

# Track-to-Track Fusion (Tracking in Distributed System)

## 目录

- 背景知识介绍
  - Centralized Fusion vs Distributed Fusion (Track-to-Track Fusion) (TTTF)
- Track-to-Track Fusion Framework
- Track-to-Track Association
  - Clustering in TTTA
    - Hard Clustering vs Soft Clustering
- **Fuzzy C-Means Clustering**
  - Fuzzy track-to-track association and track fusion approach in distributed multisensor-multitarget multiple-attribute environment
- Track Fusion
  - Covariance Intersection
  - Federated filter
    - 联邦滤波器一般结构
    - 联邦滤波器的结构
      - 零复位模式&&变比例模式
- 参考文献
- 更多资料

## 背景知识介绍

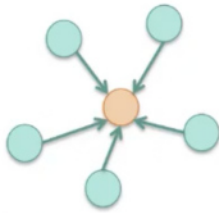
### Centralized Fusion vs Distributed Fusion (Track-to-Track Fusion) (TTTF)

中心化融合讲测量直接给Fusion Center (FC) 而 分布式融合系统每个nodes都自己做滤波或者是Tracker, 然后传递给Fusion Center. 我们的系统其实就是TTTF系统

## Centralized vs. Decentralized vs. Distributed

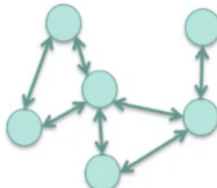
### Centralized:

- Distinguished Fusion Center (FC)
- Send all measurements to FC
- No cross covariances of tracks
- Doesn't scale with False Alarms (FA)



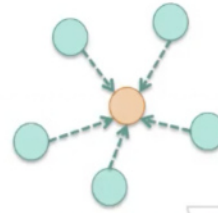
### Decentralized:

- Every node is a FC
- Send data only to neighbors
- Estimate network topology
- Account for "information incest"
- Only approximate solutions exist



### Distributed:

- Distinguished FC
- Preprocess measurements on nodes
- Send estimates to FC
- Account for X-correlations
- Scales very well in number of sensors and in FA.



© Fraunhofer FKIE

7

An Introduction to Track-to-Track Fusion and the Distributed Kalman Filter  
Felix Govaers, AESS DL

AESS

Fraunhofer  
FKIE

zoom

分布式融合有很多优点，但是也有一些很难解决的问题：有个一致性的结论，就是**中心化融合架构更加容易做到效果最优**

1. 时间同步的问题（out-of-sequence）问题**会更加严重**，抵达FC的时间不同步；
2. 由于上游做了一次滤波之后，有很严重的互相关的问题，这个互相关的问题会导致：
  - a. 如果下游把上游的结果当做一个测量，忽略相关性（Naive Fusion）**结果会过于乐观，cov会做的过小**
  - b. 滤波出来的**结果容易出现biase**，比如现在视觉的速度跟radar的速度，偏差太大，FC难以进行数值融合，只能在radar跟cam中进行挑选，做最轻量级的平滑（当然了，目前融合做的是最简单的处理策略）
  - c. 为了解决互相关的问题，最常用的手段是（**Covariance Intersection**）融合，这个技术在视频中有展示，目前不展开，后面介绍**联邦滤波**的时候再展开，但是就算用了Covariance Intersection，最终的cov也是**悲观的**。

### Tracking in Distributed Systems

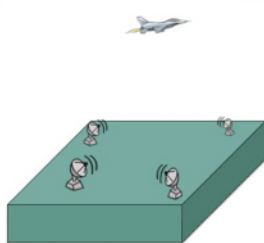
Distributed Systems have the following advantages and drawbacks.

#### Advantages:

- No single point of failure
- Cheap sensor technology
- Complementary sensors
- Spatial distribution
- Distributed computation

#### Challenges:

- Communication of data necessary
- Sensor synchronization
- Sensor registration
- Correlations



© Fraunhofer FKIE

6

An Introduction to Track-to-Track Fusion and the Distributed Kalman Filter  
Felix Govaers, AESS DL

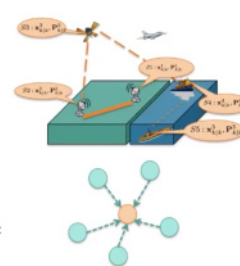
AESS

Fraunhofer  
FKIE

zoom

### Conclusion for Track-to-Track Fusion and the Distributed Kalman Filter

- Distributed and decentralized data fusion enhance spatial coverage, estimation performance, and balances the computational load.
- Approximate fused estimates are easily obtained via Naive Fusion (optimistic) or Covariance Intersection (pessimistic).
- Optimal Fusion requires full communication (Tracklet Fusion) or decorrelation of local tracks (DKF).
- The globalization of local covariances implies decorrelated local tracks (DKF), but requires remote covariances or sensor models.



46:02 / 55:50

6

An Introduction to Track-to-Track Fusion and the Distributed Kalman Filter  
Felix Govaers, AESS DL

AESS

Fraunhofer  
FKIE

zoom

i 摘自文献[3]

**Centralized tracking methods** yields **more accurate results** in comparison with distributed tracking methods. However, centralised methods in comparison with distributed methods

1. require **higher computing power** in the FC,
2. need for **high data transfer rate** for sending measurements of sensors to the FC
3. have **high vulnerability** in the case of failure in the FC.

Given the expressed issues, the distributed tracking systems have **higher acceptability and application** than that of centralized tracking systems

## Track-to-Track Fusion Framework

TTTF系统中有两个问题被广泛研究，一个是Track-to-Track Association (TTTA) 一个是Track Fusion (TF)，其中TF要解决的就是上文中提到的互相关，时间同步问题

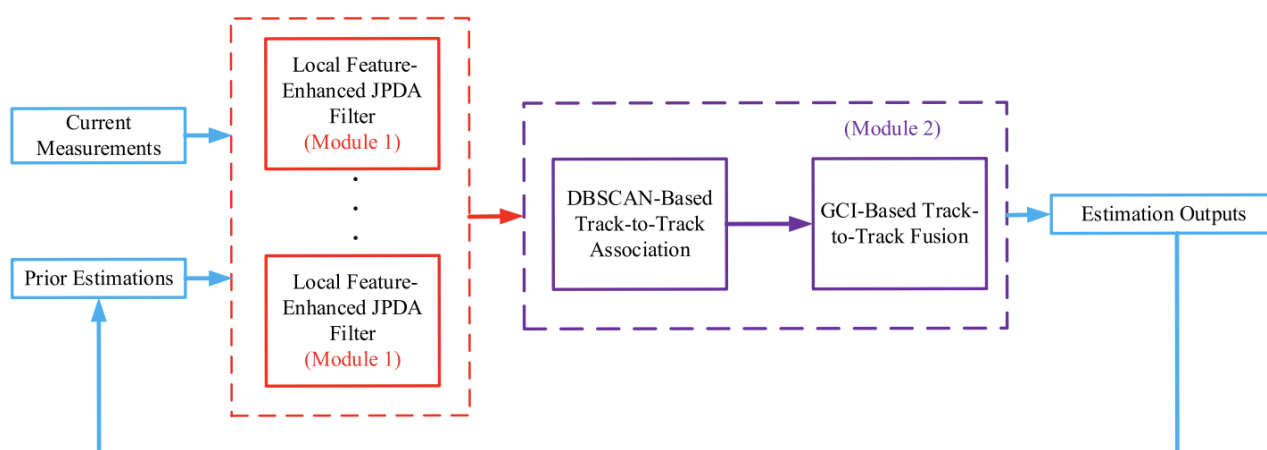
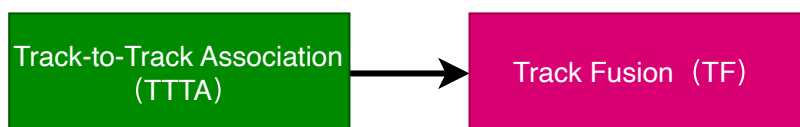


Fig. 2: Information flow of the proposed algorithm.

来自文献【2】

## Track-to-Track Association

TTTA问题最早在radar等传统传感器融合系统中被研究, 使用clustering来解决多个sensor track对应同一个target的已经成为共识。所以研究的问题集中在：

- 1. sensor之间的bias，如何估计并且如何关联，详细相关工作详见文献【3】的related work
- 2. 何种clustering算法是最适合TTTA问题的。常见clustering算法分类参见【5】，【6】，【7】

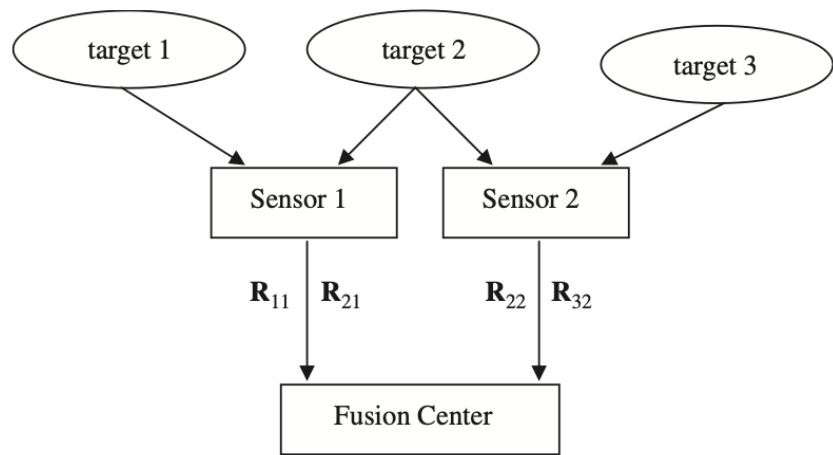


Fig. 1. MSMT environment with two sensors and three targets.

图片来自文献【1】

本章节目前不扩展bias问题怎么解决，而是集中在clustering算法的探讨。

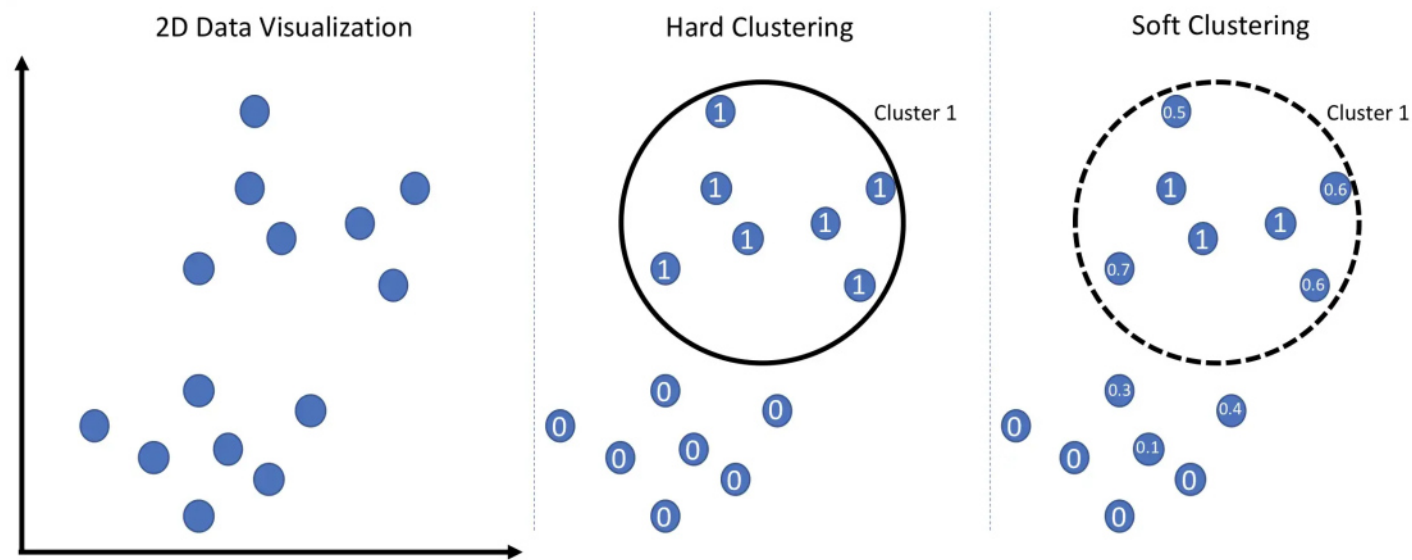
@王晓亮 @顾恺琦 补充radar bias问题怎么解决。

## Clustering in TTTA

### Hard Clustering vs Soft Clustering

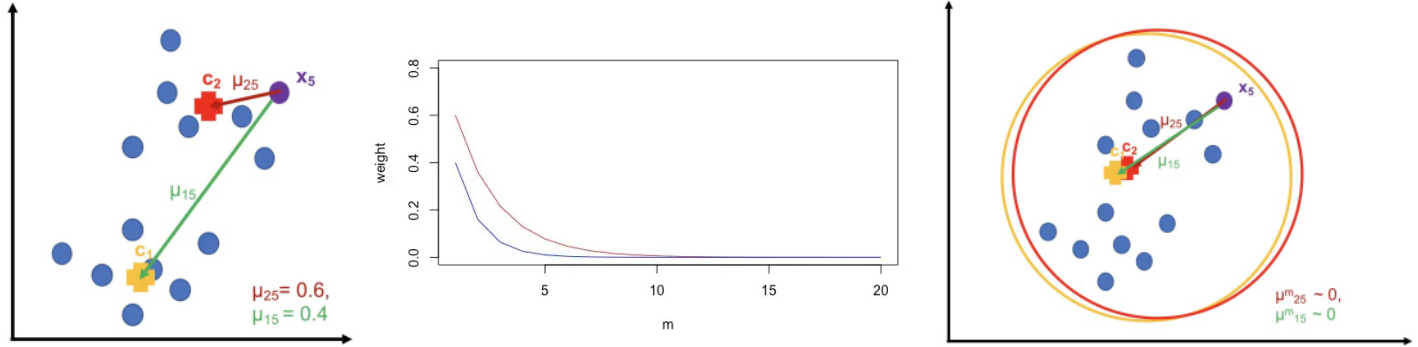
Hard and Soft clustering. Each dot represent a data point, the number in each dot is the probability of its belonging to Cluster 1, and the black circle represents the cluster boundary of Cluster 1.

(Image by author), 来自文献【4】



- ❗ 相比与Hard Clustering，Soft Clustering似乎更加适合TTTA，因为后续还要做TF，softs的fusion似乎更加合理，但是并不是绝对的，如文献【2】使用了DBSCAN来处理TTTA的问题，文献【1】【3】就是使用Soft Clustering技术，正如关联中JPDA的性能理论上比GNN最好一样。文献【8】中有详细解释DBSCAN的算法

## Fuzzy C-Means Clustering



### The Algorithm

The full FCM algorithm could be described in the figure below.

1. Initialize the matrix of  $\mu_{ij}$ ,  $\mathbf{U}$
2. Update  $\mathbf{c}_i$ :

$$c_i = \frac{\sum_{j=1}^N \mu_{ij}^m x_j}{\sum_{j=1}^N \mu_{ij}^m}$$

3. Update  $\mu_{ij}$ :

$$\mu_{ij} = \frac{1}{\sum_{k=1}^C \left( \frac{\|x_j - c_i\|}{\|x_j - c_k\|} \right)^{\frac{2}{m-1}}}$$

4. If the change of  $\mathbf{U}$  between two iterations is very small (predefined cutoff), then stop; otherwise, go to step #2.

Algorithm of FCM (Image by author)

- ❗ 详细算法详见文献【4】，解释的非常详细了，大家认真看一下。

Fuzzy C-means Clustering算法与k-means算法类似，需要确定cluster数量，这个是不合适的，在TTTA问题中，具体target的数量是不确定的

## Fuzzy track-to-track association and track fusion approach in distributed multisensor–multitarget multiple-attribute environment

@莫善会 认真看一下这篇论文，后面我会写一篇文章，用clustering来做Multiple Hypothesis 速度估计

在这篇论文中，提出一下基于Fuzzy C-meas Clustering算法的改进，能够自动确定具体target的数量。基本的思想如下：

1. 不知道target数量，可以将sensor track的位置当做c值，以大融合为例，拿最优的track当做c也可以
2. 利用FCM公式算出来的中间结果**degree of memberships**矩阵，综合对比决策，看是否需要创建一个新的cluster
3. 每个sensor track都有一个分辨率的概念，其实就是最近邻的感觉，有density聚类的感觉。

The proposed method uses current sensor data and the **known sensor resolutions** for TTTA and the selection of the most accurate sensor for tracking fused targets. The FCM algorithm **is not used in its recursive procedures**. Instead, the proposed method **utilizes the FCM equations** to generate **a fuzzy likelihood measure (metric) instead of the classical measures**. Thus, the proposed method uses the **FCM equations to generate the degree of memberships** of the sensor resolutions as well as the difference vector of the common state estimates. The obtained degrees of memberships are **then compared to decide whether the state estimates (tracks)** represent the same target or not.

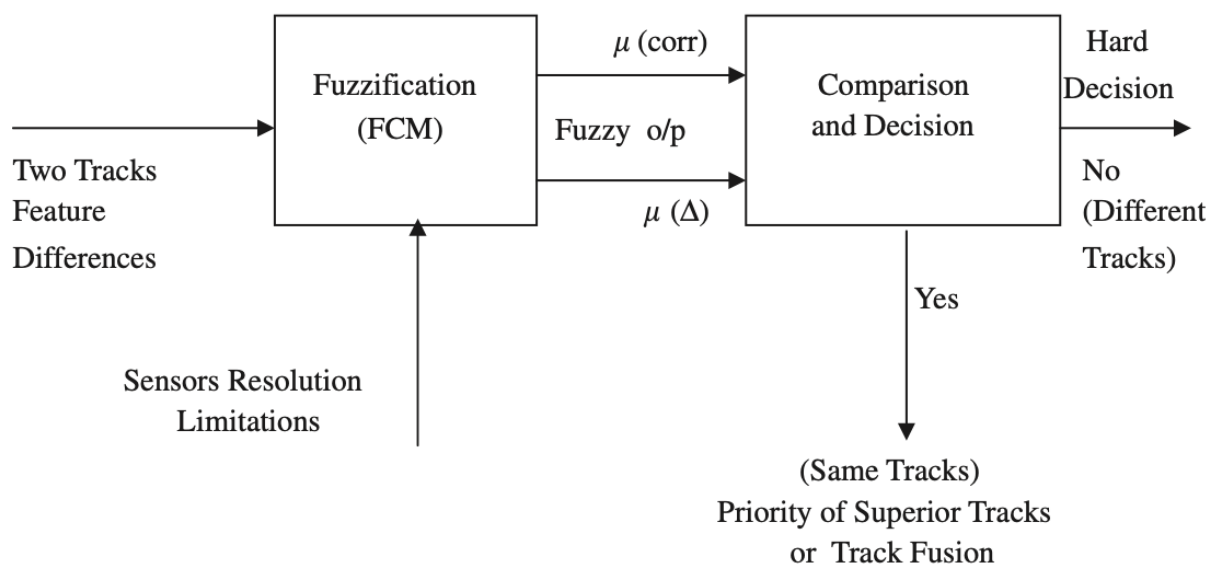


Fig. 2. Proposed fuzzy TTTA and TF approach.

## Track Fusion

@莫善会 这个章节好好看看

文献【1】直接挑选最优的Track作为状态估计的结果

**One approach** to obtain the global track is to **adopt the superior of the tracks**. The **second approach** is to **fuse the tracks according to some score (weights)**. It will be shown that under



certain conditions the performance of the fused track may perform worse than the performance of the superior track. In this case, it is recommended to adopt the superior track and TF is not recommended.

如何挑选的 @莫善会 补充

文献【2】：使用CI的方式来做，这边简单介绍一下CI，介绍资料来源于文献9

Covariance Insection

上文说到，如果每个sensor各自做滤波，那么滤波的结果是有相关性的，这种相关性如果计算出来，并且传出来，是可以去除掉这种相关性的，但是每次都算互相关性明显是一个不现实的事情。因此提出了Covariance Insection技术：

- 1. 下图左图显示：如果知道互相关矩阵，最优cov都是在两个cov insection范围里面，因此为了防止 naive fusion的过于乐观，就是cov过小的问题，转为求解一个tight Bound
- 2. 最优的tight boundary其实就是覆盖两个cov相交的面积的最小cov，这是个优化问题

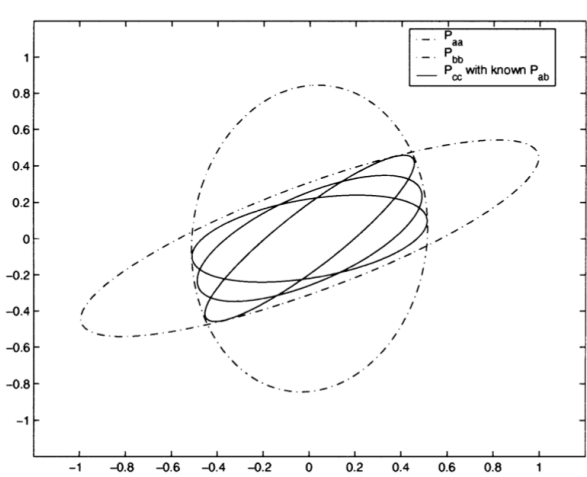


Fig. 1. Solid: Three examples of  $P_{cc}$  with  $\bar{P}_{ab}$  known. Dashed:  $P_{aa}$  and  $P_{bb}$ .

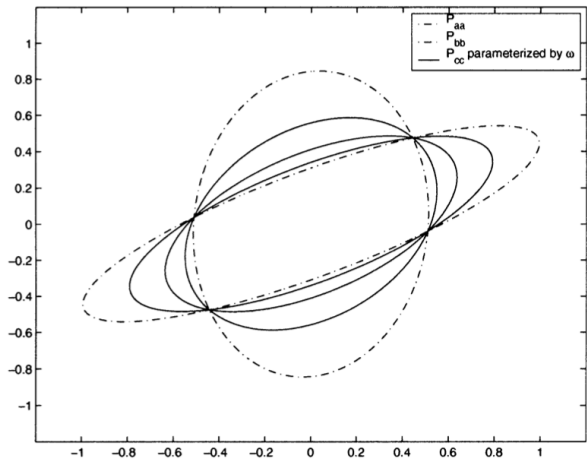
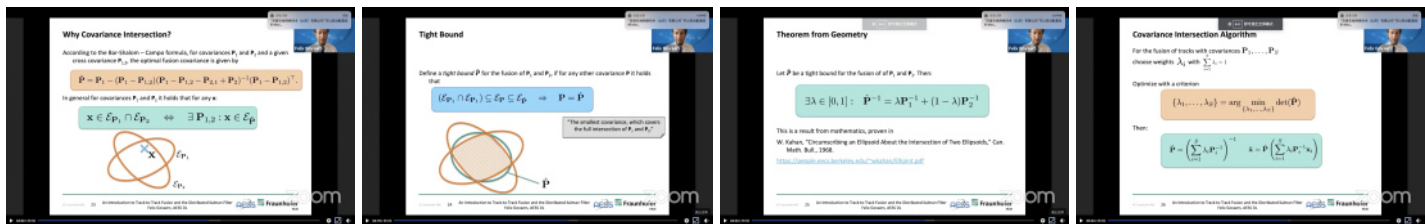


Fig. 2. Solid: Three examples of  $P_{cc}$  containing the intersection. Dashed:  $P_{aa}$  and  $P_{bb}$ .



information matrix 加权

上面第三张图显示，information matrix（inverse of covariance matrix）的进行加权得到的矩阵一定是某个bound，最优的ci结果就是优化一个最tight的边界，这块对后面联邦滤波的理解是非常重要的。

Federated filter

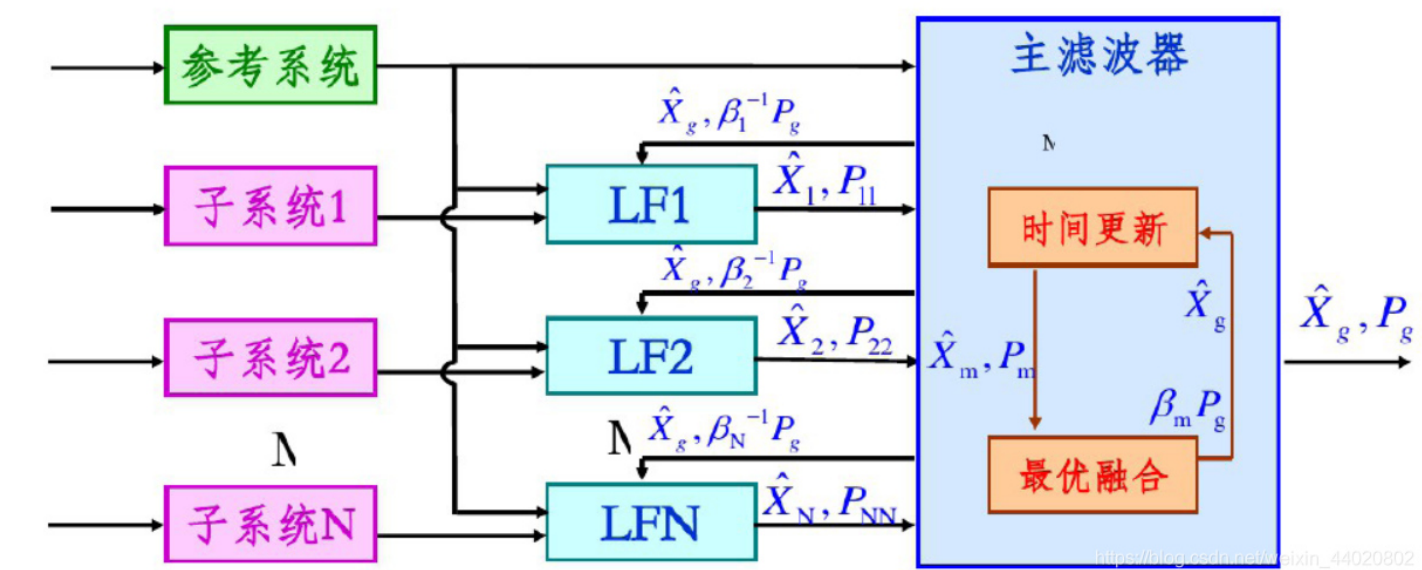
这块就别看了 耽误人

联邦滤波【12】是一种最常用的滤波架构，用于分布式的信息融合

Carlson应用方差上界技术和信息分配原理论证了当主滤波器和局部滤波器的维数都相同时联邦滤波器的全局最优性,并且信息分配系数选定后是不变的。文献【14】

联邦滤波器一般结构

下图是联邦滤波的一般结构，多个局部滤波器的融合LF与CI是十分类似的，但是存在反馈回路，并且主滤波器的结果会参与滤波，反馈的力度以及主滤波器历史状态的影响的力度都是通过实现设定的超参  $\{\beta_1 \cdots \beta_N, \beta_m\}$  决定的称为信息分配与重置。不同的信息分配与重置参数决定了这个系统的特性



联邦滤波器工作流程

a) 信息分配与重置：根据在各子滤波器和主滤波器之间分配系统的信息，包括系统的过程信息  $Q_k$ ；以及利用融合中心结果  $\hat{x}_g$  和  $P_g$  对个滤波器的状态估计进行重置。

$$\begin{cases} Q_{k+1} = P_k^T Q_k P_k + Q_k & Q_k \text{ 为过程噪声协方差} \\ P_{k+1} = P_k^T P_{k+1} & \beta_i = 0 \text{ and } \sum_{i=1}^N \beta_i = 1 \\ P_{k+1} = P_{k+1} & i = 1, 2, \dots, N, m \end{cases}$$

联邦滤波器工作流程

b) 信息的时间更新：时间更新过程在各子滤波器和主滤波器之间独立进行：

$$\begin{cases} \hat{x}_{k+1}^i = F_{k+1}^i \hat{x}_k^i \\ P_{k+1}^i = F_{k+1}^i P_k^i F_{k+1}^{iT} + \Gamma_{k+1}^{iT} Q_{k+1}^i \Gamma_{k+1}^T & i = 1, 2, \dots, N, m \end{cases}$$

联邦滤波器工作流程

c) 量测更新：主滤波器没有量测，没有量测更新。量测更新只在各个局部子滤波器中进行：

$$\begin{cases} (P_k^i)^{-1} = (P_{k+1}^i)^{-1} + (H_k^i)^T Q_k^{-1} (H_k^i) \\ (P_k^i)^{-1} \times \hat{x}_k^i = (P_{k+1}^i)^{-1} \hat{x}_{k+1}^i + (H_k^i)^T Q_k^{-1} z_k^i & i = 1, 2, \dots, N \end{cases}$$

联邦滤波器工作流程

d) 信息融合：联邦滤波器核心算法是将各个局部滤波器的局部估计信息和主滤波器的信息按下式进行融合，以得到全局的最优估计：

$$\begin{cases} P_k^g = [(P_1^g)^{-1} + \dots + (P_N^g)^{-1} + (P_m^g)^{-1}]^{-1} \\ \hat{x}_k^g = P_k^g [(P_1^g)^{-1} \hat{x}_k^1 + \dots + (P_N^g)^{-1} \hat{x}_k^N + (P_m^g)^{-1} \hat{x}_k^m] \end{cases}$$

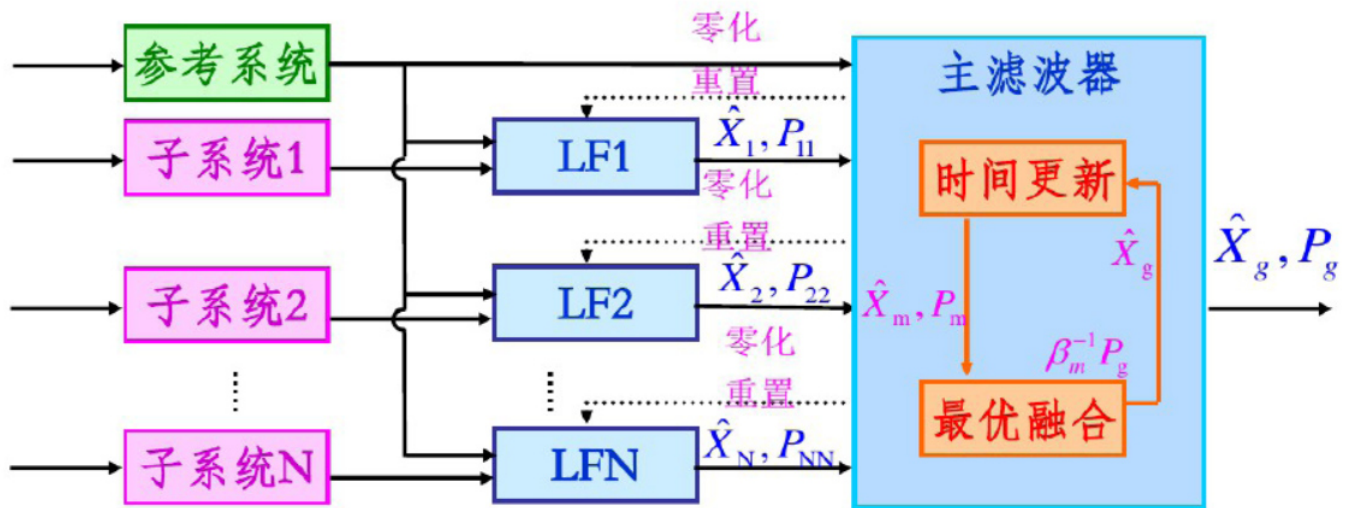
联邦滤波器的结构

根据信息分配策略不同,联邦滤波算法有4种实现模式:零复位模式；变比例模式；无反馈模式；融合一反馈模式。

零复位模式&&变比例模式

零复位模式  $\beta_i = 0, \beta_m = 1$  , 变比例模式  $\beta_i = \beta_m = 1/(N + 1)$  有重置





[https://blog.csdn.net/weixin\\_44020802](https://blog.csdn.net/weixin_44020802)

## 参考文献

1. Aziz A M. Fuzzy track-to-track association and track fusion approach in distributed multisensor-multitarget multiple-attribute environment[J]. Signal Processing, 2007, 87(6): 1474-1492.
2. He S, Shin H S, Tsourdos A. Multi-sensor multi-target tracking using domain knowledge and clustering[J]. IEEE Sensors Journal, 2018, 18(19): 8074-8084.
3. Nazari M, Pashazadeh S, Mohammad-Khanli L. An adaptive density-based fuzzy clustering track association for distributed tracking system[J]. IEEE Access, 2019, 7: 135972-135981.
4. <https://towardsdatascience.com/fuzzy-c-means-clustering-with-python-f4908c714081>
5. <https://www.heka.ai/en/our-publications/time-series-clustering>
6. <https://zhuanlan.zhihu.com/p/104355127>
7. [https://scikit-learn.org/stable/auto\\_examples/cluster/plot\\_cluster\\_comparison.html](https://scikit-learn.org/stable/auto_examples/cluster/plot_cluster_comparison.html)
8. <https://www.youtube.com/watch?v=RDZUdRSDOok>
9. <https://www.facebook.com/IEEEAEISS/videos/an-introduction-to-track-to-track-fusion-and-the-distributed-kalman-filter/316428269645401/>
10. Chen L, Arambel P O, Mehra R K. Estimation under unknown correlation: Covariance intersection revisited[J]. IEEE Transactions on Automatic Control, 2002, 47(11): 1879-1882.
11. [https://blog.csdn.net/weixin\\_44020802/article/details/108968937](https://blog.csdn.net/weixin_44020802/article/details/108968937)
12. Carlson N A. Federated filter for fault-tolerant integrated navigation systems[C]//IEEE PLANS'88., Position Location and Navigation Symposium, Record.'Navigation into the 21st Century'. IEEE, 1988: 110-119.
13. <https://zhuanlan.zhihu.com/p/64494401>
14. Qi-Tai G U, Jing F. Global optimality for generalized federated filter[J]. Acta Automatica Sinica, 2009, 35(10): 1310-1316.

# 更多资料



An\_Adaptive\_Density-Based\_Fuzzy\_Clustering\_Track\_Association\_for\_Distributed\_Tracking\_System.pdf (



Fuzzytrack-to-trackassociationandtrackfusionapproachindistributedmultisensormultitargetmultiple-attrib... 20



Multi-sensor\_multi-target\_tracking-2018.pdf (441KB)



IET Radar Sonar Navi - 2018 - Qi - Multi-radar anti-bias track association based on the reference topolo... t



IET Intelligent Trans Sys - 2018 - Lee - Sensor fusion for vehicle tracking based on the estimated probability



dan2018.pdf (2MB)



download.pdf (304KB)

