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Proactive Collision Avoidance for Autonomous Ships: Leveraging Machine Learning to Emulate Situation Awareness

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Abstract:
Autonomous ship technology is developing at a rapid pace, with the aim of facilitating safe ship operations. Collision avoidance is one of the most critical tasks that autonomous ships must handle. To support the level of safety associated with collision avoidance, this study suggests to provide autonomous ships with the ability to conduct proactive collision avoidance maneuvers. Proactive collision avoidance entails predicting future encounter situations, such that they can preemptively be avoided. However, any such actions must adhere to relevant navigation rules and regulations. As such, it is suggested to predict encounter situations far in advance, i.e. prior to risk of collision existing. Any actions can, therefore, be conducted prior to the applicability of the COLREGs. As such, simple corrective measures, e.g. minor speed and/or heading alterations, can prevent close encounter situations from arising, reducing the overall risk associated with autonomous ship operations, as well as improving traffic flow. This study suggests to facilitate this ability by emulating the development of situation awareness in ship navigators through machine learning. By leveraging historical AIS data to serve as artificial navigational experience, long-range trajectory predictions can be facilitated in a similar manner those conducted by human navigators, where such predictions provide the basis for proactive collision avoidance actions. The development of human situation awareness is, therefore, presented, and relevant machine learning techniques are discussed to emulate the same mechanisms.

Keywords: Autonomous Ships, Machine Learning, Collision Avoidance, Situation Awareness

1. INTRODUCTION

Autonomy (Krogmann, 1999) has long been the subject of much research. Autonomous functions in cars (Chan, 2017), for instance, are already implemented in vehicles, with increased levels of autonomy likely available within the next years. Many of these developments can be attributed to recent developments in machine learning that facilitate situation awareness (Endsley and Jones, 2012). Within the maritime domain, however, progress has been slower. Nonetheless, work is progressing, with various companies already planning to implement autonomous ship technology.

One of the greatest challenges in realizing autonomous ships is developing technology to replace the functions of a human navigator. Many aspects of ship navigation can be implemented via autopilot systems. This technology has, however, been available for many years, with the first automatic steering mechanisms available as early as 1911 (Fossen, 2000). Nonetheless, the primary barrier to safe autonomous operations is likely adequate situation awareness, which provides input to such systems.

Effective collision avoidance is one of the main challenges that must be addressed by autonomous ship technology. Without systems to facilitate collision avoidance, autonomous ships can not be introduced into maritime transportation systems. The majority of the literature regarding collision avoidance for autonomous vessels e.g. Hu et al. (2017); Zaccone et al. (2019); Lyu and Yin (2019), addresses how to implement COLREGs compliant actions with regards to path planning. This study, however, suggests enacting collision avoidance actions prior to risk of collision arising, i.e. prior to the applicability of the COLREGs. As such, the approach in this paper aims to negate the necessity of previous approaches by preventing encounter situations from occurring. In this manner, the overall safety of maritime operations can be enhanced by averting the risk associated with vessel encounters, as well as improve traffic flow. Such actions may, for instance, include minor speed and/or heading alterations that can reduce the risk of a future encounter situation arising.

There is currently limited research on applying such approaches to autonomous ships. Experienced navigators, however, likely leverage proactive collision avoidance, where close encounter situations are predicted far in advance, and avoided via simple proactive measures e.g. minor speed and/or heading alterations. This, however, is dependent on the navigators ability to leverage their situation awareness to simulate future ship traffic accurately.

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If an autonomous vessel were able to conduct such proactive collision avoidance measures, the overall safety of autonomous ship operations would be increased. Conducting long-range ship trajectory predictions is, however, not straight forward. In this study, the concept of proactive collision avoidance is presented in light of relevant rules and regulations. Further, the manner in which human ship navigators likely leverage situation awareness to facilitate proactive collision avoidance is presented. Machine learning techniques are then suggested to emulate human situation awareness. If successful, these techniques can provide navigational experience to autonomous ships, thereby facilitating proactive collision avoidance. Aspects of this study have also been presented in Murray (2021), and the reader is referred to Murray (2021) for further details.

2. COLLISION AVOIDANCE

In this section, the concept of proactive collision avoidance is presented as a means to enhance the safety associated with autonomous ships. First, conventional collision avoidance is discussed in light of relevant rules and regulations. Then, proactive collision avoidance measures are suggested in adherence with relevant rules and regulations.

2.1 Conventional Collision Avoidance

When one ship departs from its planned trajectory to avoid potentially coming into physical contact with another vessel at some point in the future, it is said to have conducted a collision avoidance maneuver (Huang et al., 2020). Such maneuvers are common, and necessary to maintain the safety of maritime transportation. In a collision avoidance situation, the ship under control is often referred to as the own ship, with other vessels the own ship may come into contact referred to as target ships. An autonomous ship must, therefore, have the capability of effectively avoiding collision with relevant target ships.

On conventional vessels, such actions are the responsibility of the Officers on Watch (OOW). However, any collision avoidance actions must adhere to relevant rules and regulations. These are outlined by the International Maritime Organization (IMO) in the Convention on the International Regulations for Preventing Collisions at Sea (COLREGs) (Cockcroft and Lameijer, 2011), and govern the permissible actions for vessels in encounter situations. These regulations apply to all ocean-going vessels, but local rules and regulations may come in addition.

Collision Risk Rule 7 of the COLREGs addresses collision risk, where it is stated that any two vessels in sight of one another, with no apparent alteration of compass bearing, risk of collision is deemed to exist. Collision risk is is commonly evaluated based on the estimated Closest Point of Approach (CPA). The Distance at the Closest Point of Approach (DCPA) and Time to Closest Point of Approach (TCPA) are often used as indicators of the collision risk. If these values are smaller than given thresholds, risk of collision is deemed to exist (Huang et al., 2018). Studies have also addressed utilizing a zone surrounding either the own ship or target ship, known as the ship domain (Fujii and Tanaka, 1971; Goodwin, 1975). In this approach, any infringement of the ship domain entails a risk of collision.

The process of collision risk evaluation was presented in Tam and Bucknall (2010). Initially, the planned trajectory of the own ship is discretized at regular intervals. The future trajectory of the target ship then estimated based on a linear extrapolation of the target ship's initial velocity vector. The ship domain is then evaluated based on the type of encounter, and the CPA evaluated. If the ship domain is infringed upon, a risk of collision is deemed to exist. This process then repeats for all relevant time steps.

Vessel Encounter Situation When there is risk of collision between two vessels, they are considered to be in an encounter situation, triggering the applicability of the COLREGs. Depending on the type of encounter, the COLREGs define which vessel is the give-way vessel, and which is the stand-on vessel. The give-way vessel is that which much keep out of the way of another as far as possible. Rule 16 of the COLREGs governs the actions by the give-way vessel. It is stated that early and substantial action should be taken by the give-way vessel to avoid collision. Such actions are, furthermore, addressed in Rule 8 of the COLREGs, where it is stated that any alteration of speed or course must substantial enough to be readily apparent. This implies that small alternations to the course or speed of the vessel are not permissible, as the action to avoid collision may not be observed by the stand-on vessel.

Rule 17 of the COLREGs outlines the actions of the stand-on vessel. It is stated that when one vessel must keep out of the way of the other, the other must maintain the course and speed. This vessel is known as the stand-on vessel. Any collision avoidance actions are, therefore, only permissible by the give-way vessel once risk of collision is deemed to exist. However, the stand-on vessel is required to take any action necessary to avoid collision if it becomes apparent that a collision can not be avoided by the give-way vessel's action alone.

Cockcroft and Lameijer (2011) summarized a general collision situation in the four stages outlined below. These are illustrated for a crossing situation in Fig. 1.

(1) Prior to risk of collision, both vessels are free to take any action (long-range).
(2) Risk of collision exists. The give-way vessel must take early and substantial action to pass at a safe distance. The stand-on vessel must maintain their heading and speed.
(3) In the case that the give-way vessel does not take timely and substantial action, the stand-on vessel may take action to avoid collision by their maneuver alone. However, such a maneuver should not alter their course to port, and their intention to take action should be signaled.
(4) When it becomes apparent that collision cannot be avoided by the give-way vessel's actions alone, the stand-on vessel is required to take any action necessary such as to best avoid collision.

2.2 Proactive Collision Avoidance

Conventionally, collision avoidance actions are not enacted until risk of collision is deemed to exist, triggering the

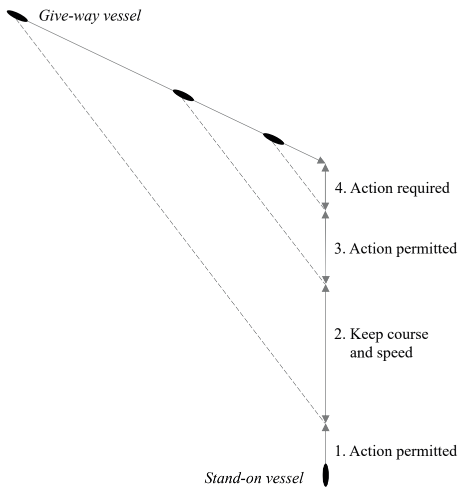

Fig. 1. Collision situation stages, adapted from Cockcroft and Lameijer (2011). The permissible actions by the stand-on vessel are illustrated.

applicability of the COLREGs. Proactive collision avoidance, however, employs actions prior to risk of collision arising. Such actions may, for instance, include minor speed and/or heading alterations that reduce the risk of a future encounter situation arising. As such, the overall safety of maritime operations can be improved by reducing the risk associated with vessel encounters. Furthermore, the need for significant evasive maneuvers should improve traffic flow.

Rule 8 of the COLREGs states that any collision avoidance actions taken by the give-way vessel must be substantial, such as to be easily observed by the stand-on vessel. Furthermore, the stand-on vessel is required to maintain their speed and heading once risk of collision is deemed to exist. Minor speed and/or heading alterations are, therefore, not permissible with respect to the COLREGs once risk of collision is deemed to exist. Stage 1 in Fig. 1, however, relates to the permissible actions by vessels at long-range (i.e. before risk of collision is deemed to exist). In this stage, both the give-way and stand-on vessels are free to take any action. Proactive collision avoidance actions must, therefore, take place during stage 1 of an encounter situation.

As discussed in Sec. 2.1.1, collision risk is traditionally evaluated using a linear extrapolation of the initial velocity vector of the target ship. Despite having intersecting trajectories at long-range, however, collision risk is not deemed to exist until the vessels are within a given range. This range will vary considerably depending on the speed, size and maneuverability of the respective vessels, as well as local environmental conditions e.g. metocean conditions and fairway geometry (Cockcroft and Lameijer, 2011).

It is suggested in Cockcroft and Lameijer (2011) that stage 1 of a collision situation lasts until a range of approximately 5-8 nautical miles in the open sea (i.e. vessels will likely have near linear trajectories). Using a conservative estimate of 15 kn as the average speed for ships on the open sea, this distance corresponds to a TCPA of 20-32 minutes. In more complex waterways, this value will likely be lower. As a result, the relevant COLREGs are generally not considered applicable before 20-32 minutes prior to the CPA. Vessels are, therefore, free to take any proactive collision avoidance actions in stage 1, including minor speed or heading alterations that can possibly avoid any close encounter situations.

To identify potential vessel encounter situations, however, vessels must be able to conduct long-range trajectory predictions of both the own ship, as well as potential target ships, up to 30 minutes into the future. If successful, such predictions can facilitate proactive collision avoidance actions. Applications of such predictions include estimating future traffic congestion, such that the own ship can minimize the risk of close-range encounter situations, and maximize the room to maneuver. Furthermore, crossing situations, as illustrated in Fig. 1, can be predicted and avoided. Potential overtaking and head-on situations can also be predicted, and optimal routes planned to minimize the future collision risk.

The future 30 minute trajectories of target ships are, however, generally unknown. Furthermore, they may be complex, and not conducive with linear extrapolations of the initial velocity vector used for short-range predictions in traditional collision risk evaluation. It is theorized that ship navigators leverage what is known as situation awareness (Endsley and Jones, 2012) to facilitate long-term predictions of ship dynamics (Sharma et al., 2019), that likely aid in reducing the risk of future encounter situations. These mechanisms are, therefore, investigated in the next section, such that they may be emulated by an autonomous vessel.

3. SITUATION AWARENESS IN SHIP NAVIGATION

Endsley (1988) defined situation awareness as *"The perception of the elements in the environment, within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future"*. Endsley (1995) also defined three levels of situation awareness as:

(1) Perception of elements in the environment
(2) Comprehension of the current situation
(3) Projection of the future status

The term situation awareness can be traced back to World War I, where it was used in reference to aircraft pilots. Since then, the term has been applied to a wide variety of domains ranging from driving to power plant operations (Endsley and Garland, 2000). Within the maritime domain, situation awareness has been found to be essential in facilitating safe ship operations. Sharma et al. (2019) investigated the situation awareness requirements of ship navigators, and found that they actively leverage all three levels of situation awareness. One of the most important tasks ship navigators are responsible for is conducting effective collision avoidance. Such actions are dependent upon adequate situation awareness of the navigator, and will be discussed further in this context in this section.

Level 1 Situation Awareness The first level of situation awareness in the case of ship navigation largely relates to acquiring relevant information e.g. metocean conditions, under-keel clearance and fairway geometry. Furthermore, perceiving relevant obstacles e.g. target ships is conducted at this level. Sharma et al. (2019) found that ship navigators identified information relating to ship traffic and obstacles as necessary to achieve level 1 situation awareness. Collision avoidance actions, for instance, will be dependent on the successful observation of target ships.

Level 2 Situation Awareness The second level of situation awareness relates to the navigator's ability to comprehend the current situation, and the implications with respect to the safety of the ship. In a collision avoidance setting, this can be considered collision risk evaluation. This is supported by the findings in Sharma et al. (2019), where the current separation between the own ship and target ships, as well as the distance to relevant obstacles were identified as relevant information necessary for level 2 situation awareness.

Level 3 Situation Awareness The highest level of situation awareness involves predicting the future dynamics of a situation. However, such predictions are more long-term than those involved in level 2 situation awareness with respect to collision risk evaluation. In an interview conducted in Sharma et al. (2019), a navigator described level 3 situation awareness as *"If there is any traffic nearby. If somebody's going to come, or if I'm going to meet someone at some point"*. Further, the projected position of the own ship as well as the projected movement of target vessels were outlined as relevant. This indicates a more long-range prediction of ship trajectories, beyond what is possible via linear predictions using the initial velocity vector of target ships. Such predictions likely facilitate proactive collision avoidance actions by ship navigators. These predictions, however, rely on the level 3 situation awareness of the ship navigator.

3.1 Long-Range Ship Trajectory Prediction

As discussed, ship navigators likely leverage long-range trajectory predictions to facilitate level 3 situation awareness. It is theorized that mental models are the key enablers of high level situation awareness (Endsley and Jones, 2012). Mental models were defined in Rouse and Morris (1985) as *"Mechanisms whereby humans are able to generate descriptions of system purpose and form, explanations of system functioning and observed system states, and predictions of future states"*. As such, ship navigators likely leverage such mental models to facilitate long-range trajectory predictions.

Mental models, however, are not innate to ship navigators. They must be developed through experience. Holland et al. (1986) outlined the development of mental models, where it was argued that the first step in model development is learning to categorize input. As individuals are exposed to recurrent situations, they begin to identify patterns, and group situations into categories with similar characteristics. These may, for instance, constitute ship routes. Furthermore, it is theorized that individuals develop transition functions that model how situations vary over time. For the case of ship behavior, these can be viewed as ship behavior models that predict the future behavior of a vessel along a given route. As such, for each category, a specific transition, i.e. behavior, model will be developed to facilitate prediction. These models are refined by comparing predictions to observations over time, and

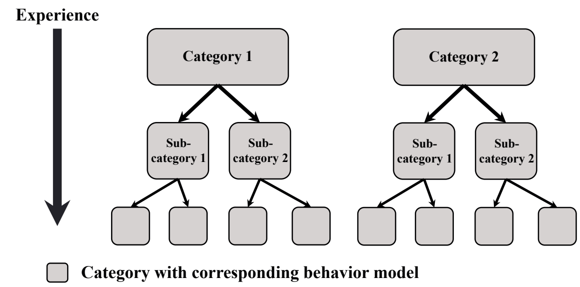

Fig. 2. Categorization functions.

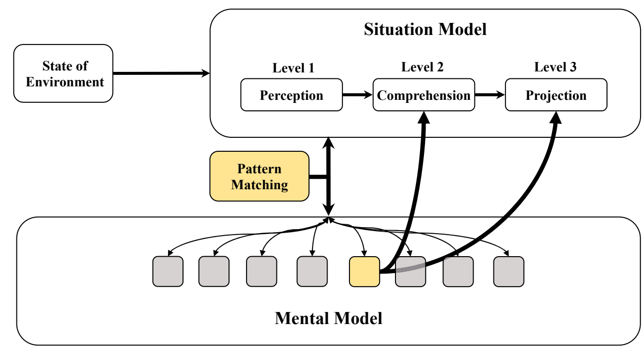

Fig. 3. Application of mental models in situation awareness, adapted from Endsley and Garland (2000).

are, therefore, dependent on the level of knowledge and experience of the individual.

With more experience, it is theorized that individuals are able to identify categories of more specific behavior. This entails a higher number of categories, illustrated in Fig. 2. Smaller categories imply more specific behavior models, enhancing the accuracy of the predictions. As such, more experienced ship navigators likely have a higher number of behavior models available to predict future ship traffic than inexperienced navigators. This is natural, as with experience, navigators will be exposed to a greater number of situations that provide the basis for model development. Experienced navigators will, therefore, likely be able to predict more complex behavior. These predictions provide the basis for level 3 situation awareness, as ship navigators are able to predict long-term ship traffic.

When applying mental models to facilitate high level situation awareness, ship navigators likely apply the following approach, illustrated in Fig. 3. First, the navigator perceives the state of the environment, e.g. the current trajectory of a target ship. Based on the the behavior of the ship, the navigator then applies pattern matching between the observed behavior, and the historical behavior stored in each category in their mental model. Once the pattern is matched, the relevant category is selected. This is then used for comprehension of the situation, and the corresponding behavior model is applied to project the future trajectory of the target ship. In this manner, human navigators are capable of long-range trajectory predictions that aid in proactive collision avoidance actions. In essence, ship navigators predict future ship traffic based on their knowledge and past experience of ship behavior in the region.

4. MACHINE LEARNING FOR PROACTIVE COLLISION AVOIDANCE

To facilitate proactive collision avoidance, future autonomous ships will need to be able to conduct long-range ship trajectory predictions. Such predictions can be utilized in conjunction with short-range predictors to facilitate an advanced ship predictor (Perera and Murray, 2019) for collision avoidance. As such, methods to provide level 3 situation awareness to autonomous ships must be developed. One approach to achieve this is to artificially represent navigational experience, and emulate human mental models that facilitate such functions. It is suggested in this study to leverage machine learning to emulate the development of mental models.

Machine learning has gained widespread attention across a variety of domains in recent years. A sub-field of machine learning, known as deep learning, has gained particular popularity due to its state-of-the-art performance in applications e.g. computer vision (Voulodimos et al., 2018) and natural language processing (Cho et al., 2014). Machine learning models are powerful in that they are able to learn from data without being explicitly programmed. In this manner, machine learning techniques facilitate data-driven models that learn to model the underlying data.

It can be argued that humans also are data-driven. Based on observation, humans generate models to describe their surroundings. This is particularly relevant with respect to situation awareness, where the development of mental models is dependent on data. With more data, i.e. experience, the models will improve. In the case of autonomous ships, however, navigational experience will need to be artificially represented. If available, such data can provide the basis for machine learning models to emulate high level human situation awareness. Deep learning, for instance, has been suggested as a method to capture the behavior of the ship navigator, and facilitate effective collision avoidance actions (Perera, 2020).

4.1 Historical AIS Data

It is suggested in this study to leverage historical AIS (Automatic Identification System) data to serve as an artificial form of navigational experience. The AIS relays information relevant to ship behavior e.g. position, course over ground, speed over ground and ship type. These AIS messages are, furthermore, stored in historical AIS databases. By investigating historical AIS data, one can gain insight into historical ship behavior. This can be thought of as analogous to a navigator's experience of the historical ship behavior for a given geographical region.

Fig. 4 illustrates one year of historical AIS position data surrounding the city of Tromsø, Norway. It is evident that there are clear patterns of ship behavior e.g. traffic routes. Such historical data can, therefore, serve as the memory of an autonomous ship with respect to ship behavior for this region. To facilitate long-range trajectory predictions, it is desirable to develop methods to emulate the development of mental models. As such, methods must first be developed to categorize the data in Fig. 4 into categories of specific ship behavior. Next, methods to facilitate pattern matching of trajectory segments to a category of ship behavior should be investigated. Finally, methods to model the dynamics within each category of ship behavior must be developed. In this manner, a novel trajectory can be assigned a given category, and its future trajectory predicted with respect to the unique behavior for that category.

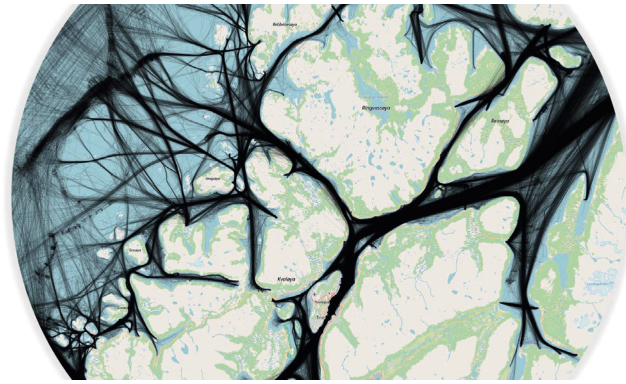

Fig. 4. AIS data surrounding the city of Tromsø, Norway.

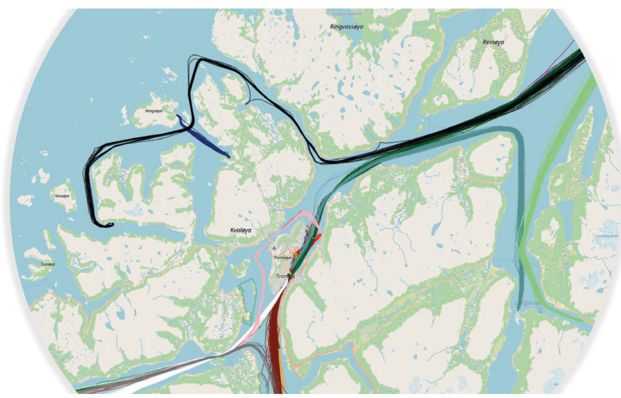

Fig. 5. Subset of clusters of historical ship behavior.

4.2 Clustering

The first step in emulating the development of mental models is to facilitate categorization functions. With respect to predicting future ship trajectories, this entails decomposing historical ship behavior into groups of specific behavior. This is analogous to clustering, a form of machine learning where similar data are grouped together to form clusters.

In the case of this study, it is desirable to cluster historical AIS trajectories as illustrated in Fig. 5. Fig. 5 illustrates a subset of trajectory clusters from the data in Fig. 4. These clusters were discovered by applying the approach in Murray and Perera (2021b). This technique leverages a Variational Recurrent Autoencoder (Fabius and van Amersfoort, 2015) to generate fixed size vector representations of historical AIS trajectories, and subsequently clusters the representations using the Hierarchical Density-Based Clustering of Applications with Noise (HDBSCAN) algorithm (Campello et al., 2013). However, clustering can also be facilitated via other methods e.g. those in Pallotta et al. (2013) and Murray and Perera (2021c).

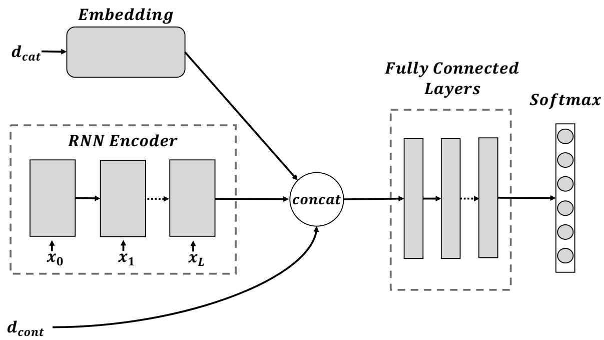

Fig. 6. Deep learning-based classification architecture, adapted from Murray and Perera (2021a).

4.3 Classification

The second step is to facilitate pattern matching of a novel trajectory to one of the existing clusters of ship behavior. As illustrated in Fig. 3, pattern matching facilitates the selection of the appropriate category used to comprehend the situation as well as employ the corresponding behavior model to project future dynamics.

In machine learning, pattern matching is referred to as classification, and can be facilitated via a myriad of techniques e.g. k-NN classification, support vector machines and neural networks. AIS data contain multiple parameters in addition to the dynamic position data. These include information pertaining to the ship type, MMSI number and length of the vessel. Such static data can also be incorporated into the trajectory to improve classification accuracy.

As suggested in Murray and Perera (2021a), one method to combine the dynamic and static data is to encode the dynamic data, $\mathbf{x} = \{\mathbf{x}_0, \mathbf{x}_1, ..., \mathbf{x}_L\}$, using a Recurrent Neural Network (RNN), and concatenate this vector with any continuous data, $\mathbf{d}_{cont}$, as well as an embedding (Mikolov et al., 2013) of any categorical data, $\mathbf{d}_{cat}$, as illustrated in Fig. 6. This vector can then be input to a fully connected network with a softmax output layer, and trained end-to-end using the cross-entropy loss. In this manner, a novel AIS trajectory can be classified to one of the existing clusters of behavior.

4.4 Prediction

To facilitate a long-range trajectory prediction, each cluster must have a behavior model. This reflects the same functionality of mental models, where each category has a transition model that is capable of predicting future dynamics. Machine learning is also capable of facilitating such regression functions. As such, a machine learning model can be applied to the data in each cluster of specific behavior, e.g. the routes illustrated in Fig. 5. In this manner, each model will be trained on an enhanced subset of data that relates to specific ship behavior. The greater the number of categories discovered, the more specific the behavior will be. This in turn yields higher accuracy, as found in Murray and Perera (2021a). Similarly, as argued in Sec. 3.1, more experienced individuals develop mental models with a higher number of categories as illustrated in Fig. 2.

Multiple machine learning techniques can be applied to facilitate such predictions. For instance, Rong et al. (2019) applied a Gaussian process model to facilitate a probabilistic prediction of the future trajectory of a vessel using AIS data. By applying the approach to a cluster of behavior, the performance can likely be further enhanced. Deep learning models, e.g. sequence-to-sequence models, can also be applied to facilitate prediction. Forti et al. (2020), for instance, applied sequence-to-sequence models to a route of historical AIS data. The results were successful, and on a scale relevant for proactive collision avoidance. Murray and Perera (2020) also presented a dual linear autoencoder approach based on locally extracted trajectory clusters. The approach yielded successful predictions on a scale applicable for proactive collision avoidance. However, the prediction models are not limited to these techniques, and alternative regression models may also be applied.

4.5 Leveraging Deep Learning to Emulate High Level Situation Awareness

Murray and Perera (2021a) developed an AIS-based deep learning framework for ship trajectory prediction that leveraged many of the aforementioned functions. However, the focus of the article was to facilitate effective trajectory predictions, and did not discuss the context and regulations relevant when utilizing such predictions for proactive collision avoidance. Murray and Perera (2021a), therefore, provides an example of how machine learning can be leveraged to emulate situation awareness in the context of this study.

In Murray and Perera (2021a), historical AIS data for a given region were clustered to reflect specific historical behavior, where a prediction model was trained for each cluster. A novel ship trajectory was then classified to one of the clusters of historical behavior, and the corresponding prediction model applied to predict the future 30 minute trajectory of the selected vessel. Such an approach matches that outlined in this study, where human situation awareness is emulated by clustering historical behavior into specific categories with corresponding behavior (i.e. prediction) models, and the appropriate model is selected via pattern matching (i.e. classification).

The results of Murray and Perera (2021a) indicate the potential of utilizing machine learning to facilitate accurate 30 minute trajectory predictions. Via the outlined approach, a mean error of approximately 500 m for the predicted 30 minute position of a selected vessel could be achieved. Furthermore, Forti et al. (2020) found that leveraging deep learning to facilitate trajectory predictions outperformed previously investigated techniques using the Ornstein-Uhlenbeck stochastic process. The approach in Forti et al. (2020) investigated utilizing sequence-to-sequence models, which Murray and Perera (2021a) expanded upon by introducing an attention mechanism that was found to improve the results.

Furthermore, Murray and Perera (2021a) found that the decomposition of historical behavior into clusters with local behavior models reduced the 30 minute prediction error by 64 % compared to a model trained on all underlying data. As such, the findings indicate that by leveraging machine learning to emulate human situation awareness, one can attain more accurate long-range trajectory predictions on a scale applicable for proactive collision avoidance.

5. CONCLUSION

In this study, proactive collision avoidance has been discussed as a method to enhance the safety of autonomous ship operations. It was found that such proactive collision avoidance actions may need to be taken as early as 30 minutes prior to the closest point of approach. Furthermore, ship navigators likely leverage high level situation awareness to facilitate such predictions. As such, the mechanisms involved in developing such prediction models were investigated, where it was found that individuals likely leverage mental models to predict future situation dynamics. These models are developed via categorization of ship behavior, where each category has a specific transition function that models future dynamics. Via pattern matching, a novel trajectory is classified to one of the existing categories, and the appropriate model applied to predict the future behavior of a given vessel.

Such prediction models are, however, dependent on the experience of the navigator. This study suggests to leverage historical AIS data to artificially represent navigational experience. Further, it was found that machine learning techniques mirror the mechanisms involved in the development of mental models utilized for situation awareness. Categorization is facilitated by clustering historical AIS trajectories, and transition models via relevant machine learning-based regression techniques. Pattern matching can also be facilitated via machine learning through relevant classification methods. As such, by leveraging machine learning to emulate the mechanisms utilized by humans to develop high level situation awareness, autonomous ships may be capable of predicting long-range ship trajectories, facilitating proactive collision avoidance.

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