QADA-PDA versus JPDA for Multi-Target Tracking in Clutter

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July 10th, 2017

Outline

Introduction (1)

QADA = **Q**uality **A**ssessment of **D**ata **A**ssociation

This presentation is an **extension/improvement** of the Fusion 2017 paper

[1] J. Dezert, A. Tchamova, P. Konstantinova, E. Blasch, A Comparative Analysis of QADA-KF with JPDAF for Multi-Target Tracking in Clutter, in Proc. of Fusion 2017 int. Conference

This QADA-PDA method for MTT has been published very recently (June 2017) in

[2] J. Dezert, A. Tchamova, P. Konstantinova, *Performance Evaluation of improved QADA-KF and JPDAF for Multitarget Tracking in Clutter*, Proc of the annual international scientific conf. "Education, Science, Innovations", European Polytechnical Univ., Pernik, Bulgaria, June 9-10, 2017.

Multi-Target Tracking (MTT) ⇒ Data Association + Tracking Filter

1. **Data Association (DA)** - important task of MTT [Bar-Shalom 1990]
DA purpose is to find the assignment matrix with most likely observation-to-track associations to keep and improve target tracks maintenance performance
    - Classical DA approach:
    -Use all observations-to-tracks pairings selected in the 1st optimal global DA solution to update tracks, . . . even if some pairings solutions are doubtful (have poor quality)
    - Sophisticate approaches:
    - Use all possible joint DA solutions and their a posteriori probas ⇒ Joint Probabilistic Data Association Filter (**JPDAF**) [Bar-Shalom Fortmann Scheffe 1980]
    - Use the 1st best global DA solution, evaluate its quality and modify the tracking filter accordingly ⇒ Quality Assessment of Data Association (**QADA**) approach introduced in [Dezert Benameur 2014]
2. **Tracking filters** The CMKF (Converted Measurement Kalman Filter) [Lerro Bar-Shalom 1993] and JPDAF are used in this work
3. **In this presentation** We compare performances of
    - QADA-PDA KF based MTT (QADA using PDA matrix and min dist. decision strategy)
    - JPDAF based MTT.

Joint Probabilistic Data Association Filter

→ proposed in [Bar-Shalom Fortmann Scheffe 1980] as an extension of PDAF for MTT

- **Main idea:**
  The meas.-to-target association probas $\beta_i^t(k) = \sum_{\Theta(k)} P\{\Theta(k)|Z^k\}\hat{\omega}_{it}(\Theta(k))$ and $\beta_0^t(k) = 1 - \sum_{i=1}^{m_k} \beta_i^t(k)$ are computed jointly across the targets from the joint posteriori probas $P(\Theta(k)|Z^k)$ and only for the latest set of measurements. The target track updates are done for $t = 1, \ldots, N_T$ by

$$\hat{x}^t(k|k) = \hat{x}^t(k|k-1) + K^t(k) \sum_{i=1}^{m_k} \beta_i^t(k)\tilde{z}_i^t(k)$$

$$P^t(k|k) = \beta_0^t(k)P^t(k|k-1) + \left(1 - \beta_0^t(k)\right)P_c^t(k) + \tilde{P}^t(k)$$

- **Assumptions of JPDAF**
  - the number N_T of targets is known and tracks have been initialized;
  - $p(x^t(k)|Z^k) \sim \mathcal{N}(x^t(k); \hat{x}^t(k|k), P^t(k|k))$, for $t = 1, \ldots, N_T$
  - each target generates at most one meas. at each scan and there are no merged meas.;
  - each target is detected with some known detection probability $P_d^t \leqslant 1$;
  - false alarms (FA) are uniformly distributed with known FA density λ_{FA} (Poisson pmf).
- **Advantages**
  - very good theoretical framework, and 0-scan-back filter (memoryless filter)
  - work well with moderate FA densities and non persisting interferences
- **Drawbacks**
  - often intractable for complex dense MTT scenarios
  - track coalescence effects in difficult scenarios

Data Association (DA) Problem

Find the global optimal assignments of measurements $z_j, j = 1, ..., N$ available at time k to targets $T_i, i = 1, ..., N_T$ by maximizing the overall gain (rewards):

$$R(\mathbf{\Omega}, A) \triangleq \sum_{i=1}^{N_T} \sum_{j=1}^{N} \omega(i,j) a(i,j).$$

- $\mathbf{\Omega} = [\omega(i,j)]$ is the **DA matrix** representing the gain of the associations of target T_i with the measurement z_j (usually homogeneous to the likelihood).
- **Assignment solution**: $N_T \times N$ binary matrix $A = [a(i,j)]$ with $a(i,j) \in \{0, 1\}$

$$a(i,j) = \begin{cases} 1, & \text{if } z_j \text{ is associated to track } T_i \\ 0, & \text{otherwise.} \end{cases}$$

How to get the optimal solution(s)

- by Kuhn-Munkres/Hungarian algorithm (1955/1957)
- by Bourgeois and Lassalle (1971) for rectangular DA matrix.
- by Murty's method (1968) which gives the m-best assignments in order of increasing cost $\Rightarrow$ used in QADA method

Main Idea behind QADA method [Dezert Benameur 2014]

- compare (z_j, T_i) in the 1st-best DA solution with (z_j, T_i) in the 2nd-best DA solution
- establish a quality indicator, associated with pairing in 1st-best DA solution, based on belief functions, PCR6 fusion rule [DSmT Books], and some decision strategy.

QADA assumes the DA (reward) matrix is known, regardless of the manner in which it is obtained. $\Rightarrow$ Several QADA-based MTT are possible depending of the choice of DA matrix construction

The QADA method

1. based on a (modified) Basic Belief Assignment (BBA) modeling
2. the computation of quality of DA (i.e. confidence) $q(i, j) \in [0, 1]$ of pairings $(T_i, z_j), i = 1, .., N_T; j = 1, .., N$ chosen in the 1st-best DA solution is based on its stability in the 2nd best DA solution and a belief Interval distance decision strategy[1]

[1] In our Fusion 2017 paper, it is based on Pignistic Probability transformation decision strategy, which is a lossy transformation.

Choice of DA matrix for QADA

Two choices of DA matrix Ω for QADA-KF have been tested

1. QADA-GNN $\Rightarrow$ DA matrix Ω is based on distances (as used in Global Nearest Neighbours (GNN) approach)
   - Elements ω_{ij} are the normalized distances $d(i,j)$ s.t. $d^2(i,j) \leqslant \gamma$ given by

$$\omega(i,j) \equiv d(i,j) \triangleq [(z_j(k) - \hat{z}_i(k|k-1))' S^{-1}(k)(z_j(k) - \hat{z}_i(k|k-1))]^{1/2}$$

2. QADA-PDA $\Rightarrow$ DA matrix Ω is based on Posterior Data Association (PDA) probas as given in PDAF
   - Elements ω_{ij} of Ω are the posterior DA probas p_{ij} given by PDAF

$$p_{ij} = \begin{cases} \frac{b}{b+\sum_{l=1}^{N} \alpha_{il}} & \text{for } j = 0 \text{ (no valid observ.)} \\ \frac{\alpha_{ij}}{b+\sum_{l=1}^{N} \alpha_{il}} & \text{for } 1 \leqslant j \leqslant N \end{cases}$$

   where $b \triangleq (1 - P_g P_d)\lambda_{FA}(2\pi)^{M/2}\sqrt{|S_{ij}|}$ and $\alpha_{ij} \triangleq P_d \cdot e^{-\frac{d_{ij}^2}{2}}$

   - The $(N+1)$th column of Ω will include the values p_{i0} associated with $H_0(k)$ DA hypothesis (i.e. no one of the validated measurements originated from the target T_i at time k).

Derivation of DA quality in QADA method

1. Build DA matrix Ω and find 1st-best and 2nd-best global DA solutions A_1 and A_2 using Murty's algo.
2. Compare $a_1(i,j)$ in A_1 (1st best solution) with $a_2(i,j)$ value in A_2 (2nd best sol.).
3. Establish a quality indicator $q(i,j) \in [0,1]$ for each optimal pairing (T_i, z_j).

Several cases are possible

- **Case 1**: $a_1(i,j) = a_2(i,j) = 0 \Rightarrow$ Agreement on non-association of T_i with z_j
  A useless stable case. We set $q(i,j) = 0$.

- **Case 2**: $a_1(i,j) = a_2(i,j) = 1 \Rightarrow$ Agreement on association (T_i, z_j)
  Stable case with different impacts on $R_1(\mathbf{\Omega}, A_1)$ and $R_2(\mathbf{\Omega}, A_2)$.
  - BBAs construction on frame $\Theta = \{X = (T_i, z_j), \bar{X}\}$ done as follows for $s = 1, 2$

    $$m_s(X) = a_s(i,j) \cdot \omega(i,j)/R_s(\mathbf{\Omega}, A_s) \quad \text{and} \quad m_s(X \cup \bar{X}) = 1 - m_s(X)$$
  - Conjunctive rule of combination (here no conflict occurs)

    $$\begin{cases} m_{12}(X) = m_1(X)m_2(X) + m_1(X)m_2(X \cup \bar{X}) + m_1(X \cup \bar{X})m_2(X) \\ m_{12}(X \cup \bar{X}) = m_1(X \cup \bar{X})m_2(X \cup \bar{X}) \end{cases}$$
  - In [1], QADA quality/confidence indicator is based on lossy pignistic proba transf.

    $$q(i,j) \triangleq BetP(X) = m_{12}(X) + \frac{1}{2} m_{12}(X \cup \bar{X})$$
  - In [2] and here, QADA quality/confidence indicator is based on min distance strategy

- **Case 3**: $a_1(i,j) = 1$ and $a_2(i,j) = 0 \Rightarrow$ **conflict in solutions** between A_1 and A_2
  - find index j_2, such that $a_2(i, j_2) = 1$
  - BBAs construction on frame $\Theta = \{X \triangleq (T_i, z_j), Y \triangleq (T_i, z_{j_2})\}$

Basic Belief Assignment (BBA) modeling

$$\begin{cases} m_1(X) = a_1(i,j) \cdot \frac{\omega(i,j)}{R_1(\Omega,A_1)+R_2(\Omega,A_2)} \\ m_1(X \cup Y) = 1 - m_1(X) \end{cases} \qquad \begin{cases} m_2(Y) = a_2(i,j_2) \cdot \frac{\omega(i,j_2)}{R_1(\Omega,A_1)+R_2(\Omega,A_2)} \\ m_2(X \cup Y) = 1 - m_2(Y) \end{cases}$$

- BBAs fusion with PCR6 fusion rule

$$\begin{cases} m(X) = m_1(X)m_2(X \cup Y) + m_1(X) \cdot \frac{m_1(X)m_2(Y)}{m_1(X)+m_2(Y)} \\ m(Y) = m_1(X \cup Y)m_2(Y) + m_2(Y) \cdot \frac{m_1(X)m_2(Y)}{m_1(X)+m_2(Y)} \\ m(X \cup Y) = m_1(X \cup Y)m_2(X \cup Y) \end{cases}$$

- In [1], QADA quality/confidence indicator is based on lossy pignistic proba transf.

$$q(i,j) \triangleq BetP(X) = m_{12}(X) + \frac{1}{2} m_{12}(X \cup Y)$$

- In [2] and here, QADA quality/confidence indicator is based on min distance strategy

Decision-Making from a BBA with min distance strategy

Belief interval of A

$$BI(A) \triangleq [Bel(A), Pl(A)] = [\sum_{B \in 2^\Theta | B \subseteq A} m(B), \sum_{B \in 2^\Theta | B \cap A \neq \emptyset} m(B)]$$

Euclidean belief interval based distance [Han Dezert Yang 2014]

$$d_{BI}^{E}(m_1, m_2) \triangleq \sqrt{\frac{1}{2^{|\Theta|-1}} \cdot \sum_{A \in 2^\Theta} d^I(BI_1(A), BI_2(A))^2}$$

$$d^I([a_1, b_1], [a_2, b_2]) = \sqrt{\left[\frac{a_1 + b_1}{2} - \frac{a_2 + b_2}{2}\right]^2 + \frac{1}{3}\left[\frac{b_1 - a_1}{2} - \frac{b_2 - a_2}{2}\right]^2}$$

Decision-making from a BBA

$$\delta = \hat{X} = \arg\min_{X \in \Theta} d(m, m_X)$$

Quality of the decision

$$q(\hat{X}) = 1 - \frac{d_{BI}(m, m_{\hat{X}})}{\sum_{X \in \Theta} d_{BI}(m, m_X)} \in [0, 1]$$

Higher is $q(\hat{X})$ more trustable is the decision $\delta = \hat{X}$

Classical Kalman Filter (KF) state estimate

$$\hat{x}(k|k) = \hat{x}(k|k-1) + K(k)(z(k) - \hat{z}(k|k-1))$$

with Kalman filter gain matrix

$$K(k) = P(k|k-1)H^T(k)[H(k)P(k|k-1)H^T(k) + R]^{-1}$$

In KF, $z(k)$ is assumed **to be correct** with the measurement noise characterized by the given covariance matrix R

- If R decreases $\Rightarrow z(k)$ is more precise $\Rightarrow$ Gain $K(k)$ increases
- If R increases $\Rightarrow z(k)$ is less precise $\Rightarrow$ Gain $K(k)$ decreases

Improved KF with QADA quality factor

The quality factor $q(i,j) \equiv q(T_i, z_j)$ expresses the confidence in the association (T_i, z_j)

- If $\mathbf{q}(T_i, z_j) \to 0 \Rightarrow$ we don't trust $(T_i, z_j) \Rightarrow z_j$ is incorrect and so **we increase** R
- If $\mathbf{q}(T_i, z_j) \to 1 \Rightarrow$ we trust $(T_i, z_j) \Rightarrow z_j$ is correct and **we keep** R **as it is**

KF gain adjustment with QADA

$$R_{QADA} = \frac{1}{q(T_i, z_j)} \cdot R \quad \Rightarrow \quad K(k) = P(k|k-1)H^T(k)[H(k)P(k|k-1)H^T(k) + R_{QADA}]^{-1}$$

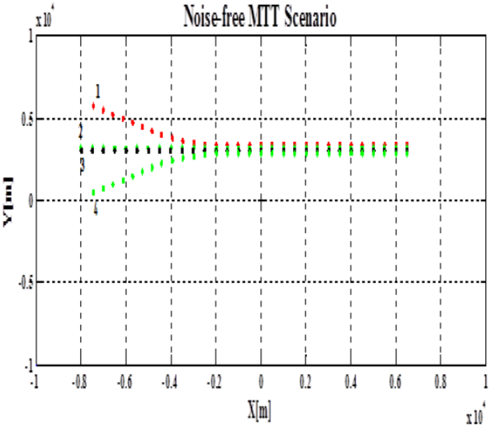
We compare the performances several MTT algorithms (using Monte Carlo simul.)

- KDA-GNN KF based MTT (GNN matrix based on Kinematic meas.)
- QADA-GNN KF based MTT (QADA using GNN matrix)
- QADA-PDA KF based MTT (QADA using PDA matrix)
- JPDAF

Criteria for MTT performance evaluation

1. **TL = Track Life** → average number of track updates before track deletion
   - A track is removed after 3 successive incorrect associations, or missed detections
   - With JPDAF, a track is removed if the true measurement is out of the gate during 3 successive scans
2. **pMC = Percentage of miscorrelation**
   → Percentage of incorrect measurement-to-track association during the scans
   → for JPDAF, pMC = % of time the true measurement is outside its target gate
   pMC for JPDAF is not equivalent to pMC for other algos
   It does reflect only partially the performances of JPDAF
3. **TP = Track purity** $\mathrm{TP} = \frac{\text{Number of correct associations}}{\text{Total number of associations}}$
4. **PPI = Probabilistic Purity Index** → used only with JPDAF

$$\mathrm{PPI} = \text{\% of correctness of measurement having the highest proba}$$



- Targets T_1, T_2, T_3, T_4 move from West to East with constant velocity $100 m/sec$ during 30 scans.
- The stationary sensor is located at the origin with range $10000 m$. The sampling period is $T_{scan} = 5 sec$
- Measurement precision: **Azimuth** $\rightarrow \sigma_{Az} = 0.2$ deg and **range** $\rightarrow \sigma_D = 40$ m.
- From scans 15 to 30, targets move in parallel with inter distance of 150 m
- FA are uniformly distributed in the surveillance region with know density
- $P_d = 0.999$ is associated with the sensor.

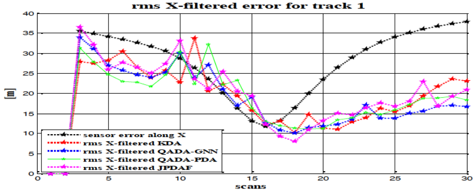
Monte Carlo results based on 200 runs

(in %)	QADA-PDA	QADA-GNN	JPDAF	KDA-GNN
Average TL	**89.39** (88.12)	89.13 (84.31)	78.42	70.02
Average pMC	2.45 (2.67)	2.39 (3.28)	5.92	5.71
Average TP	**86.14** (84.54)	85.92 (79.86)	PPI=32.96	61.95

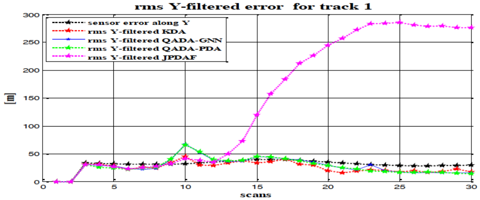
Performance results for 0.15 FA per gate on average

Note: JPDAF requires almost **3 times more computational time** than other methods because an exponential growing of number of joint association hypotheses.

Results with **0.15 FA per gate** on average

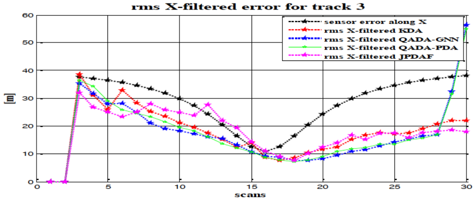


Averaged RMSE on X for track 1 with the tracking methods.

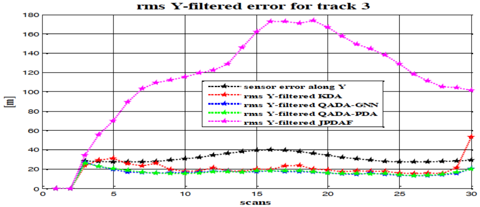


Averaged RMSE on Y for track 1 with the tracking methods.

Results with **0.15 FA per gate** on average

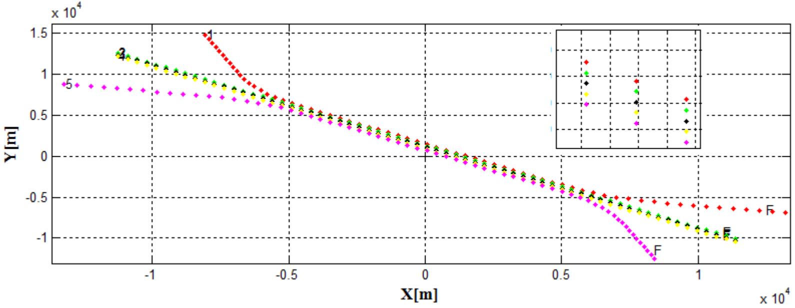


Averaged RMSE on X for track 3 with the tracking methods.



Averaged RMSE on Y for track 3 with the tracking methods.

Simulation of groups of target for scenario 2



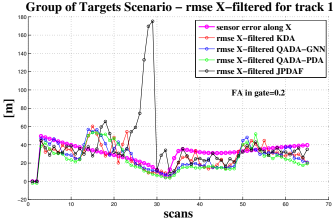
- Five air targets (T_1, T_2, T_3, T_4, T_5) moving from Norht-West to South-East with constant velocity $100 m/sec$ during 65 scans.
- The stationary sensor is located at the origin with range $20000m$. The sampling period is $T_{scan} = 5sec$
- Measurement precision: **Azimuth** $\rightarrow \sigma_{Az} =$ 0.35 deg and **range** $\rightarrow \sigma_D =$ 25 m.
- Targets move in three groups: $Group1 = T_1$, $Group2 = (T_2, T_3, T_4)$, $Group3 = T_5$
- The number of false alarms (FA) follows a Poisson distribution. FA are uniformly distributed in the surveillance region.
- $P_d = 0.999$ is associated with the sensor.

Monte Carlo results based on 300 runs

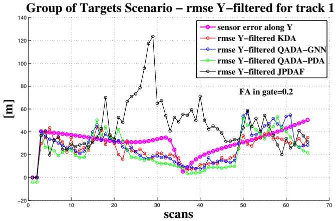
(In %)	GROUPS of Targets Scenario SigmaD=35,SigmaAz=0.2 FAingate=0.2			
	KDA-GNN	JPDAF	QADA-GNN-BetP QADA-GNN-d_BI	QADA-PDA-BetP QADA-PDA-d_BI
Average TL	50.27	66.46	81.94 83.50	90.85 91.02
Average pMC	3.35	2.98	2.10 2.02	1.75 1.78
Average TP	45.61	PPI=29.14	79.32 81.03	87.61 87.65

Performances of QADA KF methods with 0.2 FA per gate

Results with **0.2 FA per gate** on average

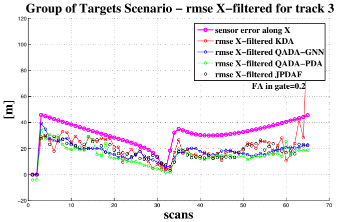


Averaged RMSE on X for track 1 with the four tracking methods.

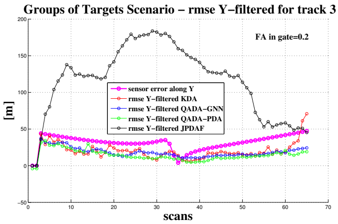


Averaged RMSE on Y for track 1 with the four tracking methods.

Results with **0.2 FA per gate** on average

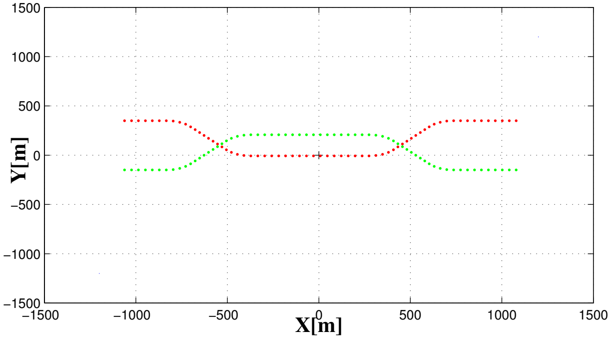


Averaged RMSE on X for track 3 with the four tracking methods.



Averaged RMSE on Y for track 3 with the four tracking methods.

Scenario 3 : Two crossing targets



- Two maneuvering targets moving from West to East with constant velocity $38m/sec$ during 65 scans.
- The stationary sensor is located at the origin with range $1200m$.
- The sampling period is $T_{scan} = 1sec$.
- $\sigma_{Az} = 0.25$ deg and $\sigma_D = 25$ m for azimuth and range respectively.
- $P_d = 0.999$ is associated with the sensor.

Simulation results for scenario 3

Monte Carlo results based on 300 runs

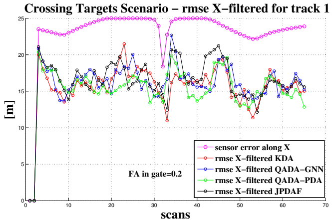
(In %)	CROSSING Targets Scenario SigmaD=25,SigmaAz=0.2 FAingate=0.2			
	KDA-GNN	QADA-GNN-BetP QADA-GNN-d_BI	JPDAF	QADA-PDA-BetP QADA-PDA-d_BI
Average TL	77.06	88.93 89.29	91.25	93.47 93.54
Average pMC	2.40	2.24 2.20	2.08	2.11 2.15
Average TP	72.78	85.64 86.11	PPI=86.29	87.96 88.01

Performances of QADA-PDA versus JPDA for 0.2 FA per gate

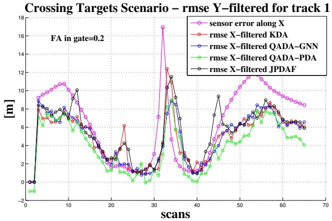
(In %)	CROSSING Targets Scenario SigmaD=25,SigmaAz=0.2 FAingate=0.4			
	KDA-GNN	QADA-GNN-BetP QADA-GNN-d_BI	JPDAF	QADA-PDA-BetP QADA-PDA-d_BI
Average TL	58.80	77.20 80.19	82.87	83.18 83.21
Average pMC	3.61	3.63 3.54	2.94	3.40 3.41
Average TP	52.90	72.01 75.30	PPI=76.94	77.15 77.23

Performances of QADA-PDA versus JPDA for 0.4 FA per gate

Results with **0.2 FA per gate** on average

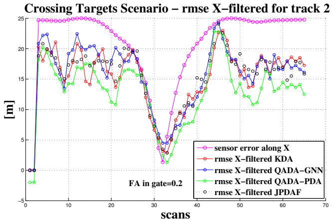


Averaged RMSE on X for track 1 with the four tracking methods.

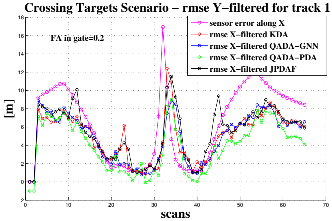


Averaged RMSE on Y for track 1 with the four tracking methods.

Results with **0.2 FA per gate** on average



Averaged RMSE on X for track 2 with the four tracking methods.



Averaged RMSE on Y for track 2 with the four tracking methods.

Conclusions

1. QADA-PDA is a zero-scan back method
2. QADA-PDA is quite simple to implement (mix of PDAF calculus and Optimal assignment search)
3. QADA-PDA is a good compromise between strict hard-assignment (GNN) and full soft-assignment (JPDA)
4. QADA-PDA avoids JPDA combinatorics/complexity
5. QADA-PDA works better than QADA-GNN, KDA-GNN and JPDA in difficult scenarios
6. QADA-PDA is a new and interesting practical method for MTT in clutter

Perspectives

1. making more precise evaluations of QADA-PDA method
2. development and test of better quality evaluation models (if any)
3. improvement of MTT performances using attribute information

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