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Data-Driven Analysis of Encounter Scenarios to Quantify COLREG-Compliant Autonomous Vessel Behavior

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As the maritime industry advances toward increased autonomy, it becomes essential to ensure that autonomous systems incorporate reliable and predictable collision and grounding avoidance algorithms. The safe and effective development of Maritime Autonomous Surface Ships (MASS) requires a deep, quantitative understanding of how human mariners navigate in complex, real-world traffic situations. While the International Regulations for Preventing Collisions at Sea (COLREG) provide a necessary legal and operational framework, their intentionally flexible and ambiguous language delegates the specifics of collision avoidance to the professional judgment of experienced navigators. To accurately reflect how COLREG is applied in practice, a data-driven approach that analyzes historical navigation behavior to model real-world decision-making is essential.

This paper presents a data-driven methodology for an automatic analysis of maritime encounter situations using historical Automatic Identification System (AIS) data to capture prevalent navigational practices. A case study is conducted in a specific region in Norway, identifying crossing encounters involving a ferry and another vessel, and the approach is designed to be scalable for application in other areas in future work. The identified encounter situations are further used to examine subsequent mariner maneuvers. In particular, we propose and compare several techniques for quantifying critical maneuver characteristics, including the predicted Distance at the Closest Point of Approach (DCPA), the resulting inter-vessel passing distance, and compliance with COLREG.

Applying this comprehensive framework to an extensive regional AIS dataset yields aggregate statistics that establish an empirical baseline of human collision avoidance behavior. These results provide valuable quantitative insights into how COLREG are interpreted in real-world scenarios and contribute to the assessment and assurance of autonomous vessel behavior with respect to COLREG compliance. Ultimately, this work contributes to bridging the gap between regulatory intent and practical seamanship, enabling the development and assurance of autonomous vessel behavior that supports safe, predictable, and seamless interaction with human operated maritime traffic.

Keywords: AIS data, COLREG, collision avoidance, autonomy, evaluation, maneuver analysis.

1. Introduction

In 1972, the International Maritime Organization (IMO) adopted the International Regulations for Preventing Collisions at Sea (COLREG) (IMO (1972)), establishing a comprehensive set of navigational rules that have guided seafarers worldwide for decades. However, regulations alone have not eliminated incidents at sea and research on collision avoidance methods remains highly relevant, as these technologies aim to reduce the number of incidents by enhancing vessel autonomy.

Increasing the level of autonomy in the maritime industry addresses the pressing challenge of a shortage of qualified personnel for marine operations onboard vessels (Hagen et al. (2023)). Furthermore, enhanced collision avoidance systems have the potential to significantly reduce incident rates, while higher degrees of autonomy may ultimately diminish, or even eliminate, the need for onboard crew (Pedersen et al. (2020)).

The concept of equivalent safety, meaning that autonomous systems must deliver a safety performance at least comparable to that of vessels operated by human crew, while simultaneously adhering to COLREG, remains a central topic of debate in current literature. This raises a critical question: How can such equivalence be measured?

The COLREG framework is inherently shaped by its origin as a set of rules written by humans for humans. For instance, Kristić and Žuškin (2024) demonstrates this by applying fuzzy logic to quantify the term “very large ship” based on expert navigational knowledge, emphasizing not only the complexity but also the extreme specificity involved in translating COLREG into precise, machine-readable requirements. Building on this, a widely discussed approach in the literature is to quantify COLREG rules systematically and use this quantification as a foundation for assessing compliance.

The proposed method provides an initial pathway for establishing reference benchmarks to compare and evaluate both protocol compliance and the safety performance of autonomous vessels. This is achieved by extracting critical statistics from evasive maneuvers, whether compliant with COLREG or not, observed in historical Automatic Identification System (AIS) data.

2. Related Work

The COLREG were originally developed for human operators and apply universally to all vessels at sea and therefore contain inherently ambiguous expressions such as "act in ample time," "proceed at a safe speed," and "with due regard to good seamanship" (IMO (1972)). The acceptable behavior of a vessel is described using qualitative terms, making compliance highly context-dependent and influenced by factors such as visibility, traffic density, vessel maneuverability, and environmental conditions. Moreover, the lack of precise numerical thresholds necessitates reliance on human judgment in navigational situations, complemented by the practical experience and common sense of navigators (Kristić and Žuškin (2024)). This inherent ambiguity poses significant challenges for designing control algorithms and developing evaluation and certification methods for autonomous vessels (Hagen et al. (2023)), as it complicates the assurance of consistent COLREG compliance across all possible scenarios.

To address this, Woerner et al. (2019) proposed a method for quantifying and evaluating the otherwise subjective nature of the COLREG rules, offering a initial pathway toward standardized assessment and certification of collision avoidance systems. Specifically, Woerner introduced an approach for assessing compliance with rules 8, 13, 14, 15, 16, and 17 in ship-to-ship encounters, including head-on, crossing, and overtaking situations, which was improved by Hagen et al. (2023).

Krasowski and Althoff (2021) proposed a method using Temporal Logic (TL) to formalize COLREG, providing a precise mathematical representation suitable for autonomous system evaluation. Building on this, Krasowski and Althoff (2024) integrated TL with Reinforcement Learning (RL), guiding exploration by constraining the agent to verified, rule-compliant actions rather than random exploration.

Torben et al. (2023) formulated verification requirements using Signal Temporal Logic (STL) and employed Gaussian Process (GP) models to estimate robustness scores and guide automated test case selection. This work was further advanced by Pedersen et al. (2025), who also utilized STL to translate COLREG into quantifiable requirements, achieving comprehensive coverage of rules 2, 6, 8, and 13–17. Additionally, Pedersen demonstrated how their proposed method can be useful also when evaluating a multi-ship encounter situation.

Nevertheless, developing a compliant data-driven verification model remains an open challenge due to the inherent ambiguity of the COLREG, which, as discussed earlier, were formulated by humans for human interpretation. A direct and fully accurate functional translation into machine-readable code is therefore not feasible (Pedersen et al. (2025)). However, to strengthen the robustness of such evaluation methods, analyzing historical AIS data offers a promising approach. By quantifying critical maneuver characteristics from AIS records, we aim to establish a baseline that reflects how vessels have historically complied with COLREG rules, in essence, how human navigators have interpreted these regulations and providing a reference that autonomous vessels should strive to match.

Historical AIS data analysis is frequently employed to identify maritime encounter situations. A widely adopted method, as demonstrated by Vestre et al. (2021), involves calculating the Closest Point of Approach (CPA) along with predicting Time to CPA (TCPA) and Distance at CPA (DCPA) to detect pairwise vessel encounters. Alternatively, encounter identification can be based on ship domain concepts, as proposed by Hassel et al. (2020), where an encounter is recognized when a vessel's domain is breached concurrently with an evasive maneuver. Another approach, presented by Snijders and Elrofai (2020), defines a "visible range" of 7.3 nautical miles around a vessel and considers overlapping trajectories within this range as indicative of an encounter.

Hagen et al. (2023) proposed a maneuver detection method using smoothed derivatives of the course over ground (COG) and speed over ground (SOG) via Gaussian convolution. The study considered only encounters where the give-way vessel executed an evasive maneuver, and in head-on or crossing situations, any course change had to be toward starboard, ensuring that only COLREG-compliant maneuvers were identified. In our work, we extend the analysis to include all encounter situations, considering cases where either the give-way or stand-on vessel executed a maneuver, as well as those where neither vessel altered its course. Another approach to maneuver detection uses filters. Labbe (2020) describes how Kalman and Bayesian filters can identify maneuvers when an object's behavior deviates from the predicted process model, resulting in a large residual, the difference between prediction and measurement. To assess whether this residual is significant, the Normalized Innovation Squared (NIS) metric checks the consistency of the filter with the measurement residual and its associated covariance (Dingler (2024)).

3. Scenario Identification

Our data collection relies on high-resolution historical AIS records from the Norwegian Coastal Administration. For this study, we focus on crossing situations involving ferries operating between Horten and Moss in the Oslofjord during the period from 1 August 2025 to 31 October 2025.

Our methodology adopts a two step approach for analyzing the large maritime datasets. First, we identify and isolate traffic encounter scenarios of interest from raw AIS data. Next, we perform a data-driven analysis of vessel trajectories and maneuvers within these scenarios to derive statistics and behavioral metrics, ultimately forming a quantitative rule set that maps human behavior at sea.

Crucially, our framework is implemented with a high degree of modularity. This structural choice divides the analysis pipeline into distinct, self-contained components, thereby providing significant advantages. This flexibility is crucial for achieving a robust and scalable method, enabling adaptation to different data sources, operational areas, vessel types, and encounter types.

Encounter scenarios are identified using a CPA-based methodology inspired by Vestre et al. (2021). The process starts with preliminary filtering of aggregated AIS data to remove irrelevant points and retain only dynamic maritime traffic. To reduce computational cost when iterating through all vessel data, vessel trajectories are downsampled into 20-second intervals, which are subsequently used to compute pairwise TCPA and DCPA values between vessels. A visual representation of TCPA and DCPA is given in Figure 1. For scenarios where these values fall within defined thresholds, the full historical trajectories of the involved vessels are extracted for detailed analysis. To address the irregularity of AIS measurements and standardize temporal resolution for kinematic studies, trajectories are interpolated at 1-second intervals. This interpolation first projects geographic coordinates (lat/lon) to the appropriate UTM zone to preserve distances, followed by linear interpolation on the planar grid.

To isolate COLREG-defined crossing encounters, we apply the method described in Woerner et al. (2019), which ensures accurate classification of encounter types. This method uses the contact angle (α) and relative bearing (β) between vessels (see Figure 1 for an illustration of the angle definitions) to distinguish among overtaking, head-on, and crossing situations, while also determining the give-way and stand-on roles for each vessel in the encounter, as illustrated in Figure 2.

Pairwise encounter analysis is highly relevant because these interactions are explicitly addressed by COLREG and are required to be followed by all vessels at sea (IMO (1972)). However, focusing solely on two vessels can overlook important

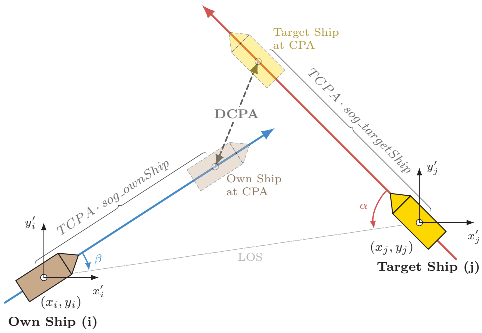

Fig. 1.: Illustration of CPA, DCPA, TCPA, relative bearing angle (β), and contact angle (α) between two vessels, including their projected positions at CPA. The Line of Sight (LOS) is the straight line connecting the two vessels' positions; β is the angle between the own ship's heading and the LOS to the target, while α is the angle between the target ship's heading and the LOS back to the own ship. The distance from from each vessel's current position to it's predicted position at CPA is computed as TCPA multiplied by the vessel's SOG.

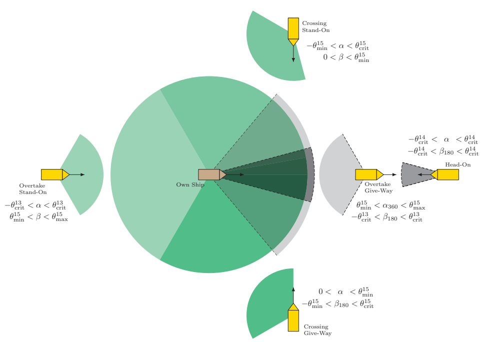

Fig. 2.: Illustration of encounter types based on relative bearing angle (β) and contact angle (α) according to Woerner's algorithm (Woerner et al. (2019)).

contextual factors, as real-world situations often involve additional vessels or obstacles not captured in a pairwise analysis. To obtain a complete operational picture, multi-vessel encounters must be considered (Nguyen et al. (2023)). This involves decomposing a multi-vessel scenario into pairwise COLREG interactions and interpreting them within the correct context, where a single vessel may take on multiple roles depending on the overall situation. To capture the complete context of an encounter, we propose a clustering approach that groups all nearby vessels, ensuring awareness of the surrounding traffic. Pairwise encounters remain the primary unit of analysis, but when unexpected vessel behavior occurs, the encounter can be interpreted within the broader cluster to reflect the complete operational situation.

We extend the pairwise approach presented by Vestre et al. (2021) with a graph-based component, illustrated in Figure 3. Vessel intervals are considered as nodes and potential interactions between vessels form edges. In order to form connected interaction graphs, we allow self-edges through time, i.e., edges that span intervals for a single vessel. Finally we apply depth-first-search to form the cluster of interacting vessels.

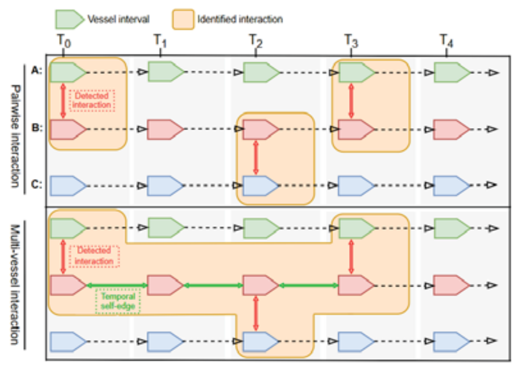

Fig. 3.: Illustration comparing the pairwise scenario identification (top) with the discussed graph-based approach (bottom). The pairwise approach results in three distinct identified scenarios. The graph based approach introduces temporal self-edges that connect the identified pairwise encounters through the time component of Vessel B resulting in one cohesive multi vessel encounter.

4. Maneuver Detection

While AIS data is a powerful tool for maritime analysis, it is inherently prone to noise, including signal dropout in congested waters, sensor-induced positioning jitter, and irregular transmission intervals. For fine-grained analysis of vessel behavior, these inaccuracies necessitate a rigorous and robust approach for segmenting the vessel trajectories into course alterations and speed changes. Our approach identifies maneuvers by analyzing the cumulative change in the derivative of a one-dimensional signal, thus is applicable for both COG and SOG. The algorithm ensures the detected maneuvers represent significant, sustained changes during transit rather than instantaneous sensor noise.

For course alterations, the COG is unwrapped to eliminate the $0°/360°$ discontinuity, converting the angular data into a continuous linear cumulative signal. To prevent false positives arising from sensor drift while vessels are stationary, a "Stationary Nullification" filter is applied. During periods where the vessel is classified as stationary, fluctuations in COG are suppressed, and the cumulative drift error is subtracted from subsequent data points to maintain trajectory continuity.

To ensure a consistent signal and to mitigate the noise amplification typically associated with numerical differentiation, the signal $x(t)$ is smoothed using a Gaussian kernel $G(t, \sigma)$, such that the smoothed signal $S(t)$ is defined by $S(t) = x(t) * G(t, \sigma)$. We then perform monotonic segmentation on the derivative of the signal. The signal is segmented into "maneuver candidates" based on the zero-crossings of the derivative. A segment is defined as a continuous time interval $[t_{start}, t_{end}]$ where the derivative maintains a consistent sign (monotonic increase or decrease).

The approach utilizes the intuitive observation that noise in the signal typically manifests as zero-mean white noise. When a vessel holds a steady course, this noise dominates the derivative, resulting in frequent zero-crossings and short candidate segments with negligible total magnitude, as illustrated in Figure 4. Conversely, during a maneuver, the physical rate of turn introduces a directional bias that skews the derivative. This bias offsets the zero-mean noise, reducing zero-crossings and yielding extended monotonic segments with substantial cumulative change.

For each candidate segment, the total magnitude of the course change is calculated as shown in Eq. (1).

$$\Delta_{total} = \int_{t_{start}}^{t_{end}} \frac{dS(t)}{dt} \, dt = S(t_{end}) - S(t_{start}) \tag{1}$$

Only segments where $|\Delta_{total}|$ exceeds a pre-defined significance threshold (T_{turn} for COG, T_{speed} for SOG) are retained as valid maneuvers.

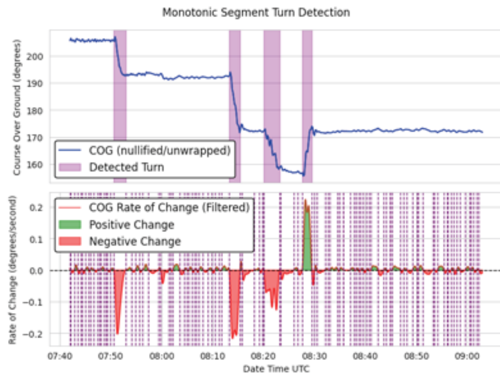

Fig. 4.: Illustrative example of COG (top) and its derivative (bottom) for a vessel. The figure demonstrates how the noisy AIS data behaves; during steady course, zero-mean noise results in negligible magnitudes and the candidate segments are ignored, while actual course alterations introduce a directional bias that offsets the noise, indicating a turn maneuver.

5. Results

The following section presents statistics on critical maneuver characteristics. Specifically, we analyze how the predicted DCPA evolves during evasive maneuvers in encounter situations and compare it with the final passing distance between vessels. The results presented here consider only turning maneuvers; however, evasive actions can also involve speed adjustments, such as slowing down or accelerating to avoid close contact.

The passing distance refers to the minimum distance between the vessels during the encounter. Comparing this with the predicted DCPA provides an indication of maneuver effectiveness. Ideally, the predicted DCPA should increase following a maneuver, resulting in a passing distance greater than the initial prediction. This demonstrates that the maneuver was truly evasive, ensuring the vessels pass at a safer distance than they would have without intervention.

To support data collection and enable straightforward comparisons, a case study was conducted in the area surrounding the ferry route between Moss and Horten, Norway. The study focuses on detecting crossing encounters between one of the Moss-Horten ferries and one other vessel, either inbound to or outbound from Oslo. The dataset, sourced from the Norwegian Coastal Administration's open-access AIS records, covers August, September, and October 2025 for the specified area.

Within the analyzed three-month AIS data period, 389 encounter situations were detected in the Moss–Horten area, with 167 evasive maneuvers identified. In some cases, both vessels executed a maneuver, resulting in 145 of the 389 crossing encounters involving at least one evasive action.

Passing distances for encounters involving evasive maneuvers are shown in Figure 5. The median passing distance is lower than the mean, stating that most vessels maintain relatively short distances while a few exhibit very large separations.

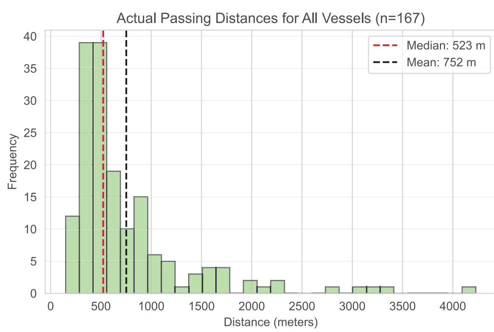

Fig. 5.: Histogram showing the passing distances between vessels during crossing encounters with a ferry on the Moss–Horten route.

The evasive maneuvers executed during crossing encounters were further analyzed using the evaluator tool developed in Pedersen et al. (2025). Maneuvers were identified using the proposed method, with the maneuver start defined as the first zero-crossing of the derivative within the turn segment. From this starting point, vessel trajectories were predicted under the assumption of constant speed and heading. This enabled a comparison with between the actual vessel trajectory and the hypothetical scenario where no evasive actions were taken. Evaluation scores were then compared between these predicted trajectories and the actual trajectories that included the evasive turn maneuver. The robustness score reflects how close a signal is to violating a requirement. A positive score indicates that the requirement is satisfied, while a negative score signifies a violation. The score is normalized and saturated, ensuring its value remains within the range [-1, 1] (Pedersen et al. (2025)). The results for the applicable COLREG rules for crossing encounters in which the ferry performed an evasive maneuver are presented in Table 1.

Table 1.: Evaluation scores for the applicable COLREG rules (IMO (1972)) are presented for both predicted and actual trajectories in the identified crossing encounters where the ferry executed an evasive maneuver (a total of 89 situations). The predicted trajectory represents the hypothetical case where vessels maintain constant speed and heading from the maneuver start time, instead of executing an evasive maneuver.

	Predicted Route		**Actual Route**	
Rule	**Mean score**	**Pass rate**	**Mean score**	**Pass rate**
2	-0.026070	39.325843	0.329003	71.910112
8	-0.073438	39.325843	0.329003	71.910112
15	-0.019464	21.348315	0.240030	59.550562
16	-0.073438	39.325843	0.329003	71.910112
17	-0.122408	48.314607	-0.569841	25.842697

The evaluation results clearly indicate that the actual trajectories demonstrate higher compliance with the relevant COLREG rules, with the exception of Rule 17, which pertains to the actions of the stand-on vessel.

Figure 6 illustrates the difference in passing distance between the actual trajectories and the predicted constant-speed, constant-heading trajectories for the identified crossing encounters. The figure shows a slight overall increase in passing distances. Further analysis indicates that outbound vessels experience a slight decrease, whereas inbound vessels show a more pronounced increase.

Figure 7 illustrates one of the identified encounters involving an evasive maneuver. In this scenario, an outbound vessel from Oslo intersects with a ferry crossing from Horten to Moss. The predicted trajectory of the outbound vessel, shown in Figure 8, demonstrates that the evasive maneuver increases the passing distance while complying with COLREG Rule 15 (IMO (1972)), as the give-way vessel, having the other vessel on its starboard side, keeps clear and crosses astern.

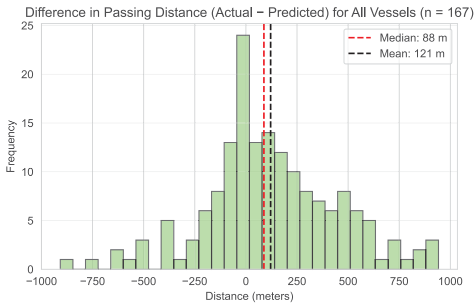

Fig. 6.: Histogram showing the difference in passing distance between the actual vessel trajectory and the predicted trajectory, i.e. with and without maneuver.

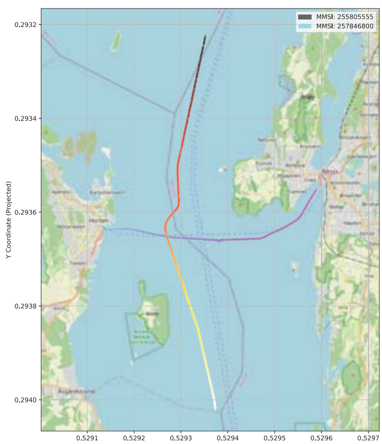

Fig. 7.: One of the identified crossing encounter situations where an outbound vessel from Oslo intersects with a ferry traveling from Horten to Moss. The outbound vessel performs an evasive maneuver to avoid collision. The trajectories are rendered in the Web Mercator projection (EPSG:3857), the standard projection used by OpenStreetMap.

6. Future Work

The proposed method serves as a foundation for mapping and establishing a reference benchmark to assess protocol compliance and safety performance by identifying key performance indicators. Although the case study focuses on a single region in Norway, AIS data from the Danish Maritime Authority and the U.S. Coast Guard were explored for broader applicability, and the methodology is designed to be adaptable to other areas, capturing local variations effectively. Future work should

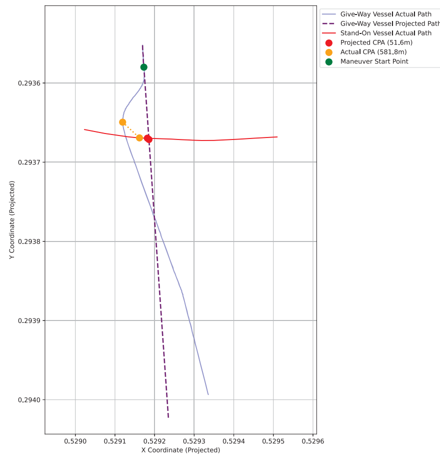

Fig. 8.: The same crossing encounter as shown in Figure 7, now with the addition of the predicted trajectory of the outbound vessel, which serves as the give-way vessel in accordance with COLREG. The figure also depicts both the predicted DCPA and the actual DCPA (i.e., the actual passing distance) for the vessels.

include applying the method to additional regions and extending the time horizon for analysis.

Future work will incorporate speed-change maneuvers alongside an even more detailed analysis of vessel maneuvers. Features to be covered will be the timing of maneuvers, i.e., when vessels initiate them relative to the CPA, as well as their magnitude, in terms of turn angle and/or speed adjustment, with the aim of deriving from historical data what constitutes ‘ample time’ and ‘early and substantial action’ (IMO (1972)).

Moreover, the calculated distance between vessels may not be fully accurate, as it is based on the position of the AIS transceiver rather than the actual ship dimensions. Future work could implement a ship-region approach to better represent the vessel’s size and identify when other ships encroach upon this defined area.

To define maneuver thresholds using the AUC method, one could adopt the membership functions proposed by Kristić and Žuškin (2024), which assign vessels to size categories ranging from *Very Small* to *Very Large* using fuzzy logic, thereby allowing maneuver significance to be scaled with vessel size. For example, a 5° change in heading may constitute a clear course alteration for a large vessel, whereas the same change for a small vessel could merely reflect wave-induced disturbance rather than an intentional maneuver.

7. Conclusion

A method of mapping how COLREG is applied in practice and defining key performance indicators by using historical AIS data has been presented. The method uses methodology from Woerner et al. (2019) and Vestre et al. (2021) partly to identify scenarios and from there identifying maneuvers, gathering encounter maneuver characteristics and evaluating their COLREG compliance with the tool developed in Pedersen et al. (2025).

As shown in Table 1, trajectories that included evasive maneuvers achieved higher COLREG compliance scores than the predicted constant-speed, constant-heading trajectories. Moreover, the increasing difference in passing distance between actual and predicted paths (Figure 6) suggests that vessels generally maintain greater separation after executing a maneuver. This improvement in both passing distance and COLREG adherence can serve as a foundation for establishing benchmarks to evaluate the performance of autonomous vessels in close encounter situations.

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