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Real-Time Controlled Safety Metric for Use in Autonomous Systems of Safety Relevance Using the Example of the Operation of an Autonomous Inland Waterway Vessel

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The idea of understanding safety- or reliability-related variables as an output variable of a continuously operating control loop and thus regulating them has been known and formulated for about two to three decades and can nowadays also be found in automation systems, e.g., to extend the service life in the case of unpredictable, future performance requirements. Up to now, classical, deterministically determined and known fixed relationships have been used to exploit the relationship between, for example, realized stress and actual service life to achieve specific goals such as remaining service life. In this article, statistically known correlations are used, e.g., for the data-based determination of relevant, safety-related variables, to adjust operating variables online, i.e., continuously in real time, in such a way that minimum safety and/or reliability requirements for those variables are maintained. As a relevant, important, and practice relevant application example, the determination of objects in the path of vessels is used, the reliable determination of which is essentially determined both by sensor quality and by data-based estimation methods used. Both are significantly influenced in their capabilities by environmental conditions. Based on a Probability of Detection reltion statistical measurement data for the overall behavior, the driving speed, and thus the resulting braking distance are automatically adjusted so that the safety requirements are controlled. The methodology provides the basics for the establishment of classic risk regulations as proof of the maintenance of safety in automated vehicles.

Keywords: Autonomous systems, inland waterway transport, probability of detection, sensor fusion, real-time control, dependent functionality.

1. Introduction

1.1. *Background and Motivation*

The development of autonomous systems has provided new opportunities in inland navigation, as in many other industries, such as increasing operational efficiency, reducing costs and improving safety. Despite these advances, the reliability of autonomous systems, and therefore the components and software that influence them, remains a critical issue, especially in real-time operation, where unforeseen system errors or changes in environmental conditions affect system integrity.

A critical aspect of autonomous navigation is the detection of obstacles in the vessel's path. The effectiveness of this detection highly depends on sensor technologies such as radar, LiDAR, and cameras, which are sensitive to environmental factors such as fog, rain, and light conditions. The functionality of sensors providing measurements has to be evaluated with the likelihood to provide reliable/correct measurements or in case of downstreamed ML-based data processing related reliability assessment methods. Conventional methods of reliability assessment often rely on predefined offline models that take into account component failure under ideal assumptions and assuming other redundant components are fully functional. This contribution focuses on a novel approach to assess functionality in the context of detection systems, with direct implications for operational safety in autonomous shipping. Instead of relying solely on predefined models, this approach evaluates the task-specific reliability of active and relevant system components, even in the presence of known faults. The aim is to assess whether the existing object detection system meets predefined safety thresholds, ensuring its functionality under real-world conditions (fog, rain etc.). This perspective enables a more adaptive and dynamic assessment of functionality, crucial for maintaining safe and uninterrupted operation (instead of to shut down operations completely due to uncertainties) of autonomous vessels in variable and unpredictable environments. The Probability of Detection (POD) approach is used providing a statistical framework for evaluating and predicting the performance of sensors under different conditions. By incorporating these insights into real-time control systems, it becomes possible to dynamically adjust operational parameters, such as ship speed, to meet safety requirements. The POD approach was choosen because it provides a continuous function of detection probability as a function of physical quantities such as signal strength or object size, allowing thresholds and non-linear relationships to be captured empirically. In comparison, BBNs typically model the probability of detection as discrete states or conditional probabilities, which represents the dependencies between variables but does not reveal continuous progressions. In addition, the POD approach directly reflects the observed detection performance, making it particularly suitable for sensor-based evaluation.

1.2. *Addressed Research Questions*

The research questions addressed in this contribution are related to the dynamic regulation of safety- and reliability-related variables within a continuously operating control loop. The study explores how these variables can be treated as dynamic outputs, regulated in real time to ensure minimum safety requirements are consistently met. A key focus is on the shift from deterministic, fixed relationships towards statistically determined correlations for the continuous adjustment of operating parameters. Specifically, this contribution investigates how the POD curve can be utilized to dynamically adjust vessel operating parameters, such as speed, to compensate for variations in sensor performance influenced by environmental conditions. In addition, the study will investigate how data-driven control of safety-critical parameters can improve the robustness and efficiency of autonomous systems under dynamic and uncertain environmental conditions.

The structure of this paper is as follows: In Section 2 the challenges in the field of autonomous inland waterway transport as well as the background on the underlying methods are outlined. In Section 3 the methodology for generating POD curves as well as the derivation of the online control approach are presented. The application is covered in Section 4. The paper concludes with a summary and outlook in Section 5.

2. Fundamentals of Autonomy in Inland Waterway Transport

Object detection can be carried out using modalities such as cameras or LiDAR systems. Early fusion techniques have shown that dependencies can be reduced by using complementary sensors (Corral-Soto and Liu, 2020). The authors in Boschmann and Söffker (2022) investigated different lidar-based object detection approaches with regard to situation-dependent performance differences and complementary potentials, showing that fusion of several detection systems improves the prediction reliability. Further, the overall detection performance can be increased by a combined evaluation. New developments aim to improve the reliability and safety of autonomous vessels in dynamic environments through advanced algorithms such as probabilistic collision avoidance and formal methods (FMs). In Lee et al. (2024), it was shown how larger and earlier avoidance maneuvers can increase resilience to LiDAR noise and distinguish real obstacles from disturbances.

The authors in Torben et al. (2022) investigated the use of FMs to specify and verify maritime control systems for Maritime Autonomous Surface Ships (MASS). These methods provide a rigorous mathematical basis to ensure safety and efficiency. The study in Johansen et al. (2023) presents a Bayesian Network (BBN) integrated with Systems Theoretical Process Analysis (STPA) to model navigation risks and improve decision-making in autonomous ship control systems. Another method of dynamic risk analysis, KPRA (K-shortest-paths Probabilistic Risk Assessment), was applied to autonomous ships in Maidana et al. (2023) to generate risk-acceptable trajectories. Bayesian networks were used to assess collision and grounding risks in real-time.

Collision avoidance is focused in the Generalized Velocity Obstacle (GVO) algorithm (Huang et al., 2019), which ensures compliance with International Regulations for Preventing Collisions at Sea (COLREG) rules. The Advanced Collision Threat Parameter Approach (CTPA) (Szlapczynski and Szlapczynska, 2017) improves decision-making in narrow waterways by presenting a method for determining and visualizing safe movement parameters for vessels in confined waters. Approaches such as a probabilistic collision avoidance system (Blaich et al., 2015), which utilizes radar uncertainties and a grid-based A* algorithm or a kernel density estimation model for dynamic collision risk assessment (Im and Luong, 2019) aim to address the reliability and adaptability of autonomous vessels.

Although there are already very promising approaches in detail (e.g., (Corral-Soto and Liu, 2020), Boschmann and Söffker (2022), Lee et al. (2024), Torben et al. (2022), Johansen et al. (2023), Maidana et al. (2023), (Huang et al., 2019), (Szlapczynski and Szlapczynska, 2017), (Blaich et al., 2015), (Im and Luong, 2019)), some central problems have not been addressed or solved:

Sensor dependencies: Image-based methods are susceptible to lighting conditions, while LiDAR-based approaches struggle with small or distant objects and noise, especially in dynamic environments (Corral-Soto and Liu (2020), Boschmann and Söffker (2022)). **Environmental uncertainties:** Real-world factors such as darkness, weather conditions, and rapid situational changes negatively impact sensor reliability and system adaptability (Corral-Soto and Liu (2020), Lee et al. (2024)). **Decision-making challenges:** Although formal methods (FMs) provide a solid mathematical basis for maritime control systems, their integration into continuously operating systems remains difficult due to dynamic changes and real-time constraints (Torben et al. (2022)). **Risk modeling limitations:** Bayesian Networks (BBN) and KPRA offer improvements for collision and grounding risk assessment, but real-time application and dynamic risk analysis are still challenging (Johansen et al. (2023), Maidana et al. (2023)). **Collision avoidance complexities:** Algorithms like Generalized Velocity Obstacle (GVO) and Advanced Collision Threat Parameter Approach (CTPA) show promise, but struggle with complex COLREG rule applications and rapidly evolving environments (Huang et al. (2019), (Szlapczynski and Szlapczynska, 2017)).

Model uncertainties: Probabilistic collision avoidance systems using radar and grid-based methods highlight adaptability issues, yet sensor and model uncertainties (Blaich et al. (2015), Im and Luong (2019)). Despite advancements, autonomous vessel reliability and safety still face challenges in dynamic, uncertain maritime environments.

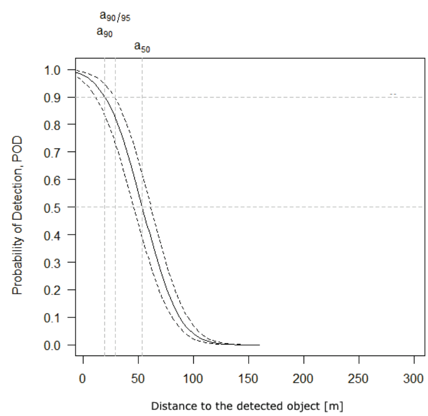

Fig. 1.: POD curve for utilized camera under foggy weather conditions

3. Methodology

3.1. *Probability of Detection Approach*

The POD evaluates the reliability and safety of technical systems, particularly in Nondestructive Testing (NDT). It quantifies detection reliability and is often represented by the a90/95 criterion which takes into account both the detection rate and the statistical uncertainty (Stepinski et al., 2013). While stricter criteria such as a99/99 seem tempting for safety-critical systems, a90/95 is based on a balance between technical feasibility and safety. The reliability and safety of sensor systems utilized for object detection are always tied to specific operational limits, which can be influenced by external conditions such as adverse weather (Zhang et al., 2023). These conditions impact the physical and algorithmic limitations of sensors. A modified POD methodology (Ameyaw et al., 2022) evaluates machine learning classifiers based on process parameters, integrating functionality, reliability, and environmental factors. Shyshova et al. (2024) applied this to assess ML-based sensor reliability as a function of object distance, considering sensor/actuator failure rates and control strategies to ensure operational safety. In relation to the case study presented, the reliability for the successful execution of the task depends not only on the failure rate of the actuators and sensors, but also on the AI-based control system in between.

3.2. *Derivation of POD Curves for Different Sensors*

The development of POD curves is based on systematic data processing and modeling. Initially, raw data from relevant publications are extracted using graphical representations. Data extraction is performed using the software (Automeris, 2024) through several steps (Sharma and Sergeyev, 2020). The *Hit/Miss* model classifies object detection as binary (“yes” or “no”), relying on signal processing rather than direct sensor data. The *Signal Response* model, uses continuous sensor output. Two statistical models are available for generating of a POD curve, depending on the data type. The latter method is employed in this study.

The POD curves are generated following the guidelines of U.S. Department of Defense (2018) using the mh1823 POD software. Signals below a threshold are treated as noise and removed (“left censoring”). Similarly, extreme values are excluded (“right censoring”). The censoring limits are either derived from publications or the smallest signal is considered noise. Depending on the data distribution, various linear regression models are examined. These models differ in axis scaling. The choice of the appropriate model is based on the best fit to the data. Once the appropriate model is selected, the POD curve parameters can be calculated, including the mean (μ) and the standard deviation (σ). The POD curve is described mathematically as follows (Georgiou, 2007)

$$POD(a) = F\left(\frac{\ln(a) - \mu}{\sigma}\right), \tag{1}$$

where F denotes the continuous cumulative distribution function, a the signal from the sensor, μ the mean, and σ the standard deviation. An example of the curve is given in Fig. 1.

In the further stages of the work, different slopes of the curves for camera, LIDAR and radar become apparent, which can be explained by the physical principles and sensitivities of the sensors. Cameras show a gradual slope as their detection rate depends on lighting conditions, contrast, and object size, while LIDAR and radar show steeper curves as they actively emit signals and are less influenced by factors such as lighting conditions and resolution. In addition, differences in data sets and test conditions used, such as object sizes or distances, can influence the shape of the curves.

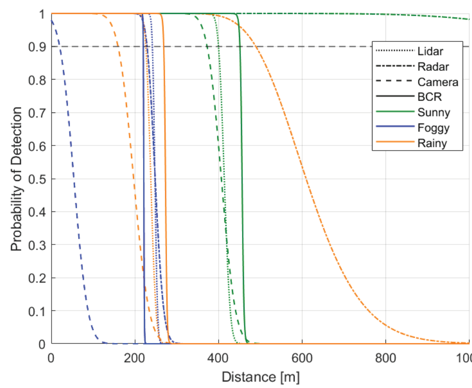

Fig. 2.: POD curves for diverse weather conditions

3.3. *Generalized Uncertainty Knowledge by Fusing POD Curves*

In addition to the presented idea of evaluating the reliability of sensor technology and downstreamed evaluation (e.g., by classification methods) (hereinafter referred to as ’intelligent sensor technology’) using POD, in this contribution a second objective is realized for the first time. Similar to classical sensor fusion (e.g., using Kalman filters), the question arises as to how the different quality and sensitivity of intelligent sensors can be used to enable safe and more reliable jointly integrated use. Based on at least two intelligent sensors, corresponding information and decision fusion processes are used to merge the information and decisions. In this paper, Bayes Combination Rule (BCR) is used for the fusion of POD curves to increase reliability. The probabilistic outputs of each intelligent sensor are combined considering their respective uncertainties to obtain a unified POD curve more robust under different conditions. The process of combining POD curves involves several important steps which are explained below. First, the individual POD curves for the intelligent sensors are aligned based on common parameters, such as distance to ensure a consistent basis for comparison and fusion. The BCR considers the probabilistic contributions of each sensor at a belief value as (Ameyaw et al., 2019)

$$\mathrm{bel} = \frac{\mathrm{POD}_l \cdot \mathrm{POD}_r \cdot \mathrm{POD}_c}{\mathrm{POD}_l \cdot \mathrm{POD}_r \cdot \mathrm{POD}_c + (1-\mathrm{POD}_l)\cdot (1-\mathrm{POD}_r)\cdot(1-\mathrm{POD}_c)}. \quad (2)$$

Here, POD_l, POD_r, and POD_c denote the probabilities of detection for the LiDAR, radar, and camera sensors, respectively. In the context of fault detection, precision is typically used as a performance measure. In this fusion process, the calculated POD values for specific features are assumed to be interchangeable with the precision value. Both metrics provide a reliability assessment. Consequently, the POD of each intelligent sensor can be used to calculate belief values according to the BCR (Ameyaw et al., 2019). This enables a robust evaluation. The fused curves of the three sensors under the considered weather conditions are shown in Fig. 2.

3.4. *Real-Time Safety Metric: Design of Sensing-Actuation Control Loop*

The idea of adapting the speed of a ship to the current obstacle detection possibilities and therefore intelligent sensor capabilities is the basic idea of this contribution. The sensor-actuator control loop is based on continuous monitoring of the environment by intelligent sensors (LiDAR, radar, camera) plus classification approaches and speed control via the propeller, with the maximum speed being derived from the stopping maneuver formula. This approach is based on the POD curve, which describes the probability with which the intelligent sensors detect an object at a certain distance under certain conditions. By determining the distance within which the intelligent sensors can detect an object with a given minimum probability (e.g., 90 %), it is possible to calculate the required stopping distance and thus the maximum permissible speed of the ship. At optimum sensor performance, the detection range is maximized so that the vessel can travel at higher speeds without compromising safety. Conversely, when environmental conditions reduce sensor performance and limit the detection range, the speed of the vessel must be reduced to ensure that the stopping distance remains within safe limits. This concept is evaluated through scenarios where environmental factors impact detection range and probability. Speed is adjusted to ensure the stopping distance remains within the detection horizon defined by the POD curve and the minimum probability threshold.

4. Application Example: Object Detection in Inland Navigation

4.1. *Scenario*

The described scenario (cf. Fig. 3) details the navigation of an inland vessel through a 1 km canal section under changing weather conditions (cf. Tab. 1). Special attention is given to visibility conditions and their impact on detection efficiency and the effective stopping distance of the vessel. To model the scenario, the visibility conditions are quantified using previously generated POD curves specific to the selected sensors.

4.2. *Requirements and Assumptions*

Calculating the deceleration and acceleration distances for a ship is crucial to ensure safe navigation and efficient operation. This section describes the physical requirements and key assumptions for calculating the braking distance for the described scenario. The approximate calculations are carried out under idealized assumptions and intended to illustrate the basic relationships. For the braking distance calculation, the following assumptions are made: The vessel's dimensions (length of 110

Table 1.: Weather conditions and derived detection performance from the POD curves

Canal section distance [m]	**Weather condition**	**Description**	**Detection performance** [%]	**Distance at POD (0.9)** [m]
0 - 200	Clear visibility	Optimal weather conditions, clear visibility.	100	452
200 - 400	Rain	Sudden weather change, visibility deterioration.	59.7	270
400 - 600	Clear visibility	Weather improves, optimal visibility.	100	452
600 - 800	Fog	Fog forms, causing visibility loss.	48.9	221
800 - 1000	Rain	Rain resumes, visibility slightly better.	59.7	270

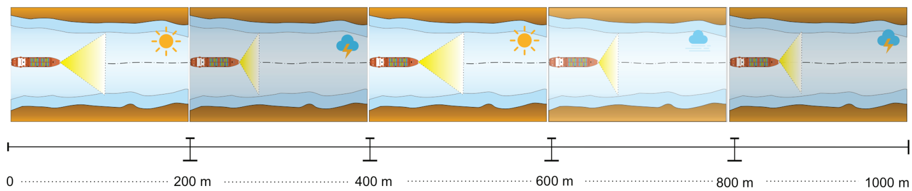

Fig. 3.: Chronological stages of the scenario's development

m, width of 11.4 m, draught of 3.5 m, weight of 2900 t and power of 1500 kW) are based on standard values for modern cargo vessels 'Großmotorgüterschiff, GMS'. It is assumed that the ship is loaded to 80 % of its maximum capacity. The deceleration and acceleration process (under the assumption that the amount of braking is equal to the amount of acceleration) is modeled using the 'breaking formula' from CESNI - European Committee for Inland Navigation Standards (2023) describing the relationship between speed and distance, taking into account empirical coefficients and resistances.

The probabilities for detecting an object at different distances and changing environmental conditions are illustrated using the merged POD curves (cf. Fig. 4 (top)). The maximum distance at which the detection probability reaches the defined threshold value (0.9 or 90 %) determines the detection horizon. This detection horizon is used to calculate the maximal allowed speed (denoted as safe) (cf. Fig. 4 (bottom)) by ensuring that the stopping distance derived from the vessel's braking capabilities remains within this distance. The following conclusions can be drawn from the POD curves regarding the maximum permissible speeds in different weather conditions: In sunny weather, the vessel can maintain a maximum speed of 6.36 m/s due to the extended detection horizon and the minimum stopping distance. In rainy weather, the maximum speed is reduced to 5.86 m/s to take account of the shorter detection range. In fog, the permissible speed must be limited to 5.14 m/s to ensure that the vessel can still brake if it encounters an object.

4.3. *Simulation Results and Discussion*

The results of the investigation are the simulated speed profiles (cf. Fig. 5) and the visibility conditions along the previously defined scenario with changing weather conditions (sunny, rainy, foggy). The speed profile adapts dynamically to the visibility conditions, with the speed being reduced as soon as visibility is restricted by rain or fog. The minimum speed occurs in fog, as the visibility limit is most restricted here (48.9 %).

4.4. *POD-Based Speed Adjustment*

More detailed information on the speeds and the distances at which the ship reaches the required speed is shown in Table 2. The delayed deceleration of the vessel, which leads to non-compliance with the required threshold, reduces the instantaneous POD and leads to uncertainties in these areas. This demonstrates the need to proactively adjust vessel speed even before weather conditions change. The illustration demonstrates the central idea that a ship must dynamically adapt its

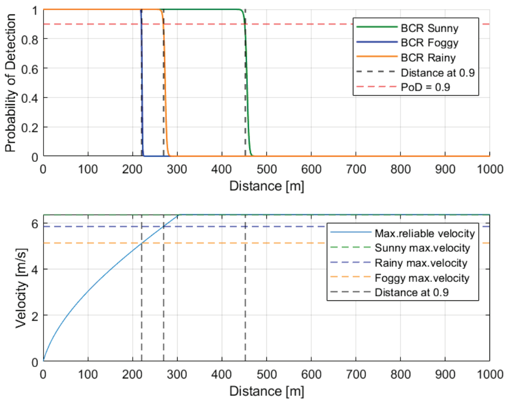

Fig. 4.: Fused POD curves and max. 'safe' speed derivation under diverse weather conditions

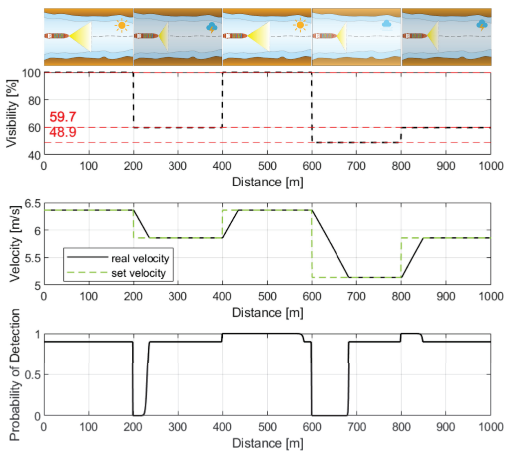

Fig. 5.: Dynamic speed adjustment

speed to changing environmental conditions and associated sensor capabilities in order to ensure safety, but also to increase efficiency. The concept is based on the fact that the sensors perform differently in different weather conditions (sunshine, rain or fog). The speed of the ship is regulated so that the required brake distance is always within the detection limit, regardless of the weather conditions. The simulation is intended to illustrate how dynamic speed adjustments can be made with the help of sensor data and defined probability limits (e.g., the POD value of 0.9). These results highlight the direct relationship between sensor performance, environmental conditions, and safe operating speeds and emphasize the importance of dynamic speed adjustments to reduce the risk of collision in bad weather.

It becomes evident that safety is ensured not only through the reliability of individual components but also by considering their functional interdependencies. The overall safety of maneuvers and operations strongly depends on the performance of these components, which cannot be addressed simply through homogeneous redundancy. Instead, ensuring safety requires the interaction of various detection mechanisms and the system's adaptive response to their functionality. Only through this interplay can a comprehensive safety strategy be achieved.

Table 2.: Weather conditions, distance, velocity

Weather condition	Driven distance (m)	Velocity (m/s)
Sunny	0-200	6.36
Rainy	200-236	Deceleration*
	236-400	5.86
Sunny	400-436	Acceleration*
	436-600	6.36
Foggy	600-683	Deceleration*
	683-800	5.14
Rainy	800-848	Acceleration*
	848-1000	5.86

* The calculation of changed velocity depends on the formula from CESNI - European Committee for Inland Navigation Standards (2023).

5. Conclusions and Outlook

Continuous speed adjustments based on sensor performance and current conditions are essential for maintaining safety. The described method provides a dynamic approach to speed regulation using POD curves that enables ships to navigate safely even in adverse weather conditions by improving early detection of hazards and minimizing the risk of collision. An additional weather early warning system could mean that speed adjustments can be implemented before the new weather situation occurs, further increasing safety. This shows that modern shipping systems should be able to adapt their operation mode to changing environmental conditions. With the presented approach, an optimal balance between safety and functionality can be achieved.

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