A Decentralized Negotiation Protocol for Collaborative Collision Avoidance of Autonomous Surface Vehicles

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Abstract—This study proposes a decentralized many-to-many negotiation protocol for collaborative collision avoidance of Autonomous Surface Vehicles (ASVs). The protocol enables heterogeneous vehicles with different collision avoidance algorithms to negotiate in the same framework using asynchronous communication. To achieve fully decentralized decision-making, the problem is modeled as a Distributed Constraint Optimization Problem (DCOP) and solved using a Distributed Stochastic Search Algorithm (DSSA). Additionally, each vehicle adjusts its decision variables within the range of egocentric and altruistic behaviors using the Monotonic Concession Protocol and Fuzzy Logic. The proposed negotiation protocol is tested with two different reactive collision avoidance algorithms, considering some of the navigational rules (COLREG), and verified both with simulation and field experiments.

Index Terms—Collision avoidance, Autonomous surface vehicle, Negotiation, Distributed constraint optimization problem, Fuzzy logic, Monotonic concession protocol, MPC, Velocity obstacle.

I. INTRODUCTION

Collision avoidance for Autonomous Surface Vehicles (ASVs) is a well-researched area. Nevertheless, the communication and the exchange of intentions between vehicles have not received the same level of research focus. Most existing studies focus on inferring other vehicles’ intentions solely based on their past or current behaviors. This inference typically relies on motion models, such as constant velocity and constant acceleration, to predict future states using observations. While some efforts explored more sophisticated techniques such as Dynamic Bayesian Networks for intention inference [1] and probabilistic trajectory calculation from historical traffic data [2], they still rely on interpreting an ASV’s actions without direct communication. Collision avoidance research utilizing communication and intention exchange between vehicles is referred to as “collaborative collision avoidance” [3]. Collaborative collision avoidance algorithms are categorized based on vehicles’ decision-making process and classified as centralized and decentralized approaches [3]. In a collision avoidance problem, solutions can be achieved centrally, with a single unit making decisions for all vehicles, or in a decentralized way, where each vehicle finds a solution for itself while considering others’ intentions. Centralized approaches utilize a master unit (e.g., Vessel Traffic Service, Remote Control Station, or a designated vehicle) and aim to calculate globally optimal solutions with complete situational awareness. However, they are vulnerable to communication failures and limited information, often exhibiting limited scalability. Decentralized approaches involve each vehicle to share information and make local decisions. While potentially suboptimal, they offer robustness to communication issues and do not need a central unit.

Studies applying a centralized approach include priority-based planning [4] where ships with lower maneuverability or stand-on COLREG responsibility are assigned a higher priority and maneuver auto-negotiation [5] where a designated leader coordinates COLREG-compliant maneuvers. More recent works explore using the A* algorithm with nonlinear optimization [6], rolling horizon optimization [7], and Particle Swarm Optimization (PSO) [8] methods for path planning.

Decentralized approaches outnumber the centralized ones in conducted research. Early examples of one-to-one collaborative collision avoidance studies include [9]–[11]. Later, [12], [13] introduced a multi-agent decentralized method using the Beliefs Desires Intentions (BDI) framework. [14]–[16] implemented Distributed Constraint Optimization Problem (DCOP) methods such as Distributed Local Search Algorithm (DLSA), Distributed Tabu Search Algorithm (DTSA), and Distributed Stochastic Search Algorithm (DSSA) respectively. Additionally, [17] investigated other DCOP methods including Synchronous Branch and Bound (SyncBB), Dynamic Programming Optimization Protocol (DPOP), and Asynchronous Forward Bounding (AFM). [18] utilized the A* algorithm and Nash Bargaining methods and [19] implemented a hierarchical approach combining the A* algorithm and Model Predictive Control (MPC) frameworks with the route exchange concept. [20]–[23] used the Alternating Direction Method of Multipliers (ADMM) method in the Distributed Model Predictive Control (DMPC) framework for collaborative collision avoidance. [24], [25] implemented variations of the Genetic Algorithm (GA) for the problem. Recently, [26] implemented the Generalised Reciprocal Velocity Obstacle (GRVO) with
cooperative game theory, and [27] proposed a deterministic and distributed search algorithm to maintain collaboration among vehicles.

The International Maritime Organization (IMO) plays a crucial role in supporting collaborative collision avoidance through its e-navigation and route exchange concepts. These concepts address both strategic and tactical information sharing. Strategic route exchange leverages the Vessel Traffic Service (VTS) infrastructure, enabling collaboration between VTS and ships. This approach facilitates the exchange of information on planned routes and intentions over a broader timescale, allowing for centralized traffic management and potential conflict identification before they occur. Tactical route exchange, on the other hand, focuses on direct ship-to-ship communication. This approach enables real-time negotiation and information exchange regarding maneuvers and immediate collision avoidance needs.

This study focuses on the tactical information-sharing concept for ship-to-ship collaboration. Nevertheless, in the maritime traffic environment, collaboration might necessitate the involvement of more than two ships. While bilateral (one-to-one) negotiation is relatively uncomplicated, the intricacies of many-to-many negotiations pose significant complexities. These complexities include conflicting objectives, challenges for coordinating communication, managing diverse priorities, and reaching mutually beneficial agreements. The future of maritime traffic introduces even more complexities. Marine vessels with mixed-autonomy levels employing diverse collision avoidance algorithms and safety parameters will require flexible negotiation strategies. Disparities in communication system capabilities can further hinder information exchange. The challenge extends beyond collaborating vessels, as some may be non-cooperative or technically limited, requiring robust algorithms that can handle these diverse scenarios. Given the challenges of collaborative collision avoidance in future heterogeneous maritime environments, this work explores the following research questions to identify methods for developing effective solutions:

1) In what ways can we apply principles of active information exchange and negotiation to enhance autonomous navigation?

2) What strategies can be employed to design a collaborative negotiation protocol suitable for multiple heterogeneous vehicles with different collision avoidance algorithms, while also considering non-cooperative vehicles in the environment?

3) How can we devise a collaborative negotiation protocol that allows asynchronous communication among vehicles?

To address the identified research questions this study contributes by:

1) Development of a decentralized negotiation protocol that enables participant agents to actively exchange intention messages, enhancing collaborative collision avoidance capabilities.

2) Design of a negotiation protocol that facilitates negotiation among multiple heterogeneous vehicles equipped with diverse collision avoidance algorithms (including non-cooperative vehicles) within a unified framework accounting for their cyber-physical system-specific parameters.

3) Introduction of a negotiation protocol supporting asynchronous communication for real-time application in cyber-physical systems, while maintaining synchronous decision-making capabilities.

The rest of the article is organized as follows, Section II presents the methodology covering the negotiation protocol, negotiation message, monotonic concession protocol for updating decision variables, collision avoidance algorithms used in the work, and decentralized decision-making process. Section III presents the results from the simulations and field experiments. Section IV delves into various aspects, including constraints inherent in the approach, encountered challenges, areas warranting enhancement, and the method’s strengths. Lastly, Section V serves as the conclusion of the paper.

II. Methodology

In this study, we assume that vehicles are equipped with a target tracking system enabling them to detect other vehicles within their environment. Vehicles are classified into three distinct categories. An ASV that actively engages in the negotiation protocol is named a “collaborative vehicle”. If an ASV possesses a collision avoidance system but chooses not to participate in the negotiation protocol is referred to as a “non-collaborative vehicle”. The third category encompasses “non-cooperative vehicle”, wherein ASV does not execute any collision avoidance maneuver. Additionally, it is assumed that collaborative vehicles are equipped with communication systems capable of exchanging negotiation messages in a predefined and mutually agreed-upon format.

A negotiation setting contains a protocol, a negotiation set, a collection of strategies, and a rule to determine when a deal is made [28]. The protocol is explained in Section II-A. Decision variables contain the intended course over ground (COG) and speed over ground (SOG) actions and constitute the negotiation set. Monotonic concession protocol and collision avoidance algorithm form the collection of strategies. These concepts are explained in Sections II-C and II-D. Lastly, the rule to determine when a deal is made is covered in Section II-E.

A. Negotiation Protocol

The proposed negotiation protocol for the collaborative collision avoidance algorithm from a single ASV’s perspective is presented as a Unified Modeling Language (UML) activity diagram in Figure 1. A UML activity diagram comprises fundamental elements including start and end nodes, action points, decision points, send and receive message symbols, fork and join indicators, and control flow connections. Let us designate the ASV we are observing from its perspective as the own ship (OS), and refer to other ASVs as the target ships (TS). The OS constantly listens to incoming negotiation messages and tracks TSs. If the distance to a TS and the closest point of approach (CPA) with a TS are both within the collision
avoidance initialization and CPA threshold parameters, the OS starts the negotiation protocol. CPA encompasses two values, namely the distance at the closest point of approach (DCPA) and the time to the closest point of approach (TCPA). These values are calculated by

\begin{align}
D_{ij}^R &= \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2} \\
U_{ij}^R &= \sqrt{(U_{x,j} - U_{x,i})^2 + (U_{y,j} - U_{y,i})^2} \\
\alpha_{ij}^R &= \frac{\chi_{ij}^R - \beta_{ij}^R - \pi}{2} \\
DCPA_{ij} &= D_{ij}^R \sin(\alpha_{ij}) \\
TCPA_{ij} &= D_{ij}^R \cos(\alpha_{ij}) \cdot \frac{1}{U_{ij}^R}
\end{align}

where \( D_{ij}^R \) is the relative distance, \( U_{ij}^R \) is relative speed, \( \beta_{ij}^R \) is the relative bearing angle, and \( \chi_{ij}^R \) is relative course angle between vehicles \( i \) (OS) and \( j \) (TS). Additionally, the negotiation protocol is activated if the OS receives a negotiation message from any TS.

The OS maintains awareness of a negotiation cycle through an “in_negotiation” variable. Initially set to “false” by default, the OS broadcasts its COG and SOG as its initial intention in a negotiation message and changes the “in_negotiation” variable to “true”. From now on, OS follows its own and all other vehicles’ “solution_state” and “intended COG and SOG” variables to iterate negotiation or apply final control actions. Moreover, the OS tracks the number of negotiation cycles by incrementing its message counter variable. When this counter reaches a user-defined threshold, the OS employs the best control actions discovered so far as a fallback strategy. This step is achieved in the “calculate optimal control variables” action node in Figure 1 and is based on User Datagram Protocol (UDP) broadcasting to all vehicles in the environment. UDP is chosen since it is convenient for real-time cyber-physical system communication due to its low overhead, fast transmission speeds, and low risk of network overload since there is no automatic re-transmission, which are crucial for real-time data exchange and time-sensitive operations in rapidly changing environments. Additionally, UDP bears a resemblance to existing Automatic Identification System (AIS) communication in the maritime domain.

C. Updating Decision Variables with Monotonic Concession Protocol

Monotonic concession protocol (MCP) is a negotiation strategy that proceeds in simultaneous rounds of proposals [29], [30]. In each round, agents evaluate whether to stick to their previous proposals or gradually concede to reach an agreement. The decision to stick to the previous proposal or to concede is the subject of the negotiation rule and is explained in Section II-E. Three key questions are 1) What should the agent’s first proposal be? 2) Does the agent need to concede and 3) If so, how much should it concede? [28] Agents’ first proposals are their current decisions that should be the most desired but not necessarily collision-free. The answer to the second question depends on the collision risk (CR) and give-way responsibility (GW) of the vehicle derived from navigational rules. The answer to the third question is challenging. The concession level of an agent should be big enough to force other agents to concede too if they have the responsibility to give-way. At the same time, the protocol should take into account that some of the agents might be non-collaborative or non-cooperative.

To address this, we propose a relaxation of the agent’s decision variables depending on the calculated concession level, i.e. a combination of collision risk and give-way responsibility. This approach enables agents to behave egocentric or altruistic according to the concession level.

Since the negotiation protocol entails exchanging COG and SOG intentions instead of trajectory plans, two reactive collision avoidance algorithms, Scenario-based Model Predictive Control (SB-MPC) and Reciprocal Velocity Obstacles (RVO), are implemented to demonstrate the protocol’s capability for allowing heterogeneous vehicles to collaborate. Lastly, grounding avoidance is not considered in this study.

B. Negotiation Message

A lightweight negotiation message is needed for the proposed method. In addition to standard header and footer sections, the body part of the message contains the vehicle identification number, intended COG, intended SOG, and a boolean solution state variable. Some previous studies such as [14], [15], [17], [27] require negotiation messages to contain cost function values. However, this approach can only be used for collaboration among vehicles using identical collision avoidance methods. The proposed negotiation message in this study does not require the sharing of cost-function values so it allows heterogeneous vehicles to collaborate in the same framework. Negotiation message exchange is presented with “publish negotiation message” and “receive negotiation messages” action nodes in Figure 1 and is based on User Datagram Protocol (UDP) broadcasting to all vehicles in the environment. UDP is chosen since it is convenient for real-time cyber-physical system communication due to its low overhead, fast transmission speeds, and low risk of network overload since there is no automatic re-transmission, which are crucial for real-time data exchange and time-sensitive operations in rapidly changing environments. Additionally, UDP bears a resemblance to existing Automatic Identification System (AIS) communication in the maritime domain.
for $DCPA$ and $TCPA$ are defined as in Figure 2 with user-defined safe distance and time parameters ($D_{safe}$ and $T_{safe}$). Fuzzy rules for collision risk ($CR_{ij}$) between vehicles $i$ and $j$ are defined as:

1. $(DCPA_{ij} = \text{LOW}) \land (TCPA_{ij} = \text{LOW}) \Rightarrow (CR_{ij} = \text{MAX})$
2. $(DCPA_{ij} = \text{LOW}) \land (TCPA_{ij} = \text{MED}) \Rightarrow (CR_{ij} = \text{AVG})$
3. $(DCPA_{ij} = \text{MED}) \land (TCPA_{ij} = \text{HIGH}) \Rightarrow (CR_{ij} = \text{AVG})$
4. $(DCPA_{ij} = \text{MED}) \land (TCPA_{ij} = \text{LOW}) \Rightarrow (CR_{ij} = \text{AVG})$
5. $(DCPA_{ij} = \text{MED}) \land (TCPA_{ij} = \text{MED}) \Rightarrow (CR_{ij} = \text{MIN})$
6. $(DCPA_{ij} = \text{HIGH}) \land (TCPA_{ij} = \text{HIGH}) \Rightarrow (CR_{ij} = \text{MIN})$
7. $(DCPA_{ij} = \text{HIGH}) \land (TCPA_{ij} = \text{LOW}) \Rightarrow (CR_{ij} = \text{MIN})$
8. $(DCPA_{ij} = \text{HIGH}) \land (TCPA_{ij} = \text{MED}) \Rightarrow (CR_{ij} = \text{MIN})$
9. $(DCPA_{ij} = \text{HIGH}) \land (TCPA_{ij} = \text{HIGH}) \Rightarrow (CR_{ij} = \text{MIN})$

Fuzzy give-way responsibility ($GW_{ij}$) considers the range ($R_{ij}$) between vehicles $i$ and $j$ and vehicles $i$’s give-way responsibility according to the COLREG rules. $R_{ij}$ membership function considers a user-defined variable $R_{safe}$ similar to Figure 2 (a). Prior to determining the fuzzy give-way responsibility, the vehicle $i$ must ascertain whether it holds the give-way responsibility in relation to other vehicles. The vehicle $i$ would have the give-way responsibility towards the vehicle $j$ if $i$ overtakes $j$ or vehicle $j$ is on the starboard side of $i$. Additionally, both vehicles would have the mutual give-way responsibility if they are in a head-on scenario. COLREG evaluation method for head-on, crossing, and overtaking scenarios is presented in Algorithm 1. The COLREG rule applied in the scenario can be estimated by using the relative bearings and speeds of the vehicles with the threshold angle values that are taken from [32]. Linguistic variables for both the range ($R_{ij}$) and give-way responsibility ($GW_{ij}$) are defined as “LOW, MED, HIGH” with the following rules:

1. $(R_{ij} = \text{LOW}) \Rightarrow (GW_{ij} = \text{HIGH})$
2. $(R_{ij} = \text{MED}) \Rightarrow (GW_{ij} = \text{MED})$
3. $(R_{ij} = \text{HIGH}) \Rightarrow (GW_{ij} = \text{LOW})$

The fuzzy concession level of vehicle $i$ toward $j$ ($CL_{ij}$) is calculated with fuzzy collision risk and give-way responsibility with the following rules:

1. $(CR_{ij} = \text{LOW}) \land (GW_{ij} = \text{LOW}) \Rightarrow (CL_{ij} = \text{LOW})$
2. $(CR_{ij} = \text{LOW}) \land (GW_{ij} = \text{MED}) \Rightarrow (CL_{ij} = \text{LOW})$

Fig. 1: UML activity diagram of the proposed negotiation protocol.
to encourage altruistic behavior.

We assume that the pure pursuit or line-of-sight guidance law (LOS) [33] calculates the desired course \(\chi_d\) considering the vehicle’s attitude compared to the path. The desired surge speed \(u_d\) is defined in the mission plan. The collision avoidance algorithms take into account other vehicles and calculate course offset \(\chi_{ca}\) and surge speed offset \(u_{ca}\) values, i.e., amounts of changes from the vehicle’s course and speed to prevent a collision. Then the desired course and speed calculated as

\[
\chi_e = \chi_{ca} + \chi_d \tag{2a}
\]
\[
u_e = u_{ca} \cdot u_d \tag{2b}
\]

are used in the course and speed controllers so the vehicle follows its trajectory while avoiding a collision with other vehicles. Figure 3 illustrates the different decision variable sets corresponding to varying concession levels. When the vehicle has a lower concession level, it exhibits egocentric behavior by narrowing its course offset \(\chi_{ca}\) and surge speed offset \(u_{ca}\) sets. Conversely, when the vehicle demonstrates altruistic behavior, it uses wider sets for \(\chi_{ca}\) and \(u_{ca}\), allowing for greater concessions.

D. Collision Avoidance Algorithms

As stated before, two reactive collision avoidance algorithms, i.e., SB-MPC and RVO, are used in the study to define heterogeneous vehicles and are explained in the following subsections.

1) Scenario-based Model Predictive Control: Scenario-based Model Predictive Control (SB-MPC) is a reactive collision avoidance algorithm based on MPC and was first proposed by Johansen et al. [34]. Later, Hagen et al. [35] simplified the tuning required to reduce oscillatory behavior of the algorithm by introducing a transitional cost term and the algorithm is validated at sea trials by [36]. Tengesdal et al. [37] introduced a probabilistic version of the algorithm by including probabilities of collision with nearby obstacles. Later, Akgd et al. [38] implemented the Informed

Algorithm 1 The COLREG responsibility of vehicle \(i\) to \(j\)

1: \textbf{procedure} The COLREG Rules
2: \hspace{1em} \(\alpha_{ij} \leftarrow\) Relative bearing of \(i\) from \(j\)
3: \hspace{1em} \(\beta_{ij} \leftarrow\) Relative bearing of \(j\) from \(i\)
4: \hspace{1em} \(U_i \leftarrow\) Speed of vehicle \(i\)
5: \hspace{1em} \(U_j \leftarrow\) Speed of vehicle \(j\)
6: \hspace{1em} \textbf{if} \((|\beta_{ij}| < 13^\circ) \land (|\alpha_{ij}| < 13^\circ)\) \textbf{then}
7: \hspace{2em} Rule \(\leftarrow\) Head-on (HO)
8: \hspace{1em} \textbf{else if} \((|\beta_{ij}| > 112.5^\circ) \land (|\alpha_{ij}| > 45^\circ) \land (U_j > U_i)\) \textbf{then}
9: \hspace{2em} Rule \(\leftarrow\) Overtaking (GW)
10: \hspace{1em} \textbf{else if} \((|\alpha_{ij}| < 112.5^\circ) \land (|\beta_{ij}| < 45^\circ) \land (U_i > U_j)\) \textbf{then}
11: \hspace{2em} Rule \(\leftarrow\) Crossing Stand-on (CRSO)
12: \hspace{1em} \textbf{else if} \((-112.5^\circ < \beta_{ij} < 0^\circ) \land (-10^\circ < \alpha_{ij} < 112.5^\circ)\) \textbf{then}
13: \hspace{2em} Rule \(\leftarrow\) Crossing Give-way (CRGW)
14: \hspace{1em} \textbf{else}\n15: \hspace{2em} Rule \(\leftarrow\) None

The final concession level of vehicle \(i\) is the maximum concession level considering all the other vehicles \(CL_i = \max(CL_{i1}, CL_{i2}, ..., CL_{ij})\).

After obtaining a crisp value of the concession level in the defuzzification step using the centroid method, we can update the vehicle \(i\)’s decision variables accordingly. A lower concession level indicates smaller collision risk and give-way responsibility, prompting the vehicle to adopt an egocentric behavior. Conversely, if the collision risk and give-way responsibility are larger, the ASV adjusts the decision variables...
SB-MPC by utilizing trajectory exchange capability between ships. The SB-MPC algorithm uses a discrete set of decision variables as offset values from the course and surge speed. The default decision variables for course offset are \( \chi_{ca} \in \{-90, -75, -60, -45, -30, -15, 0, 15, 30, 45, 60, 75, 90\} \) and normalized speed are \( u_{ca} \in \{1, 0.5, 0.25, 0\} \). The ASV dynamically adjusts these decision variables during the negotiation process, as elaborated in Section II-C.

The collision avoidance algorithm activates when another vehicle is in the range of \( d_{close} \) and the MPC method is implemented with a prediction horizon \( N_p \), a sampling period \( T_{sample} \), and kinematic maneuvering models for vehicle trajectory predictions. The cost function, i.e. hazard evaluation function, in Eq. 3 consists of collision cost \( C^k_j(t) \), risk factor \( R^k_j(t) \), COLREG compliance \( \mu^k_j(t) \), and maneuvering penalty terms of the vehicle \( i \) towards the vehicle \( j \) at time \( t \) in scenario \( k \) where \( k \) denotes the index of each scenario from decision variable combinations.

\[
\mathcal{H}^k(t_0) = \max_j \max_{t \in \mathcal{D}(t_0)} (K^c_j C^k_j(t) R^k_j(t) + \mu^k_j(t) \chi_{ca} + \Delta_{\chi}(\chi_{ca} - \chi_{last})^2 + k_u (1 - u_{ca}) + \Delta_u (u_{ca} - u_{last})^2)
\]

(3)

The collision cost \( C^k_j(t) \) depends on the velocity vectors of vehicles \( i \) and \( j \) and calculated as

\[
C^k_j(t) = \|v^k_i(t) - v^k_j(t)\|^2
\]

(4)

The risk factor \( R^k_j(t) \) in Eq. 5 is discounted when the difference between the prediction time \( t \) and current time \( t_0 \) increases. \( d_{ij}^p(t) \), \( d_{ij}^{safe} \) are the instantaneous distance between ships and safety distance parameters respectively, \( p \) and \( q \) serve as exponential tuning parameters.

\[
R^k_j(t) = \begin{cases} 
\frac{1}{(t - t_0)^p} \left( \frac{d_{ij}^p}{d_{ij}^{safe}(t)} \right)^q, & \text{if } d_{ij}^k(t) \leq d_{ij}^{safe} \\
0, & \text{otherwise}
\end{cases}
\]

(5)

The COLREG compliance penalty is calculated as

\[
\mu^k_j(t) = \begin{cases} 
\kappa_{port}, & \text{if } (HO \lor CR_{SG} \lor CR_{GW}) \land (\chi_{ca} < 0) \\
\kappa_{stb}, & \text{otherwise}
\end{cases}
\]

(6)

where a port turn is penalized more with \( \kappa_{port} > \kappa_{stb} \) if the vehicle \( i \) is in a head-on or crossing scenario with the vehicle \( j \). Rule compliance is penalized linearly with the course offset value \((\chi_{ca})\) in Eq. 3. To delve deeper into the rationale behind this heuristic, in a head-on scenario, it’s recommended for both vehicles to execute starboard turns. Alternatively, in a crossing scenario, the vehicle that spots the other on its starboard side has the responsibility of giving way. It should maneuver to keep out of the way and avoid crossing ahead of the other vessel. Although passing ahead of the stand-on vehicle is permissible, it must be done with caution, considering the vague interpretation of a safe distance. Hence, it’s common practice to adjust the course to starboard to yield the give-way responsibility. The vessel with the stand-on obligation should maintain its course and speed unless the give-way vessel fails to take evasive action. In such instances, the stand-on vessel should refrain from turning to port if the give-way vessel initiates a late starboard turn. Overtaking a vehicle from either side is acceptable, with no restrictions on the overtaken vessel’s course of action in case of a collision risk.

The maneuvering penalty terms relate to speed change from the nominal normalized speed \( (1 - u_{ca}) \) and speed and course changes from the previous commands \((u_{ca} - u_{last})\) and \( \chi_{ca} - \chi_{last} \). \( F_{coll}^k \), \( \kappa_{port} \), \( \kappa_{stb} \), \( k_u \), \( \Delta_u \), \( \Delta_{\chi} \) are tuning parameters for the cost function terms. The control action pair with the minimum hazard is selected from the decision variable combinations, i.e. scenarios in every iteration with

\[
k^* (t_0) = \arg \min_k \mathcal{H}^k(t_0)
\]

(7)

2) Reciprocal Velocity Obstacle (RVO): The SB-MPC method assesses every possible control action within the discretized decision variable set and chooses the optimal solution to prevent a collision. The Velocity Obstacle (VO) method considers relative velocities between agents, first removes decision variables that could result in collisions, and subsequently chooses the optimal solution from the remaining set.

The VO algorithm has attracted significant attention in the maritime domain. Kuwata et al. [39] pioneered an autonomous motion planning algorithm that ensures safe navigation of ASVs amidst dynamic environments while adhering to the COLREG. This framework integrates hazard avoidance strategies with COLREG compliance, utilizing VO to encode navigation rules naturally within the velocity space. Similarly, Zhao et al. [40] emphasized real-time collision avoidance systems for ASVs, integrating COLREG rules into their approach using the Evidential Reasoning (ER) theory and optimal reciprocal collision avoidance (ORCA) algorithm. Kufoalor et al. [41] introduced a proactive collision avoidance method for ASVs, focusing on interactive behaviors and uncertainty management, particularly regarding dynamic obstacles conforming to COLREG. Huang et al. [42] and Chen et al. [43] proposed VO algorithms for collision prevention
by detecting and managing collision candidates while considering non-linear ship trajectories and probabilistic scenarios. Furthermore, Huang et al. [44] introduced the Generalized Velocity Obstacle (GVO) algorithm, addressing the limitations of previous methods by offering rule-compliant evasive actions and suitability for both manned and unmanned vessels. Shaobo et al. [45] introduced a modified velocity obstacle method, enhancing it with a multistage optimization decision model that incorporates various constraints such as ship maneuverability, multi-ship scenarios, adherence to COLREG, off-course situations, and seamanship considerations. Notably, the modified method integrates a Finite State Machine (FSM) to handle the dynamic behavior of other ships. Lastly, Ren et al. [46] contributed an autonomous obstacle avoidance algorithm for ASVs, integrating improved VO methods with dynamic window algorithms and path re-planning strategies, ensuring safe navigation in multi-vehicle encounters while adhering to COLREG.

In this study, we implement a simple linear RVO as a second collision avoidance algorithm for testing the proposed negotiation protocol. The VO was originally proposed by [47] and for two agents $A$ and $B$ let $A \oplus B = \{a + b \mid a \in A, b \in B\}$ represent the Minkowski sum, and let $-A = \{-a \mid a \in A\}$ denote the agent $A$ reflected in its reference point. The ray starting from position $p$ and heading with a direction $v$ is denoted as $\lambda(p,v) = \{p + tv \mid t > 0\}$. The velocity obstacle of $B$ to $A$ is defined as

$$VO_B^A(v_B) = \{v_A \mid \lambda(p_A, v_A - v_B) \cap B \oplus (-A) \neq \emptyset\} \tag{8}$$

where the velocity $v_A$ is in the velocity obstacle of $B$ to $A$ if the ray at position $p_A$ heading in the relative velocity direction of $(v_A - v_B)$ intersects the Minkowski sum of $B$ and $-A$ centered at $p_B$. To prevent a collision, agents choose velocities outside the velocity obstacle sets. However, the original VO method can lead to oscillatory motion because the consecutive actions of agents. To resolve this issue, [48] introduced the RVO algorithm which addresses this challenge by assuming the mutual willingness of both agents to collaborate in mitigating collision risk. An agent chooses a challenge by assuming the mutual willingness of both agents 

$$\mathcal{J}(t_0) = \arg \min_k k^*(t_0) \tag{10a}$$

$$J^k(t_0) = \mu_k^i(t)|\text{ssa}(\chi_i - \chi_k)| \tag{10b}$$

where $k$ denotes a single velocity from the remaining suitable velocity set. $u_c$ and $\chi_c$ denote the new surge speed and new course, and $\chi$ is the current course of the vehicle $i$. $\mu_i^j(t)$ represents the COLREG compliance term and is explained in Eq. 6. $\chi$ and $\chi_c$ are confined to the interval $[0,2\pi)$. The smallest signed angle $\text{ssa}(\cdot)$ operator maps the difference of course angles to a value in the range of $[-\pi, \pi]$ to prevent unnecessary full rotations as defined in Definition 1.

**Definition 1 (Smallest Signed Angle):** The operator $\text{ssa} : \mathbb{R} \rightarrow [-\pi, \pi]$ maps the unconstrained angle $\tilde{x} = x - x_0 \in \mathbb{R}$ representing the difference between the two angles $x$ and $x_0$ to the smallest difference between the angles $\hat{x}_s = \text{ssa}(\tilde{x})$ where $\hat{x}_s \in S^1$. This is mathematically equivalent to

$$\text{ssa}(\tilde{x}) = \mod(\tilde{x} + \pi, 2\pi) - \pi \tag{10c}$$

where $\mod(\cdot)$ denotes the modulo operation or the signed remainder of a division [33].

However, if there are multiple vehicles, the combined RVO can take up a larger area and there might not be a suitable velocity set to evaluate from. To prevent that, first of all, RVOs are constrained with collision avoidance activation range $d_{\text{close}}$. Additionally, if there is no suitable velocity outside the RVOs, the algorithm considers velocities within the RVOs. It evaluates the time to collision with other vehicles for each unsuitable velocity. The velocity with the minimum deviation from the desired velocity and the maximum time to collision is then chosen as the optimal decision, even though it lies within the velocity obstacle.

![Fig. 4: The reciprocal velocity obstacle $RVO_B^A(v_B, v_A)$.](image)
E. Distributed Constrained Optimization for Decentralized Decision-Making

Distributed Constraint Optimization Problem (DCOP) enables decentralized, scalable, and robust problem-solving in multi-agent systems [49]. In a DCOP, a group of autonomous agents, each with its own set of preferences and constraints, collaborate to collectively optimize a global objective function while satisfying individual constraints. DCOP algorithms are primarily categorized into complete and incomplete algorithms. Complete algorithms are capable of finding optimal solutions but require large communication and computational effort. Incomplete algorithms propose faster but sub-optimal solutions which make them suitable for real-time applications. Additionally, DCOP architectures can be further categorized based on their level of centralization and then the need for synchronization. As we strived for a completely decentralized architecture with asynchronous communication, we chose to implement the Distributed Stochastic Search Algorithm (DSSA) proposed by [50] that is also used in a maritime collision avoidance application by [16].

The UML action diagram illustrating the algorithm is presented in Figure 5. Each vehicle maintains a record of its past and current intentions, collision avoidance cost function values, the count of iterations, and negotiation states. The collision avoidance algorithm, as discussed in Section II-D, iteratively computes new control actions (i.e., intentions) and evaluates corresponding cost function values. Subsequently, these new values are compared with the previous ones. If the new cost function value is equal to or greater than the previous one, the newly determined intentions are disregarded. Conversely, if the new cost value is smaller than the previous one, the vehicle may adjust its intentions with a probability of $p$. The parameter $\text{eps}_\text{gen}$ serves as a margin for determining the significance of cost reduction for generalization, albeit it is set to zero in this study. At this point, the negotiation state variable is updated to reflect the decision reached and then communicated to other vehicles. Each vehicle monitors the negotiation states of other vehicles, and once all vehicles have reached a final decision, the final intentions are implemented as control actions by each vehicle, as depicted in Figure 1.

III. RESULTS

To validate the proposed negotiation protocol, three identical Autonomous Surface Vehicles (ASVs) from the NTNU Fish Otter project are employed. The ASV demonstrated in Figure 6 is a small unmanned catamaran driven by two electric fixed thrusters. While its core components, including the hull, thrusters, and power distribution, are adapted from the Maritime Robotics Otter, the vehicle incorporates custom-designed sensors and control systems developed at NTNU [51]. This design framework is based on the LSTS toolchain\footnote{LSTS, University of Porto, \url{https://lsts.fe.up.pt/}} and utilizes DUNE as the onboard robotic middleware, Neptus for the graphical user interface, and IMC for inter-module and intra-vehicle communication. Intra-vehicle and vehicles-to-operator communication relies on an LTE/4G wireless communication link via a centralized server through an encrypted VPN connection.

A selection of scenarios illustrated in Figure 7 has been chosen to evaluate the proposed negotiation protocol. These scenarios encompass various cases such as head-on, crossing, and overtaking responsibilities for vehicles.

Each vehicle is assigned distinct profiles to depict homogeneous and heterogeneous characteristics. In homogeneous scenarios, vehicles share identical collision avoidance algorithm (SB-MPC) alongside the same collision avoidance initialization and safe distance parameters. Conversely, heterogeneous vehicles utilize SB-MPC and RVO collision avoidance algo-
rithms and are configured with different initialization and safe distance parameters. In Figure 7, vehicles utilizing the SB-MPC algorithm are represented in blue, while those employing the RVO algorithm are shown in orange.

Figure 7 (a) illustrates the benchmark scenarios involving homogeneous vehicles employing the SB-MPC algorithm without collaboration. Figure 7 (b) presents scenarios involving homogeneous vehicles equipped with collaborative SB-MPC algorithms. Collaborative heterogeneous vehicles with different collision avoidance algorithms and parameters are defined in Figure 7 (c) where the larger vehicles represent bigger initialization and safe distance parameters. The initialization and safe distance parameters are set as 150 m and 20 m in default and 200 m and 30 m for bigger vehicles in heterogeneous vehicle scenarios. In Figure 7 (d), in addition to two collaborative heterogeneous vehicles (blue and orange), there is a vehicle that is not participating in the collaboration (white with blue borderline) but calculating the evasive maneuver with the SB-MPC. In Figure (e) two collaborative heterogeneous vehicles need to evade a non-cooperative vehicle depicted in gray. Figure 7 (f) demonstrates a more complex scenario involving both collaborative (blue and orange), non-collaborative (white with blue borderline), and non-cooperative (gray) heterogeneous vehicles.

Initially, these scenarios are evaluated within a simulation environment using the LSTS framework. Subsequently, the scenarios depicted in Figure 7 (b) and (c) are further tested at sea with three ASVs.

A. Simulation tests

The results of the benchmark scenarios are depicted in Figure 8. Simulation results for collaborative homogeneous and heterogeneous vehicle scenarios are illustrated in Figure 9 and Figure 10 respectively. Furthermore, Figure 11 presents simulation results for scenarios involving collaborative, non-collaborative, and non-cooperative vehicles. The simulation is conducted five times for each scenario, and the aggregated results from the total of 90 scenario simulations are showcased in Table I. The table presents minimum distances between vehicles, average iteration time, and average number of exchanged messages in a single iteration. Collaborative scenarios yield a greater minimum distance between vehicles in contrast to benchmark scenarios. Furthermore, the trajectories generated by the collaborative approach exhibit smoother characteristics when compared to those of benchmark scenarios. The inclusion of negotiation cycles prior to the execution of decisions helps mitigate oscillatory behaviors inherent in reactive collision avoidance algorithms. It’s worth mentioning that the oscillatory behaviors of the reactive collision avoidance algorithms could also be mitigated by incorporating a transitional cost, as demonstrated in [35]. Analysis of Table I reveals that achieving consensus among vehicles typically takes around 5 seconds, which can be considered a single iteration time. On average, each vehicle transmits approximately 5 messages to reach a consensus.

B. Field tests

Scenarios with homogeneous and heterogeneous vehicles from Figure 7 (b) and (c) are tested with three NTNU-owned Fish Otter ASVs in Børsa, Trondheim Fjord, Norway. Field test results of homogeneous vehicle scenarios are demonstrated in Figure 12 and heterogeneous vehicle scenarios in Figure 13. Table II presents minimum distances between vehicles, average iteration time, and average number of exchanged messages in a single iteration. Field results demonstrated a similar behavior and statistics as in simulations.

In certain scenarios, vehicles exhibit adjustments in both their course and speed to prevent collisions. While the course change behaviors can be observed from the figures included in the manuscript, incorporating speed change graphics would significantly expand the article’s size. Therefore, comprehensive results from both simulation and field tests for each scenario, along with plot animations, are available for access.
Fig. 8: Benchmark scenarios (Figure 7 (a)) involving homogeneous vehicles employing the SB-MPC algorithm without collaboration.

Fig. 9: Scenarios of homogeneous vehicles with collaborative collision avoidance algorithms (Figure 7 (b))
Fig. 10: Scenarios of heterogeneous vehicles with collaborative collision avoidance algorithms (Figure 7 (c))

Fig. 11: (a) Heterogeneous vehicles with collaborative and non-collaborative collision avoidance algorithms (Figure 7 (d)) (b) Heterogeneous vehicles with collaborative collision avoidance algorithms and a non-cooperative vehicle in the environment (Figure 7 (e)) (c) Complex scenario with collaborative, non-collaborative, and non-cooperative heterogeneous vehicles (Figure 7 (f))

through [52] and in the link provided. In Figure 13 (b) unnecessary port turns of both vehicles are observed in the beginning of the collaboration. When we investigate the negotiation messages further, the orange vehicle’s first message starts with a port turn intention leading the blue vehicle to suggest a port turn intention too. However, both vehicles change their intentions further in negotiation cycles to comply with the rules.

2https://github.com/MelihAkdag/Decentralized-Negotiation-Protocol-for-Collaborative-Collision-Avoidance-of-ASVs-Results/tree/main

IV. DISCUSSION

A. Performance Evaluation

Simulations and field tests yielded similar results but with some key distinctions. Notably, simulations exhibited smoother trajectories due to the absence of environmental disturbances. In field tests, a southerly ocean current, observed in the afternoon due to tidal changes, impacted vehicle behavior, particularly when reducing speeds to avoid collisions. The effect of the current in the result is demonstrated in Figure 14. The southerly current led the orange vehicle to drift towards
TABLE I: Simulation scenario result statistics. Each scenario is run five times and average values are presented. The values inside the parenthesis represent standard deviations.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Minimum Distance (m)</th>
<th>Single Iteration Time (sec)</th>
<th>Message Received (count)</th>
<th>Message Sent (count)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 8 (a)</td>
<td>20.37 (1.31)</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Figure 8 (b)</td>
<td>27.99 (2.99)</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Figure 8 (c)</td>
<td>18.32 (1.15)</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Figure 8 (d)</td>
<td>22.37 (3.15)</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Figure 8 (e)</td>
<td>19.42 (2.77)</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>TOTAL (Benchmark)</td>
<td>21.69 (3.82)</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Figure 9 (a)</td>
<td>24.19 (2.88)</td>
<td>4.59 (1.73)</td>
<td>11.04 (5.18)</td>
<td>5.03 (2.45)</td>
</tr>
<tr>
<td>Figure 9 (b)</td>
<td>36.95 (3.38)</td>
<td>4.43 (1.57)</td>
<td>10.80 (4.82)</td>
<td>4.76 (2.19)</td>
</tr>
<tr>
<td>Figure 9 (c)</td>
<td>25.14 (6.24)</td>
<td>4.74 (2.07)</td>
<td>11.17 (5.23)</td>
<td>4.89 (2.26)</td>
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<td>Figure 9 (d)</td>
<td>31.57 (3.63)</td>
<td>4.86 (1.67)</td>
<td>18.80 (8.30)</td>
<td>5.31 (2.29)</td>
</tr>
<tr>
<td>Figure 9 (e)</td>
<td>31.39 (10.29)</td>
<td>5.32 (8.98)</td>
<td>17.42 (10.13)</td>
<td>4.94 (2.18)</td>
</tr>
<tr>
<td>Figure 10 (a)</td>
<td>35.22 (3.83)</td>
<td>5.03 (3.16)</td>
<td>12.20 (7.41)</td>
<td>5.44 (3.59)</td>
</tr>
<tr>
<td>Figure 10 (b)</td>
<td>38.77 (2.44)</td>
<td>4.58 (1.66)</td>
<td>11.11 (5.15)</td>
<td>4.91 (2.24)</td>
</tr>
<tr>
<td>Figure 10 (c)</td>
<td>32.85 (6.28)</td>
<td>5.29 (5.0)</td>
<td>11.95 (6.57)</td>
<td>5.36 (2.97)</td>
</tr>
<tr>
<td>Figure 10 (d)</td>
<td>36.84 (3.63)</td>
<td>5.01 (2.49)</td>
<td>20.25 (10.84)</td>
<td>5.53 (2.90)</td>
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<tr>
<td>Figure 10 (e)</td>
<td>33.78 (4.89)</td>
<td>5.81 (10.37)</td>
<td>17.11 (13.28)</td>
<td>5.26 (2.60)</td>
</tr>
<tr>
<td>Figure 11 (a)</td>
<td>30.71 (6.51)</td>
<td>4.67 (1.79)</td>
<td>10.98 (5.80)</td>
<td>5.04 (2.48)</td>
</tr>
<tr>
<td>Figure 11 (b)</td>
<td>14.73 (9.83)</td>
<td>4.69 (2.34)</td>
<td>10.36 (6.45)</td>
<td>4.95 (2.83)</td>
</tr>
<tr>
<td>Figure 11 (c)</td>
<td>24.08 (2.17)</td>
<td>4.95 (2.37)</td>
<td>25.57 (14.96)</td>
<td>5.42 (2.61)</td>
</tr>
<tr>
<td>TOTAL (Collaborative)</td>
<td>30.47 (5.24)</td>
<td>4.92 (0.33)</td>
<td>14.52 (3.92)</td>
<td>5.14 (0.20)</td>
</tr>
</tbody>
</table>

Fig. 12: Collaborative COLAV and homogenous vehicles scenarios from the field tests (Figure 7 (b))

the south and the blue vehicle demonstrated a port turn to prevent collision. Although they collaborated on a solution that prevented a collision, the resulting behaviors did not present good practice of the rules. We addressed this effect provisionally by adjusting speed change penalty parameters within the collision avoidance algorithms. However, a more permanent solution would involve incorporating environmental data into vehicle trajectory prediction and optimizing cost functions accordingly. This would enhance the robustness and adaptability of the collision avoidance system to real-world conditions, ensuring safer and more efficient autonomous navigation.

**B. Negotiation Protocol**

One particular challenge identified during testing was a tendency towards deadlocks in close-to-parallel crossing scenarios such as in Figure 9 (e) involving ASV-1 and ASV-3. This occurs when ASV-1 leaves its crossing give-way
zone (as outlined in Algorithm 1), leading to both vehicles aligning parallel to each other without a clear incentive for either to give way. Further enhancements to Algorithm 1 or the implementation of monotonic concession protocols could address this issue. Another solution would be to implement a randomized altruistic behavior so the vehicles would give way to each other in deadlock cases.

C. Validation

The scenarios illustrated in Figure 7 serve to validate the methodology and provide a proof of concept. Nonetheless, to enhance the negotiation protocol and collision avoidance parameters for wider applicability, a more extensive and systematic approach involving simulation-based testing is required.

D. Negotiation for Heterogeneous Vehicles

To accommodate different vehicle types, we employed two distinct reactive collision avoidance algorithms. A discrete decision variable set was established, and a monotonic concession protocol was utilized to refine or expand this set. However, for the negotiation protocol to be applicable to a wider range of collision avoidance algorithms, additional implementations and adaptations are necessary. A relatively straightforward approach for future endeavors involves integrating another reactive collision avoidance algorithm featuring continuous decision variables. However, integrating a trajectory planning-based collision avoidance algorithm with a reactive counterpart would demand more extensive work and effort. Additionally, a negotiation protocol based on exchanging trajectories instead of an iterative exchange of control actions would require ranking and prioritizing multiple

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TABLE II: Field test result statistics. The values inside the parenthesis represent standard deviations.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Minimum Distance (m)</th>
<th>Single Iteration Time (sec)</th>
<th>Message Received (count)</th>
<th>Message Sent (count)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 12 (a)</td>
<td>25.83</td>
<td>4.61 (1.23)</td>
<td>4.0 (1.22)</td>
<td>4.36 (1.51)</td>
</tr>
<tr>
<td>Figure 12 (b)</td>
<td>50.09</td>
<td>5.10 (2.24)</td>
<td>4.35 (1.60)</td>
<td>5.0 (2.57)</td>
</tr>
<tr>
<td>Figure 12 (c)</td>
<td>28.06</td>
<td>6.06 (2.50)</td>
<td>3.46 (2.66)</td>
<td>6.64 (3.79)</td>
</tr>
<tr>
<td>Figure 12 (d)</td>
<td>22.18</td>
<td>5.0 (1.82)</td>
<td>8.83 (3.42)</td>
<td>4.90 (2.15)</td>
</tr>
<tr>
<td>Figure 12 (e)</td>
<td>29.22</td>
<td>5.68 (2.79)</td>
<td>8.72 (4.52)</td>
<td>5.68 (3.02)</td>
</tr>
<tr>
<td>Figure 13 (a)</td>
<td>29.57</td>
<td>5.19 (1.75)</td>
<td>6.54 (6.0)</td>
<td>5.18 (2.30)</td>
</tr>
<tr>
<td>Figure 13 (b)</td>
<td>24.28</td>
<td>6.14 (9.46)</td>
<td>5.64 (12.43)</td>
<td>4.28 (1.72)</td>
</tr>
<tr>
<td>Figure 13 (c)</td>
<td>18.98</td>
<td>7.59 (7.46)</td>
<td>4.64 (5.65)</td>
<td>5.53 (2.95)</td>
</tr>
<tr>
<td>Figure 13 (d)</td>
<td>38.14</td>
<td>5.26 (1.96)</td>
<td>8.73 (3.63)</td>
<td>5.45 (2.50)</td>
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<tr>
<td>Figure 13 (e)</td>
<td>29.47</td>
<td>5.49 (3.46)</td>
<td>7.20 (3.91)</td>
<td>5.10 (2.33)</td>
</tr>
<tr>
<td>TOTAL (Collaborative)</td>
<td>29.58 (10.96)</td>
<td>5.64 (8.57)</td>
<td>6.21 (2.66)</td>
<td>5.21 (0.87)</td>
</tr>
</tbody>
</table>

Fig. 13: Collaborative COLAV and heterogeneous vehicles scenarios from the field tests (Figure 7 (c))
Fig. 14: Collaborative COLA V and heterogeneous vehicles scenario from the field tests (Figure 7 (b)). Scenario results demonstrate the effect of the current on the vehicles’ negotiation process which ends with behaviors not in compliance with good practice of rules.

Vehicles for sequential problem-solving [19].

E. Scalability and Communication Challenges

The proposed protocol was tested with a maximum of six vehicles, excluding static obstacles within the environment. While incorporating grounding hazards is possible using electronic charts, as discussed in [19], [37], the system’s capability with a larger number of vehicles remains untested due to computational resource limitations. It is anticipated that scaling up the number of agents may lead to congestion within the synchronous decision-making process and a decline in performance due to busy communication activity.

F. Cybersecurity Considerations

It’s important to acknowledge the cybersecurity vulnerabilities associated with UDP and TCP. TCP’s connection-oriented nature makes it susceptible to attacks like synchronized (SYN) flooding, while UDP lacks built-in security features, making it prone to packet spoofing. QUIC (Quick UDP Internet Connections) [53] addresses these issues by integrating encryption and security directly into the transport layer. By encrypting data and providing secure connection mechanisms, QUIC enhances security without compromising performance, offering a solution to cybersecurity concerns in UDP communication. Exploring the integration of the QUIC communication method with the LSTS framework to enhance cybersecurity resilience would be an important contribution to future research.

G. Leveraging Existing Maritime Infrastructure

Currently, 4G communication serves as a proof of concept for exchanging negotiation information. However, VHF communication with Automatic Identification System (AIS) or VHF Data Exchange System (VDES) devices could offer a method by allowing broadcasts of negotiation messages. This would integrate the proposed method with existing practices on ships and shore facilities. Additionally, intentions exchanged during negotiations could be visualized directly on the Electronic Chart Display and Information System (ECDIS) used onboard conventional ships and shore-based facilities like Vessel Traffic Service (VTS) or remote control centers.

H. Transparency and Explainability

Finally, autonomous ships could leverage negotiation messages to enhance explainability and transparency in accident investigations, similar to how voice recordings are used in conventional vessels. This data would provide valuable evidence during post-accident analysis, allowing for the reconstruction of the autonomous ship’s decision-making process and its interactions with other vessels in collaborative collision avoidance maneuvers.

V. Conclusion

In conclusion, this study introduces a decentralized many-to-many negotiation protocol tailored for collision avoidance among ASVs. The protocol facilitates negotiation among heterogeneous vehicles equipped with asymmetric collision...
avoidance algorithms within a unified framework, leveraging asynchronous communication. Employing a fully decentralized decision-making approach formalized as a Distributed Constraint Optimization Problem (DCOP) using the Distributed Stochastic Search Algorithm (DSSA), each vehicle adjusts its decision variables based on egocentric and altruistic behaviors via the Monotonic Concession Protocol and Fuzzy Logic. The efficacy of the proposed negotiation protocol is verified through simulation and field experiments, testing its compatibility with various collision avoidance algorithms and adherence to navigational rules (COLREG).

Addressing the research questions posed, this study demonstrates the application of active information exchange and negotiation principles to enhance autonomous navigation. Strategies are proposed to design a collaborative negotiation protocol suitable for multiple heterogeneous vehicles, considering both cooperative and non-cooperative entities in the environment. Furthermore, a collaborative negotiation protocol enabling asynchronous communication among vehicles is devised, providing real-time applicability in cyber-physical systems.

The contributions of this study include the creation of a decentralized and collaborative negotiation protocol fostering active exchange of intentions to enhance collision avoidance capabilities. Additionally, a framework is formulated to enable negotiation among multiple heterogeneous vehicles equipped with diverse collision avoidance algorithms. Moreover, an innovative protocol is introduced, enabling asynchronous communication while maintaining synchronous decision-making capabilities.

Simulation tests conducted across various scenarios demonstrate the effectiveness of the proposed negotiation protocol, showcasing smoother trajectories and greater minimum distances between vehicles compared to benchmark scenarios. Field tests corroborate these findings, indicating similar behavior and statistics observed in simulations. While certain scenarios necessitate adjustments in both course and speed to prevent collisions, comprehensive results from both simulation and field tests, along with plot animations, are available for further examination.

In summary, this study presents a robust and adaptable negotiation protocol for collision avoidance among ASVs, offering significant potential for enhancing autonomous navigation in real-world applications.

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VI. BIOGRAPHY SECTION

Mehl Akdağ Melih Akdağ is a Ph.D. candidate in engineering cybernetics at the Norwegian University of Science and Technology (NTNU), Trondheim, Norway. He received his BS in electric/electronic engineering from the Turkish Naval Academy in 2008 and his M.Sc. in marine and coastal protection program from Istanbul University in 2019. After serving as a Navy Officer and Navy Diver in the Turkish Navy with several years of field experience, he is now conducting his research on collaborative collision avoidance algorithms for autonomous ships. He is affiliated with the projects Centre for Autonomous Marine Operations and Systems (AMOS) and the Center for Research-based Innovation SFI AutoShip.

Hoang Anh Tran Hoang Anh Tran is a Ph.D. candidate in engineering cybernetics at the Norwegian University of Science and Technology (NTNU), Trondheim, Norway. He received his BS in automatic control and Technology (NTNU). His research focuses on developing a collaborative collision avoidance control algorithm for inland waterways ships and a communication protocol allowing autonomous ships to cooperate effectively with other manned and unmanned ships.

Nikolai Lavuvs Nikolai Lavuvs is a Ph.D. candidate in engineering cybernetics at the Norwegian University of Science and Technology (NTNU). He received his M.Sc. (2020) in engineering cybernetics from the Norwegian University of Science and Technology, specializing in embedded control systems design. His research revolves around the design and development of the FishOtter system of autonomous surface vehicles, and includes topics on autonomous vehicle control, formation control, acoustic positioning systems, GIS-based path planning, and grounding avoidance.

Tom Arne Pedersen Tom Arne Pedersen has an MSc (2002) and Ph.D. (2009) in Marine Technology from the Norwegian University of Science and Technology (NTNU). He has worked for Marine Cybernetics since 2008, holding positions as a senior project engineer, R&D Manager Drilling Systems, and Product Manager Drilling Systems. Marine Cybernetics was acquired by DNV in 2014 and Tom Arne Pedersen currently holds the position of Principle Researcher in DNV Group Research and Development, working on a testing framework for automated collision and grounding avoidance systems.
Thor I. Fossen Thor I. Fossen is a professor of guidance, navigation, and control (GNC) at the Department of Engineering Cybernetics, Norwegian University of Science and Technology (NTNU), Trondheim. He received an M.Sc. in Marine Technology in 1987 and a Ph.D. in Engineering Cybernetics in 1991. Besides cybernetics, Fossen’s field of research is aerospace engineering and marine technology. This includes GNC systems for uncrewed vehicles (AUV, UAV, USV), robotics, vehicle dynamics, and inertial navigation systems. He has been a Fulbright scholar in flight control at the Department of Aeronautics and Astronautics of the University of Washington, Seattle. Fossen is the author of the Wiley textbook Handbook of Marine Craft Hydrodynamics and Motion Control (2021). He is one of the co-founders and former Vice President of R&D of the company Marine Cybernetics, which DNV acquired in 2012. He has also co-founded ScoutDI (2017), which develops drone-based systems for fully digitalized inspections of industrial confined spaces. The Institute of Electrical and Electronics Engineers (IEEE) elevated him to IEEE Fellow in 2016. He received the Automatica Prize Paper Award in 2002 and the Arch T. Colwell Merit Award in 2008 at the SAE World Congress. He was elected to the Norwegian Academy of Technological Sciences (1998) and the Norwegian Academy of Science and Letters (2022).

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