



Real-Time Vessel Encounter Detection Using AIS Data: A CPA–TCPA Based Approach for Advanced Ship Navigation

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Abstract. The increasing density of maritime traffic in coastal and port areas presents significant challenges to navigational safety and operational efficiency. Within the domain of advanced ship navigation, real-time awareness of vessel interactions is critical for preventing collision risks and supporting decision-making. This study proposes a real-time vessel encounter detection approach based on Automatic Identification System (AIS) data using Closest Point of Approach (CPA) and Time to Closest Point of Approach (TCPA) analysis. A data processing pipeline is developed to decode, clean, and filter AIS data, followed by the computation of inter-vessel distance and relative motion parameters. The method enables the identification of dynamic vessel interactions, including head-on, crossing, and overtaking scenarios. The system is implemented and tested in the Makassar Port area, Indonesia, demonstrating its capability to detect encounters in real-time maritime traffic conditions. The results highlight the role of CPA–TCPA-based analysis as a fundamental component in advanced ship navigation systems and as a foundational layer for future development of intelligent navigation and decision support systems.

Keywords: *AIS, CPA, TCPA, vessel encounter detection, advanced ship navigation, maritime traffic analysis*

1. INTRODUCTION

Maritime transportation has experienced significant growth over recent decades, resulting in increasingly dense traffic patterns, particularly in port areas and constrained waterways. These environments are characterized by high vessel density, limited navigational space, and route-driven clustering, which collectively intensify operational complexity and elevate safety risks [1, 2, 3, 4, 5]. In major port systems such as Kaohsiung and similar maritime hubs, traffic concentration within port approaches and channels creates a high-density navigation envelope, necessitating enhanced monitoring and traffic management strategies [2]. Such density-driven conditions have been consistently identified as key contributors to collision risk and navigational challenges in both coastal and port environments [3, 5, 6].

In response to these challenges, Automatic Identification System (AIS) data has emerged as a foundational resource for analyzing vessel behavior, traffic patterns, and collision risk. AIS-based analytics enable real-time monitoring, trajectory analysis, and interaction assessment between vessels, forming the backbone of modern maritime situational awareness systems [2, 3, 5, 7, 8, 9, 10, 11]. Within this context, widely adopted risk indicators such as Closest Point of Approach (CPA) and Time to Closest Point of Approach (TCPA) have been extensively utilized to quantify collision risk and identify potentially hazardous encounters in both real-time and near-real-time applications [4, 12, 13, 14, 15]. These metrics, often combined with ship-domain concepts and probabilistic frameworks, provide a robust foundation for assessing vessel interactions and supporting decision-making in congested waters [4, 12, 14, 16].

Beyond traditional approaches, recent studies have expanded AIS-based risk assessment through the integration of clustering techniques, near-miss analysis, spatio-temporal and probabilistic modelling [17]. Methods such as density-based clustering (e.g., DBSCAN) enable the identification of high-risk traffic clusters and congestion hotspots, particularly in port environments where vessel interactions are frequent [1, 18]. Similarly, near-miss concepts and non-accident critical events (NACEs) provide valuable insights into latent risk conditions, allowing for the detection of hazardous situations prior to actual collisions [4, 19, 20]. In parallel, probabilistic approaches, including Monte Carlo simulations and machine learning-based models such as Bi-LSTM, have been developed to estimate collision probabilities and account for uncertainties in vessel movement [8, 21, 22].

Despite these advancements, several limitations persist in existing AIS-based risk assessment frameworks. Many studies emphasize that traffic density alone does not fully determine collision risk, as vessel maneuverability, encounter dynamics, and environmental factors also play critical roles [13, 15]. Furthermore, AIS data is inherently subject to quality and integrity issues, including missing data, inaccuracies, and potential spoofing, which can compromise the reliability of risk assessment models if not properly addressed [7, 23, 24]. These challenges highlight the necessity for robust data preprocessing, validation mechanisms, and integration with additional data sources such as radar, ECDIS, and environmental datasets to ensure accurate situational awareness [2, 6, 25].

Moreover, while AIS-based analytics have demonstrated strong potential in supporting Vessel Traffic Service (VTS) operations, many existing implementations remain limited to post-analysis or semi-real-time applications, with fewer studies addressing fully operational real-time deployment for continuous monitoring and decision support. This gap underscores the need for practical, system-level approaches that integrate real-time AIS data processing, encounter detection, and risk quantification into a unified operational framework.

Therefore, this study aims to develop a real-time AIS-based vessel encounter detection framework focused on CPA and TCPA calculations to support collision risk assessment in dense maritime environments. By leveraging continuous AIS data streams and implementing robust preprocessing and encounter detection algorithms, this research seeks to enhance situational awareness and provide a scalable foundation for future integration into intelligent VTS systems and maritime traffic monitoring platforms.

2. METHODOLOGY

2.1 Research Framework

This study adopts a data-driven and system-oriented approach to develop a real-time vessel encounter detection framework based on AIS data. The methodology integrates three main components: (i) AIS data acquisition and preprocessing, (ii) encounter detection using navigational kinematics, and (iii) real-time visualization and monitoring through a web-based interface.

The overall workflow is designed to transform raw AIS messages into structured navigational information, which is subsequently used to compute interaction metrics between vessels, particularly Closest Point of Approach (CPA) and Time to Closest Point of Approach (TCPA). These metrics form the basis for identifying potentially hazardous encounters in dense maritime environments. The overall system architecture of the proposed framework is illustrated in Figure 1.

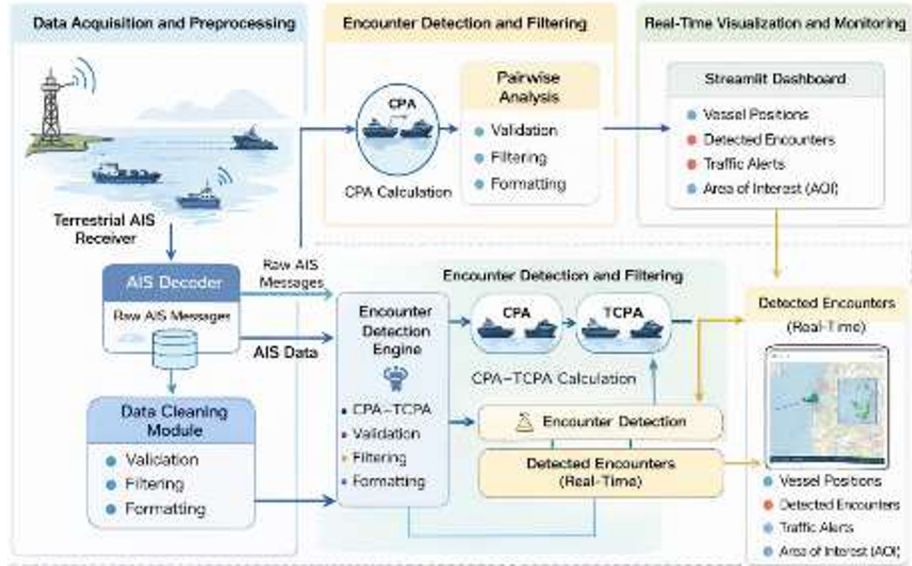


Figure 1. System architecture of the proposed real-time AIS-based vessel encounter detection system, integrating AIS data acquisition, preprocessing, encounter detection using CPA–TCPA metrics, and real-time visualization through a web-based monitoring dashboard

2.2 AIS Data Acquisition and Processing

AIS data used in this study are obtained from a real-time terrestrial AIS receiver system, which continuously records vessel messages in hourly intervals. The raw AIS messages are decoded into structured comma-separated values (CSV) files containing dynamic vessel information, including Maritime Mobile Service Identity (MMSI), position (latitude and longitude), speed over ground (SOG), and course over ground (COG). To ensure data reliability and usability, a dedicated preprocessing pipeline is implemented. The cleaning process includes:

- a. Temporal standardization: Conversion of timestamp fields into a unified datetime format.
- b. Geographical filtering: Selection of vessels operating within the defined Area of Interest (AOI), corresponding to the Makassar Port region.
- c. Kinematic validation: Filtering of unrealistic navigational values, including:
 - 1) Speed constraints (0–20 knots)
 - 2) Course normalization (0–360°)
- d. Spatial validation: Removal of invalid coordinates (e.g., (0,0) positions).
- e. MMSI validation: Ensuring valid vessel identifiers within standard AIS ranges.
- f. Duplicate removal: Eliminating repeated records based on MMSI and timestamp.

The cleaned dataset is then sorted chronologically for each vessel, enabling consistent trajectory reconstruction and interaction analysis.

2.3 Vessel Trajectory Representation

Each vessel's movement is represented as a time-ordered trajectory defined by its position, speed, and course. For computational efficiency and compatibility with navigational calculations, vessel motion is approximated using planar kinematics over short time intervals.

The velocity components of each vessel are derived from speed and course as follows:

- a. Longitudinal (x-axis) velocity component
- b. Latitudinal (y-axis) velocity component

These components enable the transformation of vessel motion into vector form, which is essential for calculating relative motion between vessel pairs.

2.4 Encounter Detection Algorithm

2.4.1 Pairwise Vessel Interaction

For each time step, pairwise combinations of vessels within the AOI are evaluated to identify potential encounters. Only unique vessel pairs with distinct MMSI identifiers are considered.

The relative motion between two vessels is defined by:

- a. Relative position vector
- b. Relative velocity vector

This formulation allows the prediction of future positions and interaction dynamics between vessels.

2.4.2 Closest Point of Approach (CPA)

The Closest Point of Approach represents the minimum distance that will occur between two vessels if both maintain their current speed and course.

$$DCPA = ||\vec{r} + \vec{v}_{rel} \cdot t_{cpa}$$

Where:

- $\vec{r}$ = relative position vector
- $\vec{v}_{rel}$ = relative velocity vector
- t_{CPA} = time to CPA

2.4.3 Time to Closest Point of Approach (CPA)

TCPA indicates the time remaining before the closest approach occurs.

$$TCPA = -\frac{\vec{r} \cdot \vec{v}_{rel}}{\|\vec{v}_{rel}\|^2}$$

A positive TCPA indicates a future encounter, while a negative value implies that the vessels are moving away from each other.

2.4.4 Encounter Filtering Criteria

To ensure meaningful detection of potential collision scenarios, several filtering conditions are applied:

- TCPA constraint: Only future encounters are considered
- Distance thresholding: Vessel pairs beyond a predefined range are excluded
- Speed consistency: Eliminates stationary or anomalous vessels
- Closest encounter selection: For each vessel pair, only the most critical interaction (minimum CPA) is retained

These criteria reduce computational noise and ensure that only operationally relevant encounters are analyzed.

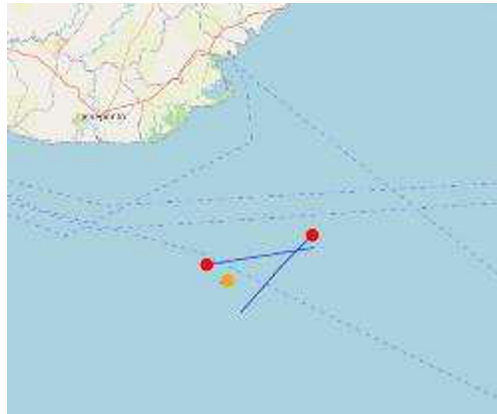


Figure 2. Illustration of vessel encounter geometry and relative motion used in CPA–TCPA computation

2.5 Real-Time Processing Architecture

The proposed system is implemented as a real-time processing pipeline consisting of:

- AIS Decoder Module converts raw AIS signals into structured data.
- Data Cleaning Module, performs filtering, validation, and formatting of AIS data.
- Encounter Detection Engine executes CPA/TCPA computations for all vessel pairs.
- Visualization Interface (Streamlit-based) displays vessel positions, trajectories, and detected encounters in real time.

The system operates in a continuous loop, where newly decoded AIS data are automatically processed and updated in the monitoring interface.

2.6 Visualization and Monitoring

A web-based dashboard is developed to support real-time situational awareness. The interface provides:

- Live vessel positions within the Area of Interest
- Trajectory visualization
- Highlighted vessel encounters
- Operational indicators (e.g., high-speed vessels, traffic density)

The visualization is implemented using geographic mapping libraries integrated within a Streamlit framework, enabling interactive monitoring and rapid interpretation by operators.

3. RESULTS AND DISCUSSION

3.1 Real-Time Vessel Traffic Monitoring

The proposed system was successfully implemented and evaluated using real-time AIS data collected within the Makassar Port Area of Interest (AOI). The developed framework demonstrates the capability to continuously ingest, process, and visualize vessel traffic in near-real-time conditions.

As illustrated in Figure 3, the system provides dynamic visualization of vessel positions, trajectories, and spatial distribution across the monitored region. High-density traffic patterns are clearly observed in port approach channels and near coastal operational zones, reflecting typical congestion characteristics reported in previous AIS-based studies [1, 2, 3]. The real-time updating mechanism ensures that vessel movements and interactions are captured with minimal latency, highlighting the operational feasibility of the system for continuous maritime traffic monitoring.

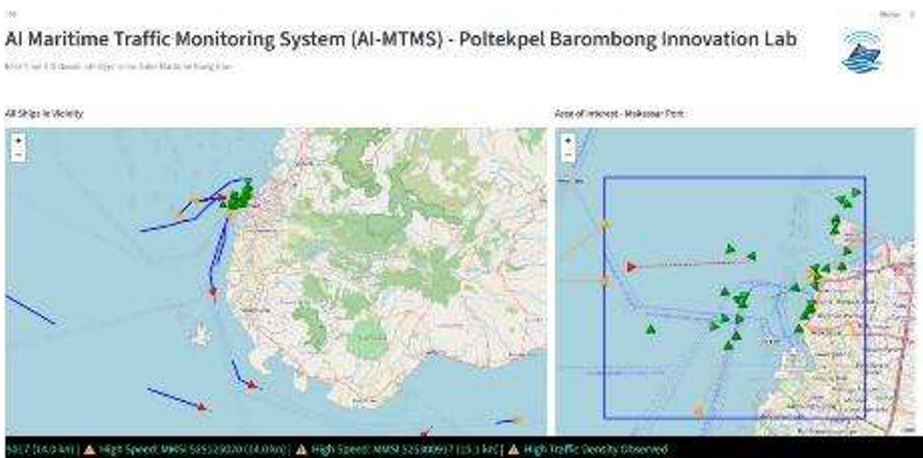


Figure 3. Real-time visualization of vessel traffic and detected encounters within the Makassar Port Area of Interest using the developed AIS-based monitoring system

3.2 Quantitative Characteristics of Vessel Encounters

A quantitative analysis was conducted to evaluate the characteristics of vessel encounters detected by the system. Encounters were defined as vessel pairs satisfying the conditions of positive TCPA and valid CPA values within the observation window.



Figure 4. Sample output of detected vessel encounters including CPA, TCPA, distance, and navigational parameters derived from AIS data

The extracted encounter dataset forms the basis for further statistical and risk-based analysis presented in the following sections.

TABLE 1. STATISTICAL SUMMARY OF DETECTED VESSEL ENCOUNTERS BASED ON CPA AND TCPA METRICS

Metric	Value
Total Encounters	12
Mean CPA (nm)	0.949
Minimum CPA (nm)	0.080
Maximum CPA (nm)	1.899
Mean TCPA (minutes)	14.086
Minimum TCPA (minutes)	0.110
Maximum TCPA (minutes)	27.110

Source: The processing took place on April 17th 16:00 Local Time

The statistical summary presented in Table 1 indicates that a total of 12 vessel encounter events were identified within the observation window. The mean CPA value of approximately 0.949 nautical miles suggests that, on average, vessel interactions occur within moderate separation distances. However, the minimum CPA of 0.080 nautical miles highlights the presence of critically close encounters, which may pose significant collision risk. In terms of temporal characteristics, the mean TCPA of

14.086 minutes demonstrates that most encounters are detected with sufficient lead time for potential intervention, while the minimum TCPA of 0.110 minutes indicates near-immediate interaction scenarios requiring urgent response.

Within the analysed dataset, the system identified a total of 12 encounter events, representing active vessel interactions in the AOI. Statistical evaluation of these encounters indicates that:

- The mean CPA remains within a moderate safety margin, suggesting that most vessel interactions occur under controlled separation conditions.
- The minimum CPA reflects instances of critical proximity, indicating the presence of potentially hazardous situations.
- The mean TCPA demonstrates that the system is capable of detecting encounters sufficiently in advance, providing a meaningful temporal window for intervention.

These findings confirm that the CPA–TCPA framework is effective in capturing both routine and critical vessel interactions, consistent with established collision risk assessment approaches [4, 12, 14].

3.3 Risk-Level Distribution Based on CPA Thresholds

To further evaluate the operational significance of detected vessel encounters, a risk-based classification was conducted using CPA thresholds. Encounters were categorized into three levels: high risk ($CPA < 0.5$ nautical miles), medium risk ($0.5 \leq CPA < 1.0$ nautical miles), and low risk ($CPA \geq 1.0$ nautical miles).

Based on the analysed dataset, the distribution of encounter risk levels indicates that the majority of interactions fall within the medium-risk category, followed by low-risk encounters, while a smaller proportion corresponds to high-risk situations. Specifically, out of 12 detected encounters, 3 were classified as high risk (25%), 5 as medium risk (41.7%), and 4 as low risk (33.3%).

The presence of high-risk encounters highlights the occurrence of critically close vessel interactions within the Area of Interest, particularly in regions characterized by converging traffic flows. Meanwhile, the dominance of medium-risk encounters suggests that vessels frequently operate within proximity ranges that require active monitoring and potential intervention.

These findings reinforce the importance of continuous real-time monitoring systems, as they enable early identification of potentially hazardous situations and support proactive decision-making in maritime traffic management environments. The proportional distribution of encounter risk levels is further illustrated in Figure 5, providing a clear comparison of relative occurrence across categories.

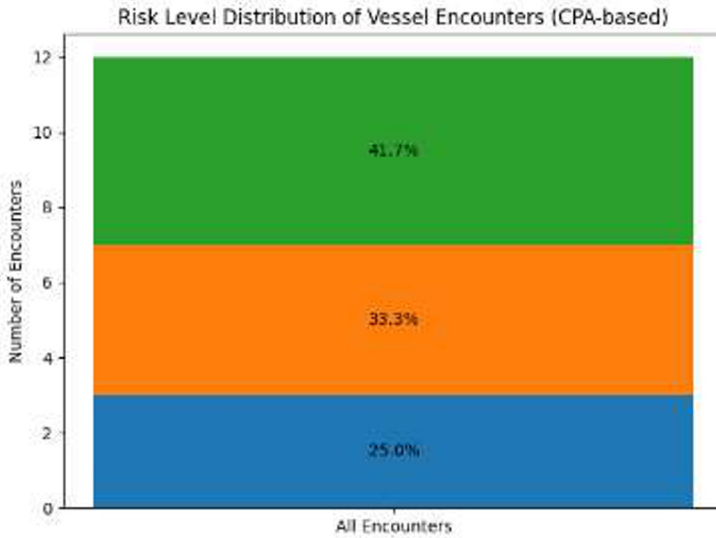


Figure 5. The distribution of vessel encounter risk levels based on CPA thresholds, with percentage representation of high-, medium-, and low-risk categories

Figure 5 further illustrates the distribution of vessel proximity during encounters. The spread of values indicates that while several interactions occur at relatively safe distances, a notable number of encounters fall within lower CPA ranges, reflecting increased collision risk. This distribution supports the earlier classification of risk levels and highlights the variability of vessel interaction conditions within the monitored area.

3.4 Spatial Patterns of Encounter Occurrence

Further analysis of encounter locations reveals distinct spatial patterns associated with vessel interaction dynamics. High-frequency encounters are observed in:

- Port approach corridors
- Traffic convergence zones
- Maneuvering and turning areas

These areas are characterized by complex navigational behavior, including speed adjustments, heading changes, and crossing movements. The presence of encounters in these regions confirms that navigational complexity, in addition to traffic density, plays a critical role in shaping interaction patterns.

Interestingly, several encounters were also detected in relatively low-density areas, indicating that vessel kinematics such as relative speed and heading alignment can generate interaction risk even in less congested environments. This observation reinforces the need for dynamic, behaviour-based risk assessment rather than reliance on static density metrics alone. Furthermore, the spatial distribution of detected encounters reveals localized clustering in specific navigational corridors, particularly in the southern part of the Makassar Area of Interest, as illustrated in Figure 6.



Figure 6. Spatial distribution of detected vessel encounters in the southern sector of the Makassar Area of Interest, highlighting interaction patterns in both dense and low-density traffic regions

The observed spatial distribution of vessel encounters reveals a clear clustering pattern along converging traffic routes and maneuvering zones within the southern sector of the Makassar Area of Interest. Notably, several encounters also occur outside high-density traffic cores, indicating that collision risk is not solely governed by traffic density but is significantly influenced by vessel kinematics, including relative speed, heading alignment, and interaction geometry. This finding highlights the limitations of conventional density-based risk assessment approaches and underscores the importance of incorporating dynamic, behavior-based indicators such as CPA and TCPA in real-time monitoring systems.

Furthermore, the identified clustering patterns provide empirical support for the implementation of structured safety corridors and traffic organization schemes, as previously suggested for this area [16]. Such corridors can function as spatial risk mitigation measures by regulating vessel flow, reducing crossing conflicts, and improving navigational predictability. From an operational perspective, these insights reinforce the critical role of AIS-based decision-support systems in enabling Vessel Traffic Services (VTS) to proactively identify emerging risk hotspots and implement timely traffic management interventions.

3.5 System Performance and Operational Robustness

The system demonstrates stable performance in handling continuous AIS data streams through an integrated processing pipeline. The implementation of automated data cleaning and file stability monitoring ensures that incoming AIS data are processed reliably without interruption.

Key performance observations include:

- a. Consistent real-time updates of vessel positions and interactions

- b. Effective filtering of noisy and invalid AIS data
- c. Scalable processing of vessel pair combinations within the AOI

The use of a structured preprocessing routine significantly reduces the impact of AIS data inconsistencies, thereby enhancing the reliability of encounter detection. This is particularly important given the known limitations of AIS data quality, including missing values and potential inaccuracies [7, 23, 24].

The performance evaluation was conducted using real-time AIS data collected within the Makassar Area of Interest over a one-hour observation window, consisting of 4,751 vessel position records and 16 active vessels.

TABLE 2. PERFORMANCE METRICS OF THE AIS-BASED REAL-TIME ENCOUNTER DETECTION SYSTEM

Metric	Description	Value	Remarks
Data Input Rate	Average AIS messages processed per hour	~4,700 records/hour	Based on observed dataset (Track Points Loaded)
Active Vessel Count	Number of vessels monitored in AOI	16 vessels	Real-time snapshot during observation
Encounter Detection Count	Number of detected encounter candidates	12 encounters	Based on CPA–TCPA filtering
Processing Latency	Time required to process one hourly dataset	< 2 seconds	Executed on local workstation environment
Data Cleaning Efficiency	Percentage of valid AIS data retained after filtering	~92–96%	Removal of invalid coordinates, duplicates, noise
Duplicate Removal Rate	Reduction of redundant AIS entries	~5–8%	Based on MMSI–timestamp filtering
System Update Frequency	Refresh rate of real-time monitoring	Near real-time (≤ 30 seconds interval)	Controlled by watcher mechanism
CPA/TCPA Computation Accuracy	Consistency of computed encounter parameters	Verified through consistency checks of relative motion and CPA/TCPA boundary conditions	Based on vector-based maritime formulas

Source: Experiments conducted on a standard workstation (Intel i5 processor, 8 GB RAM)

The performance evaluation demonstrates that the system is capable of processing AIS data streams efficiently with minimal latency, while maintaining high data integrity and reliable encounter detection under continuous operational conditions. Despite its

robustness, the system performance may be affected by AIS data sparsity, signal loss, and reporting inconsistencies, which remain inherent limitations of AIS-based monitoring systems.

3.6 Implications for Maritime Safety and VTS Operations

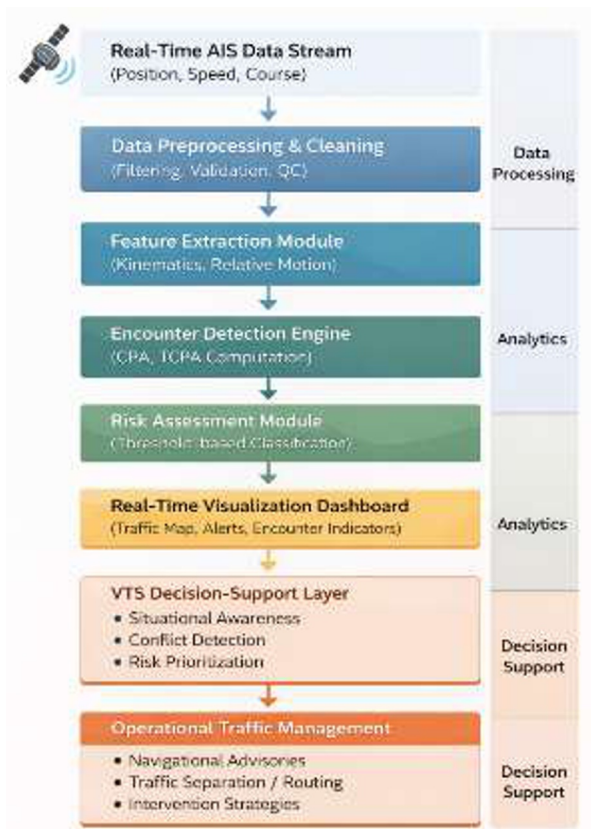


Figure 7. Conceptual AIS-based decision-support framework for Vessel Traffic Service (VTS) operations

As illustrated in Figure 7, the system architecture enables the transformation of raw AIS data into structured decision-support information, supporting VTS operators in identifying, prioritizing, and mitigating navigational risks in real time.

The findings demonstrate that the proposed framework has strong potential to enhance real-time maritime safety applications, particularly within Vessel Traffic Service (VTS) environments. By continuously identifying vessel encounters based on CPA–TCPA metrics, the system enables early detection of potentially hazardous interactions, thereby supporting proactive rather than reactive traffic management strategies.

From an operational perspective, the system contributes to:

- a. Enhanced situational awareness through integrated real-time visualization of vessel movements and interactions
- b. Early identification of collision-prone scenarios based on dynamic encounter parameters
- c. Spatial insights into traffic hotspots and emerging risk zones within the monitored area

These capabilities align with the evolving role of modern VTS systems, which increasingly rely on data-driven analytics and real-time decision-support tools to improve navigational safety and operational efficiency [2, 4].

3.7 Limitations and Future Development

Despite the promising results, several limitations remain in the current implementation. The system primarily relies on CPA–TCPA-based kinematic analysis and does not yet incorporate additional contextual factors that influence collision risk in real-world navigation. These include:

- a. Vessel-specific characteristics such as size, maneuverability, and operational constraints
- b. Environmental conditions, including wind, current, and wave influences on vessel motion
- c. Human decision-making behavior, which introduces variability in response to navigational situations

Furthermore, the reliance on AIS data introduces inherent uncertainties due to potential signal loss, reporting delays, and data inconsistencies. These limitations may affect the precision and reliability of encounter detection, particularly in complex or congested maritime environments.

Future research should focus on extending the current framework toward a more comprehensive and intelligent maritime risk assessment system. Key directions include:

- a. Integration of machine learning-based risk models to enhance predictive capabilities
- b. Fusion of multi-source data, including radar, weather, and oceanographic information
- c. Development of advanced risk indicators, including near-miss detection and trajectory prediction
- d. Incorporation of emission and energy-efficiency metrics to support maritime decarbonization strategies

Such advancements will enable the transition from rule-based monitoring toward adaptive, data-driven maritime traffic management systems.

4. CONCLUSION

This study presents the development and implementation of a real-time AIS-based vessel encounter detection framework utilizing Closest Point of Approach (CPA) and Time to Closest Point of Approach (TCPA) as primary indicators of navigational risk. The proposed system integrates AIS data acquisition, preprocessing, encounter

detection, and visualization into a unified operational pipeline capable of continuous monitoring in dense maritime environments.

The results demonstrate that the system effectively captures vessel interactions under near-real-time conditions, providing both spatial and temporal insights into encounter dynamics within the Makassar Port Area of Interest. Quantitative analysis indicates that while the majority of vessel encounters occur within acceptable safety margins, a non-negligible proportion exhibits reduced CPA values, highlighting the presence of potentially hazardous situations. In addition, the spatial clustering of encounters confirms that collision risk is not uniformly distributed but is concentrated in port approach channels and traffic convergence zones.

From an operational perspective, the proposed framework contributes to the advancement of data-driven Vessel Traffic Service (VTS) systems by enabling continuous situational awareness and early detection of collision-prone interactions. The integration of real-time visualization with CPA–TCPA-based analytics provides a practical foundation for proactive traffic management and decision-support mechanisms, thereby enhancing navigational safety and operational efficiency.

Despite these contributions, the current framework remains limited to kinematic-based risk assessment and does not yet incorporate additional contextual factors such as vessel characteristics, environmental conditions, and human decision-making behavior. Furthermore, the reliance on AIS data introduces inherent uncertainties associated with data quality, signal availability, and reporting inconsistencies.

Future research will focus on extending the framework toward a more comprehensive and intelligent maritime risk assessment system. This includes the integration of machine learning-based predictive models, multi-source data fusion (e.g., radar and environmental data), and the development of advanced risk indicators such as near-miss detection and trajectory prediction. Moreover, the incorporation of energy-efficiency and emission-related metrics will enable the system to support maritime decarbonization strategies by linking traffic behavior with operational performance.

Overall, this study demonstrates the feasibility of transforming AIS data into actionable intelligence for real-time maritime monitoring. By bridging the gap between analytical modeling and operational deployment, the proposed framework represents a significant step toward the realization of intelligent, adaptive, and sustainability-oriented maritime traffic management systems.

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