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High-Precision Real-Time Object Tracking Via Robust Kalman Filtering

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Abstract: The real-time, high-precision determination of a moving object's geological position (latitude, longitude, altitude) is a critical challenge in fields such as autonomous navigation, precision agriculture, and geophysical surveying. While Global Navigation Satellite Systems (GNSS) provide the primary data source, raw signals are susceptible to errors from atmospheric delays, multipath effects, and receiver noise, leading to positional inaccuracies. This article presents a monitoring system that leverages an advanced mathematical framework based on an Adaptive Unscented Kalman Filter (AUKF) to fuse multi-sensor data and achieve centimeter-level precision. Building directly on our previous work in robust filtering and error-specific modeling, we develop a non-linear state-space model that incorporates advanced tropospheric and ionospheric delay corrections. The AUKF core dynamically estimates and compensates for state and measurement uncertainties in real-time. Simulation results demonstrate a significant improvement in positional accuracy and robustness compared to standard Extended Kalman Filter (EKF) approaches, particularly during periods of high dynamics and signal degradation, validating the concepts proposed in our earlier theoretical research.

Keywords: Real-time Kinematic, Sensor Fusion, Kalman Filtering, Geopositioning, GNSS, Error Modeling, Autonomous Navigation.

1. Introduction

The demand for high-precision, real-time geological positioning has surged with the advent of autonomous systems and intelligent infrastructure. Applications ranging from unmanned aerial vehicle (UAV) mapping to automated land surveying require continuous and accurate knowledge of an object's three-dimensional coordinates in a global reference frame [1]. Although GNSS technology is ubiquitous, the standard standalone positioning accuracy of several meters is insufficient for these precision-critical tasks.

The primary limitation of GNSS lies in the various error sources that corrupt the satellite signals. As detailed in our prior analysis, factors such as ionospheric scintillation and tropospheric refraction introduce significant biases, a problem we specifically addressed in our work on advanced correction models [2]. Furthermore, receiver noise and multipath effects in urban environments degrade the positional solution. To mitigate these issues, sensor fusion algorithms, particularly variants of the Kalman Filter (KF), are employed to integrate GNSS data with inputs from inertial measurement units (IMUs), odometers, and other complementary sensors [3].

The standard EKF has been widely used for this purpose; however, it suffers from two major drawbacks: the linearization of non-linear system dynamics using Jacobian matrices can introduce significant errors, and its performance is highly sensitive to predefined noise statistics. Our foundational work on a novel robust filtering strategy for nonlinear systems with uncertainties formally demonstrated the limitations of the EKF during rapid maneuvers and under model mismatches [4].

In this paper, we propose a high-precision monitoring system centered on an Adaptive Unscented Kalman Filter (AUKF). This approach directly addresses the shortcomings of the EKF by using the

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unscented transform to propagate state distributions through the non-linear system model more accurately, without the need for linearization. Furthermore, we incorporate an adaptive mechanism for online estimation of process and measurement noise covariance matrices, extending the robust estimation concepts we initially introduced in [4]. The core mathematical theory of this AUKF framework, which integrates our specific error models from [2] into a unified, adaptive architecture, is the primary contribution of this work.

2. Mathematical Theory and System Model

The foundation of our monitoring system is a discrete-time non-linear state-space model. The state vector x_k at time step *k* is defined to encapsulate the object's geological position, kinematics, and relevant sensor error states.

The state vector is defined as:

$$x_k = \left[\varphi, \lambda, h, v^N, v^E, v^D, a^N, a^E, a^D, b_a, b_g, I, T\right]^T$$

where: φ, λ, h: Latitude, Longitude, and Ellipsoidal Height (the primary geological coordinates); v^N, v^E, v^D: North, East, Down velocity components in the local navigation frame; a^N, a^E, a^D: North, East, Down acceleration components; b_a, b_g: Accelerometer and gyroscope bias states; I, T: State parameters for ionospheric and tropospheric delay residuals, allowing for the integration of the advanced correction models we developed in [3].

The system's non-linear dynamics are described by the process model:

$$xk = f(x\{k-1\}, u_k, w_k)$$

where $f(*)$ is a non-linear function that propagates the state based on inertial navigation equations [3], u_k is the control input (raw IMU measurements), and w_k is the process noise.

The measurement model relates the state to the GNSS observations:

$$z_k = h(x_k) + v_k$$

where $h(*)$ is the non-linear measurement function that projects the state onto the GNSS observables (pseudoranges, carrier phases), incorporating the state parameters I and T to apply real-time atmospheric corrections based on [4].

The Unscented Kalman Filter (UKF) Algorithm. The UKF bypasses the linearization required by the EKF by using a deterministic sampling technique known as the unscented transform.

Propagate the predicted sigma points through the measurement model:

$$Z_i = h(y_i^*)$$

The Unscented Kalman Filter (UKF) is an advanced version of the Kalman Filter designed to estimate the state of nonlinear systems with higher accuracy. Unlike the traditional or extended Kalman filter, which relies on linearization and Jacobian matrices, the UKF uses a statistical approach called the Unscented Transform. This method represents the system's probability distribution using a carefully chosen set of sample points known as sigma points [5]. These sigma points capture the true mean and covariance of the state distribution and are propagated through the nonlinear system and measurement models directly, without any need for derivatives. After propagation, the transformed points are recombined to generate a new estimate of the mean and covariance, resulting in a more precise prediction and update process.

The UKF operates in two main steps: prediction and update. In the prediction step, sigma points are generated based on the previous state and propagated through the system model to predict the next state and its uncertainty. In the update step, the predicted sigma points are passed through the measurement model, and the actual sensor data are used to correct the prediction. This method allows the filter to adapt effectively to nonlinearities present in the system dynamics and sensor measurements [6].

The main advantages of the UKF are its higher estimation accuracy for nonlinear systems, its avoidance of Jacobian computation, and its improved numerical stability compared to the Extended Kalman Filter. It is widely applied in areas such as drone navigation, GNSS and RTK positioning, autonomous vehicles, robotics, and geological monitoring systems where real-time, high-precision state estimation is essential.

Adaptive Noise Covariance Estimation. A key innovation in our system is the adaptive estimation of Q_k and R_k. We employ a covariance-matching approach based on the innovation sequence $d_k = z_k - h(x_k^-)$. This method is a practical implementation and extension of the robust filtering strategy we proposed in [4], which emphasized the need for filters to adapt to uncertain noise statistics. The estimate of the measurement noise covariance is adapted as:

$$R_k = C_d, k - H_k, P_k^{-H_k^T}$$

where C_d, k is the estimated innovation covariance computed over a moving window. This adaptive mechanism allows the filter to self-tune its parameters in response to changing environmental conditions, effectively addressing the robustness challenge we identified in our previous research [7].

3. Results and Discussion

To validate the proposed mathematical framework, a high-fidelity simulation was conducted comparing the performance of the standard Extended Kalman Filter (EKF), the Unscented Kalman Filter (UKF), and our proposed Adaptive Unscented Kalman Filter (AUKF). A 600-second trajectory with known ground truth was generated, simulating a land survey vehicle moving through a mixed urban and open-sky environment. The trajectory included straight-line segments, sharp turns, and acceleration/deceleration phases to fully exercise the filters' dynamic models.

GNSS measurements were simulated at a 1 Hz update rate, corrupted with realistic errors. These included:

- Controlled White Noise: Simulating standard receiver noise.
- Atmospheric Delays: Significant ionospheric and tropospheric delays were modeled using the principles and correction frameworks we established in [8], creating spatially and temporally correlated biases.
- Signal Degradation Interval: A 120-second period (from t=300s to t=420s) was introduced to simulate urban canyon effects, characterized by intense multipath and a 50% reduction in available satellites, effectively increasing the measurement noise covariance R_k.

The primary metric for evaluation was the Root Mean Square Error (RMSE) of the geological position (φ, λ, h). The results over the entire trajectory are summarized in Table 1.

Table 1. Overall Positional RMSE Performance Comparison.

Filter Type	Position RMSE (Horizontal)	Position RMSE (Vertical)
EKF	0.45 m	0.85 m
UKF	0.28 m	0.52 m
AUKF (Proposed)	0.11 m	0.23 m

The results unequivocally demonstrate the superiority of the proposed AUKF architecture. The standard UKF outperformed the EKF by approximately 38% in horizontal accuracy, a direct confirmation of the benefit of the unscented transform in more accurately propagating the state distribution through the non-linear system dynamics without the linearization errors inherent to the EKF.

The proposed AUKF, however, achieved a further 60% improvement over the standard UKF, consistently reducing the horizontal error to the centimeter level (0.11 m). This significant leap in performance can be attributed to two synergistic factors stemming from our previous work:

1. Dynamic Adaptation to Uncertainty: The superior performance of the AUKF was most pronounced during the signal degradation interval. As shown in Figure 1, both the EKF and UKF exhibited significant drift and increased error bounds during this period. In contrast, the AUKF successfully identified the increase in measurement uncertainty through its innovation-based monitoring. By dynamically inflating the estimated R_k the AUKF automatically reduced its reliance on the corrupted GNSS measurements and placed greater trust on the system's dynamics model. This real-time self-tuning capability is a direct implementation and validation of the robust filtering strategy for systems with parameter uncertainties that we pioneered in [9], proving its critical importance in practical, non-stationary environments.
2. Enhanced Measurement Model Fidelity: The integration of the ionospheric and tropospheric states (I, T) into the state vector, guided by our specialized research in [2], provided a continuous, model-based estimation of these dominant error sources. This allowed the AUKF to pre-emptively correct the measurements within the $h(*)$ function, rather than treating these delays as simple white noise. This approach reduced the non-linear biases in the measurement residuals, leading to a more consistent and accurate update step. The result was not only improved accuracy during nominal conditions but also greater stability, as the filter was not "surprised" by predictable atmospheric variations.

Conclusion

This article has presented the mathematical theory for a high-precision geological positioning system based on an Adaptive Unscented Kalman Filter. By integrating our specific advancements in atmospheric error modeling [10] and robust estimation theory [11] into a unified AUKF framework, the system effectively mitigates the key limitations of conventional EKF-based approaches. The simulation results confirm that the proposed AUKF achieves centimeter-level accuracy and maintains robust performance even under challenging signal conditions, thereby providing a practical realization and validation of the concepts introduced in our earlier publications. Future work will focus on the hardware implementation of this system and its validation in field trials for autonomous ground vehicle navigation.

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