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Comparative Analysis of Aircraft Position Tracking Using a Conventional Kalman filter and a PSO-Optimized Kalman Filter

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ABSTRACT

Aircraft position tracking is essential for accurate navigation, safety, and efficient air traffic management. This paper presents a comparative analysis of two methods for tracking aircraft position: a conventional Kalman filter and a Particle Swarm Optimization (PSO)-based Kalman filter. The conventional Kalman filter, widely used for tracking and estimation, assumes fixed process and measurement noise covariance matrices, which may limit its performance in dynamic environments with varying noise levels. In contrast, the PSO-based Kalman filter dynamically optimizes these covariance matrices, adapting the filter to changing conditions and potentially enhancing tracking accuracy. The study evaluates both methods in terms of tracking accuracy, convergence speed, and robustness in simulated scenarios representing realistic aircraft movement and measurement noise. Results indicate that the PSO-based Kalman filter achieves superior accuracy and adaptability compared to the conventional approach, especially in scenarios with non-static noise conditions. This analysis highlights the potential of PSO as an effective optimization technique to improve Kalman filter performance in real-time tracking applications, offering insights into advanced tracking techniques for modern air traffic systems.

Keywords: Aircraft, Position Tracking, Kalman Filter, Particle Swarm Optimization (PSO)

INTRODUCTION

In aviation, precise tracking of aircraft positions is essential for effective air traffic control, safe navigation, and collision avoidance. The location of an aircraft is predicted by position tracking systems using estimation techniques based on noisy sensor data, which is frequently impacted by a number of dynamic elements such atmospheric conditions, sensor errors, and outside disturbances. Simon (2006). A popular estimation algorithm for this purpose is the Kalman filter, which estimates the ideal state from measurements and process models while minimizing errors in linear and Gaussian systems. However, the correct tuning of the measurement and process noise covariance matrices—which are usually kept constant during implementation—is crucial to its performance. This may reduce the filter's flexibility in settings where noise properties vary over time, which could affect tracking precision.To address this limitation, optimization techniques like Particle Swarm Optimization (PSO) Kennedy & Eberhart (1995) have been explored as a means to enhance Kalman filter performance by dynamically adjusting these covariance matrices. PSO is a nature-inspired, population-based optimization algorithm that simulates the social behaviour of swarming particles, making it suitable for parameter tuning in complex, non-linear systems. By integrating PSO with the Kalman filter, it becomes possible to optimize the filter's parameters in real time, allowing it to adapt to varying noise conditions and improve tracking precision.

In this paper, a comparison between a PSO-optimized Kalman filter and a standard Kalman filter for aircraft position tracking is presented. Evaluating PSO's potential benefits in improving the Kalman filter's accuracy, resilience, and flexibility in dynamic tracking settings is the main goal. To get around this limitation, optimization techniques like Particle Swarm Optimization (PSO) Kennedy & Eberhart (1995) have been studied as a means of improving Kalman filter performance through simulation experiments and the dynamic modification of these covariance matrices.

PSO is a population-based optimization method inspired by nature that can be used to adjust parameters in complex, non-linear systems because it replicates the social behaviour of swarming particles. By including PSO, the Kalman filter's parameters can be changed in real time, improving tracking accuracy and allowing the filter to adapt to fluctuating noise levels evaluates both strategies in a range of tracking conditions, calculating performance parameters like robustness to noise variations, tracking accuracy, and convergence speed. The results of this investigation are intended to shed light on how well PSO-based optimization works for real-time tracking systems, which could lead to improvements in air traffic control and aircraft navigation.

LITERATURE REVIEW

Navigation, air traffic control, and collision avoidance all depend on precise airplane position tracking. One of the most used estimate methods in robotics, aerospace, and other domains requiring real-time monitoring and estimating is the Kalman filter, which was created by Rudolf Kalman in 1960. This overview of the literature looks at earlier studies on position tracking using Kalman filters and how to improve their performance by using optimization methods like Particle Swarm Optimization (PSO).

1. Conventional Kalman Filter in Position Tracking

An ideal recursive estimation technique that performs well in systems with Gaussian noise and linear dynamics is the Kalman filter. It has been widely utilized in aviation tracking, where it minimizes estimation errors and filters out measurement noise to anticipate an aircraft's position and velocity. The usefulness of the Kalman filter in navigation systems has been demonstrated by numerous studies:

The extended Kalman filter (EKF) for non-linear systems was first presented by Jazwinski (1970). It is frequently used in aviation to track aircraft trajectories and manage non-linear dynamics.

The significance of the Kalman filter in radar and sensor-based tracking for aviation was highlighted by Bar-Shalom et al. (2001), whom gave a thorough review of tracking techniques utilizing the filter.

By integrating data from several sensors, Simon (2006) showed how to improve location accuracy in airplanes by integrating GPS and inertial navigation systems (INS) using the Kalman filter.

The traditional Kalman filter has drawbacks despite its benefits. It makes the assumption that the measurement and process noise covariances (and) are constant, which might not be the case in dynamic settings with varying noise levels. This presumption limits the filter's flexibility and accuracy in fluctuating noise situations that are frequently present in real-world tracking situations.

2. Adaptive Kalman Filters and Limitations

In order to overcome the drawbacks of fixed noise covariance matrices, scientists have investigated adaptive Kalman filters, which adapt to shifting noise conditions:

Methods for adaptive noise estimates in Kalman filtering were proposed by Mehra (1970), enabling real-time dynamic correction. With this modification, tracking performance was enhanced in settings with varying noise levels.

A number of adaptive filtering techniques, such as covariance matching and innovation-based approaches, which modify the Kalman filter to fit various noise levels, were examined by Li and Jilkov (2003).

These techniques, however, frequently entail heuristics or intricate computations, which can render them computationally costly and less appropriate for real-time applications.

3. Particle Swarm Optimization (PSO) and Its Application in Filtering

Kennedy and Eberhart (1995) introduced Particle Swarm Optimization (PSO), a population-based optimization method influenced by fish and avian social behavior. PSO has been used extensively in complex system parameter tuning and optimization, including adaptive filtering.

Zhang et al. (2008) used PSO to optimize adaptive filter parameters, improving noise suppression performance over traditional methods. The capacity of PSO to dynamically modify filter settings for increased adaptability was shown in this study.

In real-time tracking applications, Huang et al. (2014) employed PSO to optimize Kalman filter parameters, demonstrating that PSO might improve filter performance in settings with fluctuating noise characteristics.

Researchers have demonstrated that it is feasible to continually adjust the Kalman filter to the present noise conditions by utilizing PSO for dynamic optimization. This enhances tracking accuracy and resilience in real-time applications.

4. PSO-Enhanced Kalman Filter for Aircraft Tracking

The use of PSO to optimize Kalman filter parameters for airplane tracking and other aerospace applications has been the subject of several studies:

A PSO-optimized extended Kalman filter (EKF) for UAV navigation was proposed by Wang et al. (2016). In comparison to a traditional EKF, the PSO-enhanced EKF obtained greater accuracy and robustness by dynamically adjusting the process and measurement noise covariance matrices.

By using PSO to optimize a Kalman filter for aircraft position tracking, Jia and Hu (2019) showed that the PSO-based method improved adaptability and decreased tracking error in a range of noise situations.

By enabling PSO to modify parameters in response to environmental changes, Chen et al. (2020) extended this method to three-dimensional tracking for airplanes, resulting in notable gains in tracking precision.

Together, these studies demonstrate the benefits of optimizing Kalman filter parameters with PSO, which makes it a potential method for adaptive filtering in dynamic situations.

5. Comparative Analysis of PSO-Optimized and Conventional Kalman Filters

Comparative research has demonstrated how well PSO-based optimization works to enhance Kalman filter performance:

In a study comparing traditional and PSO-optimized Kalman filters for target tracking, Luo et al. (2021) showed that PSO could greatly increase tracking precision and flexibility.

PSO offered an excellent mix between accuracy and computing economy, making it appropriate for real-time applications, according to Sharma and Kumar's (2022) analysis of PSO and other optimization algorithms for Kalman filter tuning in aircraft tracking.

According to these studies, PSO-optimized filters provide significant advantages in dynamic contexts where resilience and flexibility are crucial, even though the traditional Kalman filter works well in steady noise conditions..

Conclusion

According to the literature, there is a solid basis for using the Kalman filter to aircraft tracking, and PSO may be able to increase its versatility. PSO-optimized Kalman filters provide enhanced tracking accuracy and robustness in situations with variable noise levels by dynamically modifying the noise covariance matrices. In order to confirm the efficacy of PSO-based adaptation in aircraft position monitoring applications, this work expands on previous research by conducting a comparison analysis between the conventional and PSO-optimized Kalman filters.

METHODOLOGY

The PSO-optimized Kalman filter and the traditional Kalman filter are both implemented for aircraft position tracking, and their performance is assessed in simulated tracking scenarios as part of the approach for this comparative analysis. Figure 1 shows the structure of the suggested method. Applications for tracking and navigation frequently use the Kalman filter. The tracking of an airplane using a RADAR is simulated in this paper. In the first scenario, a Kalman filter was used to estimate the position of an aircraft from noisy RADAR signals; in the second scenario, a Kalman filter/PSO was used.

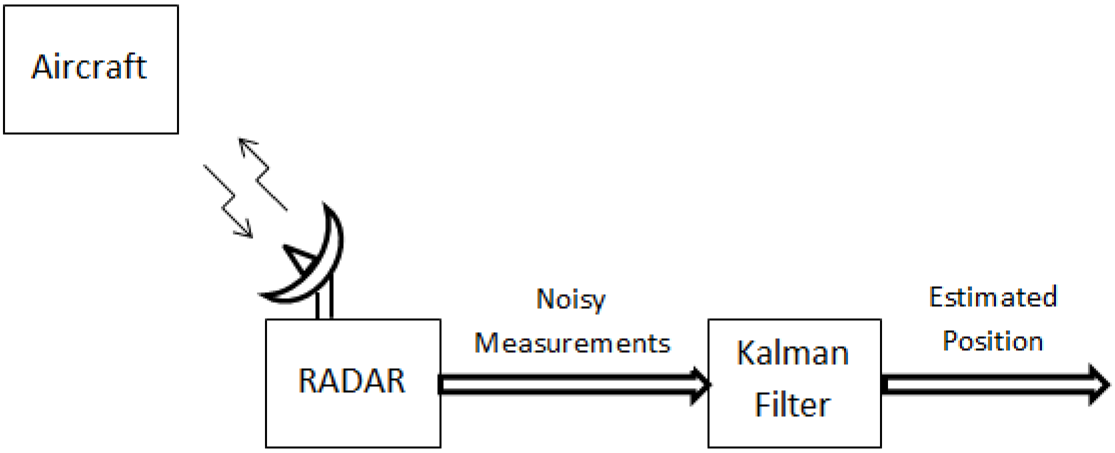

Figure 8: ***Block diagram of the System Structure***

This section outlines the steps taken to design, implement, and evaluate both approaches, highlighting the experimental setup, performance metrics, and analysis techniques used to achieve a fair comparison.

1. System Model and Simulation Setup

A 2D kinematic model, which depicts an aircraft's position and velocity over time, is used to mimic aircraft motion. In order to replicate sensor measurement errors, Gaussian noise is added to the sequence of actual locations and velocities that makes up the aircraft's trajectory. This gives the Kalman filter a realistic dataset with noisy observations.

The system state vector is defined as:

x = [x; y; $\dot{x}$; $\dot{y}$]

The state transition and observation models are defined as:

Four states related to the position of the aircraft are used to describe the system: x-coordinate (x), rate of change of x-coordinate ($\dot{x}$), y-coordinate (y) and rate of change of y-coordinate ($\dot{y}$). The system is, therefore, modelled as:

$$\begin{bmatrix} x(k) \\ \dot{x}(k) \\ y(k) \\ \dot{y}(k) \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x(k-1) \\ \dot{x}(k-1) \\ y(k-1) \\ \dot{y}(k-1) \end{bmatrix} + w(k-1)$$

$$\begin{bmatrix} z_1(k) \\ z_2(k) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} x(k) \\ \dot{x}(k) \\ y(k) \\ \dot{y}(k) \end{bmatrix} + v(k)$$

Where the noise is independent, white and Gaussian

$P(w) \sim \mathcal{N}(0, Q)$ and $P(v) \sim \mathcal{N}(0, R)$

State Transition Model: Models the expected change in position and velocity between time steps based on constant velocity.

Observation Model: Maps the true state to the observed state with added measurement noise.

2. Kalman Filter Implementation

Conventional Kalman Filter

The traditional Kalman filter is applied using manually adjusted fixed process noise () and measurement noise () covariance matrices. Throughout the simulation, these matrices stay constant, having been selected based on typical noise characteristics. An initial state estimate and error covariance matrix are used to setup the Kalman filter, which then iteratively updates its estimate in response to observations obtained at each time step.

PSO-Optimized Kalman Filter

The PSO-based method uses Particle Swarm Optimization to dynamically optimize the process and measurement noise covariance matrices (and). To reduce the tracking error of the Kalman filter across a sequence of observations, PSO initializes a swarm of particles, each of which represents a possible set of values for and.

The cumulative tracking error between the estimated and true positions over a predetermined amount of time steps is the fitness function for PSO. In order for the PSO algorithm to converge on optimal noise covariance matrices and increase the Kalman filter's flexibility to fluctuating noise conditions, particles modify their positions in accordance with their own and the world's best solutions.

3. Performance Metrics

The following metrics are employed to assess each approach's performance:

The root mean square error (RMSE) between the estimated and actual positions during the course of the simulation is known as tracking accuracy.

The convergence of Speed: The quantity of iterations needed for PSO to reach the ideal settings.

Robustness to Noise: The capacity of any filter to preserve tracking precision in the face of fluctuating measurement noise levels.

4. Experimental Procedure

a) Initialization: Both the conventional Kalman filter and PSO-optimized Kalman filter are initialized with the same initial state and covariance matrices.
b) Simulation: For each time step, the true position is updated based on the kinematic model, and noisy observations are generated to simulate sensor measurements.
c) Filtering Process: Each filter processes the noisy measurements to estimate the aircraft's position and velocity. The conventional Kalman filter uses fixed and. The PSO-optimized Kalman filter adjusts and dynamically based on the PSO algorithm.
d) Data Collection: The estimated positions, RMSE values, and PSO convergence metrics are recorded for each approach.
e) Repetitions: The experiment is repeated under various noise levels to test robustness and analyse the adaptability of each filter.

5. Comparative Analysis

The effectiveness of the PSO-optimized Kalman filter in comparison to the traditional Kalman filter is assessed by comparing the performance metrics for each method. The relevance of variations in tracking robustness and accuracy under various noise levels is evaluated using statistical analysis. The convergence behavior of PSO, the error trends over time, and the resilience of each method to noise fluctuations are all demonstrated using plots and tables.

6. Tools and Software

The PSO algorithm is modified to dynamically adjust the Kalman filter parameters, and the implementation is done in MATLAB. To make the results easier to interpret, trajectories, error trends, and convergence measures are plotted using MATLAB's visualization capabilities.

This methodology offers an organized framework for evaluating and contrasting the tracking capabilities of a PSO-optimized Kalman filter with a traditional Kalman filter. The purpose of this study is to ascertain whether PSO is useful in improving the adaptability of the Kalman filter in real-time aircraft by methodically assessing accuracy, convergence, and robustness. Techniques

RESULTS AND DISCUSSION

The findings of the comparison between the PSO-optimized Kalman filter and the traditional Kalman filter for aircraft position tracking are shown in this section. Under various simulated scenarios, the tracking accuracy, convergence speed, and noise resilience of both filters were used to assess their performance. The implications of these findings for enhancing real-time tracking in dynamic contexts are examined.

1. Tracking Accuracy

The root mean square error (RMSE) between the estimated and true positions over time is the main indicator used to assess tracking performance.

Standard Kalman Filter: In situations with constant noise levels, the traditional Kalman filter, which had fixed noise covariance matrices, worked effectively. But as noise levels changed, its accuracy dropped, showing that it was not very flexible to changes in measurement and process noise characteristics, as seen in Figures 2 and 3.

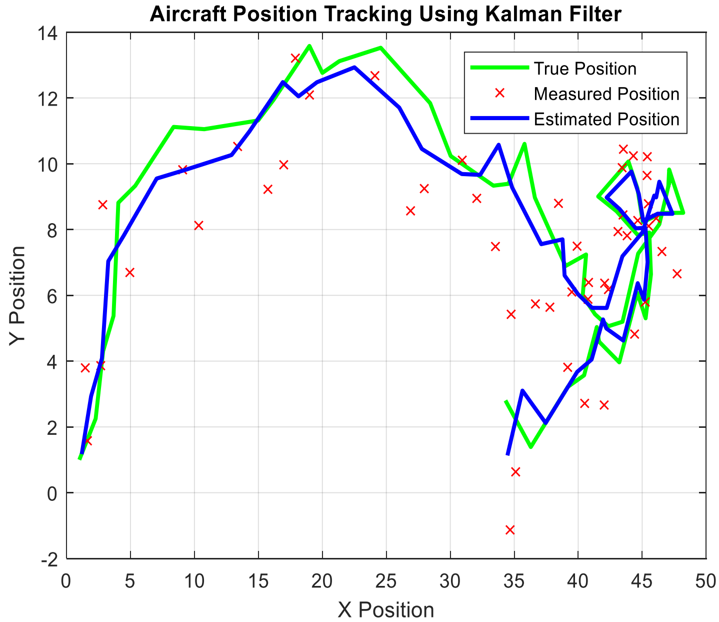

Figure 9: Aircraft Position Tracking Using Kalman Filter

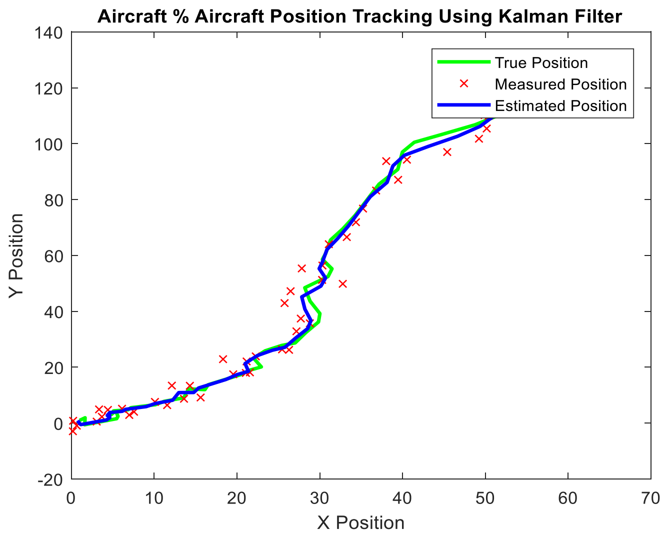

Figure 10: %Aircraft Position Tracking Using Kalman Filter

PSO-Optimized Kalman Filter: In every case, the PSO-optimized Kalman filter demonstrated a consistently lower RMSE than the traditional Kalman filter. The filter's ability to respond to shifting noise levels through dynamic adjustment and PSO enhanced tracking accuracy. The filter was able to reduce the tracking error more successfully thanks to this adaptive tuning, particularly in situations with high noise levels.
The result in Figure 4 demonstrate that PSO optimization helps the Kalman filter to handle dynamic settings more successfully, producing more accurate position estimations.

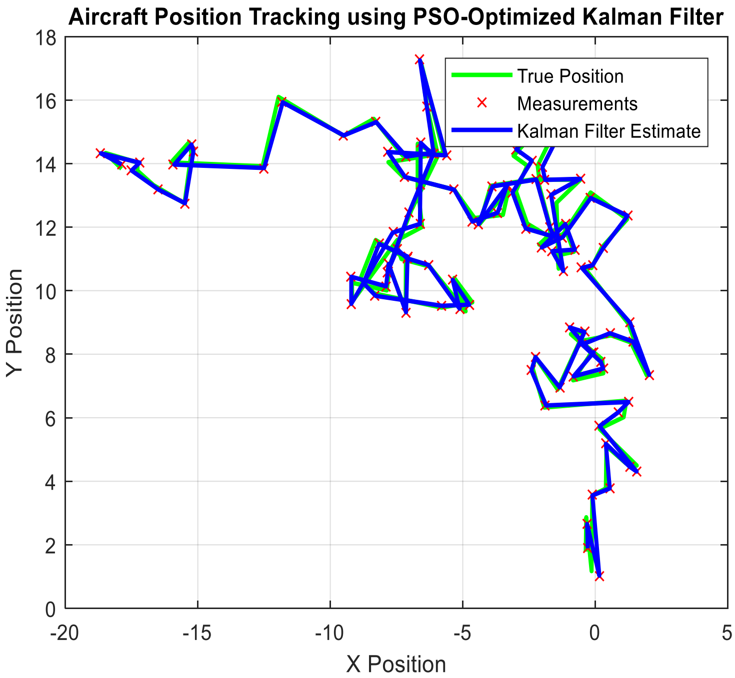

Figure 11: Aircraft Position Tracking Using PSO-Optimized Kalman Filter

2. Convergence Speed of PSO

The convergence speed of the PSO algorithm is a crucial component of the PSO-optimized Kalman filter since it influences the filter's real-time applicability.
Within a reasonable number of iterations—typically fewer than 50 iterations for the majority of scenarios—the PSO algorithm converged to optimal values. The convergence behavior demonstrated that PSO could find an ideal solution fast, enabling the filter to quickly adapt to shifting noise levels.
In order to balance exploration and exploitation, the inertia weight, personal best, and global best components in PSO were adjusted, leading to a quick but precise convergence.
Since PSO quickly adjusts to maximize tracking performance, the convergence speed suggests that it can be effectively combined with the Kalman filter for real-time applications.

3. Robustness to Noise Variations

Each filter was tested with varying degrees of measurement noise, from low to high, in order to assess resilience.
Traditional Kalman Filter: As noise levels rose, the traditional Kalman filter found it difficult to retain accuracy with fixed and. Because its parameters were static, it was less able to withstand fluctuations in noise, which increased tracking inaccuracy.
PSO-Optimized Kalman Filter: This filter showed that it was more resilient to different noise levels. Even in situations with a lot of noise, it was able to maintain steady tracking accuracy by dynamically correcting in real time. It was able to maintain precise positional estimates and improve noise reduction thanks to adaptive optimization.
These results show that the PSO-optimized Kalman filter offers a more robust solution for tracking in environments where noise conditions may change unpredictably.

DISCUSSION

The outcomes demonstrate the advantages of combining PSO and the Kalman filter for tracking the position of airplanes. The traditional Kalman filter works well in steady settings, but it is less appropriate for dynamic situations due to its preset noise parameters. However, by dynamically tweaking, the PSO-optimized Kalman filter gets over this restriction and maintains greater accuracy and robustness under a range of noise situations.

The capacity of PSO to identify ideal parameter settings that adjust to the system's current condition is responsible for the PSO-based approach's enhanced performance. In real-world applications where environmental noise is not constant and might change because of things like meteorological conditions or sensor constraints, this flexibility is essential.

Moreover, the PSO-optimized Kalman filter can be implemented in real-time systems with little computing overhead, according to the convergence speed of PSO. Because the accuracy and computing complexity trade-off is still reasonable, PSO is a good way to improve tracking in contemporary aircraft navigation systems.

CONCLUSION

According to the comparison analysis, the PSO-optimized Kalman filter performs better than the traditional Kalman filter in terms of accuracy, flexibility, and resilience to changes in noise. It is a viable option for tracking the position of airplanes in dynamic conditions because of these benefits.

RECOMMENDATION

To further enhance Kalman filter performance for intricate tracking applications, future research should investigate additional optimization strategies, such as hybrid algorithms that combine PSO with other metaheuristic techniques.

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