CoMPass: A Roadmap to Collaborative Perception and Autonomy in Maritime Systems

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Future Advancements in Collective Maritime Autonomous Ships

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***Abstract*—Maritime shipping carries nearly 80% of global trade, yet over 80% of maritime accidents from 2014 to 2023 were caused by human error. This underscores the need for Maritime Autonomous Surface Shipss (MASSs), which rely on real-time perception to ensure safe navigation and compliance with International Regulations for Preventing Collisions at Seas (COLREGs). However, perception is challenged by sensor limitations, environmental conditions, and heterogeneous vessel equipment.**

Collaborative perception—sharing sensor data across vessels—can address these issues, but current communication infrastructure, especially AIS, lacks the bandwidth for real-time data exchange. While technologies like 5G offer higher capacity, their limited range hinders widespread use at open sea.

This paper explores these challenges and proposes a research agenda based on SISSY techniques to extend perception coverage. The proposals include self-adaptive multi-relay communication network, navigation-aware network reconfiguration, perception-driven relay optimization, and a perception-centric model for autonomous behaviour. Together, these approaches aim to improve communication capabilities in maritime environments, adapting to the physical communication infrastructure available, and therefore support autonomous maritime operations.

***Index Terms*—Self-Improving System Integration, Self-Awareness, Autonomous Ferry, Self-Explanation, Maritime Autonomous Surface Ships.**

I. Introduction

Maritime shipping is the backbone of global trade, accounting for around 80% of the volume of international trade, according to the United Nations Conference on Trade and Development [1]. At the same time, between 2014 and 2023, approximately 80.1% of maritime accidents were attributed to human error, highlighting the potential of autonomous systems to mitigate such risks[1].

The maritime sector is now experiencing a technological shift towards autonomy driven by reducing operational costs, while enhancing the robustness of global supply chains, and improving safety. MASS rely on their ability to perceive and understand the environment situation in real time, to adhere to the Convention on the International Regulations for Preventing Collisions at Sea (COLREGs). However, performing perception is challenging because the environmental conditions affect sensors performance [2].

In maritime context, perception refers to the process by which a vessel—whether autonomous or human-operated—acquires, interprets, and maintains an up-to-date understanding of its surrounding environment to support safe navigation and operational decision-making. This process relies on the integration of data from multiple onboard sensors and, information shared by other vessels or infrastructure through communication networks. The goal of maritime perception is to enable the vessel to detect, classify, and track objects —like other ships, obstacles, and navigational aids—, assess environmental conditions such, and comply with regulatory requirements like the COLREG.

However, the maritime environment is highly heterogeneous. Not all vessels are equipped with the same sensors—or any sensors at all. While some may carry radar, LiDAR, cameras, or sonar, many ships rely on limited sensing capabilities. This variability can hinder the adoption and effectiveness of MASS algorithms. One way to overcome these limitations is collaborative perception: vessels can enhance their individual situational awareness by sharing sensor data. By cooperating in this way, ships can gain knowledge about events or hazards that may lie beyond the detection range of their own onboard systems.

Current maritime communication infrastructure is ill-suited to support real-time, high-quality sensor data sharing. The existing Automatic Identification System (AIS) is primarily designed for low-bandwidth message transmission—measured in bits per second—which is insufficient for exchanging rich sensor information. Emerging technologies, such as 5G networks, offer high data rates but are limited in range, typically covering only coastal areas. As a result, vessels operating outside of this coverage would fall back to the AIS protocol, which is not designed to exchange sensor data.

This gap in communication capabilities presents a significant barrier to MASS implementation. To support autonomous behaviour, the maritime communication infrastructure must evolve to enable scalable, high-throughput, and resilient data exchange. However, infrastructural improvements are expensive and long-term, in the meanwhile, software improvements

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[1]https://archive.is/GZ322

can be adopted to maximise infrastructure availability, which we discuss in this contribution.

In this paper, we investigate the challenges arising from the maritime scenario, identify key opportunities for improvement, and propose a research roadmap leveraging SISSY techniques to expand perception coverage in maritime environments. Our contribution includes:

- **Self-Adaptive Multi-Relay Communication Network**: We propose establishing a decentralised, self-adaptive network among vessels to bypass the limitations of current infrastructure, without requiring significant new physical deployments.
- **Navigation-Aware Network Reconfiguration**: We explore how navigational data can guide the dynamic reconfiguration of the communication network to optimise relay paths and maintain connectivity.
- **Perception-Driven Relay Optimisation**: By incorporating vessels' sensing and computing capabilities, we discuss how this would improve the placement and function of relays within the adaptive network.
- **Modeling Autonomy via Perception-Centric Behaviour**: Since our proposed network relies on perception, navigation, and computation, we advocate for modeling autonomous vessel behaviour where perception events are first-class entities in the domain model.

The paper is structured as follows: we first discuss related work in the direction of collaborative perception and communication(Section II); we then introduce our reference scenario, from which we collect challenges (Section III); given the challenges we discuss the opportunities that still are not addressed in this context (Section IV); and finally we propose our research agenda driven by the identified challenges (Section V).

II. Related Work

@ Ghassan: From me: A clear edge has to be defined and presented between collaborative vs. cooperative vs. distributed vs.aggregated fusion/perception. What must be exposed in the goal of our work is the collaborative perception. This includes:
1. The trade-off-between the communication and the fusion accuracy (for tasks like localisation, and navigation definition (?) and ?). This affects the clustering in the communication and the selection of relays.
2. Distributed processing of the fusion data based on: the local comprised sensors, computation capability, latency and enery cost for data transfer and ??
3. Cooperative perception, by assigning the tasks of perception in the cluster (here clusters have further dimensions than the communication capabilites, including: computation capabilites, optained sensing capabilites and their perception and range limitations, location-significance within the cluster—such as occlusion (see my notes for the definition), and the navigation characteristics (direct, speed, ...)
4. Somehow, I have to present how the collaborative perception is build on the top of pillars like: distributed fusion, cooperative perception, adaptive-relay-scheme communication.

IMPROVEMENT: TL; Make me shorter!

MISSING: Related work for aggregated comminication clustes for story two

Conventional maritime navigation relies on a combination of legacy sensory and human expertise for environmental perception. **asv!**s (**asv!**s) have evolved from traditional navigation systems that primarily depend on radar, GPS, and AIS for situational awareness. These conventional systems provide basic positional information and collision avoidance capabilities, but are limited in their ability to provide comprehensive environmental understanding required for fully autonomous operations. Despite multi-sensor integration in **asv!**s, fundamental limitations persist across all sensing modalities. Radar systems struggle with clutter in congested areas and small non-metallic targets, while Light Detection and Ranging (LiDAR) performance degrades significantly in fog, heavy rain, and sea spray. Optical cameras remain heavily dependent on lighting conditions, and Global Navigation Satellite System (GNSS) faces jamming vulnerabilities. Inertial sensors suffer from cumulative drift in dynamic maritime environments, while sonar systems exhibit narrow beam patterns and acoustic noise sensitivity.

@ Martina: The following paragraphs about sensors fusion is interesting, however it seems disconnected from our story... Written like this i propose to remove it out (or drastically summarise) for this paper.

There exist sensor fusion techniques aimed to combine information coming from multiple sensors to produce more accurate, reliable and comprehensive understanding of the environment than what a single sensor could achieve on its own. Beyond individual sensor constraints, single-node fusion, also known as centralised fusion architecture, involves sending all raw data from multiple sensors directly to a central node for state estimation and decision-making. While theoretically capable of optimal solutions, this architecture presents several significant limitations, particularly as the system scales [3]. These limitations include temporal synchronization issues [4], computational bottlenecks [3], sensor-shared blind spots [5], sensor failure propagation [6], and inflexibility to changes [3], that cannot be resolved through local integration alone.

These inherent limitations of individual sensors and single-node fusion architectures necessitate collaborative perception frameworks that leverage multi-agent data sharing and distributed sensing to overcome spatial constraints, eliminate blind spots, and provide fault-tolerant maritime situational awareness through complementary sensor perspectives across multiple platforms.

In the automotive domain, significant advances have been made in cooperative perception technologies, particularly through Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication systems [7], [8]. These systems enable vehicles to share sensor data and perception results to overcome individual limitations such as occlusion and restricted sensor range. Various approaches employ different *multi-node* fusion strategies (cf. [9]), including: (i) *early fusion*, where raw sensor data is broadcast among nodes, enabling rich perception but incurring high communication and processing costs, (ii) *intermediate fusion*, which involves exchanging processed features, offering a trade-off between information richness and efficiency, though the size of deep feature representations can still impose significant bandwidth demands, and (iii) *late fusion*, where only final perception outputs are shared, minimising bandwidth usage but potentially limiting accuracy due to reduced contextual information [10].

In the domain of robotics, swarm robots leverage collaborative perception to overcome individual perception limitations and to facilitate efficient task execution, especially in timecritical scenarios. Robotic systems have demonstrated successful implementation of distributed sensing and cooperative localisation across various domains, including ground, aerial, and underwater applications [7]. Heterogeneous multi-robot systems are increasingly employed for complex tasks such as mapping unstructured environments and multi-domain sensing. For instance, collaborative autonomy in heterogeneous multi-robot systems has been explored for tasks requiring diverse sensing capabilities [11], [12]. Recent research has focused on developing robust communication protocols and distributed algorithms that can handle network failures and dynamic team compositions [13].

Collaborative perception in the maritime domain remains relatively underdeveloped compared to automotive and terrestrial robotics applications [14], [15]. Current maritime collaborative systems primarily focus on coordinated navigation and task allocation rather than shared environmental perception. Multi-sensor fusion approaches have been applied to individual maritime vehicles, combining radar, LiDAR, and camera data for improved environmental understanding [16]. Recent efforts have explored multi-**asv!** coordination for tasks such as area coverage and formation control [17], but these applications typically rely on independent perception with coordination at the planning level rather than true collaborative perception.

MISSING: @ALL: We shall differentiate between multi-node (or distributed fusion), and collaborative (and distributed) fusion!
What we propose is collaborative solution than extends further the distributed soluion.
Somehow we need to address that at some point → Maybe in conclusion?!

@ Ghassan: use this: distributed multi-sensor data fusion is not without technical challenges to overcome: namely, dealing with cross-correlation and inconsistency among state estimates and sensor data. [3]

Despite significant advancements in collaborative perception across automotive and general robotics applications, the maritime domain still faces unique and substantial research gaps. While the principles of multi-agent collaboration are transferable, the harsh and dynamic nature of the marine environment introduces complexities that are not fully addressed by existing state-of-the-art solutions. Specifically, traditional maritime perception systems are inherently limited by the single-point sensing paradigm, leading to vulnerabilities in data overload, deception, and detection uncertainty. Although collaborative perception offers a promising avenue, current research in maritime applications often focuses on specific sub-problems, such as cooperative navigation or multi-domain sensing for fixed targets, rather than a holistic, robust, and adaptive collaborative perception framework for dynamic maritime scenarios with the ability to fuse heterogeneous sensor data from diverse Line-of-Sights (LoSs) and under challenging communication constraints.

@ Ghassan: use this: flexibility, robustness to failure and cost effectiveness in infrastructure and communication.

Effective maritime perception encompasses both (i) *local perception*, where a vessel processes data from its own sensors, and (ii) *collaborative perception*, where information is shared among multiple vessels or with shore-based infrastructure to enhance situational awareness capabilities of any single platform [12]. This collective approach is particularly important in heterogeneous fleets, where vessels may differ significantly in their sensing and computational capabilities, and where spatial distribution can limit the effectiveness of individual perception systems.

III. The Scenario

Autonomous navigation is recognised as the future of maritime operations. By autonomous, we refer to the capability of a system, entity, or agent to operate independently——making decisions and executing tasks without human intervention [18]. An autonomous agent perceives the state of its environment and selects actions that are expected to best achieve its goals [19].

In the context of autonomous navigation, determining optimal actions is particularly complex. What may be optimal for an individual vessel can be globally sub-optimal when considering the collective behaviour of the fleet. Conversely, computing globally optimal decisions introduces latency and may overlook locally significant events that require rapid, context-specific adjustments.

@ Ghassan: Also connect to Intowoven systems, where multiagents interaction and mutual effect plays a role the decision optimality.

Effective environmental perception is a prerequisite for autonomy. This necessitates onboard sensors to collect raw data and sufficient computational resources to process it. However, comprehensive perception is often unattainable due to two main factors: (i) the heterogeneity of vessels' competency, and (ii) their spatial distribution patterns. Vessel heterogeneity refers to the variation in both sensing and computational capabilities among vessels. While some vessels are equipped with advanced sensors such as radar, LiDAR, and multi-camera systems, others may rely solely on basic positioning technologies like GPS and AIS. In addition to these differences in sensor suites, vessels also vary significantly in their onboard computational resources—that is, in their ability to process sensor data efficiently and in real time. This includes differences in processing power, memory, and the ability to run complex perception or decision-making algorithms. While the spatial distribution is influenced by maritime traffic patterns; vessels tend to be more dispersed in open seas and more concentrated in harbours and coastal areas. Even if autonomous navigation algorithms could be universally applied, it is unlikely that all vessels will become fully autonomous, because human-operated vessels will continue to navigate. Therefore, autonomous behaviour must remain predictable and compliant with established maritime practices, particularly the Collision Regulations (International Regulations for Preventing Collisions at Sea (COLREG)).

@ Ghassan: Check for repetition. I.e., if the last sentence is not mentioned before

A. Current State

@ Ghassan: Missing the current state of perception

Currently, vessels communicate their information using the AIS standard, which transmits navigation-relevant data such as identity, position, course, and speed over Very-High Frequency (VHF) channels. While AIS enhances situational awareness, it suffers from limited data throughput and is suitable only for short-range, line-of-sight (**LoS!** (**LoS!**)) communication. **SatCom!** (**SatCom!**) systems provide broader, near-global coverage, but they often come with high latency and operational costs [20]. These limitations make existing communication infrastructure insufficient for the high-throughput and low-latency requirements of modern autonomous systems and sensor-rich applications.

In recent years, mobile broadband——particularly 5G—— has made significant progress, primarily to support terrestrial mobile communication. 5G technology offers enhanced bandwidth and coverage compared to traditional maritime options. An increasing number of 5G antennas are being deployed in coastal areas, initially aimed at serving mobile users but also beneficial for nearby vessels. These vessels can achieve substantially higher data rates via 5G than through satellite, LoRa, or Wi-Fi. However, 5G coverage remains limited to near-shore environments and cannot replace satellite communication in the open sea. Yet, no alternative offers similar bandwidth at global scale.

B. Networked Collaborative Perception in Maritime Systems

@ Ghassan: The proposed method to overcome the challenges of networking multidomain agents → challenges shall be covered before then!

@ Ghassan: Add the big picture of the proposed research to introduce the two following subsection about the story sides
Story One: Aggregated Perception
Story two: Aggregated Communication clusters
Then the challenges in the summary can come.

@ Ghassan: Illustrations to make the digestion of the subject easier is required

@ Ghassan: Or Schematic of the process flow will be more meaningful

Despite significant advances in individual vessel autonomy [21], [22], [23], as well as in the development of advanced sensing and connectivity technologies [24], [25], [26], the realisation of fully coordinated and intelligent maritime systems remains an open and promising research direction

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. However, the transition toward fully autonomous fleets remains beyond near reach, primarily because equipping every vessel with the requisite sensing and decision-making hardware is neither practical nor affordable at scale. Retrofitting legacy ships with high-resolution cameras, LiDAR units, radar arrays, and the onboard AI necessary for real-time navigation would cost prohibitive capital. Beyond the vessels themselves, shore-based infrastructure —from ports and traffic management centres to dedicated maritime communication networks— would need comprehensive upgrades to support the massive data flows and low-latency control links that autonomy demands. Regulatory frameworks, cybersecurity standards, and crew training programmes would also have to evolve to meet the new requirements, adding additional complexity and expense. Consequently, in this paper, we advocate an intermediate approach: a situational awareness layer that unifies heterogeneous fleets by exploiting the existing perception and communication resources of each ship. By bridging current capabilities —ranging from basic AIS transponders to advanced MASS sensors— this solution offers a pathway toward fully autonomous maritime operations of the future.

@ Ghassan: Mention somewhere that the targeted output is situational awareness and 2D representation of the operation field.

C. Summary → Challenges

@ Ghassan: This subsection will be consumed in the previous subsection

@ Ghassan: privacy, adverserial attacks, faulsified (intentionally or through processing) data. Missing transmission for collaborative localisation → dead-reckoning as outlook research

The main context features and constraints emerging from the scenario are summarised in this section.

(i) **Heterogeneity**: Vessels differ in shape, dynamics, computing resources, sensor suites, and communication capabilities.
(ii) **Conflicting Goals**: Locally optimal decisions for individual vessels may conflict with globally optimal strategies.
(iii) **Dynamic System**: Vessel movements and environmental changes (e.g., weather, human decisions) introduce unpredictability.
(iv) **Varying Vessel Density**: Vessel density varies geographically, with sparse distributions in open seas and dense traffic in ports and coastal regions.
(v) **Mixed Autonomy**: Human-operated and autonomous vessels are expected to coexist within the same maritime environment.
(vi) **Compliance with COLREGs**: Autonomous systems must adhere to established maritime navigation rules.
(vii) **High Data Volumes**: Advanced sensors generate large amounts of data, necessitating high data-rate transmission capabilities.
(viii) **Expanding 5G Infrastructure**: Coastal 5G deployment is increasing, offering higher bandwidth and lower latency near shore, though not in open sea.
(ix) **Network Limitations**: AIS is bandwidth-limited, 5G lacks offshore coverage, and satellite solutions are costly and complex.
(x) **Multi-Modal Communication**: Vessels often utilise a combination of communication technologies onboard.

IV. Direction and Opportunities

Although substantial progress has been made in the autonomy of individual vessels

MISSING: citations

, as well as in sensing and connectivity technologies

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, the development of fully coordinated and intelligent maritime systems remains an open and promising research direction. This section identifies and explores key opportunities that arise from the contextual features described in Section III. These opportunities aim to enhance perception coverage for autonomous maritime navigation, thereby improving the knowledge base necessary for the advancement of MASS.

Given that integration of 5G and LEO satellite relay antennas on vessels is feasible, alongside existing communication technologies, ships can act as dynamic relay nodes. Vessels can opportunistically utilise nearby ships as communication intermediaries to extend coverage into regions far from shore. This dynamic hybrid network infrastructure has the potential to enable near-global connectivity. With access to multiple communication technologies, vessels can dynamically select the most efficient communication channel available—typically the one offering the highest data rate at a given moment. This flexibility not only enhances communication performances but also increases system robustness under varying conditions. Furthermore, vessels equipped with high-performance antennas can adapt their trajectories to maintain or improve connectivity for neighboring ships, particularly in remote areas. This capability requires intelligent coordination and real-time decision-making mechanisms at the fleet level.

The maritime environment is marked by considerable heterogeneity in sensing, computing, and communication capabilities across vessels. This asymmetry is expected to grow, as newer ships are equipped with advanced sensors and processors, while legacy vessels continue to operate with limited hardware. Older vessels can benefit from shared environmental data, since ships operating in the same geographical area will be likely to perceive similar environmental states, perception data from one vessel can be leveraged by others in proximity. This collaborative perception model offers an opportunity to enhance situational awareness and decision quality, particularly for less capable vessels. However, implementing such a strategy requires a high-throughput, low-latency communication network to support efficient data exchange. Once sensory data is collected, it must be processed to extract meaningful information. Again, not all vessels possess the computational resources to perform this analysis independently. Relying on centralised processing at shore stations may be viable for monitoring but introduces latency that is unacceptable for real-time autonomous decision-making. Moreover, centralised systems handle a more complex and global information space than what may be necessary locally. To address this, a distributed processing model is preferable, where nearby vessels collaboratively process and share data relevant to their local environment. This distributed approach can improve responsiveness and reduce computation and communication overhead, provided robust communication protocols and local data fusion algorithms are employed.

While most current research treats vessels as individually autonomous agents, some scenarios—such as anticipatory traffic management or cooperative route planning—benefit from considering groups of vessels as collective entities. This motivates a dual-layer autonomy model, where vessels retain individual decision-making abilities but also participate in higher-level group behaviours. Such a model enables selective integration of global objectives into local planning processes, aligning individual actions with broader system-wide goals without sacrificing autonomy.

Opportunities \ Context	Heterogeneity	Large data (sensors)	Network limitations	Varying density	Conflicting goals	Dynamic System	Expanding 5G infrastructure	Multiple communication technologies	Autonomous and sailed ships in the same env	Pre-existing rules (COLREGs)
Asymmetric data collection and processing	✓	✓	✓				✓	✓		✓
Groups of ships as first-class entities			✓	✓						
Mixed adaptation (groups vs. single decisions)	✓			✓	✓	✓			✓	✓
Data locality			✓	✓		✓		✓		
Trajectory optimization to improve coverage	✓				✓	✓			✓	✓
Hybrid communication between ships	✓	✓	✓				✓	✓		
Steer the system behaviour using autonomous vessels	✓					✓			✓	✓

Fig. 1: Matrix charts representing the opportunities emerging from context properties. Each tick represents a correlation.

A. Summary

In this section, we extract the key opportunities from the direction described previously, and briefly discuss their connection with context properties discussed in Section III-C. The relationships between context properties and identified opportunities are visually summarised in Figure 1.

(i) **Asymmetric Data Collection and Processing**: Vessel heterogeneity challenges consistent perception but also allows for richer data-sharing. High-capability ships can support less-equipped ones by sharing localised perception data, enhancing decision-making across the fleet.

(ii) **Groups of Vessels as First-Class Entities**: Treating groups of ships as coordinated units enables collective behaviours, e.g. cooperative navigation, congestion management, and perception coverage.

(iii) **Mixed Adaptation (Group vs. Individual Decisions)**: A dual-layer control strategy allows autonomous vessels to operate independently while aligning with collective goals and perceptions when necessary.

(iv) **Data Locality**: Processing perception data near its point of collection reduces the latency of transmitting to shore station and gather back the perception computed, it also enables to share this information with less capable vessels.

(v) **Trajectory Optimization for Network Coverage**: Ships can dynamically adjust their routes to maintain or enhance communication links with others, particularly in sparse or remote areas.

(vi) **Hybrid Ship-to-Ship Communication**: Leveraging multiple communication technologies maximises datarate and communication range for inter-vessel networking.

(vii) **Steering System-Wide behaviour via Autonomous Vessels**: Strategically placed autonomous vessels can influence broader maritime traffic patterns, promoting safety, and efficiency.

V. Research Agenda

@ Martina: 250627: The illustration of Centralised, semi, and autonomous

@ Ghassan: Missing: In the lack of open-source dataset for maritime multi-modal perception, the development and validation environment →
1. Simulation based capable of emulating the detection zone of different sensor and enabling flexible non-destructive test scenarios generation.
2. Future validation and further adaptation in a dynamic environement like the fjord of Kiel.

In this section, we outline a research agenda to address the opportunities identified in Section IV. The agenda is structured into four main phases (Figure 2, each building on the previous one to progressively enhance the capabilities of maritime autonomous systems to go towards autonomous maritime operations. This research combines distributed computing paradigms, multi-agent coordination strategies, and adaptive networking. Briefly, the phases are:

- Phase 1: Develop a multi-relay self-adaptive communication algorithm.
- Phase 2: Extend the algorithm to consider dynamic vessel positions in the environment.
- Phase 3: Integrate perception coverage into the self-adaptive communication algorithm.
- Phase 4: Enable local autonomy using the developed network.

A. Phase 1: Develop a multi-relay self-adaptive communication algorithm

Depending on the geographical positions of ships, a self-adaptive software system can dynamically select the most appropriate communication channel (e.g., 5G, satellite, or VHF) to maximise data transmission rates and to minimise communication overhead. *Aggregate computing* [27] emerges as a promising paradigm to manage such dynamic and distributed environments, since it ensures decentralised coordination of devices, while exposing a self-adaptive behaviour. In other words, it handles faults, disconnections, and dynamic changes in the network topology, while keeping decisions locally. In this model, devices (in our scenario, vessels) are viewed not as isolated nodes but as part of a computational collective, where all nodes execute the same algorithm and adapt based on local context.

This algorithm would address opportunities:

- **Groups of vessels as first-class entities**
- **Hybrid communication between ships**

B. Phase 2: Dynamic reconfiguration of the algorithm using navigational data

In addition to vessel positions, metadata from AIS—such as heading and speed—can further refine the clustering algorithm. For instance, vessels moving in the same direction can be grouped together, while ships traveling in opposite directions are discouraged from clustering. This strategy minimises relay hops and reduces the frequency of cluster reshaping events due to divergent trajectories.

C. Phase 3: Integration of perception and computation capabilities in communication algorithm

Importantly, not all sensor data must be relayed to centralised shore stations, because it is likely that information is redundant, so it is discarged. For example, three vessels are sending the video stream of the same portion of the sea. Instead, the system can support localised knowledge sharing among vessels within communication range, organised into dynamically-formed clusters. Within each cluster, one vessel can be selected as a leader to summarise and forward only essential information to shore stations, thereby reducing network congestion and latency.

@ Ghassan: Here futher description about centralised, semi-decentralised, distributed would help

.

This addresses the following opportunities:

- **Asymmetric data collection and processing**
- **Groups of vessels as first-class entities**
- **Data locality**
- **Hybrid communication between ships**

D. Phase 4: Improve local decisions based on perception exchanges with the communication algorithm

We then propose the integration of **AC!** (**AC!**) for global perception with localised autonomous behaviour driven by the Beliefs, Desires, Intetions (BDI) agent model. The BDI framework offers a structured model for decision-making in autonomous agents, particularly when operating in dynamic, partially observable, and multi-agent environments such as maritime domains. This hybrid approach enables each vessel to function as an intelligent agent within a **MAS!** (**MAS!**), capable of acting autonomously while also leveraging distributed, aggregated insights from the surrounding environment. The BDI architecture provides a structured cognitive framework:

- **Beliefs**: the vessel's knowledge of its state and surroundings,
- **Desires**: goals or objectives (e.g., destination),
- **Intentions**: the cognitive representation of actions the ship is currently pursuing.

An illustrative example involves vessels equipped with 5G relay antennas. These ships can autonomously decide whether to adhere to their globally-optimised pre-planned trajectory or deviate temporarily to improve network coverage in poorly connected areas. Such decisions can be performed for example by communicating with other sorrounding vessels (using the **AC!** hybrid network) and perform an auction. This direction supports seamless coordination between centralised perception-sharing and localised decision-making, enabling scalable, intelligent behaviour across the maritime network.

This research direction addresses:

- **Asymmetric data collection and processing**
- **Mixed adaptation (group vs. individual decisions)**
- **Steering system-wide behaviour through autonomous vessels**
- **Trajectory optimization for improved network coverage**

Fig. 2: The four-phase research roadmap for collaborative environment perception in heterogeneous ship networks, highlighting the progressive optimisation of multi-relay communication clusters from static positioning, through dynamic navigation, to the integration of perception and computation capabilities.

VI. Conclusion

——— Conclusions: stuff + going in the direction of reaching comprehensive fleet autonomous maritime operations ———

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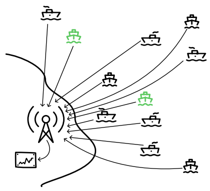
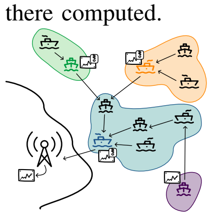
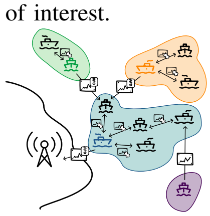


(a) Full centralization of perception: raw sensors information is sent towards shore stations and there computed.



(b) Redundant sensor information fusion at decentralised level, so that only useful information is transmitted over the network. Still, in this configuration the perception is computed at centralized level—the shore station—for the whole area of interest.



(c) Vessels with higher computational capabilities are used to compute perception at distributed-level. In this scenario, perception can be locally-computed and information flows between vessels without the need to wait for the centralised monitor—the shore station—to compute it. In the picture, each ship sends <u>pieces</u> of information (represented with the puzzle symbol), i.e. the local-sensed data, to a ship selected for its computation capabilities which performs the operation of sensors fusion (represented