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Adaptive Unscented Kalman Filter for Robust Localization in Ship Ad hoc Networks

[1] Anfal K. Ibraheem, [2] Sumaya A. Hamad*

[1]Department of Computer Science, Computer Sciences and Information Technology, University of Anbar – Iraq

[2]Department of Information Technology, Computer Sciences and Information Technology, University of Anbar –Iraq

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Corresponding Author:

Full Name

sumayah.hamad@uoanbar.edu.iq

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Abstract

Reliable ship localization is critical for tracking and collision avoidance in Ship Ad hoc Networks (SANETs), yet traditional localization systems like Global Positioning System (GPS) and Automatic Identification System (AIS) often struggle with noise and signal loss. In this paper, we developed a network-aware Adaptive Unscented Kalman Filter (AUKF) to enhance ship localization. Our method improves the standard UKF by dynamically tuning the process noise covariance matrix using SANETs topological data (node degree and connected component size). This method maintains high accuracy even during irregular ship movements or communications drops. The evaluations using real-world and simulated ship datasets show the proposed framework outperforms the classical UKF. The AUKF achieved a 38.8% drop in Mean Absolute Error (MAE) and a 24.6% reduction in Root Mean Square Error (RMSE), alongside a 42.8% decrease in the 95th percentile error (P95). These findings prove that the network features fused with physical filters are highly effective to enhance localization accuracy in dynamic marine environments.

1. Introduction

Ship Ad hoc Networks (SANETs) are a type of ad hoc network that is characterized by providing self-organizing and infrastructure-free communications in maritime environments. In this type, ships act as mobile nodes that form communication links to support navigation, localization, safety operations, etc. The large ocean scale and ship traffic create highly variable network topologies and reduce link stability [1][2]. Maintaining stable communication and avoiding collisions in such an environment requires knowing exactly where each ship is. Available positioning methods, such as AIS and GPS, have some drawbacks. Bad weather conditions often lead to signal loss, sensor noise, and inconsistent update rates. Thus, real marine tracking often straggles from low localization accuracy. [3] [4].

The researchers used nonlinear estimation techniques to obtain stable tracking. They employ an Unscented Kalman filter (UKF) because it effectively deals with the dynamics of the nonlinear system [5]. The UKF outperforms the extended Kalman filter (EKF) in terms of numerical stability and estimation accuracy when applied to complex motion models [6] [7]. The UKF suffers from some limitations. it depends on a fixed process noise covariance matrix. When the marine environment changes rapidly, the filter's performance decreases. Recent studies have explored adaptive filtration to address this issue. Ji et al. [8] modified the noise parameters using residual statistics. Peng et al. [9] introduced a robust UKF to reduce the impact of outliers in the measurements. Hajiyev and Sokin [10] also applied a Q tuning mechanism for underwater vehicles. All these adaptive approaches share one drawback. They modify the filter based solely on the statistical properties of the measurements and ignore the topological features of the network.

The spatial distribution of vessels in SANETs is not random. It reflects interaction behaviors and movement constraints in marine environment. Therefore, this paper proposes a new network-aware adaptive UKF. Unlike previous methods, our approach dynamically tunes the process noise covariance matrix using the topological features of the SANET. First, we apply a Unit Disk Graph (UDG) model to extract features (node degree and the size of connected components). Then this structural data is input to the filter to adjust its uncertainty directly according to how well the network is connected. This technique boosts accuracy across both sparse and densely populated maritime zones.

The following are the contributions we provide in this article:

1- In this paper we develop a network-aware adaptive UKF filter that integrates SANETs features with a filtering loop.
2- A new mechanism is proposing to adjust process noise depending on node degrees and connected component sizes.
3- We use simulated and real data to verify the accuracy of the proposed model.
4- We demonstrate that AUKF outperforms traditional UKF by reducing both MAE and RMSE which contributes to making maritime navigation safer.
5- The remainder of this article is arranged as follows: the next section provides a quick summary of a selection of the most relevant works. In section 3 we discuss in detail our methodology and localization model. Experimental results and discussions are illustrated in section 4. Finally, the conclusions and future works are stated in section.

2. Related work

2.1 Research on SANETs and Graph-Based Networks

SANETs are considered a new type of ad hoc network. Where water transport means have great military and civilian advantages. The need to develop these networks that benefit water transport and the continuation of the network service during the water is one of the obstacles and possibilities that benefit the development of this technology[11]. Mishra et al.[1] provided Sea Ad Hoc Networks (SANETs) as an infrastructure based marine communication. It simulates ship to ship communication based on mobility and proximity, in which information is shared when ships are within communication range. Wang et al.[2] reviewed background studies related to ad hoc network, autonomous ships, ship communication, and ship interaction. The authors proposed to build a ship mobile ad hoc network (MANET). The network is modeled through a distance-based connectivity model, in which ships act as nodes and communication links are established according to transmission range and relative motion. Abdulameer and Ali [12] indicated the dynamic nature of maritime nodes makes precise localization an important requirement for maritime safety and good communication. The authors introduced a dynamic clustering technique to facilitate these requirements. In the same way, Hamad et al. [3] proposed a model for localization based on clustering algorithm in SANETs. They used travelling distance from the centers and the previous position by applying the average distance measure to calculate the position. The experimental results show, the position estimation error was small and they have an accurate result. Many previous studies have focused on graph techniques for modeling mobile wireless networks. Abdallah and Abdallah [13] presented review on geographical based topology control algorithms for ad hoc networks. This study focused on evaluation dimensions that are directly relevant to distance-based network construction. Additionally, it draws attention to the fundamental communication assumption behind geometric graph construction these resulting graph is called a unit disk graph (UDG). Bose et al. [14] proposed distributed range-based localization methods in wireless sensor networks modeled as a UDG. Their work aims to determine node localization in networks based merely on relative distances. This model proves its ability to find spatial correlations among neighbors within communication radius.

2.2 Research on Localization Based on Kalman Filters

Researchers have recently begun to use Kalman filter techniques for tracking and estimating position in ad hoc networks due to the problems of data interruptions and noise that plague other localization technologies. Fossen and Fossen [15] addressed the problem of ship motion estimation using AIS and EKF design. This study indicated the EKF can predict the future motion of ships and different evasive maneuvers were analyzed in a collision avoidance scenario. In a high dynamic environment, EKF has limitations due to its reliance on Jacobian matrices that can lead to filter instability and increase computation cost. Due of the mathematical constraints of EKF, the researchers prefer the UKF. The UKF clearly bypasses these linearization flaws and reduces the complexity as originally demonstrated by Wan and van der Merwe [5]. Assaf et al. [16] utilized it for accurate GPS track estimation, while Cole and Schamberg [17] developed a geodetic UKF for long-distance AIS tracking to avoid local coordinate frame restrictions. Wang et al. [7] verified by extensive compressions that UKF gives a more accurate ship kinematics estimate than the EKF. The performance of the UKF can be degraded when the system and measurement noise statistics (covariance matrices Q and R) fluctuate over time or become inaccurate. Therefore, recent research has focused on adaptive UKF (AUKF). Deng et al. [18] proposed this mechanism for dynamic vessel positioning. The measurement noise covariance in UKF is adapted based on the residual covariance matching method and the process noise covariance is adjusted by using an adaptive scaling factor. As a result, the proposed AUKF significantly improves estimation accuracy. Peng et al. [9] developed a robust UKF to overcome the harmful effects of sensor outliers. This filter dynamically modulates the measurement noise matrix (R) to reduce the impact of error measurements. The adaptation in the field marine environment, Hajiyev and Soken [10] presented Q adaption for underwater vehicles to ensure filter stability against changes in water currents. Wang et al. [19] recently indicated the critical need for data-driven adaptive filters to compute ship states under complex conditions and multi ship interactions. As seen in works like Chen et al. [19] almost all current adaptation mechanisms are strictly statistical and they rely entirely on analyzing innovation sequences or residuals. In SANET, the communication distances and topologies change constantly. There are no existing studies that exploit the spatial and structural characteristics of the network itself to guide the filter adaptions.

This gap is addressed in this study by introducing adaptive network-aware UKF. Our approach translates node density and geographic distribution into topological data using the UDG model. This information is used to adjust the process noise covariance matrix. We provide a high efficient tracking framework that maintains robust localization regardless of marine environment changes.

3. Methodology

This study proposes an adaptive Kalman filter (AUKF) based on the features of SANETs. It combines a standard nonlinear filter with network spatial features to improve ship position estimation in SANETs. Our framework contains three phases as showed in Figure 1, including data collection and preprocessing, network construction, and AUKF-based localization.

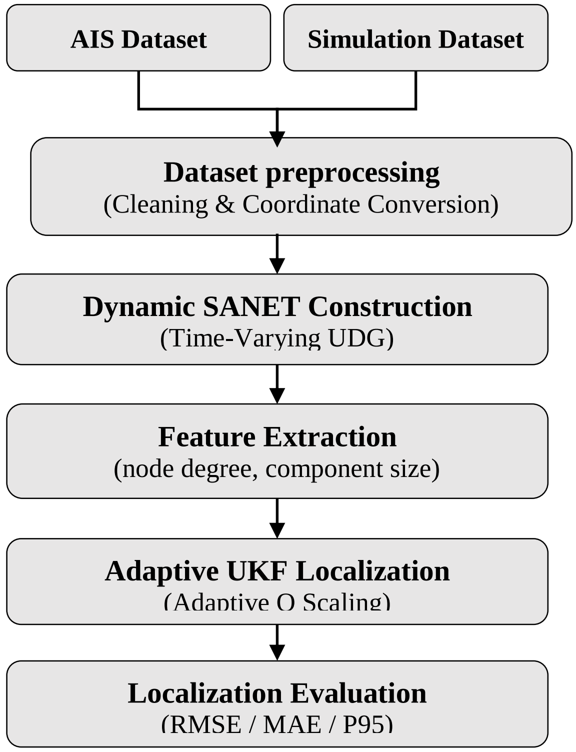

Figure (1) Proposed adaptive UKF framework for localization in SANETs

3.1 Data Collection and Preprocessing

In this paper two datasets are utilized. The AIS dataset contains about 74,000 records for 100 ships. All ships are sailing in the Gulf of Mexico over two weeks. The records of the dataset include ship identification, geographic coordinates (latitude and longitude), speed, direction, and timestamp information. In the preprocessing stage the invalid records are eliminated to ensure trajectory consistency.

A simulation dataset is generated using the NS2. It mimics dynamic SANETs scenarios under controlled maritime conditions. The simulation dataset consists of 20,000 records for 100 ship nodes. This dataset also consists of data about time, ship position, velocity, and heading parameters. The real and simulated datasets are used in this work to assess the proposed framework under maritime navigation behavior and controlled scenarios.

The initial latitude and longitude are transformed into a local cartesian coordinate system (x, y) measured in meters. This transform step is important to ensuring numerical stability in the filtering stage. The speed is converted from knots to meters per second using the standard factor of 0.51444 m/s. Furthermore, ship headings are also converted from degrees to radians by equation (1). This stage considers stable foundation for the next phases.

$$rad = \deg * \left(\frac{\pi}{180}\right) \qquad (1)$$

3.2 Network Construction and Feature Extraction

The static UDG model is extended to a time-varying formulation to represent dynamics SANETs. A time-varying SANETs was constructed as a sequence of graphs based on Euclidean distance, resulting in bidirectional communication between neighboring ships. Each time interval represents the communication topology among ships. For each time interval t, an undirected graph is defined as:

$$G_t = (V_t, E_t) \qquad (2)$$

Where:

V_t: denotes the set of ships (nodes) at time interval t. and E_t: denotes the set of communication links (edges).

The communication links arises between ships i and j if the Euclidean distance between them is within the maximum communication range R_{max}.

$$E_t = \{(v_i, v_j) | i \neq j, d_{ij} \leq R_{max}\} \quad (3)$$

For each node $i \in V_t$, topology-based SANET features were extracted for every node from G_t:

1-Node Degree: The degree of node i represents the number of neighboring ships within the communication radius:

$$D_i^t = |N_i^t| \quad (4)$$

In this formulation, N_i^t denotes the localized neighborhood set, defined as $\{j \in V_t | (i,j) \in E_t\}$.

2- Connected Component ID and Size

Let $C_k^t \subseteq \mathrm{V}_t$ denote the k-th connected component in time interval t . For each node $i \in \mathrm{V}_t$ the component identifier is defined as:

$$ID_i^t = k \quad if \ \ i \in C_k^t \quad (5)$$

Where k is the index of the connected component containing node i and ID is an integer label indicating which connected component node i belongs to. This feature is useful to distinguish whether two vessels are in the same connected cluster or separated into different network partitions. The component size is defined as:

$$S_i^t = |C_k^t| \ where \ i \in C_k^t \quad (6)$$

Where $|C_k^t|$ denotes the number of nodes in the connected component. A larger component size indicates better network connectivity and greater potential for cooperative awareness. In contrast, a component size of 1 indicates an separated vessel with no neighbors within R_{max}. These SANET features are employed in the next stage to quantify network connectivity and density, and consequently to adapt the process noise covariance Q in the UKF localization framework according to the current network conditions.

3.3 Proposed Adaptive UKF-Based Localization Framework

The Unscented Kalman Filter (UKF) is utilized in this stage to estimate ship positions. The process noise covariance (Q) is scaling according to the network conditions that are gathered from SANETs (node degree and component size) to make the UKF adaptable. The objective is to reflect higher uncertainty in weakly connected network states and lower uncertainty in well connected conditions.

3.3.1 Filter Inputs and Observations

Ship state information comes from AIS and simulation datasets. The filter uses this information as input vector at each time step t:

$$X_t = [x_t, y_t, v_t, \theta_t]^T \quad (7)$$

Where x_t, y_t represents ship position in meters, while v_t is speed and θ_t is heading. These data form the state vector and the measurement vector. The filter uses these input data with SANETs features for adaptive modeling.

3.3.2 Motion and Measurement Models

This model propagates ship position based on its speed and heading. At time interval Δt, the state transition is:

$$\begin{bmatrix} x_t \\ y_t \\ v_t \\ \theta_t \end{bmatrix} = \begin{bmatrix} x_{t-1} + \mathrm{v}_{t-1} \cos(\theta_{t-1}) \, \Delta\mathrm{t} \\ y_{t-1} + \mathrm{v}_{t-1} \sin(\theta_{t-1}) \, \Delta\mathrm{t} \\ v_{t-1} \\ \theta_{t-1} \end{bmatrix} + w_{t-1} \quad (8)$$

Where $w_{t-1} \sim N\ (0, Q)$represents the process noise. It takes into account uncertainty in ship speed and heading due to sea currents and maneuvering behavior. The measurement function is used to map the system state into the observation domain:

$$z_t = h(x_t) + n_t \qquad (9)$$

Where $n_t \sim N(0, R)$ represents measurement noise. The measurement noise covariance is defined as:

$$R = Diag(\ \sigma_x^2\ , \sigma_y^2, \sigma_v^2, \sigma_\theta^2)$$

3.3.3 Adaptive Process Noise Modeling Using SANET Features

The behavior of maritime traffic is related to network density. A ship that is isolated and not part of a dense SANETs will face very few navigational constraints. This ship will have complete freedom to change its direction and speed suddenly without restrictions. Therefore, the filtering mechanism must dynamically increase internal uncertainty to be prepared for such rapid changes in state. In contrast, ships sailing within dense network groups are under severe constraints due to collision avoidance regulations. This makes them navigate highly predictable routes. In this case, the filtering mechanism must suppress process noise to ensure a stable and consistent estimation of the state.

As a result, this study proposed adapting Q using SANET features. These feature uses to calculate a scaling factor that increases process uncertainty in weak connectivity conditions. From Eq. (5) and (6) the node degree and component size are computed then the adaptive scaling factor is defined as:

$$Q_{scale} = 1 + \delta\left(1 - \frac{D_i^t}{S_i^t}\right) \qquad (10)$$

Where δ is control adaptation sensitivity. The linear scaling formula is chosen to provide a smooth and computationally stable adaptation between network connectivity and process uncertainty. Because the ratio $(\frac{D_i^t}{S_i^t})$ is inherently confined within the interval [0,1], the linear mapping ensures a proportional adjustment of the variance without introducing abrupt nonlinear changes that could destabilize the filtering process. In dynamic SANETs environments, gradual changes in network structure are expected to produce similar gradual changes in motion uncertainty. Therefore, the proposed linear formula provides a practical balance between responsiveness, numerical stability, and computational simplicity.

Furthermore, nonlinear mapping, such as exponential or logarithmic scaling, is not adopted because it could amplify minor fluctuations in network structure and lead to excessive adjustment of the variance under rapidly changing marine connectivity conditions. Such behavior could impact the stability of the UKF and increase the estimation oscillation.

For each time step Δt, the base process noise covariance matrix is defined as:

$$Q_{base} = \begin{bmatrix} \frac{\Delta t^4}{4}Q_a & 0 & 0 & 0 \\ 0 & \frac{\Delta t^4}{4}Q_a & 0 & 0 \\ 0 & 0 & \Delta t^2 Q_a & 0 \\ 0 & 0 & 0 & \Delta t^2 Q_\theta \end{bmatrix} \qquad (11)$$

The adaptive process noise covariance is obtained by scaling the base matrix:

$$Q_{adaptive} = Q_{scale} \cdot Q_{base} \qquad (12)$$

This formulation increases uncertainty for larger sampling intervals and dynamically adapts it depending on SANET conditions. The adaptive covariance matrix $Q_{adaptive}$ is then used in UKF prediction step to compute prior state covariance at each time step.

3.3.4 Localization Procedure

Basic steps of the UKF are sequential according to the standard model, but their internal implementation differs. Before the filter's prediction operation begins, a new framework derived from the SANET architecture is added, as shown in figure 2. The parameters extracted after network construction are directly used to adjust the process noise variance matrix (Q). This design ensures that each subsequent localization update is adapted to the ship's spatial context by directly integrating this spatial knowledge into the mathematical filtering loop.

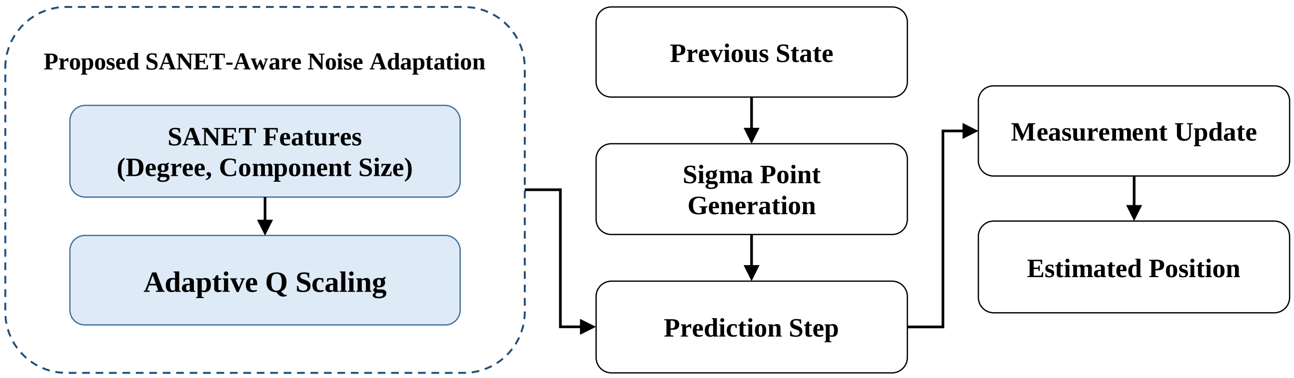

Figure (2) The proposed adaptive UKF localization framework**.**

The main steps of proposed localization model are:

1- Load the two datasets and extracted SANET features.
2- Initialize the state and measurement vectors.
3- For each time step:
   - Compute Q_{scale} .
   - Update $Q_{adaptive}$.
   - Perform UKF prediction.
   - Perform UKF update.
4- Output estimated ship trajectories.

3.4 Experimental Setup and Parameter Selection

The proposed algorithm for localization in SANET was programmed using Python and implemented in Google Colab. The algorithm is tested on two types of data, as previously mentioned, proving that the proposed framework can handle different maritime environments.

The process noise (Q) and measurement (R) in the UKF are selected based on values reported in previous studies on marine positioning systems. These values are used to provide a fair comparison with existing methods based on the UKF and to ensure filter stability.

Regarding the network architecture, the communication radius controlling the SANET network architecture is experimentally chosen. The radius in AIS used 3000 meters to reflect actual marine communication coverage. A smaller radius of 30 meters was chosen in simulation data to maintain dynamic and controlled changes in the network architecture.

The sampling interval is set to 3 minutes for the real dataset and 3 seconds for the simulated dataset to reflect the difference between the actual AIS reporting frequency and the simulation paths.

Both the standard UKF and the proposed AUKF are evaluated under identical experimental conditions, including the same datasets and parameters. The only difference lies in the adaptive formulation of the process noise in the proposed method.

4. Results and Discussion

4.1 Evaluating localization performance

The proposed adaptive model was compared with the standard UKF, EKF and KF in our work. The same parameters were applied to all models using two types of data to demonstrate the actual improvements in the performance of the proposed model. The overall localization accuracy was evaluated using the root mean squared error (RMSE) and the mean absolute error (MAE). In addition, the robustness of the frame against kinematic anomalies was assessed during the 95th percentile error (P95).

4.1.1. Evaluation using AIS Data

Test results shown in Table 1 and Figure 3 demonstrate the superiority of the proposed AUKF. The constant noise process value reduces the performance of the conventional UKF. The high decrease in the P95 (42.8%) compared to the RMSE (24.6%) indicates the effectiveness of the AUKF in mitigating the impact of anomalies and sudden navigational maneuvers. UKF struggles to handle the abrupt path changes often found in AIS data due to its strict reliance on a constant Q value.

Table (1) The performance metrics using AIS dataset

Metric	UKF	AUKF	Improvement
RMSE (m)	9.31	7.02	24.6%
MAE (m)	2.11	1.29	38.8%
P95 (m)	11.05	6.32	42.8%

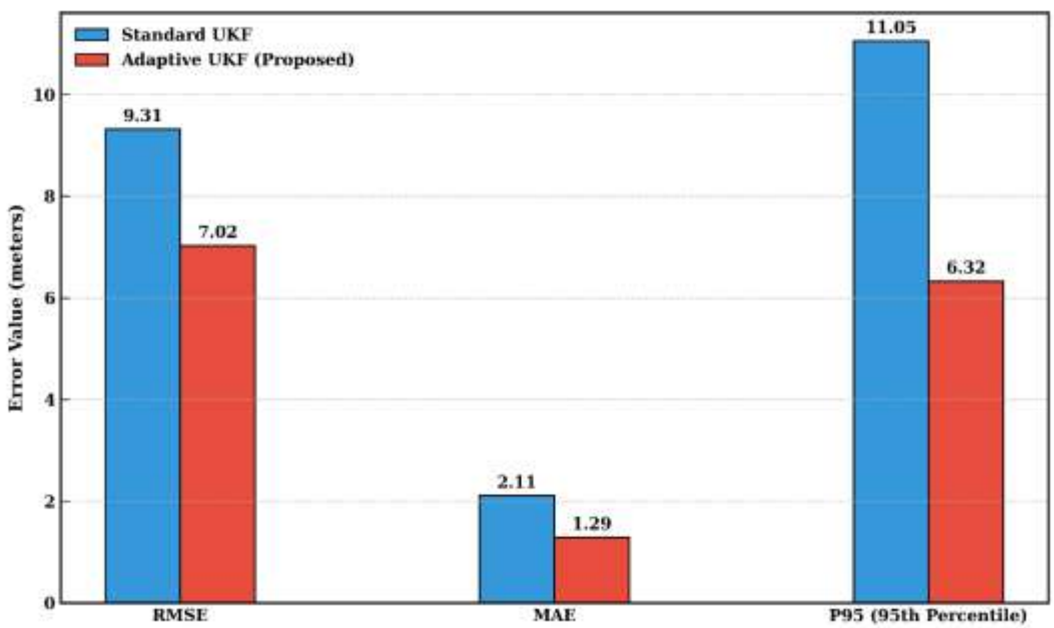

Figure (3) Performance metrics of the standard and proposed AUKF models

The five worst performing ships with the highest error rates in the conventional model were analyzed. The improvements for these ships are between 13.34% to 45.93%, as shown in Table 2. The enhancement findings in all vessels with high error rates demonstrate that the proposed adaptation mechanism significantly enhances the filter's result during complex maneuvers. The variation in improvements is attributed to differences in the connectivity of the SANETs to which the vessels are connected.

Table (2) The improvements in RMSE for the most complex ship trajectories using AIS data

MMSI (Ship ID)	UKF RMSE (m)	AUKF RMSE (m)	Improvement

366954420	27.21	21.54	20.84%
369990195	27.10	14.65	45.93%
636017077	24.94	21.61	13.34%
311733000	24.29	20.07	17.36%
338499698	22.39	13.83	38.24%

The error over time for a ship number 338499698 is analyzed. As shown in Figure 4, the largest error value observed in the standard UKF (143.7 meters) typically occurs at the beginning of a maneuver where the vessel's path or speed changes abruptly. The UKF fails in this situation because it uses constant process noise. Under the same conditions, the AUKF reduces this error by relying on the spatial context. The filter modifies the uncertainty limits and allows for position estimation close to the actual course through utilizing SANETs features.

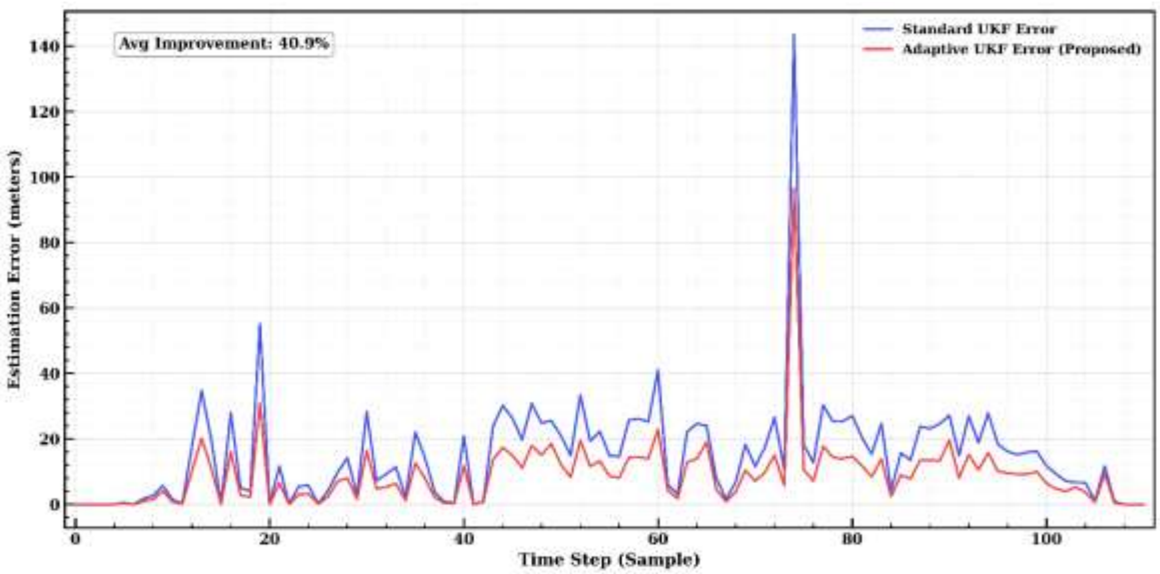

Figure (4) The error over time for ship no. 338499698

4.1.2 Evaluation using simulation data

This section presents a comparative analysis of the results obtained from the proposed SANET-based AUKF model and the UKF model using simulation data. That result clearly highlighting the importance of the proposed model. As Table 3 the findings confirm that the Adaptive UKF model provide continuous improvement. When compared to the UKF, the adaptive model's ability to keep closer tracking actual position of ship is demonstrated by the 19.54% decrease in MAE.

Table (3) performance metrics for simulation data.

performance metrics	UKF	AUKF	Improvement
RMSE (m)	6.40	5.43	15.16%
MAE (m)	3.48	2.80	19.54%
P95 (m)	15.48	12.59	19.25%

Figure 5 shows that the 19.25% improvement in the P95 metric reflects the algorithm's efficiency in handling exceptional situations and sharp maneuvers that typically cause significant estimation errors. The SANETs model can represent the spatial relationships and connections between ships even in a simulation environment. This ability gives the filter added flexibility in correcting and adapting estimation based on density. These results contribute to enhancing ship traffic control and collision avoidance systems, where accurate tracking is a cornerstone of the maritime safety.

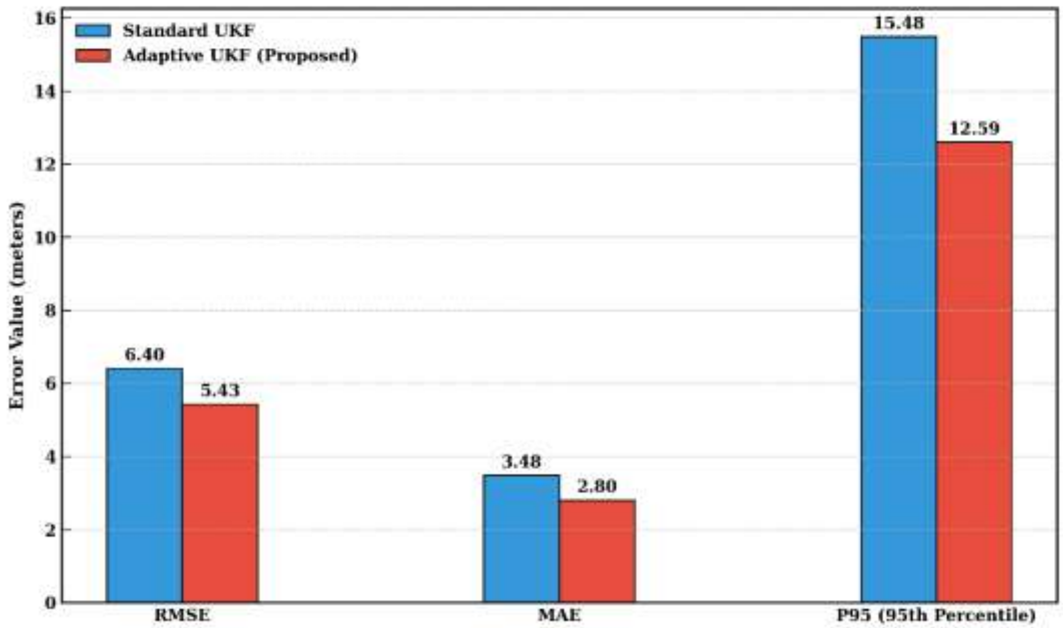

Figure (5) UKF vs. AUKF using simulation data

Overall, the comparative and experimental results presented in this section prove that adaptive physical filter introduces the optimal solution to the problems of noise and data loss in maritime navigation. Achieving high accuracy meets the requirements for building reliable ship ad hoc networks (SANETs) and ensures a high level of awareness and collision avoidance for autonomous ships.

4.2 Baseline Comparison with KF, EKF, and UKF

Comparisons are made to evaluate the proposed model. The results, presented in Table 4, demonstrate the superiority of the proposed model. The KF recorded the highest error rate. This is due to its linear nature. KF fails in complex and nonlinear movements of ships in marine environments; therefore, it is unsuitable for accurate tracking. EKF performed significantly better than the KF, but its reliance on linearization via Jacobian matrices still introduces deviations in the results.

The classical UKF gets high accuracy by using sigma points. It captures the statistical characteristics of the motion without simplifying the equations; thus, it reduces the error compared to the previous models. The proposed AUKF obtains the best result across all metrics (RMSE, MAE, P95). It is able to automatically adapt to changes in process noise based on the topology conditions of SANETs.

These results indicate that combining SANETs connectivity characteristics into the adaptive mechanism of the filter largely enhances positioning robustness and tracking accuracy in marine environments. AUKF can minimize errors caused by signal interruptions or sharp maneuvers.

Table (4) Comparative localization performance using both dataset

Dataset	Model	RMSE (m)	MAE (m)	P95 (m)
AIS	KF	49.75	19.13	107.46
	EKF	15.59	4.44	27.04
	UKF	9.31	2.11	11.05

	Proposed AUKF	**7.02**	**1.29**	**6.32**
Simulation dataset	KF	26.65	21.61	51.32
	EKF	11.83	9.06	23.53
	UKF	6.40	3.48	15.48
	Proposed AUKF	**5.43**	**2.80**	**12.59**

4.3 Sensitivity Analysis of δ Parameter

The adaptive sensitivity value δ is selected experimentally. To assess the effect of this value, several values are tested while keeping the same experimental settings.

Table (5) Sensitivity analysis of adaptation parameter

Values of δ	RMSE (m)	MAE (m)	P95 (m)
0.5	7.62	1.50	7.52
0.8	**7.02**	**1.29**	**6.32**
1.0	7.19	1.35	6.68

The results shown in Table 5 indicate that small values of δ reduce the response of the adaptive process noise mechanism, leading to poor adaptation under structural changes. In contrast, large values lead to excessive adjustment of the covariance measurement process. The best localization result is achieved when the value of δ is 0.8. It provides the optimal balance between adaptive sensitivity and estimate stability. Therefore, this value is adopted for all future experiments.

4.4 Comparison with Related Works

To demonstrate the validity of our proposed model (AUKF), we conducted a comparative analysis between the results of adaptive model and those reported in several recent studies that addressed ship tracking using AIS data and Kalman filters. Table 6 summarizes this comparison:

Table (6): Comparative analysis of localization accuracy between the proposed model and related works

Ref.	Method	Data Type	Study Objective	RMSE Result
Assaf et al., 2020 [16]	Standard UKF	AIS	Ship track estimation	55 m – 291 m
Cole et al., 2021 [17]	Geodetic UKF	AIS	vessel tracking without planar projection	4.17 m – 328 m
Yang et al., 2022 [20]	IMM-SCKF	AIS	Trajectory tracking in dynamically changing states	6 m -15 m
Proposed Model	AUKF	AIS	Enhance localization for ship ad hoc networks	7.02 m

The previous studies suffer from high variance in tracking accuracy. The study by Cole et al. appears a large error ranging from 4.17 m to 328 m. This means that their algorithm provides accurate position in regular conditions and it loses control under others scenario such as sharp maneuvers.

Our model, as proven by results, achieves high stability with accuracy of up to 7.02 meters. The dynamic adjustment mechanism used in the proposed model prevents large errors. This stability is a major advantage for our work in providing safe and stable ship tracking.

5. Conclusions

In this paper we proposed a new network-aware UKF to enhance the accuracy of maritime localization in Ship Ad Hoc Networks (SANETs). The proposed framework effectively adapts to varying network densities and complex ship dynamics by dynamically tuning the process noise covariance matrix based on network features. Experimental evaluations using both real AIS data and simulation data demonstrate that the proposed AUKF outperforms the conventional UKF. In real scenarios characterized by irregular maneuvers and high uncertainty, this method achieves a 38.8% reduction in MAE and up to a 42.8% reduction in P95. These results indicate that adding network awareness to nonlinear state estimation increases localization accuracy and successfully suppresses large position errors, providing more stable and reliable trajectory estimation. Future work will focus on applying machine learning methods for predictive topology modeling and we hope that our proposal can be employed in real time.

Conflict of Interest: The authors declare there are no conflicts of interest associated with this paper.

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