

# Crowdsourcing Arctic Navigation Using Multispectral Ice Classification & GNSS

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## BIOGRAPHY

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**Todd Walter** is a senior research engineer in the GPS Research Laboratory in the Department of Aeronautics and Astronautics at Stanford University. He received his Ph.D. from Stanford in 1993 and has worked extensively on the Wide Area Augmentation System (WAAS). He is currently working on dual-frequency, multi-constellation solutions for aircraft guidance. He received the Thurlow and Kepler awards from the ION. In addition, he is a fellow of the ION and has served as its president.

**Per Enge** is a Professor of Aeronautics and Astronautics at Stanford University, where he is the Vance and Arlene Coffman Professor in the School of Engineering. Here, he directs the GPS Research Laboratory which develops navigation systems based on the Global Positioning System (GPS). He has been involved in the development of WAAS and LAAS for the Federal Aviation Administration (FAA). He has received the Kepler, Thurlow, and Burka Awards from the ION. He also received the Summerfield Award from the American Institute of Aeronautics and Astronautics (AIAA) as well as the Michael Richey Medal from the Royal Institute of Navigation. He is a fellow of the Institute of Electrical and Electronics Engineers (IEEE), a fellow of the ION, a member of the National Academy of Engineering, and has been inducted into the Air Force GPS Hall of Fame. He received his Ph.D. from the University of Illinois in 1983.

**Ananda Fowler** is a unique individual who brings a unique perspective. Having started at the bottom of the geospatial profession as a simple, machete-wielding Rodman, he has worked his way through the profession to his current role as the Manager of Terrestrial Laser Scanning Software Development for RIEGL Laser Measure Systems in Horn, Austria.

## ABSTRACT

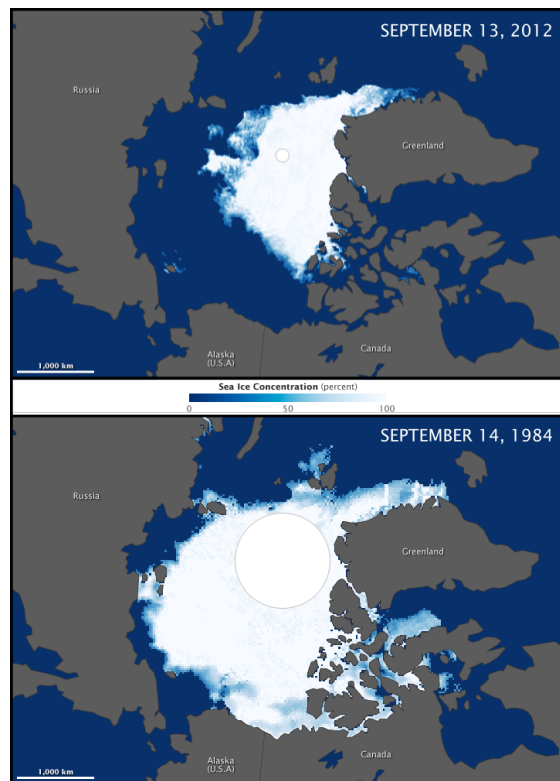
Safe marine navigation in the Arctic is becoming more important with a growing interest in the region in recent years. With the summer Arctic sea ice extent having decreased by 50% since 1980, this now opening waterway has given rise to serious interest in commercial activities in the Arctic. There are several navigational challenges that face ships operating in Arctic waters. Sea charts are known to be untrustworthy, navigational equipment can be problematic, and there is the constant danger of multi-year and glacial ice collisions. Here we focus on the threat of ice. Knowledge of its whereabouts is crucial to the safe planning of routes and in the avoidance of sometimes-fatal collisions. With increased traffic and without proper detection systems in place, there is a danger of accidents in the Arctic that may result in loss of life or have severe environmental ramifications.

Here we propose a modernized system which offers improvements in the two major components of the current ice mitigation strategy, namely, on the ship-based monitoring side and on the ship-to-ship aiding side. Ship-based monitoring today is a largely manual process which requires a skilled and experienced crew to interpret radar data and scan the area visually to correctly identify dangerous ice. This relies heavily on the use of expert lookouts, as radar is known to fall short of the requirements needed to reliably detect all forms of hazardous ice. Ship-to-ship aiding exists today in the form of organizations such as the North American Ice Service (NAIS) where icebergs and ice conditions are reported in part by passing ships. However, most ice reports are

based on visual sightings whose accuracy is likely not high. Here, we propose crowdsourcing ice navigation based on a GNSS data registration system. In this scenario, ice detection and classification is done robustly and automatically based on a redundant multispectral system. This data is then geo-referenced using GNSS, enabling reliable ship-to-ship aiding in systematic way. The high integrity sharing of ice data offers a framework in which to perform path planning in a reliable and automated way, finding the safest route with the available information and relying less on the expertise of the crew.

## INTRODUCTION

The Arctic sea ice extent, that is the amount of ice that covers the Arctic Ocean, has greatly diminished in the last 30 years, giving rise to an increased interest in the now accessible Arctic. In fact, the summer minimum sea ice extent has decreased by more than 50% since 1980 [1] and is projected to continue decreasing [2]. Figure 1 shows this decay from 1984 to 2012. This decrease in ice coverage has triggered the expansion of many industries into the area, some prospective and some very real and rapidly expanding. Ships operating in Arctic waters face many challenges in terms of navigation and it is our ultimate aim that these new operations be done as safely as possible to avoid loss of life and environmental disasters.

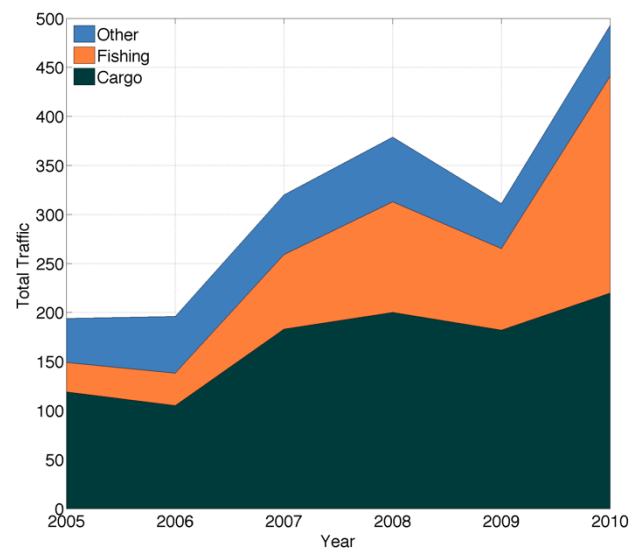


**Figure 1.** Comparison of summer minimum arctic sea ice extent from 1984 to 2012 (source: Wikimedia commons).

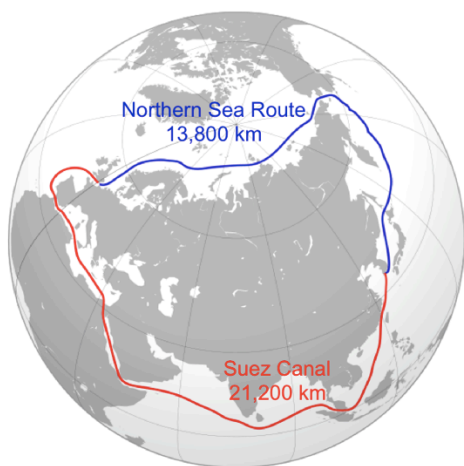
## Trends in Arctic Traffic

Many natural resources are estimated as being present and untapped in the Arctic, one of the main being oil and gas. The United States Geological Survey (USGS) has estimated there to be 30% of the world's undiscovered gas and 13% of the world's undiscovered oil to be in the Arctic Circle [3]. This is certainly attracting commercial resource exploration and exploitation though this is not the only industry expanding into the Arctic. Figure 2 shows that both fishing and cargo transportation activities have increased in the Canadian Arctic in recent years. Commercial shipping is a prospect mainly because the decrease in sea ice coverage has opened many previously inaccessible routes in the summer months. Figure 3 shows an example of why such routes are attractive as they can allow for significantly shorter distances than traditional shipping lanes through the Suez or Panama Canals [4]. Most studies indicate, however, that although there will be a rise in Arctic marine traffic it will mostly be destinational not trans-Arctic as many shipping companies are reluctant to invest in Arctic routes due to their increased risk [4, 5].

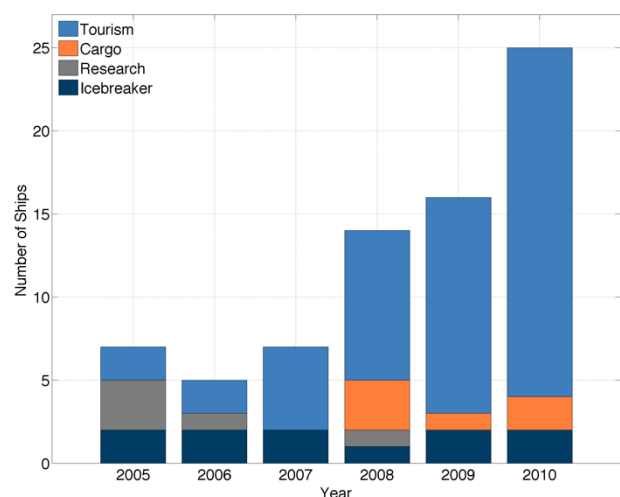
Figure 4 shows the increase in traffic in the Canadian Northwest Passage over the period between 2005 and 2010. This highlights the rapid increase in tourism in this part of the Arctic, a trend seen in other areas such as Greenland [5], as well as Russia where tourists can take a trip to the geographic North Pole onboard a nuclear icebreaker [6]. Although only a handful of cargo ships have traversed the Northwest Passage to date, the Northeast Passage along the northern shores of Russia has been a major commercial waterway for quite some time [6].



**Figure 2.** Trends in the total ship traffic in the Canadian Arctic (based on data from [4]).



**Figure 3.** Example of a shorter shipping route through the Arctic Ocean (adapted from Wikimedia commons).



**Figure 4.** Ship traffic in the Canadian Northwest Passage (based on data from [4]).

### Navigation in The Arctic and The Threat of Ice

Navigation in the Arctic has many unique challenges. Sea charts are known to be untrustworthy, navigational aids such as compasses have limitations at high latitudes, GNSS suffers from poor geometry and ionospheric activity, and there is the constant threat of collision with ice [7]. Here we focus on the threat of ice.

Safe navigation in ice-infested waters requires technological aids such as radar as well as an experienced crew. Sea ice is typically broken down into five major categories which are summarized in Table 1. The first is freshly frozen seawater known as new ice or nilas. Nilas is a soft slushy material, typically less than 10 cm thick, and does not pose a danger to ships. Young ice has been around longer in the season and can be up to 30 cm thick and much harder than nilas. This can pose a danger to non-ice-strengthened ships under certain circumstances. Ice of one year's growth is known as first-year ice. This

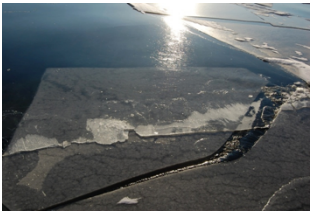




ranges in thickness from 30 cm to 2 m and is a danger to non-ice-strengthened ships. Multi-year ice is a material that has survived through several seasons. As such, it has had time to grow and compact into a very thick (2 to 4+ m) and hard material. This is a threat to any non-polar class ship. The standards in place for what constitutes a seaworthy ship operating in ice conditions ultimately depends on the type of ice that is being encountered. As such, there are several classes of polar ship ranging from commercial ships operating in first-year ice known as Polar Class 6 or 7 (Baltic Class) to the strongest nuclear icebreakers which routinely power through multi-year ice on their way to the North Pole known as Polar Class 1. These classes are summarized in Figure 5.

The last category is icebergs. These are composed of very hard land-based glacial ice which is many years, sometimes centuries, old. Icebergs break off large land-based glaciers in a process known as calving. As these can break off in a variety of shapes and sizes, icebergs are further classified into the categories shown in Table 2. Those which pose the principal danger to ships are bergy bits and growlers. The reason for this is that they have very little material above the waterline, typically only a few meters, and much mass below making them both very difficult to detect and very dangerous to hit.

Figure 6 shows a breakdown of ship collisions by ice type from 1980 to 2011. This shows that bergy bits, growlers, and multi-year ice cause the most damage to ships. The reason for this is that these can be the most difficult to detect [8]. Small floes of multi-year ice can be mixed in with regions of first-year ice and typical marine radar may not allow for a clear distinction. Bergy bits and growlers have so little above the waterline that they can be lost in the sea clutter when using radar in their pursuit [9-12]. As such, current detection techniques rely heavily on the experience of the crew where lookouts serve as the primary means of detection as radar is deemed unreliable [7, 13].

Season	Summer/Autumn					Year Round			
Ice Type	First-Year					Second-Year	Multi-Year	All	
Min Ice	0.15 m	0.25 m	0.35 m	0.5 m	0.7 m	1.0 m	1.3 m	1.8 m	3.0+ m
	Polar Class					PC 4	PC 3	PC 2	PC 1
Baltic Class	IC	IB	IA	IA*					
<div> <div> <p>AHTS Balder Viking (2000) PC 7 83 m, 13 MW, 6ktonnes</p> </div> <div> <p>CCGS Henry Larsen (1987-) PC 4/5 100 m, 12 MW, 6ktonnes</p> </div> <div> <p>NS 50 Let Pobedy (2007-) PC 1 160 m, 55 MW (N), 26ktonnes</p> </div> <div> <p>Sevmorput (1988-) PC 6 260 m, 30 MW (N), 62ktonnes</p> </div> <div> <p>MS Norilskiy Nickel (2006-) PC 4/5 170 m, 13 MW, 30ktonnes</p> </div> <div> <p>USCGC Polar Star (1976-2011) PC 2 122 m, 56 MW, 13ktonnes</p> </div> </div>									

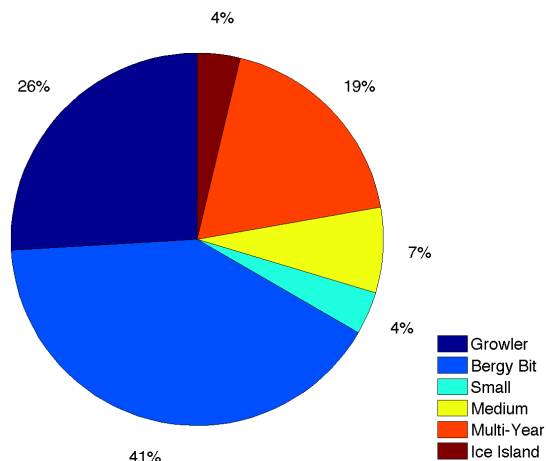
**Figure 5.** Classes of polar ships (based on data from [14-16]).

Ice Type	Thickness	Danger
New Ice (Nilas) 	< 0.1 m	Not a danger to ships.
Young Ice 	0.1 – 0.3 m	Potential danger to non-ice strengthened ships.
First-Year Ice 	0.3 – 2 m	Danger to non-ice strengthened ships.
Multi-Year Ice 	2 – 4+ m	Polar class ship required.
Glacial Ice 	1 – 5+ m	Polar class ship required.

**Table 1.** Types of ice encountered at sea and their danger to ships (based on data from [13, 16-18]).

Description	Height Above Sea Level [m]	Relative Size	Mass [tonnes]
Very Large	> 70	Merchant Ship +	>180,000
Large	48 – 70		
Medium	16 – 48		
Small	< 16		
Bergy Bit	1 – 5	Small House	5,400
Growler	< 1	Grand Piano	120

**Table 2.** Iceberg classification by size (based on data from [12]).



**Figure 6.** Ice collision breakdown by ice type around North America, Greenland, and parts of Europe 1980-2011 (based on data from Brian T. Hill's Ship Iceberg Collision Database [19, 20]).

### Current Ice Mitigation Strategies

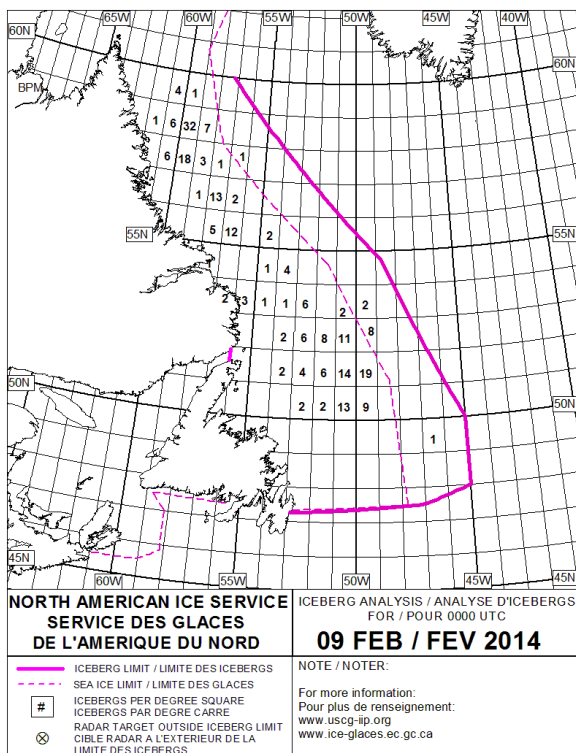
The current ice mitigation strategy around areas of high traffic around North America consists of two major components. The first is ice reports generated by the North American Ice Service (NAIS). This organization consists of a joint effort between the United States' International Ice Patrol (IIP) and the Canadian Ice Service (CIS) who broadcasts daily ice warnings for the North Atlantic.

The NAIS service began in 1912 as a result of the Titanic's collision with an iceberg which resulted in a tremendous loss of life. Figure 8 shows the region patrolled by the NAIS, an area which is prone to icebergs and commonly referred to as iceberg alley. Currents draw icebergs from the coast of Greenland to areas of high shipping traffic near mid-latitudes in the North Atlantic. The efforts of the NAIS are primarily to bound the area containing icebergs so that ships can plan routes around it. This boundary is shown in the February 9, 2014 ice report given in Figure 7 as an example. The numbers listed in the grid boxes on the report represent the number of known icebergs in that particular area.

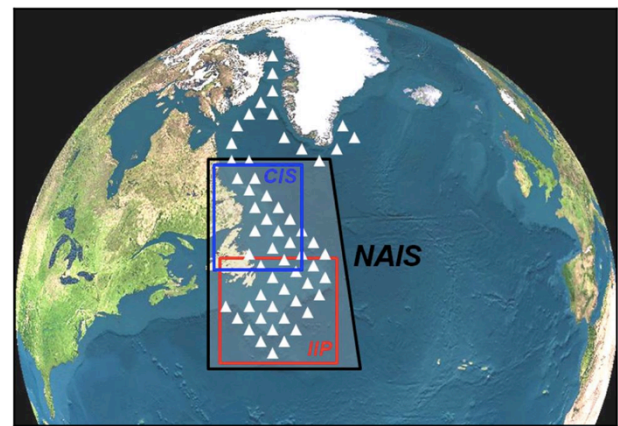


Ice is reported by a variety of means to the NAIS including coast guard ships, reconnaissance aircraft, satellite imagery, commercially hired reconnaissance, and by merchant ships. Figure 9 shows the breakdown of iceberg reports by type for the year 2012. Focusing on the last column, that of boundary setting icebergs, we see that merchant ships account for nearly 10%, satellite imagery less than 5%, government reconnaissance 45%, and the remainder by commercially hired reconnaissance at 40% [17]. Note the strong reliance on merchant ships to share their iceberg sightings, so much so that it is incentivized in the form of the annual Carpathia Award which awards the ship with the most reports [17].

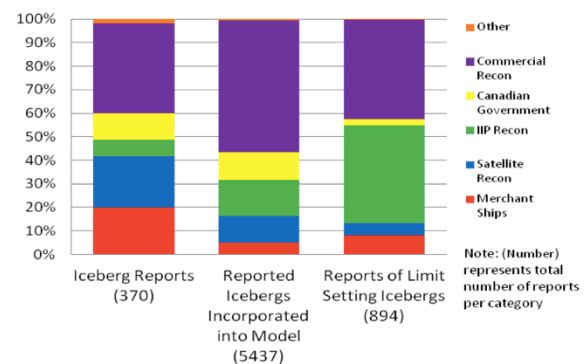
The second and last line of defense against ice are the ship-based sensors. Radar is a useful tool, but it is highly advised not to solely rely on it [7, 13]. The most reliable method is to make use of lookouts onboard the ship, that is skilled crew scanning the horizon with binoculars for signs of dangerous ice [13]. This can be seen in the iceberg reports to the NAIS whose breakdown is given in Figure 10. This shows that nearly half of icebergs are detected by visual inspection (43%) while the other half is detected by a combination of visual and radar confirmation (47%). Only 10% of these are found via radar alone but these are typically very large and outside of visual range. Thus, iceberg detection is a largely manual process which relies heavily on the experience of the crew.



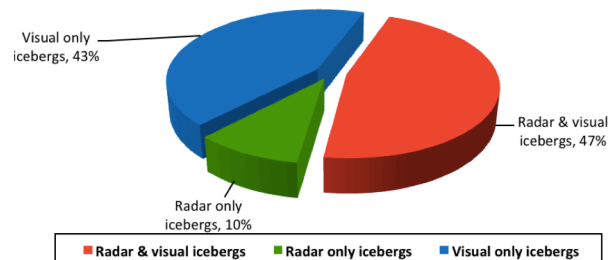
**Figure 7.** Typical report of the North American Ice Service (NAIS) (source: NAIS).



**Figure 8.** The coverage of the North American Ice Service (NAIS) (source: [17]).



**Figure 9.** Breakdown of iceberg report source by method for the year 2012 (source: [17]).



**Figure 10.** Breakdown of iceberg reports by detection method for the year 2012 (source: [17]).

## Ice Collisions

The ship based detection methods rely heavily on the experience of the crew, though this is sometimes not enough. Figure 11 shows what can happen when this system fails. In 2007, the MS Explorer, a passenger cruise ship, suffered a fatal collision with glacial ice in the Bransfield Strait off of King George Island, Antarctica. The accident occurred as the crew mistook an area of glacial ice for much more benign first-year ice. As a result, the ship sank within 20 hours. Thankfully, all 100 passengers were saved though this highlights the danger

associated with the misclassification of ice and how it can happen even today.



**Figure 11.** The MS Explorer sinking after a collision with ice in the Bransfield straight near Antarctica in 2007 (source: Chilean Navy).

In recent years, in areas around North America, Greenland, and parts of Europe, there are still more than 2 major collisions with ice each year. Furthermore, when a ship does have a collision with ice, data shows that it has a 1 in 6 chance of being lost. These figures are based on the most current data from Brian T. Hill’s Ship Iceberg Collision Database from the period between 1980 and 2011 and are summarized in Table 3.

Figure 12 shows the number of collisions that have occurred with ice each year from 1900 to 2011. Note that these are also broken down by ice type. Clearly the number of collision occurring each year is not decreasing though the nature of the collisions has changed over the years. Starting in 1945, which corresponds to the advent of ship-based radar, the number of collisions with large icebergs drops drastically. In fact, there are no more reported collisions with large icebergs in subsequent years. The consistent threat throughout the years has been bergy bits and growlers and in recent years multi-year ice. Multi-year ice has likely always been a culprit, though it was perhaps not properly reported and is likely seen in the ‘unknown’ category. This further supports that radar is an effective tool in detecting large icebergs but still falls short in the detection of the smaller bergy bits, growlers, and small floes of multi-year ice.

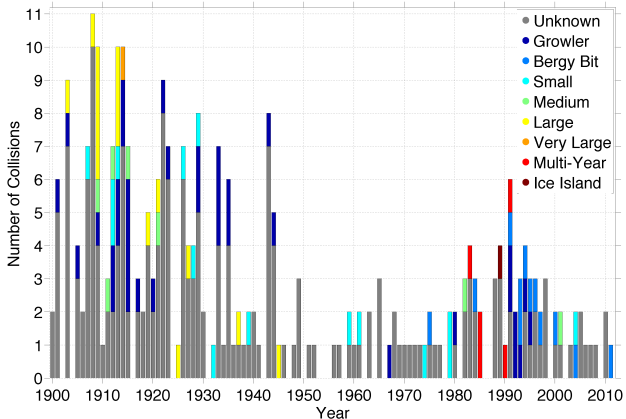
Figure 13 shows where major collisions have occurred in the period between 1980 and 2011. Many are concentrated in the so-called iceberg alley off the coast of Newfoundland and Labrador where currents bring icebergs down from the coast of Greenland. This is also the focus area of the NAIS. It further shows that ships don’t have to be operating in the Arctic Circle to be wary of dangerous ice. Figure 14 shows the ice collision breakdown by latitude and demonstrates that most happen below the boundary of the Arctic Circle, typically defined as the 66° north latitude mark.

Collision rate*	> 2 per year
Likelihood of ship being lost*	1/6
Probability of collision**	1/2000
Probability of ship being lost	1/12000

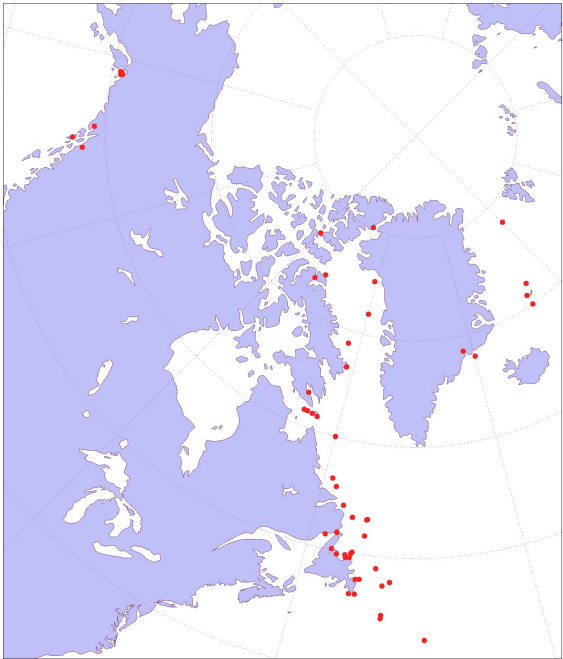
**Table 3.** Summary of ship ice collision statistics.

\* Based on data between 1980-2011 from Brian T. Hill’s Ship Ice Collision Database [19, 20].

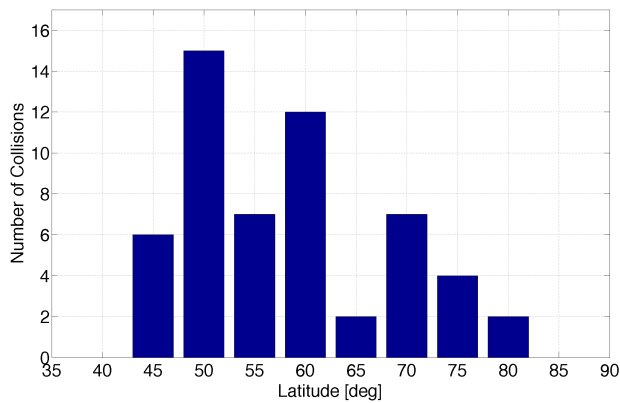
\*\*Based on [19].



**Figure 12.** Number of ice collisions around North America, Greenland, and parts of Europe 1900-2011 (based on data from Brian T. Hill’s Ship Iceberg Collision Database [19, 20]).



**Figure 13.** Location of ice collisions around North America, Greenland, and parts of Europe 1980-2011 (based on data from Brian T. Hill’s Ship Iceberg Collision Database [19, 20]).



**Figure 14.** Ice collision breakdown by latitude in areas around North America, Greenland, and parts of Europe 1980-2011 (based on data from Brian T. Hill's Ship Iceberg Collision Database [19, 20]).

## PROPOSED SYSTEM OVERVIEW

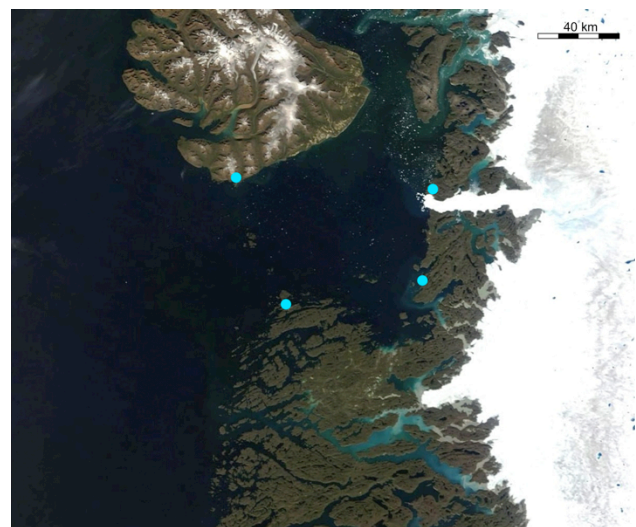
In this section, we propose a modernized system which offers improvements in the two major components of the current ice mitigation strategy, namely, on the ship-based monitoring side and on the ship-to-ship aiding side. Ship-based monitoring today is a largely manual process which requires a skilled and experienced crew to interpret radar data and scan the area visually to correctly identify hazardous ice. Ship-to-ship aiding exists today in the form of organizations such as the NAIS where icebergs and ice conditions are reported in part by passing ships. However, most ice sightings are based on visual sightings whose accuracy is likely not high. Here, we propose crowdsourcing ice navigation based on a GNSS data registration system. In this scenario, ice detection and classification is done robustly and automatically based on a redundant multispectral system. This data is then geo-referenced using GNSS, enabling reliable ship-to-ship aiding in systematic way. The high integrity sharing of data allows for paths through the ice to be planned both safely and economically, relying less on the human factor and the experience of the crew.

### Crowdsourcing

To demonstrate how such a system could be implemented, we will build on a working example throughout this text. To do so, we chose a real place near Disko Island in Greenland shown in Figure 15. Depicted here in the summer months, there are four medium sized ports in this area, the Ports of Qeqertarsuaq, Ilulissat, Aasiaat, and Qasigiannnguit. Figure 16 shows the same area in winter with much snow and ice coverage, where landmasses are highlighted in red. For this example, we will assume hypothetical ship traffic over a period of three days for the purpose of explanation. On the first day, Figure 16 shows the paths taken by these theoretical ships. At the scale of this image, the width of the path

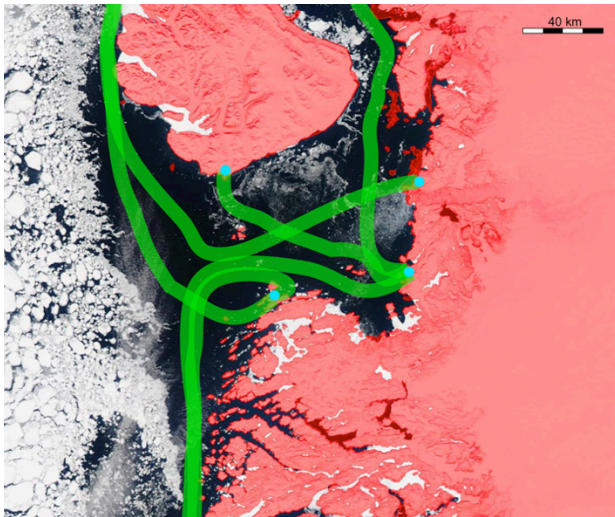
lines represents the coverage of the onboard ship sensors, assumed at roughly 6 km in all directions. Thus, green areas represent the information gathered by passing ships on day 1. The instant the data is collected, however, it is volatile as it begins to drift with ocean and wind currents. Thus, we require the ability to propagate this information forward in time in order to estimate its drifted location so that it is useful to a ship passing through at a later epoch. To accomplish this, a ship can make a variety of wind, ocean current, and other meteorological measurements in conjunction with its collected ice information that can be fed into a propagation model. As there will be uncertainty in the propagation scheme, as well as other ice outside of these tracks that may get mixed in over time, the older the track, the less a ship can trust its information.

Figure 17 shows the ice conditions at the beginning of the second day. If all the information collected on day 1 is referenced to an epoch at the beginning of day 2, we see that some tracks have drifted. This represents both the information propagation and decay. The decay or age of data represents the level of uncertainty and is indicated by the track color, green being the least uncertain and newest data, orange being the most uncertain and oldest data. Figure 18 shows the state of information at an epoch on day 3. Here, we have tracks from day 2 (shown in green) and previous information from day 1 which has decayed even further (shown in red). If we are a ship, as shown in the northwest corner of Figure 18, trying to use this data to plan a safe passage through the area to the highlighted port it must somehow account for the known data's sparsity, varying levels of inherent safety (ice conditions) and degradation (age of data). This is a problem in path planning, one that will be addressed later in this paper, we first need to address the problem of how to trust the information gathered by another ship in the first place.

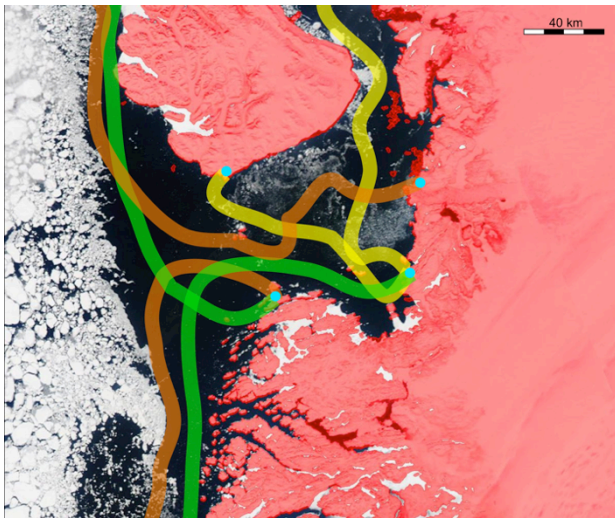


**Figure 15.** Four ports near Disko Island, Greenland. (source: AQUA/TERRA satellite imagery, ocean.dmi.dk/arctic/)

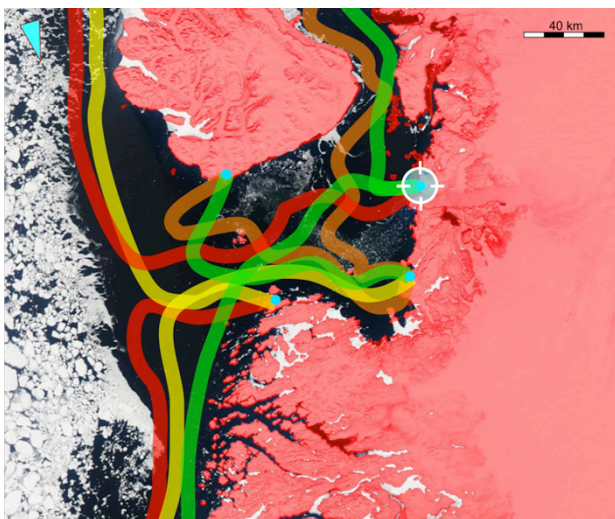




**Figure 16.** Hypothetical ship traffic and collected ice data on day 1.



**Figure 17.** Ice data from day 1 propagated forward in time to a reference epoch on day 2. Green represents the newest data, orange the oldest and most uncertain.



**Figure 18.** Ice data from days 1 and 2 propagated forward in time to a reference epoch on day 3. Green represents the newest data, red the oldest and most uncertain.

## Improved Ship-Based Sensing

In order for a ship to trust the information that is gathered by others, the data must be collected reliably and consistently to ensure a high level of integrity. To ensure this, ice detection and classification must be robustly automated and tied to a universal coordinated system using GNSS.

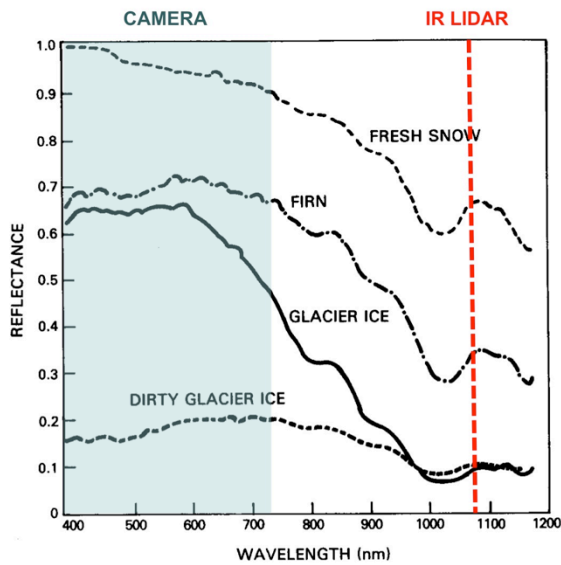
For inspiration, we turned to another problem of automated perception, that of self-driving automobiles. Autonomous vehicles such as Stanford University's Stanley, which won the Defense Advance Research Project Agency (DARPA) Grand Challenge in 2005 and Google's self-driving car, which today routinely navigates busy city streets and highways, make use of a multispectral system to perceive their environment. A combination of video processing and lidar is used in the case of Stanley [21] and an additional radar system is employed in the case of Google's self-driving car [22].

In the context of ice classification, different types of ice and snow have different electromagnetic properties in different bands [12]. Figure 19 shows the spectral reflectance signatures of an assortment of glacial ice and snow in visible bands where a video camera can see as well as the infrared bands where a lidar system would be. From the reflectance information alone, cross checks can be done to offer classification redundancy in these different spectra. Other aspects of these technologies can also be used to identify areas of dangerous ice. Lidar systems can generate high-resolution 3D maps which can be used to find patterns and shapes to further aid in the classification process. Furthermore, since much of the ice classification is currently performed by some form of human visual inspection, many of these procedures can likely be automated in the processing of video images.

Both lidar and video rely heavily the ability to judge what is dangerous by what's going on at the surface, as they do not possess the power to penetrate the top layer of snow cover if one is present. Radar, a very new technology for cars but a very old one for ships, does possess this penetrating power. Much work has been done on using different forms of radar such as X- and S-Band linearly polarized radar for ice classification. Further information on this topic can be found in [8-12, 23-26]. However, there are still many situations where radar falls short of the performance requirements needed for ice navigation such as in the detection of small floes of multi-year ice or glacial ice such as bergy bits or growlers [8].

We now see how these systems qualitatively complement each other and how in their combination we can potentially achieve higher redundancy than we do with any of them on their own. Radar falls short on resolution, lidar and video processing on surface penetration. The

challenge ahead is in leveraging their individual strengths and combining them in a meaningful and robust way.

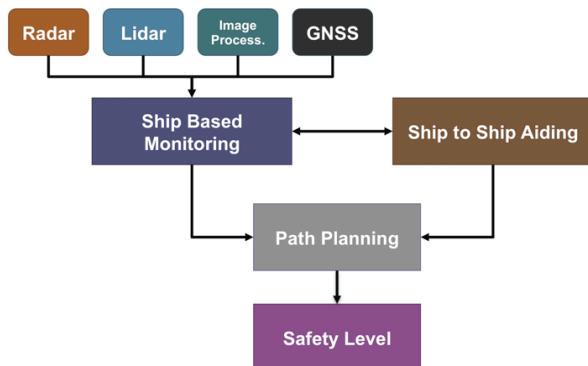


**Figure 19.** Spectral reflectance of different types of snow and glacial ice in the visible and infrared spectrum. (adapted from [27, 28]).

## GNSS Data Registration

Improved ship-based sensing is only one small part of this picture. For a ship to effectively navigate ice-infested waters, it requires accurate knowledge of ice conditions well in advance so that it may effectively plan a route through it.

Registering the sensor data recorded by the ship with GNSS allows for a global coordinate system to be employed and ship-to-ship consistency to be achieved. This is what enables ship-to-ship aiding in this framework. High integrity GNSS, however, is currently unavailable at high latitudes though some have argued its necessity in the Arctic and how it can be attained by Satellite Based Augmentation Systems (SBAS) [29, 30]. The proposed ice navigation system is summarized in Figure 20.



**Figure 20.** Proposed ice navigation system.

## SHIP-BASED LIDAR

To obtain a first assessment of lidar as a tool for ice detection and classification onboard a ship, we obtained access to a dataset whose original intention was glaciology research. RIEGL Laser Measurement Systems (LMS) in collaboration with environmental research scientist David Finnegan of the Cold Regions Research and Engineering Lab (CRREL) of the United States Army Corps of Engineers (USACE) worked to develop the RIEGL VZ-6000 Terrestrial Laser Scanner, a 1064 nanometer wavelength lidar system purpose built for high performance on ice and snow. This system has a range of over 6 km and is able to resolve angular measurements to better than  $0.0005^\circ$  which corresponds to less than 1 cm at a range of 1 km and 5 cm at 6 km. In addition, it has a beam width or resolution cell which is characterized by a laser beam divergence of 0.12 milliradians, which corresponds to 1.2 cm at a range of 1 km and 72 cm at 6 km. The system is also integrated with GNSS, a desirable feature for the proposed ice navigation system. The RIEGL VZ-6000 is shown set up next to the data collection site in Figure 21.



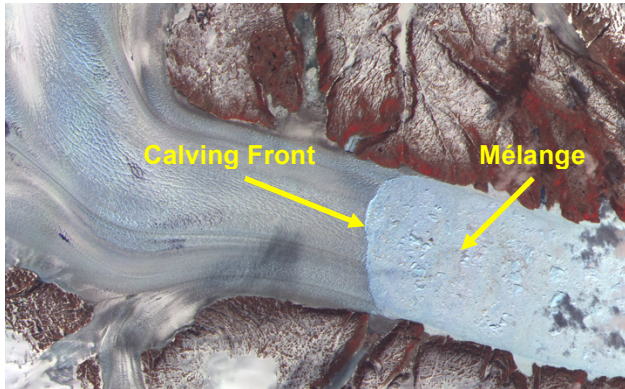
**Figure 21.** RIEGL VZ-6000 overlooking the Helheim Glacier in Greenland (source: rieg.com).



**Figure 22.** Location of the data collection site, the Helheim Glacier in Greenland (source: Google Maps).



The data used in this analysis was taken by a small team which consisted at its core of David Finnegan and Ananda Fowler of RIEGL LMS. For more information on this effort, please refer to [31]. The data collection site was the Helheim Glacier in Greenland whose location is shown in Figure 22. The lidar data is of the so-called glacial mélange portion of the site. Shown in Figure 23, this represents the area ahead of the glacial calving front where pieces of ice shear off the main body of the glacier. As the name suggests, this region contains ice of different ages as well a mixture of dirt and snow. Since we are interested in the classification of different types of ice and snow, this area is ideal for this study.



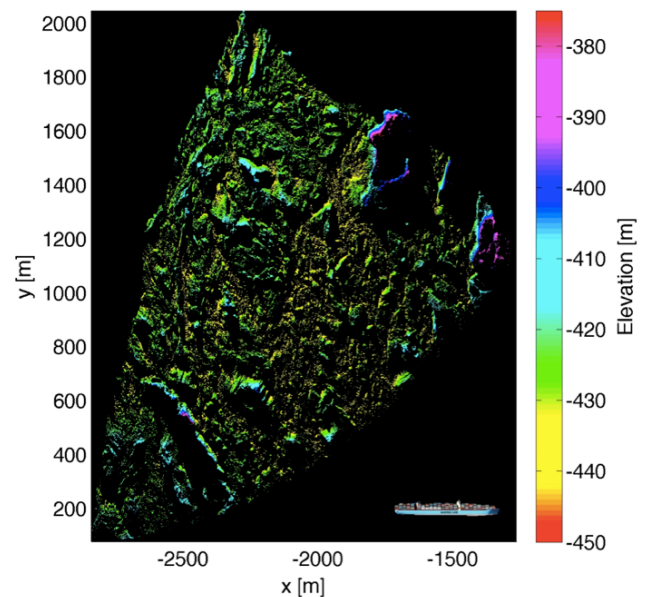
**Figure 23.** Glacial mélange and calving front of the Helheim Glacier (source: NASA Earth Observatory).

Figure 24 shows the lidar system set up on the fjords alongside the Helheim Glacier. This set up is ideal for this study as it is not dissimilar from the configuration such a system would have onboard a ship in terms of height above targets and grazing angles. To give a sense of the range performance of the system in practice, the banks opposite to the lidar scanner (also shown in Figure 24) are roughly 6.8 km away and results demonstrate that the system is capable of scanning to that distance, thus outperforming the listed specifications.

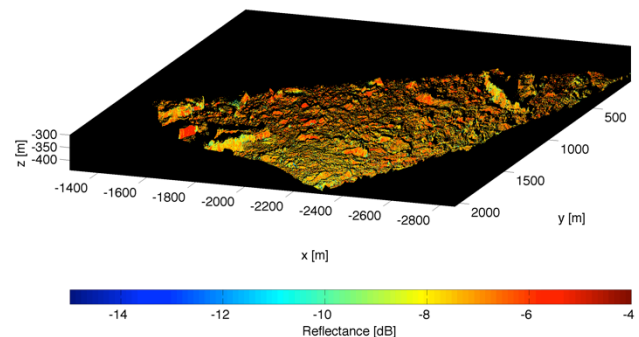


**Figure 24.** Experimental setup of the RIEGL VZ-6000 lidar system on the banks of the Helheim Glacier (source: riegl.com).

Figure 25 shows a top view elevation map of the 3D point cloud mapped by the lidar system. This is only one small section of the entire scan, though it does give a sense of the scale of the ice; note the commercial container ship in the bottom right corner of the image. The black areas between colored points represent shadows behind objects the lidar could not see. These occur because the lidar is not scanning from above but rather on the banks, giving rise to areas behind large pieces of ice for which there is no line of sight. A view better aligned with the vantage point of the scanner is given in Figure 26. This plot shows the parameter most important for classification, namely, the reflectance. RIEGL LMS post-processed this data to correct for path loss ( $1/s^4$ ) as well as atmospheric losses, thus this plot represents the inherent reflectivity of the material.



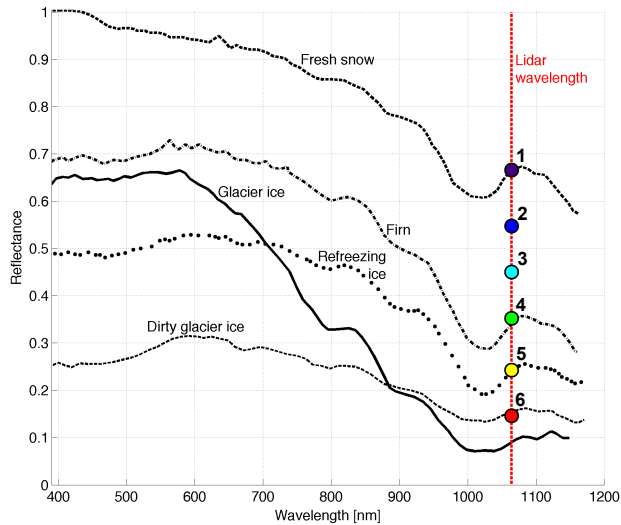
**Figure 25.** Elevation map of a section of the Helheim Glacier mapped by the RIEGL VZ-6000.



**Figure 26.** Lidar reflectance map of a section of the Helheim Glacier mapped by the RIEGL VZ-6000.

We are now tasked with using this reflectance data for material classification. We want the data to inform us of what categories are inherent to it, rather than blindly trying to categorize it based on reflectance alone. As such,

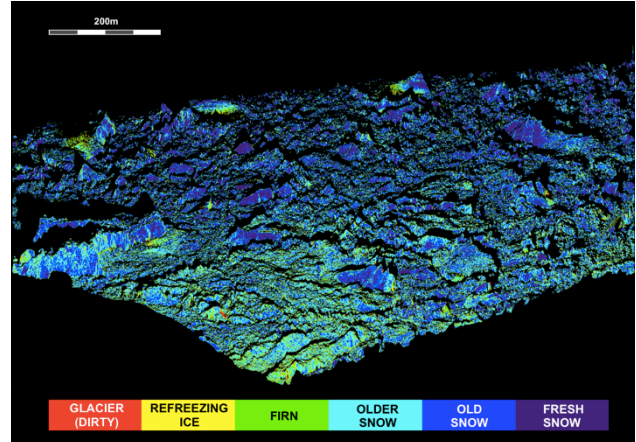
we made use of a machine learning algorithm known as  $k$ -means clustering to determine the categories intrinsic to the data.  $k$ -means clustering works by finding the principal  $k$  clusters which represent a given dataset. In this case, we performed clustering based on similar material reflectance. Results for the case of  $k = 6$  clusters are shown in Figure 27. Six categories were used as this found dominant clusters which best matched expected results. Each point labeled 1 through 6 represents a category where 1 represent the most reflective and 6 the least reflective. From this plot, it is clear that we are able to identify materials which are snow and firm (old recrystallized snow) and those which are ice. Category 1 represents fresh snow. This matches exactly with the expected result as it was used as the point of calibration for the data, i.e. the most reflective category was taken as that of fresh snow. Category 4 represents firm or old recrystallized snow. Categories 2 and 3 represent snow types which are somewhere between fresh snow and older firm. Category 5 represents refreezing glacial ice, namely, areas of glacial ice that melt and refreeze during the season. Category 6 is that of solid glacial ice, in this case predominantly that which has dirt and other debris mixed into it.



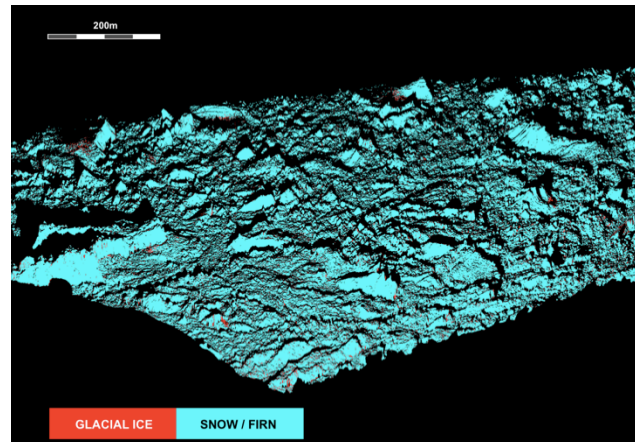
**Figure 27.**  $k$ -means clustering results with 6 clusters (reflectance spectrums adapted from [28]).

The geographic location of these color-coded categories is given in Figure 28. Here, we see that the majority of the top layer is different types of snow and firm, though there are some areas of ice shown in yellow and red. Figure 29 shows these further categorized into areas of snow (blue) and those of ice (red). Again, we see largely snow cover, though here it is easier to see the structure of the ice. We see ice signatures at the base of the large jagged structures. These are likely snow-covered pieces of glacial ice whose true colors shine through at their base where constant movement likely wears off the snow. Figure 30 shows areas of ice only. From this it is clear that the entire

underlying structure is that of glacial ice, an expected result as this is an area filled completely with glacial ice albeit covered in snow. This result does highlight one of the major drawbacks of a lidar system on its own for ice navigation, its inability to penetrate the snow to find areas of ice hiding underneath.



**Figure 28.** Map of  $k$ -means clustering results with 6 clusters.



**Figure 29.** Clustering results separated into categories of snow / firm and ice.



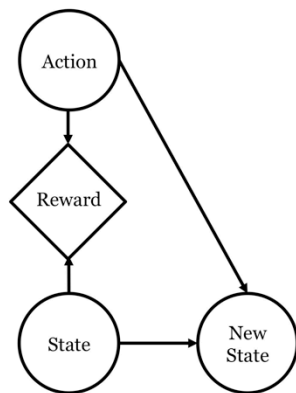
**Figure 30.** Clustering results highlighting areas of glacial ice only.



Ultimately, this analysis gives only a first glimpse into the potential that such a system has for ice detection and classification onboard a ship. This method does not yet represent a robust classifier but merely indicates that such a system is capable of performing snow and ice classification and identify areas of potential danger based on the material reflectance.

## PATH PLANNING FRAMEWORK

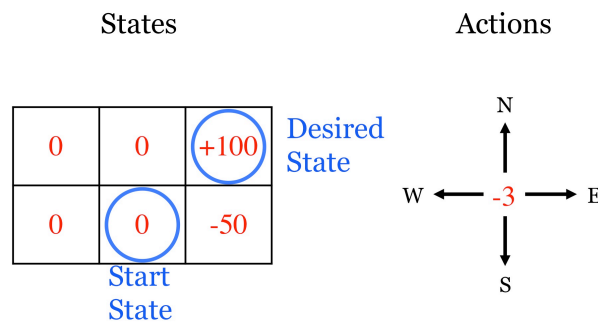
We now return to the problem of path planning through the ice using the measurements of others. This problem can be set up in the framework of a sequential decision making process, specifically that of a Markov Decision Process (MDP). In its simplest form, a MDP is a model of the system dynamics. Shown in Figure 31, the transition from a given state, say a geographic location, to another state, a new location, requires some action, perhaps the thrust from engines onboard a ship. Both actions and states can have rewards associated with them. Actions such as thrust require fuel, a negative reward since fuel is expensive. States such as locations may have a negative reward if they are an area of danger such as land or glacial ice or a positive reward if it is an area of open water. In planning a path from some initial state to some final state, we want to maximize the cumulative reward along a given path to find that which is optimal in terms of both safety and fuel expenditure.



**Figure 31.** Markov Decision Process (MDP).

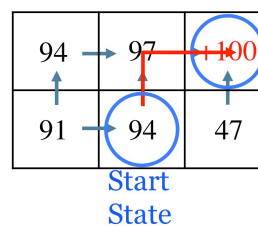
To do this, consider the simple example of that shown in Figure 32. Here the states, shown on the left, are boxes in a 2D world and can be thought of as six possible geographic locations. On the right, we have the possible actions that can be taken: north, east, south, or west. In red, we have the reward associated with both states and actions. Most states (2D locations) are neutral but the northeast corner is a great place to be, the desired destination at +100, and the southeast corner is to be avoided at -50 representing an area of hazardous ice. The actions, assumed to be deterministic in this example, also

have a penalty associated with them at -3 representing the cost of fuel expenditures.



**Figure 32.** Simple example of a MDP.

The problem we wish to solve is how to get from the starting state to the desired state in an optimal way. To do this, we wish to maximize the cumulative reward along a path. For this simple example, we can start from the final state and backtrack to find the answer. Starting at the desired state and moving west, the best we could have done had we started at this location is a cumulative reward of 97. The reason is that we start with 0, incur a cost of 3 for moving east and gain a reward of 100. Had we started south of the goal in the southeast corner, the best we could have done is a cumulative reward of 47. Just by being there, we would start at -50, incur a cost of 3 for moving north, and finally gain 100 at the final destination. Clearly, no optimal route would choose to go through this point, as there is just too large of a penalty for passing through it. Thus, if we start in the southern middle box, we should go north, not east as we would incur an additional cost of 50 on top of the cost of 6 for moving twice in both cases. Thus, the optimal solution to our problem is to go north then east. We can continue to fill out the remaining boxes by backtracking in this way, the final result of which is given in Figure 33. This resultant 2D map is known as the value function and represents the maximum total reward that can be attained by starting in each box. A greedy algorithm can be used to plan the path for this simple case. In other words, starting from any given point, always look for the largest neighboring value and follow that path. This results in a policy that gives the optimal path for any given starting point.

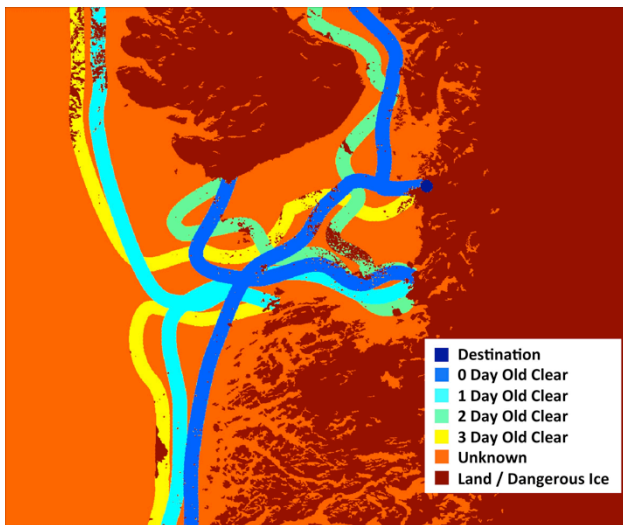


**Figure 33.** Value function and optimal path.

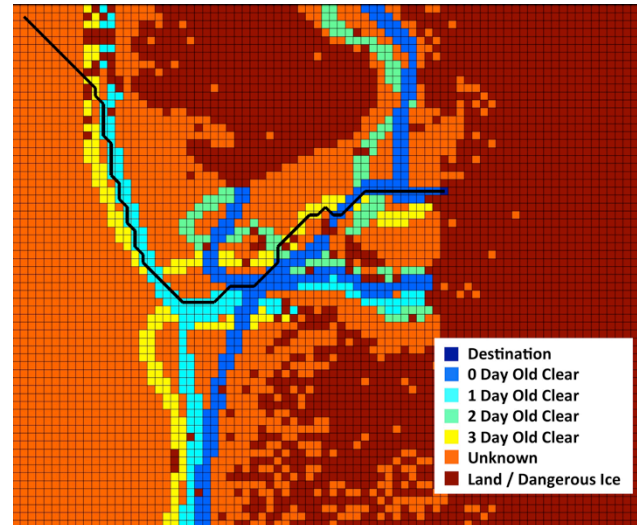
We will now apply this to the problem of path planning in the area around Disko Island, Greenland given in Figure 18. Figure 34 shows the data known after a hypothetical three days of traffic in the area where colors ranging from blue to red can be thought to represent the reward associated with each location, blue being positive and red being negative. We see the final destination has the highest reward and areas that are either land or hazardous ice have the least reward or highest penalty. We also see how the age of data diminishes the reward associated with tracks of open water. The older they are, the less they are trusted.

To further make this look like the example given in Figure 32, we can grid the 2D area as shown in Figure 35. Now the color associated with each box qualitatively represents the reward associated with each location, blue being positive, red being negative. We now solve for the value function as shown by the contour map given in Figure 36. Employing a greedy algorithm on the value function, we can solve for the optimal path starting from the ship location given in Figure 18 in the northwest corner. This optimal path is shown in both Figures 35 and 36. This path is found to gravitate towards areas of open water, especially those which have the youngest age of data, avoids all areas of hazardous ice as well as areas which are unknown, and ultimately arrives at the desired destination.

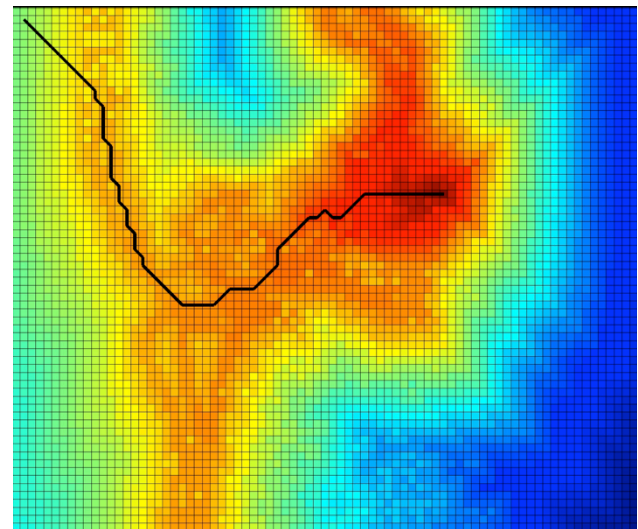
Ultimately, this problem is more complex than that which was described here as we have to account for the probabilistic nature of the system as well as how to incorporate the new measurements taken by the ship on the fly. As such, this problem will be built into the framework of a Partially Observable Markov Decision Process (POMDP) where the underlying state of ice will be only partially observable.



**Figure 34.** Known information after 3 days of traffic, blue indicates desirable areas, red indicates areas of danger.



**Figure 35.** Known information after 3 days of traffic gridded in 2D, the color of each box represents the reward associated with each location, blue being positive and red being negative. The optimal path using the available information is overlaid in black.



**Figure 36.** Value function and optimal path through the ice from the given starting location to the desired destination.

## CONCLUSION

A proposal for a modernized ice navigation system has been presented. This system offers improvements in the two major components of the current ice mitigation strategy, namely, in ship-based sensing and in ship-to-ship aiding. Improvements in local ship-based ice awareness can be achieved by making use of advancements in sensing technology found in autonomous vehicles. Multispectral sensing based on a combination of lidar, radar, and video processing could offer the redundancy needed to achieve a robust method of autonomous ice detection and classification. This would reduce the need for experienced lookouts to manually determine ice conditions by visual inspection.

This improved ship-based sensing will not be enough on its own to guarantee the highest level of safety. Ships require knowledge of ice conditions well in advance to plan routes both safely and economically. As such, we need to crowdsource this ship-based ice data and tie it together using GNSS. This enables a universal coordinate system and ship-to-ship level consistency. Furthermore, this offers a framework in which to perform path planning in a reliable and automated way, finding the safest route with the available information.

As ship traffic increases and there are less experienced persons operating in the Arctic, technology which automates operations in ice-infested waters will be essential. Our aim is to get ahead of the trends in Arctic traffic in the development of such a system. This will allow for safer operations in the Arctic, striving towards the prevention of collisions with hazardous ice in the hopes of preventing major accidents which could result in loss of life or severe environmental impact.

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