Maritime Transport Research 3 (2022) 100077

Contents lists available at ScienceDirect

Maritime Transport Research

journal homepage: www.sciencedirect.com/journal/maritime-transport-research

Safe and efficient maneuvering of a Maritime Autonomous Surface Ship (MASS) during encounters at sea: A novel approach

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ARTICLE INFO

Keywords:
Maritime Autonomous Surface Ships (MASS)
COLREG
Collision avoidance
Cluster analysis
Decision transparency

ABSTRACT

When introducing a collision avoidance system on a Maritime Autonomous Surface Ship (MASS) for encounters at sea, it may seem reasonable to assume that an approaching ship will follow the procedures presented in the International Regulations for Preventing Collisions at Sea (COLREG). Experience has shown, though, that mariners sometimes, based on good seamanship, make situational adaptations where they deviate from the steering rules in the COLREG. Their goal may be to improve efficiency in own operations or simply due to courtesy of a perhaps less maneuverable approaching ship. In this paper an analysis has been performed to characterize the situations when such deviations typically occur and to estimate the conditional probability of such deviations, given the respective situation. Furthermore, the paper proposes a design for how an artificial intelligence (AI) system may handle these situations through an *Extended Timeframe for AI Decision (ETAD)*. We suggest that the AI system search through the available clusters of situations before it normally would suggest an evasive maneuver. If the identified situation is similar to situations where the probability of an approaching ship deviating the COLREG and give way is significant, the AI could be given an extended timeframe, await its maneuver, and thereby improve the efficiency of the operation without jeopardizing the safety.

Abbreviation or term	Explanation
AI (Artificial Intelligence)	Perceiving, synthesizing and inferring information - demonstrated by machines
AIS (Automatic Identification System)	The automatic identification system (AIS) is an automatic tracking system that uses transceivers on ships
ARPA (Automatic Radar Plotting Aid)	The system can calculate the tracked object's course, speed, CPA, TCPA, and BCR, thereby knowing if there is a danger of collision with the other ship or landmass.
BCR (Bow Crossing Range)	How close to the bow of an ownship a targeship will pass
COLREG (Convention on the International Regulations for Preventing Collisions at Sea, 1972)	The "rules of the road" for ships and other vessels at sea
CPA (Closest Point of Approach)	Closest Point of Approach between two ships if there is no adjustment of course or speed
DCPA (Distance to Closest Point of Approach)	

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https://doi.org/10.1016/j.martra.2022.100077
Received 28 September 2022; Received in revised form 15 November 2022; Accepted 16 November 2022
Available online 26 November 2022
2666-822X/

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EBL/VRM (Electronic Bearing Line / Variable Range Marker)	Tools on navigation systems used to measure directions and range between ownship and targetship
ETAD (Extended Timeframe for AI Decision)	Concept for extending an AI-systems decision time
GDPR (General Data Protection Regulation)	The EU General Data Protection Regulation
MASS (Maritime Autonomous Surface Ships)	A ship which, to a varying degree, can operate independently of human interaction
Ownship	Ship that represents the "point of view" when investigating a situation
Targetship	Ship that is interacting with an ownship
TCPA (Time to Closest Point of Approach)	
VHF (Very High Frequency Radio)	Radio for ship to ship and ship to shore communication

1. Introduction

Maritime Autonomous Surface Ships (MASS) has for some years been a subject for considerable research and development within maritime transportation and are now becoming a reality. In Norway, the vessel Yara Birkeland was put into commercial operation during spring 2022, so far with seafarers onboard, but shall after a test period go through a gradual transition towards full autonomous sailing (Yara International, 2022). We assume that the first steps for commercial MASS on a global scale would be high-end autopilots, with integrated artificial intelligence (AI) for collision avoidance and decision support systems for onboard operators as described in the International Maritime Organization's (IMO) scoping exercise (IMO, 2021).

One of the main arguments for launching autonomous ships is increased safety. This may be achieved by e.g. reducing the number of fatalities on board (Adams, 2014; Rødseth, 2017) or reducing the number of collisions (Wróbel et. al., 2017). Wróbel et al. (2017) argues further that removing humans from the ship will reduce the frequency of maritime incidents, even though the potential positive number of incidents prevented by human operators only rarely are reported and therefore are likely to be underestimated.

Since the business models must be sustainable, it is reasonable to assume that efficiency also should be of importance in the development of MASS. DNV's guideline for autonomous ships (DNV, 2018), stating that the objective is to maintain as good safety as for manned ships, seems to be in line with this understanding.

One of the major challenges for MASS with AI systems is their coexistence with conventional manned ships. All ships must comply with the regulations stated in the COLREG, but the COLREG was developed for human navigation and does not address the peculiarities of a MASS. Even though algorithms in an AI system may be developed to comply with parts of the COLREG, the parts of the regulations that refer of e.g. "ample time", "ordinary seamanship", and "if circumstances admit" are much more difficult for an AI system to take into account. Furthermore, to increase efficiency or safety, experienced mariners sometimes deviate from the steering rules in Section B part 2 of the COLREG to adapt to the situation (Rutledal et al., 2020). A "too strict" reaction from an AI system with respect to the requirements of the COLREG, may in some such situations jeopardize both efficiency and safety.

The COLREG rule 15 states that in a crossing situation, *"…the vessel which has the other on her own starboard side shall keep out of the way…"*. In Fig. 1 below, the first picture illustrates such a situation. Even though most maneuvers during encounters at sea will carried out according to the regulations (outcome 1), some situations may deviate the rules as illustrated in outcome 2.

The reasons for deciding to deviate the COLREG can be many. Here, it might be that it's favorable for vessel B to alter course to port with respect to its destination, other traffic in the area which must be considered, or that Vessel B can be more maneuverable, hence the maneuver can be seen as a courtesy to vessel A. In this way such a maneuver to avoid collision can be viewed as a social skill. If vessel A is controlled by an AI system, a strict response would in such a case be to change course even more to starboard, which again may lead to vessel B maneuvering even further to port, and thereby creating an undesirable situation.

This paper explores the data from a Norwegian fjord collected and presented by Rutledal et al. (2020). We are using cluster analysis to identify when an approaching ship typically will not maneuver according to part B Section 2 in the COLREG (i.e., deviating from the COLREG), and then estimating the conditional probability of such a deviation, given the respective situation. The results can be

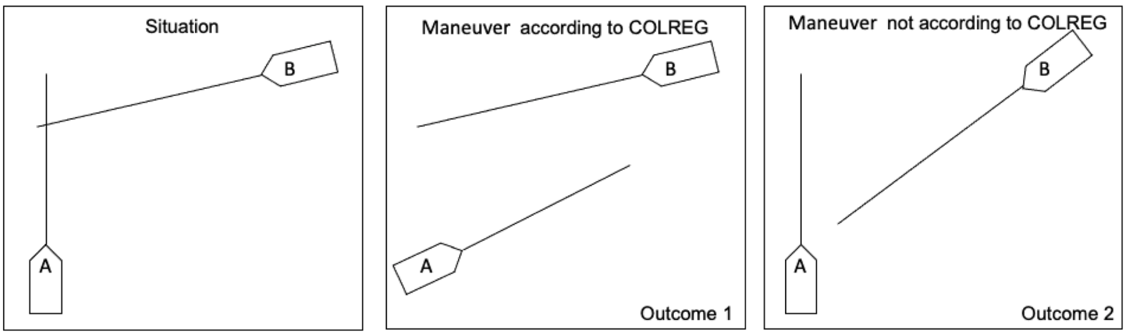

Fig. 1. Illustrating a MASS (Vessel A) meeting a conventional ship (Vessel B), where the MASS should give way according to the COLREG. Two possible maneuvers are illustrated.

utilized to prevent undesirable adjustments of course and speed by allowing an AI system to remain efficient while still being at least as safe as manned ships. Furthermore, the analysis builds a foundation for developing algorithms to search for similar beneficial procedures based on big data.

2. Background

2.1. COLREG

The international regulations for collision avoidance at sea are set by the COLREG (IMO, 2019) which is divided into six parts; A, B, C, D, E, and F.

Part A–General
Part B–Steering and Sailing
Part C–Lights and Shapes
Part D–Sound and Light Signals
Part E–Exemptions
Part F–Verification of compliance with the provisions of the Convention

The most important rules for decision-making during collision avoidance are primarily provided in Part B. Part B provides steering and sailing rules and are divided into three sections. Section 1 defines general conduct of vessels in any condition of visibility, Section 2 defines the conduct of vessels in sight of one another, and Section 3 the conduct of vessels in restricted visibility. As mentioned in the introduction, the COLREG are prescriptive on how traffic situations shall be resolved, with words like "ample time", "ordinary seamanship", and "if circumstances admit". This is understood as beneficial since it opens for situational adaptations by the mariner. The ordinary practice of seamanship allows the mariner to take action to avoid a collision that may deviate from parts of the COLREG, if necessary. Due to the rules' prescriptive nature, and the fact that they are made to be interpreted by a human, it is difficult to create algorithms for the same tasks.

2.2. Collision avoidance systems

A key feature for a MASS is a collision avoidance system. Dependent on level of autonomy, such systems should either be able to make informed decisions by itself, in collaboration with a human operator, or by providing decision support to the operator. The future development of such systems will probably rely on the interpretation of big data and use of AI. Such AI systems need to make the AI's decisions transparent to the stakeholders interacting with it, like onboard or remote operators, or mariners on other ships, because experience with human behavior tells us that it is not at all clear that a mariner necessarily will follow advice they do not understand (Aarset and Johannessen, 2022). Humans are reticent to adopt techniques that are not directly transparent, interpretable, and explainable (Aarset and Johannessen, 2022). To be successful, such a decision support system will therefore need to be based on what has been named XAI (*eXplainable Artificial Intelligence*) (Barredo Arrieta et al., 2020).

Traditionally, path planning algorithms originate from rule-based expert systems or iterative non-deterministic optimization algorithms. Generally, such algorithms have major difficulties with incorporation of COLREG and the practicing of seamanship (Tam et al., 2009). In recent years many researchers and developers have been making collision avoidance algorithms based on different methods like e.g. fuzzy logic (Fiskin et al., 2021; Wu et al., 2020), deep learning (Xu et al., 2022), and collaborative collision avoidance (overview in Akdağ et al. 2022). Murray and Perera (2021) propose to make regional path planning decisions through deep learning based on historical data. Burmeister and Constapel (2021) evaluates 48 publications on collision avoidance at sea and finds, among others, that a majority of the algorithms only address overtaking, head on, and crossing situations, without going into the specifics of further COLREG rules. They conclude that there is a need to focus on new approaches covering also other parts of the COLREG.

Here, we are discussing how an algorithm can handle ship encounters when an approaching ship deviates from the COLREG. Furthermore, we discuss how it can be ensured that AI systems do not make too strict rule-based maneuvers based on the COLREG, and thereby performing less efficient and less safe than a human operator would.

3. Method

With the scientific advancements of AI, cluster analysis has in the recent decades reached new popularity as a technique within machine learning (Murphy, 2012). Based on the data provided by Rutledal et al. (2020), we are utilizing cluster analysis to characterize situations occurring during encounters at sea and investigate the (dis)similarity of situations where human navigators deviate the COLREG. This is meaningful, since a path planning algorithm must consider that humans may deviate the steering and sailing rules of the COLREG. The objective of cluster analysis is to identify groups in (large) data sets such that the objects (i.e. situations) in the same group are similar to each other and objects in different groups are as dissimilar as possible.

Before any meaningful computation can be performed as part of a cluster analysis, though, human intervention is called for in the following four steps (Aarset and Johannessen, 2022).

1 Selection of attributes to characterize the objects (i.e. situations during encounters at sea).

2 Selection of metrics to quantify the different attributes.
3 Selection of dissimilarity to measure the distance between objects.
4 Selection of algorithm to create the clusters.

As algorithm we have chosen the *K*-means clustering, which is an unsupervised learning algorithm within AI. The algorithm was run on IBM SPSS Statistics, which uses the Euclidean distance to measure the distance (dissimilarity) between observations. The dissimilarity between the objects $X = (X_1, \ldots, X_J)$ and $Y = (Y_1, \ldots, Y_J)$ (here situations characterized by J attributes with respect to maneuvering during encounters at sea) is defined by

$$d(X, Y) = \sqrt{(X_1 - Y_1)^2 + \ldots + (X_J - Y_J)^2} \tag{1}$$

The dissimilarity using the Euclidean distance is greatly affected by difference in scale, combining e.g. nautical miles, degrees, and minutes. To rectify this, the metrics for all non-binary attributes were standardized by

$$\frac{value - mean}{std.\ error} \tag{2}$$

In our analysis, there was no prior knowledge of the number of clusters (*K*). We tested with *K* equal to 2, 3, 4, and 5, but the algorithm did not produce meaningful clusters of situations unless *K* was set to 5. When for example *K* was set to 3, the three clusters identified were situations where a ship came from starboard, from port, and when ships were classified as not maneuverable.

The *K*-means analysis uses centroids (i.e., average values in each cluster of the metric for each respective attribute) and is thus sensitive to outliers. In the dataset used in this study, no outliers were identified.

The attributes and metrics we selected were selected because they represent information that generally is available to mariners on board a ship through nautical charts, radar and AIS, and make up some of the most important decision-making sources for a mariner. A detailed overview of the attributes is found in Section 4.4.

4. Workflow of the analysis

The overall objective of the analysis was to investigate the (dis)similarity in ship encounter situations where actions to avoid collisions were taken, and to investigate if the probability of deviating from the COLREG was different in the five different clusters of situations.

4.1. Procedure

The workflow of the analysis is illustrated in Fig. 2 and further explained in Sections 4.2, 4.3, 4.4 and 4.5.

4.2. Data collection

The data used in the analysis in this paper were collected by Rutledal et al. (2020). The data were collected using the following sensors and sources: (1) Automatic Identifications System (AIS), (2) a 360° pan-tilt-zoom (PTZ) camera, and (3) a solid-state radar with Automatic Radar Plotting Aid (ARPA). Together, this gave an almost complete overview of the marine traffic in the area. The information from these units were integrated, recorded and presented on a costal monitoring system named *TimeZero*, delivered by Furuno Norway (Fig. 3).

Using the camera and ARPA allowed us to interpret more aspects of the traffic situations than previous studies focusing solely on AIS data. Due to the General Data Protection Regulation (GDPR) restrictions, though, it was not possible to record audio recordings of VHF traffic in the area, which entails that some of the maneuvers deviating the COLREG could have been agreed upon without our knowledge.

The equipment monitored an area in Storfjorden (Fig. 4), a fjord located in the north-western part of Norway. The area is a

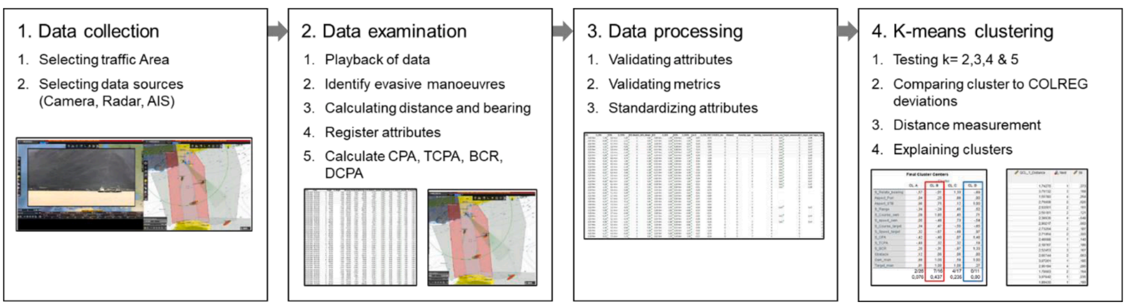

Fig. 2. Workflow illustration.

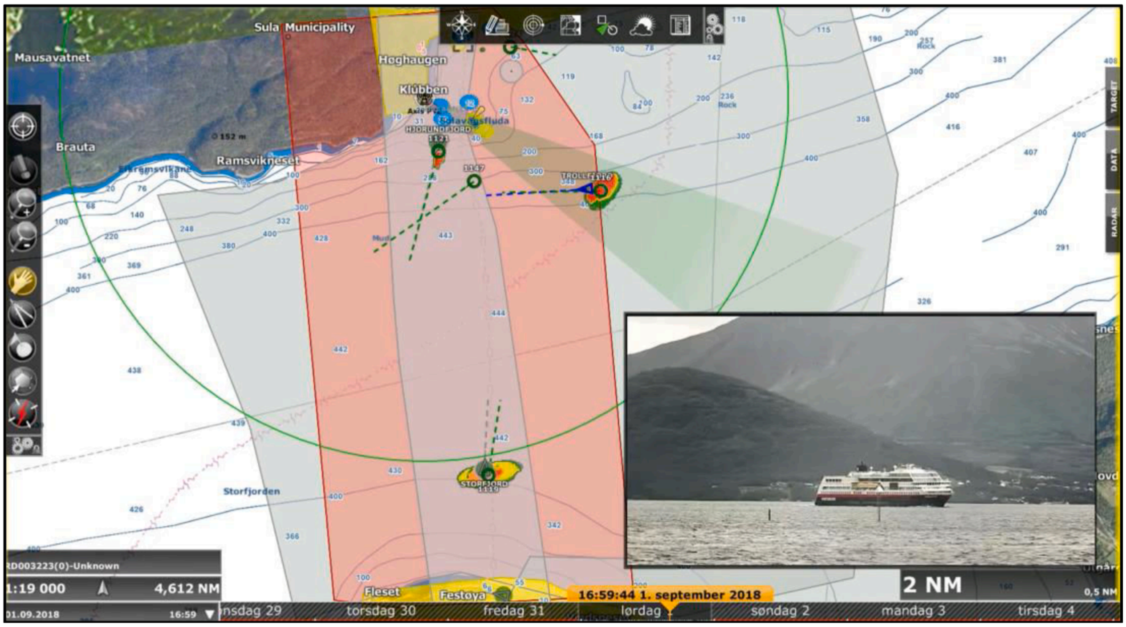

Fig. 3. Screenshot of the monitored area on a TimeZero software with nautical chart, camera, Radar/ARPA, and AIS overlay.

designated test area for autonomous vessels where DB Schenker is planning to put an autonomous container feeder in operation in 2024 (Schencker, 2022).

The location was selected based upon three criteria; (1) it is the most traffic congested area in Storfjorden, (2) it has access to electrical power, and (3) the length of the crossing is within the ranges of both camera and radar. The monitored area is a ferry crossing with two coastal ferries. At the point of the ferry crossing, the fjord is more than three nautical miles wide and was thus not considered to be a narrow channel. The data was played back on the TimeZero software and all targets entering the defined area were categorized in a spreadsheet. Evasive maneuvers were assessed by experienced mariners to determine whether they were conducted in accordance with the COLREG or not.

4.3. Data set

The original data set (Rutledal et al., 2020) consisted of a total of 1010 ships crossing the defined area, not including the coastal ferries, with 84 evasive maneuvers identified. The dataset is a record file in TimeZero, a spreadsheet with timestamps for all traffic crossing the area, and a record indicating if an evasive maneuver was carried out or not.

Based on the original recordings, we assessed all the situations with evasive maneuvers and excluded situations as described in Fig. 5. 14 situations were excluded from the analysis because it was not possible to either identify the exact moment for when the maneuver was carried out or extract attributes for the situations as listed in Section 4.4. This was typically (1) small leisure crafts close

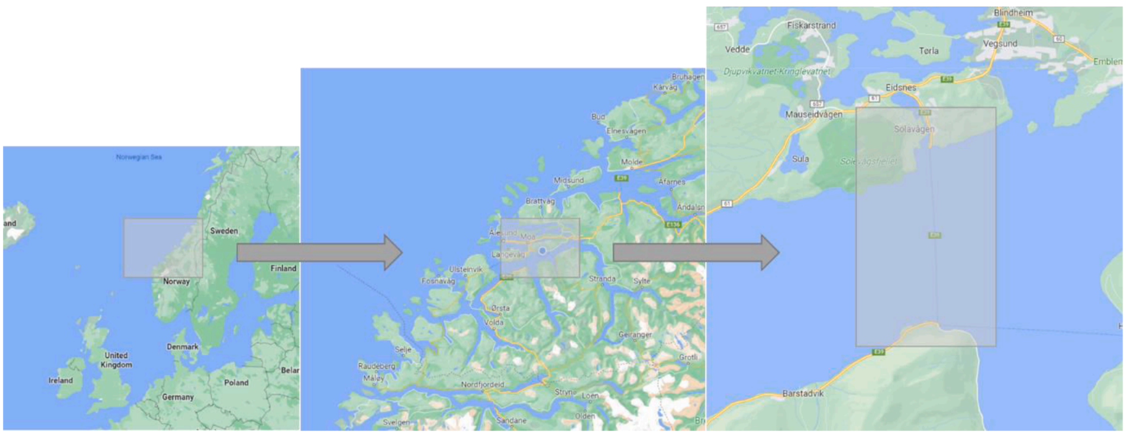

Fig. 4. The monitored area.

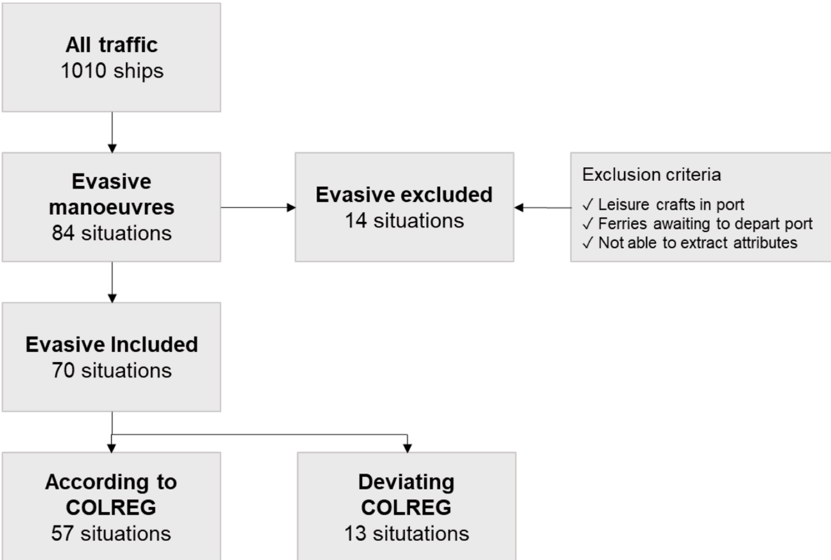

Fig. 5. Overview of data extracted from original dataset.

to the quay side with many alterations of course and speed or (2) the coastal ferries delayed its departure to avoid situations. During the analysis we discovered a situation deviating the COLREG which was labeled as according to COLREG in the original dataset, making it a total of 13 deviating situations.

4.4. Data examination

In this study, all situations where an evasive maneuver was performed were put into a new spreadsheet. The respective situations were then played back on the TimeZero software, allowing us to identify the exact positions and moments of the maneuvers. Then, the attributes range and bearing between the vessels were measured using an EBL/VRM tool (Electronic Bearing Line and Variable Range Marker) (See Fig. 6).

Furthermore, the course, speed, type of ship, a possible obstacle (land) preventing a maneuver, flag, size, and ships name (if available) were noted in the spreadsheet and the maneuvers were classified as deviating or not deviating from the COLREG by a team of experienced mariners. The ships were in each situation classified either as "*ownship*" or "*targetship*" on random, except in situations where a ship deviated from the COLREG. In these situations, the ships that performed the evasive maneuver were classified as *targetship*. Hence, the ownship would be the ship that should have given way according to the regulations.

Then we extracted the following attributes as illustrated in Fig. 7: (1) *Closest Point of Approach* (CPA), (2) *Time to Closest Point of Approach* (TCPA), (3) *Distance to Closest Point of Approach* (DCPA), (4) *Bow Crossing Range* (BCR).

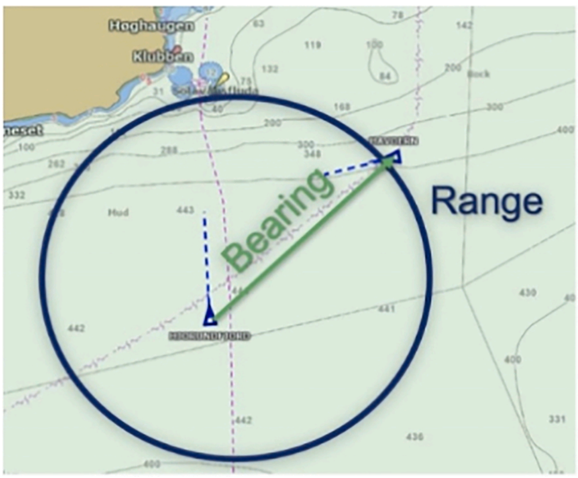

Fig. 6. Screenshot from TimeZero software, with illustration of tools measuring the range and bearing between ownship and targetship.

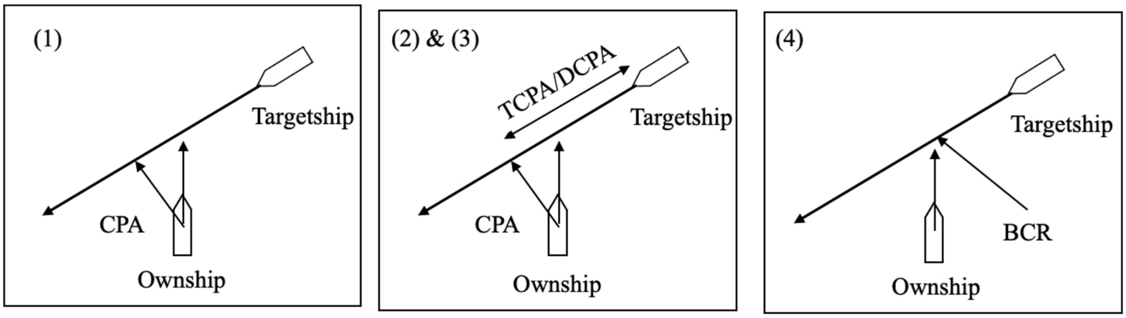

Fig. 7. Illustration of attributes calculated from vessels course, speed, range and bearing between the vessels.

Further we extracted: (5) relative bearing and aspect from the ownship's point of view, and (6) a binary attribute for deviating the COLREG. The last attribute was not used in the clustering, but in the postprocessing to estimate the probability of an evasive action not according to COLREG. Attributes for (7) nationality flag, (8) size, and (9) year-built were collected from ships equipped with AIS.

4.5. Data processing

During analysis, DCPA and bearing were excluded from the analysis as this information basically is contained in the TCPA. Attributes for flag, size, and year-built were not found significant and were also excluded from the model. Information of the course of the "give way" vessel is only interesting with respect to the relative bearing between the vessels. Therefore, the vessels courses are excluded from the analysis. Still, these attributes might prove significant in other datasets.

All navigational statuses of the ships involved in the traffic situations investigated in this paper were either "underway using engine" or "underway using sails". This was verified either by AIS or camera identifying lanterns or day signals. There were no ships in the dataset with "restricted ability to maneuver" or other statuses influencing the decision making as mentioned in COLREG R18. The combination of radar, AIS and camera also made it possible to verify the aspects of the encountering ships. There were no situations in the data with reduced visibility evoking COLREG part B Section 2 "conduct of vessels in restricted visibility".

All types of vessels were evaluated and classified as "maneuverable" or not. This classification was based on the vessel's actual maneuverability in terms of maneuvering arrangements, size and if it was carrying passengers. For instance, an approximately 120 meters coastal ferry carrying cars and passengers was considered maneuverable, but a cruise ship not considered as maneuverable, even though it might have good maneuvering arrangements. We expect that the mariners on board a cruise ship is more reluctant to make sharp maneuvers due to the impact the motion of such a maneuver would have on the passengers.

As mentioned in Section 3, the dissimilarity using the Euclidean distance is greatly affected by difference in scale. To rectify this, the metrics for all non-binary attributes were standardized.

4.6. K-means clustering

Following the procedure described above, the dataset consisted of 70 situations, each characterized by 11 attributes as described in Table 1. A K-means cluster analysis was executed with $K = 5$ utilizing IBM SPSS.

5. Results and discussion

5.1. Identified clusters

In Fig. 8 below, the 5 identified clusters are characterized by some of their most prominent characteristics. These characteristics

Table 1
Attributes included in the final clusters, see glossary for more detailed explanations of the attributes.

Attribute	Metric
Range	Nautical miles
Relative bearing	Degrees
Aspect	Starboard, port, or stern
Speed (ownship/targetship)	Knots
CPA: Closest point of approach	Nautical miles
TCPA: Time to closest point of approach	Minutes
BCR: Bow Crossing Range	Nautical miles, ahead or stern
Type of ship (ownship/targetship)	If considered maneuverable 1, if not 0
Obstacle	If an obstacle may prevent a maneuver 1, if not 0

Cluster A
1 of 5 situations deviate COLREG
Largest range
Targetship has higher speed then ownship
Largest CPA, TCPA & BCR
Ownship is always classified as manoeuvrable
20% likelihood for deviating the COLREG

Cluster B
2of 18 situations deviate COLREG
Shortest range
Similar speed between ships
Shortest CPA,TCPA & BCR
All ships involved is classified as manoeuvrable
11% likelihood for deviating the COLREG

Cluster C
8 of 17 situations deviate COLREG
2nd shortest range
Ownship has higher speed then targetship
Short CPA and medium TCPA
Short BCR (astern)
Targetship is always classified as manoeuvrable
47% likelihood for deviating the COLREG

Cluster D
2 of 10 situations deviate COLREG
2nd largest range
Ownship has higher speed then targetship
Medium CPA and large TCPA
Larger BCR (Astern)
Targetship is always classified as manoeuvrable
20% likelihood for deviating the COLREG

Cluster E
0 of 20 situations deviate COLREG
Medium range
Targetship has significantly higher speed then ownship
Medium CPA, BCR and 2nd shortest TCPA
Ownship is always classified as manoeuvrable
0% likelihood for deviating the COLREG (All according)

Fig. 8. Cluster characteristics.

were identified by comparing the centroids in the respective clusters (see Table 2) as well as consulting the raw data. In 13 of the situations, deviations from the COLREG were identified.

Table 2 illustrates the (dis)similarity between the centroids of the clusters. The values are normalized. The table shows that cluster A has a long BCR (ahead), cluster E has a shorter BCR (ahead), cluster B has a very short BCR (ahead), while cluster D has large BCR (astern), and cluster C a slightly shorter BCR (astern).

5.2. Quality of the clustering

A method for interpretation and validation of consistency of clusters of data is the silhouette value. It is a measure depending on the cohesion and the separation of clusters. Calculations of the silhouette values for each identified cluster have been performed to make a graphical representation of how well the traffic situations have been clustered (Fig. 9).

Let X be an object (i.e. a situation) in cluster A, $a(X)$ the average dissimilarity of X to all other objects of cluster A, and d(X, C) the average dissimilarity of X to all objects of another cluster C. Define

$$b(X) = min_{C \neq A} d(X, C). \tag{3}$$

The cluster for which this minimum is attained is called the neighbor of object X. Now, the silhouette is defined by (Kaufman and Rousseeuw, 1990)

$$s(X) = \frac{b(X) - a(X)}{\max\{a(X), b(X)\}}. \tag{4}$$

We see that $-1 \leq s(X) \leq 1$, where 1 indicates that the “within” dissimilarity $a(X)$ is much smaller than the smallest “between” dissimilarity $b(X)$. Therefore, it’s reasonable to say that X is “well classified” if $s(X)$ is close to 1. If $s(X)$ is about zero, then $a(x)$ and $b(X)$ are approximately equal and hence it is not clear whether X should have been assigned to this or another cluster. If s(X) is close to -1 then $a(X)$ is much larger than $b(X)$, so X lies on the average much closer to another cluster than the cluster it has been assigned. The object may be said to have been “misclassified”.

The quality of the overall clustering is said to be *mediocre* when the silhouettes are in the interval (-1, 0.2), *suitable* when the silhouettes are in the interval (0.2, 0.5), and *good* when the silhouettes are above 0.5 (Kaufman and Rousseeuw, 1990).

As illustrated in Fig. 9, the mean silhouettes for cluster A, D and E are between 0.30 and 0.40, while cluster B and C stands out with lower silhouette values. Since cluster A, D and E represents a low likelihood of deviating from the COLREG, it is plausible that these clusters are more homogenic than C. The clusters are identified in an 11-dimentional space, and reality is of course even more complex. As a result, the silhouette values are relatively low, but still, realistic and informative.

Table 2
Illustrating (dis)similarity between the centroids of the identified clusters.

	A	B	C	D	E
Relative Bearing	29.8	158.0	60.9	325.0	44.1
Aspect Port	0.0	0.4	0.1	1.0	0.1
Aspect STB	1.0	0.6	0.9	0.0	1.0
Range	2.2	0.7	1.2	2.0	1.3
Speed ownship	8.5	8.6	11.9	12.4	9.0
Speed targetship	9.9	8.7	9.0	8.7	14.1
CPA	0.45	0.16	0.19	0.18	0.23
TCPA	8.96	3.11	5.27	7.23	4.06
BCR	0.67	0.07	-0.25	-0.33	0.33
Obstacle	0.0	0.2	0.1	0.0	0.1
Ownship maneuverability	1.0	1.0	0.6	0.6	1.0
Targetship maneuverability	0.6	1	1	1	0.45

Large value
Medium value
Low value

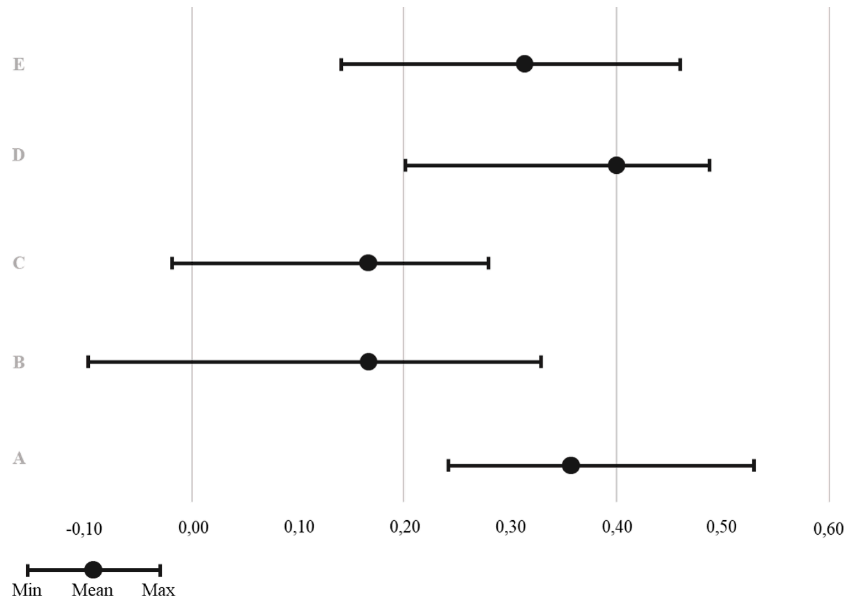

Fig. 9. Cluster silhouettes, with the minimum, mean, and maximum silhouette value of each cluster.

5.3. *Estimated probability of deviations from the COLREG*

A total of 11 attributes were used to identify the 5 clusters among the 70 situations available by the *K*-means clustering technique. Cluster C was the cluster of situations where mariners most often deviated from the COLREG regulations. We observed 8 deviations among the 17 situations assigned to cluster C. In both clusters A, B and D deviations were less frequent, both absolute and relative to the number of situations in the respective clusters. We also identified a cluster of situations where none of the mariners deviated from the COLREG (cluster E).

The first graph in Fig. 10 illustrates the size of the clusters and the relative number of deviations. Observe that in cluster E, there is no deviations.

A Chi-square test (Murphy, 2012) was used to test the hypothesis

H_0: The probability of a maneuver deviating from COLREG during an encounter at sea is equal in the 5 identified clusters against the alternative hypothesis
H_A: The probability of a maneuver deviating from COLREG during an encounter at sea is not equal in the 5 identified clusters.

The Chi-square test produced a p-value of 0.006, leading to a rejection of the null hypothesis $H_{0,}$ and indicating that it is not the same probability to deviate from the COLREG regulations in the different clusters.

Furthermore, a binary logistic regression analysis (Murphy, 2012) was conducted with deviation from the COLREG as dependent variable and cluster membership as the covariate. Cluster C produced a p-value of 0.002, indicating that membership in cluster C is a significant explanatory variable for explaining variation in the probability of deviation from the COLREG. Membership to other

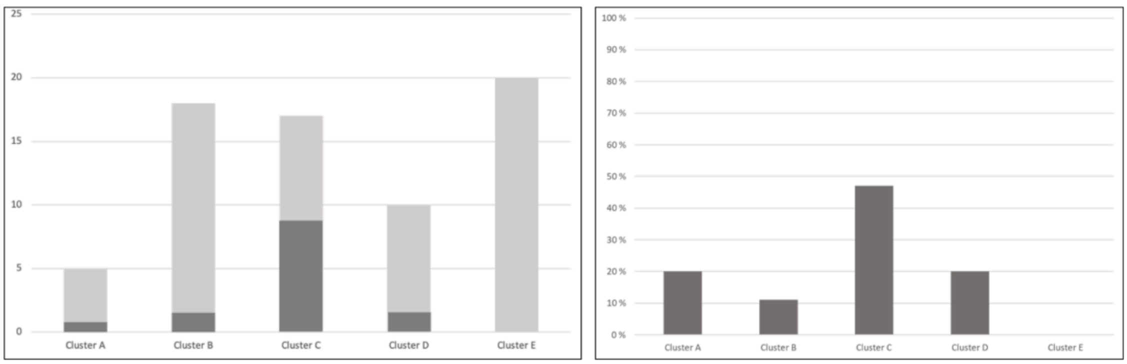

Fig. 10. First graph illustrates the cluster sizes (n=70) with the number of deviations from COLREG per cluster, second graph illustrates the likelihood for an approaching ship to deviate the COLREG in each cluster.

clusters were not found significant in these regression analyses.

The results of these analyses might not be directly applicable in other areas, and further testing of the cluster method should be carried out. In other areas, we expect there are other attributes that will play a role that have not been included here. Could there, for instance, be a difference if it's the captain or mate who is officer on watch? Furthermore, we find it plausible that the mariner's working experience is of importance. One could also discuss if the analysis would be helpful for unmanned MASS, since we still do not know anything about the interaction of manned ships and autonomous ships. Will mariners exercise the same courtesy to what is believed to be a machine?

5.4. Extended timeframe for AI decision (ETAD)

Based on these results, this paper proposes the concept of *Extended timeframe for AI decision (ETAD)*. In this concept, we suggest that an AI system search through the available clusters before it normally would suggest an evasive maneuver. If the situations are similar to situations where approaching ships usually deviate the COLREG and give way (in the Storfjorden case situations classified in cluster C), the AI could be given an extended timeframe, await the maneuver, and thereby improve the efficiency of the operation without jeopardizing the safety. See Fig. 11 for more details.

By applying ETAD in certain situations and allowing the AI to await its maneuver while still defining a point of no return were an action to avoid collision must be performed, allows the AI to further assess the situation. The decision to apply ETAD must be based on a statistical significance, making the AI systeḿs decision transparent and easy to understand for a remote operator. By applying ETAD in certain situations, one might avoid unnecessary maneuvers, remain efficient, while still maneuvering according to the COLREG.

On the other hand, complicating the collision avoidance algorithms could make the AI's decision less transparent and harder to explain. Allowing an algorithm to deviate from the COLREG in the same manner as a human, might create unknown secondary effects, make it less trustworthy, less predictable and create liability issues. Perera and Batalden (2019) expects that though, that *"… onboard intelligent systems can develop human friendly decision-making capabilities in the future to support autonomous vessels."* They also believe that this will enable MASS to take actions in similar ways as a human operator would. This could in many ways be beneficial and contribute to efficiency and seems to match both the results and the proposal from this analysis.

If a function like the ETAD is included in an algorithm, it is vital that the decision to apply it, and alternative decisions are visible and available for a human operator. In Fig. 12 a possible design is illustrated.

The ETAD should be considered in the design of a collision avoidance algorithm. Any such algorithm would in any case determine if it should be generalized to operate globally or adapted for a regional function. Any such collision avoidance algorithm with ETAD must go through a class approval process. If approved, it could contribute to enhanced alert management functions as required in the design principle in the DNV guideline for autonomous ships (DNV, 2018), ensuring sufficient supervision. As an example, one could avoid raising unnecessary alarms, and in turn inhibit "cry wolf" situations.

One might also suggest that an AI system should await its maneuver at all times, to achieve increased efficiency. This would of course not be true, since the longer you await a maneuver, the larger the maneuver to avoid collision needs to be. Such an algorithm would deviate from COLREG R8 with regards to ample time. Indeed, efficiency would often be achieved by early maneuvers, emphasizing the need for statistical significance when applying ETAD to achieve increased efficiency with regards to the observance of good seamanship.

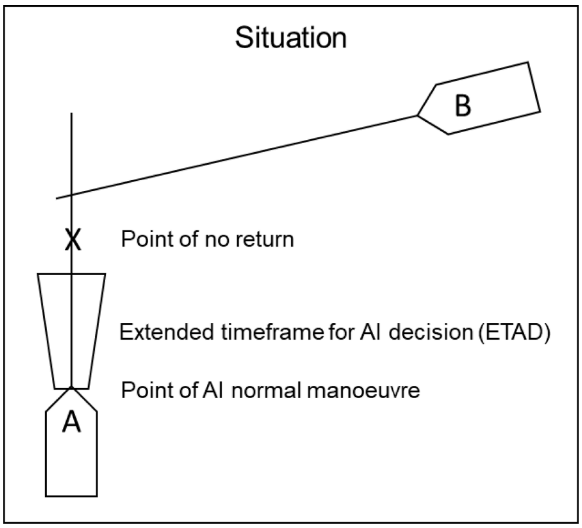

Fig. 11. Illustrating a point of no return (X) where vessel A must make a decision to uphold her CPA/TCPA limits and an extended timeframe for AI decision (ETAD).

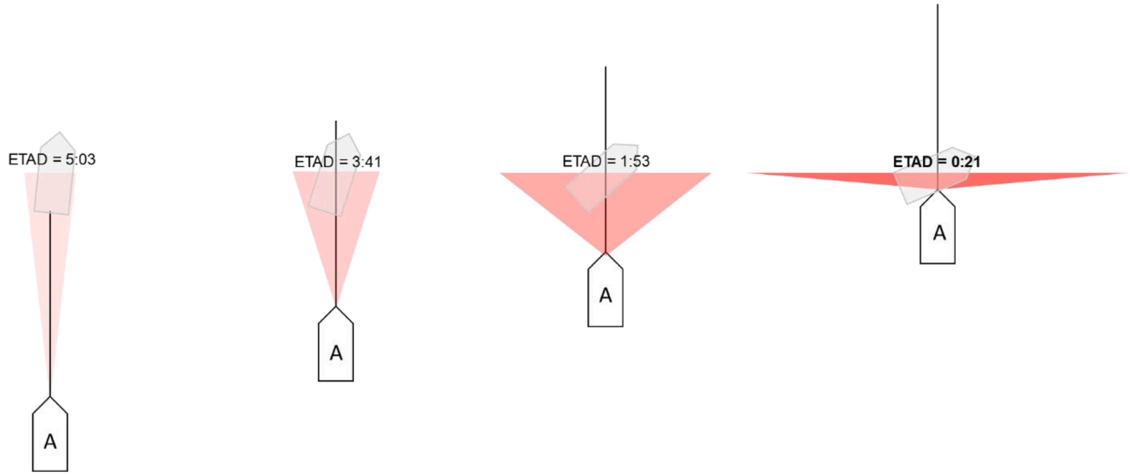

Fig. 12. Design sketch for visualization of ETAD, illustrating that an adjustment of course or speed needs to be larger, the longer one awaits a maneuver.

6. Conclusions

As shown by Rutledal et al. (2020), mariners deviate from the COLREG to adapt to some situations, with the goal of increasing both efficiency and safety. While MASS projects with different levels of autonomy are starting up, the need to make collision avoidance algorithms for MASS as efficient as conventional ships is key. This paper demonstrates that it is possible to anticipate deviations from the COLREG in compliance with good seamanship and proposes how an AI system might cope with such deviations. The method can be used for regional ship predictions allowing a MASS to deviate from the COLREG, if an approaching manned ship is expected to. By introducing ETAD before performing a maneuver, we expect increased efficiency and safety. Furthermore, by utilizing the ETAD, the system decides that a situation do not require an operator to intervene - yet.

Funding

This work was supported by the Center for Research-based Innovation AutoShip (309230), Norway.

Recommendation on further work

Test the method or algorithm on different dataset. Search for new/other attributes. Search for similar clusters in big data.

CRediT authorship contribution statement

Andreas Nygard Madsen: Conceptualization, Investigation, Formal analysis, Writing – original draft, Writing – review & editing. **Magne Vollan Aarset:** Conceptualization, Investigation, Formal analysis, Writing – original draft, Supervision, Writing – review & editing. **Ole Andreas Alsos:** Supervision, Visualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

The authors acknowledge the support from Lars Ole Alstad in computing the CPA, TCPA, DCPA, and BCR. Further we would like to thank Dag Rutledal for providing us access to the dataset collected in 2018, which are used in this study.

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