2025 IEEE/SICE International Symposium on System Integration (SII)
January 21-24, 2025, Munich, Germany

Integration of AIS Data for Efficient Drone Navigation in Maritime Real-Time Ship Inspection Missions

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***Abstract*—The increasing use of drones for maritime inspections in near-coastal areas has highlighted the need for more sophisticated tools that can assist operators in optimizing mission planning and flight paths. Despite advancements in drone technology, challenges remain in efficiently combining available data to enhance range, increase available inspection time, and overall mission effectiveness. This paper proposes a novel application that integrates Automatic Identification System (AIS) data into the drone navigation and mission planning process. By leveraging real-time AIS data, including ship positions, speeds, and headings, the system provides dynamic waypoint suggestions to operators, facilitating more precise and efficient path planning. Additionally, the integration of wind correction factors into the flight planning algorithm further enhances battery management, allowing for extended mission durations. Through simulations and real-world experiments, the proposed system demonstrates significant improvements in mission planning efficiency, drone range, and inspection time, offering a promising solution for the growing demands of maritime inspections.**

Keywords—AIS Data, MissionPlanner, Maritime, UAV

I. INTRODUCTION

As the maritime industry increasingly embraces greener and more sustainable practices [1], the need for rigorous pollution control inspections has become more critical than ever. Ensuring that ships adhere to environmental regulations is vital for protecting marine ecosystems and reducing the industry's carbon footprint. In this effort, Unmanned Aerial Vehicles (UAVs), or drones, have proven to be indispensable tools. Their versatility, speed, and ability to access hard-to-reach areas make them ideal for swiftly assessing potential pollution sources on ships and conducting essential measurements [2].

Despite their numerous advantages, drones face significant limitations that can hinder the effectiveness of maritime inspections. A primary challenge is their limited battery life, which is further constrained by the heavy payload equipment required for pollution monitoring. This limitation directly reduces the available time for inspections, making it crucial to optimize every aspect of the drone's mission. Typically, drones are launched from the coast and visually guided to the target ship. However, this manual approach often results in suboptimal flight paths [3] that fail to account for the ship's movement and environmental factors such as wind, leading to increased flight time and reduced efficiency.

To overcome these challenges, this paper investigates the integration of AIS data into drone mission planning software. AIS data provides real-time information on the location, speed, and heading of ships, which can be used to dynamically adjust the drone's flight path. By automating the navigation process and incorporating corrections for ship movement and wind conditions, the proposed system aims to minimize reliance on visual navigation and optimize the drone's flight path. This approach not only reduces unnecessary flight time but also enhances battery management [4], allowing for more comprehensive and efficient inspections.

The synergistic utilization of data from sources such as AIS providers enables more effective monitoring of maritime activities. This data fusion enhances situational awareness, allowing for more precise tracking of vessel movements, early detection of potential compliance violations, and optimized planning of inspection missions. The outcome is a more efficient and proactive approach to maritime monitoring, contributing to improved safety, security, and environmental protection within the maritime domain. Through the integration of AIS data and advanced flight path planning, this research seeks to enhance the operational efficiency of drones in maritime pollution inspections, thereby supporting the broader goal of a greener and more sustainable maritime industry.

II. LITERATURE REVIEW

A. UAV Applications in Maritime Inspections

The use of UAVs for monitoring ship emissions has become increasingly important due to the need for efficient pollution assessment in maritime activities. UAVs, equipped with advanced sensors, can remotely sense pollutants like SOx, NOx, and PM, providing real-time data crucial for regulatory compliance and environmental monitoring. They offer a cost-effective alternative to traditional methods, with the added advantage of accessing hard-to-reach areas like busy shipping lanes and ports. The integration of UAVs with data analytics and machine learning further enhances their effectiveness [5], making them a valuable tool for reducing the environmental impact of ship emissions.

B. AIS Data Utilization

A study [6] on the Port of Naples investigates emissions by integrating local-scale measurements with AIS data, demonstrating the effectiveness of correlating pollutant concentrations with maritime traffic. Similarly, research on the Port of Klaipeda [7] uses AIS data to estimate air pollution, caused by ship emissions offering a detailed analysis based on ship types and operational activities. Additionally, a study [8] on emissions monitoring at the Port of Tianjin developed a high temporal-spatial ship emission inventory using a “bottom-up” method based on AIS data by combining localized emission factors. Moreover, as Huan et al. [9] state, AIS-based models can be prepared for automatic operation and, in the future, perform accounting automatically.

C. Gap Analysis

While AIS data is commonly used to generate pollution inventory maps and estimate emissions from maritime traffic, its application in enhancing UAV navigation for real-time gas monitoring missions remains largely unexplored [10]. Traditional approaches focus on static analysis of ship emissions, without considering how AIS data can be dynamically integrated into UAV operations to optimize flight paths and improve monitoring efficiency.

Our proposed research aims to fill this gap by using AIS data to guide UAVs more accurately during gas monitoring missions. This innovation could significantly enhance the efficiency of UAV operations, reducing flight time and energy consumption while increasing the accuracy and coverage of emission data collection. Additionally, leveraging real-time AIS data to adjust UAV flight paths based on current maritime traffic could provide a more responsive and effective method for pollution monitoring and regulatory enforcement in maritime environments.

III. AIS DATA

AIS is an automated tracking system primarily used in maritime environments to monitor the location, speed, and course of vessels. Each ship equipped with AIS transmits this data regularly, which includes not only positional information but also vessel identification, type, and other relevant navigational details. AIS data is crucial for enhancing maritime safety, managing vessel traffic, and supporting environmental monitoring efforts, as it provides real-time and historical insights into ship movements, enabling detailed analysis and decision-making in various maritime operations.

A. AIS Data Providers

AIS data providers play a crucial role in collecting, processing, and distributing real-time and historical AIS data from ships worldwide. These platforms utilize a vast network of satellites and terrestrial receivers to track vessel movements, offering a range of services such as detailed vessel information, predictive analytics, route optimization, and environmental monitoring. In this study, we utilize the AISStream.io API [11] due to its free access to real-time AIS data, which is crucial for enhancing the navigation of UAVs during gas monitoring missions. By integrating AIS Data Stream, we can precisely track maritime traffic, allowing our UAV to optimize their flight paths for efficient coverage and accurate data collection. This integration supports our goal of improving the effectiveness and efficiency of pollution monitoring in maritime environments without incurring additional costs, making it a practical and cost-effective solution for real-time environmental monitoring.

B. Data Processing

Processing AIS data for UAV missions requires an efficient algorithm due to the vast amount of ship tracking information available. To optimize performance, our algorithm dynamically filters the AIS data based on the UAV's position, retrieving only the ships within a 25 nautical mile radius. This targeted approach not only reduces the data load but also ensures that the UAV focuses on large vessels like tanker or cargo ships, which are more likely to be significant sources of gas pollution.

In addition to identifying nearby ships, the algorithm also gathers essential navigational and operational details such as the speed, heading, engine type, and vessel size. These characteristics are crucial for determining the potential emission levels of each ship, allowing the UAV operator to prioritize monitoring targets more effectively. By combining this detailed AIS data with real-time UAV positioning, the system operator can conduct more accurate and efficient pollution monitoring missions in maritime environments. This process is specifically designed to detect polluters, enabling targeted interventions and ensuring that the most significant sources of emissions are addressed promptly, even in cases where the user chooses not to proceed with preplanned inspections.

TABLE I. RETRIEVED AIS DATA

Data	Data Type
Ship Name/ID	Unique identifier for the ship.
Position	Current coordinates of the ship.
Speed	Current speed of the ship.
Heading	Current heading or direction of the ship.
Ship Size	Physical dimensions of the ship.
Engine Type	Type of engine used by the ship

Ship Type	Category of the ship
Destination Port	Intended destination port
Estimated Time of Arrival	Estimated time of arrival at port.
Current Status	Current operational status of the ship.

IV. Flight Path Correction

A. Challenges

Implementing flight path correction for UAVs using AIS data presents several challenges that must be carefully addressed to ensure effective and efficient operations. Real-time data processing is essential but can be demanding, as the UAV needs to handle large volumes of AIS information quickly to make timely adjustments. Moreover the low update rate presents another significant challenge, as any delay in receiving updated information can result in outdated flight path corrections, thereby reducing the accuracy of the UAV's monitoring efforts.. Additionally, environmental factors such as strong winds or adverse weather conditions can impact both the UAV's stability and the precision of AIS data, complicating the correction process. Moreover, integrating flight path adjustments with collision avoidance systems adds complexity, requiring sophisticated algorithms to navigate safely while maintaining the mission's objectives. Finally, frequent path corrections can increase energy consumption, potentially limiting the UAV's operational range and mission duration, while ensuring data integrity and security [12] is crucial to prevent disruptions caused by corrupted or spoofed AIS data.

B. Moving Target Navigation Guidance

Pursuit and intercept navigation are two distinct approaches used in tracking and engaging moving targets, each with its own strategic applications. In pursuit navigation, the drone continuously adjusts its heading so that its velocity vector always points directly at the moving ship. While this mode ensures that the drone is always oriented towards the target, it comes with significant drawbacks. One major disadvantage is that, in most scenarios, this guidance method will eventually bring the drone into a tail-chase situation, especially towards the end of the flight. This tail-chase scenario often requires the drone to fly longer distances, increasing the risk of depleting its battery before reaching the target. Additionally, pursuit course mode demands more frequent and intense maneuvering from the drone compared to other guidance laws, such as intercept guidance [13], which could lead to inefficient flight patterns and increased energy consumption, further complicating the mission's success.

In contrast, intercept navigation involves predicting the future position of the target and navigating directly towards that point. This method is more efficient, as it typically results in a shorter engagement time by anticipating where the target will be rather than where it currently is. Intercept navigation requires accurate calculation of the target's speed, direction, and any changes in its movement, allowing the drone to meet the target at a predetermined location rather than simply following behind it. The advantages of intercept navigation is evaluated by many research works [14] [15] and a simplified visualized example can be found in Fig.1.

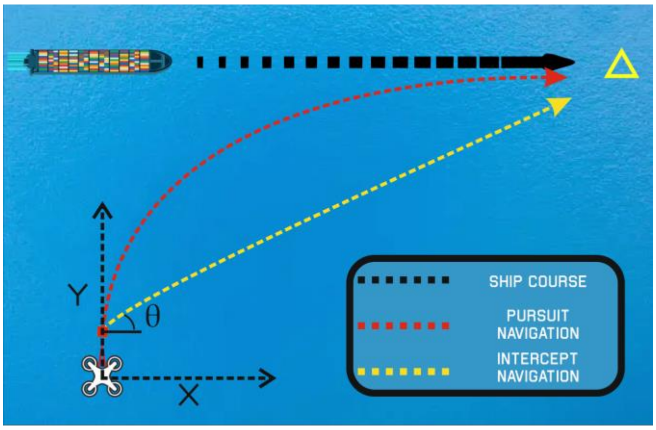

Fig. 1. Pursuit vs Intercept Navigation

C. Intercept Navigation Algorithm

The intercept algorithm developed for our framework is designed to optimize the drone's navigation towards a moving target, such as a ship, by dynamically calculating the most efficient path based on real-time and periodically updated AIS data. The algorithm takes into account the target ship's position, heading, and speed, as well as the drone's own location, ground speed, and heading, to determine an initial intercept point. The intercept point function transforms geographic coordinates into a local Cartesian system (ENU), perform intercept calculations, and then convert the results back to latitude and longitude.

For both the drone and the ship, their velocities are decomposed into x (East) and y (North) components using their speed and heading (1) (2).

$$v_{speed\_x} = v_{speed} \times \cos(\Theta_{heading}) \tag{1}$$

$$v_{speed\_y} = v_{speed} \times sin(\Theta_{heading}) \tag{2}$$

The function calculates relative velocity (3) and position (4) as its crucial for determining the intercept point.

$$v_{relative\_x} = v_{drone\_speed\_x} - v_{ship\_speed\_x} \tag{3}$$

$$\Delta_{relative\_x} = x_{ship\_position} - x_{drone\_position} \tag{4}$$

The time to intercept is derived from relative positions and velocities (5).

$$t_{intercept} = \frac{\Delta_{relative\_x} \times v_{relative\_x} + \Delta_{relative\_y} \times v_{relative\_y}}{v^2_{relative\_x} + v^2_{relative\_y}} \tag{5}$$

Finally, by determining the time to intercept, we calculate the intercept point's ENU coordinates. These coordinates can then be converted back to WGS84 latitude and longitude, allowing seamless integration into the drone's navigation system for precise and efficient guidance.

This approach allows the drone to maintain an optimal path towards the intercept point, minimizing deviations as it closes the distance to the moving target. One of the key strengths of this algorithm is its ability to maintain a relatively stable intercept point between AIS updates, despite the lower update rate of AIS data. This stability is largely due to the relatively constant speed and heading of large ships, which minimizes significant changes in the intercept point during the intervals between data updates. However, this reliance on stable ship movement could be a limitation if unexpected changes in ship behavior occur, potentially necessitating more frequent adjustments or predictive modeling to further refine the intercept calculations. Overall, the algorithm effectively balances the need for real-time responsiveness with the practical constraints of AIS data transmission rates, leveraging precise calculations of intercept angles to enhance the accuracy and efficiency of the drone's navigation.

D. *Wind Correction*

The algorithm incorporates wind correction by utilizing the drone's ground speed and ground track, ensuring that these variables are accurately adjusted for wind effects. The wind data is directly measured through the drone's Inertial Measurement Unit (IMU), allowing real-time compensation for wind disturbances. This approach, as demonstrated in previous work [16], ensures that the drone maintains a precise flight path, even in challenging wind conditions, ultimately improving the accuracy and reliability of the intercept and pursuit maneuvers.

V. Simulation Results

For our simulations, we utilized generated AIS data from two different ship types: a Carrier with an average speed of 10 m/s and a Tanker with an average speed of 7 m/s [17]. The drone's initial conditions were consistent across all scenarios, starting airborne at a speed of 25 m/s with its heading vector directed at the ship's location. To control the drone and implement our algorithm, we developed a Ground Control Station (GCS) software [18] that uses MAVLINK messages to manage the drone's operations.

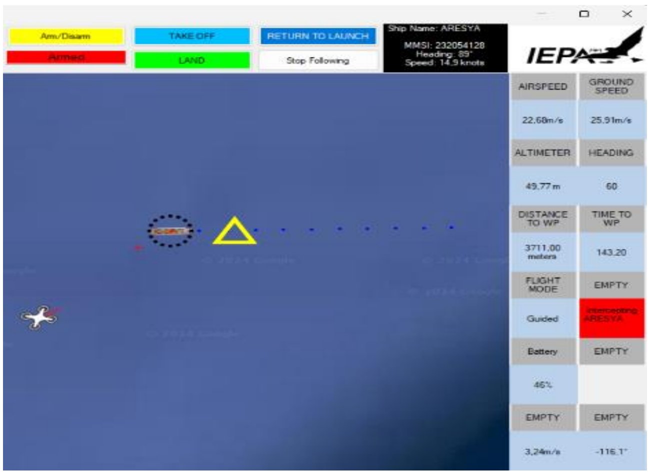

Fig. 2. IERAX Ground Control Station GUI Intercept Phase

The drone itself was simulated using Software In The Loop (SITL), allowing us to accurately replicate flight dynamics and evaluate the algorithm's performance. Additionally, we simulated (Fig. 2) various ship heading cases, such as the ship heading offset 30 to 60 degrees away or being exactly 90 degrees to the drone, providing a comprehensive test of the algorithm under different maritime conditions.

The comparative analysis of the Pursuit and Intercept algorithms as shown in Table II, reveals a clear advantage for the Intercept method in drone navigation towards a moving ship. The Intercept algorithm consistently demonstrates greater efficiency, achieving shorter travel times and distances across various ship headings and speeds. For instance, at a 30° offset heading with the ship moving at 10 m/s, the intercept method reaches the target 25 seconds faster (160 seconds vs. 185 seconds) and covers 613 meters less distance (4012 meters vs. 4625 meters) compared to the pursuit method. The most significant improvement is observed at a 90° offset heading with the ship at 10 m/s, where the intercept method cuts 23 seconds off the time to target (125 seconds vs. 148 seconds) and reduces the distance traveled by 575 meters (3125 meters vs. 3700 meters).

In terms of efficiency, the intercept method shows a reduction in travel distance ranging from approximately 4% to 13%, with time savings of up to 15%. These efficiency gains become even more pronounced in scenarios involving greater distances or drones with lower speeds, where the advantages of predicting the target's future position rather than chasing its current position are magnified. For such scenarios, the intercept method could potentially offer even greater reductions in time and distance, making it an even more effective strategy for optimizing drone navigation.

The results underscore the importance of using predictive and real-time calculations in navigation, particularly in dynamic environments. Overall, the Intercept algorithm is a more reliable and effective strategy for ensuring timely and resource-efficient mission completion.

TABLE II. SIMULATION RESULTS

SHIP DATA		**PURSUIT**		**INTERCEPT**	
Offset Heading	***Speed (m/s)***	***Time to Target (sec)***	***Distance (m)***	***Time to Target (sec)***	***Distance (m)***
30	10	185	4625	160	4012
45	10	157	3925	153	3835
60	10	149	3725	145	3613
90	10	148	3700	125	3125
30	7	200	5000	189	4736
45	7	191	4775	177	4435
60	7	172	4300	163	4064
90	7	154	3850	131	3273

VI. Conclusion

The simulation results between pursuit and intercept navigation through AIS data, have demonstrated the potential for greater efficiency and reduced travel time to the area of interest. By accurately predicting the ship's movement and optimizing the drone's flight path, this approach could significantly enhance the drone's ability to perform inspections more effectively, making it a valuable component of future navigation strategies. For future work, we plan to explore the implementation of intercept navigation as an alternative to the current pursuit manual course mode, particularly in scenarios where AIS data may not be available. Leveraging machine vision techniques, as discussed in recent research [19], could enable the drone to visually track the ship and predict the meeting point, providing a more efficient and less maneuver-intensive approach. This integration of machine vision could enhance the drone's ability to maintain optimal flight paths, reduce energy consumption, and improve overall mission success, even in the absence of reliable AIS data. Additionally, our Ground Control Station (GCS) software is open access, as to allow future researchers to build upon our work and optimize their missions, particularly in the area of maritime pollution monitoring, where efficient and effective drone navigation is crucial.

Acknowledgment

The present work was undertaken in the context of the "Aerial Surveillance and Measurement of Vessel Emissions Around Ports" (IERAX) co-¬financed by the European Union and Greek national funds through the Operational Program Attica (project code: ATTP4-0346379).

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