

Shore-Side Collision Risk Surveillance for Autonomous Surface Vehicles Using CPA/TCPA Encounter Assessment

Dedtri Anwar^{1*}, Zainal Arifin², Siwi Woro Herningsih³, Deny Adi Setyawan⁴, Setyawan Ajie Sukarno⁵

(Received: 7 August 2026 / Revised: 13 August 2026 / Accepted: 20 August 2026 / Available Online: 28 September 2026)

Abstract—Autonomous surface vehicles (ASVs) require reliable encounter assessment to support safe operation in restricted and coastal waters. Existing onboard collision-avoidance systems can react to detected obstacles, but remote operators also need information about how an encounter develops over time. The objective of this paper is to develop and evaluate a CPA/TCPA-based collision-risk surveillance method for ASVs using navigation telemetry and encounter records. The method uses own-ship position, heading, speed, target information, relative motion, mission status, and telemetry continuity. Relative-position and velocity relationships are used to formulate Closest Point of Approach (CPA) and Time to Closest Point of Approach (TCPA) assessment rules, while available encounter records are mapped into operational alert states. Evaluation used waypoint-navigation records, ten dynamic-obstacle trials, web-monitoring measurements, and fail-safe data. Simulation and field navigation produced mean waypoint errors of 0.49 and 1.15 m and mean heading errors of 4.21° and 10.8°, respectively. All ten obstacle trials achieved successful avoidance and mission recovery, with a mean observation-to-maneuver time of 0.881 s. End-to-end monitoring latency remained below 250 ms. The results demonstrate the technical feasibility of telemetry-based encounter surveillance, although full numerical CPA/TCPA validation requires continuous own-ship and target trajectories.

Keywords—Encounter geometry; Maritime safety; Operator awareness; Remote supervision; Traffic conflict.

*Corresponding Author: dedtrianwar@gmail.com

I. INTRODUCTION

Autonomous Surface Vehicles (ASVs), also referred to as Unmanned Surface Vehicles (USVs), are increasingly used for hydrographic survey, environmental observation, maritime surveillance, and missions in shallow or hazardous waters. These platforms reduce human exposure while enabling flexible, repeatable, and remotely supervised maritime operations [1], [2]. Their adoption is also supported by the growing use of unmanned marine platforms for fauna monitoring, bathymetric mapping, and coastal observation [3], [4].

As ASVs move toward more complex deployment, collision risk becomes one of the most important safety issues. Modern ASV systems commonly integrate perception, navigation, path planning, and autonomous decision-making to avoid obstacles and comply with maritime encounter rules [5], [6]. Previous reviews have shown that collision avoidance in unmanned vessels requires not only vehicle control, but also situational awareness, encounter interpretation, and risk evaluation before maneuver decisions are made [7], [8].

Many studies on ASV safety focus on onboard collision avoidance. COLREGs-aware navigation methods, velocity-obstacle techniques, dynamic window approaches, and deep reinforcement learning have been developed to support autonomous maneuver generation during head-on, crossing, and overtaking situations [9], [10]. Hybrid collision avoidance architectures have also been proposed to combine global planning, mid-level collision avoidance, and short-term emergency response for autonomous surface vehicles [11], [12]. These studies are important, but their main contribution remains focused on onboard decision-making and maneuver execution.

For shore-side operation, collision safety must also be interpreted from the perspective of remote supervision. Vessel Traffic Services (VTS) provide a conceptual basis for monitoring vessel movement, assessing developing encounters, and supporting navigational safety from a shore-based station [13], [14]. In addition, the increasing discussion on Maritime Autonomous Surface Ships highlights the need for reliable supervision, operator awareness, and risk indicators that can be presented to shore control centers [15], [16]. Therefore, collision-risk surveillance for ASVs should not only rely on onboard avoidance logic, but also provide operator-oriented risk information. Figure 1 illustrates the conceptual positioning of the proposed shore-side collision risk surveillance framework, in which ASV telemetry and target-track information are processed at a shore-side monitoring station to generate CPA/TCPA-based encounter alerts rather than onboard maneuver commands.

As shown in Figure 1, the proposed surveillance layer complements onboard autonomy by translating relative-motion information into operator-oriented collision-risk states. Collision risk assessment in maritime navigation

Dedtri Anwar is with Departement of Nautika, Politeknik Pelayaran Banten, Tangerang, 15330, Indonesia. E-mail: dedtrianwar@gmail.com

Zainal Arifin is with Departement of Nautika, Politeknik Pelayaran Banten, Tangerang, 15330, Indonesia. E-mail: znl33stip@gmail.com

Siwi Woro Herningsih is with Departement of Nautika, Politeknik Pelayaran Banten, Tangerang, 15330, Indonesia. E-mail: siwiworo83@gmail.com

Deny Adi Setyawan is with Departement of Nautika, Politeknik Pelayaran Banten, Tangerang, 15330, Indonesia. E-mail: setyawandenyadi@gmail.com

Setyawan Ajie Sukarno is with Departement of Automation Engineering, Politeknik Manufaktur Bandung, Bandung, 40135, Indonesia. E-mail: ajie@ae.polman-bandung.ac.id

commonly uses encounter geometry and motion prediction. Automatic Identification System (AIS) data have been widely used for maritime traffic analysis, anomaly detection, route prediction, and collision-risk identification [17], [18]. Classical and data-driven approaches have evaluated ship-ship collision risk using indicators such as distance, relative bearing, Distance to

Closest Point of Approach (DCPA), and Time to Closest Point of Approach (TCPA) [19], [20]. More recent works also show that CPA/TCPA-based indicators can be extended with uncertainty modeling, ship domains, and traffic-conflict analysis to support safer navigation in restricted waters [21], [22].

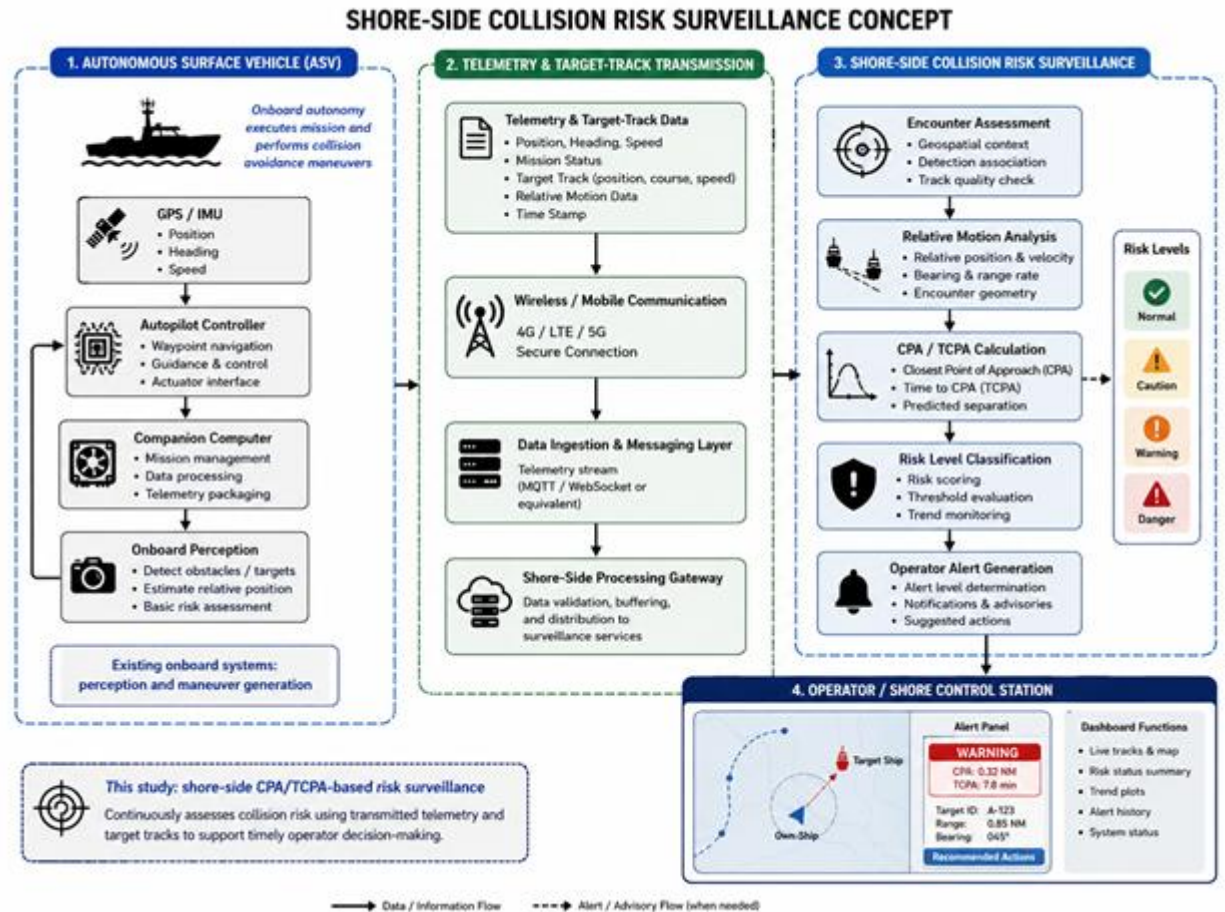


Figure 1. Conceptual positioning of shore-side CPA/TCPA collision risk surveillance for ASVs.

Despite these developments, most collision-risk studies are designed for conventional ships, AIS-based maritime traffic, or onboard autonomous avoidance. Limited attention has been given to shore-side collision risk surveillance for small and medium ASVs using their own telemetry and target-track information. Existing works on collision-risk quantification and maritime safety index development provide useful analytical foundations [23], [24]. However, the integration of ASV telemetry, encounter assessment, and operator-oriented alert levels remains underdeveloped, especially for ASVs operating in restricted or coastal waters. Table 1 summarizes the research positioning of the proposed study by comparing previous collision-risk, maritime monitoring, and ASV-supporting studies with the proposed shore-side CPA/TCPA-based surveillance framework.

Previous studies have separately addressed several technical components relevant to ASV supervision. Command-and-control and fail-safe systems support

telemetry acquisition, mission monitoring, and emergency response [25], [26]. Web-integrated monitoring platforms provide remote access to navigation and operational data [27], [28], while route-planning and autonomous-navigation studies focus on mission execution and vessel guidance [29], [30]. More directly related studies have investigated collision-risk inference and continuous risk identification for autonomous vessels [31], [32], as well as safety-oriented path planning and collision avoidance for ASVs [33]. However, a practical problem remains for small ASVs operating with limited traffic-sensor infrastructure: own-ship telemetry and target observations may be available, while their combined operational meaning during a developing encounter is not directly presented to the remote operator. The objective of this paper is therefore to develop and evaluate a CPA/TCPA-based encounter-surveillance method using ASV telemetry and target information. The novelty lies in integrating own-ship motion, target-track information, predicted closest

approach, remaining approach time, mission status, and telemetry continuity within a single monitoring workflow, and in using the resulting encounter state as

decision-support information for remotely supervised ASV missions.

TABLE 1.
COMPARISON OF PREVIOUS COLLISION-RISK AND ASV-SUPPORTING STUDIES WITH THE PROPOSED FRAMEWORK

Study Category	Main Focus	Main Output	Limitation Related to Shore-Side CPA/TCPA Surveillance
COLREGs-aware collision avoidance	Autonomous maneuver generation using maritime encounter rules [9], [10]	Collision-avoidance decisions and maneuver commands	Focuses on onboard avoidance rather than shore-side risk surveillance
Hybrid ASV collision avoidance	Combination of planning, avoidance, and emergency response [11], [12]	Autonomous navigation and collision-avoidance behavior	Does not emphasize operator-oriented CPA/TCPA alerting
VTS and MASS supervision	Shore-based traffic monitoring and autonomous-ship regulatory supervision [13], [14]	Conceptual basis for vessel monitoring and shore control	Not specifically formulated for small and medium ASV telemetry
Shore control and risk indicators	Risk indicators and shore-control operator considerations [15], [16]	Navigational risk and operator-awareness analysis	Does not integrate ASV telemetry and target-track data into encounter alerts
AIS-based maritime traffic analysis	Traffic pattern analysis and collision-risk identification using AIS data [17], [18]	Vessel trajectory analysis and traffic-risk estimation	Mainly intended for conventional vessels with AIS-based datasets
Classical collision-risk assessment	DCPA/TCPA and ship-ship collision-risk analysis [19], [20]	Quantitative collision-risk indicators	Not directly adapted into ASV shore-side monitoring architecture
Extended collision-risk modeling	Ship-domain, uncertainty, and holistic collision-risk assessment [21], [22]	Enhanced collision-risk estimation	Requires adaptation for real-time ASV operator alert generation
Maritime safety index and risk review	Collision-risk quantification and safety-index development [23], [24]	Review and analytical foundation for maritime risk assessment	Does not provide an ASV-specific CPA/TCPA surveillance framework
ASV command and fail-safe systems	Command unit, water-observation interface, and lost-link safety response [25], [26]	Operational support, telemetry, and emergency response	Focuses on platform support and safety response, not encounter-risk surveillance
ASV monitoring and ground-control systems	IoT-based monitoring and web-based ground control station [27], [28]	Remote monitoring, dashboard, and telemetry visualization	Does not convert target encounter data into CPA/TCPA risk alerts
Route and navigation support	Multi-agent route optimization and GPS-based autonomous navigation [29], [30]	Routing and autonomous navigation support	Does not address shore-side collision-risk surveillance
This study	Shore-side CPA/TCPA-based collision risk surveillance for ASVs	Encounter assessment, risk classification, and operator alert levels	Provides a surveillance layer that translates ASV and target-track data into collision-risk alerts

II. METHOD

A. Research Design.

This study adopts an engineering-design and telemetry-based evaluation approach to develop a shore-side collision risk surveillance framework for Autonomous Surface Vehicles (ASVs). The proposed method does not generate onboard avoidance maneuvers. Instead, it transforms ASV telemetry, target-track information, relative-motion indicators, and communication status into operator-oriented collision-risk alerts. This design is consistent with the concept of shore-based maritime supervision, in which vessel movement and developing traffic conflicts are monitored to support navigational safety [13], [14].

The research workflow consists of five stages: surveillance architecture definition, encounter data modeling, relative-motion calculation, CPA/TCPA-based risk assessment, and alert-level classification. The framework is designed to complement onboard autonomy by providing a shore-side interpretation layer for collision risk. This approach is aligned with recent

discussions on autonomous vessel supervision, operator awareness, and risk indicators for shore control centers [15], [16].

B. Surveillance System Architecture

The system architecture comprises four functional layers: ASV telemetry, target-track acquisition, encounter processing, and operator display. The ASV telemetry layer provides position, heading, speed, mission mode, timestamp, and communication status. The target-track layer supplies the estimated position, course, speed, range, and bearing of nearby objects.

The processing node synchronizes both data streams and calculates encounter geometry, CPA, TCPA, and alert status. The dashboard then displays the latest tracks, predicted separation, remaining approach time, and associated advisory information. Existing command-and-control, fail-safe, and web-monitoring components provide the required acquisition and interface functions [25]–[28].

C. Encounter Data Model

The encounter data model contains two input categories: own-ship telemetry and target-track information. Own-ship telemetry describes the current ASV state, whereas target-track information represents

the motion of nearby vessels or obstacles. Table 2 lists the required variables and their role in encounter assessment.

TABLE 2.
ENCOUNTER DATA VARIABLES USED IN THE PROPOSED SURVEILLANCE FRAMEWORK

Data Category	Variable	Description	Function in Collision Risk Surveillance
Own-ship telemetry	Own-ship position	Current ASV latitude and longitude	Defines the ASV location for encounter geometry
Own-ship telemetry	Own-ship heading	Current ASV heading angle	Supports direction and relative-bearing analysis
Own-ship telemetry	Own-ship speed	Current ASV speed	Used to estimate own-ship velocity vector
Own-ship telemetry	Mission status	Active mission, hold, manual, return, or fail-safe mode	Interprets operational context
Own-ship telemetry	Timestamp	Time of telemetry reception	Synchronizes own-ship and target-track data
Target-track data	Target position	Estimated target latitude and longitude	Defines the location of the encounter object
Target-track data	Target course	Estimated target movement direction	Used to calculate target velocity vector
Target-track data	Target speed	Estimated target speed	Used to calculate relative velocity
Target-track data	Relative bearing	Bearing from own-ship to target	Indicates encounter direction
Target-track data	Relative range	Distance between own-ship and target	Indicates current spatial separation
Communication status	Telemetry availability	Availability and continuity of incoming data	Determines surveillance reliability
Surveillance output	Risk level	Normal, caution, warning, or danger	Provides operator-oriented collision-risk status

The selected variables follow the general principle of maritime collision-risk assessment, where vessel position, speed, course, relative distance, and relative bearing are used to identify developing encounters [17], [18]. Classical collision-risk analysis also uses distance, relative motion, DCPA, and TCPA as important indicators for evaluating whether two vessels may approach each other in an unsafe manner [19], [20].

D. Relative Motion and CPA/TCPA Calculation

Before calculating CPA and TCPA, the geographic coordinates of own-ship and target objects are converted into a local Cartesian reference frame. This conversion allows relative position and velocity to be calculated using planar vector operations, which is suitable for small operating areas such as inland waters, ports, reservoirs, and coastal test zones.

Let the own-ship position and velocity be represented as:

$$p_o = [x_o, y_o] \quad (1)$$

$$v_o = [v_{ox}, v_{oy}] \quad (2)$$

and let the target position and velocity be represented as:

$$p_t = [x_t, y_t] \quad (3)$$

$$v_t = [v_{tx}, v_{ty}] \quad (4)$$

The relative position vector r and relative velocity vector v_r are calculated as:

$$r = p_t - p_o \quad (5)$$

$$v_r = v_t - v_o \quad (6)$$

The Time to Closest Point of Approach (TCPA) is calculated using:

$$TCPA = -(r \cdot v_r) / \|v_r\|^2 \quad (7)$$

where $r \cdot v_r$ is the dot product between relative position and relative velocity, and $\|v_r\|$ is the magnitude of the relative velocity vector. If TCPA is positive, the vessels are predicted to approach a closest point in the future. If TCPA is negative, the closest point has already occurred or the objects are moving away from each other.

The predicted distance at the closest point of approach is calculated as:

$$D_{CPA} = \|r + v_r TCPA\| \quad (8)$$

where D_{CPA} represents the predicted minimum separation between own-ship and the target. A smaller D_{CPA} combined with a positive and short TCPA indicates a higher collision-risk condition. This formulation follows the common use of CPA/TCPA indicators in maritime encounter and collision-risk assessment [21], [22].

E. Collision Risk Classification

The classification module applies rule-based logic to DCPA, TCPA, relative-bearing change, range trend, mission status, and telemetry continuity. A transparent rule set was selected because its thresholds can be inspected and adjusted for different operating areas. Table 3 presents the decision rules and the corresponding operator response.

The alert level is determined by the highest-risk condition among the monitored indicators. For example, an encounter with moderate D_{CPA} but rapidly decreasing TCPA may be classified as warning because the available reaction time is limited. Conversely, a nearby target with negative TCPA may remain normal if

the vessels are moving away from each other. This logic follows the idea that collision risk depends not only on

current distance, but also on relative motion and predicted future separation [23], [24].

TABLE 3.
CPA/TCPA-BASED COLLISION RISK CLASSIFICATION RULE

Alert Level	Encounter Condition	Operator Interpretation
Normal	D_CPA is above the safe-distance threshold, TCPA is negative, or relative range is increasing	No immediate collision risk is detected
Caution	D_CPA approaches the caution threshold and TCPA is positive, but the encounter is still developing slowly	Operator should increase attention and monitor the target track
Warning	D_CPA is below the warning threshold, TCPA is positive and decreasing, or relative range continuously decreases	Operator should prepare advisory action or intervention
Danger	D_CPA is below the minimum safety threshold, TCPA is short, telemetry is degraded, or mission status changes unexpectedly during an encounter	Operator should initiate emergency response or fail-safe procedure

F. Scenario-Based Evaluation

Scenario-based analysis covered stable separation, a developing approach, a crossing encounter, a close-range encounter, and degraded telemetry. Each scenario was evaluated using relative distance, relative bearing, DCPA, TCPA, mission status, and data continuity. The resulting status was compared with the expected interpretation for each encounter condition.

This evaluation approach extends previous ASV monitoring and navigation studies. Earlier studies reported telemetry transmission, navigation execution, ground-control visualization, and fail-safe response as separate functions [25], [27]. In this paper, those functions are integrated conceptually into a collision-risk surveillance layer that supports shore-side encounter assessment and operator alerting.

G. Performance Metrics

Performance was evaluated through classification consistency, alert latency, surveillance availability, and interpretability. Classification consistency measures whether comparable encounter conditions produce equivalent status outputs. Alert latency represents the interval between the arrival of updated track data and the display of a new status. Availability measures the continuity of the assessment process, while

interpretability considers whether the displayed information supports an unambiguous operational response.

The proposed metrics are designed to complement, not replace, onboard collision avoidance metrics. Onboard collision-avoidance studies usually evaluate maneuver success, avoidance time, path recovery, or rule compliance [9], [12]. In contrast, the proposed shore-side surveillance framework evaluates whether a developing encounter can be interpreted and presented to the operator as a clear risk status. Therefore, the main output of the method is not a maneuver command, but a CPA/TCPA-based collision-risk alert that supports shore-side situational awareness

III. RESULTS AND DISCUSSION

A. Evaluation Dataset and Surveillance Readiness

The evaluation combined five record groups: waypoint-navigation logs, dynamic obstacle trials, IoT monitoring measurements, ground-control latency records, and fail-safe response data. Table 4 summarizes the variables and benchmark values available for encounter analysis. Together, these records provide own-ship motion, hazard timing, communication delay, interface responsiveness, and emergency-response information.

TABLE 4.
DATASETS AND SUPPORTING RECORDS USED FOR COLLISION RISK SURVEILLANCE EVALUATION

Data Group	Main Variables or Metrics	Key Result	Function in This Study
Own-ship data waypoint-navigation data	Position, heading, waypoint error, heading error, mission status	Simulation mean waypoint error: 0.49 m; simulation mean heading error: 4.21°; real-world mean waypoint error: 1.15 m; real-world mean heading error: 10.8°	Provides own-ship motion baseline for encounter assessment
Dynamic obstacle encounter data	Obstacle relevance, risk score, avoidance activation, maneuver timing, mission recovery	10 dynamic obstacle trials; 100.0% success rate; 100.0% mission recovery rate	Provides encounter cases for surveillance interpretation
IoT-based monitoring data	GPS position, sensor data, data fetch, transmission time, web visualization	GPS error: 3.66 m; data fetch time: 199 ms; transmission time: 165 ms [27]	Supports real-time telemetry availability for shore-side monitoring
Web-based GCS data	Telemetry monitoring, remote control, MQTT, WebSocket, waypoint mission planning	Average command RTT: 178 ms; end-to-end monitoring latency below 250 ms [28]	Supports browser-based operator interface and alert delivery
Fail-safe response data	Battery accuracy, low-battery detection, communication-loss detection, RTH, loiter	Voltage accuracy: 99.87%; low-battery detection: 2.5–3.0 s; communication-loss detection: 6–15 s [26]	Supports emergency response after high-risk alert conditions

The navigation logs support relative-motion calculation, while the obstacle records describe the timing and persistence of hazardous encounters. Communication measurements indicate whether updated status information can reach the monitoring interface within an operationally useful interval. Fail-safe records provide additional evidence for conditions in which track continuity or mission execution becomes unreliable.

As shown in Table 4, the available datasets support the minimum functional requirements for shore-side collision risk surveillance. Own-ship telemetry provides the navigation state required for relative-motion analysis. Obstacle encounter data provide risk cases for evaluating alert interpretation. Communication and GCS data support the delivery of surveillance information to the operator interface. Fail-safe data provide a safety-response pathway when collision-risk alerts escalate into critical operational conditions.

B. Own-Ship State and Telemetry Performance

Own-ship state estimation is the first requirement for CPA/TCPA-based surveillance because relative motion cannot be evaluated without position, heading, speed, and timestamp information. The available waypoint-navigation dataset showed that the ASV could maintain autonomous navigation under both simulation and real-world operating conditions. In simulation, the mean waypoint error was 0.49 m and the mean heading error was 4.21°. In real-world testing, the mean waypoint error increased to 1.15 m and the mean heading error increased to 10.8°.

The difference between simulation and real-world values indicates the effect of GPS uncertainty, sensor noise, vehicle dynamics, and water-surface disturbance. This finding is consistent with previous ASV studies showing that real operating environments introduce uncertainties that affect motion behavior and navigation

accuracy [9], [10]. The field variation must therefore be accommodated when relative position and velocity are calculated. Thresholds that ignore GPS and heading uncertainty could produce premature status escalation during otherwise stable mission execution.

The telemetry infrastructure further supports the implementation of shore-side risk surveillance. IoT-based monitoring achieved a GPS error of 3.66 m, data fetch time of 199 ms, and transmission time of 165 ms [27]. In addition, the web-based ground control station achieved an average command round-trip latency of 178 ms and end-to-end monitoring latency below 250 ms [28]. These values indicate that the monitoring infrastructure is suitable for operator-level risk visualization, although high-speed or dense-traffic scenarios may require stricter latency validation.

C. Dynamic Obstacle Encounter Results

The dynamic obstacle records provide ten encounter cases with measurable hazard response. Table 5 reports risk score, activation delay, observation-to-maneuver time, avoidance duration, thruster difference, mission recovery, and trial success.

All trials completed successfully and returned to the mission state. The visual-risk score reached 1.000 in every case, while the mean activation delay was 0.004 s. The mean observation-to-maneuver interval of 0.881 s describes the practical delay between initial detection and actuator response, and the mean duration of 54.184 s represents the period during which the hazard condition remained active.

These timing records characterize encounter development and recovery. However, the visual-risk score should not be treated as a direct CPA or TCPA measurement; it serves only as supporting evidence of encounter severity.

TABLE 5.
DYNAMIC OBSTACLE ENCOUNTER PERFORMANCE SUMMARY

Metric	Mean	Std. Dev.	Minimum	Maximum	Surveillance Interpretation
Maximum risk score	1.000	0.000	1.000	1.000	All encounter cases reached the highest observed visual-risk condition
Avoidance activation delay	0.004 s	0.013 s	0.000 s	0.040 s	Hazard-state activation occurred almost immediately after risk confirmation
Observation-to-maneuver time	0.881 s	0.436 s	0.469 s	1.621 s	Practical delay from visual observation to maneuver command generation
Avoidance duration	54.184 s	6.417 s	44.805 s	65.786 s	The hazard state was maintained until the obstacle condition was cleared
Maximum thruster difference	0.565	0.000	0.565	0.565	Maneuver intensity was consistent across trials
Mission recovery rate	100.0%	N/A	N/A	N/A	The ASV returned to mission state after avoidance
Success rate	100.0%	N/A	N/A	N/A	All dynamic obstacle trials were completed successfully

D. CPA/TCPA-Oriented Encounter Interpretation

Continuous target coordinates were unavailable for every obstacle trial. Consequently, the analysis in Table 6 represents a rule-based CPA/TCPA interpretation rather than measured closest-approach values for each encounter. The mapping links approach tendency, visual-

risk evidence, mission state, and telemetry continuity to the expected close-approach condition

Table 6 shows that distance alone is insufficient to identify an unsafe encounter. A nearby object may remain non-threatening when separation increases or TCPA becomes negative. Conversely, an object at a greater initial range may require attention when

predicted separation decreases and the remaining approach time becomes short [21], [22].

TABLE 6.
CPA/TCPA-ORIENTED ENCOUNTER INTERPRETATION FOR SHORE-SIDE SURVEILLANCE

Encounter Condition	Main Indicators	CPA/TCPA-Oriented Interpretation	Alert Level	Operator Meaning
Stable navigation without nearby target	Own-ship telemetry available; no relevant target detected	No predicted close approach	Normal	Continue monitoring
Target detected but range does not decrease	Target exists; relative range stable or increasing	CPA is not expected to violate safety threshold, or TCPA is negative	Normal	Target is observed but not hazardous
Relevant target with developing approach	Target relevance increases; relative range decreases gradually	CPA may approach caution threshold with positive TCPA	Caution	Operator should increase attention
High-risk target with maneuver response	Maximum risk score reaches 1.000; avoidance mode becomes active	Predicted separation is potentially unsafe and reaction time is limited	Warning	Operator should prepare advisory action or intervention
High-risk target with degraded telemetry or abnormal mission state	High-risk encounter occurs with telemetry loss, mode change, or failed recovery	Risk cannot be reliably supervised or remaining time is insufficient	Danger	Operator should initiate emergency response or fail-safe procedure

E. Alert Generation Results

Table 7 applies the classification logic to the available navigation, obstacle, communication, and fail-safe records. Stable simulation data provide a baseline status, while the larger real-world navigation variation requires closer observation. High visual-risk events and active avoidance periods produce elevated status outputs because the encounter remains unresolved.

Communication loss represents the most critical condition because the operator can no longer verify target development or mission recovery. Conversely, successful mission recovery allows the displayed status to return to its baseline condition. The monitoring latency below 250 ms indicates that the available interface can deliver these updates during low-speed trials [28].

TABLE 7.
COLLISION RISK ALERT GENERATION RESULTS

Surveillance Input Condition	Supporting Result	Generated Alert	Interpretation
Own-ship navigation remains stable	Simulation waypoint error: 0.49 m; heading error: 4.21°	Normal	Own-ship state is reliable for baseline surveillance
Real-world navigation variation occurs	Real-world waypoint error: 1.15 m; heading error: 10.8°	Caution	Field disturbance may influence relative-motion interpretation
Obstacle detected but not yet critical	Target is detected; relative approach remains moderate	Caution	Operator should monitor target-track trend
High-risk dynamic obstacle appears	Maximum visual risk score: 1.000	Warning	Encounter should be treated as a significant collision-risk event
Avoidance mode is activated	Mean activation delay: 0.004 s; observation-to-maneuver time: 0.881 s	Warning	Onboard system responds, while shore-side operator should observe recovery
Hazard condition persists	Mean avoidance duration: 54.184 s	Warning	Risk state remains active until obstacle condition is cleared
Mission recovery succeeds	Mission recovery rate: 100.0%	Normal after recovery	Risk status can return to normal after validated recovery
Telemetry or communication failure occurs	Communication-loss detection: 6–15 s [26]	Danger	Operator awareness is degraded and fail-safe response is required
Browser-based monitoring remains responsive	Monitoring latency below 250 ms [28]	Operationally available	Alert visualization can be delivered to the shore-side interface

F. Discussion

The results reveal several findings that are important for encounter surveillance. First, own-ship state uncertainty increased substantially during field operation. The mean waypoint error increased from 0.49 m in simulation to 1.15 m in real-world testing, an increase of approximately 134.7%, while the mean heading error increased from 4.21° to 10.8%, or approximately 156.5%. All waypoint missions were nevertheless completed successfully. These results show that larger field errors do not necessarily represent

navigation failure, but they can influence the relative position and velocity vectors used in CPA/TCPA calculations. Risk thresholds should therefore accommodate realistic GPS and heading uncertainty to avoid premature escalation during otherwise stable ASV operation.

Second, the dynamic-obstacle records provide information about both hazard development and recovery. All ten encounters achieved successful avoidance and mission recovery, while the maximum visual-risk score reached 1.000 in every trial. The mean

activation delay was 0.004 s, the mean observation-to-maneuver interval was 0.881 s, and the hazardous condition remained active for an average of 54.184 s. The long duration relative to the initial detection response indicates that an encounter is not adequately described by a single obstacle-detection event. For surveillance purposes, the persistence and evolution of the hazard are therefore as important as the initial detection itself.

Third, the communication results define an important boundary for remote monitoring. End-to-end monitoring latency below 250 ms indicates that updated navigation information can be delivered rapidly during the low-speed experiments. This result supports near-real-time visualization but should not be interpreted as proof of adequate response time for every maritime encounter. The fail-safe records also show communication-loss detection between 6 and 15 s [26]. Such an interruption may be tolerable for some low-speed missions but requires further investigation for faster vessels or denser traffic, where several seconds of missing target information could significantly reduce confidence in a predicted closest approach.

The findings also clarify the contribution relative to existing research. Conventional CPA/TCPA studies primarily quantify ship-to-ship encounter geometry [19]–[24], while autonomous-vessel research commonly uses risk estimates to support onboard collision-avoidance decisions [9]–[12], [31]–[33]. The present work uses the same fundamental encounter variables for a different operational purpose: maintaining an interpretable risk picture at the remote monitoring station using navigation, communication, and mission-state information available from a small ASV. This integration is the principal novelty of the study.

The evidence should nevertheless be interpreted as technical feasibility rather than complete operational validation. Continuous target trajectories were unavailable for every obstacle trial, so Table 6 represents a rule-based CPA/TCPA interpretation rather than measured DCPA and TCPA values for all encounters. Further experiments with synchronized own-ship and target tracks are required to determine numerical accuracy, optimize threshold values, and measure the amount of decision time available to an operator before intervention becomes necessary.

G. Limitations

Several limitations remain. First, the evaluated obstacle dataset does not yet contain complete continuous target-track coordinates for each encounter, so the CPA/TCPA assessment is presented at the surveillance-interpretation level rather than as a full trajectory-by-trajectory D_{CPA} and TCPA computation. Second, the alert thresholds should be refined using additional experiments with measured target position, target speed, target course, and relative bearing. Third, the current dataset represents small ASV operation in restricted water environments, so further validation is required for coastal waters, multi-target encounters, and higher traffic density. Future work should include continuous target tracking, AIS or radar-like target

fusion, numerical CPA/TCPA validation, operator response-time analysis, and integration with VTS-ready multi-ASV supervision.

IV. CONCLUSION

This paper examined whether existing ASV navigation, obstacle, communication, and fail-safe records could support CPA/TCPA encounter assessment in restricted-water operations. The proposed framework organized these heterogeneous data into a unified monitoring workflow for evaluating developing encounters.

The ten obstacle trials completed successfully and returned to the original mission state, while the available ground-control records showed end-to-end monitoring latency below 250 ms. These findings establish data and communication readiness for encounter assessment. However, they do not constitute full numerical CPA/TCPA validation because continuous target trajectories were unavailable for every trial.

Future evaluation should compute DCPA and TCPA from synchronized own-ship and target tracks, validate scenario-specific thresholds, examine multi-target encounters, and measure operator response time. Such testing is required before the method can be applied to denser coastal traffic or integrated into formal VTS operations.

REFERENCES

- [1] J. E. Manley, "Unmanned maritime vehicles: 20 years of commercial and technical evolution," in Proc. OCEANS 2016 MTS/IEEE Monterey, Monterey, CA, USA, 2016, pp. 1–6.
- [2] Y. Gu, J. C. Goetz, M. Guajardo, and S. W. Wallace, "Autonomous vessels: State of the art and potential opportunities in logistics," *International Transactions in Operational Research*, vol. 28, no. 4, pp. 1706–1739, 2021.
- [3] U. K. Verfuss et al., "A review of unmanned vehicles for the detection and monitoring of marine fauna," *Marine Pollution Bulletin*, vol. 140, pp. 17–29, 2019.
- [4] O. Lewicka et al., "Integration data model of the bathymetric monitoring system for shallow waterbodies using UAV and USV platforms," *Remote Sensing*, vol. 14, no. 16, p. 4075, 2022.
- [5] Y. Qiao, J. Yin, W. Wang, F. Duarte, J. Yang, and C. Ratti, "Survey of deep learning for autonomous surface vehicles in marine environments," *IEEE Transactions on Intelligent Transportation Systems*, vol. 24, no. 4, pp. 3678–3701, 2023.
- [6] G. Wu, D. Li, H. Ding, D. Shi, and B. Han, "An overview of developments and challenges for unmanned surface vehicle autonomous berthing," *Complex & Intelligent Systems*, vol. 10, no. 1, pp. 981–1003, 2024.
- [7] T. Statheros, G. Howells, and K. McDonald-Maier, "Autonomous ship collision avoidance navigation concepts, technologies and techniques," *The Journal of Navigation*, vol. 61, no. 1, pp. 129–142, 2008.
- [8] C. Tam and R. Bucknall, "Collision risk assessment for ships," *Journal of Marine Science and Technology*, vol. 15, no. 3, pp. 257–270, 2010.
- [9] Y. Kuwata, M. T. Wolf, D. Zargitsky, and T. L. Huntsberger, "Safe maritime autonomous navigation with COLREGS, using velocity obstacles," *IEEE Journal of Oceanic Engineering*, vol. 39, no. 1, pp. 110–119, 2014.
- [10] J. Woo, C. Yu, and N. Kim, "Collision avoidance algorithm based on COLREGs for unmanned surface vehicle," *Journal of Marine Science and Engineering*, vol. 9, no. 8, p. 863, 2021.
- [11] E. Meyer, A. Heiberg, A. Rasheed, and O. San, "COLREG-compliant collision avoidance for unmanned surface vehicle using deep reinforcement learning," *IEEE Access*, vol. 8, pp. 165344–165364, 2020.

- [12] B.-O. H. Eriksen, G. Bitar, M. Breivik, and A. M. Lekkas, "Hybrid collision avoidance for ASVs compliant with COLREGs rules 8 and 13–17," *Frontiers in Robotics and AI*, vol. 7, p. 11, 2020.
- [13] International Association of Marine Aids to Navigation and Lighthouse Authorities, IALA Guideline G1089 on Provision of Vessel Traffic Services, IALA, 2022.
- [14] International Maritime Organization, "Regulatory scoping exercise for the use of maritime autonomous surface ships," IMO Maritime Safety Committee, MSC.1/Circ.1638, 2021.
- [15] L. Wróbel, P. Krata, and K. Montewka, "Development of risk indicators for losing navigational control of autonomous ships," *Ocean Engineering*, vol. 248, p. 110823, 2022.
- [16] L. Ramos, F. Utne, I. B. Mosleh, and A. K. Nordahl, "Collision risk analysis of maritime autonomous surface ships considering mental workload of shore control center operators," *EII Journal*, 2026.
- [17] E. Tu, G. Zhang, L. Rachmawati, E. Rajabally, and G.-B. Huang, "Exploiting AIS data for intelligent maritime navigation: A comprehensive survey," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 5, pp. 1559–1582, 2018.
- [18] P. A. M. Silveira, A. P. Teixeira, and C. G. Soares, "Use of AIS data to characterise marine traffic patterns and ship collision risk off the coast of Portugal," *The Journal of Navigation*, vol. 66, no. 6, pp. 879–898, 2013.
- [19] J. M. Mou, C. van der Tak, and H. Ligteringen, "Study on collision avoidance in busy waterways by using AIS data," *Ocean Engineering*, vol. 37, no. 5–6, pp. 483–490, 2010.
- [20] F. Goerlandt and P. Kujala, "On the reliability and validity of ship–ship collision risk analysis in light of different perspectives on risk," *Safety Science*, vol. 62, pp. 348–365, 2014.
- [21] X. Qu, Q. Meng, and L. Suyi, "A quantitative method for the analysis of ship collision risk using AIS data," *Reliability Engineering & System Safety*, vol. 203, p. 107075, 2020.
- [22] J. Chen, Y. Wang, and X. Zhang, "A novel method for holistic collision risk assessment in the precautionary area using AIS data," *Ocean Engineering*, vol. 296, p. 116936, 2024.
- [23] L. P. Perera and C. G. Soares, "Collision risk detection and quantification in ship navigation with integrated bridge systems," *Ocean Engineering*, vol. 109, pp. 344–354, 2015.
- [24] D. N. Utama, D. M. Rosyid, and I. S. Arief, "A comprehensive review of ship collision risk assessment and safety index development," *Safety*, vol. 12, no. 2, p. 57, 2026.
- [25] S. A. Sukarno, H. Rudiansyah, H. T. Maulana, M. Kadir, and F. S. Adi, "Design and development of a command and control unit (CCU) on an unmanned surface vehicle (USV) for water observation," *International Journal of Marine Engineering Innovation and Research*, vol. 10, no. 4, pp. 1124–1132, 2025.
- [26] S. A. Sukarno, H. Nuruliman, and Ridwan, "Design and implementation independent battery and lost-link fail-safe module for USV safety," *International Journal of Marine Engineering Innovation and Research*, vol. 11, no. 2, pp. 755–765, 2026.
- [27] A. A. Priadi, T. Cahyadi, L. Barasa, S. A. Sukarno, N. Suranta, and M. Yando, "Development of IoT-based monitoring for unmanned surface vessels (USV)," *Journal of Engineering Science and Technology, Special Issue on STIPCON2024*, vol. 20, no. 5, pp. 1–10, 2025.
- [28] A. M. Baharudin, S. A. Sukarno, and M. H. K. Saputra, "Design and development of web-based USV ground control station for ocean observation," *International Journal of Marine Engineering Innovation and Research*, vol. 11, no. 2, pp. 497–507, 2026.
- [29] S. A. Sukarno, R. B. Atitallah, and M. Djemai, "Approximation algorithm for 3-dimensional vehicle routing problem for fleet of multi-agents," in *Proc. 6th International Conference on Control Engineering & Information Technology*, Istanbul, Turkey, 2018, pp. 1–6, doi: 10.1109/CEIT.2018.8751928.
- [30] B. Sampurno, I. F. Putra, M. Mashuri, and Suhariyanto, "GPS navigation system on autonomous ship as an effort to increase fish catch for fisherman in Pamekasan Indonesia," *International Journal of Marine Engineering Innovation and Research*, vol. 8, no. 4, pp. 735–750, 2023.
- [31] H. Namgung and J.-S. Kim, "Collision Risk Inference System for Maritime Autonomous Surface Ships Using COLREGs Rules Compliant Collision Avoidance," *IEEE Access*, vol. 9, pp. 7823–7835, 2021, doi: 10.1109/ACCESS.2021.3049238.
- [32] Z. Qiao, Y. Zhang, and S. Wang, "A Collision Risk Identification Method for Autonomous Ships Based on Field Theory," *IEEE Access*, vol. 9, pp. 30539–30550, 2021, doi: 10.1109/ACCESS.2021.3059248.
- [33] A. Vagale, R. Oucheikh, R. T. Bye, O. L. Osen, and T. I. Fossen, "Path planning and collision avoidance for autonomous surface vehicles I: A review," *Journal of Marine Science and Technology*, vol. 26, pp. 1292–1306, 2021, doi: 10.1007/s00773-020-00787-6.