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ORIGINAL PAPER

Improved multi-target tracking crossing paths in MIMO FMCW 8 × 16 radar system using a new hybrid AMC-JPDAF algorithm

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Abstract

This research paper deals with multi-target tracking in a MIMO radar system, which presents complex data that can result in correlation problems and create technical difficulties. The objective is to resolve these issues and prevent divergence in object-tracking scenarios. However, when the cross-path phenomenon occurs, the process of assigning target measurements in MIMO radar systems becomes more complicated, and the interference phenomenon can disturb the received signal and disrupt the state estimation process. We have created a new algorithm called AMC-JPDAF that is a combination of the particle filter with the adaptive Monte Carlo (AMC) method and the joint probabilistic data association filter (JPDAF). This replaces the conventional extended KALMAN filter (EKF) used in EKF-JPDAF. We incorporated an entropy calculation and resampling sub-algorithm to overcome the limitations of EKF-JPDAF, which resulted in a more accurate estimation of two crossing targets and reduced trajectory loss in various tracking scenarios. Our experiments demonstrate that AMC-JPDAF is effective in preventing possible divergence phenomena when simulating two intersecting drones tracking scenarios. We report that the coherent measurement ambiguity is resolved at the crossover point of the trajectories corresponding to each target, giving us a low trajectory loss rate of 3.9%, which is significantly better than the 18.7% and 10.8% reported by simulations that do not affect the trajectory estimation process. We employed the MATLAB software development framework to design a system that satisfies the goals initially established by AMC-JPDAF. We then validated the system's performance by using an experimental database collected from the MIMO-FMCW 8 × 16 radar system.

Keywords Radar systems · Multi-target tracking · Crossing paths · MIMO-FMCW radar · Target associations

Abbreviations

MTT	Multi-target tracking
AMC	Adaptive Monte Carlo
PF	Particular filter
JPDAF	Joint probabilistic data association filter
EKF	Extended KALMAN Filter
FMCW	Frequency modulation continuous wave
MIMO	Multiple input multiple output
SR	Systematic resampling
MC runs	Number of Monte Carlo simulation
RMSE	Root mean square error
MMIC	Monolithic microwave integrated circuits
CDMA	Code-division multiplex modulation

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1 Introduction

The latest design of a multiple-input multiple-output (MIMO) radar system consists of multiple transmitter and receiver antennas, which improve the radar's overall spatial resolution [1]. In the past, waveforms such as continuous wave (CW), pulse, and frequency modulated continuous wave (FMCW) were used in MIMO systems to enhance target detection and tracking scenarios. However, the MIMO-FMCW radar system overcomes the challenges of multipath and crossing paths, resulting in improved radar performance, including detection and tracking. In this system, multi-target tracking (MTT) scenarios are reliable in estimating the number of moving targets within a given area and predicting their trajectories based on sensor measurements. In our previous research [2], we introduced a novel architecture utilizing an ultra-wideband (UWB) SiGe chipset that operates based on MIMO-FMCW principles. This chipset features a four-channel phase-shifting transmitter operating between 1 and 30 GHz and a four-channel receiver operating between 1 and 65 GHz, increasing the number of transmitters to 8 Tx and receivers to 16 Rx.

In reference [2], the authors utilized SiGe-BiCMOS technology, which is trending towards smaller form factor MIMO radar systems. Monolithic microwave integrated circuits (MMICs) integrate digital control logic and analog low and high frequency circuits for signal generation, transmission, reception, and waveform modulation. They established a compact K-band MIMO radar system that uses code-division multiplex modulation (CDMA) for TX-separation.

This new radar architecture requires an intelligent algorithm that can improve multi-target tracking performance, as the choice of intelligent tracker [3, 4] has a direct impact on this. Despite various constraints such as low sensor performance, the number and behavior of targets, real-time processing, and data association uncertainty, multi-target tracking (MTT) in radar systems is highly reliable. The crossing path phenomenon [5, 6] is a real challenge where multiple targets may become obscured and lose their trajectory during the tracking period.

1.1 Problem statement

Tracking multiple targets with crossing paths in MIMO radar systems poses a significant challenge, particularly when intersecting paths occur, leading to filter divergence. This can result in inaccurate target state estimates, biased trajectories, and overall disruption of the estimation process. To address these challenges, attribution problem has to be addressed and various techniques have been proposed. Here, we present a new solution, the AMC-JPDAF algorithm, to tackle this problem.

2 Related works

In the literature, various methods have been proposed to address the challenges of multi-target tracking (MTT) in MIMO radar systems, including both Bayesian and non-Bayesian filters. One example is the Markov Chain Monte Carlo Data Association (MCMCDA) proposed in [7], which aims to improve the conventional method, multiple hypothesis tracking (MHT), by handling low signal-to-noise ratio (SNR) during pre-processing. To evaluate the proposed method, experiments were conducted in a real-world indoor environment, demonstrating the ability to accurately track multiple targets in real-time, even with crossing paths. The authors suggest that the system has potential applications in various fields, such as security, surveillance, and healthcare. The paper offers a comprehensive description of the system architecture, signal processing techniques, and experimental results, as well as a discussion of the limitations and future potential improvements. Overall, the paper proposes an innovative approach to indoor tracking of multiple persons within a limited range, using a 77 GHz MIMO FMCW Radar system.

Nevertheless, the Gaussian mixture (GM) combined with the probability hypothesis density (PHD) as an algorithm GM-PHD [8] provides a favorable framework for treating the measurements of several sensors.

The PHD filter is applied to MIMO radar data by representing the received signals as a sum of individual signals from each target. The authors show that the PHD filter can estimate the number of targets, their positions, and velocities accurately, even in the presence of clutter and measurement noise.

The paper also includes simulation results that demonstrate the effectiveness of the proposed method compared to other tracking methods. The results show that the PHD filter outperforms other methods in terms of tracking accuracy and computational efficiency once the clutter is appeared. This new method has not efficient to enhance the multi-target tracking with cross paths phenomenon.

With the intention of solving the target state estimation and multipath data association, a joint optimization called distributed expectation-conditional maximization (DECM) has been suggested in [9] to replace the over-the horizon radar (OTHR).

The algorithm is based on the expectation conditional maximization (ECM) framework and can be implemented in a decentralized scenario, making it suitable for large-scale tracking scenarios in the presence of multipath and unknown ionospheric heights. It has demonstrated promising results in target tracking performance, but may experience divergence in scenarios involving multiple and crossing paths.

The authors of the paper reviewed various tracking methods that deal with the measurement data from several sensors and found that the Gaussian mixture (GM) combined with the probability hypothesis density (PHD) algorithm, known as GM-PHD, is a favorable framework for this purpose. The PHD filter is applied to MIMO radar data to estimate the number of targets, their positions, and velocities accurately, even in the presence of clutter and measurement noise.

While the PHD filter outperforms other methods in terms of tracking accuracy and computational efficiency, it lacks efficiency in enhancing multi-target tracking with cross paths phenomenon. To address this issue, a joint optimization method called distributed expectation-conditional maximization (DECM) has been proposed in [9] to replace the over-the-horizon radar (OTHR). This algorithm is based on the expectation conditional maximization (ECM) framework and is suitable for large-scale tracking scenarios in the presence of multipath and unknown ionospheric heights. It has shown promising results in target tracking performance but may experience divergence in scenarios involving multiple and crossing paths.

In the field of multiple target tracking (MTT), various algorithms have been proposed to solve the track selection problem and deal with issues such as inconsistent processing and multipath effects. One approach is to use the Nash equilibria method (NEM), as shown in [10], while a hybrid algorithm based on the nearest neighbor data association (NN) and extended KALMAN filter (EKF) has been recommended in [11].

In cases where multiple targets cross paths, Bayesian filters like the joint probabilistic data association filter (JPDAF) are necessary. The JPDAF algorithm calculates association probabilities between validated measurements and tracked targets based on current time information and linear state and measurement equations. The JPDAF has been widely used in MTT applications, with algorithms such as multiple detection JPDAF (MD-PDAF) proposed in [12], and an improved probabilistic data association-feedback particle filter (PDA-FPF) for multiple target tracking applications presented in [13].

Additionally, the multi-sensor sequential joint probabilistic data association (S-MSJPDA) [14] has been shown to be more effective than the parallel multi-sensor joint probabilistic data association (P-MSJPDA) architecture for MTT in passive multi-static radar systems. A novel data association method called RL-JPDA, based on reinforcement learning (RL), has also been presented in [15], where RL is used to select measurements and purchase information.

Traditional MTT algorithms face high computational burdens in complex environments due to their need to generate all possible joint assignments between measures and track paths while considering measurement paths. To address this, authors in [16] proposed a new approach named multi-path linear multi-target integrated probabilistic data association (MP-LM-IPDA) that avoids generating all possible joint assignment scenarios. Another multi-path MTT algorithm called multiple detection joint integrated track splitting (MD-JITS) was introduced in [17]. This algorithm addresses measurement origin uncertainty and measurement path model uncertainty by jointly solving them and was compared with OTHR methods in the presence of clutter and failed target detections to validate its efficiency.

In contrast, the authors in [19–21] focused on the target tracking data association problem in complicated environments. They proposed a novel probabilistic data association algorithm that uses distance weighting to improve the association probability and state of the target measurements with the use of a KF for real-time processing and accurate tracking. They also proposed an improved algorithm using a combined interactive multiple model probabilistic data association algorithm to track maneuvering targets in densely cluttered environments through Monte Carlo simulation. In [18], an improved joint probabilistic data association (JPDA) filter has been proposed to handle multi-target tracking scenarios with cross-path maneuvering targets, but the results show a high RMSE position.

Although the aforementioned papers presented theoretical frameworks of various filters such as MDJPDA, PDA, JPDA, RL-JPDA, MD-JITS, KF-JPDA filter and the novel fixed interval smoothing LMITS (FIsLMITS) method, along with simulation results demonstrating their effectiveness in tracking multiple targets in cluttered environments in terms of tracking accuracy and false track rate, they may not be adequate in handling measurement assignment to targets, particularly when targets cross paths. This can make the data association process more complex at the crossing point, which may lead to the interruption of the radar tracker's tracking scenario.

The present paper introduces a novel algorithm, the adaptive Monte Carlo joint probabilistic data association filter (AMC-JPDAF), which aims to efficiently track multiple targets in complex scenarios by addressing the problem of data correlation and filter divergence that can occur in MIMO radar systems when targets intersect each other.

The paper is organized into related works in Sect. 2, the proposed algorithm in Sect. 3, experimental results in Sect. 4, and the conclusion and future works in Sect. 5.

3 Methods

In this section, we will present our novel hybrid algorithm that has been specifically developed to tackle the multi-target tracking (MTT) problem in a MIMO-FMCW radar system.

3.1 Joint probabilistic data association filter (JPDAF)

The 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 $\{\theta_k = \theta_k^i\} \in \{1, 2 \ldots N_{(k/k-1)}$ 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 $\theta_k^i = j$ means the j^{th}

measurement is originated from the ith target and $\theta_k^i = 0$ 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:

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

3.2 The particle filter based on adaptive Monte Carlo algorithm (AMC)

The AMC algorithm is a sequential Monte Carlo technique that is designed for state estimation in non-linear and non-Gaussian dynamic systems. Unlike analytic filters based on the extended KALMAN filter (EKF), the AMC algorithm approximates the full probability distribution using Np random samples, not just the mean and covariance. The method uses sequential resampling to prevent filter divergence, particularly in scenarios with high non-linearity and non-Gaussian distributions. In addition, the algorithm requires sufficient probability under the observed region, which is achieved through a probabilistic interpretation that involves probabilistic interpolation:

$$I(f) = E[p(X/Y)] = \int_1^{N_p} f(X) \cdot p(X/Y) \quad (2)$$

3.3 The proposed hybrid AMC-JPDAF algorithm

- Initialization

Set $k = 0$, generate N Samples for all targets during 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 k=1.
For i=1... N predict new particles.

$$\tilde{X}_{t,k}^{i*} = F * X_{t,k+1}^i + V_{t,k-1}^i \quad \text{(Eq.3)}$$

Where; $\tilde{X}_{t,k}^{i*}$ presents the predicted target state, $X_{t,k+1}^i$ present the current target state matrix, F present the state Matrix and $V_{t,k-1}^i$ the processing noise.

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

$$W_{t,k}^i = \frac{w_{t,k}^i}{\sum_{i=1}^N w_{t,k}^i} \quad \text{(Eq.4)}$$

- Calculate the effective sample size: $\tilde{T}_{eff} = \frac{1}{\sum_{i=1}^{N_p} (W_k^i)^2}$ (Eq.5)
- Calculation of Entropy: $\varepsilon = -\sum_{i=1}^{N_p} W_k^i \,.\, W_k^i$ (Eq.6)
- Calculation of optimal entropy: $\varepsilon_{opt} = N_p$
- **Resampling Sub algorithm**: 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 $P\ (X_{t,k}^i = X_{t,k}^{i*}) = \tilde{W}_{t,k}^i$. (Eq.7)
- Increase k, Loop
- End.

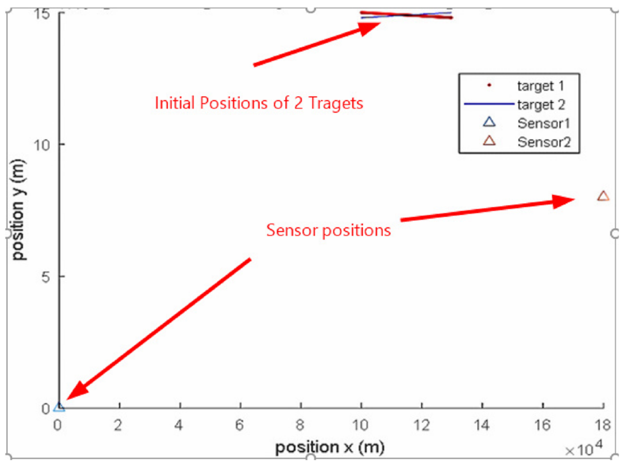

Fig. 1 The multi-target crossing scenario in spatial and ambiguous measurements

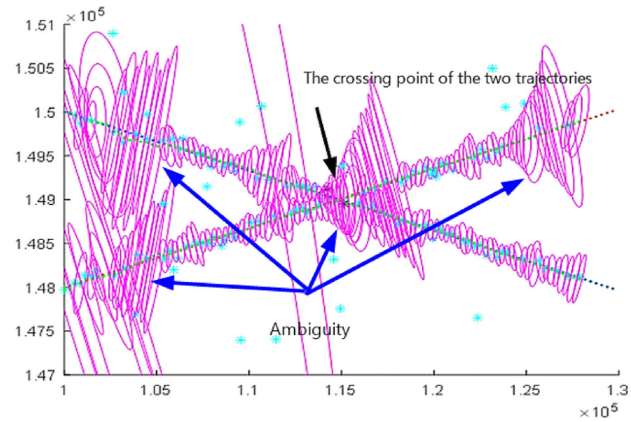

Fig. 2 Trajectories of two crossing targets estimated using the EKF-JPDAF algorithm. Blue dot: represents the true target states. Green dot: represents the estimates. Cyan star: represents the resolved measurements. Black star: represents the unresolved measurements

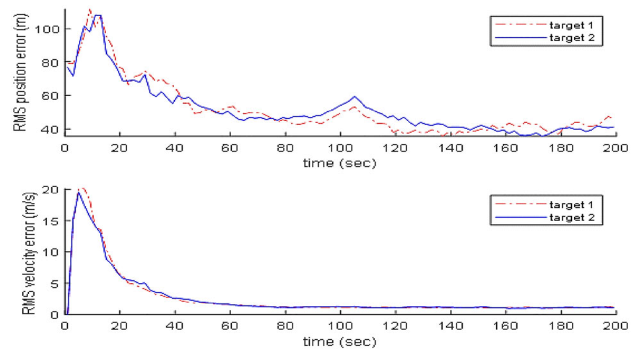

Fig. 3 Root mean square error (RMSE) position and velocity for each target results of EKF-JPDA

4 Experimental results

The main objective of this study is to showcase the efficacy of the novel AMC-JPDAF algorithm in accurately modeling and simulating target-tracking parameters. Specifically, we aim to enhance the state estimation of two intersecting targets in 2D by leveraging two independent sensors in a classical MIMO radar 2×2 configuration with two Tx independent sensors. We will compare the performance of the AMC-JPDAF algorithm with that of a MIMO FMCW radar system, and the evaluation will be carried out using MATLAB software.

4.1 Simulation scenarios

In the following section, we will present the sensor-target geometry used for tracking two crossing targets (Fig. 1):

- Sensor 1: (0, 0).
- Sensor 2: (1.8e5, 0.8e5).

The initial state of the targets is:

- Target 1: (100e3, 150, 150e3, − 10).
- Target 2: (100e3, 150, 148e3, 10).

To implement our algorithm and ensure accurate results interpretation, we have selected several variables and metrics, as follows:

- Time (T) = 200 s.
- Number of Monte Carlo simulations (MC runs) = 100 samples.
- Root mean square error (RMSE); the position RMSE is used to evaluate filtering performance.
- The path loss rate for each target; Target 1 and Target 2 in different tracking scenarios

4.1.1 Two crossing targets tracking using EKF-JPDAF algorithm

To start the tracking scenario of two crossing targets in 2D, we use the EKF-JPD AF algorithm. We then obtain the estimated trajectories and RMSE values, which are presented in Fig. 2.

The path loss rate correspond to each target, calculated using MATLAB as follows:

- Target 1: 0.187 or 18.7% (shown in red).
- Target 2: 0.172 or 17.2% (shown in blue).

According to Figs. 2 and 3 and Table 1 above, it can be observed that the tracking of the two targets using the EKF-JPDAF algorithm is more complex, resulting in higher trajectory losses, particularly when the crossing phenomenon

Table 1 Estimated RMSE of each target given by EKF-JPDAF

Target	RMSE position (m) at $T = 200$ s
Target 1	50
Target 2	46

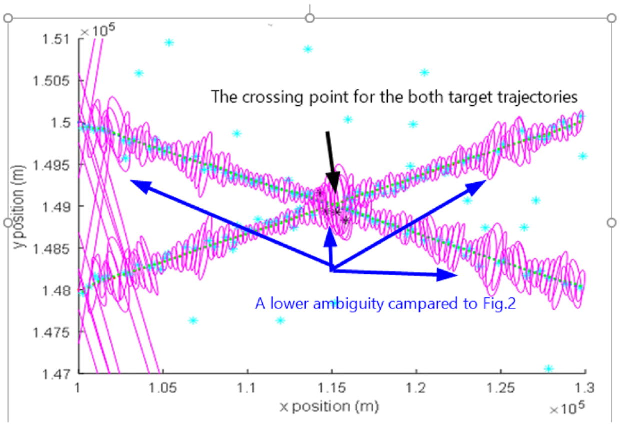

Fig. 4 Trajectories of two crossing targets estimated using the AMC-JPDAF algorithm. Blue dot: represents the true target states. Green dot: represents the estimates. Cyan star: represents the resolved measurements. Black star: represents the unresolved measurements

occurs. Specifically, the percentage of trajectory losses for target 1 is 18.7%, and for target 2, it is 17.2%.

4.1.2 Two crossing targets tracking using the suggested AMC-JPDAF algorithm

To enhance the tracking outcomes achieved by EKF-JPDAF, we utilized a novel numerical filter known as AMC-JPDAF. The algorithm was applied to track two intersecting targets in 2D over the same 200-s estimation period. The resulting trajectories and RMSE values are shown in Fig. 4.

The path loss rate correspond to each target, calculated using MATLAB as follows:

- Target 1: 0.06 or 6% (shown in red).
- Target 2: 0.07 or 7% (shown in blue).

The results demonstrate that the proposed algorithm has a lower trajectory losses rate, a lower ambiguity compared to the EKF-JPDA algorithm, as shown in Fig. 4. Furthermore, Fig. 5 illustrates that within a 20-s period; the proposed algorithm reduces the amplitude of the RMSE position from approximately 80 to 20 m and decreases the RMSE velocity from 22 to 0.5 m/s (Table 2).

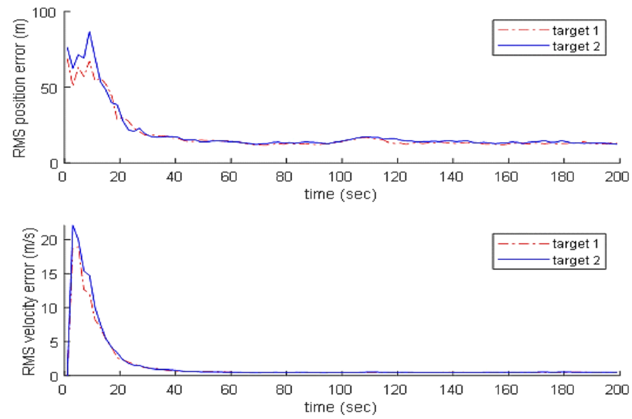

Fig. 5 Root mean square error (RMSE) of estimated position and velocity for each target given by AMC-JPDA

Table 2 Estimated RMSE of each target given by AMC-JPDA

Target	RMSE position (m) at $T = 200$ s
Target 1	20
Target 2	20

4.2 Implementation of AMC-JPDAF on MIMO-FMCW radar

In this scenario, we create a detection database for two crossing drones using an 8 × 16 MIMO FMCW radar operating at a frequency of 24 GHz. The radar system is manufactured using the BiCMOS and SiGe architecture described earlier. The PC, connected to the radar system via an Ethernet cable, is responsible for calculating the detection results. Figure 6 provides a visual representation of the setup.

Our goal was to validate the effectiveness of the AMC-JPDA method for real-time tracking of two crossing drones. To achieve this, we utilized the detection results obtained from the MIMO-FMCW 8 × 16 SiGe BiCMOS radar and performed tracking over a time interval of $T = 101$ s. The aim was to demonstrate the improved tracking of multiple targets using our approach.

The simulation variables for this scenario have been pre-initialized with the following values:

- Number of targets: 2 crossed targets (drones).
- Initial coordinates of drone 01: [− 1.3839e3; 3.8322e3; 0].
- Initial coordinates of drone 02: [− 1.3839e3; 4.0322e3; 0].
- Radar architecture: MIMO-FMCW 8 × 16 SiGe BiCMOS.
- MIMO-FMCW radar position (in cm): [0; − 4e5].
- Simulation time (T): 101 s.
- Monte Carlo simulation iterations (MC runs): 100.

applied on a MIMO-FMCW 8 × 16 radar system."

Fig. 6 Tracking scenario scene of two crossing drones using the MIMO-FMCW 8 × 16 radar system

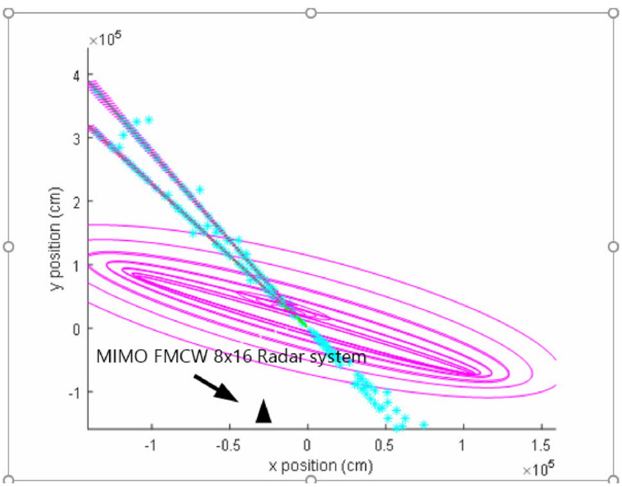

Fig. 7 The two estimated crossed trajectories of two drones using the AMC-JPDAF algorithm

The efficiency of the hybrid AMC-JPDA algorithm is illustrated in Fig. 7. The estimated trajectories for the two crossing drones are more discernible with reduced red clutter and the ambiguity phenomenon. Furthermore, the blue dots indicating estimated states are highly concentrated and closely match the true target states. The shape of the estimated trajectory in line with the simulation results indicates the filter's effectiveness.

The mean square error (RMSE) of each target trajectories is given in the following.

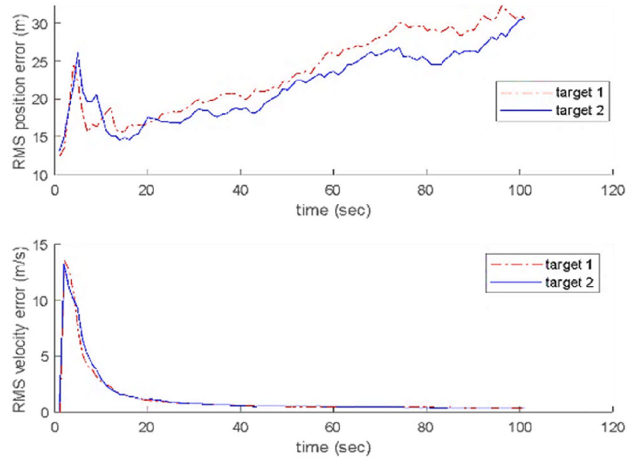

Fig. 8 The obtained RMSE for each target results of AMC-JPDAF algorithm

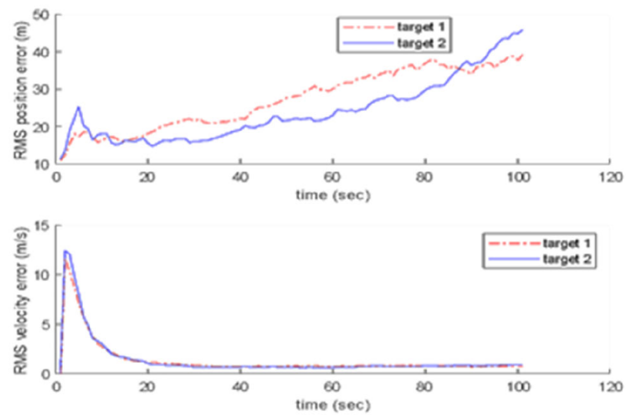

Fig. 9 The obtained RMSE for each target results of EKF-JPDAF algorithm

The trajectory losses rate for each target, calculated using MATLAB, are as follows:

Figure 8:

Drone 1: 0.049505 or 4.9% (shown in red).

Drone 2: 0.039604 or 3.9% (shown in blue).

Figure 9:

Drone1: 0.1082 or 10.8% (shown in red).

Drone 2: 0.1338 or 13.3% (shown in blue).

4.3 Discussion

The table below presents a comparison of the performance of the two algorithms using simulation results from the 2 × 2 MIMO radar and validation results obtained from the 8 × 16 MIMO-FMCW radar.

The comparison presented in Table 3 confirms that the AMC-JPDAF algorithm outperforms the EKF-JPDAF algorithm in terms of mean squared error (RMSE) for both simulation scenarios. The results demonstrate that the new

Table 3 Comparative results

Judgment metrics		EKF-JPDAF	AMC-JPDAF
MIMO Radar 2Rx	RMSE position (m) at T = 200 s	Target 1 = 50 Target 2 = 46	Target 1 = 20 Target 2 = 20
	Target 1: percentage of trajectory losses	18.7%	6%
	Target 2: percentage of trajectory losses	17.2%	7%
Radar MIMO-FMCW 8 × 16	Drone 1: percentage of trajectory losses	10.8%	4.9%
	Drone 2: percentage of trajectory losses	13.3%	3.9%
	RMSE position (m) for Drone 1 at = 101 s	40 m	30 m
	RMSE position (m) for Drone 2 at = 101 s	46 m	28 m

algorithm is more effective in classical MIMO radar systems with two sensors and has a lower tracking risk than the EKF-JPDAF algorithm. Moreover, we introduced trajectory loss percentage as a new metric to further evaluate the performance of the algorithms. The results show that our new hybrid algorithm has a trajectory loss percentage of no more than 7%, indicating its robustness (Fig. 10).

The utilization of the 8 × 16 MIMO-FMCW radar for detection has resulted in improved tracking performance using our hybrid algorithm based on the AMC-JPDAF filter compared to the EKF-JPDAF. The experimental results support our theoretical assumptions and validate the effectiveness of our approach, as it has reduced target trajectory loss by 4.9% and 3.9% in comparison to 13.3% and 10.8%, respectively, for the EKF-JPDAF (Fig. 11).

The efficiency of the SiGe BiCMOS-based 8 × 16 MIMO FMCW radar in tracking scenarios is evident, especially

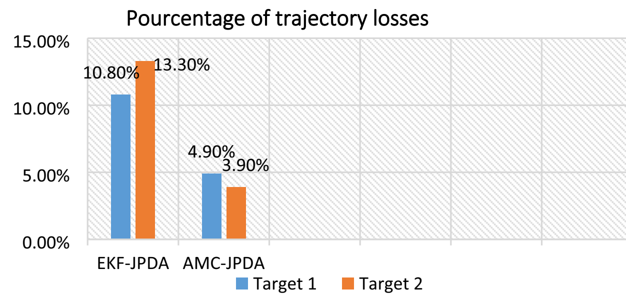

Fig. 10 Trajectory loss percentage for the both targets

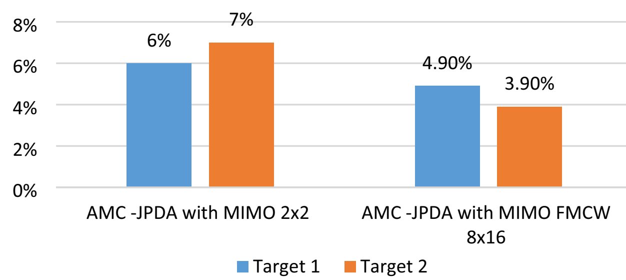

Fig. 11 Trajectory loss percentage for both targets compared to simulation results

when utilizing the novel AMC-JPDA hybrid algorithm, which outperforms conventional MIMO radars.

5 Conclusion and future works

In this paper, we introduced a novel approach to develop multi-target tracking (MTT) in MIMO radar systems, which overcomes the limitations associated with conventional MTT methods. By addressing the data association issue and filter divergence during the tracking scenario, the proposed AMC-JPDAF approach yields more efficient results than the EKF-JPDAF approach in complex scenarios and is also compared with the results mentioned in the literature, Such as [18, 21]. This was demonstrated through experimental validation, which confirmed the superior performance of the AMC-JPDAF method. In a real-time tracking scenario of two crossing drones, the AMC-JPDAF algorithm demonstrated fast calculation times; quick convergence to effective states with low RMSE position reach to20 m, then a low path loss rate did not exceed 3.9%. While our results are promising, future research will focus on extending the method to multiple maneuvering targets to further improve its effectiveness.

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Data availability The results in this paper were obtained using a dataset from the MIMO FMCW 8 × 16 radar system during my research collaboration at the Fraunhofer Research Laboratory in Germany [as we mentioned previously], and for this reason the data cannot be shared publicly.

Declarations

Conflict of interest The authors declare no conflict of interest.

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