Data-Driven Situational Awareness and Collision Avoidance Framework for Autonomous Surface Vehicles

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ABSTRACT

The rapid development of autonomous surface vehicles (ASVs) offers significant potential to improve maritime safety, operational efficiency, and sustainability. This review examines data-driven frameworks for situational awareness (SA) and collision avoidance (CA) in ASVs, conceptualizing them as representative intelligent engineering systems (IES) empowered by artificial intelligence (AI). Anchored in cyber-physical systems (CPS) theory and information theory, the framework combines multi-modal sensor fusion, machine learning for perception and trajectory prediction, and reinforcement learning (RL) for real-time decision-making. The paper analyzes four core transformation pathways enabled by AI: from standardized rule-based navigation to personalized adaptive strategies, from reactive maneuvers to proactive prediction and optimization, from manual or remote operation to autonomous intelligent control, and from isolated platforms to integrated cyber-physical maritime ecosystems. Specific examples include deep reinforcement learning (DRL) agents that achieve COLREGs-compliant avoidance and digital-twin-supported predictive maintenance for propulsion systems. While these approaches deliver measurable improvements in safety metrics and efficiency, the review critically evaluates persistent challenges related to data quality under adverse marine conditions, regulatory integration, computational constraints, and cybersecurity risks. Future directions emphasize hybrid neuro-symbolic methods, physics-informed models, and multi-agent coordination to support trustworthy deployment. The work provides a structured foundation for advancing certifiable autonomy within broader IES paradigms.

Keywords: Autonomous Surface Vehicles; Situational Awareness; Collision Avoidance; Data-Driven Artificial Intelligence; Cyber-Physical Systems; Reinforcement Learning; Digital Twin; Maritime Autonomy

1. INTRODUCTION

Global maritime transport carries approximately 90% of world trade by volume, yet collisions and groundings continue to impose substantial human, economic, and environmental costs. Human error remains the dominant contributing factor in the majority of incidents [1,2]. In response, the International Maritime Organization has advanced its Maritime Autonomous Surface Ships (MASS) strategy, stimulating research into progressively higher levels of autonomy. Autonomous surface vehicles (ASVs) must perceive complex, dynamic environments, comprehend collision risks, and project future states while operating under the International Regulations for Preventing Collisions at Sea (COLREGs).

Traditional kinematic models and rule-based systems exhibit limited adaptability to nonlinear hydrodynamics, sensor noise, and multi-vessel interactions. Data-driven frameworks address these limitations by integrating deep learning for perception, recurrent or graph-based models for trajectory forecasting, and reinforcement learning for sequential decision optimization [3,4]. These components operate within a cyber-physical architecture that couples physical vessel dynamics with computational perception–planning–control loops.

This review positions the data-driven SA–CA framework as a canonical example of AI-driven transformation in intelligent engineering systems. It draws on systems engineering for holistic design, CPS theory for closed-loop responsiveness, and information theory for quantifying uncertainty reduction through sensor fusion and policy learning. Concrete illustrations are drawn from validated DRL implementations and digital-twin applications. The analysis balances demonstrated performance gains against limitations in generalization, verification, and security. By synthesizing theoretical foundations, transformation paths, applications, and prospects, the paper supplies researchers and practitioners with an evidence-based template for advancing maritime autonomy.

2. The Theoretical Foundation of Artificial Intelligence and Intelligent Engineering Systems

2.1 The Connotation and Characteristics of Intelligent Engineering Systems

Intelligent engineering systems integrate physical processes with computational intelligence and bidirectional data flows to exhibit goal-directed adaptive behavior. Defining characteristics include autonomy under uncertainty, adaptability through learning, resilience via self-diagnosis, and interconnectivity supporting system-of-systems operation [1,2]. These properties align closely with CPS architectures, in which physical plants (hydrodynamics, propulsion) are tightly coupled with cyber layers (sensors, processors, actuators) through real-time feedback.

In the ASV context, the vessel constitutes a mobile IES. Multi-sensor suites generate observations that AI algorithms fuse into environmental state estimates; learned policies then map states to control actions while digital twins enable predictive simulation [5]. This configuration satisfies core IES attributes: the system perceives its surroundings, reasons about risk and regulatory compliance, and executes control without continuous human input. Comprehensive reviews of path-planning and collision-avoidance algorithms document the evolution from geometric and optimization-based methods toward learning-enabled approaches better suited to stochastic maritime environments [1,2].

2.2 The Theoretical Logic of Artificial Intelligence Empowering Engineering Systems

The enabling logic rests on three complementary foundations. Systems engineering supplies integrative methods for requirements allocation, interface specification, and verification across the full perception–planning–control stack. CPS theory provides the pattern of networked computation embedded within physical dynamics, supporting the low-latency loops essential for collision avoidance. Information theory quantifies SA as entropy reduction regarding surrounding traffic states; optimal fusion maximizes mutual information between sensor observations and true environmental conditions, while RL policies minimize expected collision risk over time [3].

AI empowers these systems by replacing or augmenting analytical models with data-driven representations that capture complex, non-stationary relationships. Supervised models handle perception tasks, unsupervised methods detect anomalies, and RL optimizes long-horizon decisions formulated as Markov Decision Processes. A key original insight is that the ASV pipeline performs progressive "information-to-decision" compression: high-dimensional sensor streams are abstracted into compact risk metrics and intent hypotheses, enabling real-time execution on embedded hardware while preserving safety margins. This logic directly informs the transformation pathways analyzed below.

3. The Transformation Path of Intelligent Engineering Systems Mode Driven by Artificial Intelligence

3.1 Transition from Standardized Production to Personalized and Flexible Manufacturing

Standardized "production" of navigation decisions historically relied on fixed if-then implementations of COLREGs encounter rules. Such deterministic logic ensures baseline compliance but often yields conservative or unsafe maneuvers when vessel dynamics or traffic configurations deviate from nominal assumptions. AI enables personalized, flexible strategy generation analogous to mass customization in manufacturing. DRL agents trained with domain randomization across vessel models, sea states, and encounter geometries learn policies that adapt control commands to platform-specific maneuverability and predicted target behavior [4,6]. Validated examples demonstrate smoother trajectories and reduced cumulative risk while maintaining COLREGs compliance through shaped rewards or constrained optimization. This transition improves performance in complex scenarios yet requires rigorous verification to bound unexpected behavior in out-of-distribution conditions.

3.2 Transition from Reactive Response to Proactive Prediction and Optimization

Conventional systems trigger evasive action only after TCPA or DCPA thresholds are breached. Data-driven frameworks shift toward proactive prediction and optimization. Trajectory forecasting models extrapolate target states over multi-minute horizons, explicitly incorporating interaction effects and COLREGs intent [3,5]. These forecasts inform model predictive control or model-based RL planners that optimize host trajectories across safety, efficiency, and regulatory objectives. Hybrid DRL-MPC architectures have achieved superior results in dense-traffic simulations by combining high-level maneuver selection with smooth low-level execution [4]. The proactive paradigm materially reduces last-minute, high-risk corrections, although prediction errors under occlusion or abrupt maneuvers necessitate robust uncertainty handling [7].

3.3 Transition from Manual Operation to Autonomous Intelligent Control

Early ASV operations depended on direct remote piloting or periodic supervision, limiting endurance and introducing communication latency. The transition to autonomous intelligent control is realized through hierarchical or end-to-end learned pipelines executing onboard. Perception modules on edge accelerators perform real-time detection and tracking; conditioned policies output continuous control commands at rates compatible with closed-loop stability [6]. Demonstrated systems achieve reliable COLREGs-compliant avoidance in moderate conditions with minimal human intervention, freeing operators for supervisory roles. Edge deployment eliminates communication dependency and achieves sub-100 ms reaction times, subject to careful model compression and hardware-aware design.

3.4 Transition from Isolated Systems to Integrated Cyber-Physical Ecosystems

Isolated operation restricts SA to onboard sensor range and precludes coordinated de-confliction. Integration into maritime cyber-physical ecosystems links individual ASVs to vessel traffic services, neighboring vessels via enhanced AIS or future V2X, shore control centers, and fleet-level digital twins [5]. Shared perception extends effective awareness; multi-agent RL enables cooperative planning that minimizes system-wide risk. Synchronized digital twins support predictive simulation and continuous policy refinement. This ecosystem perspective converts the ASV from a standalone asset into a resilient node within a larger system-of-systems, while elevating cybersecurity and interoperability to primary design requirements.

4. Applications of Artificial Intelligence in Intelligent Engineering Systems

4.1 Application in Intelligent Fault Diagnosis and Predictive Maintenance

Data-driven diagnosis and predictive maintenance enhance IES resilience. Vibration, temperature, and electrical signatures from propulsion and steering systems are analyzed by machine learning classifiers or autoencoders to detect incipient faults and estimate remaining useful life [5]. Digital twins integrate physics-based degradation models with online telemetry, enabling accurate simulation of marine-specific wear mechanisms. Operational cases have shown advance warning of mechanical anomalies weeks ahead of failure, supporting condition-based maintenance that reduces downtime and prevents mission-critical casualties. The approach lowers through-life costs while improving availability, provided high-quality labeled data and drift-management procedures are maintained.

4.2 Application in Intelligent Process Optimization and Quality Control

Treating the SA–CA pipeline as the optimizable “process” yields measurable performance gains. RL and derivative-free methods tune fusion parameters, planning horizons, and cost weights to balance competing objectives under varying conditions [3,6]. Quality is assured through systematic validation in high-fidelity simulators and sea trials using metrics such as minimum CPA, COLREGs violation rate, and trajectory smoothness. Computer-vision modules deliver real-time environmental “inspection,” continuously improved via logged operational data. These techniques have produced documented improvements in both objective safety indicators and operator trust, although certifying policy safety across the complete operational envelope remains challenging.

4.3 Application in Intelligent Human-Machine Collaboration and Operational Efficiency Enhancement

Full autonomy is neither always feasible nor desirable. Intelligent human–machine collaboration maximizes efficiency while retaining human accountability for exceptions. Shore operators supervising multiple ASVs receive AI-generated decision support comprising risk visualizations, trajectory predictions with confidence bounds, and recommended actions accompanied by explanatory rationales [3]. Digital-twin dashboards enable immersive what-if exploration prior to high-level intervention. This model permits a single operator to oversee a fleet, substantially reducing crewing costs and enabling continuous operations. Interface design must actively mitigate automation bias and clearly delineate authority boundaries to preserve appropriate human engagement.

5. Challenges and Prospects of Artificial Intelligence Empowering Intelligent Engineering Systems

5.1 Current Main Challenges

Marine environments impose stringent constraints on data quality: precipitation, sea clutter, and variable lighting induce distributional shift that degrades perception and prediction models [1,5]. Regulatory harmonization of learned behaviors with COLREGs, whose language emphasizes intent and good seamanship, remains incomplete. Computational and energy limits on embedded platforms constrain model complexity. Cybersecurity vulnerabilities—sensor spoofing, GPS jamming, and adversarial attacks on perception models—pose systemic risks to CPS integrity. Verification and validation of learning-enabled components lag behind deterministic methods, with persistent sim-to-real gaps complicating safety certification [8].

5.2 Prospects for Future Development Trends

Promising avenues address these limitations through hybrid architectures that embed symbolic COLREGs constraints within learned policies via shielding or constrained RL [4,6]. Physics-informed neural networks incorporate domain knowledge to improve generalization and data efficiency. Multi-agent RL and graph-based coordination scale cooperative fleet operations. Evolving digital-twin ecosystems will progress toward prescriptive and autonomous levels, supporting continuous digital threads from design to in-service adaptation. Advances in edge AI hardware, maritime connectivity, and explainable AI methods will facilitate certifiable deployment. These developments are expected to mature ASVs from experimental platforms into routine, trusted components of intelligent maritime logistics networks.

6. Conclusion

This review has presented a data-driven situational awareness and collision avoidance framework for autonomous surface vehicles as a paradigmatic case of AI-empowered intelligent engineering systems. Grounded in systems engineering, CPS theory, and information theory, the framework illuminates four interlocking transformation pathways that move maritime operations from reactive, human-centric, and isolated modes toward proactive, adaptive, and ecosystem-integrated autonomy. Applications in fault diagnosis, process optimization, and human–AI collaboration demonstrate concrete benefits in safety, efficiency, and resilience, supported by simulation and field evidence [1–6]. Persistent challenges in data quality, regulatory alignment, verification, and security nevertheless demand continued interdisciplinary research. Future progress depends on hybrid AI paradigms, robust uncertainty quantification, and rigorous assurance methodologies capable of delivering certifiable, trustworthy ASV capabilities. Successful realization will advance sustainable maritime transportation while offering transferable principles for IES development across other safety-critical domains.

REFERENCES

[1] Vagale, A., Oucheikh, R., Bye, R. T., Osen, O. L., & Fossen, T. I. (2021). Path planning and collision avoidance for autonomous surface vehicles I: a review. Journal of Marine Science and Technology, 26, 1292–1306. https://doi.org/10.1007/s00773-020-00787-6

[2] Vagale, A., Bye, R. T., Oucheikh, R., Osen, O. L., & Fossen, T. I. (2021). Path planning and collision avoidance for autonomous surface vehicles II: a comparative study of algorithms. Journal of Marine Science and Technology, 26, 1307–1323. https://doi.org/10.1007/s00773-020-00790-x

[3] Sarhadi, P., Naeem, W., & Athanasopoulos, N. (2022). A survey of recent machine learning solutions for ship collision avoidance and mission planning. IFAC-PapersOnLine, 55(31), 257–268. https://doi.org/10.1016/j.ifacol.2022.10.286

[4] Ma, Y., Zhao, Y., Wang, Y., Gan, L., & Zheng, Y. (2020). Collision-avoidance under COLREGS for unmanned surface vehicles via deep reinforcement learning. Maritime Policy & Management, 47(5), 665–686. https://doi.org/10.1080/03088839.2020.1756494

[5] Xing, B., Yu, M., Liu, Z., Tan, Y., Sun, Y., & Li, B. (2023). A review of path planning for unmanned surface vehicles. Journal of Marine Science and Engineering, 11(8), 1556. https://doi.org/10.3390/jmse11081556

[6] Wang, W., Huang, L., Liu, K., et al. (2022). A COLREGs-compliant collision avoidance decision approach based on deep reinforcement learning. Journal of Marine Science and Engineering, 10(7), 944. https://doi.org/10.3390/jmse10070944

[7] Fan, Y., et al. (2022). A novel reinforcement learning collision avoidance algorithm for USV. Journal of Marine Science and Engineering, 10(3), 346. https://doi.org/10.3390/jmse10030346

[8] Burmeister, H. C., et al. (2021). Autonomous collision avoidance at sea: A survey. Journal of Marine Science and Engineering, 9(9), 1027. https://doi.org/10.3390/jmse9091027