A Suspicious Transshipment Detection Framework with AIS Data Adaptive Reconstruction

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***Abstract*—Effective vessel tracking and the identification of unusual behaviors are crucial for maritime security, particularly in detecting loitering activities that may signal potential illicit operations. This paper introduces an innovative framework for detecting suspicious transshipment activities using Automatic Identification System (AIS) data. Our approach combines AIS data reconstruction and behavior classification to detect loitering and coordinated vessel movements, even when AIS data is incomplete or missing. Experimental results demonstrate the effectiveness of this foundation in identifying suspicious maritime activities such as transshipment and loitering behaviors.**

***Index Terms*—Automatic Identification System (AIS), Loitering Vessel Detection, Vessel Tracking, AIS Reconstruction, Illegal Transshipment**

I. Introduction

The maritime industry plays a critical role in global trade, but it faces increasing challenges from illegal activities such as Illegal, Unreported, and Unregulated (IUU) transshipment, loitering, fishing, piracy, and smuggling [1]. Among these, detecting illicit transshipment and loitering behaviors is essential for ensuring maritime safety and security. Traditional surveillance systems, which heavily rely on manual observation, often fail to detect these abnormal behaviors in real-time, necessitating more effective automated solutions.

Vessel tracking is a cornerstone of maritime navigation, ensuring the safety of vessels and enhancing the efficiency of port operations, search and rescue missions, and overall maritime traffic management. The Automatic Identification System (AIS) plays a central role in this process by providing real-time data on vessel location, speed, course, and other vital parameters [2]. However, raw AIS data often suffers from gaps, noise, and irregularities, making accurate trajectory prediction and behavior detection challenging, especially when data is missing or sparse.

In the last few decades, the expansion of maritime activities has raised significant concerns about Maritime Surveillance (MS) and Maritime Situational Awareness (MSA), with vessel trajectory reconstruction emerging as a key focus [3]. The ability to reconstruct a vessel's position and movement direction over time (from several minutes to several hours) is essential for various MSA and MS applications, including traffic control, route planning, and collision avoidance in congested port environments.

This paper proposes a novel framework for detecting illegal transshipment and loitering behaviors by combining AIS data reconstruction with trajectory forecasting. Our method can accurately track vessel movements and detect suspicious behaviors even in the presence of incomplete or noisy AIS data. By integrating AIS data reconstruction and behavior detection, we provide a robust solution for real-time anomaly detection, offering significant improvements over traditional and existing methods.

The key contributions of this study are:

- A novel framework for detecting suspicious transshipment activities.
- Capability to handle incomplete or noisy AIS data, a common challenge in maritime surveillance.
- Experimental validation demonstrating the robustness and accuracy of our method in identifying transshipment and loitering behaviors in real-world maritime environments.

The remainder of this paper is organized as follows. Section II reviews related work and current limitations in AIS-based trajectory prediction. Section III introduces the proposed method and architecture. Section IV presents our experimental results, and Section V concludes with a discussion of future directions and potential improvements.

II. Problem Statement and Related Work

A. Problem Statement

Detecting suspicious illegal transshipment and loitering behaviors is a critical challenge for Maritime Situational Awareness (MSA) and Surveillance (MS) [4]. Such activities often involve vessels remaining stationary for extended periods, moving slowly in close proximity to other ships, or coordinating along-side maneuvers to transfer cargo or catch at sea. These behaviors are difficult to identify in real-world scenarios due to incomplete, noisy, or sparse AIS data, which

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can occur when vessels turn off transponders, move through low-coverage areas, or experience transmission delays.

The primary goal of this work is to accurately identify these suspicious behaviors by reconstructing missing trajectory data and analyzing vessel movements. Let $X_T = \{X_1, X_2, \ldots, X_T\}$ represent the historical AIS trajectory of a vessel over T time steps. The task is to reconstruct any missing or unreliable segments in this trajectory and then predict or classify vessel behavior over the subsequent L time steps, denoted $\hat{Y}_L$, using the reconstructed data:

$$[X_1, X_2, \ldots, X_T] \rightarrow [\tilde{X}_1, \tilde{X}_2, \ldots, \tilde{X}_T] \rightarrow \hat{Y}_L \quad (1)$$

Here, $\tilde{X}_t$ represents the reconstructed trajectory points that correct gaps or errors in the original AIS data. The reconstructed trajectories serve as a foundation for detecting three types of suspicious transshipment behaviors:

1) **Rendezvous Transshipment**: Detecting vessels that loiter or stay stationary, indicating potential cargo transfer.
2) **Moving Transshipment**: Identifying vessels moving slowly in close proximity, suggesting rendezvous behavior.
3) **Along-Side Transshipment**: Detecting vessels moving in coordination, analyzing their spatial and temporal alignment.

By integrating adaptive trajectory reconstruction, along with behavior classification for stopping, moving, and along-side events, this method addresses the challenges posed by incomplete AIS data and provides a robust framework for real-time detection of suspicious illegal transshipment activities. This problem formulation emphasizes both data integrity and behavioral analysis, making it suitable for monitoring vessels in complex and sparsely covered maritime environments.

B. Related Work

Several methods have been proposed to detect suspicious illegal transshipment and loitering behaviors, which are crucial for maritime security [5]–[9]. These approaches can be categorized into rule-based systems, machine learning models, and hybrid methods.

Vasudevan et al. used machine learning (ML) models with spatial-temporal data, such as AIS signals, to detect transshipment events [6]. Their ensemble classifiers, like Extra Trees and Random Forests, achieved high accuracy (F1 score of 0.998). However, their approach faces challenges, including interruptions in AIS signals when vessels turn off their transponders and regulatory complexities, particularly in regions with weak enforcement. Additionally, the method does not address the common issue of incomplete AIS data, which is prevalent in real-world maritime environments.

Miller et al. employed a rules-based method to identify two main transshipment behaviors: "two-vessel encounters" and "single-vessel loitering [7]." While their approach captures basic behavior patterns effectively, it does not address the problem of noisy or missing AIS data, leading to potential false negatives. Furthermore, their method lacks a unified solution for classifying behaviors in the real-world scenario.

Deng et al. proposed a hybrid model combining rule-based systems and unsupervised learning, incorporating traffic density as a feature to reduce misidentifications, especially in high-traffic areas [8]. Despite this, their approach relies on static thresholds, making it less adaptable to dynamic maritime environments and varying sea conditions.

Zhou et al. focused on ship behavior classification based on port visits, identifying coopering behaviors that may signal illegal activities [9]. While effective for detecting certain behaviors in fishing vessels, their method is limited to fishing vessels and lacks integration with AIS data reconstruction techniques, struggling with real-time detection of incomplete data in remote maritime areas.

In contrast, our method offers a comprehensive framework applicable to a wide range of scenarios, integrating AIS data reconstruction, and behavior detection classification. Key innovations include addressing missing or noisy AIS data through interpolation methods, enabling precise trajectory reconstruction. Additionally, our system detects loitering, moving, and along-side behaviors, providing a more flexible and detailed detection system compared to methods that rely solely on proximity or speed thresholds.

Additionally, we incorporate traffic density as a modulating factor to minimize false positives, especially in high-traffic areas like ports, and remove near-coastline trajectory data where vessels are stationary at the port [10]. By applying unsupervised clustering to dynamically adjust thresholds based on specific sea areas, our approach is more flexible and scalable across diverse maritime environments. This comprehensive framework addresses the limitations of existing methods, offering a robust and accurate solution for detecting illegal transshipment activities.

III. Proposed Model

A. AIS Data Reconstruction

To address anomalies and fill in missing trajectory segments in AIS data, this approach utilizes short-distance and long-distance interpolation techniques, ensuring data continuity and accuracy across varying time gaps.

1) Kinematic Trajectory Interpolation: For small gaps between data points, we apply a Kinematic Interpolation technique. The trajectory is projected onto a 2D plane, and the vessel's velocity components in the east-west ($u_{p,m}$) and north-south ($v_{p,m}$) directions are calculated using the speed over ground (SOG) and course over ground (COG):

$$u_{p,m} = \mathrm{SOG}_m \cdot \sin(\mathrm{COG}_m) \quad (2)$$

$$v_{p,m} = \mathrm{SOG}_m \cdot \cos(\mathrm{COG}_m) \quad (3)$$

The displacement ($\Delta_x(\Delta\tau)$) and velocity ($v_x(\Delta\tau)$) in each direction $x \in \{p, m\}$ after a time interval $\Delta\tau$ are calculated using kinematic equations:

$$\Delta_x(\Delta\tau) = v_{0x} \cdot \Delta\tau + \frac{1}{2} a_x \cdot \Delta\tau^2 \quad (4)$$

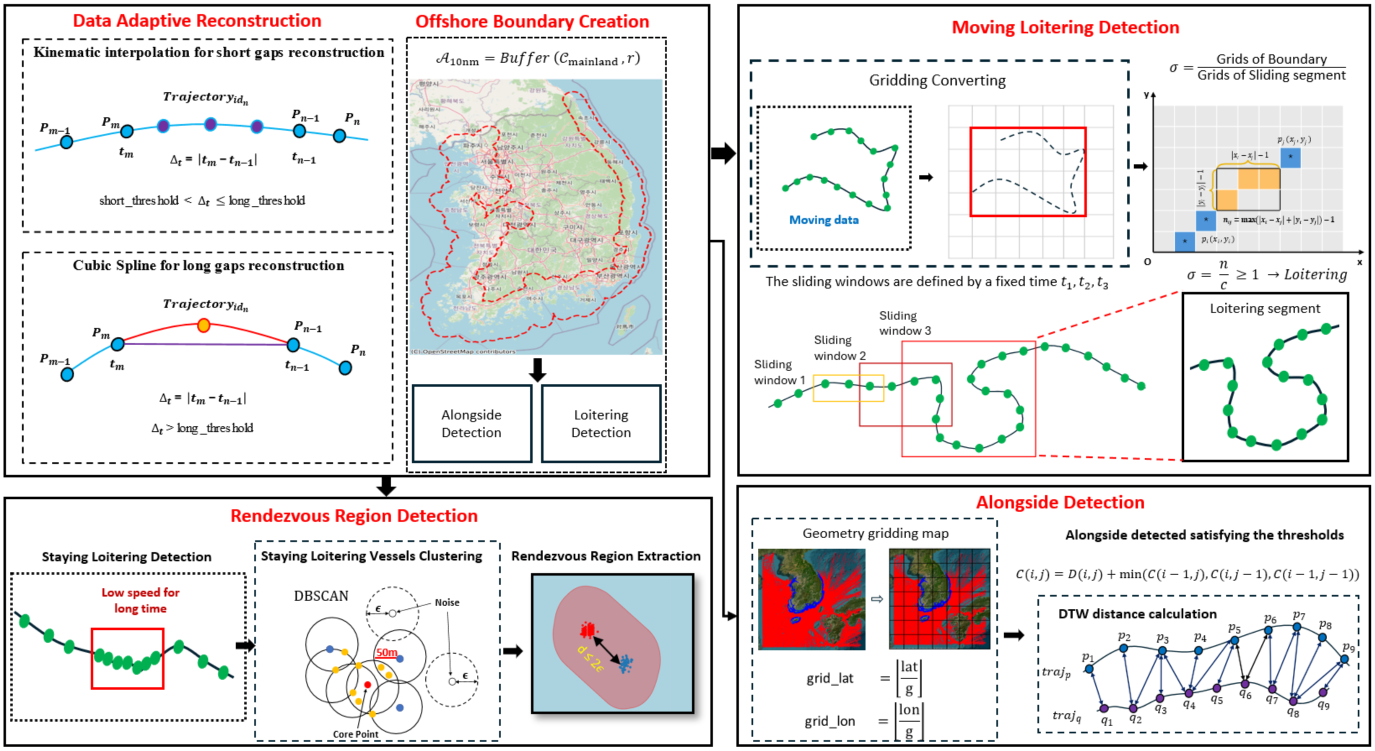

Fig. 1: Proposed framework for detecting illegal transshipment and loitering behaviors using adaptive AIS data reconstruction. The system integrates advanced techniques for detecting **Rendezvous Transshipment**, **Moving Transshipment**, **Along-Side Transshipment**.

Where a_x is the constant acceleration assumed during the missing segment. For each interpolation, the error between the simulated and actual end points is calculated as:

$$\epsilon_x = S_{\text{model}} - S_{\text{real}} - \Delta_x(\Delta\tau) \tag{5}$$

This error is then corrected using an adjustment function:

$$C_x(\Delta\tau) = a_x \cdot \Delta\tau^3 + b_x \tag{6}$$

Where b_x is derived from the cumulative error, and the final interpolated position is:

$$S_x(T) = S_{0x} + \Delta_x(\Delta\tau) + C_x(\Delta\tau) \tag{7}$$

2) Cubic Spline Trajectory Interpolation: For larger gaps, we utilize historical data from similar vessels. First, potential candidate trajectories (traj_p) are selected based on their spatial and temporal proximity. The similarity between the target trajectory (traj_q) and each candidate is assessed using Dynamic Time Warping (DTW):

$$\begin{aligned}\varphi(i,j) = d(a_i,b_j) + \min\big(&\varphi(i-1,j-1),\\ &,\varphi(i-1,j),\varphi(i,j-1)\big)\end{aligned} \tag{8}$$

Where $d(a_i, b_j)$ represents the Euclidean distance between two trajectory points a_i and b_j, and $\varphi(i,j)$ is the cumulative cost matrix. The optimal alignment is then determined by:

$$DTW(\text{traj}_r, \text{traj}_q) = \varphi(p,q) \tag{9}$$

Once the most similar trajectory is identified, missing trajectory points are reconstructed using Spline Interpolation for both the X and Y coordinates:

$$X(\theta) = \text{Spline}(t, X), \quad Y(\theta) = \text{Spline}(t, Y) \tag{10}$$

Time scaling is applied to adjust for the duration of the missing segment:

$$\theta' = \beta \cdot (T_r - T_0) \tag{11}$$

Where $\beta = \Delta T_{\text{candidate}}/\Delta T_{\text{target}}$ is the scaling factor. The final interpolated coordinates are computed as:

$$X' = \text{Spline}_X(\theta') + X_0, \quad Y' = \text{Spline}_Y(\theta') + Y_0 \tag{12}$$

Reprojecting these coordinates into the WGS84 coordinate system, we obtain the reconstructed positions $(\text{lon}_q, \text{lat}_q)$.

3) Adaptive Reconstruction Framework: The adaptive reconstruction framework addresses both short and long distance gaps in AIS data, ensuring accurate interpolation and maintaining trajectory continuity. It uses different interpolation methods for short and long gaps based on the time difference between consecutive points.

For short gaps, where Δt is small, kinematic-based interpolation is applied, effectively handling the vessel's short-term dynamics. For long gaps, with Δt exceeding the short gap threshold, historical trajectory migration with cubic spline interpolation is used to estimate intermediate points.

The time constraints for Kinematic-based interpolation are as follows:

$$\text{short\_threshold} \leq \Delta t \leq \text{long\_threshold} \tag{13}$$

The time constraints for Cubic Spline interpolation are as follows:

$$\Delta t > \text{long\_threshold} \tag{14}$$

The thresholds short_threshold and long_threshold determine which method to use, ensuring accurate reconstruction across varying time gaps.

This framework efficiently reconstructs missing data, preserving trajectory continuity and temporal resolution for reliable anomaly detection in maritime environments.

B. Suspicious Transshipment Detection

1) Offshore Boundary Creation: The offshore boundary is defined to specify valid maritime areas for anchoring behavior classification. Coastline data, represented as a set of points $c = \{c_i\}_{i=1}^{N}$, is obtained from a GeoJSON file. We filter the coastline by length, retaining only segments longer than a threshold L_{min}, forming mainland seed segments $S_{\cup}$:

$$S_{\cup} = \{c_i \mid \text{Length}(c_i) > L_{\text{min}}\} \tag{15}$$

Next, a buffer zone B_{main} with a radius of $r = 10\,\text{nm}$ is applied around the mainland segments to mark areas where anchoring behavior is valid:

$$B_{\text{main}} = \left\{ x \in \mathbb{R}^2 \;\middle|\; \min_{s \in S_{\cup}} \|x - s\| \leq r \right\} \tag{16}$$

This approach ensures that only relevant mainland regions are considered for further analysis, providing a robust classification for anchoring activities.

2) Rendezvous Transshipment Detection: Rendezvous transshipment detection focuses on identifying vessels exhibiting loitering behaviors that may indicate transshipment activities. This process involves tracking the movement trajectories of vessels to detect suspicious rendezvous events, where vessels meet in close proximity for extended periods.

The detection begins by defining an Arrival Region around the mainland coastline. This region is represented by a buffer zone with a radius of 10 nautical miles (nm), marking the area of interest for detecting offshore loitering vessels:

$$A_{10\text{nm}} = \left\{ x \in \mathbb{R}^2 \;\middle|\; \min_{c \in C} \|x - c\| \leq r \right\}, \quad r = 10\,\text{nm} \tag{17}$$

Where r denotes the distance from the coastline, typically set to 10 nm, which forms the boundary for the offshore area [11].

Moving vessel trajectories are then extracted and analyzed to identify loitering behavior, characterized by vessels moving slowly and remaining in the same area for extended periods. Loitering behavior is detected by segmenting the trajectory and examining the vessel's movement. If the vessel's speed falls below a predefined threshold and the trajectory shows minimal movement over a given period, the vessel is flagged as loitering.

After detecting loitering vessels, clusters of vessels that remain within close proximity (e.g., within 100 meters) for an overlapping time window (e.g., 1 hour) are identified using the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm [6]. This clustering groups vessels based on spatial proximity and temporal overlap. A minimum of two vessels is required to form a valid rendezvous event.

Upon identifying a rendezvous cluster, the convex hull H_j of the cluster is computed to define the boundaries of the rendezvous region:

$$H_j = \text{ConvHull}\left(\{p_i\}_{i=1}^{n_j}\right), \tag{18}$$

where $\{p_i\}_{i=1}^{n_j}$ are the spatial positions of vessels in cluster j. A 25-meter buffer zone is added around the convex hull to form the final rendezvous region R_j:

$$R_j = H_j \oplus B(0, 25\,\text{m}), \tag{19}$$

where $\oplus$ denotes the Minkowski sum and $B(0, 25\,\text{m})$ is a disk of radius $25\,\text{m}$ centered at the origin.

This region is flagged as suspicious, indicating a potential location for illegal transshipment activities.

The detection results are visualized on maps that show the arrival regions, loitering vessels, and rendezvous areas. These visualizations assist in tracking and identifying suspicious vessels operating in close proximity, which could be involved in transshipment. Alerts are generated for any identified rendezvous areas, facilitating further investigation by maritime authorities.

3) Moving Transshipment Detection: Moving transshipment detection focuses on identifying vessels exhibiting low-speed movement over extended periods, which could indicate potential rendezvous activities between ships. This method uses a sliding window approach to analyze vessel trajectories, enabling the detection of suspicious rendezvous behavior, where vessels move along similar paths in close proximity.

First, geographical coordinates (latitude and longitude) are converted into a grid-based system to simplify vessel movement analysis and clustering. The conversion equations are:

$$x = \frac{360 \cdot (\text{lon} + 180)}{2^z}, \tag{20}$$

$$y = 2^{-1} \ln \left[\tan\left(\frac{\text{lat}}{180}\right) + \sec\left(\frac{\text{lat}}{180}\right) \right] \times 2^z \tag{21}$$

Where:

- x and y are the grid coordinates,
- lon and lat are the longitude and latitude of the vessel,

Table I: Trajectory Reconstruction RMSE (km) Comparison

Method	RMSE (km)
Linear Interpolation	0.271
Cubic Spline Interpolation	0.183
Kalman Filter (KF)	0.429
Extended KF	0.354
Ours	**0.161**

- z is the zoom level that determines the grid resolution.

The sliding window approach segments the vessel's trajectory into small time intervals. Each window $W_t = \{p_1, p_2, p_3\}$ consists of trajectory points, including the ship's MMSI, timestamp, latitude, longitude, speed, and heading. The sliding window moves across the data, tracking ship trajectories over time:

$$W_t = \{p_1, p_2, p_3\} \tag{22}$$

Where k is the number of trajectory points within the time window t. For this method, we consider time intervals of 1, 2, and 4 hours. The use of these time intervals helps detect both short- and long-term behaviors: a 1-hour window p_1 identifies immediate movements, a 2-hour window p_2 detects medium-duration behaviors, and a 4-hour window p_3 captures larger events or extended interactions.

Loitering is defined when the vessel's trajectory shows redundancy, suggesting the ship is moving in a repetitive or circular path, a common indicator of transshipment behavior. As shown in Figure 1, The redundancy σ is calculated as the ratio of the trajectory length n to the area of the minimum bounding rectangle c:

$$\sigma = \frac{n}{c} \tag{23}$$

Where:

- n is the total trajectory length,
- c is the area of the minimum bounding rectangle around the trajectory.

If $\sigma \geq 1$, the vessel is classified as loitering, suggesting potential transshipment activity.

This approach efficiently detects moving transshipment behavior by leveraging sliding window analysis, trajectory grid-based calculations, and the redundancy criterion.

4) Along-side Detection using Dynamic Time Warping (DTW): Along-side detection identifies potential transshipment events by analyzing the alignment and proximity of vessel trajectories over time. This is achieved using Dynamic Time Warping (DTW), which compares vessel trajectories in both spatial and temporal dimensions. The key steps in along-side detection are as follows:

First, the map is divided into smaller grid cells based on latitude and longitude, providing a structured way to analyze vessel movements. Each grid point is represented by a coordinate pair $(\text{grid\_lat}, \text{grid\_lon})$:

$$\text{grid\_lat} = lat/g, \quad \text{grid\_lon} = lon/g \tag{24}$$

Where g is the grid resolution factor, determining the size of each cell. DTW also used to compares segments of two vessel trajectories within a predefined time window. The Euclidean distance between points $A_i = (x_i, y_i)$ and $B_j = (x_j, y_j)$ is computed as:

$$D(i,j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{25}$$

The DTW algorithm aligns vessel trajectories by adjusting for time shifts, considering both spatial proximity and temporal overlap. Along-side transshipment is detected if:

- The DTW distance between segments is below 100 meters.
- The time difference between segments is less than 30 minutes.

If both conditions are met, vessels are classified as involved in along-side transshipment. The method uses gridding, buffering along the coastline, and DTW to detect suspicious transshipment events in maritime AIS data.

IV. Experimental Evaluation

A. Dataset Overview & Evaluation Metrics

We validate our approach on a large-scale AIS corpus from the Korean Exclusive Economic Zone (EEZ), spanning November 2023–March 2024. The dataset contains over 133,000 distinct voyages from fishing vessels, cargo ship — collected via AIS messages. Each record includes core fields (MMSI, timestamp, latitude, longitude, speed over ground, and course over ground). The mix of diverse trajectories and segments with missing transmissions enables a comprehensive assessment of our approach.

In terms of quantitative aspect, we adopt Root Mean Square Error (RMSE) metric to evaluate the core reconstruction modules. We have measured using RMSE based on the haversine distance between predicted and true vessel positions. The RMSE over a reconstructed trajectory is defined as:

$$\text{RMSE}_{\text{traj}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\delta_i^2} \tag{26}$$

where δ_i is the geodesic error (in km) at the i-th point and N is the number of reconstructed points. Lower RMSE values indicate more accurate trajectory estimation.

B. Results

Table I compares the performance of our method with baseline models, such as the Extended Kalman Filter (EKF). The results show a significant improvement in both the maximum and mean RMSE for vessel trajectory prediction.

Table I shows that our method has the lowest error (0.161 km). Relative to the baselines, RMSE decreases by 0.022 km vs. Cubic Spline (0.183 km), 0.110 km vs. Linear Interpolation (0.271 km), 0.193 km vs. EKF (0.354 km), and 0.268 km vs. KF (0.429 km). The pronounced gap between spline- and filter-based approaches indicates that simple kinematic models in (E)KF underfit the non-linear, irregularly

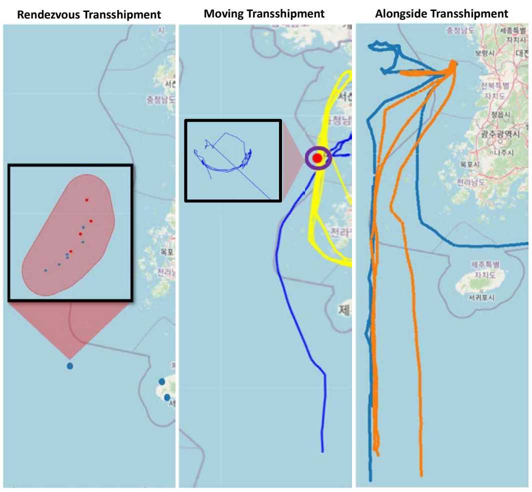

Fig. 2: Detected Suspicious Transshipment Visualization

sampled AIS trajectories, whereas our method better captures trajectory geometry and handles missing data.

The corpus spans 21,000 vessels across 133,787 voyages (mean $\approx$ 6.33 voyages/vessel). We detect 7,233 suspicious interaction instances in total. Rendezvous clusters (3,354; 2.51% of voyages) and moving loitering (3,285; 2.44%) occur at comparable rates (ratio ≈ 1.02), each about 25 rendezvous detections per 1,000 voyages and $\approx$ 24 moving vessels per 1,000 vessels. Alongside transshipment pairs are rarer (594; 0.45% of voyages; ≈ 4.47 per 1,000 voyages; 2.83 per 100 vessels), comprising only 8.21% of all detections. Overall, rendezvous slightly dominates, followed closely by moving loitering, indicating that cluster-based encounters are at least as prevalent as single-vessel loitering behaviors in this dataset.

The figure 2 shows visualizations of loitering and suspicious transshipment: *Rendezvous*—multiple vessels co-locate at low SOG; *Moving*—brief close-approach while underway with partial heading alignment; *Alongside*—near-parallel co-movement with tight lateral separation. The detector relies on proximity, kinematic alignment (COG/SOG), and temporal persistence, which explains the higher incidence of rendezvous and moving events compared with the stricter alongside pattern.

These experiments show that our reconstruction method outperforms common baselines, providing tighter paths with less drift under irregular sampling. The improved tracks enhance proximity/heading features, enabling more reliable detection of rendezvous, moving, and alongside events. While the detection framework shows high accuracy, further evaluation, such as cross-checking with satellite imagery, is needed to confirm the findings and ensure full certainty.

V. Conclusion

We presented a robust pipeline for detecting loitering and suspicious transshipment from AIS, combining trajectory reconstruction and downstream behavior analysis. Across large-scale EEZ data, the method yields markedly lower reconstruction error than classical filters (e.g., EKF) and interpolation baselines, producing tighter tracks that strengthen proximity/heading cues for encounter detection.

The approach is lightweight—linear in the number of points—and suitable for near-real-time monitoring at EEZ scale. A key limitation is sensitivity to severe AIS gaps and spoofed messages. In future work we will integrate auxiliary signals (e.g., weather, radar) and explicit multi-vessel interaction modeling, and refine the taxonomy and classification of complex behaviors to further improve reliability and interpretability.

Table II: Detection Outcomes (Normalized by Total Voyages)

Pattern	Count	% of Voyages
Moving loitering	3,285	2.47%
Alongside pairs	594	0.45%
Rendezvous clusters ($\geq$2 vessels)	3,354	2.52%
Total	**7,233**	–

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