Comparative Analysis on Diverse Heuristic-Based Joint Probabilistic Data Association for Multi-target Tracking in a Cluttered Environment

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Abstract The target tracking using the passive multi-static radar system produces various detections via distinct signal propagation paths. Trackers solve the uncertainties that arise from the measurement path as well as the measurement origin. The existing multi-target tracking algorithms suffer from high computational loads, because they require the entire probable joint measurement-to-track assignments. This paper proposes to develop a comparative analysis on diverse heuristic algorithms for implementing the optimized JDPA model for tracking multiple targets using multi-static passive radar system in the presence of clutter. Here, the nature-inspired algorithms like Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO) are used for analyzing the optimized JDPA model for tracking multiple targets in multi-static passive scenario. This paper further, aims to tune the position and velocity of the tracker towards the target using two heuristic algorithms, and intends to analyze the effect of those algorithms on improving the performance of multiple target tracking. The key objective of the proposed model is to minimize the Mean Absolute Error (MAE) between the estimated trajectory of the track and the true target state.

Keywords Mean absolute error · Joint probabilistic data association · Multi-target tracking · Grey wolf optimization · Particle swarm optimization

1 Introduction

The target tracking in the existence of cluttered measurements is a challenging problem due to measurement origin uncertainty. This problem gets further complex for multi-static passive scenario. Generally, there is a need to handle two problems [1]. The initial problem is the data association and the next problem is the False

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Track Discrimination (FTD). The track component count of Joint Integrated Track Splitting (JITS), Integrated Track Splitting (ITS), and Multiple Hypotheses Tracking (MHT) increase in a sequential time, and the probabilistic data association (PDA) [2] is adopted to merge the tracked components into a single trajectory estimate having a Gaussian probability density function. Joint probabilistic data association (JPDA) [3] is employed for tracking multiple targets in the case of cluttered environments having known target counts. The JIPDA and JITS are the multitarget trackers that employ the optimal multiple target data association scheme of estimating and enumerating the entire possible joint measurement for tracking the associations [4]. Authors in [5], proposed two new composite methods for data association based on soft and evolutionary computing for tracking different targets in the existence of electronic countermeasures (ECM), clutter, and false alarms. In the presence of jamming, [6] proposed a novel clustering-based data association technique for tracking multiple targets.

Multiple target tracking (MTT) is a significant task in sonar, radar, and various surveillance systems. Generally, the measurements reported by the surveillance systems from the unintended sources are called as clutter. In recent years, passive radar gained significant interest in military and civilian applications [5]. The traditional transmitters (FM, DVB, etc.) are exploited by the passive radar in the form of opportunity illuminators. Hence, the additional hardware requirement and the frequency allocation are eliminated. So, in the passive radar, the target detection is continuous, covert, and inexpensive [7]. When multiple transmitters are exploited in a simultaneous manner, passive multi-static radar (PMSTR) is obtained. Here, the trajectory, as well as the location of a potential target, is defined by merging the measurements from various transmitter–receiver pairs having sharable coverage. As a result, the PMSTR provides noteworthy advantages [8].

Still, majority of the researches are dependent on the existing resampling mechanism and the weight degeneration problem is not handled in a fundamental manner. The detailed study of swarm intelligence optimization algorithm along with the particle filter is a novel technique for enhancing the performance of the Particle Filter (PF) [9, 10]. Few algorithms merge the PF with the generalized interactive genetic algorithm that may easily fall into premature convergence and leads to inaccurate filtering process. Therefore, there is a strong need to develop alternative heuristic-based data association techniques for PMSR scenarios.

The major contribution related to this paper is shown below:

- To implement the optimized JPDA model based on particle swarm optimization and grey wolf optimization for the tracking of multiple targets using passive radar with consideration of the constraints such as the position and the velocity.
- To minimize the MAE among the true target state and the estimated trajectory of track by tuning the position as well as the velocity.
- To perform the comparative analysis using diverse heuristic-based algorithms such as GWO, and PSO on JPDA for the multi-target tracking for PSMR scenario.

The organization of the paper is shown below: Sect. 2 describes a general JPDA-based target tracking algorithm for tracking multiple targets. Section 3 presents optimized JPDA based on diverse heuristic algorithms for tracking multiple targets. Section 4 highlights the simulation setup, plots, and briefs the results. Finally, Sect. 5 gives the conclusion remarks for the paper.

2 Optimized Joint Probabilistic Data Association Tracker for Multitarget Radar Tracking

2.1 JPDA-Based Tracking

Generally optimized JPDA algorithm is applied for multiple target tracking. In the initial step, the measurement model and motion models are defined. Thereafter, the multiple targets tracking algorithm is denoted. The track management is performed in three steps: initialization of the track initiation, updation of the track, and termination of the track. The track update is accomplished by the data association, which associates the measurements as whether these are target-originated or clutter-originated measurements to the existing tracks by means of the track filtering step [11].

Track Motion and Measurement Models: The vector denoting target state XC_{kc} at frame kc is defined into the Cartesian domain by including the target size as displayed in Eq. (1).

$$XC_{kc} \stackrel{\Delta}{=} \left[xc_{kc}^{\tau, pc}, \; yc_{kc}^{\tau, pc}, \; xc_{kc}^{\tau, vc}, \; yc_{kc}^{\tau, vc}, \; lc_{kc}, \; wc_{kc} \right]^{TC} \tag{1}$$

In the above equation, the length and width of the target is defined by lc_{kc} and wc_{kc}, and the velocity and the position components are defined by $xc_{kc}^{\tau, vc}, yc_{kc}^{\tau, vc}$ and $xc_{kc}^{\tau, pc}, yc_{kc}^{\tau, pc}$ in the region of the $xc-$ and $yc-$ directions, respectively. The target dynamic is described by the nearly constant velocity model as shown in Eq. (2).

$$XC_{kc} = FCXC_{kc-1} + \Gamma wc_{kc} \tag{2}$$

The term FC is denoted in Eq. (3).

$$FC = \begin{bmatrix} IC_2 \otimes F\tilde{C} & 0_{4 \times 2} \\ 0_{2 \times 4} & IC_2 \end{bmatrix} \tag{3}$$

This equation denotes the state transition model, which is applied to the previous state XC_{kc-1} as displayed in Eqs. (4) and (5).

$$\Gamma = \begin{bmatrix} IC_2 \otimes \tilde{\Gamma} & 0_{4 \times 2} \\ 0_{2 \times 2} & IC_2 \end{bmatrix} \tag{4}$$

$$F\tilde{C} = \begin{bmatrix} 1 & TC_{sc} \\ 0 & 1 \end{bmatrix} \tag{5}$$

In the above equation, the term TC_{sc} denotes the sampling time, $\otimes$ denotes the Kronecker product, IC_{dc} denotes the unit matrix with dimension dc, $0_{r \times c}$ denotes the zero matrix with r rows and c columns, wc_{kc} denotes the process noise, which is forecasted to be drawn from a zero mean multivariate normal distribution with covariance QC, such that $wc_{kc} \approx \aleph(0_{4 \times 1}, QC)$ and $\tilde{\Gamma} = \left[TC_{sc}^2 / 2, TC_{sc} \right]^{TC}$ as portrayed in Eq. (6).

$$QC = diag\left(\sigma_{pc}^2, \sigma_{vc}^2, \sigma_{lc}^2, \sigma_{wc}^2\right) \tag{6}$$

Here, the terms σ_{wc}^2, σ_{lc}^2, and σ_{vc}^2 define the variances for the width, length, and acceleration, and $diag(\bullet)$ defines the diagonal matrix. The measurement vector ZC_{kc} at frame kc is shown in Eq. (7).

$$ZC_{kc} \overset{\Delta}{=} \left[zc_{kc}^{rc}, zc_{kc}^{\varphi}, zc_{kc}^{lc}, zc_{kc}^{wc}, zc_{kc}^{\theta} \right] \tag{7}$$

In the above equation, the terms zc_{kc}^{wc} and zt_{kc}^{lc} define the length of the minor and major axes, zc_{kc}^{φ} and zc_{kc}^{rc} defines the azimuth and the range measurements of the ellipse center, which best fits the cluster, and zc_{kc}^{θ} defines the orientation of the ellipse. The measurements originated from the target are shown in Eq. (8).

$$ZC_{kc} = hc(XC_{kc}) + \omega_{kc} \tag{8}$$

Equation (9) defines the term $hc(XC_{kc})$.

$$hc(XC_{kc}) \overset{\Delta}{=}$$
$$\left[\sqrt{xc_{kc}^2 + yc_{kc}^2}, \ \arctan\left(yc_{kc}/xc_{kc}\right), lc_{kc}, wc_{kc}, \arctan\left(yc_{kc}^{\tau, vc}/xc_{kc}^{\tau, vc}\right) \right]^{TC} \tag{9}$$

The above equation denotes the measurement function and the instrumental noise vector is defined by ω_{kc}, which is presumed to be the Gaussian with zero mean as well as the covariance matrix as displayed in Eq. (10).

$$RC = diag\left(\sigma_{rcrc}^2, \sigma_{rc\varphi}^2, \sigma_{rclc}^2, \sigma_{rcwc}^2, \sigma_{rc\theta}^2\right) \tag{10}$$

Here, the terms σ_{rcwc}^2 and σ_{rclc}^2 define the variances for the two sizes, $\sigma_{rc\theta}^2$ defines the variation for the orientation of the ellipse, and $\sigma_{rc\varphi}^2, \sigma_{rcrc}^2$ defines the variances in azimuth and range, respectively. The ETT takes the target orientation as logical with consideration to the motion orientation such as $\theta_{kc} = \arctan\left(\dot{yc}_{kc}/\dot{xc}_{kc}\right)$.

A random group of false or noisy clutter measurements is received by the sensor in every scan [12]. The noisy measurement count present in the surveillance space is designed using a Poisson distribution with known intensity called the clutter measurement density. The clutter measurement density having measurement $ZT_{kt,it}$ is represented with the help of the shortcut $\rho\left(ZT_{kt,it}\right)$. The amount of the surveillance space at time kt is denoted by VT_{kt}, and hence the probability that the clutter measurement count that equals mt in VT_{kt} at time kt tends to follow the Poisson distribution as in Eq. (11).

$$ut_{FT}(mt) = e^{-\int\limits_{VT_{kt}} \rho_{kt,it}\,dVT}\, \frac{\left(\int\limits_{VT_{kt}} \rho_{kt,it}\,dVT\right)^{mt}}{mt!} \tag{11}$$

In the above equation, the clutter measurement density is denoted by $\rho_{kt,it} = \frac{PT_{far}}{VT_{src}}$, where VT_{src} and PT_{far} represents the sensor resolution cell volume and probability of false alarm. The probability of false alarm persistently makes an effect on the clutter measurement count, meaning that when the probability of false alarm PT_{far} rises, the disorder measurement density $\rho_{kt,it}$ also rises, and the mean clutter measurement count present in the surveillance space VT_{kt} rises, thereby generating an enhanced clutter measurement count at every time kt. In the case of target tracking, the clutter measurement density describes either a priori known or an estimated priori in an adaptive manner on the basis of the current measurements.

Multiple Target Tracking Procedure: The tracking process works on the basis of the JPDA, where a Bayesian technique associates the checked measurements to the tracks by means of the probabilistic weights [13]. The management of the track follows the M/N logic. The filtering stage is performed by the unscented KF. The predicted or updated target state having its covariance at frame kc is defined by $XC_{kc/kc}^{jc}\left(XC_{kc/kc-1}^{jc}\right)$ and $PC_{kc/kc}^{jc}\left(PC_{kc/kc-1}^{jc}\right)$. At frame kc, a cluster of JC_{kc} active or preliminary tracks are described as $T_{kc} = \left\{T_1(kc), \ldots, T_{jc}(kc), \ldots, T_{JC_{kc}}(kc)\right\}$, where $T_{jc}(kc)$ assumes the jcth track. A validation gate region ζ_{kc}^{jc} for each $jc \in [1, \cdots, JC_{kc}]$ is formed. The target-originated measurements denote the Gaussian that is spread on the outer of a predicted measurement $ZC_{kc/kc-1}^{jc}$ of the target jc, and then the gate is defined as displayed in Eq. (11).

$$\zeta_{kc}^{jc} = \left\{ ZC : \left(ZC - ZC_{kc/kc-1}^{jc}\right)^{TC} \left(SC_{kc}^{jc}\right)^{-1} \left(ZC - ZC_{kc/kc-1}^{jc}\right) < \gamma \right\} \tag{12}$$

In the above equation, the threshold γ represents the gating probability PC_{GC}, and the innovation covariance that is the difference between the prediction and its measurement is defined by SC_{kc}^{jc}. The gating probability defines the probability, in which a measurement evolved by target jc is checked in an accurate manner.

2.2 Tracking Steps

The developed multiple target tracking system employs the optimized JPDA algorithm for handling the data association problem in the path of the targets of objects in an effective manner [14]. The different steps in the track management are shown in Fig. 1.

Initiation of Track: The association of measurement to $T_{jc}(kc)$ if it lies in the gated region. The unassociated measurement is termed as the initiator and a temporary track is generated. After detecting the initiator, the gate set up is started. If the detection lies in the gate region, then the track is called a preliminary track; elseways, it is referred to as dropped. The initialization of JPDA is done to set up the gate for the next frame. Beginning with the third scan, the logic of M detections out of N scans is utilized for the gates that follow. Finally, for the scan number $N + 2$, if the necessity of logic is completed, then the track is called as a confirmed or active track; elseways, it is called as a discarded track.

Termination of the Track: The track terminates when the following conditions are checked: no detection was validated in the previous $N*$ sampling times; the track uncertainty reached the threshold, and the output represents an impossible maximum velocity $vc_{\max}$.

Updation of the Track: All the tracks update the target state via the JPDA application rule. The updation of the state of the target is based on the measurement-to-track JPDA association rule and the prediction of the state of the target is considered from the motion model.
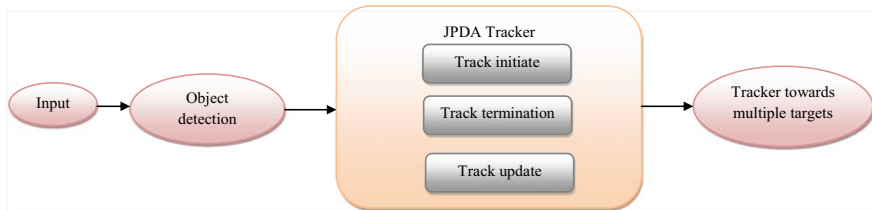

Fig. 1 Multi-target tracking model on the basis of the optimized JPDA algorithm

3 Contribution of Diverse Heuristic Algorithms for Target Tracking

3.1 Tracker Update and Objective

The position and the velocity of the object target are considered as $xc_{kc(u)}^{\tau,pc}$, $yt_{kc(u)}^{\tau,pc}$ and $xc_{kc(u)}^{\tau,vc}$, $yc_{kc(u)}^{\tau,vc}$, in which $u = 1, 2, \ldots, NV$, and NV denotes the total considered target count. Here, the tracker points with position as well as velocity are considered as $xc_{tr-kc(u)}^{\tau,pc}$, $yc_{tr-kc(u)}^{\tau,pc}$, and $xc_{tr-kc(u)}^{\tau,vc}$, $yc_{tr-kc(u)}^{\tau,vc}$, respectively. The position as well as the velocity of the tracker are updated by the heuristic algorithms in the path of the target. In every instant, the position as well as the velocity of the tracker in the path of the multiple targets are updated by the heuristic algorithms.

The major objective of updating the tracking points using the heuristic algorithms is to reduce the MAE among the targeted point and the tracked point. The novel position as well as velocity is used to track the position as well as the velocity. The MAE between the target as well as the tracked output is computed. The optimization happens for each time instance for reducing the error in each instance. The experiments are accomplished for 2 targets, 3 targets, and 5 targets. The objective model is displayed in Eq. (12).

$$Ob = \underset{\left\{ xc_{kc(u)}^{\tau,pc}, yc_{kc(u)}^{\tau,pc}, xc_{kc(u)}^{\tau,vc}, yc_{kc(u)}^{\tau,vc} \right\}}{\arg\min(MAE)} \tag{13}$$

In the above equation, the objective model is described by Ob, the position of the object target is defined by $xc_{kc(u)}^{\tau,pc}$, $yc_{kc(u)}^{\tau,pc}$, and the velocity of the object target is defined by $xc_{kc(u)}^{\tau,vc}$, $yc_{kc(u)}^{\tau,vc}$. MAE is, "a measure of difference between two continuous variables", as shown in Eq. (13).

$$MAE = \frac{\sum_{kc=1}^{pc} \left| xc_{kc(u)}^{\tau,pc} - xc_{tr-kc(u)}^{\tau,pc}, \; yc_{kc(u)}^{\tau,pc} -, \; yc_{tr-kc(u)}^{\tau,pc}, \; xc_{kc(u)}^{\tau,vc} - xc_{tr-kc(u)}^{\tau,vc}, \; yc_{kc(u)}^{\tau,vc} - yc_{tr-kc(u)}^{\tau,vc} \right|}{pc} \tag{14}$$

Here, the tracker points with position and velocity is defined by $xc_{tr-kc(u)}^{\tau,pc}$, $yc_{tr-kc(u)}^{\tau,pc}$ and $xc_{tr-kc(u)}^{\tau,vc}$, $yc_{tr-kc(u)}^{\tau,vc}$, respectively.

3.2 Comparative Heuristic Algorithms

The heuristic algorithms like PSO-based JPDA, GWO-based JPDA are compared with multi-target tracking using JPDA in terms of cost function and the mean absolute error.

GWO: GWO [6] is a novel meta-heuristic optimization algorithm. The major aim is to criticize the behaviour of the grey wolves for hunting in a cooperative manner. It represents a large-scale search technique that is centered on three optimal samples. To model the leadership structure, four sorts of grey wolves are considered: "alpha, beta, delta, and omega" "Hunting, looking for the prey, surrounding the prey, and assaulting the prey" are the three key processes employed here. It can also handle classical engineering design problems [17].

PSO: PSO [15] defines a population-oriented stochastic optimization algorithm. The structure is modified to attain the best performance. The distinct topology structures and various parameters configuration are also considered into effect. Hence, it is used for different application sectors. This algorithm initiates with the swarm population initialization and the particle fitness interpretation. Moreover, it also computes the swarm (global) optimal position and the individual (personal) best-suited position. It also updates the velocity of the position and the particle. This process stops when the most appropriate solution is achieved.

Target tracking can be thought of as a numerical optimization issue in which the local mode of the similarity measure is tracked using particle swarm optimization. The objective function is based on a multiple patch-based target representation and an area covariance matrix. The goal positions and velocities obtained in this manner are then used in a particle swarm optimization-based algorithm to optimize the paths obtained in the early step. After that, the final optimization is done using a conjugate process. To find strong local minima, the particle swarm algorithm is used, and the conjugate gradient is utilized to accurately identify the local minimum [16].

4 Results and Discussions

4.1 Simulation Setup

The DVB-based passive radar network which consists of four transmitters of opportunity located on ground is used for tracking multiple targets. Three different scenarios are considered for simulation: In scenario 1 two crossing targets moving with equal and uniform velocities are considered, scenario 2 presumes two crossing targets with an additional target moving along straight path and lastly scenario 3 five targets moving with uniform velocity are assumed. Further, it is assumed that all the targets appear simultaneously and are corrupted by heavy clutter and noise. Simulation of targets is carried out for 30 s with sampling period of 1 s and the simulation is carried out for 100 Monte Carlo runs. The heuristic algorithm-based JPDA for tracking multiple targets using multi-static passive radar system is implemented in MATLAB 2020a, and the results are tabulated and analyzed. The proposed variants of JPDA algorithms optimize the position and velocity of the targets for minimizing the MAE between the estimated trajectory of the track and the true target state.

4.2 Convergence Analysis

The convergence analysis of the suggested and existing heuristic-based JPDA for multiple targets tracking with passive radar system having multiple radar sites is portrayed in Fig. 2. From Fig. 2a for scenario 1, at 100th iteration, the cost function is better in the case of JPDA. Similarly, in Fig. 2b for scenario 2, at 100th iteration, the cost function is improved in the case of PSO-JPDA. Moreover, while considering Fig. 2c for scenario 3, at 100th iteration, the cost function is better with the PSO-JPDA. Hence, it is clear that cost function is better with distinct heuristic algorithms in considering the multi-target tracking scenarios. Also, from the convergence plots, we can infer that the PSO-based JPDA converges faster to the optimized range and velocity values even for complex scenarios like 2 and 3.
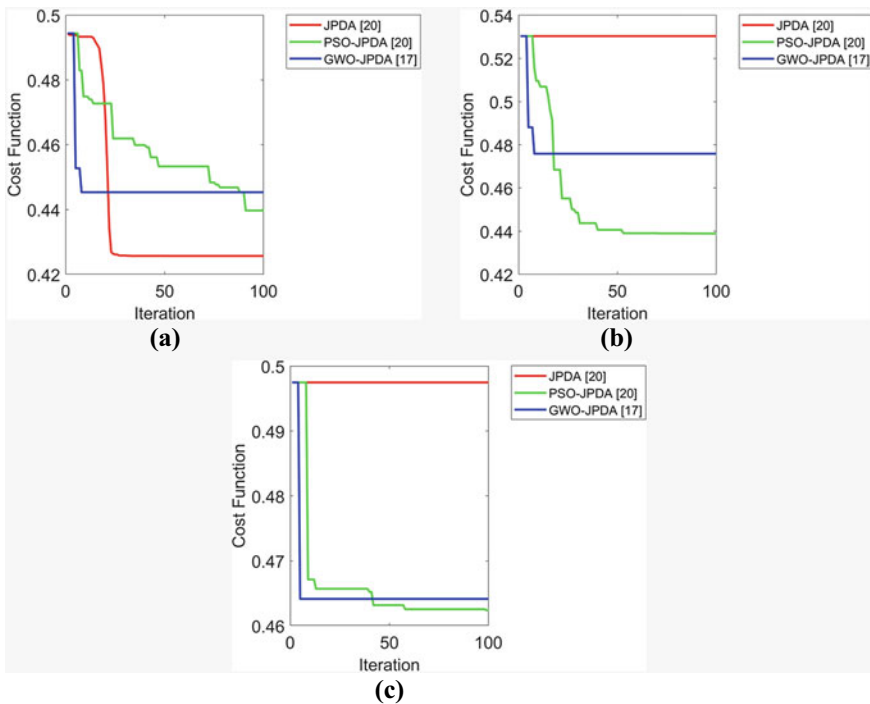

Fig. 2 Convergence analysis of the distinct heuristic-based JPDA for multiple target tracking with multi-static passive radar system for **a** Scenario case-1, **b** Scenario case-2, and **c** Scenario case-3

Table 1 Overall MAE analysis for multiple targets tracking using multistatic passive radar system for three different cases

Algorithm	Scenario 1	Scenario 2	Scenario 3
JPDA	0.52227	0.56051	0.56668
GWO-JPDA	0.5111	0.54319	0.55192
PSO-JPDA	0.4991	0.52483	0.53723

4.3   Overall MAE Analysis

The overall MAE analysis for the multiple targets tracking for the aforementioned three scenarios is portrayed in Table 1 and plotted in Fig. 3. MAE is a statistic that calculates the average magnitude of errors in a sequence of estimates without accounting for the course of the predictions. It is the average of the modulus of the differences between estimates and actual observations over the test sample, where all individual differences are given equal weight. Compared to MAE, the root mean square error (RMSE) is difficult to understand and does not adequately explain the average error. So in this work, we computed MAE instead of RMSE. The mean absolute error is calculated on the same scale as the data and hence called as scale-dependent accuracy. From the computed MAE, we can infer that for all scenarios the PSO-based JPDA gives the minimum mean absolute error and JPDA-based tracker has slightly higher MAE compared to the other two algorithms.
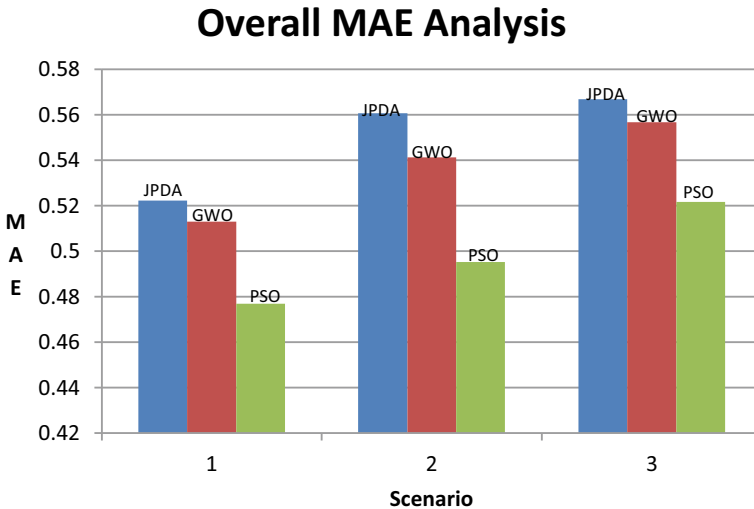

Fig. 3 Mean absolute error for JPDA, GWO-JPDA, and PSO-JPDA based multiple target tracking for Scenario case-1, Scenario case-2, and Scenario case-3

5 Conclusion

This paper has developed a comparative analysis on diverse heuristic algorithms for developing the optimized JDPA model for tracking multiple targets using a multi-static passive radar system in the presence of clutter. The algorithms such as GWO, and PSO were utilized for analyzing the optimized JDPA model for tracking multiple targets using passive radar system. It also tuned the position as well as the velocity of the tracker towards the target by means of distinct algorithms, and intended to analyze the effect of those algorithms on enhancing the multi-target tracking. As a major objective, it minimized the MAE between the estimated trajectory of track and the true target state. The cost function value for the scenario considering more than two targets is minimum for PSO-based JPDA and converges faster. The MAE for all the three scenarios under consideration is minimum for PSO-based JPDA making a good choice for multiple target tracking using optimal JPDA-based tracker. Further, the genetic algorithm-based optimization may be adopted for the data association in multi-target tracking and compared with the traditional JPDA.

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