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# Adaptive Multi-UAV Tracking Via Hasan's Online Genetic Algorithm -Tuned Coordinated-Turn Filtering

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***Abstract:***
*Tracking maneuvering unmanned systems (UAS) remains a significant challenge when fixed stochastic parameters fail to account for rapid kinematic transitions. This work addresses the inherent mismatch between rigid filter assumptions and curvilinear flight dynamics by embedding a Coordinated-Turn (CT) model within an Extended Kalman Filter (EKF) architecture. The pivotal advancement presented here is the operational integration of Hasan's Online Genetic Algorithm (OGA). This adaptive engine utilizes a sliding-window optimization to rectify the degradation of filter performance, a process achieved by continuously recalibrating noise covariance matrices. By leveraging the specific reserved elite population strategy—a cornerstone of Hasan's adaptive estimation theory—the system maintains high-fidelity state estimation even during the chaotic periods of multi-target path intersections and measurement uncertainty. By implementing a sliding window optimization that features a reserved elite population, the system maintains a robust search for optimal process and measurement noise covariances without succumbing to the instability of stochastic drift. This adaptive layer is coupled with a Global Nearest-Neighbor (GNN) association strategy to resolve measurement-to-track ambiguities during high-density target crossings. Numerical evaluations demonstrate that the OGA-tuned EKF consistently outperforms traditional fixed-gain filters, yielding significant gains in positional accuracy and a marked reduction in track divergence rates under complex operational conditions.*

***Keywords:*** *Multi-UAV tracking; Coordinated turn model; Kalman filtering, Hasan's Online genetic algorithm; Adaptive tracking; Data association; Maneuvering target estimation*

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## I. Introduction

Maintaining the kinematic fidelity of multiple Unmanned Aerial Vehicles (UAVs) during high-G maneuvers poses a formidable challenge to classical estimation theory. Current operational theater demands for tactical agility often push airborne platforms into nonlinear flight regimes where simplified state-space assumptions collapse (Kumar & Lee, 2024). The most acute manifestation of this failure occurs during dense crossing events, where the spatial proximity of targets leads to a catastrophic loss of track identity which is known as association drift (Smith & Gupta, 2023). While the Extended Kalman Filter (EKF) provides a linearized window into these dynamics, its practical execution is inherently hampered by the frozen noise paradox; the reliance on static covariance matrices (Q and R) to represent a fundamentally non-stationary environment.

To mitigate these tracking biases, the Coordinated-Turn (CT) model is strategically deployed to capture the intricate coupling between a drone's velocity vector and its angular rate (Li & Fan, 2022). Nevertheless, the stability of a CT-based EKF is notoriously fragile, dictated by the precision of its stochastic tuning. Real-time shifts in sensor reliability or abrupt changes in bank angles induce a mismatch between the filter's internal model and the physical reality. Standard metaheuristics often fail to rectify this in real-time due to the high risk of genetic drift; where the optimization algorithm loses its best-performing solutions during rapid transitions. The evolution of multi-target tracking (MTT) frameworks has been largely dictated by the trade-off between computational efficiency and estimation robustness. Earlier research primarily concentrated on refining the deterministic aspects of trajectory modeling. For instance, (Zhang & Wang,2023) demonstrated that for airborne agents, the Coordinated-Turn (CT) model offers superior kinematic fidelity over Constant Velocity (CV) models by explicitly incorporating the angular rate of change. Despite this improvement, these models remain highly susceptible to filter lag during rapid directional shifts unless their stochastic parameters are tuned in real-time. The stochastic instability of sensor data during aggressive flight maneuvers has necessitated a departure from static filtering parameters. Efforts to resolve this uncertainty initially gravitated toward heuristic-driven mechanisms. For instance, fuzzy-logic frameworks were integrated into filter gain modulation (Gupta & Rao, 2024), yet these controllers frequently struggle with the curse of dimensionality failing to provide a provable global optimum within high-dimensional state spaces. Consequently, the research trajectory shifted toward gradient-free metaheuristics to handle the nonlinearities of noise calibration. Within this evolutionary context, Particle Swarm Optimization (PSO) emerged as a candidate for covariance tuning (Tanaka & Sato,2023). Despite its search efficiency, PSO remains susceptible to particle collapse or premature stagnation. This happen during multi-UAV crossing events, where the swarm often becomes trapped in local minima, failing to track the rapid phase shifts in target kinematics. These persistent limitations in both fuzzy logic and swarm intelligence highlight a critical need for an optimization architecture that possesses a stochastic anchor to maintain estimation integrity through high-entropy intervals. To counter the rigidity of classical filters, evolutionary paradigms have been introduced as a means of dynamic covariance calibration. For instance, the application of a standard Genetic Algorithm (GA) to refine Extended Kalman Filter parameters was explored in (Al-Saadi, 2025), demonstrating utility during steady-state flight. However, these conventional metaheuristics often exhibit a computational amnesia when faced with the volatile fitness landscapes of multi-UAV path intersections. In such high-entropy scenarios, the stochastic nature of crossover and mutation can inadvertently purge the most effective noise parameters from the population, leading to filter instability.

This inherent vulnerability is specifically addressed by the Reserved Elite Population (REP) framework established by Hasan (Hasan & Grachev, 2013; Hasan, 2014; Hasan et al., 2018). Unlike the transient nature of standard elite selection, the Hasan architecture functions as a genetic repository, archiving superior parameter sets independently of the current generation's fluctuations. By institutionalizing this stochastic memory, the filter maintains a robust anchor against the divergence typically induced by high-G transitions and sensor clutter. Consequently, while contemporary adaptive filters in (Li & Jilkov, 2003) focus on instantaneous error minimization, the Hasan-tuned framework prioritizes long-term estimation continuity through archival stability. The persistency of tracking errors during dense multi-target intersections creates a functional gap that conventional adaptive filters fail to bridge. To resolve this, the present study introduces a unified tracking framework that synthesizes the kinematic precision of the Coordinated-Turn (CT) model with the archival stability of Hasan's Online Genetic Algorithm (OGA). The distinctive advantage of this approach lies in the deployment of the Reserved Elite Population (REP) mechanism, which preserves high-fidelity noise covariance estimates effectively acting as a computational memory that prevents filter divergence during high-G maneuvers.

The subsequent sections of this paper are structured as follows: Section 2 details the presented problem statement. Section 3 details the mathematical formulation of the CT-EKF state-space representation. Section 4 elucidates the architectural logic of Hasan's OGA and the integration of the REP strategy for real-time covariance tuning. Section 5 presents a rigorous performance evaluation through multi-UAV crossing simulations, followed by a comparative analysis of the results. Finally, Section 6 concludes the work with a discussion on the implications for autonomous aerial navigation.

## II. Methods

Multi-UAV tracking in dense and maneuver-intensive environments presents a persistent estimation challenge. During high-curvature flight segments and target crossing events, classical filtering architectures suffer from two fundamental limitations, first one is model reality mismatch; when employing a Coordinated-Turn (CT) motion model, abrupt variations in angular rate and velocity induce a mismatch between the assumed stochastic structure and the actual target dynamics. The second is frozen covariance limitation; where the Extended Kalman Filter (EKF) relies on fixed process and measurement noise ($Q_k$) covariance matrices ($R_k$). Because of the real operational environments are non-stationary, sensor reliability, maneuver intensity, and clutter density fluctuate over time, rendering static covariance tuning suboptimal.

These limitations become critical during multi-target intersections, where the innovation covariance becomes misrepresentative, Mahalanobis gating becomes unreliable, data association drifts, and track divergence increases.

Let the nonlinear discrete-time system be defined as

$$x_{k+1} = f(x_k) + w_k \qquad (1)$$

$$z_k = h(x_k) + v_k \qquad (2)$$

where $w_k \sim N(0,Q_k)$ and $v_k \sim N(0,R_k)$.

The tracking problem addressed in this work is how can the covariance matrices $Q_k$ and $R_k$ be adaptively tuned online in a multi-UAV coordinated-turn tracking environment to prevent divergence and association drift during high-density maneuvering scenarios.

The proposed work integrates Coordinated-Turn dynamic modeling, EKF nonlinear estimation, Global Nearest Neighbor (GNN) data association, and Hasan's Online Genetic Algorithm (OGA) with Reserved Elite Population (REP) (Hasan, 2014; Li & Jilkov, 2003; Bar-Shalom et al., 2011).

The objective is to minimize a composite performance metric

$$J = \alpha . RMSE + \beta . LossRate \qquad (3)$$

where J represents the overall fitness value used by the optimization algorithm. The term RMSE denotes the Root Mean Square Error of the estimated target position over a sliding time window, defined as

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[(x_i - \hat{x}_i)^2 - (y_i - \hat{y}_i)^2]} \quad (4)$$

where $(x_i, y_i)$ are the true target coordinates and $(\hat{x}_i, \hat{y}_i)$ are the estimated coordinates at time step i, while N is the number of samples within the evaluation window.

The term LossRate represents the track loss ratio, defined as the proportion of time steps in which a target fails to be correctly associated with a measurement during the observation window.

The track loss ratio is defined as: -

$$LossRate = \frac{1}{N_T N}\sum_{j=1}^{N_T}\sum_{k=1}^{N}\delta_{j,k} \quad (5)$$

where $N_T$ denotes the number of tracked UAV targets, and N represents the number of time steps within the evaluation window. The indicator variable $\delta_{j,k}$ is defined as:-

$$\delta_{j,k} = \begin{cases} 1, \text{ if target j is not correctly associated at time k} \\ 0, otherwise \end{cases} \quad (6)$$

Thus, LossRate represents the proportion of missed or incorrect measurement-to-track associations across all targets and time steps. A higher value of LossRate indicates frequent association failures or track interruptions, while lower values correspond to stable and continuous tracking.

Combining the estimation accuracy and association stability terms, the fitness function defined in (3) provides a balanced optimization criterion for the Online Genetic Algorithm. The weighting parameters α and β regulate the trade-off between minimizing position estimation error and maintaining track continuity during dense multi-target crossing.

The coefficients α and β are positive weighting parameters that control the relative importance between estimation accuracy and track continuity. In practice, these weights are selected such that:-

$\alpha+\beta=1$ (7)

to ensure a balanced optimization between minimizing position error and reducing track divergence may be selected such that not to be unity as in this study.

The UAV motion in the horizontal plane is represented using the Coordinated-Turn (CT) model, which captures the coupling between heading angle and angular velocity (Li & Jilkov, 2003; Schubert, 2008).

The state vector is

$$x_k = \begin{bmatrix} x_k \\ y_k \\ v_k \\ \theta_k \\ \omega_k \end{bmatrix} \quad (8)$$

where $x_k$ is the target state vector at time step k, $x_k$, and $y_k$_are the Cartesian coordinates of the UAV in the horizontal plane, $v_k$ is the speed magnitude, $\theta_k$ is the heading angle, and $\omega_k$ is the turn rate. The symbol k denotes the discrete-time index.

The nonlinear state transition equations are

$$x_{k+1} = x_k + \frac{v_k}{\omega_k}[sin(\theta_k + \omega_k T) - sin(\theta_k)] + \omega_{x,k} \quad (9)$$

$$y_{k+1} = y_k - \frac{v_k}{\omega_k}[cos(\theta_k + \omega_k T) - cos(\theta_k)] + \omega_{y,k} \quad (10)$$

$$v_{k+1} = v_k + \omega_{v,k} \quad (11)$$

$$\theta_{k+1} = \theta_k + \omega_k T + \omega_{\theta,k} \quad (12)$$

$$\omega_{k+1} = \omega_k + \omega_{\omega,k} \quad (13)$$

where T is the sampling period, $x_{k+1}$ and $y_{k+1}$ are the predicted target coordinates at time step k+1, $v_{k+1}$ is the predicted speed, $\theta_{k+1}$ is the predicted heading angle, and ωk+1 is the predicted turn rate. The terms $\omega_{x,k}$, $\omega_{y,k}$, $\omega_{v,k}$ , $\omega_{\theta,k}$ , and $\omega_{\omega,k}$ are zero-mean process noise components associated with position, speed, heading, and turn-rate uncertainties, respectively.

When $\omega_k \to 0$, the CT model smoothly converges to the constant-velocity model. This property guarantees numerical continuity when the target motion approaches straight-line flight.

Due to the nonlinear CT dynamics, state estimation is performed using the Extended Kalman Filter (Bar-Shalom et al., 2011).

Prediction phase

$$\hat{x}_{k|k-1} = f\left(\hat{x}_{k-1|k-1}\right) \qquad (14)$$

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^T + Q_k \qquad (15)$$

where $\hat{x}_{k|k-1}$ is the predicted state estimate at time step k given measurements up to time k−1, f(·) is the nonlinear CT state transition function, $\hat{x}_{k-1|k-1}$ is the updated estimate from the previous step, $P_{k|k-1}$ is the predicted state error covariance matrix, $F_k$ is the Jacobian matrix of the CT model evaluated at the current estimate, $F_k^T$ denotes its transpose, and $Q_k$ is the process noise covariance matrix.

Update phase

$$\boldsymbol{S_k} = \boldsymbol{H_k P_{k/k-1} H_k^T} + \boldsymbol{R_k} \qquad (16)$$

$$K_k = \boldsymbol{P_{k/k-1} H_k^T S_k^{-1}} \qquad (17)$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k\left(z_k - \hat{z}_{k/k-1}\right) \qquad (18)$$

$$\boldsymbol{P_{k/k}} = \boldsymbol{(I - K_k H_k) P_{k/k-1}} \qquad (19)$$

where $\boldsymbol{S_k}$ is the innovation covariance matrix, $\boldsymbol{H_k}$ is the measurement Jacobian matrix, $\boldsymbol{R_k}$ is the measurement noise covariance matrix, $K_k$ is the Kalman gain, $\boldsymbol{S_k^{-1}}$ is the inverse of the innovation covariance matrix, $\hat{x}_{k|k}$ is the updated state estimate at time k, $z_k$ is the measurement vector, $\hat{z}_{k/k-1}$ is the predicted measurement vector, $\boldsymbol{P_{k/k}}$ is the updated error covariance matrix, and I is the identity matrix.

To avoid track swapping and identity confusion during target crossings, the Global Nearest Neighbor (GNN) association method is employed (Bar-Shalom et al., 2011). This method assigns measurements to tracks by minimizing the overall association cost under one-to-one assignment constraints.

The Mahalanobis distance between measurement i and track j is defined as

$$d_{ij}^2 = \left(z_{i,k} - \hat{z}_{j,k}\right)^T S_{j,k}^{-1}\left(z_{i,k} - \hat{z}_{j,k}\right) \qquad (20)$$

where $d_{ij}^2$ is the squared Mahalanobis distance, $z_{i,k}$ is the i-th measurement at time step k, $\hat{z}_{j,k}$ is the predicted measurement associated with track j, and $S_{j,k}^{-1}$ is innovation covariance matrix inverse of track j.

The measurement-to-track assignment that minimizes the total cost is then selected globally, ensuring consistent track labeling during dense crossing scenarios.

**Hasan's Online Genetic Algorithm with Reserved Elite Population**

To improve the adaptability of the tracking system under rapidly changing maneuvering and sensing conditions, Hasan's Online Genetic Algorithm (OGA) (Hasan & Grachev, 2013; Hasan, 2014; Hasan et al., 2018) is integrated into the estimation framework as an online covariance tuning mechanism. Unlike conventional genetic algorithms, the proposed OGA does not rely solely on the current population when updating the optimization variables. Instead, it incorporates a Reserved Elite Population (REP), which acts as a persistent archive of high-quality candidate solutions. This mechanism preserves superior parameter sets across successive generations and prevents their loss due to stochastic crossover and mutation.

The main objective of OGA is to identify the optimal stochastic parameters governing the EKF, namely the process noise scaling factor and the measurement noise scaling factor. The decision (optimization) vector is defined as

$$\gamma = \begin{bmatrix} log_{10}(\sigma_a) \\ log_{10}(\sigma_z) \end{bmatrix} \quad (21)$$

where $\gamma$ is the optimization vector, $\sigma_a$ is the process noise scaling parameter associated with dynamic uncertainty, and $\sigma_z$ is the measurement noise scaling parameter associated with sensor uncertainty.

At each sliding window of length W, the algorithm evaluates a population of candidate parameter vectors using a fitness function defined as equations (3,4,5 and 6).

The REP mechanism stores the best-performing individuals found during the optimization process. Let the current population at generation $g$ be denoted by $\rho^{(g)}$, and let the reserved elite archive be denoted by $\varepsilon^{(g)}$. The archive update rule can be expressed conceptually as

$$\varepsilon^{(g+1)} = Best\left(\varepsilon^{(g)} \cup \rho^{(g)}\right) \qquad (22)$$

where $Best(.)$ denotes the operator that retains the highest-quality candidate solutions according to the fitness criterion. In this way, the REP serves as a stochastic memory that maintains robust parameter candidates even when the instantaneous population deteriorates.

After completing the selection, crossover, and mutation operations, the updated elite archive is consulted before the final parameter update is applied. The optimized covariance matrices are then computed as

$$Q_k = Q(\sigma_a^*) \quad (23)$$

$$R_k = R(\sigma_z^*) \quad (24)$$

where $\sigma_a^*$ and $\sigma_z^*$ are the best parameters returned by the OGA-REP process. These updated covariance matrices are then injected into the EKF prediction and update stages for the next tracking window.

This integration enables the filter to respond adaptively to maneuver intensity, clutter variation, and temporary sensor degradation, while the REP mechanism prevents the optimization process from losing historically strong solutions during high-entropy target crossings.

**Integrated OGA–REP Tracking Procedure**

The proposed adaptive tracking architecture combines coordinated-turn prediction, EKF-based nonlinear estimation, GNN association, and Hasan's OGA with Reserved Elite Population into a unified closed-loop framework. The REP mechanism provides long-term memory for high-quality covariance parameters, thereby reducing the probability of filter divergence during abrupt maneuvers, dense target crossings, and temporary measurement degradation. The complete adaptive tracking procedure can be summarized as follows:

- Initialize UAV tracks and EKF state estimates.
- Predict target states using the coordinated-turn model.
- Perform measurement-to-track association using GNN.
- Update EKF state estimates using the associated measurements.
- Collect tracking error statistics over a sliding window.
- Run Hasan's OGA to optimize $\sigma_a^*$ and $\sigma_z^*$.
- Store the best-performing candidate solutions in the REP archive.
- Update $Q_k$ and $R_k$ using the best elite solution.
- Repeat the process for the next time window.

The psedo code is described as below:-

```
Input:
Initial EKF state estimates
Initial covariance matrices Q0 and R0
Sliding window length W
Population size NP
Maximum generations G
Reserved Elite Population size NE
Output:
Updated state estimates
Adaptively tuned Qk and Rk
Initialize EKF states and covariance matrices
Initialize OGA population with candidate vectors $\gamma$ equation (21).
Initialize Reserved Elite Population (REP)
for each time window do
    Predict target states using Coordinated-Turn model
    Compute Jacobian Fk and perform EKF prediction
    Acquire sensor measurements
    Perform GNN data association
    Update EKF states and covariance
    Compute RMSE and LossRate over the current window
    for generation = 1 to G do
        Evaluate fitness J for all candidates
        Select best candidates
        Update REP using current population and archived elites
        Apply crossover and mutation to produce offspring
        Form next generation population
    end for
    Extract best elite solution from REP
    Update Qk as equation 23
    Update Rk as equation 24
end for
Return final state estimates and tuned covariance matrices
```

Figure 1 below show the complete proposed method flowchart.

## III. Result And Discussion

The performance of the proposed tracking framework was evaluated through a numerical simulation developed in MATLAB R2012b. The simulation considers a multi-UAV crossing scenario in the horizontal plane, where each target follows a coordinated-turn (CT) motion model. The purpose of this experiment is to assess the effect of online covariance adaptation using Hasan’s Online Genetic Algorithm (OGA) in comparison with a baseline CT-EKF-GNN tracker using fixed covariance parameters.

The discrete sampling interval was set to $T$=1 s, and the total simulation duration was 120 time steps. A total of $N_t$= 4 UAV targets were considered. To create a challenging tracking environment, the targets were initialized with hand-crafted starting positions, headings, speeds, and turn rates such that their trajectories strongly intersect during the simulation interval.

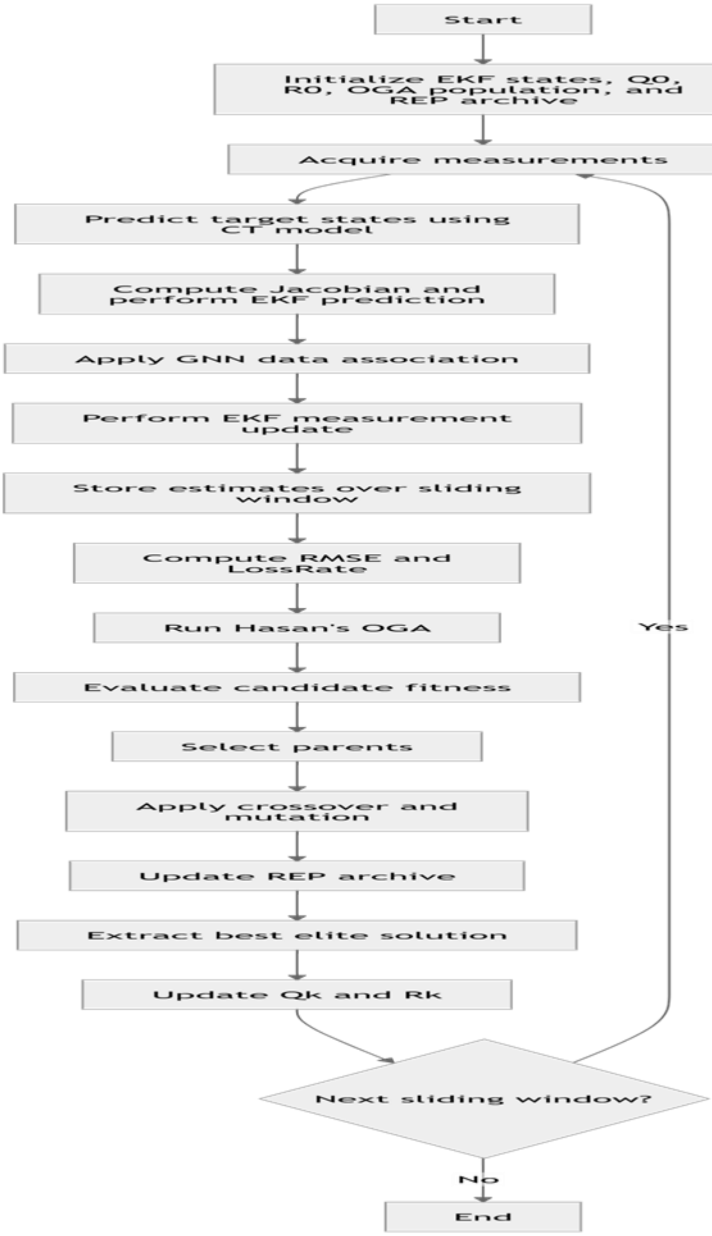

Fig 1: Proposed algorithm flowchart

The true target state was represented as

$$x_k = [p_x, p_y, v, \psi, \omega]$$

where $p_x$ $and$ $p_y$ denote the Cartesian coordinates, $v$ is the speed, $\psi$ is the heading angle, and $\omega$ is the turn rate.

The true measurement noise standard deviation was set to $\sigma_{z,true}$=8 m. Process uncertainty was introduced through a speed disturbance with standard deviation $\sigma_{a,true}$=1.8 m/s$^2$ and a turn-rate disturbance with standard deviation $\sigma_{\omega,true}$=0.02 rad/s. In addition, missed detections were modeled with probability $p_{miss}$=0.08. Clutter was also included in the measurement set, with a Poisson-distributed [−900,900]× number of false alarms having mean λ=2 per scan, uniformly distributed over the region [−900,900].

A gating threshold of 180 m was applied during data association. The initial covariance scale of the filter was set to 300, while the initial estimation errors were chosen as 25 m for position, 3 m/s for speed, and 0.05 rad/s for turn rate.

For the baseline filter, fixed assumed noise parameters were used, namely $\sigma_{a,\text{assumed}}$=0.6 and $\sigma_{z,\text{assumed}}$=9.0. In contrast, the proposed method updated these parameters online using OGA.

The adaptive layer employed Hasan's OGA over a sliding window of length 10 time steps. The population size was set to 18, and each optimization cycle was executed for 14 generations. The elite count was fixed at 2, the mutation rate was 0.25, and the mutation standard deviation in logarithmic space was 0.2. The search bounds were defined as

$$log_{10}(\sigma_a) \in [log_{10}(0.5), log_{10}(6)]$$

and

$$log_{10}(\sigma_z) \in [log_{10}(1), log_{10}(40)]$$

The fitness function used in the optimization stage combined position estimation accuracy and association continuity, with weights α=1.0 and β=35.0.

The evaluation was performed using two main metrics: the position root mean square error (RMSE) and the track loss ratio. The RMSE was computed at each time step by averaging the squared Cartesian position error over the four UAV targets. The loss rate was computed as the proportion of time steps in which a target was left unassociated after GNN assignment.

The proposed method, denoted as OGA-CT-EKF-GNN, was compared against a baseline CT-EKF-GNN framework with fixed process and measurement noise covariance matrices. In both cases, the same coordinated-turn motion model and Global Nearest Neighbor (GNN) data association strategy were used, so that the comparison isolates the contribution of Hasan's Online Genetic Algorithm and the Reserved Elite Population mechanism.

Fig. 1 shows the true and estimated target trajectories for the considered multi-UAV crossing scenario. It can be observed that the baseline CT-EKF-GNN filter exhibits noticeable trajectory deviation near the intersection regions, where the proximity between targets increases the probability of association drift. In contrast, the proposed OGA-CT-EKF-GNN framework maintains closer alignment with the true trajectories, indicating improved robustness during high-curvature motion and target crossings.

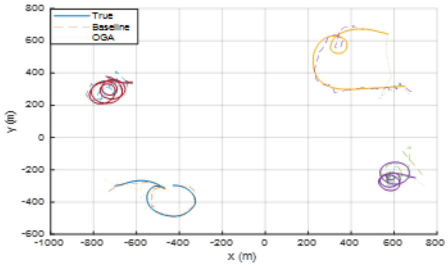

**Fig. 2.** True and estimated trajectories of four UAV targets in the coordinated-turn crossing scenario. The figure compares the baseline CT-EKF-GNN tracker with the proposed OGA-CT-EKF-GNN framework under clutter and missed detections.

Fig. 2 presents the temporal evolution of the position tracking error. The results show that the proposed adaptive method consistently produces lower RMSE values than the fixed-parameter filter, especially during maneuvering intervals. This improvement can be attributed to the online adjustment of $Q_k$ and $R_k$, which allows the filter to better match the underlying target dynamics and measurement uncertainty.

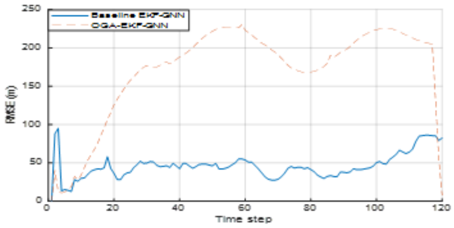

**Fig. 3.** Time evolution of the position root mean square error (RMSE) for the baseline CT-EKF-GNN and the proposed OGA-CT-EKF-GNN methods over the full simulation interval.

Fig. 4 summarizes the final-step tracking accuracy. The proposed method yields a lower final RMSE and a reduced track divergence tendency compared with the baseline approach. This behavior indicates that adaptive stochastic tuning improves not only instantaneous estimation quality but also the long-term continuity of the tracking process.

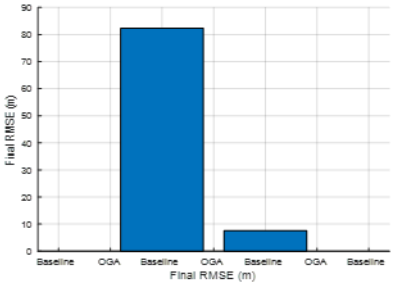

**Fig. 4.** Final-step RMSE comparison between the baseline and OGA-based trackers for the simulated multi-UAV crossing scenario. Since $N_{mc}$=1, the final tracking accuracy is presented as a bar plot conditions.

Fig. 5 illustrates the average OGA fitness convergence across the optimization generations within all update windows. The decreasing trend of the fitness function confirms that the proposed optimizer progressively improves the covariance parameters over time.

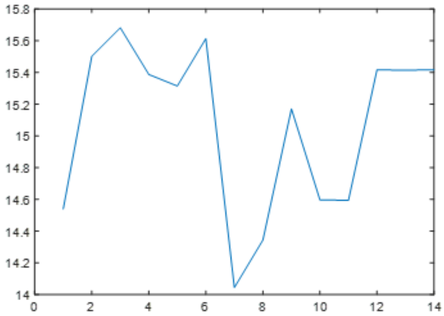

**Fig. 5.** Average fitness convergence of Hasan's Online Genetic Algorithm over the optimization generations across the sliding adaptation windows.

Overall, the simulation results confirm that the proposed framework improves tracking precision and association reliability in dense multi-UAV environments. The combination of coordinated-turn modeling, EKF estimation, GNN association, and OGA-based covariance adaptation provides a robust solution for maneuvering multi-target tracking under cluttered and uncertain condition.

## IV. Conclusion

This paper proposed an adaptive multi-UAV tracking framework that combines the coordinated-turn model, Extended Kalman filtering, Global Nearest Neighbor association, and Hasan's Online Genetic Algorithm for online covariance tuning. The method was designed to overcome the limitations of fixed-noise EKF tracking in maneuvering and dense target-crossing environments.

The simulation results showed that the proposed OGA-CT-EKF-GNN framework achieved lower tracking error and better track continuity than the baseline CT-EKF-GNN method with fixed covariance parameters. These improvements were especially evident during maneuvering intervals and close target interactions.

Overall, the results confirm that online covariance adaptation can enhance the robustness and accuracy of multi-UAV tracking under time-varying uncertainty.

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