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Shipborne sea-ice field mapping using a LiDAR*

Andrei Sandru¹, Arto Visala¹ and Pentti Kujala²

Abstract—The increasing interest for autonomous ships has motivated research in numerous areas. One such area is the safe navigation through ice-infested waters, for which a sensor instrumentation and automated process are proposed for near-field, sea-ice 3D scanning and mapping using a ship mounted LiDAR, with attitude compensation from inertial and satellite positioning sensors. Data were collected both at the Aalto Ice Tank laboratory and on board the icebreaker S.A. Agulhas II during its voyage to the Antarctic waters. The implemented process enables automated acquisition of detailed 3D point cloud maps, containing highly valuable information for icy waters going ships currently operated by a human crew and, in the near future, supporting the development of autonomous ships. Compared to other methods using satellite, aerial or underwater data, the proposed method is a more cost-effective and easy to integrate solution into current and future icy waters going ships, thus enabling a higher level of situational awareness.

Keywords: LiDAR, sea ice, IMU, ship

I. INTRODUCTION

The world economy’s increasing demands for cost-efficient and environmentally friendly transport of goods has led to a yearly boost in seaborne trade [1]. This increase in shipping demands has motivated the exploration of new options, from establishing new routes in polar regions, which reduce both the shipping times and costs (see e.g. [2][3][4]); to an increase in the ships’ autonomy level and efficiency [1][5]. However, navigating through ice-infested waters requires high degrees of expertise and experience, and may pose a serious threat for the vessel itself and its human companions. From a ship’s perspective, the inclusion of a light detection and ranging (LiDAR) sensor into its body of sensors will increase its situational awareness level, leading to smarter maritime operations not only in local operations, such as docking or navigating in harbours and narrow passages; but also in open sea navigation through icy waters, by detecting in-water hazards (i.e. thick ice), and avoiding them in a preemptive manner, or for more efficient path planning. In addition, the mapping and analysis of the sea-ice field can be used to monitor climate change and as an input for weather models.

Sea-ice mapping with LiDAR has traditionally been carried out by either using manned aerial vehicles (MAV) such as small aeroplanes (see [6][7]), or satellite data (see [8][9]). The first case offers high spatial and temporal resolutions (on demand, where available), however, their operations are limited by external factors (i.e. weather conditions, daytime) as well as availability. In the second case, satellite operations are not influenced by external factors and they offer large area scans, but are limited by both sparse spatial and temporal resolutions. In both cases, the advantages of selective areas analyses are somewhat diminished by the medium-high costs of obtaining the data, ranging from several thousands of dollars per hour for MAVs, to tens of thousands of dollars for high-resolution satellite imagery; both figures obtained during informal discussions with experts from both fields. We propose, instead, to use icy waters going ships as platforms for data collection, which offers both high spatial and temporal resolutions, albeit to being constrained to their pre-defined routes (in a similar fashion as the authors have carried out using machine vision cameras in [10]). The authors in [11] have followed a similar idea, where a ship-based laser recording system was implemented, focusing on identifying sea-ice types based on surface roughness. In contrast, our proposed experimental setup can scan a much larger area (up to 40 metres away from the ship at the present stage), and it includes 3D point-cloud mapping aided by dynamic attitude change compensation.

In this paper we explore a first approach at using a commercial, and relatively low-cost LiDAR device aimed at the automotive industry; to detect and analyse sea-ice field properties. We show that it is possible to use such devices, together with attitude estimation and compensation from an Inertial Measurement Unit (IMU) and a Global Navigation Satellite System (GNSS), to detect and map sea-ice. The proposed experimental setup, was tested both in a synthetic stage), and it includes 3D point-cloud mapping aided by dynamic attitude change compensation.

The present work is structured as follows. In section II, we describe the methodology required to analyse the data coming from the experimental setup in two different ice scenarios (i.e. ice tank and on a ship), and obtain the results presented in Section III. Then, those results are discussed in Section IV, followed by a conclusion in Section V.

II. METHODS

The following subsections describe the steps and related methods involved in the process of mapping sea-ice from...
on board a vessel. Before dealing with a full scale measurement, the expected accuracy of the LiDAR recorded data is determined in the context of detecting ice. Then, full-scale measurements need to undergo a number of steps to obtain a 3D map of the ice field.

A. Performance metrics of a LiDAR in ice measurements

1) Plane fitting to point cloud: In order to estimate the expected accuracy of a LiDAR sensor (i.e. model its measurement error), and more specifically when recording a sea-ice point cloud, our proposed approach is to record a completely flat surface of ice, fit a plane to the resulting point cloud, and then calculate the shortest distance (i.e. error) from each individual point to the estimated plane, thus obtaining a histogram, and later a probability density function describing the error in the scans of sea-ice. The proposed plane fitting method is found in a robust estimator described in [12] and termed MLESAC, and which uses the RANSAC approach for producing hypothetical solutions, but instead of choosing the best solution based on the maximum number of inliers, it favours the solution which maximises a log likelihood estimate (including both inliers and outliers).

2) Point cloud to plane distance: From well-established geometric formulations, and using the Euclidean space, the shortest distance of a point \( P = [x_1, y_1, z_1] \) and a plane \( s \) defined by its equation \( Ax + By + Cz + D = 0 \), is given by:

\[
d = \frac{|Ax_1 + By_1 + Cz_1 + D|}{\sqrt{A^2 + B^2 + C^2}}
\]

where \( d \) is the minimum distance between the plane \( s \) and point \( P \), along a line perpendicular to the plane and through the point.

3) Local entropy measure: When dealing with natural ice field environments, where no “perfectly flat” ice sheets can be found, an additional performance measure is introduced: a local entropy value (defined in [13]) as a measure of randomness or local change in the distances between a group of points and the horizontal plane. Such value is calculated for a defined neighbourhood size using the equation in (2), where \( p(X) \) contains the normalized histogram of distance counts. Then, a sliding window approach is used on the whole point cloud map, and their sum leads to a single entropy value.

\[
H(X) = -\sum p(X) \log p(X)
\]

B. Mapping of sea-ice from LiDAR, IMU and GNSS data

1) Estimation of transformations: An efficient technique for fusing world data from different sources involves estimating and using transformations between frames, as described in [14] and [15]. Such frames are commonly used in robotics to relate data between different coordinate systems. In the present case, 3D point cloud information in the LiDAR’s coordinate system must be transformed to the world coordinate system. This transformation is given by:

\[
W q' = W^L M^L q = (W^L R)^L q
\]

where \( L q \) is a 3D point in the LiDAR’s frame, \( W q' \) is a point described in World coordinates, and \( M \) is the transformation matrix composed of a rotation matrix \( W^L R \) and translation vector \( W^L t \) from LiDAR to World coordinates.

The rotation matrix \( W^L R \) is formed as:

\[
W^L R = W^L R^S R^W,
\]

where \( S^W R \) is the rotation matrix from LiDAR to Ship coordinates, \( I^S R \) from Ship to IMU, and lastly \( W^L R \) is the IMU’s own rotation estimate in World coordinates.

In case the LiDAR and IMU sensors cannot be calibrated together, the rotation matrices \( I^S R \) and \( I^W R \) in (4) can be determined while the ship is at rest (e.g. while docking). In this case, the matrix \( I^W R \) can directly be obtained from the IMU’s own attitude estimate at that particular moment, by assuming that the rotation frame of the ship and world are identical. Regarding the LiDAR’s attitude relative to the ship’s coordinate system, it can be determined by fitting a plane to the point cloud of a flat, horizontal surface of the ship (e.g. fore-deck). The fitted plane’s normal unit vector \( n \) can then be used to build the matrix \( S^W R \) as follows: starting from the premises that the inverse of a rotation matrix is also its transpose, and that the columns of a rotation matrix equals to the images of the three basis vectors, we need to find an orthonormal basis which includes our normal unit vector, and will be the rows of the required rotation matrix:

\[
S^W R = \begin{bmatrix} v_1 & v_2 & v_3 \end{bmatrix} = \begin{bmatrix} n_x & -n_y & n_z \\ \sqrt{n_x^2 + n_y^2} & \sqrt{n_x^2 + n_z^2} & \sqrt{n_y^2 + n_z^2} \\ n_x & n_y & n_z \end{bmatrix}
\]

where \( v_3 \) is obtained directly from the normal unit vector \( n = [n_x, n_y, n_z] \), \( v_1 \) is a normalized vector perpendicular to both \( n \) and the unit vector of the horizontal plane (i.e. \( v_1 = n \times [0 \ 0 \ 1] \)), and lastly \( v_2 = n \times v_1 \) is an orthogonal vector to both \( n \) and \( v_1 \).

Lastly, the rotation matrix \( W^L R \) in (4) is obtained dynamically from the IMU’s own attitude estimation algorithm, which should fuse data from accelerometers, gyroscopes and magnetometers for a robust estimate.

Continuing with the transformation in (3), we start by first calculating the translation of the Ship’s frame with respect to the World frame:

\[
W P_{SORG} = W G - S^W R S^G
\]

where \( W P_{SORG} \) is the translation vector of the Ship’s coordinate origin in the World frame, \( W G \) is the location estimate from the GNSS sensor in World frame, \( W^L R \) is the Ship’s rotation in World frame and obtained as \( W^L R = W^L R S^W R \), and \( S^G \) is the translation vector of the GNSS sensor in the Ship’s frame.

Next, a 3D point-cloud in the LiDAR’s frame \( L q \) is described in the Ship’s coordinate frame \( S^W q \), using the rotation matrix \( S^L R \) between the LiDAR and Ship’s frames, and
transformation (or position) vector $SP_{LORG}$ of LiDAR frame origin relative to Ship frame:

$$SP = \frac{1}{2}PR_{L}q + SP_{LORG} \quad (7)$$

Then, a 3D point-cloud in the Ship’s frame $SP$ is described in the World’s coordinate frame $Wq$, using the rotation matrix $WR_{L}$ of Ship frame relative to World frame, and the translation (or position) vector $WP_{SORG}$ of the Ship’s frame origin relative to the World frame:

$$Wq = WR_{L}SP + WP_{SORG} \quad (8)$$

Lastly, by combining (4), (6), (7) and (8), and reorganizing; we obtain the full transformation of a 3D point-cloud from the LiDAR’s frame, to the World’s coordinate frame first introduced in (3):

$$Wq = WR_{L}SP + WG + \frac{1}{2}R(SP_{LORG} - SG) \quad (9)$$

Navigation data from a GNSS is usually recorded at a lower frequency (e.g. 1Hz) in comparison to the attitude estimate from an IMU (e.g. 250Hz), and therefore interpolation is required. Taking into account the slow dynamics nature of a ship, we propose the use of the Akima algorithm [16] for interpolation between data points, which avoids overshoots in flat regions (e.g. maintaining course), while at the same time preserving slopes (e.g. changes in heading or elevation).

2) Point cloud registration: In the previous step, information from all the laser beams of the LiDAR perpendicular to the ship’s path are incrementally added to a large point cloud. However, this approach may suffer from induced scanning errors given the dynamic nature of the environment mapped (i.e. the ice field seen by the first laser beam pointed further along the ship’s moving path, may have moved until is reached by the last laser beam pointed further back). To compensate for such behaviour, we propose two possible approaches: either perform the mapping as described in the previous step individually for each of the laser beams of the LiDAR, thus obtaining a number of 3D point cloud, ice-maps equal to the number of laser beam lines and then run analysis algorithms on each one of them; or fuse those 3D maps by means of a point cloud registration algorithm. For the latter case, we propose the use of the iterative closest point (ICP algorithm), described in detail in [17]. The ICP algorithm can handle all six degrees of freedom (rotation and translation) and, since in our case the point cloud maps from successive laser beams present small increments in attitude changes, the algorithm is expected to converge to a global minimum. In the following section, the results of the three approaches are presented and compared.

III. EXPERIMENTS AND RESULTS

The Experiments and Results chapter is divided in two sections, based on the collection site and purpose of the data. Data collection was performed first at the Aalto Ice Tank [18], analysed offline, and then the full-scale experiment was conducted, with its recorded data analysed offline at a later stage. In both cases, the experimental setup used to acquire point cloud data of the sea-ice, primarily consists of a commonly used LiDAR sensor in automotive applications, namely a Velodyne VLP-16. The main characteristics of this rotating LiDAR sensor include a 100m range with a typical accuracy of ±3cm, 903nm wavelength Class 1 Eye-safe laser, 16 vertical channels (i.e. laser beams) with an angular resolution of 2.0°, a 360° field of view with an angular resolution of 0.1°-0.4°, a rotational rate of 5-20Hz (set to 10Hz), and an operating temperature range of −10°C to 60°C [19]. The LiDAR sensor and its coordinate frame are depicted in Fig. 1. Data from the LiDAR sensor were recorded on a standard laptop running Windows 7. Furthermore, the setup includes as well a GoPro Hero 7 Black camera, used solely as a means for visual inspection of the recorded environment. The processing of data was performed in Matlab® environment and using functions from the Lidar and Point Cloud Processing Toolbox [20].

In addition to the above experimental setup, for the on-site collection of data (i.e. on board a ship), the LiDAR sensor was coupled with a Garmin GPS18x LVC GPS antenna for position and time stamping, and an IMU sensor. However, the latter presented continuous interruptions in data recording. Instead, data from a secondary IMU sensor (namely a MicroStrain® 3DM™-GX5-25 AHRS [21]) were used for the dynamic attitude estimation of the ship. The secondary IMU, as well as a low cost GNSS antenna [22], were mounted at the crow’s nest of the ship, and their data recorded on a secondary laptop running Ubuntu 18.04. Lastly, navigation data (position, speed over ground, heading over ground and satellite time) were recorded from the ship’s own central system.

Device synchronization for the full scale measurements was achieved through satellite timestamps, with an estimated accuracy in the order of few tens of milliseconds. The LiDAR sensor incorporates satellite timestamps to each of the recorded scans at a hardware level. Navigation data includes satellite timestamps by default and was recorded at 1Hz, using interpolation between data points as described in the Methods section. Regarding the IMU, data interpolation was not required since it was set to estimate and record its
A. Laboratory experiments at Aalto Ice Tank

The first experiment was conducted at the Aalto Ice Tank during the northern summer of 2019, with the objective to test the ability of the LiDAR sensor to detect and discern sea-ice, as well as its functional capacity in relatively cold conditions. For this purpose, an ice sheet of 2cm thickness was created in the tank through spraying, with an estimated surface flatness down to the millimetre.

The laser sensor was mounted with its rotation axis (i.e. z-axis) perpendicular to the normal of the horizontal plane at roughly 4.67m above the ice sheet, on the carriage structure above the ice tank (which was kept static during the measurements). The GoPro camera was attached on top of the LiDAR, both of which are depicted in Fig. 2 (left), as well as an example image from the GoPro of the flat ice sheet in Fig. 2 (right). The LiDAR’s rotation rate was set to 10Hz, and the GoPro was set in video recording mode at 4K resolution.

Using the method described in the previous section, a plane was fit to a section of the point cloud, which encloses solely the points belonging to the ice sheet, and for up to 200 scans (i.e. at 10Hz rotation speed, for a duration of 20 seconds). Fig. 3 displays the histogram of the distances from all the points in a single point cloud capture to a fitted plane (assumed to be the ice sheet), as well as their probability density function which models the measurement error of the sensor for ice. Additionally, from this experiment it was determined that the maximum angle of incidence, defined as the angle between a LiDAR’s laser beam vector and the normal of the ice sheet plane, is at most $60^\circ$ for all of the laser beams, while for some of the laser beams it can be as large as $76^\circ$.

B. Sea-ice mapping at the Marginal Ice Zone in Antarctica

For the full-scale experiment case, we recorded the data on board S.A. Agulhas II in the marginal ice zone (MIZ) of Antarctica, during the SCALE2019 expedition between October-November, at roughly $54.5^\circ$ - $59.5^\circ$ South and $0^\circ$ - $24^\circ$ East.

The experimental setup consisted of a custom made enclosure, integrating the LiDAR and its GPS antenna, a failing IMU sensor (not used), and a GoPro camera, all being powered using a DC adapter; while the data recording platform (laptop) was positioned inside a heated room. The LiDAR’s rotation axis (i.e. z-axis) was mounted at an angle with respect to the horizontal plane’s normal (roughly $50^\circ$ for both locations), in order to detect the sides of the freeboard (i.e. floating ice pieces) and following the idea of a “moving ship-based laser profiler”, the sea-ice ought to be scanned as the icebreaker moved through it, effectively creating a 3D-map scan of the sea-ice. Fig. 4 presents the reader with the two installation points of the same experimental setup on the port side shoulder of the ship and the sensors’ individual coordinate frames, as well as a virtual representation of the ice scanning process of a sea-ice floe. The ship’s coordinate frame was set at its centre of buoyancy, estimated using its metacentric data, and set to 55.65 metres from stern forward, midpoint between port to starboard, and 8.79 metres from kiln up. Initially, the planned mounting position of the experimental setup was on top of a mast, at the front-most position on the ship, scanning the ice field in front of the ship (marked as “Ideal Position” in Fig. 4). However, “technical difficulties” (i.e. the captain’s objection) constrained the mounting positions to the two aforementioned.

Fig. 5A and 5B presents two raw, point cloud scans of the ice field and part of the ship structure. In both cases, the ship’s flat deck (green points) is used to estimate the LiDAR’s attitude with respect to the ship’s coordinate frame,
while the translation vector is obtained from the ship’s technical drawings with an expected accuracy in the order of few centimetres.

Next, the previously estimated transformation from LiDAR to Ship coordinates is used together with the data (and transformation matrices) from the IMU and GNSS sensors, to obtain the transformation matrix in (3) to the World coordinate frame. First, a new rotation estimate is obtained from the IMU sensor for each of the point cloud frames, as well as an updated translation vector from the GNSS sensor. Processed data from various sensors is presented in Fig. 6, including the IMU’s attitude estimate (Fig. 6a), instantaneous speed of the ship (Fig. 6b) and final result of a 3D mapped sea-ice field (Fig. 6c). Imagery data from the GoPro camera is included as well in Fig. 6d, as a visual comparison between the environmental conditions being mapped and the end result. In addition, Fig. 7 offers a “side view” comparison from water level, of the same mapped ice field, by using or not using the attitude estimation and correction provided by the IMU sensor.

As introduced in the Methods section, a different approach at mapping a dynamic environment using a multi-beam LiDAR sensor, is by first individually mapping each of the laser scans (thus obtaining 16 point cloud maps in our case). Then, the analysis algorithms may be run either on each of the maps individually or, by using a registration algorithm, on a single point cloud obtained from fusing the individual maps. Fig. 8, presents a visual comparison between a point cloud constructed iteratively using all the laser beams (8A), a point cloud map from a single laser beam (8B) and lastly, a point cloud map resulting from using the ICP registration algorithm to fuse the 16 maps obtained from individual laser beams (8C). A point-to-plane-distance performance metric was chosen to compare all three approaches, where the plane is determined by the vector $[0\ 0\ 1]$ (horizontal plane in World coordinates, located in this case at the same height as the Ship’s coordinate frame). The idea behind this approach is that, given a relatively flat ice field, the distances distribution from all the points in each of the point clouds to the aforementioned plane should be represented by a narrow distribution with a peak roughly located at the height difference between the two planes (i.e. horizontal plane and ice field plane), similar to the results obtained in Fig. 3. The histogram results for the three methods are shown in Fig. 9, with a peak value at $\approx 2$ m for all cases. Lastly, an overall entropy value was calculated for each map in Fig. 8, as described in the methods section, and the results are
Fig. 8. Point cloud ice maps obtained by using data from all laser beams at once (A), compared to using a single laser beam (B), and using the ICP algorithm for registration between the point cloud maps from individual laser beams (C). The elevation differences in the Z-axis direction are emphasized using a color scale from orange (higher) to dark blue (lower) height.

Fig. 9. Performance comparison between the three mapping methods proposed, plot as histograms of all the points’ distances to the horizontal plane.

presented in Table I.

<table>
<thead>
<tr>
<th>Method</th>
<th>Number of points</th>
<th>Entropy value</th>
</tr>
</thead>
<tbody>
<tr>
<td>All laser beams at once</td>
<td>1171999</td>
<td>13.9577026</td>
</tr>
<tr>
<td>Single laser beam</td>
<td>73199</td>
<td>11.1849623</td>
</tr>
<tr>
<td>Registration using ICP</td>
<td>1170542</td>
<td>13.9575815</td>
</tr>
</tbody>
</table>

IV. DISCUSSION

The Discussion section has been divided in two subsections, analogue to the division in the previous section.

A. Laboratory experiments at Aalto Ice Tank

The laboratory experiments, conducted under controlled conditions at the Aalto Ice Tank basin, confirmed the ability of the selected LiDAR sensor to detect sea-ice; at least, to the extent of the type of ice created at the basin (with specific properties such as density, porosity, grain size, crystals shape and orientation) and a minimum thickness of 2cm. From Fig. 3 it can be derived that the sensor has met and even slightly surpassed the manufacturer’s claimed accuracy (±3cm versus the measured ±2.41cm with a confidence of 95%). The most probable explanation for this behaviour is that the manufacturer claims the worst accuracy expected at the maximum range of the sensor. However, during our tests, the LiDAR’s range while mapping ice fell far below its maximum expected range to around 18 metres at a 76° incidence angle (versus the claimed 100 meters maximum range), which we attribute to the reflective nature of the ice sheet (i.e. the laser ray is reflected away from the LiDAR, instead of back). In more recent LiDAR datasheets, the manufacturers claim at least two accuracy levels depending on the distance to the sensor (e.g. for near field and at maximum range), thus an increased accuracy is expected at these shorter distances (not specified in this particular model’s datasheet).

One interesting observation that can be extracted from Fig. 2 (left) and which is replicated in [23], is that at this particular laser wavelength and power levels, the LiDAR does not “see” open water. This implies that it detects only the ice floes (and other objects above surface level, such as other vessels, buoys, piers, etc.), therefore decreasing the complexity of segmenting sea-ice floes (or other objects) among themselves.

B. Sea-ice mapping at the Marginal Ice Zone in Antarctica

The installation locations for the experimental setup, although not ideal, provided us with all the required data to develop a working sea-ice mapping algorithm from on board a ship. In Fig. 4, Location 1 was placed roughly 30 meters above the water level, which provided a substantial scanning distance from the ship, albeit at a lower point cloud density; while Location 2 was placed roughly at 8 meters above the water level and provided a higher point cloud density at the expense of a shorter scanning distance range away from the ship (seemingly due to the same reason which affected the limited distance range in the ice tank scans).

Fig. 6 presents the reader with the mapping results for a sequence of 25 seconds in pancake ice conditions (i.e. small rounded sea-ice floes, of usually less than 3m diameter and with elevated rims). This type of ice conditions was selected since the expected sea-ice floe sizes are smaller than the maximum range of the LiDAR sensor, thus allowing to individually distinguish ice pieces (rather than one continuous, flat ice sheet). While the method outputs encouraging results, it is important to mention that the resulting point cloud does not accurately define the sea-ice floes, but rather in a “blurred” manner. This is because, even though we accurately estimate the LiDAR’s attitude in the world frame, the sea-ice field is not static with respect to
the World frame, and therefore it induces scanning errors. Even at relatively high speeds of the ship, the movement of the ice field is enough to affect the mapping process. The influence of the sea movement can be seen clearly from Fig. 7, where a comparison is made between mapping the sea-ice while compensating for the ship’s attitude changes in World frame, and without compensating. Although the change is subtle, it clearly shows a trend where by using the IMU’s attitude estimate, we obtain a “wavy” map of the sea-ice, in contrast to allowing the LiDAR to rotate influenced by the sea movements, presumably at a similar rate as the ice field (and therefore obtaining a more “flat” ice field map).

Lastly, an experiment was conducted using three distinct mapping approaches to obtain a point cloud of the sea-ice field. The resulting point cloud maps are presented in Fig. 8. Despite the fact that using a single laser beam to map the ice field produces far less dense point clouds (Fig. 8B), at the same time, the results recreate well-defined surfaces in comparison to using all the beams (Fig. 8A) or the point cloud registration algorithm (Fig. 8C). Given that the mapped ice field consists of sea-ice floes of different sizes, but which are expected to have (in this particular case) a flat horizontal surface, a number of peaks are expected to appear in the histogram plot from Fig. 9, which is the case only for the single beam mapping, while the other two methods present a more uniform distribution. Once again, the same result can be seen from Table I, where the entropy value estimate (as a measure of randomness) is considerably lower (i.e. better) when using a single laser beam. At the same time, the entropy value is almost an exact match between the methods of all the laser beams at once, or by creating individual maps from each laser beam and then using the ICP registration algorithm to fuse them together. The latter concludes that the results from both approaches are comparable in the present context, although the registration process is much more computationally expensive; and that a single line scanning LiDAR may suffice for sea-ice field mapping.

V. CONCLUSION

We proposed an automated process for mapping sea-ice using a LiDAR, inertial and satellite navigation systems mounted on board a ship. We are able to create detailed 3D point cloud maps of the sea-ice field, at a local scale, with the proposed sensors and methods. Data were collected both at the Aalto Ice Tank laboratory, as well as on board the icebreaker S.A. Agulhas II during its SCALE2019 spring voyage to the Antarctic Marginal Ice Zone in 2019. Compared to other sea-ice mapping methods using satellite, aerial or underwater data, we propose a cost-effective and easy to integrate solution, to current and future icy waters going (semi-)autonomous ships, which increases their situational awareness level.

Future work should be focused towards increasing the precision of the mapped 3D point cloud by, for example, the inclusion of visual odometry estimates from the camera recording the ice field. This would lock the attitude change of the LiDAR with respect to the motion of the ice field, creating an apparent static ice field. Furthermore, algorithms for information extraction (e.g. ice thickness) from the point cloud need to be added to the main mapping algorithm.

The initial results reveal that our automated process for mapping sea-ice has a great potential in increasing a ship’s situational awareness level, thus helping in the current navigation of ice infested waters by a human crew and, in the near future, enabling the operations of fully autonomous ships. The process can provide highly valuable information to detect and avoid in a preemptive manner in-water hazards for ships navigating in icy waters, such as the detection and avoidance of thick ice, or efficient path planning.

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