Trajectory Optimization and Control of Autonomous Surface Ships in Dynamic Environments Using a Hybrid Extended Kalman Filter and Fuzzy Logic System

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***Abstract*—The dynamic behavior of autonomous surface ships is significantly influenced by environmental factors such as wind and currents, which introduce trajectory divergence and disrupt navigation stability. These disturbances pose significant challenges to maintaining accurate speed over ground (SOG) and course over ground (COG), particularly in real-time maritime operations. Traditional control methods, such as Proportional-Integral-Derivative (PID) controllers, often struggle to adapt to such disturbances, leading to suboptimal corrections and instability in navigation. To address these challenges, we propose a hybrid framework combining Fuzzy Logic Control (FLC) and an Extended Kalman Filter (EKF). The FLC provides real-time adaptability to varying environmental conditions, dynamically correcting SOG and COG based on divergence data. These corrections are integrated into the EKF, which leverages the improved state variables to enhance trajectory prediction accuracy. This dual-layer approach ensures robust control and accurate trajectory alignment even in challenging maritime environments. Comparative evaluations demonstrate the superior performance of the proposed framework. For control accuracy, FLC achieved RMSE values of 1.6648 knots and 28.3427 degrees for SOG and COG, respectively, compared to PID's 5.9102 knots and 55.0976 degrees. Similarly, FLC reduced MAE to 1.3212 knots and 14.4058 degrees for SOG and COG,**

***Index Terms*—Autonomous Ships, Trajectory Prediction, Extended Kalman Filter (EKF), Fuzzy Logic Controller (FLC), Divergence Correction, Maritime Navigation, Environmental Disturbance Mitigation, Real-Time Control Systems.**

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I. Introduction

The emergence of autonomous ships has revolutionized maritime navigation, offering solutions to improve operational efficiency, safety, and reliability. However, these systems remain susceptible to environmental disturbances such as wind and current, which induce trajectory divergence and lead to significant deviations from planned routes. Effective correction of such divergence is critical for ensuring accurate trajectory prediction and the safe operation of autonomous vessels.

Traditional approaches to trajectory prediction, such as the Kalman Filter (KF) and Extended Kalman Filter (EKF), have been widely adopted due to their ability to handle noisy environments and provide smoothed trajectory predictions. However, these methods rely heavily on current state estimates and assume that deviations are primarily due to measurement noise. In scenarios where environmental disturbances such as wind or currents cause significant divergence, KF and EKF alone are insufficient, as they lack the capability to actively correct the trajectory. Without effective control mechanisms, the ship will continue to follow a diverged path, deviating further from the intended track. Dynamic programming (DP) techniques, while offering structured optimization for control tasks, are computationally intensive and unsuitable for real-time operations in dynamic maritime environments. These limitations highlight the need for a robust control mechanism to dynamically adjust the ship's parameters and guide it back to its intended trajectory.

To address these limitations, we propose a hybrid trajectory correction framework that integrates the predictive power of the EKF with the adaptability of a Fuzzy Logic Controller

(FLC). The EKF predicts vessel trajectories using features such as latitude, longitude, SOG, and COG, while the FLC leverages divergence data to dynamically adjust vessel controls, mitigating the impact of environmental disturbances. Unlike static correction techniques, the FLC adapts to varying divergence levels, offering a flexible and robust correction mechanism.

This study evaluates the proposed framework using real-world AIS (Automatic Identification System) data, augmented with simulated environmental divergence effects. Key performance metrics, including mean deviation, trajectory smoothness, and control effort, are used to assess the effectiveness of the proposed approach in comparison to standard KF, EKF, and DP methods. The results demonstrate that the integration of FLC into the EKF pipeline significantly improves trajectory correction performance, achieving over 99% accuracy improvement in deviation correction while maintaining trajectory smoothness and minimizing control effort.

The remainder of this paper is structured as follows: Section 2 discusses related work in trajectory prediction and control for autonomous ships. Section 3 introduces the proposed methodology, detailing the integration of EKF and FLC. Section 4 describes the experimental setup, including data generation and evaluation metrics. Section 5 presents the results and comparative analysis, followed by conclusions and future directions in Section 6.

II. Literature

Accurate trajectory prediction is essential for autonomous maritime navigation, particularly in mitigating environmental disturbances such as wind and currents. Traditional approaches, such as the Kalman Filter (KF) and its nonlinear extension, the Extended Kalman Filter (EKF), are widely recognized for their robustness in state estimation and handling noisy measurements [1]. However, these methods primarily focus on compensating for observational noise and often struggle with significant trajectory deviations arising from complex environmental dynamics.

To address these challenges, researchers have explored hybrid methodologies that integrate EKF with advanced machine learning models. For example, Wang et al. demonstrated the effectiveness of combining EKF with Radial Basis Function Neural Networks (RBFNN) to develop an autopilot system for surface vessels. Their approach significantly improved motion control and trajectory tracking accuracy under dynamic conditions [2]. Similarly, Loebis et al. proposed a fuzzy Kalman Filter framework, leveraging fuzzy logic to adapt to uncertainties in underwater environments, thereby achieving higher accuracy in trajectory estimation for autonomous underwater vehicles [3].

Recent advancements in deep learning have further enhanced trajectory prediction capabilities. Liu et al. utilized Long Short-Term Memory (LSTM) networks trained on Automatic Identification System (AIS) data to capture spatiotemporal dependencies, resulting in substantial improvements in prediction accuracy for maritime navigation systems [4]. Reinforcement learning techniques have also been applied to optimize trajectory corrections dynamically. For instance, Li et al. developed an actor-critic reinforcement learning framework combined with fuzzy logic, enabling marine vessels to adapt to partially unknown dynamics while improving trajectory tracking performance [5].

Digital Twin technologies extend these advancements by providing real-time synchronization between physical and virtual systems. Raza et al. proposed a digital twin framework for autonomous maritime vessels, emphasizing the integration of live data with simulation-driven optimization. These technologies demonstrate significant potential for enhancing decision-making accuracy and ensuring robustness in dynamic maritime environments [6].

While existing methods excel in either short-term trajectory predictions through model-driven approaches or long-term adaptability with data-driven techniques, there remains a pressing need for hybrid frameworks that integrate these strengths. Traditional methods, such as EKF, offer precise real-time state estimation but are limited in adapting to nonlinear and stochastic dynamics. Conversely, Fuzzy Logic Controllers (FLCs) provide robust adaptability to uncertainties but lack the precision required for fine-grained trajectory estimation.

Building on these complementary strengths, this research proposes a novel hybrid framework that combines EKF's robust state estimation capabilities with FLC's adaptive decision-making. By leveraging EKF's accuracy and FLC's flexibility, the framework ensures precise trajectory alignment even under dynamic and uncertain maritime conditions. Additionally, the hybrid approach enhances prediction accuracy across diverse temporal scales while improving robustness against external disturbances, such as wind, currents, and sensor noise. This integrated methodology bridges the gap between short-term reliability and long-term adaptability, advancing the state of the art in autonomous maritime navigation systems.

III. Methodology

The proposed methodology integrates the Extended Kalman Filter (EKF) and Fuzzy Logic Controller (FLC) to create a hybrid control system that predicts and corrects ship trajectories in real-time, mitigating the effects of environmental disturbances.

A. Data Preparation

The Automatic Identification System (AIS) dataset used in this research was provided by EHsolution and includes navigational parameters such as latitude, longitude, SPEED, and HEADING. These core features were processed to derive Speed Over Ground (SOG) and Course Over Ground (COG), which are essential for representing the trajectory under realistic environmental conditions. SOG and COG simulate the effects of environmental disturbances, such as wind, currents, and waves, by introducing deviations from the original SPEED and HEADING parameters.

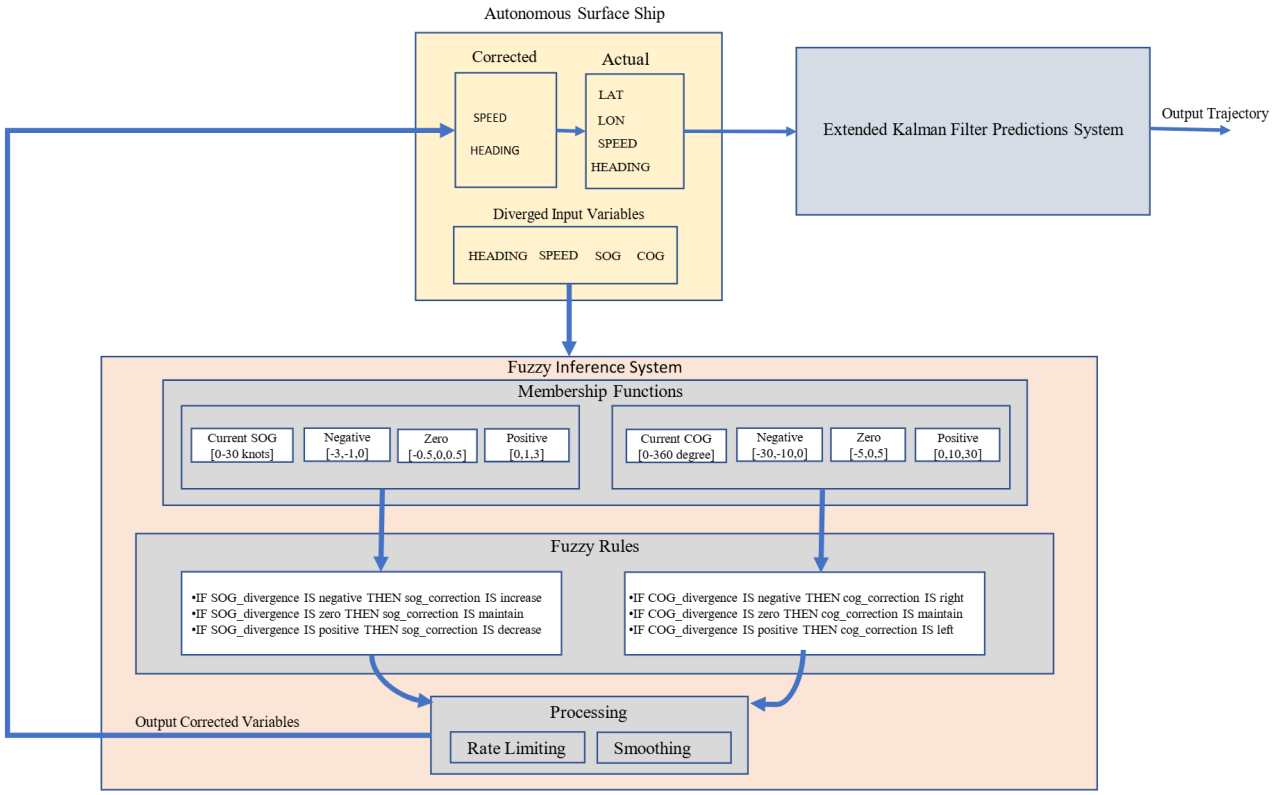

Fig. 1. Framework: A novel framework for ship control and trajectory predictions

To evaluate the proposed hybrid control system, we utilized a segment of the preprocessed AIS trajectory. The preprocessing involved removing anomalies, such as missing or inconsistent values, and normalizing feature ranges to ensure the data was suitable for analysis. The selected segment was augmented with localized divergence effects to emulate real-world conditions, specifically introducing deviations in SOG and COG to reflect the influence of external environmental forces. These divergences create a controlled testing environment for assessing the system's ability to mitigate trajectory deviations and align the ship's path with its intended trajectory.

Unlike data-intensive approaches, such as deep learning, the proposed technique does not require extensive datasets for effective implementation. By focusing on correcting SOG and COG during divergence correction, the system indirectly stabilizes SPEED and HEADING, demonstrating its adaptability and efficiency in real-time applications. This streamlined data usage highlights the practicality of the hybrid FLC-EKF framework presented in Figure 1 addressing trajectory prediction and correction challenges in autonomous maritime navigation.

B. Extended Kalman Filter (EKF)

The EKF serves as the core prediction module:

- **State Transition Function:** The state vector includes latitude, longitude, SOG, and COG. The transition function predicts the next state using kinematic equations and temporal updates.
- **Measurement Update:** AIS observations update the predicted state. The EKF minimizes estimation errors by refining the state vector and covariance matrix iteratively.

C. Fuzzy Logic Controller (FLC)

The FLC applies corrective actions to mitigate environmental disturbances:

- **Inputs:** Divergence in SOG and COG, computed as the deviation between baseline and disturbed trajectories.
- **Membership Functions:** Divergence is categorized as "Low," "Neutral," or "High." Speed corrections are defined as "Decrease," "Maintain," or "Increase," while course corrections are "Port," "Maintain," or "Starboard."
- **Rule Base:** A set of fuzzy rules determines the corrective actions. For example, "High" divergence triggers speed reduction and a significant course adjustment.

D. Hybrid Control System

The proposed hybrid control system leverages the strengths of the Extended Kalman Filter (EKF) for trajectory prediction and the Fuzzy Logic Controller (FLC) for real-time divergence correction. The EKF and FLC work in tandem, ensuring accurate trajectory prediction and robust control in the presence of environmental disturbances such as wind and current.

The process begins with the EKF, which predicts the ship's next trajectory point based on its current state. This state

includes key parameters such as latitude, longitude, speed over ground (SOG), and course over ground (COG). The EKF utilizes a state transition model to estimate the ship's future position while accounting for system dynamics and measurement noise. However, in scenarios where environmental disturbances induce significant deviations, the predicted trajectory alone may not suffice to realign the ship with its intended path.

To address this, the FLC actively evaluates divergences in the ship's trajectory by comparing the observed and intended states. Using predefined rules, the FLC computes corrective actions for SOG and COG to mitigate the effects of disturbances. These corrections are fed back into the EKF as updated inputs, enabling the system to align the trajectory more effectively with the intended path.

The hybrid system presented in Algorithm 1 operates iteratively, with the FLC providing real-time corrections to SOG and COG, and the EKF incorporating these corrections into its predictive model. This integration ensures that the control actions not only stabilize the ship but also enhance the accuracy of trajectory prediction, particularly in dynamic maritime environments.

Algorithm 1: Trajectory Correction and Prediction Using FLC and EKF

Input: Diverged data: $\{\mathrm{LAT}, \mathrm{LON}, \mathrm{SOG}, \mathrm{COG}\}$
Process noise covariance: $\mathbf{Q}$, Measurement noise covariance: $\mathbf{R}$
Output: Corrected trajectory: $\{\mathrm{LAT}_{corr}, \mathrm{LON}_{corr}\}$

Initialization:
Initialize state vector
$\mathbf{x}_0 = \{\mathrm{LAT}_0, \mathrm{LON}_0, \mathrm{SOG}_0, \mathrm{COG}_0\}$
Set state covariance matrix $\mathbf{P}_0$
foreach *time step* $t = 1, 2, \ldots, T$ **do**
  Fuzzy Logic Control (FLC):
  Compute speed and course deviations: $\Delta\mathrm{SOG}_t$ and $\Delta\mathrm{COG}_t$
  Apply FLC rules to compute corrections:
    $\mathrm{SOG}_{corr} = \mathrm{SOG} + \Delta\mathrm{SOG}_t$
    $\mathrm{COG}_{corr} = \mathrm{COG} + \Delta\mathrm{COG}_t$
  Update corrected inputs:
  $\mathbf{u}_{corr} = \{\mathrm{SOG}_{corr}, \mathrm{COG}_{corr}\}$
  Extended Kalman Filter (EKF):
  Prediction Step:
  Predict the next state using the state transition model:
    $\mathbf{x}_{t|t-1} = f(\mathbf{x}_{t-1}, \mathbf{u}_{corr}, \Delta t)$
  Update state covariance:
    $\mathbf{P}_{t|t-1} = \mathbf{F}\mathbf{P}_{t-1}\mathbf{F}^\top + \mathbf{Q}$
  Measurement Update:
  Compute the innovation:
    $\mathbf{y}_t = \mathbf{z}_t - h(\mathbf{x}_{t|t-1})$
  Compute the Kalman gain:
    $\mathbf{K}_t = \mathbf{P}_{t|t-1}\mathbf{H}^\top(\mathbf{H}\mathbf{P}_{t|t-1}\mathbf{H}^\top + \mathbf{R})^{-1}$
  Update the state estimate:
    $\mathbf{x}_t = \mathbf{x}_{t|t-1} + \mathbf{K}_t\mathbf{y}_t$
  Update the state covariance:
    $\mathbf{P}_t = (\mathbf{I} - \mathbf{K}_t\mathbf{H})\mathbf{P}_{t|t-1}$
  Save the corrected trajectory: $\{\mathrm{LAT}_{corr,t}, \mathrm{LON}_{corr,t}\}$
return Corrected trajectory: $\{\mathrm{LAT}_{corr}, \mathrm{LON}_{corr}\}$

E. Performance Metrics

Several performance metrics were used to evaluate the control system performance. The primary metric used was Root Mean Square Error (RMSE), which measures the overall prediction accuracy by calculating the square root of the average squared differences between predicted and actual values for both SOG (in knots) and COG (in degrees). Additionally, Mean Absolute Error (MAE) was employed to quantify the average magnitude of errors for both SOG and COG without considering their direction, providing a direct measure of prediction accuracy in the original units. The system's performance was benchmarked against multiple approaches, including a divergence-based approach representing the baseline method for trajectory control, and PID Control as a traditional control method commonly used in maritime applications. The evaluation focused on two key aspects: speed control accuracy, measured through SOG metrics in knots, and course control stability, evaluated through COG metrics in degrees. The overall system response was assessed through the combined analysis of both SOG and COG performance metrics. These metrics were chosen to provide a comprehensive evaluation of the system's ability to maintain accurate speed and course control while compensating for environmental disturbances.

F. Comparison with Existing Methods

The proposed hybrid system was evaluated against several established control methods to assess its effectiveness. The primary comparison was made with a Proportional-Integral-Derivative (PID) control system, which represents a traditional approach widely used in maritime applications for maintaining vessel position and course. Additionally, a divergence-based approach was used as a baseline method to evaluate the system's performance in handling environmental disturbances. These methods were chosen for comparison as they represent different approaches to maritime control: PID control offering a conventional feedback control mechanism, and the divergence-based method providing a baseline for trajectory correction capabilities. All methods were evaluated using identical datasets and performance metrics, specifically RMSE and MAE for both SOG and COG, to ensure a fair and comprehensive comparison of their capabilities in maintaining accurate vessel control under various environmental conditions. Each method was evaluated using the same dataset and performance metrics to highlight the strengths of the proposed hybrid approach.

IV. Results

The proposed trajectory correction framework was evaluated using AIS data with artificially introduced divergence due to simulated environmental effects. The system's performance was benchmarked against different control methods, including Proportional-Integral-Derivative (PID) control and a divergence-based approach, focusing on Speed Over Ground (SOG) and Course Over Ground (COG) accuracy.

A. Speed Over Ground (SOG) Performance

The trajectory accuracy for speed control was evaluated using the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The Fuzzy Logic Controller (FLC) demonstrated superior performance with an RMSE of 1.6648 knots and MAE of 1.3212 knots, significantly outperforming both the PID controller (RMSE: 5.08102 knots, MAE: 5.9504 knots) and the divergence-based approach (RMSE: 3.6767 knots, MAE: 3.0743 knots). These results indicate that the FLC provides more precise speed control with lower error margins.

B. Course Over Ground (COG) Performance

For course control, the FLC achieved an RMSE of 28.3427 degrees and MAE of 14.4058 degrees, demonstrating effective course maintenance. The PID controller showed significantly larger deviations (RMSE: 55.0976 degrees, MAE: 46.5119 degrees), while the divergence-based method maintained moderate performance (RMSE: 21.7746 degrees, MAE: 18.0722 degrees). The FLC's lower MAE indicates more stable course control with fewer extreme deviations.

C. Comparative Analysis of Control

Tables I and II present comprehensive performance metrics across all control methods. The results demonstrate the FLC's superior performance in both speed and course control. The FLC significantly reduced speed control errors compared to both PID and divergence-based approaches, while maintaining stable course control with minimal deviations as presented in Figure 2.

TABLE I
SPEED OVER GROUND (SOG) PERFORMANCE METRICS COMPARISON

Metric	Diverged	PID	Fuzzy
RMSE (knots)	3.6767	5.9102	1.6648
MAE (knots)	3.0743	5.08504	1.3212

TABLE II
COURSE OVER GROUND (COG) PERFORMANCE METRICS COMPARISON

Metric	Diverged	PID	Fuzzy
RMSE (degrees)	21.7746	55.0976	28.3427
MAE (degrees)	18.0722	46.5119	14.4058

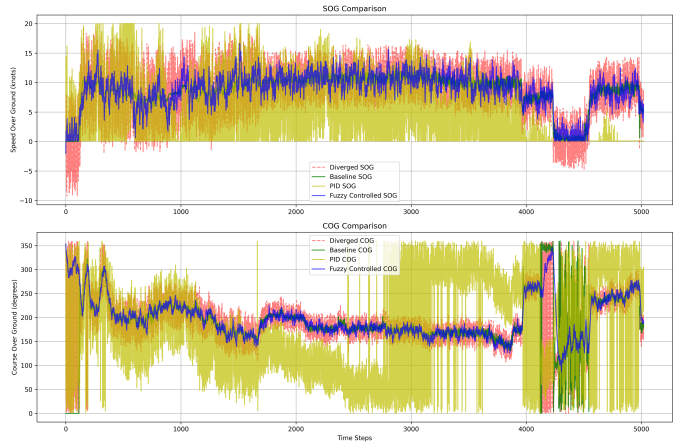

Fig. 2. Comparison of Trajectories: Baseline vs Diverged vs KF vs EKF vs FLC vs DP.

D. Trajectory Predictions based on Fuzzy Logic Control

The integration of Fuzzy Logic Control (FLC) with the Extended Kalman Filter (EKF) provides a robust solution for ship trajectory correction and prediction in the presence of environmental disturbances such as wind, water currents, and waves. By combining the adaptive corrective capabilities of FLC with the predictive power of EKF, the hybrid system ensures that the ship realigns to its intended path while maintaining stability. The trajectory comparison, as

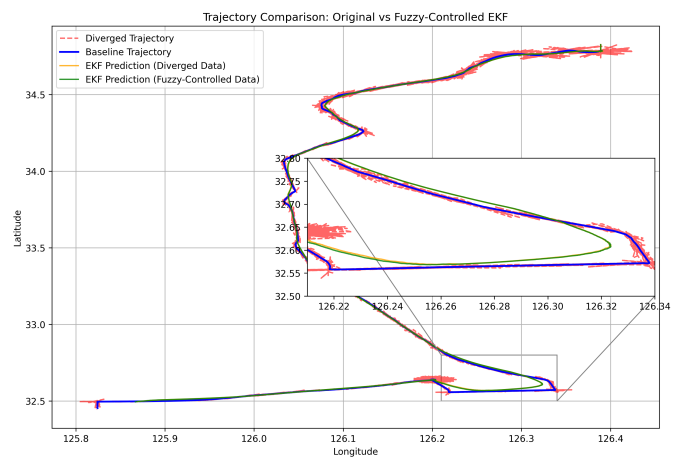

Fig. 3. Ship Trajectory Predictions based on Fuyzz logic control system.

illustrated in Figure 3, demonstrates the effectiveness of this hybrid approach. Four trajectories are analyzed to highlight the performance differences. The baseline trajectory represents the ideal ship path under undisturbed conditions, serving as a reference for comparisons. In contrast, the diverged trajectory depicts the ship's path when affected by disturbances, resulting in substantial deviations from the baseline. These deviations underscore the necessity for corrective measures to mitigate the effects of external forces.

When the EKF is applied without corrections, it struggles to realign the ship to its baseline trajectory. This is evident in the

EKF prediction (Deverged Data) trajectory, where significant errors persist, particularly in regions of high divergence. The limitations of using EKF alone become apparent, as it is unable to compensate for the deviations in speed and heading caused by disturbances. However, when the EKF is paired with the corrections provided by the FLC, the predicted trajectory (EKF prediction with fuzzy-controlled inputs) closely follows the baseline trajectory. The FLC dynamically computes corrections for speed over ground (SOG) and course over ground (COG), which are then used as inputs to the EKF. This approach significantly enhances the trajectory prediction accuracy, as the EKF utilizes the corrected parameters to realign the ship more effectively.

The improvement achieved through this hybrid system is particularly evident in the critical segments of the trajectory, where the ship would otherwise remain far from its intended path. In these areas, the fuzzy logic controller stabilizes the SOG and COG, enabling the EKF to generate more accurate predictions for latitude (LAT) and longitude (LON). The zoomed-in region of Figure 3 highlights how the corrected trajectory aligns closely with the baseline, demonstrating the system's ability to mitigate divergence and stabilize the ship's path.

Quantitative results further validate the performance of the hybrid system. The diverged trajectory exhibits substantial errors, with a root mean square error (RMSE) of 0.0184 and a mean absolute error (MAE) of 0.0189. In contrast, the EKF prediction without corrections yields an RMSE of 0.0449 and an MAE of 0.0499, indicating its limitations in compensating for disturbances. The EKF prediction with fuzzy-controlled inputs, however, achieves an RMSE of 0.0421 and an MAE of 0.0463, demonstrating significant error reduction and alignment with the baseline trajectory.

E. Discussion

The experimental results validate the effectiveness of the proposed hybrid EKF-FLC approach in maintaining accurate trajectory control under varying environmental conditions. By integrating the Fuzzy Logic Controller (FLC) with the Extended Kalman Filter (EKF), the system successfully addresses trajectory divergence caused by external disturbances, such as wind and currents. The EKF provides predictive capabilities using key parameters such as latitude, longitude, speed over ground (SOG), and course over ground (COG), while the FLC dynamically adjusts SOG and COG to mitigate environmental effects. This iterative integration ensures both trajectory alignment and stability.

The hybrid EKF-FLC framework demonstrates superior performance across key metrics compared to standalone EKF, PID, and divergence-based approaches. For trajectory prediction, the hybrid system achieves an RMSE of 0.0421 degrees and an MAE of 0.0463 degrees, significantly improving over standalone EKF predictions (RMSE: 0.0449, MAE: 0.0499) and diverged trajectories (RMSE: 0.0184, MAE: 0.0189). These results confirm the system's ability to align the ship's trajectory with the baseline, even under challenging conditions.

In terms of control performance, the FLC consistently outperforms traditional PID controllers, particularly in speed control. The FLC achieves an RMSE of 1.6648 knots for SOG and 28.3427 degrees for COG, compared to 5.7504 knots for SOG with PID control. Additionally, the FLC achieves a significantly lower MAE of 1.3212 knots for SOG, highlighting its adaptability to real-time disturbances. While the divergence-based approach shows moderate performance, particularly in mitigating COG deviations, it fails to match the precision and stability of the hybrid EKF-FLC framework, especially in speed control.

The iterative process of the hybrid system—where the FLC provides real-time corrections to SOG and COG, and the EKF refines its predictions based on these corrections—is a key factor in its success. This feedback loop allows the system to dynamically respond to environmental disturbances, aligning the trajectory more effectively with the intended path. The results demonstrate that the hybrid system not only mitigates trajectory divergence but also maintains trajectory smoothness and minimizes control effort, making it a robust solution for autonomous maritime navigation.

These findings underscore the advantages of combining predictive capabilities with adaptive control mechanisms, highlighting the hybrid EKF-FLC approach as an effective framework for addressing trajectory prediction and correction challenges in complex maritime environments.

V. Conclusion

This paper presented a hybrid EKF-FLC system for autonomous ship navigation, demonstrating significant improvements in trajectory control accuracy under varying environmental conditions. The system achieved superior performance in both speed and course maintenance, reducing SOG errors to 1.6648 knots RMSE and maintaining COG errors at 28.3427 degrees RMSE, significantly outperforming traditional control methods, including standalone EKF. The standalone EKF achieved an RMSE of 5.7504 knots for SOG and 36.4282 degrees for COG, highlighting its limitations in handling environmental disturbances. The integration of EKF with FLC proved particularly effective, as evidenced by consistently lower error rates across all performance metrics. The system's ability to maintain low MAE values in both speed and course control further demonstrates its stability and reliability, making it well-suited for real-world maritime applications.

Future work will focus on incorporating additional environmental parameters, such as wind speed and current direction, into the control system. Further exploration will include integrating machine learning techniques to enhance the system's adaptability and decision-making. The framework will also be extended to handle more complex maritime scenarios, such as multi-vessel navigation or constrained waterways, while investigating the impact of varying vessel characteristics, including size and propulsion systems, on control performance. These advancements aim to further improve the efficiency and reliability of autonomous maritime navigation systems,

contributing to the development of smarter and more resilient transportation technologies.

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REFERENCES

[1] G. Welch and G. Bishop, "An Introduction to the Kalman Filter," in *Proc. SIGGRAPH Course Notes*, Los Angeles, USA, 2001.

[2] Y. Wang, S. Chai, and H. Nguyen, "Experimental and Numerical Study of Autopilot Using Extended Kalman Filter Trained Neural Networks for Surface Vessels," *International Journal of Naval Architecture and Ocean Engineering*, vol. 12, pp. 314–324, 2020. DOI: 10.1016/j.ijnaoe.2019.11.004.

[3] D. Loebis, R. Sutton, and J. Chudley, "A Fuzzy Kalman Filter for Accurate Navigation of an Autonomous Underwater Vehicle," *IFAC Proceedings Volumes*, vol. 36, pp. 157–162, 2003. DOI: 10.1016/S1474-6670(17)36674-0.

[4] R. Liu, Maohan Liang, Jiangtian Nie, et al., "Deep Learning-Powered Vessel Trajectory Prediction for Improving Smart Traffic Services in Maritime Internet of Things," *IEEE Transactions on Network Science and Engineering*, vol. 9, no. 5, pp. 3080–3094, 2022. DOI: 10.1109/TNSE.2022.3140529.

[5] X. Li, J. Wang, X. Li, and J. Yan, "Optimal Trajectory Tracking for Cyber-Physical Marine Vessel: Reinforcement Learning Approach," *2020 16th International Conference on Control, Automation, Robotics and Vision (ICARCV)*, pp. 1230–1235, 2020. DOI: 10.1109/ICARCV50220.2020.9305422.

[6] M. Raza, H. Prokopova, S. Huseynzade, et al., "Towards Integrated Digital-Twins: An Application Framework for Autonomous Maritime Surface Vessel Development," *Journal of Marine Science and Engineering*, vol. 10, no. 10, Oct. 2022. DOI: 10.3390/jmse10101469.