A Practical Methodology for Safety Assessment of Autonomous Navigation Systems: Integrating STPA and Scenario-Based Analysis

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Abstract: Autonomous navigation systems can address various industry and societal challenges, such as crew shortages, infrastructure maintenance, and cost reduction. However, ensuring safety remains paramount, particularly in demonstrating safety equivalence to conventional vessels.
One of the primary challenges lies in developing specific methodologies for safety assurance tailored to autonomous navigation systems. Effective risk assessment methods must capture emergent hazards and understand system behavior comprehensively. While System-Theoretic Process Analysis (STPA) has been utilized for risk assessment, its qualitative nature sometimes needs a deeper understanding of system behavior. On the other hand, quantitative simulation has to deal with scenario coverage and computational time. This study proposes a practical risk assessment methodology combining STPA and scenario-based analysis. The methodology aims to assess risk effectively by extracting loss scenarios using STPA and conducting numerical analysis. Additionally, Gaussian process regression (GPR) is employed for scenario-based analysis, aiding in understanding the operational design domain (ODD) and considering performance metrics. A case study focusing on collision scenarios illustrates the efficacy of the proposed methodology. The simulation results highlight ODDs where safety thresholds are not met, providing valuable insights for designing ODDs and implementing fallback measures. Integrating STPA with scenario-based analysis and simulation offers a deeper understanding of system behavior and aids in defining functional requirements for simulators. This methodology is crucial for ensuring the safety of autonomous vessels and facilitating their widespread implementation in maritime industries.

Keywords: Autonomous navigation, Safety assessment, STPA, Scenario-based analysis.

1. INTRODUCTION

Maritime Autonomous Surface Ships (MASS) are expected to address various issues in industries and societies, such as reducing maritime accidents, which account for about 80% due to human error, resolving crew shortages, maintaining routes to remote islands, decreasing human exposure to hazardous areas both on board and off, enhancing operational efficiency and design flexibility of vessels leading to economic benefits, as well as avoiding human casualties caused by piracy through crewless operations, and mitigating social isolation among crew members due to remote operation [1]. Research and development, as well as demonstration experiments, on autonomous vessels are progressing worldwide. In recent years, the Nippon Foundation launched the crewless navigation ship project MEGURI2040 in 2020, supporting the development of autonomous navigation technology. In 2022, it succeeded in the world's first demonstration experiment of fully autonomous navigation in inland ships, aiming to foster further technological development to drive the transformation of logistics, economy, and social infrastructure [2].

Ensuring the safety of autonomous vessels is a fundamental aspect of discussing legal and liability issues, and it is unavoidable in the process of societal implementation [3,4]. To prevent accidents, it is crucial to identify existing hazards, assess their risks, implement appropriate risk reduction measures, and document these risk assessments until residual risks are reduced to an acceptable level (as low as reasonably practicable: ALARP). According to IMO MSC.1/Circ.1455 Guideline for Approval of Alternatives and Equivalents [5], when introducing new technologies, it is necessary to demonstrate that they ensure safety equivalent to existing ones. Guidelines on autonomous navigation and remote operation by classification societies such as ABS [6] and ClassNK [7] outline the basic principles of safety assurance based on MSC.1/Circ.1455. However, specific methods for ensuring equivalent safety have yet to be provided. There is a need to establish safety assurance methods that sufficiently assess the reduction of unforeseen events and reduce residual risks to an acceptable level.

2. ANALYSIS OF CHALLENGES IN SAFETY ASSURANCE

2.1. Challenges of Risk Assessment

As autonomous vessels are complex systems with many subsystems, unexpected hazardous events can occur even without equipment failure. For these unknown hazardous events, it is necessary to increase the "Known" areas as much as possible and to reduce residual risks, as shown in Figure 1. In the automotive field, the part of the standard that is not covered by ISO 26262, the standard for functional safety to prevent hazards caused by system failures, was newly standardized in 2022 as Safety of the Intended Functionality (SOTIF) as ISO 21448 [8]. It aims to prevent hazardous events without failures, such as performance limitations, effects of the external environment, and misuse or misoperation by users or traffic participants.

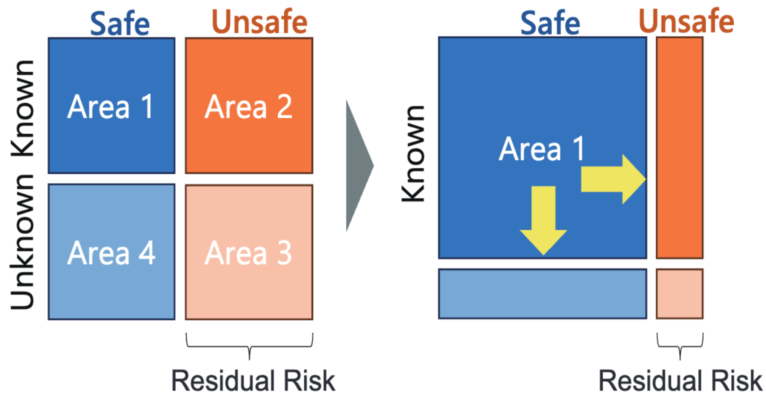

Figure 1. Approach for unknown events (modified from [8]).

A safety analysis method based on STAMP (Systems-Theoretic Accident Model and Processes) called STPA (System-Theoretic Process Analysis) has attracted attention as an approach to addressing these unknown risks [9]. Conventional risk assessment methods such as FMEA (Failure Mode and Effects Analysis) and FTA (Fault Tree Analysis) primarily focus on accidents caused by component failures and have limitations in identifying potential accident scenarios resulting from interactions between components, detecting causes, and extracting appropriate controls [10]. Using descriptive models, STPA can be understood as a method to extract emergent hazards (systemic risks) resulting from interactions between its elements. STPA conducts risk analysis in four steps, as shown in Figure. 2 [9].

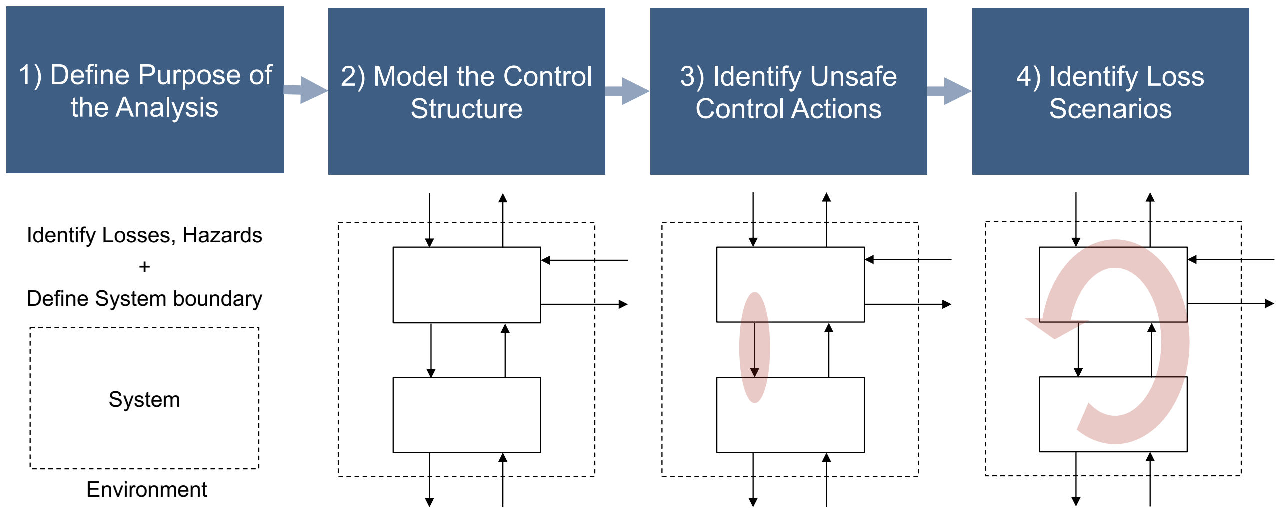

Figure 2. Four steps of STPA [9].

While autonomous vehicles target a single driver's driving task, ships involve multiple humans in the lookout, navigation, engine maintenance, and mooring operations. Consequently, the tasks targeted for autonomy and the degree of autonomy vary widely. Additionally, because of the long-term maritime duties of crew members, remote operation is often considered in addition to autonomous operation, necessitating a shift of operational activities ashore. Considering the roles of seafarers and shore operators and the interaction between humans and machines can be essential for risk assessment for autonomous vessels.

Although there are many examples of utilizing risk analysis during the conceptual design of autonomous vessels [11,12,13], the final outputs are often lists of hazards and barriers without quantitative information. This may limit understanding of the system's behavior [9], and in operational terms, it may lead to a patchwork response to new events, deviating from a proper understanding of the system. Therefore, it is essential to understand the system's behavior as loss scenarios and to clarify its relationship with the Operational Design Domain (ODD), defined by a set of conditions, including environmental, geographical, time of day, and other conditions.

2.2. Challenges of Scenario-based Simulation

In autonomous driving, scenario-based verification is becoming mainstream. For example, Zhang et al. [15] introduced eight methods for constructing scenarios for autonomous driving system, as shown in Figure. 3.

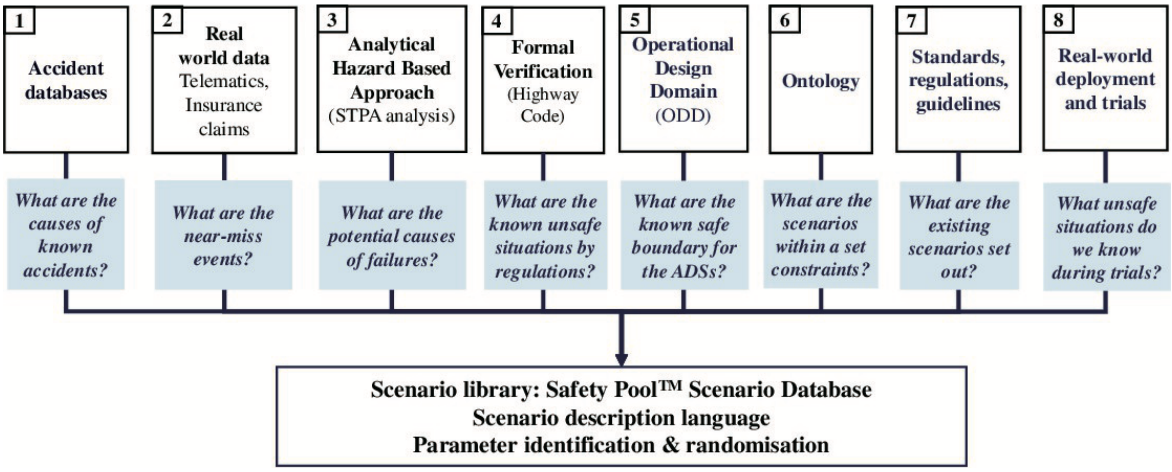

Figure 3. Eight different scenario creation methods [15].

Menzel et al. [16] categorize scenarios for automated driving systems into three levels of abstraction: Functional, Logical, and Concrete. A Functional Scenario outlines the core concepts, such as vehicle behavior, interactions with other road users and objects, road geometry, and basic descriptions of other components. A Logical Scenario builds on the Functional Scenario by defining the scope and distribution of each element (e.g., lane widths in meters) with quantitative information. Finally, a Concrete Scenario assigns specific values to each element from the Logical Scenario and serves as input for simulation. Scenario generation typically progresses from Functional to Logical to Concrete.

Scenario-based verification is also gaining attention in the marine industry [14]. However, these methods differ significantly in their applicability due to the differences between ship and automobile contexts. For example, while accident databases are essential, ships are manufactured as unique products, making it challenging to process accumulated data statistically. Furthermore, real-world data collection is difficult because autonomous ships have not yet been deployed on a large scale.

Formal Verification is a method that logically verifies whether the subject meets specifications by setting top-level rigorous requirements. However, the International Regulations for Preventing Collisions at Sea (COLREGs) do not cover all encounter situations, necessitating adaptable and flexible responses. Efforts are underway to model crew decision-making processes and quantify their skills [17,18,19], but the relatively ambiguous navigation rules make it difficult to define strict requirements.

Additionally, fewer numerical models and simulators are available for verification in the marine industry compared to the automotive industry. Identifying critical scenarios and developing a verification strategy based on simulator availability is essential. Organizing necessary data and understanding hazardous events using STPA and ODD will be effective for developing autonomous navigation systems. Challenges for each scenario creation method in Figure 3 are shown in Table 1.

Table 1. Scenario creation methods and application challenges for autonomous navigation system.

Scenario Creation Method	Main Usage	Challenges for autonomous navigation system
Accident databases	F/L/C	Manual analysis of causal factors is required
Real world data	F/L/C	Lack of data (not yet implemented)
Analytical Hazard Based Approach (STPA)	F/L	Possible before construction, even at the conceptual design level
Formal Verification	F/L/C	Relatively ambiguous navigation rules make it difficult to define a strict requirement
Operational Design Domain	L/C	Possible if use cases and operational conditions can be defined
Ontology	L/C	Possible if functional scenario needs to be defined
Standards, regulations, guidelines	F/L/C	Currently no documents for test scenario extraction
Real-world deployments	L/C	Limited demonstration

F: Functional Scenario, L: Logical Scenario, C: Concrete Scenario

3. PROPOSAL OF RISK ASSESSMENT METHODOLOGY

This paper proposes a study of practical safety argumentation methods based on the above issues. Designing autonomous vessels to ensure safety is difficult, especially in the high-level design. There are two points to solve this problem: 1) Conduct STPA at the concept layer and define loss scenarios to understand the system behavior, and 2) Perform numerical analysis using the extracted loss scenarios. Results are mainly used as a risk assessment method for designing ODDs.

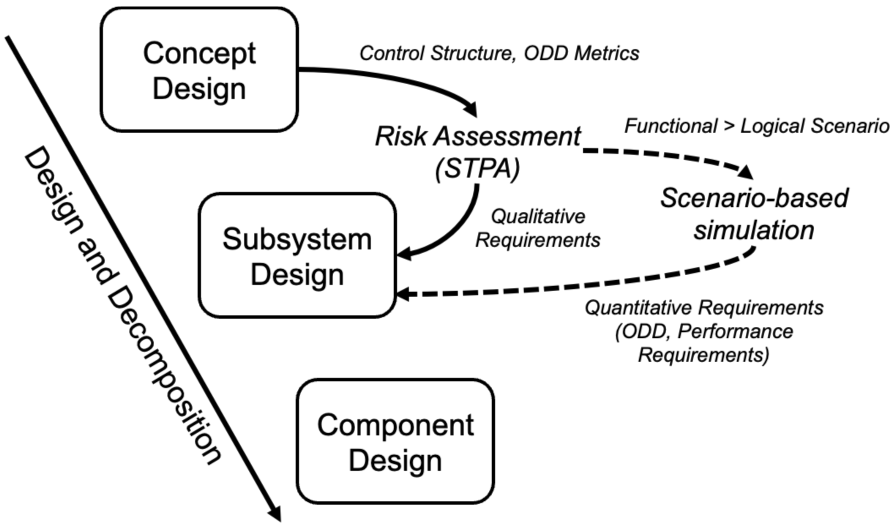

Figure 4. Risk assessment by STPA and scenario-based simulation.

3.1 Scenario extraction

We refer to the scenario extraction method using STPA for autonomous driving systems [20]. Step 1 defines the analysis objectives (loss, hazards, safety constraints), followed by the construction of a control structure diagram in Step 2. Subsequently, in Step 3, Unsafe Control Action (UCA) extraction is performed.

During UCA extraction, potential violations of safety constraints are identified by considering situations such as "not provided," "provided," "too early or too late timing," and "too long or too short duration" concerning the control actions defined in the control structure diagram [9]. Then, the context in which UCAs occur is specified, considering navigation areas (taking into account changes in speed and required actuators depending on operations such as berthing, harbor navigation, and ocean navigation), their transitions, autonomy levels (degree of human involvement), transitions, and ODD categories. Subsequently, loss scenarios are defined by analyzing factors and resulting consequences.

We can appropriately extract causal factors based on the context by analyzing the discrepancy between the reality and the process model that causes UCA and the factors that cause the discrepancy. A process model is a controller's 'belief' of the state of a controlled process (synonymous with a mental model when the controller is a human). STAMP believes that the main cause of emergent accidents is an inaccurate process model (inconsistency between the process model and the system's actual state) and emphasizes the process model's derivation in identifying the cause [9].

Since the process of extracting the process model is an individualistic task, in this study, the discrepancies in the process model were extracted using three guide words: "excessive trust in the input," "excessive expectation of the output result," and "assumptions/assumptions in the situation recognition. By using these guidewords, it is easier to extract situations in which process model discrepancies may occur, such as "the sensor information is recognized as correct," "the actuator is recognized as moving normally," and "other vessels conduct risk analysis based on the assumption of constant velocity linear motion," respectively.

3.2 Scenario-Based Analysis

Even during the conceptual design stage, scenario-based analysis can aid in understanding ODD and considering performance metrics. ODD can be expressed as logical scenarios and their ranges, but simulations are discrete and need to cover this range comprehensively. While random sampling is feasible, more efficient methods like Sobol' sequences used in quasi-Monte Carlo methods or Latin hypercube sampling can cover the domain more effectively. Bolbot et al. [21] proposed a method where conditions are sampled from regions indicated by multiple indicators' ranges using Sobol' sequences. Scenarios are clustered using risk vectors, and the most dangerous scenarios are extracted from each cluster. They propose four risk vectors: Distance at the Closest Point of Approach (DCPA), Time to the Closest Point of Approach (TCPA), evasive area, maneuverability, and weather. However, the validity of these risk vectors needs to be demonstrated, as clusters of similar scenarios may change depending on the risk vectors used. Additionally, the settings of clustering algorithms and assumptions of holonomic movement in ships are mentioned as challenges.

Furthermore, Torben et al. [22] proposed a method using Bayesian optimization to sample regions while focusing on potentially high-risk parts efficiently. They use Signal Temporal Logic (STL) to formalize requirements in formal logic language and continuously ensure that these requirements are met using response functions. However, they do not consider other vessels' agencies.

Sawada et al. [23] derive the required scenario set from the coverage of COLREGs rules. In terms of safety verification, a representative scenario can be insufficient without validation in a continuous parameter space.

4 CASE STUDY

4.1 Scenario extraction

The STPA results themselves are omitted from this study. For details, please refer to Nakashima et al. [24]. Instead, we present an analysis case using a multi-agent simulator for navigation, focusing on the scenario "During an oceangoing situation at a calm sea, sudden appearance of another vessel (due to sensor performance limit) makes the close distance to another ship." In this session, the logical scenario extraction the ODD metrics is described.

Situations recognizing obstacles with collision potential are assumed based on parameters such as "speed of the other vessel" and "heading relative to own vessel." It is assumed to detect vessels in states with collision potential under all circumstances, and from there, it is shown that a certain distance is ensured from other vessels once recognized. Here, encountering another vessel is assumed to be a single vessel and "crossing and give way" situation according to COLREGs Rule 15 [23]. In this study, we set the other vessel's speed v_{target} ranging from 8 to 12 knots and its detection position θ_{target} ranging from 67.5 to 168.75 degrees as shown in Figure 5. Although scenario parameters such as detection distance, position and attitude of target ship could also be considered, for this study, simulations were conducted assuming a situation where other vessels with collision potential are recognized, with the collision point fixed 1 NM ahead of the own vessel.

Evaluation metrics can be set in various ways, but the distance from other vessels is used as the Robustness Score in this study. The Pass Criteria is set to ensure that Robustness Score does not fall below 100 (m) with a 99.5% confidence interval. Additionally, this study assumes minimal influence from oceanographic and meteorological conditions during ocean navigation, and constraints such as bathymetry, obstacles other than vessels, geographical conditions, oceanographic and meteorological conditions, and other infrastructure and navigation rules are not considered for this case study.

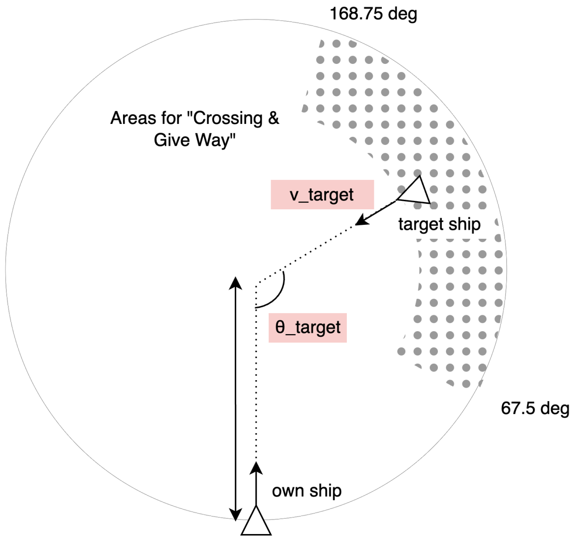

Figure 5. Sample logical scenario of "crossing and give way" situation.

We use Gaussian process regression (GPR) to evaluate the safety in the continuous ODD space by discrete simulation results. In GPR, setting the kernel (covariance) function that defines the similarity and correlation between data is crucial as it affects the performance and reliability of predictions of the model. The selection of the kernel function and hyperparameters should be based on the data's characteristics and the model's objectives. In this study, we used the ARD (Automatic Relevance Determination) Mat'ern 5/2 Kernel, which has been used in ship collision evaluation cases [22]. This kernel allows separate characteristic length scales σ_m for each predictor m, which can vary the smoothness. Based on simulation results, the characteristic length scales were determined through maximum likelihood estimation. The kernel used in this study is formulated as follows, where θ represents the kernel parameters, and σ_f is the noise standard deviation.

$$k(x_i, x_j|\theta) = \sigma_f^2\left(1 + \sqrt{5}r + \frac{5}{3}r^2\right)\exp\left(-\sqrt{5}r\right) \tag{1}$$

$$r = \sqrt{\sum_{m=1}^{d} \frac{\left(x_{im} - x_{jm}\right)^2}{\sigma_m^2}} \tag{2}$$

4.2 Simulation Results

In this study, sampling using Sobol' sequence is used to ensure continuity using response functions based on Gaussian process regression for rough estimation of ODD ranges rather than rigorous verification. It is assumed that each sample (in this study, simulation trial results for a single concrete scenario) is generated independently and follows the same distribution. We picked up concrete scenarios from the logical scenario defined above as inputs of the navigation simulator.

The general information of the simulator is shown in Appendix. Figure 6 shows the results of conducting Gaussian process regression with 200 simulations trials (degree of Sobol' sequence). The X axis represents the speed of the other vessel v_{target}, the Y axis represents the detection position of the other vessel θ_{target}, and the Z axis represents Robustness Score in the 3D plot. Each point represents the trial result of each case, and the two-dimensional plane represents the regression model obtained by GPR. From the figure, it can be observed that although most regions defined by the scenarios exceed the safe separation distance, the value of the Robustness Score decreases in situations where v_{target} is relatively large and θ_{target} is small. Taking into account the variance of the function output by GPR, the lower limit of the lower confidence interval corresponding to the lower 0.5 percentile is shown on the right side of Figure 6. The results show that even situation classified under the same basic scenario have different phenomena and the need for sampling in continuous space.

Also, by including cognitive uncertainty, the robustness of the sensor to accuracy can be evaluated. In the above simulation, the uncertainty in the perception of other vessel's relative angle σ_s is set to 0. Figure 7 shows the result of simulation setting σ_s as 0.01. We can see there are several cases which cannot keep the safe separation distance if the relative angle is below 90 degrees. Such situations can be considered out of ODD, and appropriate fallback measures (such as human supervision or override) need to be implemented. We could utilize this quantitative information to design an autonomous navigation system in the concept phase. Because ship operations are more flexible in their situation than those of automobiles due to the lack of roads and signs, it is necessary to set up scenarios while considering the continuous space of several ODD metrics.

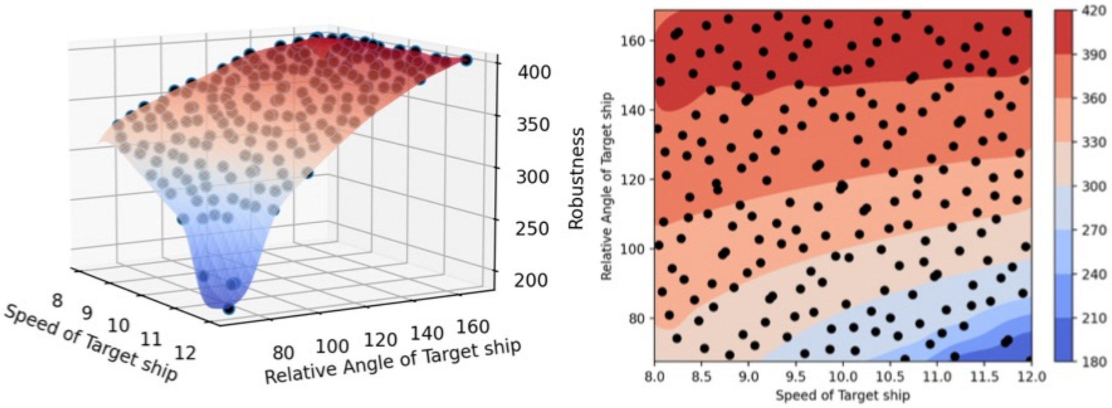

Figure 6. Simulation results without perception uncertainty. Black dots shows simulation results, and surface shows the GPR function (left: 3D of mean surface, right: 2D of lower 0.5 percentile surface).

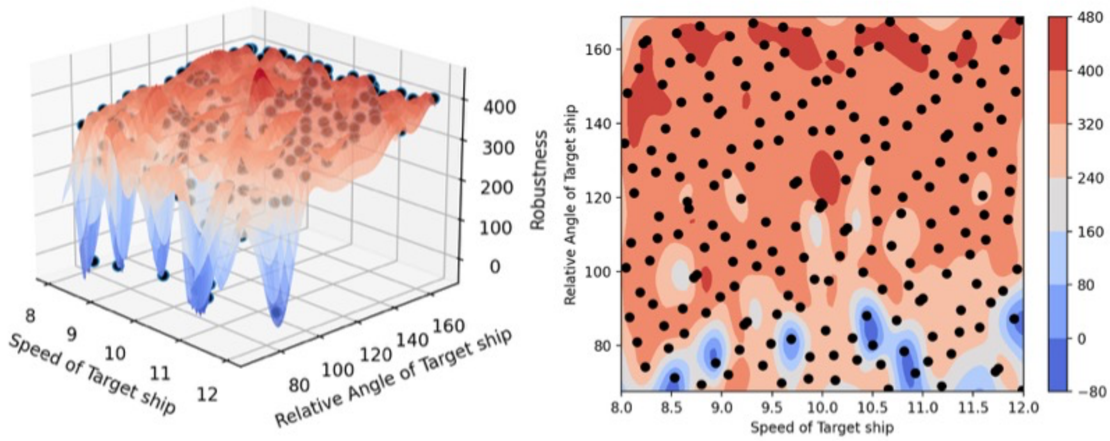

Figure 7. Simulation results with perception uncertainty Black dots shows simulation results, and surface shows the GPR function (left: 3D of mean surface, right: 2D of lower 0.5 percentile surface).

5. CONCLUSION

In this study, we identified two main activities, risk assessment, and simulation-based verification, that are necessary to ensure the safety of autonomous vessels. We then proposed an approach in which specific scenarios are constructed step by step from STPA, a qualitative risk analysis method. The scenarios are verified in continuous space and used to establish ODDs, which are areas that can be safely operated. A case study using a simple simulator is also presented.

Effective risk management for autonomous navigation systems necessitates a comprehensive understanding of system behavior and its interaction with the operational environment. This approach is anticipated to extend beyond discussions on autonomous system design and verification, contributing to establishing functional requirements for simulators in addition.

While our proposed approach shows promise, it is important to note that further work is needed to extend the scenarios and examine the applicability of this approach to other scenarios and ODDs. The example we have used, a simple avoidance problem, is just the tip of the iceberg. There are numerous components of ODDs, such as environmental conditions and topography, that need to be considered. This presents a rich field for future research and development. Metrics and simulators should be developed to represent these components appropriately, further enhancing the robustness of our approach. As there are several options on how to set kernel and parameters in GPR, it is necessary to develop a robust method by referring to Marel and Iooss [25].

Acknowledgements

I thank Mr. Rui Kureta, Mr. Jun Nakamura, and the members of the Autonomous Ship Team of MTI Co., Ltd., and Mr. Yuki Maeda and Laboratory of Intelligent Systems Design, the University of Tokyo for their advice in conducting this research.

APPENDIX

Overview of the Simulator

A simplistic simulator is utilized for the testing of this study. Each vessel possesses autonomous navigation functions of perception (awareness of own vessel situation, destination, understanding of other vessels), decision-making (formulation of collision avoidance plans), and operation (adjustment of rudder angle and output following collision avoidance plans). The simulator's time interval is set to one second, and the fourth-order Runge-Kutta method is employed for time integration.

Situation Awareness Current commercial ships perceive their own positions and attitudes using GNSS and compasses. The positions and attitudes of other vessels are recognized using RADAR (X-band, S-band) and AIS (Automatic Identification System), supplemented by visual observation. In the case of assuming autonomous navigation, the deployment of visible light cameras, IR cameras, LiDAR, etc., is being considered instead of visual observation. The performance of each sensor in capturing and tracking obstacles depends on external conditions (time, oceanographic conditions, meteorological conditions, size and position of other vessels, density, etc.). Moreover, defining the performance of situational awareness is difficult as it significantly varies depending on the method of integrating information from the sensor above. In this simulator, the accuracy of sensor position estimation is set by assuming Gaussian distributions for deviations from ground truths of own vessel perception and other vessel's crossing angle perception, with standard deviations σ_l and σ_s, respectively.

Collision Avoidance Planning In this study, the autonomous navigation algorithm utilizes the model by Nakamura and Okada [26]. It is an algorithm that considers both the risk calculated from TCPA, etc., determined from relative position and relative speed and the intentions of the ship's operator. As it closely resembles existing navigation patterns, the automatic exchange of intentions of autonomous ships is assumed in this study. However, the method can also be applied to cooperative navigation methods between autonomous and existing ships or between existing ships.

$$Ev\left(X_{\triangle Co,\triangle V}\right) = Pb\left(X_{\triangle Co,\triangle V}\right) - \alpha \max R\left(X_{\triangle Co,\triangle V}\right) \tag{3}$$

$$Pb\left(X_{\triangle Co,\triangle V}\right) = \exp\left(-a_c \triangle Co\right) \exp\left(-a_v \triangle V\right) \tag{4}$$

$$R\left(X_{\triangle Co,\triangle V}\right) = \max\left(R_x, R_y\right)\left(1 - \frac{\mathrm{TCPA}}{W_{\mathrm{TCPA}}}\right) \tag{5}$$

Here, $Ev\left(X_{\triangle Co,\triangle V}\right)$ represents the evaluation function used for decision making, $Pb\left(X_{\triangle Co,\triangle V}\right)$ represents the preference of the ship operator, and $R\left(X_{\triangle Co,\triangle V}\right)$ represents the risk of collision with other vessels. α is the risk weight. ΔCo represents the planned course, and ΔV represents the planned speed. R_x and R_y represent the risk in the lateral and longitudinal directions of the target vessel, respectively, and are determined using the closest distance to each axis [26]. Collision avoidance plans are formulated every three seconds. Other parameters are shown in Table 2.

Table 2. Parameter setting of planning module.

Item	Parameter
W_{TCPA} (s)	500
ΔV (knot)	0 - 12
ΔCo (deg)	-60 - 60
ac (-)	1.0
av (-)	0.2
α (-)	1.0

Control and Motion The rudder angle and engine RPM are calculated based on the output of collision avoidance plans to match the speed and heading order. This study uses PID control to adjust the rudder angle, and speed changes are controlled by setting maximum acceleration to ensure compliance with the specified speed. Control-related parameters are shown in Table 3.

Table 3. Parameter setting of control module.

Item	Parameter
Rudder angle range (deg)	-15 - 15
Maximum Speed (knot)	12
Maximum Acceleration Ratio (m/s^2)	1
P (-)	0.5
I (-)	0.1
D (-)	0.1

The motion of each vessel is represented using the KT model [27] as follows: The rate of turn r is determined based on the rudder angle δ. The values of K and T are set for ships assumed by Sawada et al. [28]. It is assumed in this study that these values do not change with speed changes. Here, the uncertainty in control σ_c is set to 0.1 [s]. Other parameters including specifications of each vessel assumed in this study are shown in Table 4.

$$Tr' + r = K\delta \tag{6}$$

Table 4. Each ship specification

Item	Parameter
LOA (m)	106
Beam (m)	16.2
K (s)	0.05
T (1/s)	50
TE (s)	2.5

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