incorporating the cross-terms of the covariance matrices of the two estimates, providing a weighted distance test method under correlated conditions. To ad-

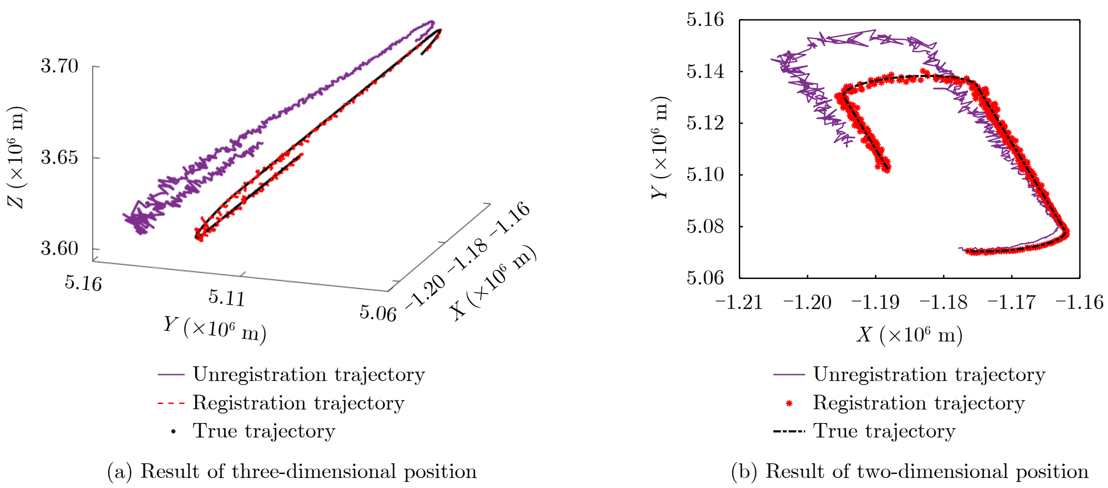


Fig. 5 Registration results before and after registration in the WGS84 coordinate system[82]

dress issues of inaccurate or missed associations in scenarios involving track crossings or splits, Professor He and others[85,86] adapted the idea of sequential detection from radar signals and introduced the independent sequential track association method, which enhances track association performance by incorporating historical track information. Furthermore, inspired by the concept of dual-threshold signal detection, a dual-threshold track association algorithm was proposed in Ref. [87]. This algorithm enhances the system's adaptability to complex environments by increasing the number of associated samples detected using chi-square distribution thresholds.

Methods based on fuzzy mathematics use uncertainty models to describe relationships between tracks. These methods establish membership functions and confidence measures, which evaluate the degree of membership or confidence between tracks to determine their relationships[88,89]. Typical approaches within this framework include fuzzy dual-threshold track association and fuzzy comprehensive evaluation track association. In addition to the mainstream track association methods, machine learning techniques have been applied to improve track association performance. For example, a multiple-feature combination track association method based on histogram statistical features was proposed in Ref. [90]. This approach leverages object motion characteristics, extracts velocity difference distribution histograms between tracks, combines these features, and finally performs track association using machine learning methods. Fig. 6 illustrates typical track association methods and their classifications.

In wide-area multi-sensor scenarios, as the number of targets and sensors increases, the assignment issue in track association evolves from 2-D assignment to S-D assignment. S-D assignment presents an N-P hard problem. Currently, apart from an exhaustive global search, no superior strategy exists for obtaining the optimal solution. Classical assignment methods employ Lagrangian relaxation and sequential m-best algorithms to seek suboptimal solutions to this problem while maintaining computational efficiency. Incorporating Lagrange multipliers into the original objective function eliminates a set of constraints, successively reducing the dimensions of the high-dimensional assignment. A critical aspect of this method lies in selecting suitable Lagrange multipliers to ensure that the optimization problem satisfies the removed constraints[91]. The sequential m-best algorithm sequentially conducts 2D assignments in a predetermined order to acquire $m$ optimal assignment outcomes, which are iteratively allocated in the subsequent rounds[92,93].

In the context of scenarios with varying numbers of detected targets across multiple sensors, a method using ambiguity functions was introduced in Ref. [89]. This approach establishes ambiguity factor sets between tracks based on target state estimates. However, its parameter setup is complex, necessitating extensive simulation for parameter fine-tuning, resulting in a high computational burden. To address this challenge, Ref. [82] proposes the Sequential m-best Track Association algorithm based on the New Target Density (SMBTANTD). This algorithm iteratively introduces tracks from the next sensor at each step and associates these tracks with previous results. By introducing the concept of new target density, targets detected by the subsequent sensor are treated as new targets, effectively resolving the cost allocation issue arising from inconsistencies in the number of measured targets across multiple sensors with reduced computational complexity.

We conducted a comparative analysis of the

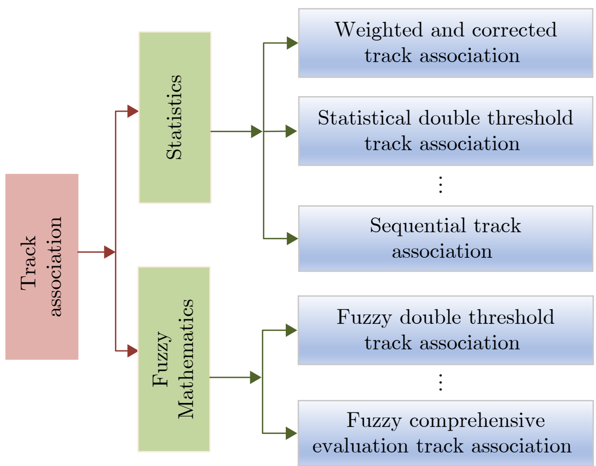


Fig. 6 Classification of track-to-track association methods

performance of three typical track association algorithms in scenarios with uneven numbers of detected targets across multiple sensors. The track association scenario in a common coordinate system is depicted in Fig. 7, where sensors 1, 3, and 4 detect targets 1, 2, and 3, respectively, whereas sensor 2 can only detect targets 1 and 2.

Tab. 4 and Fig. 8 present two distinct representations of the correct track association rates in the scenario illustrated in Fig. 7. Compared with methods based on traditional generalized likelihood and fuzzy function algorithms, the SMBTANTD demonstrates significantly improved correct association rates under reduced computational complexity.

### 4.2 Distributed sensor spatial registration and track association

In the realm of data fusion, spatial registration and track association are pivotal components of multi-sensor information integration, directly influencing the subsequent fusion performance[94]. These processes are interdependent prerequisites. However, research simultaneously addressing track association and sensor spatial registration remains limited. Most spatial registration algorithms assume that the track association issue is resolved, and vice versa for track association algorithms. In practice, however, track association and spatial registration are closely intertwined. Erroneous track associations can lead to imprecise spatial registrations, whereas flawed spatial registrations can disrupt data acquisition, confusing track association[95,96].

Existing solutions for the coupling between track association and spatial registration generally fall into two main categories. The first category involves joint estimation of track association and system errors. For example, Ref. [97] proposed a method that integrates sensor association, registration, and fusion by combining the Expectation Maximization (EM) algorithm with the KF. This approach iteratively obtains parameter estimates through alternating E-steps and M-steps iterations. Ref. [98] introduces a robust iterative algorithm for jointly estimating track association and system errors, treating incorrectly associated results as outliers in system error estimation. This method is particularly effective in environments with significant system errors and high false alarm rates. In addition, Ref. [99] models track association problems in system error environments as Global Nearest Pattern (GNP) data association problems, providing a maximum likelihood solution to the assignment problem by considering biases between observation sets. The second category involves designing track association algorithms based on target features that are insensitive to system errors. For example, Ref. [100] constructs a cost matrix using the topological features of targets and then determines association relationships based on linear assignment algorithms.

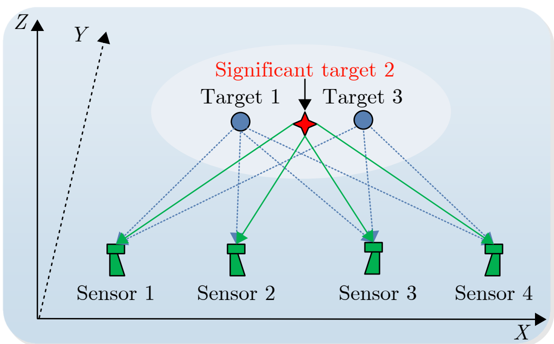


Fig. 7 Scene of track-to-track association

**Tab. 4 Comparison of multi-sensor track-to-track association methods**

| Association algorithm | Association rate (%) | Time consumed (s) |
|---|---|---|
| SMBTANTD[82] | 99.6 | 3.4 |
| Generalized likelihood[15] | 97.4 | 2.8 |
| Fuzzy function[89] | 96.7 | 8.1 |

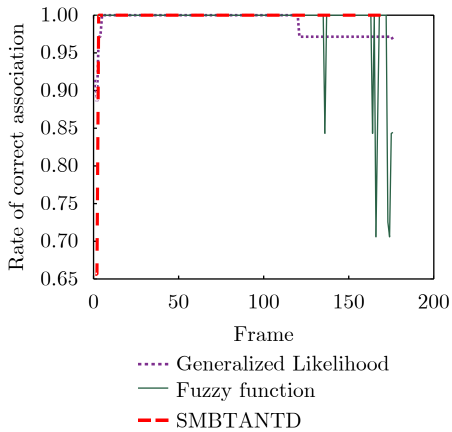


Fig. 8 Accuracy of track association[82]

To address the coupling issue between track association and spatial registration, Ref. [82] introduces an alternate iterative ddecoupling algorithm based on significant targets, as depicted in Fig. 9. Initially, a single stable and prominent target is selected based on target feature attributes such as radar cross-section, high-resolution distance image, micro-motion, and altitude. Subsequently, using appropriate filters like Kalman filters, filtered tracking is performed on the spatially registered multi-sensor multi-target measurements to derive target trajectories for each sensor. Finally, sensor-target trajectories are linked, with targets that exhibit high association rates identified as key targets for subsequent spatial registration.

By repeating this process, the precision of both spatial registration and track association can be significantly enhanced.

## 5 Research Progress of Distributed Sensor Data Fusion

DMMT, or distributed multi-sensor data fusion[15], functions within a system where each local sensor first employs single-sensor multi-target tracking algorithms to determine the target trajectories. These trajectories are then sent to a fusion center for spatiotemporal alignment and trajectory association. Then, the fusion center uses specific fusion criteria to estimate and merge trajectories from the same target. As a result, stable and high-precision global trajectories are created. Sections 2–4 provide detailed summaries of target tracking, sensor registration, and trajectory association. These sections primarily focus on reviewing and summarizing the estimation fusion criteria involved in DMMT systems, along with distributed multi-sensor target tracking methods based on these criteria.

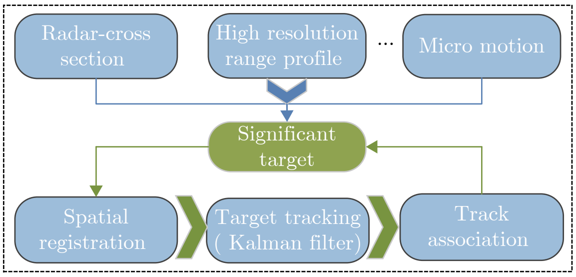


Fig. 9 Relationship of track-track association and spatial registration[82]

### 5.1 Distributed sensor estimation fusion criteria

Sensor estimation fusion, or fusion for estimation problems, involves the seamless integration of traditional estimation theory with data fusion theory. It pertains to the process of enhancing the accuracy of estimating target states by effectively leveraging valuable information from multiple datasets during the estimation of unknown quantities. Fig. 10 illustrates the estimation fusion process for Gaussian random variables. The figure demonstrates that under the condition of unbiased estimates from each sensor, the precision of the target state estimation following sensor fusion notably surpasses that obtained from any individual sensor.

Distributed multi-sensor trajectory fusion stands out as a key domain for the application of estimation fusion techniques. This fusion involves the optimal amalgamation of trajectory data from multiple sensors in accordance with specific fusion rules to derive more precise target state information. Tab. 5 presents various algorithms for distributed trajectory estimation fusion, including the simple convex combination fusion algorithm, the Bar-Shalom-Campo fusion algorithm, and the MAP state estimation fusion. The simple

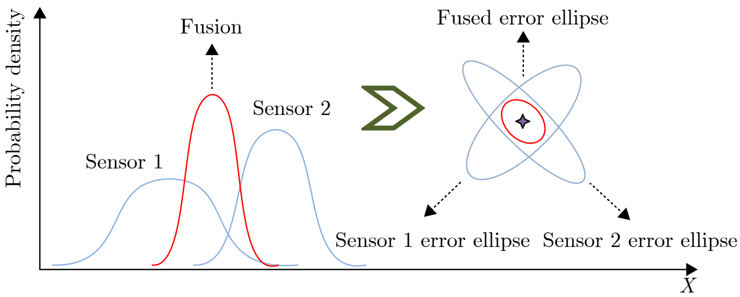


Fig. 10 Distributed multi-sensor estimation fusion

**Tab. 5 Comparison of multi-sensor estimation fusion methods**

| Estimation fusion method | Whether to consider track correlation | Computational complexity | Fusion accuracy | Sensor type |
|---|---|---|---|---|
| Simple convex combination fusion | No | Low | Low | Homogeneous |
| Bar-Shalom-Campo fusion | Yes | Higher | Higher | Homogeneous |
| MAP fusion | Yes | Higher | Higher | Homogeneous |
| CI fusion | Yes | Higher | Higher | Homogeneous |
| GCI fusion | Yes | Higher | Higher | Homogeneous \ Heterogeneous |
| AA fusion | Yes | Higher | Higher | Homogeneous \ Heterogeneous |
| EKF fusion | No | Higher | Higher | Homogeneous \ Heterogeneous |
| UKF fusion | No | Higher | Higher | Homogeneous \ Heterogeneous |
| PF fusion | No | High | High | Homogeneous \ Heterogeneous |

convex combination approach offers the best fusion estimate under the assumption of uncorrelated local sensor estimation errors, yielding fusion results equivalent to those of centralized fusion[101,102]. The Bar-Shalom-Campo fusion algorithm accounts for correlations in local sensor estimates arising from common process noise. This approach provides the optimal estimate in a Maximum Likelihood (ML) context and reduces the uncertainty of the fused estimate by up to 70% compared with the original and by 50% under the assumption of independent local sensor estimates[103,104]. Correlated data information is difficult to acquire. To address this challenge, Uhlmann[105] introduced the Covariance Intersection (CI) fusion algorithm. However, CI fusion is limited by Gaussian inputs. Hurley[106] proposed the Generalized Covariance Intersection (GCI) fusion method based on Bayesian principles to enable the fusion of arbitrary probability density functions. Professor Chang and collaborators[107] introduced the Maximum A Posteriori probability (MAP) estimation fusion approach to fully exploit local estimation data, leveraging each sensor's local estimates as prior information for computing the global trajectory estimate.

Trajectory fusion is categorized into optimal distributed fusion without feedback and optimal distributed fusion with feedback based on whether global information feeds back to local estimators[108,109]. Professor Zhu's team[110] from Sichuan University has confirmed that while feedback does not enhance the tracking performance of global trajectories, it reduces the error covariance of local estimates. Addressing the challenge of trajectory fusion involving nonlinear transformations due to differing target state spaces in local sensors (one in Cartesian coordinates and the other in polar coordinates), Bar-Shalom *et al.*[111–113] derived the Linear Minimum Mean Squared Error (LMMSE) estimation method and its cross-correlation computation for this particular scenario.

In recent years, the concept of average consensus fusion has attracted widespread attention from scholars globally. This fusion approach is categorized into Arithmetic Average (AA) fusion and Geometric Average (GA) fusion. Ref. [114] suggested that GA fusion outperforms AA fusion in terms of false alarm suppression. Nevertheless, AA fusion is highly regarded by scholars for its robustness, computational efficiency, and strong resilience against local faults and missed detections. To delve deeper into this topic, Professor Tiancheng Li's team[115–117] from Northwestern Polytechnical University conducted a comprehensive comparative analysis and review of the performance of AA fusion versus GA fusion. Furthermore, they extended the application of AA fusion to distributed multi-sensor multi-target detection and tracking.

The fusion of trajectory information from two or more heterogeneous sensors is highly advantageous due to the specific weaknesses of single-type sensors when deployed as independent systems. When dealing with heterogeneous sensor trajectory fusion, the data are initially divided into complete and incomplete measurements based on whether the spatial location details of the target are incomplete. The completeness of measurements dictates whether the results can be directly transformed into Cartesian coordinates. For example, a three-coordinate radar can provide complete measurements by simultaneously capturing the target's elevation, azimuth, and slant range in the measurement coordinate system. Post-target tracking, a comprehensive target state estimate in Cartesian coordinates can be derived. By contrast, passive sensors might only offer angular information about the target in the measurement coordinate system, leading to incomplete measurements. Consequently, heterogeneous sensor trajectory fusion often involves the use of incomplete measurement information in the measurement coordinate system to update the complete target state estimate in Cartesian coordinates. This process is achieved through nonlinear filtering methods[118,119]. Common nonlinear filtering methods include EKF, UKF, and Particle Filter fusion (PF)[120–122].

### 5.2 Distributed multi-sensor target tracking based on estimation fusion

DMMT is developed on the basis of single-sensor multi-target tracking. It requires simultaneous consideration of multi-target tracking methods and fusion criteria. The performance of DMMT is influenced by variations in these factors. As shown in Tab. 6, similar to the framework of single-sensor multi-target tracking, DMMT is categorized into data association and RFS methods. Research on data association-based DMMT methods has earlier origins, with notable representatives, such as Distributed Multi-Sensor multiple Cheap Joint Probability Data Association (DMS-CJPDA)[123] and DMS Multiple Hypothesis Tracking (DMS-MHT)[124,125].

The development of DMMT based on RFS has made significant strides with the introduction of GCI fusion, which can accommodate any probability density. In 2013, Üney *et al.*[126] integrated RFS with GCI fusion criteria to establish a consistent method for DMMT. This approach yielded explicit formulas for Exponential Mixture Densities (EMD), enabling the implementation of a distributed PHD filtering algorithm grounded in GCI fusion principles. Concurrently, Battistelli *et al.*[127] proposed a distributed CPHD filtering approach that leveraged network consensus theory to derive a numerical solution for distributed CPHD filtering based on GCI fusion criteria. This approach enhances the scalability of distributed sensor fusion networks. Compared with PHD and CPHD filters, the MB filter offers improved performance, computational load balance, robustness, and stability. Addressing challenges, such as unknown measurement correlations among multiple sensor network nodes, Ref. [128] introduced the GCI criterion-based MB distributed filtering fusion algorithm (GCI-MB). This work provided an analytical expression of the posterior distribution for GCI-MB fusion, establishing foundational prerequisites for distributed fusion methodologies. However, given that these approaches do not assign tracks to multiple targets, in 2018, Fantacci *et al.*[129] pioneered a label-oriented multi-target distributed fusion methodology. This approach, premised on the assumption of shared label spaces across different sensors, yielded closed-form expressions for GLMB and LMB filters using GCI fusion criteria. Despite its advancements, this

**Tab. 6 Performance comparison of multi-sensor multi-target tracking methods**

| Types of multiple target tracking | Fusion criteria | Tracking methods | Computational complexity | Tracking accuracy |
|---|---|---|---|---|
| Data association | CI Fusion | JPDA | Medium | Medium |
| | Simple convex combination fusion | MHT | High | Medium |
| Random finite set | GCI/GA fusion | PHD | Low | Low |
| | | CPHD | Medium | Medium |
| | | MeMBer | Medium | Medium |
| | | GLMB | High | High |
| | | LMB | Medium | High |
| | AA fusion | PHD | Low | Low |
| | | CPHD | Medium | Medium |
| | | MeMBer | Medium | Medium |
| | | GLMB | High | High |
| | | LMB | Medium | High |

method failed to offer further insights into the underlying implications of shared label spaces among diverse sensors, nor did it validate the conditions under which this assumption remains valid. Subsequently, Li *et al.*[130] formulated a mathematical model to address label inconsistency issues among filters within the labeled RFS theory framework. Their quantitative analysis of label inconsistency's impact on GCI fusion performance underscored the sensitivity of GCI fusion to label inconsistencies among filters. Building on this analysis, Li *et al.*[131] proposed a label-free robust GCI fusion algorithm in 2018, extending its application to distributed GLMB and LMB filters.

GCI fusion, also known as generalized average fusion, and AA fusion, average consensus fusion methods, effectively avoid redundant computations of common information and are considered approximate suboptimal distributed fusion methods. Contrary to GCI-distributed fusion, Li *et al.*[115,116] from Northwestern Polytechnical University extended AA fusion to distributed multi-sensor PHD and MeMBer filters. Simultaneously, researchers, including Gao *et al.*[132,133] from the University of Electronic Science and Technology of China, broadened the application of AA fusion to distributed multi-sensor CPHD, GLMB, and LMB filters. In summary, compared with DMMT theories based on association classes, DMMT technologies rooted in RFS are a current focal point in the field of information fusion. However, despite its prominence, the theoretical research in this area still faces numerous issues that require further resolution and refinement.

## 6 Problems and Development Direction of DMMT

Currently, DMMT has made notable advancements and finds widespread applications in military and civilian domains. However, several challenging aspects persist in critical technical areas, such as target tracking, spatial registration, track association, and track fusion.

(1) Multi-Target Tracking: In complex scenarios, the presence of dynamic unknown clutter poses a severe challenge to weak target detection and tracking. Dynamic clutter can compromise target detection effectiveness, leading to a high volume of false measurements and decreased tracking performance. Therefore, studies on integrated detection and tracking, along with adaptive clutter dynamic estimation, are crucial in multi-target tracking.

(2) Spatial Registration: System biases that evolve over time introduce complexities. While online spatial registration algorithms based on filtering exist, these algorithms may exhibit lower registration accuracy under target maneuvering conditions due to mismatches in target motion models. In addition, achieving high-precision, real-time spatial registration in complex scenarios is crucial, especially in scenarios requiring non-cooperative target spatial registration.

(3) Track Association: Existing track association algorithms with varying threshold values based on scene dynamics pose challenges in setting appropriate thresholds. Tracks with residual biases present difficulties in effective association. While deviation-resistant association algorithms based on track shape features exist, effective track association in scenarios involving dissimilar track associations and sensor limitations in obtaining target track shape information remain unresolved.

(4) Track Fusion: Residual biases influence track fusion, where errors from different sensors are overshadowed by estimated position variations among locally tracked segments awaiting fusion. This scenario often leads to fusion estimates deemed unreasonable. Real-time assessment of residual biases for each track through establishing detection thresholds is essential. However, the complexity lies in setting these thresholds, making real-time quality evaluation of fused tracks critical for future track fusion development.

## 7 Conclusion

The robustness and scalability of DMMT have led to its increasingly widespread application across diverse fields. This study outlines key algorithms associated with target tracking, sensor registration, track association, and data fusion within the framework of DMMT. It systematically examines the advantages, drawbacks, and conditions of applicability for these algorithms. It also addresses spatial registration challenges in scenarios with incomplete measurements, using a spatial registration method based on residual bias. Furthermore, for scenarios where the number of detected targets varies among multiple sensors, a track association algorithm centered on new target density is introduced.Finally, the article thoroughly analyzes the difficulties and future trajectories of essential technologies in DMMT within complex scenarios, offering valuable insights for prospective research endeavors in this domain.

**利益冲突** 所有作者均声明不存在利益冲突

**Conflict of Interests** The authors declare that there is no conflict of interests

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