Improve the Tracking of Two Crossing Targets in MIMO Radar system using MONTE CARLO -JPDA Algorithm

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Summary

The multi-target tracking system is a new challenge for researchers in order to improve the radar system performances, since the measurements taken are generally subjected to a complex association of data, to additive noise which interrupt the received signal, to missed detection. The uncertainty of the data correlation, the real-time processing requirements and the maneuverability of the crossing targets can lead to biased or even complete corruption of the estimation results. In order to avoid most of these problems, in this paper we have improved the tracking scenario in a 2D MIMO radar system using two sensors. Indeed, a new data classification method has proposed named the probability data association filter (PDAF) is developed to combine and classify the data issue of each target .In order to optimize the estimator and reducing the calculation cost we used the Sequential MONTE CARLO algorithm (SMCA).The simulation results prove that the system designed meets the objectives set for SMCA by referring to an experimental database using the MATLAB Software Development Framework.

Key words:

Tracking, MIMO Radar, Multi targets, Monte Carlo

1. Introduction

Multiple-input multiple-output (MIMO) radar 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 to significantly improve radar functions such as detection and parameter estimation. MIMO radar is distinct from other types of array radars such as phased array or STAP algorithm, which processes the signals of closely spaced elements and, hence, cannot capitalize on the spatial characteristics of targets. [20] In this scenario, the MIMO radar is able to observe the targets from different directions. One of the advantages of these radars is exploitation of Doppler frequencies from different transmitter-target-receiver paths. The extracted Doppler frequencies can be used for estimation of target velocity vector so that, the radar can be able to track the targets by use of its velocity vector with reasonable accuracy.[21] MIMO radar systems provide tracking accuracy advantages that grow proportionally with the number of transmitting and receiving radars However, increasing the number of transmitting and receiving radars leads to increased communication needs and computational load, These depend on the specific and intelligent tracker employed [17] [22] .Multiple target tracking (M.T.T) in radar system is extremely challenging, due to a lot of constraints like uncertain data association, the nature and size of the target illuminated and real time processing , to cope with these problems a good many methods have been proposed.

In MIMO Radar system the MTT methods aims to improve the position, velocity and acceleration estimations of multi targets simultaneously, and gives its own trajectories , contrarily to the classical single target tracking (S.T.T) was not sufficient in difficult scenarios.

1.1 Related works

For detection and tracking problems of unresolved targets in radar beam, various methods have been proposed in the literature, some involve special antenna configuration, array signal processing in real time, to cope with these challenges, considerable researches have been undertaken in the literature. A majority of early approaches concentrated on dealing with the processing of measurement- track association problem such as the Joint detection and tracking method that integrate detection and tracking processing separated has great potential to deal with unresolved targets. The Finite Set Statistics (FISST) theory has offered a new theoretical Framework for the joint detection and tracking under complex conditions, in [1] [3] [24] respectively some methods adopting probability hypothesis density (PHD) filter [Zhiyong Song, Fei Cai, and Qiang Fu] , Coordinal zed probability hypothesis density (CPHD) Filter ,Extended KALMAN Filter and Auction Algorithmn,[K.V. Ramachandra],[X.Rang Li] and [Vesselin P.Jilkov], were addressed to resolve the detection and tracking of unresolved targets. In [12] [Min-Hyun Cho1, Min-Jea Tahk] propose the pseudo-measure filter is designed to alleviate the problems of bias of the extended Kalman filter, it extends the conventional pseudo-measure filter model, including range, elevation and azimuth information, to a model that also uses distance rate measurement. The tracking of a single target using the particular filter in [24] was used to process the converted position and range-rate measurements sequentially to reduce the approximation error in the second-order EKF .Unfortunately, the majority of these methods does not have effective solutions , are

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limited by the number of targets and the order of filter estimator.
The idea of multi target tracking was proposed in [15, 18, 22] as a new requirement to improve tracking in the radar system, a new applied technique based on particle filtering and the data association occurs for multiple target tracking applications compared to NN association method and the classical EKF.
This paper is organized as follows in section 2 we present the problem statement, section 3 presents The Multi targets tracking blocks, Section4 Presents the proposed algorithms, section 5 presents the results of simulation experiments performed using they algorithms, the conclusion study are finally presented in section 6.

2. 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, motion-based MTT is extremely different in practice and confronts serval challenges like the number of targets to detect, uncertain data association, dense clutter disturbance and real time processing.
According to the nature of movement of the target and the motion-based tracking, the target states and the measurement are firstly modeled in discrete time via prior knowledge, then the filtering algorithm propagates the target states iteratively usually employs the dynamic state-space (DSS) modeling approach to describe the target motion, the DSS approach based on MARKOV process and it modelled the state space by

$$\begin{cases} X_k = F * (X_{k-1}, U_{k-1}) \\ Y_k = H * (X_k; U_k) \end{cases}$$

Where, F (.) and H (.) are target motion model and measurement model respectively, X is the multi target state has the form X= $\emptyset$, $\{X_1\}$, $\{X_1, X_2\}$,…, $\{X_1,…,X_n\}$, where X=$\emptyset$ indicates the presence of the target . The task of tracking is to determine $X_k$from $Y_k$then F (.) tries to extract target information via introducing prior knowledge while the measurement model H (.) explains how the target motions are reflected in the sensor.
In this paper, we propose the particular filter based on MONTE CARLO approach (MC) and Joint Probabilistic Data Association (JPDA) Filter as a solution compared to the old algorithms as Auction algorithm and KALMAN Filter, in order to improve the tracking of two crossing targets using two receiver sensors, when the tracking interleaving occurs in 2D. [5][6][7][8] [17]

3. Multi target tracking Receiver using two sensors

This section, introduces the multiple target tracking structure in a MIMO radar receiver, using two sensors Rx1 and Rx2.

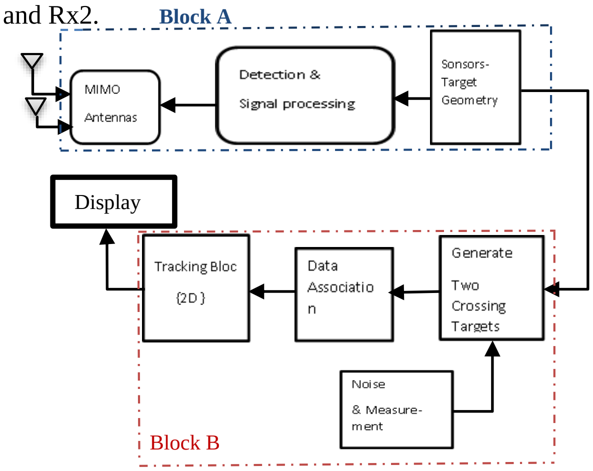


Fig. 1 Block Diagram of Multi Target Tracking using two sensors

The composition of a MIMO Radar system is complex and can be divided into several modules, including:
Block A: Beamforming process, detection and signal processing module including Sensor-target models.
Block B: Signal receiving module, the association data bloc and the target tracking module.
Radar targets can reflect electromagnetic waves in space. For different kinds of radar targets, the characteristics of the reflected signals are different. Generally, the radar cross-section (RCS) is used to measure the characteristics of the target.

$$\sigma = (4\pi . A^2)/\lambda^2$$

The σ, A, and λ parameters represent the radar target RCS, the irradiated area, and the operating wavelength of radar, respectively. For most complex scattering targets, RCS represents the equivalent area. The larger σ is, the more likely the target is to be detected by radars. For the opposite condition, it is not easily detected and has excellent stealth performance. [18]
We are interested in block B in red , which presents our proposed algorithm to improve the tracking of two crossing targets using two spaced sensors and JPDA classifier block followed by a target state estimator block based on the MONTE CARLO algorithm.
The JPDA is a selective and combine filter for different trajectories from each targets the filter uses a joint probabilistic data association to assign detections to each track and applies a flexible assignment in which multiple detections can contribute to each track. [10].

4. Proposed Algorithms

4.1 Joint Probabilistic data association Filter (JPDA filter)

JPDA algorithm aims to calculate the marginalized association probability based on all possible joint events for data association. 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 $\{\theta_k=\theta_k^i\}$ $\in \{1, 2,\ldots,N_{(k/k-1)}\}$, denote the joint association event. For each pre-existed target i $\in\{1,2,\ldots, N_{(k/k-1)}\}$, $\theta_k^i \in\{0,1,\ldots, M_k\}$ 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:[19][23]

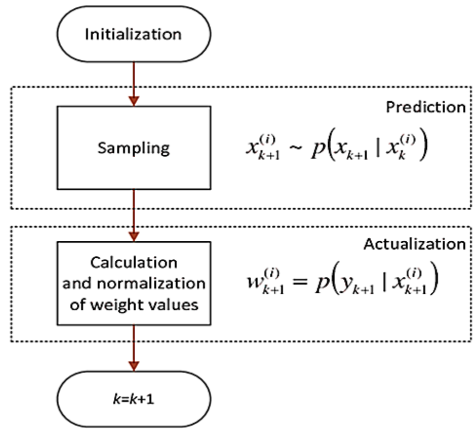
$P\,(X_k^i/e_k^i$=1,Z_k=$\sum_{\theta_k^i}(X_k^i\,/\theta_k^i, e_k^i\,=1.Z_k)$.$p(\theta_k^i/e_k^i$=1,$Z_k)$.

(Equation02)

4.2 The Particular Filter based on MONTE CARLO algorithm

Sequential Monte Carlo techniques is 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 Monte Carlo method consists to represent the probability of the region observed by the concentration of their sequential samples Np. The goal is to approach a probability distribution that is usually impossible to compute analytically in order to estimate the state X_k^i of each target. [5] Which, i and k represents the state of each target and the time. [11][12][14][15] [16]



4.3 MONTE CARLO -JPDA 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,…, N* particles and set k=1.

2- For i=1,…,N predict new particles.

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

3- For each particles compute the weights for all measurements (j=0,…,M_k) to targets (t=1,…, τ) associations $W_{t,k}^i$=$\sum_\theta p(\theta/Z_k)$. (SeeEquation 02) And normalise 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 P($X_{t,k}^i$=$X_{t,k}^{i*}$)=$\widetilde{W}_{t,k}^i$

5- Increase k and loop

5. Simulation part

In this part we attempt to prove the ability on the proposed algorithm ' MONTE CARLO - JPDA ' to do this an accurate model was modelled and simulated based on target parameters, this algorithm presents our contribution, in order to improve the state estimation of two crossing targets in 2D, we compare the results obtained from MATLAB software, when we use a single sensor and two sensors.

5.1 Pre –Simulation part

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

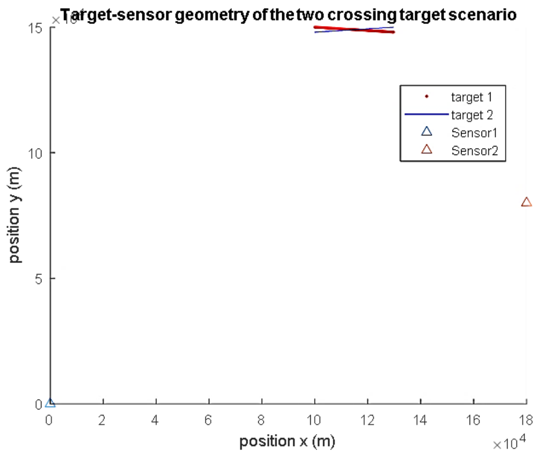


Fig. 2 Initial Target-Sensor Geometry

This figure displays the measurements of two crossing targets scenario from two sensors.

5.2 Simulation Scenarios

To simulate our model, parameters were selected as follow:
Time (T) = 200 s
Number of Monte Carlo simulation (MCruns) = 100 samples
Root Mean Square error (RMSE)
Average Normalized Estimation Error Squared (ANEES)
The track loss is based on the 99% Chi-square region of the NEES
Losses Track 1 & Losses Track 2 respectively, of two targets
Hard Assignment Simulation: Using Auction Algorithm, KALMAN Filter with MC runs
Soft Assignment Simulation: using JPDA Classifier with MC runs.

5.2.1 Tracking in 2D in Hard Assignment and in soft assignment

We start the tracking of two crossing targets in 2-D hard assignment using. Auction Algorithm classifier and Extended KALMAN Filter, as follows:

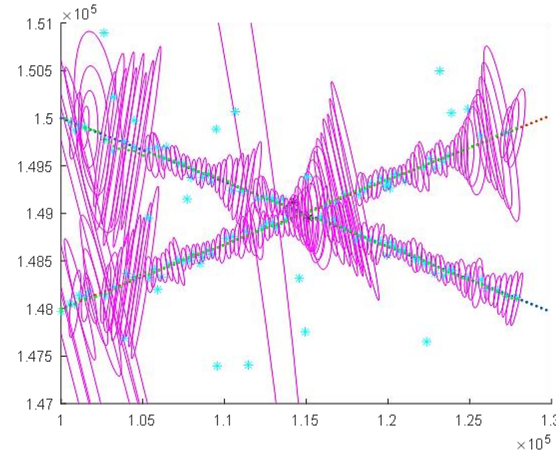


Fig. 3 Trajectories of two crossing targets using measurements from the two sensors in Hard Assignment

- Tracking of two crossing targets using the both sensors in 2D Soft assignment using JPDA algorithm.

Where, blue dot: true target states
Green dot: estimates
Cyan star: resolved measurements, including FAs
Black star: unresolved measurements

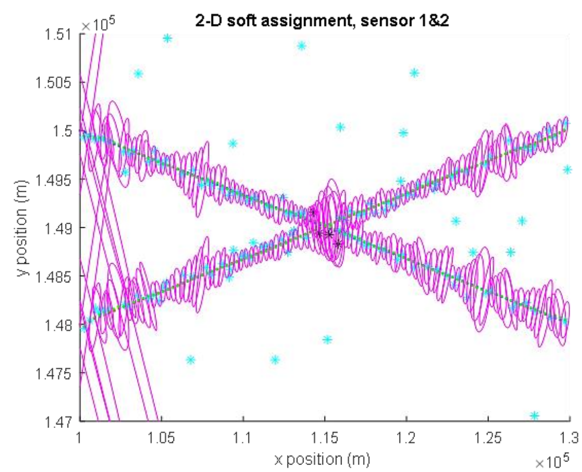


Fig. 4 Trajectories of two crossing targets using measurements from both sensors 1&2

The two graphs above shows us that the smoothing of the two trajectories is clearer in figure 05, with less clutter coloured in red, which it complies with our proposed theory.

5.2.2 MONE CARLO Simulation for Comparison of different Data Association Algorithms

In this section, we used MONTE CARLO runs to compare the different data association approaches.
To estimate errors, are linked by velocity and position, we must calculate the RMSE position and RMSE velocity, the track error metrics system object are used to compare the tracks from each target.

- Measurement errors of two crossing Targets in Hard assignment scenario
- Measurements errors of two crossing targets using one sensor

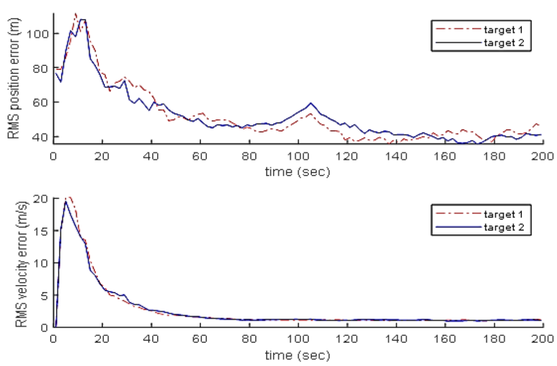


Fig. 5 The Root Mean Square Error of each target in position and in velocity from one sensor

- Measurement errors of two crossing targets using the both sensors 1& 2

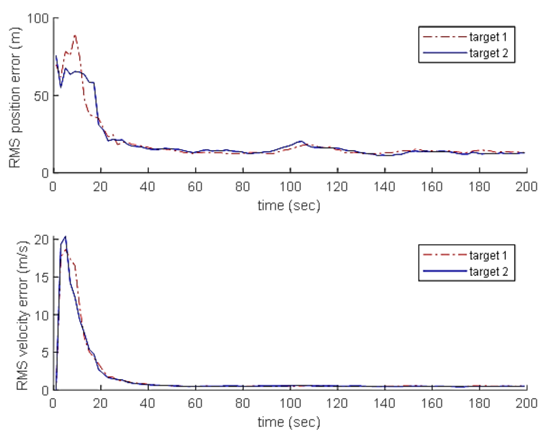


Fig. 6 The Root Mean Square Error of each target in position and in velocity from sensor 1&2 both

According to the figures above, it is noted that the tracking of the two targets in Hard assignment shows losses of trajectories even when using the two antennas simultaneously, such as: Percentage of Track 1 losses= 0.14 and Percentage of Track 2 losses= 0.8

- Result Comparison: Tracking of two crossing Targets in 2D soft assignment using sensors 1&2

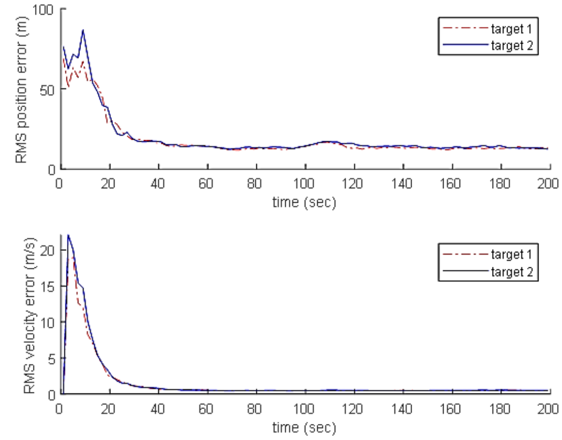


Fig. 7 The root mean square error (RMSE) of target 1 & 2 in position and in velocity

5.2.3 Results Analysis

In 2D soft Assignment based on JPDA classifier associated by MONTE CARLO runs, we obtained lower trajectories losses values compared to the other results obtained by hard assignment simulations especially when we use the two sensors, such as:
In figure 06, the amplitude of the RMSE position is reduced from 80 m to 20 m approximately, just after 20 seconds of calculations. Also, concerning the Velocity, the RMSE value goes from 22 m / s to 0 m / s just after 20 seconds of calculation.
On the other hand, the MATLAB calculator gives us the percentage values of the lost tracks are lower than that given in the hard scenario, such as:

Percentage of Track 1 losses: 0.06
Percentage of Track 2 losses: 0.06

5.3 Comparative study

We can classify the obtained results from MATLAB software in the following comparative table.

Table 1: Two target tracking comparison in hard assignment and soft assignment

		Hard assignment	***Soft Assignment***
One Sensor	RMSEPos (m) T = 200 s	Target1= 43 Target2= 44	Target1= 42 Target2=42
	RMSEVel (m/s) T =200s	Target1= 3 Target2=3	Target1=1 Target2= 1
	95%of NEES T= 100 s	Target1= 3 Target2=2	Target1= 1.9 Targe2= 2.8
	Track Losses Target 1	0.07	0.04
	Track Losses Target 2	0.13	0.13
Sensor 1&2	Track Losses Target 01	0.14	0.06
	Track Losses Target 02	0.8	0.06

5.4 Interpretation

To interpret the Table1above, exhibits that the majority of values obtained by soft assignment simulation is better compared to the Hard assignment simulation, especially when we use the both sensors Rx1 and Rx2. the simulations are approved by comparison metrics such as ,the RMSE Pos Value of two targets at 200 s from the both sensors it equal to 20 m losses given by soft assignment simulation ,then the latest it minimizes the position estimation error also the velocity estimation error to 0 m/s and give us the desired results .

Therefore, it is possible to conclude that the soft assignment based on JPDA Filter and MONTE CARLO runs, gives us an improved tracking, such as the track losses value obtained is equal to 0, 06 compared to 0,14 and 0,8 in hard assignment for the target 1 and target 2 respectively.
The proposed algorithm MONET CARLO – JPDA shows us faster convergence in long time (T=200s) than the analytic algorithm

6. Conclusion and Future works

According to the obtained results, the theatrical methods are verified, the motion-based Multi target tracking using multiple receiver sensors it be better than single sensor, in order to avoid the dense clutter disturbance. On other hand, MONTE CARLO - JPDA algorithm has proposed as a solution to solve the data association and the real time processing problems. It is possible to conclude that we find the desired solution, to fight against the constraints previously proposed, our proposed approach gives us better results in order to improve the tracking in real time of two crossing targets using two receiver antennas in 2D.
We will do the same tracking scenarios using MIMO radar 8x8 24 GHz to track more number of targets, in order to prove the proposed algorithm.

Nomenclature

MTT: Multi Target Tracking
MC: Monte Carlo
PF: Particular filter
JPDA: Joint Probabilistic Data Association
KF: KALMAN Filter
FISST: Finite Set Statistics
DSS: Dynamic State-Space
MIMO: Multiple Input Multiple Output
$\boldsymbol{X_k}$**: State estimation**
$\boldsymbol{Y_k}$**: Measurement function**
$\boldsymbol{P_k}$**: General Covariance Matrix**
R: Covariance Matrix of measurement noise
Q: Covariance Matrix of Process noise
$\boldsymbol{\widetilde{W}_k^i}$**: Importance weight estimated**
ε: Entropy function
P$(\boldsymbol{X_{0:k}}/\boldsymbol{Y_{0:k}})$**: The posterior Law**
MC runs: Number of Monte Carlo simulation

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