Chapter

Improved Multi Target Tracking in MIMO Radar System Using New Hybrid Monte Carlo–PDAF Algorithm

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Abstract

This article deals with the multi-target tracking problem (MTT) in MIMO radar systems. As a result, this problem is now seen as a new technological challenge. Thus, in different tracking scenarios, measurements from sensors are usually subject to a complex data association issue. The MTT data association problem of assigning measurements-to-target or target-state-estimates becomes more complex in MIMO radar system, once the crossing target tracking scenario arises, hence the interference phenomenon may interrupt the received signal and miss the state estimation process. To avoid most of these problems, we have improved a new hybrid algorithm based on particle filter called "Monte Carlo" associated to Joint Probabilistic data Association filter (JPDAF), the whole approach named MC-JPDAF algorithm has been proposed to replace the traditional method as is known by the Extended KALMAN filter (EKF) combined with JPDAF method, such as EKF-JPDAF algorithm. The obtained experimental results showed a challenging remediation. Where, the MC-JPDAF converges towards the accurate state estimation. Thus, more efficient than EKF-JPDAF. The simulation results prove that the designed system meets the objectives set for MC-JPDA by referring to an experimental database using the MATLAB Software Development Framework.

Keywords: radar system, target tracking, MIMO radar, multi target tracking

1. Introduction

Multiple-input multiple-output (MIMO) radar system is a multistatic architecture composed of multiple transmitters and receivers, which seeks to exploit the spatial diversity of radar backscatter. In conjunction with centralized processing, MIMO radar has the potential [1] to remediate the multipath effects and improve the radar performances such as the detection, then the Multi target tracking (MTT).

In MIMO radar system, the objective of MTT is to estimate jointly at each scan the number of targets continuously moving in a given region and estimates their trajectories from noisy sensor measurements [2].

MIMO radar systems provide tracking accuracy advantages that grow proportionally with the number of transmitting and receiving radars. However, increasing the number of transmitters and receivers in MIMO radar system needs to implement new intelligent algorithms leads to increased tracking performances, these depend on the specific and intelligent tracker employed [3, 4]. Multiple target tracking (MTT) in radar system is extremely challenging, due to a lot of constraints such as the low performance of the sensor, the nature and the number of the target illuminated, the real time processing and the uncertainty of data association at that time the crossing path phenomenon is appear [5, 6], then some targets may go undetected and lead to loss their trajectories during the tracking interval.

1.1 Problem statement

In this paper, we concern the Motion–based Multi target tracking (MTT) problem with single sensor, which is the foundation for more complex tracking. Then, the data association problem of assigning measurements-to-target or target-state-estimates becomes more complex into MIMO radar, once the crossing target tracking phenomenon arises. Thus, the data association problem must be handled. To overpass these issues a several methods have been proposed in literature.

2. Related works

In order to deal with the MTT data association issues, we found in literature several methods are classified into Bayesian and other non-Bayesian filters, has been applied to address different scenarios, such as, Markov Chain Monte Carlo Data Association (MCMCDA) was proposed in [7] as a solution to replace the conventional method as known by The Multiple Hypothesis Tracking (MHT), to handle the low Signal-to-Noise Ratio (SNR) in the pre-processing phase. On the other hand, the Gaussian mixture (GM) combined with Probability Hypothesis Density (PHD), then the full GM-PHD algorithm [8] provides a promising framework to process the several measurements from multi sensors.

In [9], a joint optimization called distributed expectation-conditional maximization (DECM), has been suggested instead of the old method named Over-The Horizon Radar (OTHR) to solve the target state estimation and multipath association. Nash Equilibria method [10] is used to perform the track selection problem in MTT. The MTT by MIMO radar systems with widely distributed antennas and non-coherent processing is considered as a problem in [11], thus a hybrid algorithm is proposed based on Nearest-Neighbor Data Association (NN) and Extended KALMAN Filter (EKF).

The data association problem occurs for MTT applications and becomes more challenging in nonlinear and non-Gaussian estimation problems, hence, it is necessary to apply a Bayesian filter such as the Joint Probabilistic Data Association Filter (JPDAF) in different tracking scenarios. Thus, The JPDA algorithm calculates the association probabilities to the target being tracked for each validated measurement at the current time information, since the state and measurement equations are assumed to be linear. Therefore, in various related works we find it widely used in MTT issues, such as in [12] a new algorithm is used named Multiple Detection JPDAF (MD-PDAF) to avoid the arising multipath propagation effects for each target detection and tracking. Moreover, A Probabilistic Data Association-Feedback Particle Filter (PDA-FPF) for Multiple Target Tracking Applications is used in [13]. For multi Target tracking in passive multi-static radar system, the sequential of a multi-sensor joint probabilistic data association (S-MSJPDA) [14] has great potentials compared to the parallel architecture of a multi-sensor joint probabilistic data association (P-MSJPDA).

To avoid the data association phenomenon in MIMO radar system, our main contribution is:

- The development of a new approach based on particle filter that we called Monte Carlo – Joint probabilistic data association filter (MC-JPDAF) algorithm, to make tracking more efficient.

This paper is organized as follows; Related works in section 2. Section 3, presents our algorithm which have been used in tracking scenarios, Experimental results are discussed in sections 4, finally, the conclusion and the future works are given in section 5.

3. The proposed algorithm

3.1 Joint probabilistic data association filter (JPDAF)

JPDA algorithm aims to calculate the marginalized association probability based on all possible joint events for data association. In [12, 15], a joint event is an allocation of all measurements to all tracks. In JPDA, a feasible joint event is defined as one possible mapping of the measurements to the tracks such that: (1) each measurement (except for the dummy one) is assigned to at most one target and (2) each target is uniquely assigned to a measurement. Let $\{\theta_k{=}\theta_k^i\} \in \{1, 2, \dots, N_{(k/k-1)}\}$, denote the joint association event. For each pre-existed target $i \in \{1,2, \dots, N_{(k/k-1)}\}$, $\theta_k^i \in \{0,1, \dots, M_k\}$ denotes the association event, where θ_k^i=j means the jth measurement is originated from the ith target and θ_k^i=0 represents the dummy association in which the ith target is miss detected. JPDA assumes that each single association event is independent and the posterior of each target is:

$$P\left(X_k^i/e_k^i = 1, Z_k = \sum\nolimits_{\theta_k^i} \left(X_k^i/\theta_k^i, e_k^i = 1.Z_k\right).p\left(\theta_k^i/e_k^i = 1, Z_k\right)\right. \tag{1}$$

3.2 The particle filter based on MONTE CARLO algorithm (MC)

Sequential Monte Carlo techniques are a marginal particular filter are useful for state estimation in non-linear, non-Gaussian dynamic target. These methods allow us to approximate the joint posterior distribution using sequential importance sampling.

The MC algorithm uses the sequential resampling process to avoid the filter divergence scenario during the state estimation period, particularly when using high non-linear target models and non-Gaussian distributions. Further, the process needs sufficient probability under the observed region. Accordingly, it's necessary to provide a probabilistic interpretation through the following probabilistic interpolation:

$$\mathrm{I(f) = E\ P[f(X)/Y]} = \int_1^{\mathrm{Np}} \mathrm{f(X).P(X/Y)} \tag{2}$$

3.3 The general MC-JPDAF algorithm

1. Initialization

   Set k = 0, generate N Samples $X_{t,0}^{i}$ for all targets t = 1, … ,τ indecently. $X_{t,0}^{i}$ Is drown from p $(X_{t,0})$, with initial weight $W_{t,0}^{i}=\frac{1}{N}$, for $i = 1, \dots, N$ particles and set k = 1.

2. For i = 1, … ,N predict new particles.

$$X_{t,k}^{i*} = \mathrm{F}{*}X_{t,k+1}^{i} + V_{t,k-1}^{i}$$

3. For each particles compute the weights for all measurements (j = 0, … ,M_k) to targets (t = 1, … , τ) associations $W_{t,k}^{i}=\sum_{\theta} p(\theta/Z_k)$. (See Eq. (1)) And normalize the weights for each target:

$$W_{t,k}^{i} = \frac{w_{t,k}^{i}}{\sum_{i=1}^{N} W_{t,k}^{i}}$$

4. For each target, generate a new set $\{X_{t,k}^{i}\}_{i=1}^{N}$by resampling with N times from $\{X_{t,k}^{i*}\}_{i=1}^{N}$, where $\mathrm{P}(X_{t,k}^{i}=X_{t,k}^{i*})=\tilde{W}_{t,k}^{i}$

5. Increase k and loop

4. Experimental results

In this part, we attempt to prove the ability of the proposed algorithm “MONTE CARLO-JPDA” to model simulate a precise model based on target tracking parameters. This algorithm contributes to improving the state estimation of two crossing target in 2D using two separated sensors in a MIMO radar system. We will compare the results obtained from the MATLAB software.

4.1 Presimulation part

Firstly, we show the sensor-target geometry for tracking two crossing targets as follows (**Figure 1**):

Sensor 1:$Rx_1(0; 0\ )$; Sensor 2: Rx_2 (1.8e5; 0.8e5).

Initial state of the targets:

Target 1: (100e3 150; 150e3 (-10))

Target 2: (100e3 150; 148e3 10)

4.2 Simulation scenarios

In order to implement our algorithm, there are different variables and metrics for more accurate results interpretation were selected as follow:

- Time (T) = 200 s

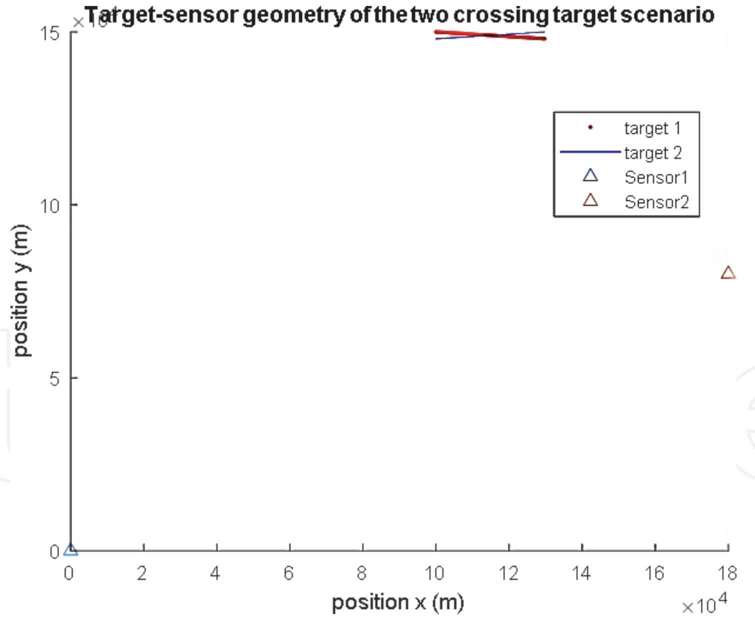

Figure 1.
Initial target-sensor geometry.

- Number of Monte Carlo simulation (MCruns) = 100 samples
- Root Mean Square error (RMSE)
- Losses Track 1 & Losses Track 2 respectively, of two crossing targets in different scenarios
- Hard assignment Simulation: using EKF-JPDAF.
- Soft assignment Simulation: using MC-JPDAF.

4.2.1 Two crossing targets tracking using EKF-JPDAF algorithm

We start the tracking scenario of two crossing targets in 2-D using the conventional algorithm as known by EKF-JPDAF, the estimated trajectories and the RMSE values are given as follows (**Figures 2** and **3**):

Where: Blue dot: true target states
Green dot: estimates
Cyan star: resolved measurements
Black star: unresolved measurements
The trajectory losses of each target is given as follows:
Trajectory losses of target1: 0.187 (18.7%)
Trajectory losses of target2: 0.172 (17.2%)

According to the figures above, it is noticed that the tracking of the two targets once using EKF-JPDAF algorithm is more complex, more losses of trajectories are showed especially when the cross path phenomenon is appear, such as: Percentage of Trajectory losses for target1 is 18.7% and Percentage of Trajectory losses for target 2 is 17.2%.

4.2.2 Two crossing targets tracking using the suggested MC-JPDAF algorithm

In order to improve the tracking scenario regarding the obtained results by EKF-JPDAF, we implement our new approach based on numerical filter called MC-JPDAF to

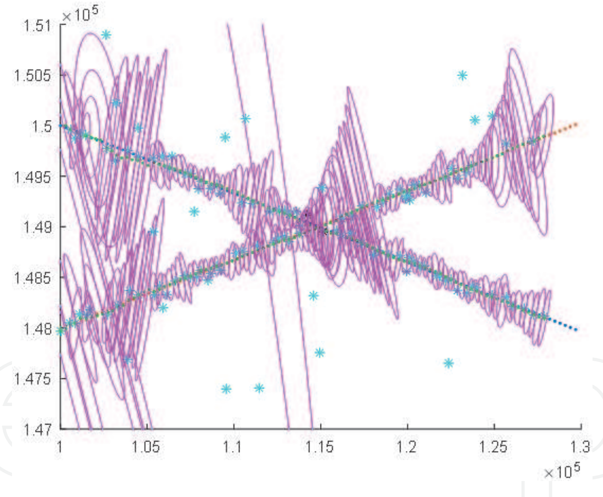

Figure 2.
Trajectories of two crossing targets using measurements from the two sensors estimated by EKF-JPDAF algorithm.

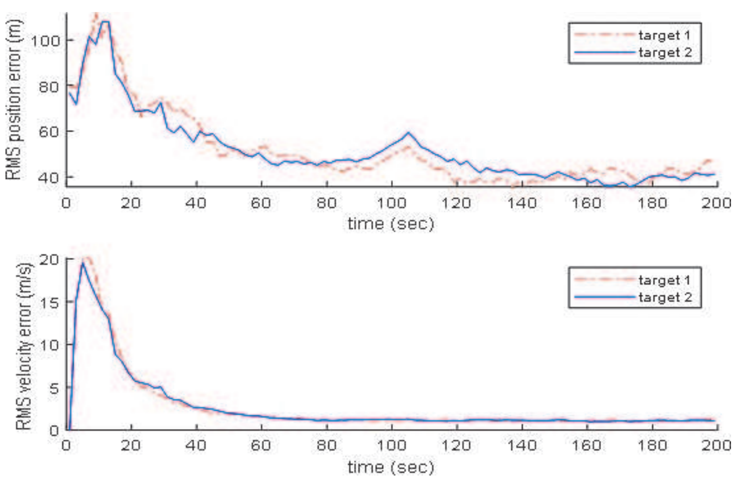

Figure 3.
The RMSE position and RMSE velocity of each target.

perform the tracking of two crossing targets in 2-D during the same estimation period (200 s). The estimated trajectories and the RMSE values are given as follows:

Where: Blue dot: true target states.

Green dot: estimates.

Cyan star: resolved measurements.

Black star: unresolved measurements.

The trajectory losses of each target is given as follows:

Trajectory losses of target1: 0, 06 (6%)

Trajectory losses of target2: 0, 07 (7%)

As shown in **Figure 4**, JPDA classifier associated to MONTE CARLO runs, provides a lower trajectories losses compared to EKF-JPDA results, such as; in **Figure 5**, during 20s the amplitude of the RMSE position is reduced from 80 m to 20 m approximately. Likewise, the RMSE velocity value goes from 22 m / s to 0.5 m / s evenhanded after 20 seconds of calculation.

The acquired results of both simulation scenarios are compared and classified in the **Table 1** hereunder.

4.3 Discussion

In order to strengthen the theoretical comparison in the previous section, it's clear from the results presented in **Table 1** that the EKF-JPDAF's average Ratio

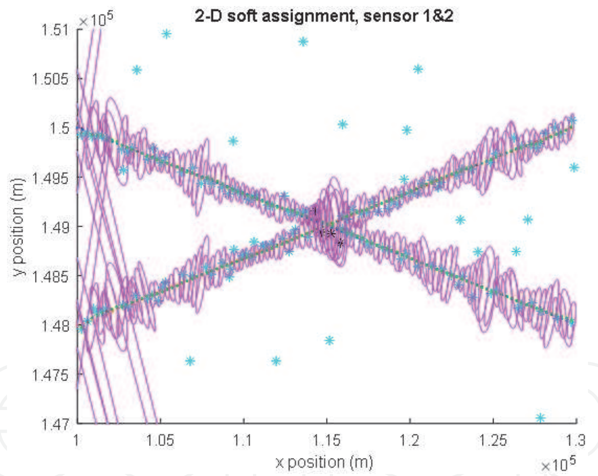

Figure 4.
Trajectories of two crossing targets using measurements from both sensors estimated by MC-JPDA algorithm.

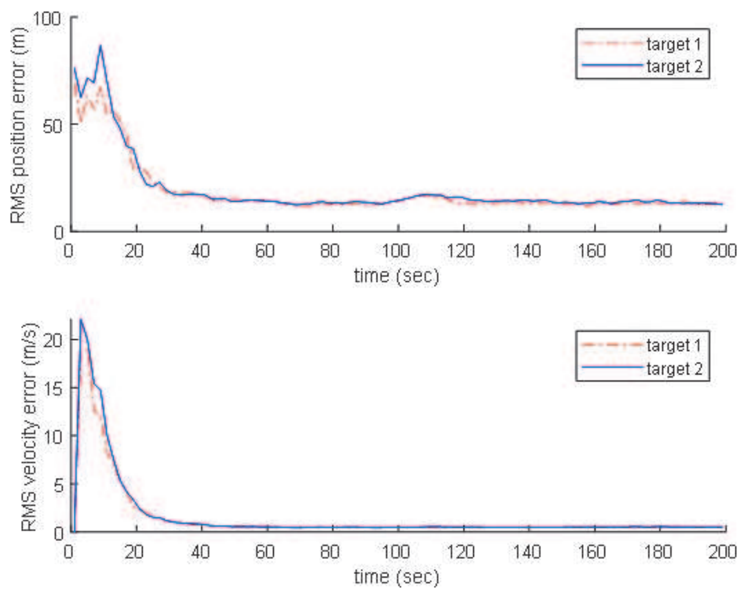

Figure 5.
The RMSE position and RMSE velocity of each target.

		EKF-JPDAF	MC-JPDAF
MIMO Radar 2x2	RMSE Position (m) at T = 200 s	Target1 = 50	Target1 = 20
		Target2 = 46	Target2 = 20
	RMSE Velocity (m/s) at T = 200 s	Target1 = 2.5	Target1 = 0.6
		Target2 = 2.5	Target2 = 0.6
	Trajectory Losses For target 1	18.7%	6%
	Trajectory Losses For target 2	17.2%	7%

Table 1.
Comparative results.

Mean Square Error (RMSE) is much higher than the RMSE of MC-JPDAF algorithm in both simulation scenarios. Our new MC-JPDAF method is more effective in MIMO radar system with two sensors, it gives minus tracking risk than EKF-JPDAF.

In addition to RMSE, we have added the trajectory losses percentage as a new metric for more accurate results interpretation. Thus, we notice from **Table 1** that our new hybrid algorithm have a low trajectory percentage that does not exceed a 7% of losses, which reflects the robustness of our algorithm.

The simulations are approved by comparison metrics. Therefore, in the light of this investigation, it is possible to conclude that our contribution has been verified. The new proposed hybrid MC-JPDAF algorithm estimates the state of tow crossing targets more accurately than the EKF-JPDAF algorithm. Thus it's clear to see the robustness of our approach during a long period (200 s) without performance degradation especially once the cross path phenomenon is by using a large number of Monte Carlo runs up to 100 samples.

5. Conclusion and future works

In conclusion, in this paper we presented a new approach to improve the MTT in MIMO Radar system as well as to avoid the filter divergence performances degradation once the crossing path phenomenon is arises.

We overcame the constraints related to the multi target tracking as mentioned in the problem statement at that point we avoided the data association issue and the filter divergence phenomenon during the tracking period. The experimental results validate what we mentioned in the theoretical part.

The MC-JPDAF approach is more efficient in complex cases which cannot be observed experimentally and even when simulated by EKF-JPDAF diverges to inappropriate results.

MC-JPDAF has a fast calculation time and converges rapidly to its related effective states. Thus, it can be used in real-time tracking.

Then, finally we have undoubtedly increased the MIMO radar system performances in MTT process by using this new approach, as a consequence we avoid the data association problem likewise the performance filter degradation. Even though having these persuasive results the method could be ameliorated by multiplying the number of targets. In our future research, we aim to implement this method aiming to enhance the multi targets tracking.

Acknowledgements

This work has been contributed with Dr. Ibrahim BenAbdallah and the professor Cherif Adnan the editor-in-chief of the Research unit: Analysis and Signal processing of Electrical and Energetic Systems (ASPEES), department of Physics at the Faculty of sciences of Tunis- Tunisia, 2095.

Conflict of interest

The authors declare no conflict of interest.

Acronyms and abbreviations

MTT	Multi Target Tracking
MC	Monte Carlo
PF	Particular filter

JPDAF	Joint Probabilistic Data Association Filter
EKF	Extended KALMAN Filter
MIMO	Multiple Input Multiple Output
MC runs	Number of Monte Carlo simulation
RMSE	Root Mean Square error

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