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Artificial intelligence for ship speed management during navigation in the Arctic

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ABSTRACT

Difficult ice conditions are one of the major threats to ships, shipboard crew, and cargoes carried in Arctic waters. Ship-speed choice is influenced by many factors including the navigational conditions (ice, weather, bathymetry, etc.), the purpose of the voyage, personal preferences of the ship master (and/or the ice pilot) as well as onboard regulations (e.g., ice passport, polar water operational manual). Faults and incidents during navigation in ice (i.e., excessive ship speed) almost always results in ship damage. This can be fixed with the help of electronic environments that are sensitive and responsive to the presence of ice. This work describes AI-infused systems that can capture details of ice conditions around the ship and place them in the context of safe ship speed and ice conditions reporting. The focus is on online sensors-to-service solutions that run in the background and rely on shipboard sensors. Apart from just being AI-infused information systems, some solutions could also be applied to provide an early alert to the user if the user is approaching potentially dangerous ice object(s) at elevated speeds. The presented systems are not tested during real ship operations, but we provide illustrative examples for exploration of the solution space based on Arctic data. Ice navigation is about masters taking decisions and keeping ships and their crew safe. AI is to enhance human performance and not to replace human operators.

KEY WORDS: Ice; Safe Speed; Artificial Intelligence; Machine Learning; Ship Information Management System; Ocean Engineering

INTRODUCTION

Global demand for transport will continue to grow dramatically over the next three decades, with global freight demand expected to triple by 2050. By this time, ships will carry out more than three-quarters of all goods movements (International Transport Forum, 2019). Increased shipping activity in the Arctic is almost certain (Arctic Monitoring and Assessment Programme, 2017), and the consequences, which will be associated to this reality, may be catastrophic. In the Svalbard region, cruise ships sail long distances, resulting in a higher probability of accidents (Kystverket, 2015). The cruise ships arriving to Svalbard are getting bigger, and in 2017 they carried between 600 and 4200 passengers (Kornfeldt, 2017). Data received from the interviews with the Longyearbyen Power Supply, Longyearbyen local government, Visit Svalbard, Avinor, LNS Spitsbergen, Norwegian coal mining company, Marine Supply, the Governor of Svalbard, and from Lufttransport AS (see Hovden, 2018) show that the overseas cruise ship segment is growing. At the same time, the government plans to limit the size of the passenger vessels in Svalbard waters. Freight shipping in the Arctic is also expected to increase in the coming years. This is linked to opening of the new trade routes in the Arctic, as well as resource exploration, commercial fisheries, and research activities.

Faults and incidents during navigation in the remote Arctic could have catastrophic consequences since search and rescue operations in this region are much more difficult with regards to response time and available resources. In 2019, 16 passengers needed an evacuation in the Hinlopen Strait, because of the Swedish expedition vessel MS Malmö got stuck in ice. Timely detection and clean-up of oil spills could be impossible due to presence of ice.

Complex Environment

There is a severe law incompleteness (as defined in Pistor & Xu, 2003) and rule inconsistencies in some parts of the Arctic, which may negatively affect the ships' safety in ice infested waters. The law incompleteness stems from an inability to regulate vessel speeds in all relevant ice conditions. As examples, neither the Polar Code nor the new rules of the Norwegian Maritime Authority (NMA) for passenger ships (NMA, 2020) provide direct guidance on how to set speed limits in frequently encountered ice conditions around Svalbard (i.e., icebergs trapped within the first-year ice, broken ice fields). For instance, in Annex 10, page 54 of the Polar Code, it is stated: "The Polar Water Operation Manual should contain guidance for the use of low speeds in the presence of hazardous ice." It is not clear what the hazardous ice is and most importantly who decides whether the ice is hazardous. Is this the master (or the chief mate) of the ship who is responsible for the ship/passenger safety or ship owners and operators who are responsible for achieving compliance with the Polar Code? Clearly defined safe-speed limits are highly important for safety of ships. Excessive speeds in ice can cause ship damage and, in some cases, environmental pollution. Too low speed can lead to ship besetting in ice, or drift ashore, with a consequent need for a rescue operation.

Today, there is no consensus on how one should estimate a ship-specific safe speed when ice is present, as several competing approaches exist; see e.g., Dolny (2018) and Tryaskin et al. (2009). The COLREGs safe-speed rules are rather descriptive, thus safe speed decisions heavily rely on the expertise of the master. To guide maritime stakeholders on how to tailor their operational speeds to the ice conditions, some IMO recommendations exist and are based on calculations of the so-called risk index outcomes (IMO, 2016). If the risk index outcome (r) is between 0 and 10, speed reduction is recommended; however, for r>10, no speed restrictions are offered.

Furthermore, some rule inconsistencies have been identified when regulating- or recommending the access to the waters of the Kara Sea (Kim & Panchi, 2021). Comparative analysis of the POLARIS recommendations and the updated Rules for Navigation in the Water Area of the Northern Sea Route shows that the national rules generally impose stricter access criteria than international recommendations; however, under an icebreaker escort, the PC7/Arc4 ice class ships can operate when the international recommendations suggest an elevated operational risk. This situation gets even more complicated when climate change is considered.

In Arctic waters, safety and environmental provisions for ships are regulated by the International Code for Ships Operating in Polar Waters (Polar Code). In addition, the Arctic Coastal States can adopt and enforce non-discriminatory laws and regulations in ice-covered areas in their exclusive economic zone (Article 234 of UNCLOS 1994). This Article 234 reads:

"*Coastal States have the right to adopt and enforce non-discriminatory laws and regulations for the prevention, reduction and control of marine pollution from vessels in ice-covered areas within the limits of the exclusive economic zone, where particularly severe climatic conditions and* ***the presence of ice covering such areas for most of the year*** *create obstructions or* *exceptional hazards to navigation, and pollution of the marine environment could cause major harm to or irreversible disturbance of the ecological balance. Such laws and regulations shall have due regard to navigation and the protection and preservation of the marine environment based on the best available scientific evidence*."

Owing to ice-free summers and lower sea ice extent in winters, less areas will be covered by ice most of the year. Thus, the Arctic Coastal States may lose their legal right to introduce extra measures for environmental protection and navigational safety. In this view, ship management systems (or ship information management systems) for operations in Arctic will become even more important for ship owners and operators, who need to keep costs down and still meet safety- and environmental standards under existing uncertainties that may increase the costs and complexity of operations or even change business practices.

In parallel, the maritime industry has identified digital services as a key enabler for improved operations, both in terms of efficiency, safety, and environmental impact (Erikstad, 2019). Despite large quantities of gathered data over recent years (e.g., onboard optical cameras, infrared and thermal cameras, radars, and other ship sensors), the capacity to use them for decision support remains limited and is largely underexplored. Shipboard optical cameras are installed in non-optimal locations and have low resolution and a constant sampling frequency that is often too low for operations in difficult ice conditions. At the same time, digital services for Polar shipping lag the advancements made in artificial intelligence and machine learning fields.

To address this situation and the real-world needs of shipping companies, this work describes AI-infused systems that were developed at the Department of Marine Technology at NTNU and can capture details of ice conditions around the ship and place them in the context of safe ship speed and ice conditions reporting. The focus is on online sensors-to-service (S2S) solutions that run in the background and rely on shipboard sensors. The presented solutions can be integrated into a ship information management system with a view to collect, store, retrieve, and exchange ship information more efficiently and enable better ship operations. For a broader overview of solutions, refer to Garvin (2020).

BACKGROUND

To provide a basic understanding of needs among shipping stakeholders and of the corresponding functions of the presented systems, the sections below describe three real-world ice-related challenges during design and operational decision making among ship owners and managers, that is speed, ice conditions, and reporting challenges.

Speed Challenges

The ships' speed in ice is one of the major contributors to ship and shipboard crew safety. Excessive ship speed almost always results in ship damage (Canadian Coast Guard, 2012). The subject of the ship's speed can be approached from three different perspectives: safety, economy, and environmental impact.

Safety perspective

<u>Risk-based (or statistical) approach</u>: There is a link between the ship's speed and the probability of an accidental event, e.g., see the recommended procedure by IMO (2016). It should be noted that for normal operational conditions, when the probability of an accident is low (or $r \geq 0$), the speed policies are not specified by Transport Canada (2019).

<u>Design and structural integrity approach</u>: There is a relationship between attainable ship speed

and ice thickness (also known as h-v curve). For each vessel, additional safe (reduced) speeds limits may be determined by calculation depending upon the specific design of the ship, hull shape, displacement, and power plant output. The results of the calculation constituting graphical dependencies of the allowed ship's speeds (or admissible speeds) for different ice conditions and icebreaker escorting parameters (channel width, form, and concentration of broken ice in the channel) are summarized in the form of a document (also called the Ice Passport or Ice Certificate) regulating the speed while navigating in ice. It should be noted that backcalculating the speed at which the ice pressure will exceed the structural resistance is easier when the design procedure and underlying assumptions (for ship scantlings) are explicitly known and when the underlying ice pressure formulation is speed dependent.

Operational approach: Any ice feature is considered as an obstacle during operations, and the ship should proceed at a speed so that she can take effective action to avoid collision and being stopped. This means that the speed must not be reduced so the vessel loses its maneuverability. The engine must be ready to go full astern and stop the vessel at any time. Conversely, it may be required to immediately give full power in order to keep the ship moving. It is the ship's master who is ultimately responsible for the safety of the ship and its crew, cargo, and passengers. It is the master's responsibility to choose the speed while navigating in icy waters.

Economy perspective: In addition to meeting safe speed requirements, some vessels (e.g., cargo ships) should also try meeting charter party requirements, adhere to the agreed route, and undertake the voyage at the best possible speed in a cost-effective manner.

Environmental impact perspective: It is expected that by lowering the ship's speed, the fuel consumption and ship emissions are also reduced.

Note that there is a difference between the terms "attainable speed", "safe (reduced) speed", and "best possible speed" (Rutkowski, 2016). The concept of "safe speed", despite existing regulations, is difficult to implement in practice. Speed choice is influenced by many factors including navigational conditions (ice, weather, bathymetry, etc.), the purpose of the voyage, personal preferences (perception and experience) as well as onboard regulations (e.g., ice passport/certificate, polar water operational manual). The speed choice could become complicated if a conflicting speed requirement arises. For example, during escort/convoy operations in ice, the nominated ships' speed could be higher than that prescribed in the ship's own operation manual. Furthermore, owing to the uncertainty in ice forecasts, there could be a need for local deviations from the planned route to avoid the most dangerous ice. Thus, it could be difficult (or impossible) to meet charter party requirements and adhere to the speed requirements in a cost-effective manner.

Ice Conditions Challenge

Safe ice navigation requires qualified judgement of the conditions of ice around the ship, a skill that takes years of training to master. Reliably distinguishing between first year-, second year-, and multi-year ice is not always possible (Johnston & Timco, 2008) before the ship hits the ice. Distinguishing between different ice types (deformed ice, brash ice, etc.) is highly dependent on a persons' experience and work conditions, varying from person to person and possibly from day to day. Empirical data in Pedersen and Kim (2020) show that in fog, snow, and darkness, the ice identification task becomes more difficult, and human performance slightly deteriorates. Wrong judgement about severity of the ice can lead to ship damage or to getting stuck.

Ice information products (e.g., ice charts) for navigation have limited validity range and bear some degree of uncertainty. Figure 1 shows the difference in the manual derivation, by human experts, of sea ice concentration (CT) from two sources of ice charts, yet in some areas, there are significant differences of over 50%. Typically, these differences are caused by varying access to satellite data, or level of expertise of the analyst, and it is necessary to consult a further independent source of data or the original satellite data to understand the cause.

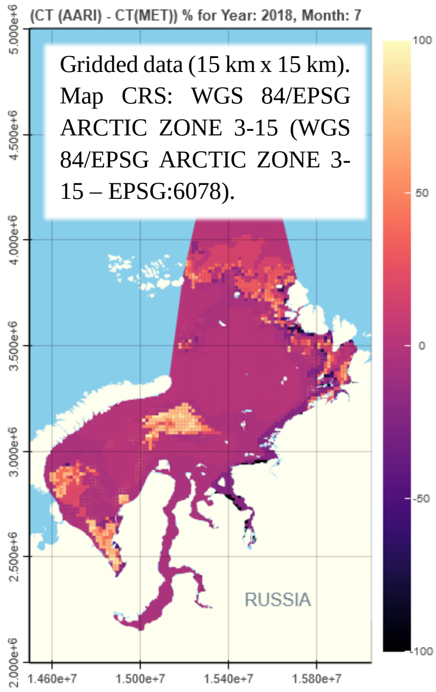

Figure 1. Difference between total ice concentration (CT, in %) reported by the Norwegian Meteorological Institute (MET) and the Arctic and Antarctic Research Institute (AARI) in July 2018.

A ground truth validation of the ice information products is needed in the areas of operation that are prone to uncertainties.

Direct observation of ice conditions is the gold standard technique. The observed ice conditions are then can be linked to the choice of ship speed, which in turn is linked to safety of the ship, its crew, passengers, cargo, and the environment.

Reporting Challenge

Today, many publicly-available systematic ship-based observations of ice conditions are based upon Arctic Ship-Based Sea Ice Standardization protocols (Ice Watch, 2019), although other procedures exist (e.g., AARI, 2011). Visual observations are conducted from the ship, and the data are manually recorded in a structured form. This happens once per hour (or per three hours). Hence, ice conditions around the ship are determined every 10–20 km, depending on the speed of the ship, which result in limitations when ice conditions rapidly change (e.g., within straits). Furthermore, these protocols require manual interpretation of the ice scenes by a trained expert. Therefore, these are limited by the subjective nature of human observers, availability as well as the biases of inexperienced and experienced observers, as well as problems associated with the visibility of ice conditions (e.g., foggy conditions, darkness). The requirement of manual interpretation also limits the number of observations collected per expedition and cause errors and missing information fields.

Sometimes, what is reported is the ice concentration but not the ice thickness, etc. It must be understood that the quality and quantity of the reported data on threatening or extreme/abnormal ice features are always limited. Historically, severe, or extreme ice conditions are being avoided, and once threatening ice conditions are encountered, no attempts are usually made to record these. In case of an ice-related incident/accident, underlying ice conditions are rarely described in detail.

The above challenges can also be expressed from the perspective of an end-user goal as follows:

> *"As an officer of the watch, I would like to spend less time on reporting ice conditions."*
>
> *"As a vessel operator I would like to know what the ice conditions along the route were."*
>
> *"As a vessel operator/owner I would like to know if the ship always transits at a safe speed."*
>
> *"As an insurer, I would like to know what the ship speed and the corresponding ice conditions at a time of an accidental event were."*

AI-INFUSED SYSTEMS FOR ARCTIC NAVIGATION

Below we describe four systems (see Table 1) that provide electronic environments that are sensitive and responsive to the presence of ice via onboard ship sensors (marine radar, optical camera systems, and motion and position sensors), machine-learning algorithms (deep learning, decision trees, support vector regression). The optical camera systems can be divided into two groups: 1) downward looking camera systems, and 2) forward/backward looking camera systems. The first camera group captures processes at the direct contact between ice and the hull, whereas the second camera group captures ice situation ahead (and/or) around/behind the ship.

Table 1. Summary of intelligent systems (IMU − inertial measurement unit, SAR − synthetic aperture radar, GPS – global positioning system).

ID	Sensors	Algorithm	References
01	Ship's SAR, GPS	Ice drift velocity estimation	Kjerstad et al. (2018)
02	IMUs in ship hull	Classifying the ice condition governing the ice-ship interaction	Heyn et al. (2020)
03	Camera group 2	Classification of ice objects	Kim et al. (2019a) Pedersen & Kim (2020)
04	Camera group 2	Identification and localization of ice and non-ice objects at a scene	Panchi et al. (2019) Kim et al. (2019b)

The sections below briefly describe the approaches and summarize the algorithms (Table 2), whereas the detailed information can be found in the literature listed in Table 1.

Table 2. Outline of the algorithms.

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Algorithm 01: Ice drift velocity estimation
Pre-processing (radar image processing)

Get GPS signal and radar image.
Prepare image by cropping, converting to grayscale, removing the noise, and computing a cornermetric matrix.
Detect and track distinctive features (landmarks)
Calculate measurement vectors for each individual distinctive feature relative to the ship's position.
Distinctive features are captured in the ship centered North-East frame.

State estimation

Reset start estimation if distinct feature is lost or a new feature added.
Estimate position and velocity of the ship and individual distinctive features by applying a linear Kalman filter.

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Algorithm 02: Ice condition classification
Pre-processing

Collect motion data.
Apply Chebyshev lowpass filter.
Calculate roll and pitch.
Correct for altitude of sensors.

Parameter estimation

Find most-likely parameters of the bivariate t-distribution.

Ice condition assessment Method 1 – Hypothesis test

Calculate test statistics.
Find most likely ice condition.
In case two pretrained conditions have the same divergence to the observed distribution, choose the more severe of these.

Ice condition assessment Method 2 – Entropy test

Calculate statistical entropy.

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• *Remove distinct features that do not originate from the ice cover (e.g., other ships)* • *Estimate ice drift by applying Unscented Kalman Filter.* • *The positions and velocities are measured in a geo-fixed North-East (NE) frame.* ***Result*** *Geo-defined NE ice drift velocity of the ice cover averaged over a set of N distinctive features/landmarks in the radar image stream.*	• *Evaluate ice conditions against predefined thresholds for hypothesis testing and entropy-based classification (tabulated values).* ***Ice condition assessment Method 3 – ML*** • *Decision Tree Model* • *Support Vector Regression Model* • *Both models are trained with statistical data, specifically the components of the correlation matrix of the accelerations and the degrees of freedom.* ***Result*** *Vector with decision on ice conditions at the bow: {open water; broken ice; close ice; very close ice}*
Algorithm 03: *Classification of ice objects* ***Pre-processing*** • *Collect image data in a certain format and resolution.* • *Normalize each image to the mean and standard deviation as per torchvision documentation.* ***Classification of ice objects – deep learning model*** • *Pass image though the trained CNN model.* • *The last fully connected layer of a pre-trained CNN (ResNet34) is replaced with a new block. Loss function is modified to math human performance.* • *The model is trained on labelled images of ice cover by following labelling rules with a consequent label verification.* ***Results*** *Vector with decision on ice classes: {level ice; broken ice; deformed ice; iceberg; brash ice; floeberg; floebit; ice floe; pancake ice}.*	**Algorithm 04:** *Identification and localization of ice and non-ice objects* ***Pre-processing*** • *Same as in Algorithm 3.* ***Identification and localization of objects – deep learning*** • *Pass image though the trained CNN model.* • *The model is the modified UNet (i.e., a ResNet architecture backbone).* • *The model is trained on labelled images of ice cover by following labelling rules with a consequent label verification.* ***Post-Processing*** *Denoise by applying convolutional conditional random field.* ***Results*** *2-n array with decision on ice object and non-ice object class such as level ice, open water, melt pond, shore, sky, etc., predicted for every pixel of the image.*

Ice drift velocity estimation: This is a target tracking system that uses the ships' marine radar image streams and GPS signals (ships' position measurements) to estimate the ice-drift vector in the vicinity of the ship (0.5-6 nautical miles). The algorithm uses image processing techniques to automatically detect and track the motion of multiple targets (or distinct features) in the radar images, and two Kalman filters to select these targets and decouple the vessel motion. The outline of this algorithm is given in Table 2 (Algorithm 01). It consists of two parts: image processing and state estimation. The latter is a filter structure that can reconstruct the complete system state in real-time, using radar and ship motion measurements combined with kinematic system models. The image processing is based on the corner detection methods and the optical flow method. Validation of the described system was done by comparing the outcome of the algorithm with the records from six ice-drift beacons deployed in the vicinity on the ice cover.

Classification of ice condition: This system opens a possibility for monitoring and logging ice condition using inertial measurement units distributed along the hull of the ship, preferably close to main ice interaction zones in the hull. An outline of the method is given in Table 2 (see Algorithm 02). Data from in-plane accelerometers are used to find a statistical model of local ice induced vibrations, and the corresponding parameters for four ice conditions: open water (ice concentration < 10%), broken ice (11%-60%), close ice (61% - 80%), and very close ice (81% - 100%). In the paper describing the method, optical data from Camera group 1 is used as a reference for validation purpose. Under ship operations, the distribution parameters are estimated for a short moving time window and compared to the parameters of the statistical model. To find the ice condition that best describe the measured data, three methods were investigated: (1) – the modified Kullback-Leibler divergence, (2) the change in signal entropy, and (3) a machine learning approach. The approach was tested and validated using data obtained during transit of an icebreaker (see Figure 2).

Classification, identification, and localization of ice and non-ice objects: Studies by Pedersen and Kim (2020a, 2020b) indicate that deep learning models may be more superior in classifying ice objects than human experts and novices under good visibility conditions. Therefore, video streams from optical-, infrared-, and thermal cameras coupled with deep learning algorithms (Algorithms 03 and 04 in Table 2) can be used to automatically detect and report ice formations and their locations around the ship (e.g., deformed ice, level ice, icebergs, brash ice, broken ice, etc.). Figure 3a shows a photograph of an iceberg in broken ice. For comparison, the heatmaps were produced using the Grad-CAM technique (Selvaraju, et al., 2020) and show which parts of an input image that were looked at by the CNN model (Pedersen & Kim, 2020a) for assigning object as an iceberg.

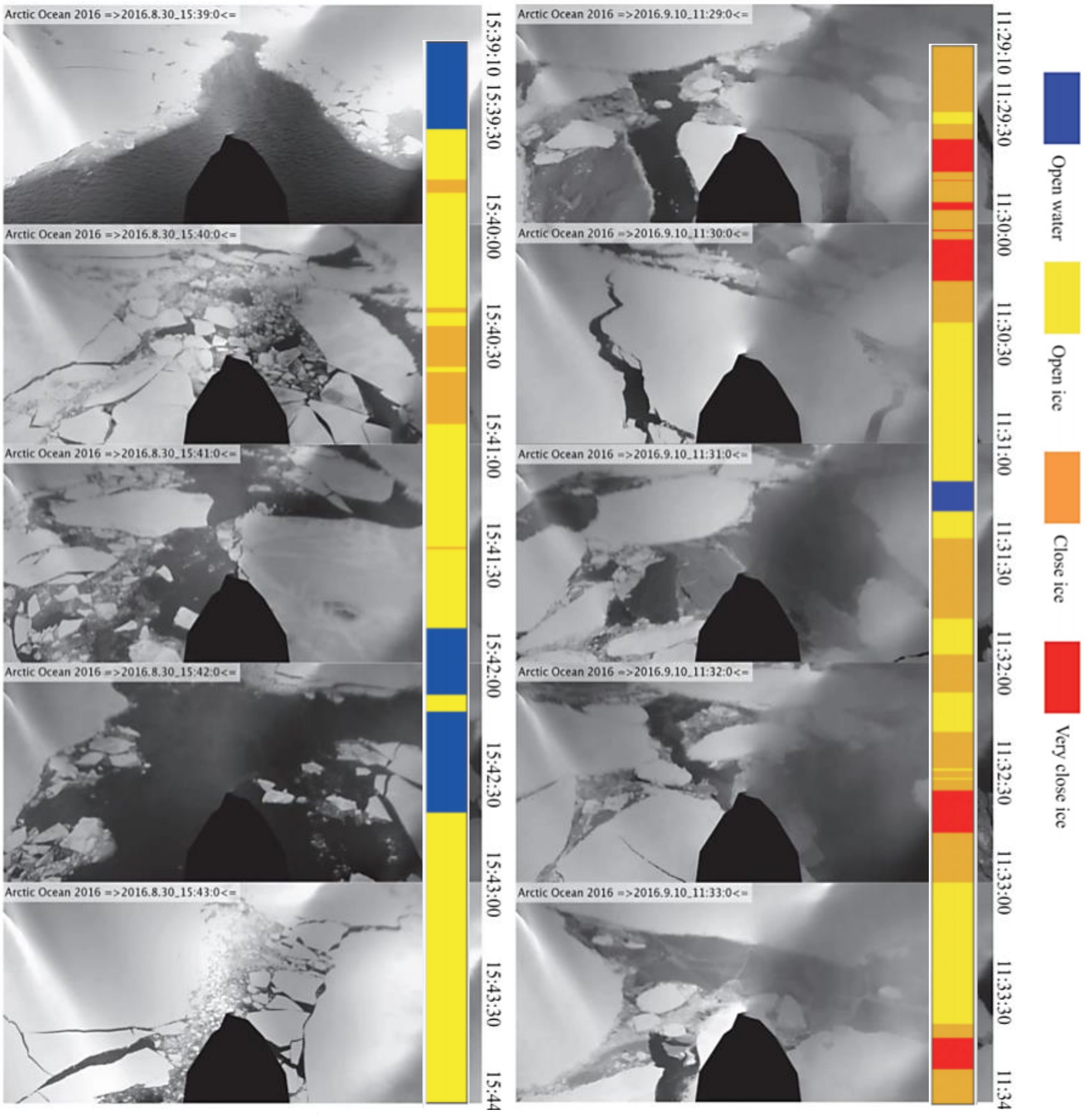
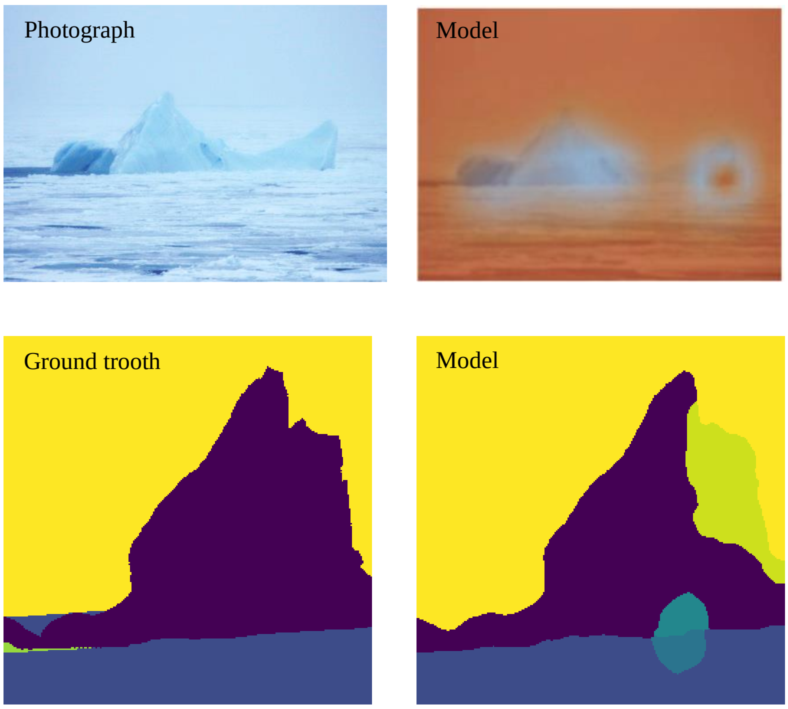


Figure 2. Sequence of shipborne photographs (black and white) and ice conditions classification (in color) by Algorithm 02 (Heyn, et al., 2020).

The image interpretation based on the Approaches 03 and 04 can be considered as a part of a system that could, in the future, be mounted on the bridge of ships operating in or passing through the ice area. Eventually, it may be possible to reduce the requirement of interpretation of ice scenes by trained observers and increase frequency and accuracy of ice recordings. Algorithm-based analysis of ice scenes will also ensure a more objective quantification of the sea ice parameters that could otherwise be subjective due to the difference in human experiences and opinions. Application example of Algorithm 04 for processing of a video stream from a bridge camera is presented in Figure 4. Details are in Panchi et al. (2021).

DISCUSSION

In this work we have described four intelligent systems that can capture details of ice conditions around the ship, thus placing them in the context of safe ship speed and ice conditions reporting. The focus has been on online S2S solutions that run in the background and rely on shipboard sensors such as IMUs, optical cameras, ship's SAR, GPS, and gyrocompass. We have also provided illustrative application examples for three systems. Apart from just being AI-infused information systems, some solutions could also be applied to provide an early alert to the user if the user is approaching potentially dangerous ice object(s) at elevated speeds.



(a) Original ice scene (on the left, a photograph by Roger Skjetne) and GradCAM-images (on the right) showing the parts of the original image that pushed the network towards classifying the objects as iceberg (Pedersen & Kim, 2020a) This technique serves as a visual explanation of the CNN predictions and does not necessarily capture the entire iceberg.

(b) Human cognition of iceberg, open water, and sky (image on the left), ML model image segmentation results (on the right), Panchi et al. (2019).

Figure 3. Application examples of Algorithm 03 (a) and Algorithm 04 (b) for processing individual images containing icebergs.

The described systems and their algorithms will need to mature in terms of the accuracy when deployed in the real world. None of the presented systems (01−04) have been tested during real ship operations. To realize the presented approaches in the real-world, one would need to follow a four-step process. Recruit ships – Collect and store the data – Annotate (label) the data – Develop and deploy the model(s). In this context, paradigms such as edge computing and federated (or collaborative) learning will become increasingly important. For example, a common machine learning model and (or) a statistical model could be trained on the data from several shipping companies without sharing data; however, during operations the model can be deployed onboard of the vessel, closer to the data stream, thus improved the computational time.

For the real-world applications of Algorithm 01, the operator's interactions with the radar's display must be recorded and linked to the activation of dead reckoning mode of the target motion Kalman filter. This is to avoid unreliable measurements due to changes in the radar images upon the crew interaction with the radar display. Alternatively, the raw data from the radar should be used instead of the display image capture (frame grabber). Since the algorithm parameters were set manually by trial and error, further studies and more testing are needed to address automation of parameter tuning during an actual operation in various ice and weather conditions (rain, show, etc.). Since the output of the Algorithm 01 is the velocity of multiple targets (ice objects), possibilities of using this approach to detect and characterize ice compression events should be further investigated. Moreover, the possibility of embedding ice drift velocity and ice compression data in an AIS message and their automatic transmission should be explored.

Limits on how many ice objects (targets) and classes can be detected at a time still needs to be further explored within the context of the Algorithm 04. We have only presented examples using optical images. In future similar approaches could be applied to infrared and thermal images of ice cover.

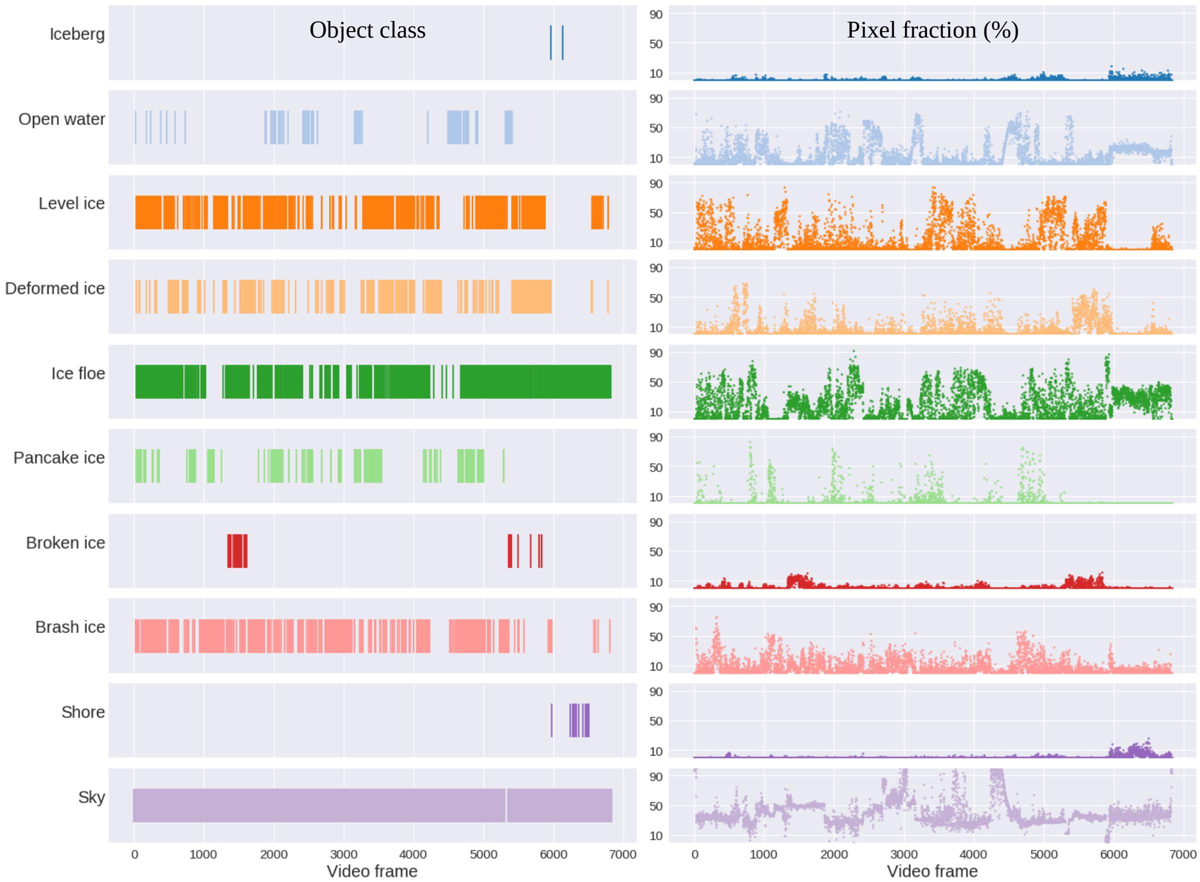


Figure 4. An application of Algorithm 04 to a sequence of shipboard images.

Today, many new ice-going ships are equipped with ice load monitoring systems (e.g., SENSFIB Ice Load, ARC ILMS) providing real-time feedback on ice load levels. Integrating ice load records with ship speed and surrounding ice conditions will provide needed data for offline (or post-event) validation of the physics-based ice load models and speed limits as well needed information to justify any deviations from a planned route.

We anticipate that the complexity of the shipboard monitoring and logging systems will only increase in the future, and this will allow online monitoring of complex situations with a view to enhance human performance and efficiency of ship operations (e.g., ship handling in ice, human actions in response to changing environment, etc.). Deployment of the presented approaches in the real-world will enable a better understanding of ship operations in ice, document reasons for operational decisions such as deviations from a planned route and will aid in refining operational procedures to improve their efficiency.

During the data collection process, the attention needs to be paid to data fairness and model bias. One must make sure that the outcome of the machine learning models (ice objects detection and localization) is not influenced by the weather conditions, ships operational profile, geographical area of operation, etc.

In addition to the need of collecting more sensor data in a view of the presented algorithms, there could be also a need to simultaneously record how the ship master responds (or not) to the data to start determining best practices. This could be more challenging as many ship masters may not want this data collected. Thus, in future, equally important will be developing policies for data collection and analyses that are agreeable to all parties. A multi-stakeholder approach is a way forward. Technology experts must collaborate with sensor and system providers, ship masters, owners, managers, ship designers, class, and others to help solving the challenges highlighted in this work.

CONCLUSIVE REMARKS

We have described AI-infused and intelligent systems that can capture details of ice conditions around the ship and place them in the context of safe ship speed and ice conditions reporting. These are: *ice drift velocity estimation, ice condition evaluation and logging, sea ice classification, identification and localization and logging*. The focus has been on online sensors-to-service solutions that run in the background and rely on shipboard sensors. Ice navigation is about masters taking decisions and keeping ships and their crew safe. Faults and incidents during navigation in ice can be mitigated by the help of electronic environments that are sensitive and responsive to the presence of ice. AI technologies presented in this work have been proposed to enhance human performance and not to replace human operators.

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