Subsea pipeline tracking using a forward-looking imaging sonar for autonomous underwater vehicle

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Key words: AUV, ROS, segmentation, object tracking, imaging sonar

SUMMARY

A worldwide network of subsea pipelines supplies energy to several countries. One associated risk is a pipe rupture on one of the pipelines. Such a scenario leads to the leakage of the transported medium and thus to enormous ecological and economic damage. To prevent this, the pipelines must be regularly monitored and maintained. However, monitoring with a survey vessel involves increased fuel consumption and significant impacts on marine life. To avoid the need for monitoring with a surveying vessel, an autonomous underwater vehicle (AUV) is being developed as part of the research project CIAM (Comprehensive integrated and fully autonomous subsea monitoring). Using various sensors, like a multibeam echo sounder or a sub-bottom profiler, autonomous inspection will be performed. A central task is the automatic detection and tracking of a pipeline. This requires an algorithm that automatically detects the pipeline in the recorded measurements. A major challenge is a limited visibility underwater. In clear water, good results can be achieved with optical systems such as a camera-laser system. In turbid waters, these systems are severely limited. A promising alternative for working in these hard conditions is the use of an imaging sonar, which provides acoustic images. An alignment of this sensor towards the direction of travel even offers the additional advantage that the course of the pipeline is known at an early stage. This can be considered when planning the further route. Using acquired data sets of a forward-looking sonar, a promising approach is developed to identify a pipeline in imaging sonar measurements. The concept underlying this approach assumes that a pipeline represents an elongated, contiguous set of points. Selected segmentation algorithms and a following geometric analysis of all remaining features reliably filter out these objects. Subsequent comparison with the approximated nominal pipeline size detects point clusters that have a high probability of representing a pipeline. Based on the developed concept, an algorithm is implemented and tested in the robot operating system (ROS). The algorithm continuously and reliably detects a pipeline in imaging sonar observations.

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1. Introduction

Subsea pipelines transport large quantities of gas, oil, and other resources continuously over long distances. Compared to other transportation methods, the use of pipelines is associated with lower emissions and costs (Atteridge & Lloyd, 2019). Moreover, subsea pipelines are very reliable and safe, as they are protected against weather conditions. However, there are also drawbacks related to the use of subsea pipelines. The costs of laying and maintaining these pipelines are very high (Götz, 2004). Furthermore, leaks in the pipelines cause significant economic and environmental damage if they are not detected and repaired in time (Umweltbundesamt, 2022). The operation of pipelines therefore requires comprehensive inspection and maintenance to ensure that potential environmental impacts are minimized.

Traditional inspection methods rely on large survey ships, which require significant fuel consumption and have a potential negative impact on the underwater environment. To mitigate these impacts, the research project CIAM (Comprehensive Integrated And Fully Autonomous Subsea Monitoring) is developing an autonomous underwater vehicle (AUV). This AUV will be equipped with various sensors and will perform an autonomous inspection of pipelines (shown in figure 1). Using an AUV has the advantage that the sensor platform operates closer to the pipeline and thus measures it more accurately. Additionally, the sound penetrating water column is reduced and therefore the impact on marine wildlife.

An important factor in the development of efficient AUVs for pipeline inspection is the ability to automatically detect and track pipelines (Kraft, 2022). However, this is a major challenge due to poor visibility and complex conditions that prevail in many underwater environments. While optical systems such as camera-laser combinations can work well in clear waters, they are often inadequate in more challenging conditions and areas of poor water quality. A promising complement is the use of an imaging sonar sensor that can provide acoustic images of the environment. By using acoustic sensors, accurate results are obtained in both clear and turbid waters. An imaging sonar has a key advantage over other acoustic sensors such as multibeam echo sounders, singlebeam echo sounders, or sub-bottom profilers: it can be directed forward in the direction of travel. As a result, it detects the pipeline's path several meters ahead, which helps optimize the AUV's route planning. This method offers substantial cost and time savings by enabling the AUV to navigate around obstacles more effectively and avoid unnecessary diversions.

In this paper, an algorithmic approach integrated into the Robot Operating System (ROS) is presented for the automatic detection of pipelines in forward-looking imaging sonar data.

The approach is evaluated on real test data, where a pipeline was surveyed with an AUV. To filter out the pipeline from the imaging sonar measurements, the data is preprocessed in the first step. Here, a method was developed to filter out the important measurement area. Meaning, the area in the data that contains the seafloor and thus a possible pipeline. Segmentation algorithms filter out all point clusters from the remaining point cloud, which are potential objects detected by the imaging sonar. A subsequent RANSAC algorithm, which takes the approximated target width of the pipeline into account, allows reliable detection of the pipeline.

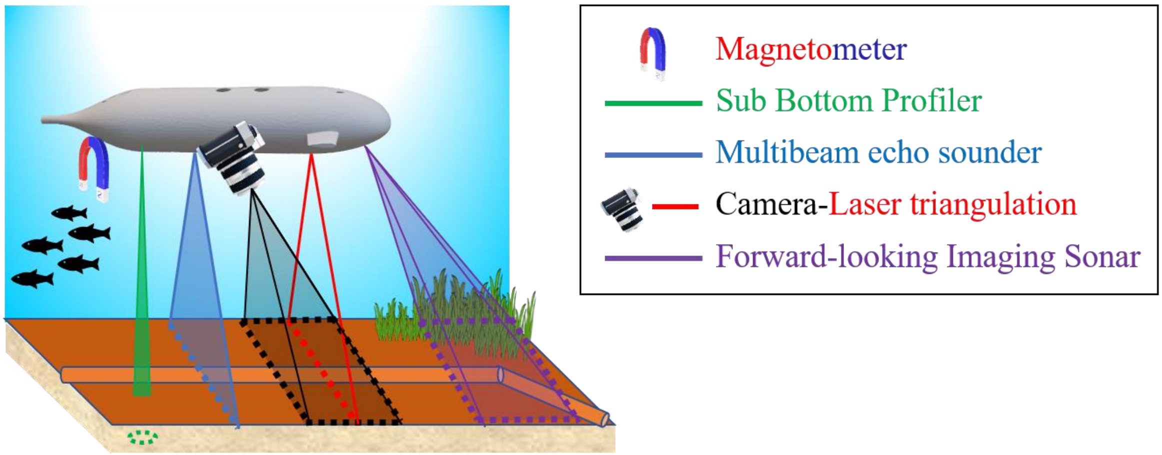


Figure 1: Schematic representation of the various sensor options that can be installed on an autonomous underwater vehicle to enable automatic identification of pipelines in its environment.

2. Data acquisition

To record test data from a pipeline and to implement and evaluate algorithms, a forward-looking imaging sonar was installed on a test platform. Section 2.1 first describes the functionality and characteristics of the installed imaging sonar. Then, section 2.2 describes the acquisition of data in a real test environment.

2.1. Imaging Sonar

In many cases, the area where the pipeline needs to be inspected and positioned is not accessible to natural light. In addition, visibility in subsea areas may be further limited by solvents and suspended solids, even when powerful light sources are used. Therefore, sonar measurements are suitable for surveying in these challenging conditions for monitoring the pipeline state. An imaging sonar aligned ahead in the direction of travel offers an additional advantage: it enables the pipeline’s path in the AUV’s future route to be determined. This can lead to more efficient and time-saving route planning.

To survey the underwater environment, an imaging sonar emits a horizontal fan of high-frequency beams, typically in the range of 600-800 kHz, to the water column. This fan is constructed as shown in figure 2 a and consists of a certain number of beams. Each of these beams has a certain number of bins that continuously record measurements of the reflected signal (shown in figure 2 a). The Tritech Gemini 720is imaging sonar, used for this project and installed on the AUV, has 512 beams and 6032 individual intensity measurements within one beam (Tritech, 2021).

Using the additional measured sound velocity sv and the times of the individual measurements t_i, the range r_i from the sensor to the object can be calculated:

$$r_i = sv \cdot t_i$$

To calculate the x and y coordinates in the image plane, the azimuth angle θ of the respective beam (shown in figure 2 a) and the following formula is used (Hurtos et al., 2012):

$$\boldsymbol{P_i} = \begin{bmatrix} x_s \\ y_s \end{bmatrix} = \begin{bmatrix} r_i \cdot \cos\theta \\ r_i \cdot \sin\theta \end{bmatrix}$$

The z coordinate depends on the elevation angle ϕ, which cannot be measured directly by the imaging sonar (shown in figure 2 b). The only known is the vertical aperture angle for the imaging sonar, which is 20°. To obtain a value for the z-coordinate for the detected points, the measured intensity is used as an approximation for the z-coordinate.

In the following paper, a bin, as circled in orange in figure 2 a & b, is meant to be a complete semicircle in the data. A frame refers to the entirety of a measurement of the 6032 bins. These frames are recorded differently often depending on the set measuring frequency.
It is also worth noting that the output values from the sonar are analyzed by a node running on the ROS core of the AUV.

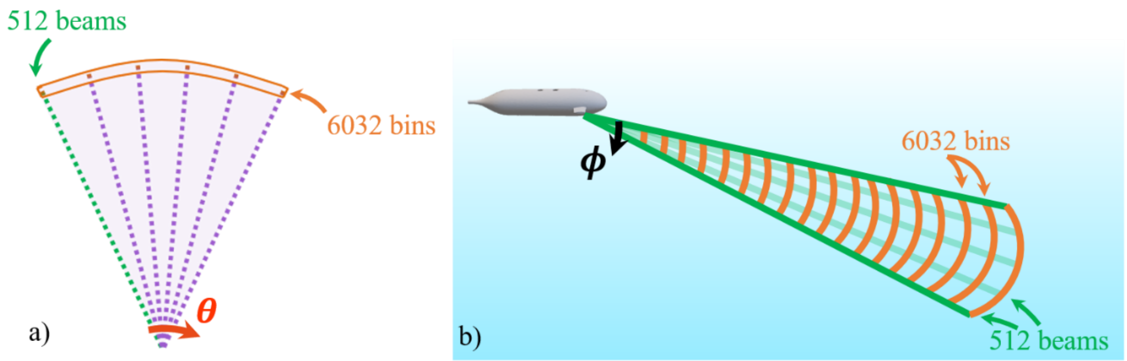


Figure 2: a) Structure of the result of a measurement with an imaging sonar. The instrument used, the Tritech Gemini 720is, has 512 beams and 6032 bins. The angle is the azimuth angle θ, which provides information about the direction of the measurement beams. b) The schematic illustration shows an imaging sonar measurement from the side. The elevation angle ϕ gives information about the vertical position of the measurement relative to the horizontal of the sensor. Theoretically, the angle indicates where the object is located in the Z-plane of the local coordinate system. However, since this cannot be measured directly by the imaging sonar, the z coordinate is approximated.

2.2. Acquired test data

A pipeline mock-up was submerged in a reservoir to obtain data from an underwater pipeline. This mock-up consists of 8 separate components, each with a diameter of 219 mm, and has the shape of a closed octagonal ring with a diameter of 40 meters. This structure was observed with a test platform equipped with many sensors. Among them are the imaging sonar described in section 2.1 and an inertial navigation system for positioning. The test platform has traveled underwater at an approximate distance of 2.3 m above the pipeline (Smith et al., 2022).

The survey, conducted with imaging sonar, provided data that included not only the pipeline but also individual rocks in the reservoir. This data was stored in a rosbag format that allows easy reproduction of the survey process and feeding of the data into various algorithms, even after the initial survey (Linzer et al., 2022).

3. Automatic identification of pipelines using an imaging sonar

The concept is based on the assumption that a pipeline is represented as a linear, uninterrupted array of connected points in the point clouds. The process of detecting these objects is divided into three steps. First, the raw data is preprocessed to reduce measurement noise (see section 3.1). Then, selected segmentation algorithms filter out all contiguous point clusters from the resulting data (see section 3.2). Finally, a geometric analysis is performed to sort out clusters that have a high probability of corresponding to a pipeline (see section 3.3).

3.1. Reduction of measurement noise

To increase the performance of the pipeline identification, two automatic preprocessing steps are performed to reduce the data volume and remove unnecessary measurements. The first step involves identifying the essential measurement area and cutting off the other areas. The essential area comprises the bins highlighted in green in figure 3, which contain measurements providing information about the seafloor and any pipelines that run there. The bins highlighted in orange represent the area between the sensor and the seafloor that is not required to find pipelines. The purple area corresponds to the missing signal because all of the signal has already been reflected off the bottom, resulting in measurement noise. These areas are also visible in the real measurement shown in figure 4. For real-time data processing and navigational purposes, it is intended to filter out the essential measurement area automatically.

An automated filtering method has been developed based on analyzing the standard deviation of the individual bins. The method assumes that the standard deviation in the area between the sensor and the seafloor is low due to the lack of reflections, while the standard deviation in the back area (i.e., measurements into the ground) is high due to the absence of reflections and the sensor gain noise. Figure 5 a shows the standard deviations for the measurement frame from figure 4 for each of the 6032 bins. The first area between the sensor and the seabed is well identifiable because the standard deviation there is almost zero. The back area where the measurements into the bottom take place is also well identifiable because there are very high outliers in the seafloor reflection, followed by very high standard deviations that remain in a similar range and are considered measurements in the ground.

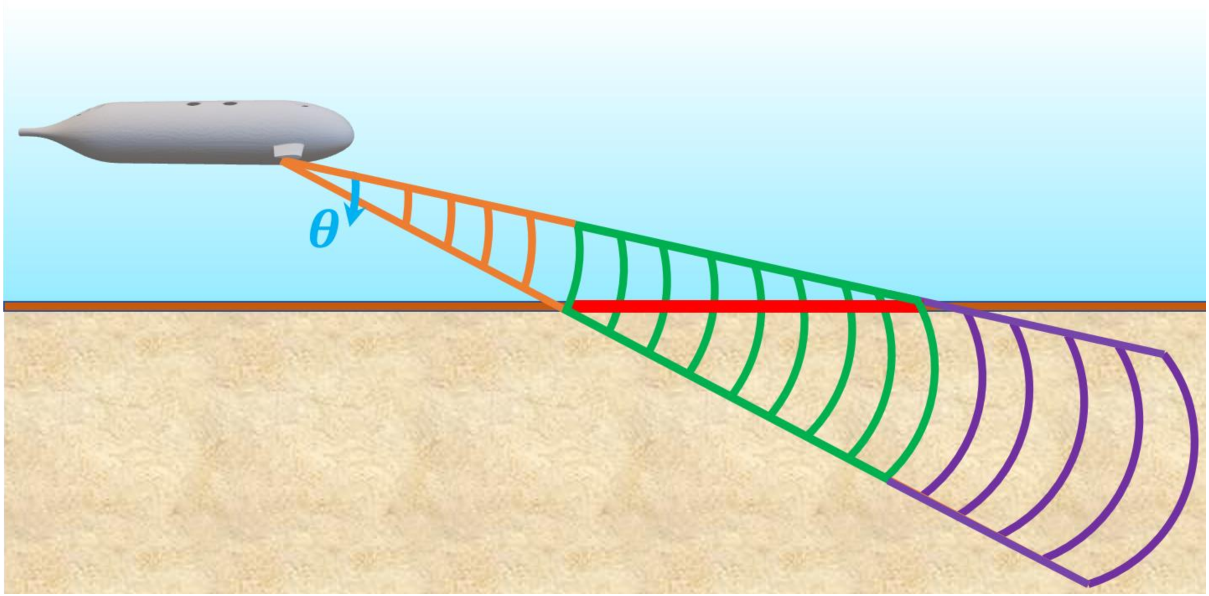


Figure 3: This schematic shows a side view of a measurement taken with an imaging sonar aimed at the seabed. The orange bins do not contain any crucial information for detecting pipelines, while the green bins represent the important measurement area that includes information about the seafloor and potential pipelines located there. For the purple area, the entire signal has already been reflected away from the seafloor, making accurate measurements impossible.

To filter out these two areas with an algorithm, a Savitzky-Golay filter of order 2 is applied to the calculated standard deviations (Savitzky & Golay, 1964). This helps isolate the two regions of interest. To filter the front region, a static threshold is utilized. The standard deviation is checked from the first bin to determine at which point it becomes greater than zero. To filter the back region, the peak value of the Savitzky-Golay filter is employed (shown in figure 5 b). The peak value results from the point distribution in the posterior region, which has a receptive trend and a linear progression afterward. This approach has proven successful after visual inspection, and all subsequent bins are filtered out. Figure 6 a illustrates the results of the automatic filtering.

In the second preprocessing step, points with low information are eliminated by setting an intensity value based on experience as a threshold. All points with a lower value are removed (shown in figure 6 b). This step decisively reduces the point set, which not only speeds up but also simplifies the search for pipelines.

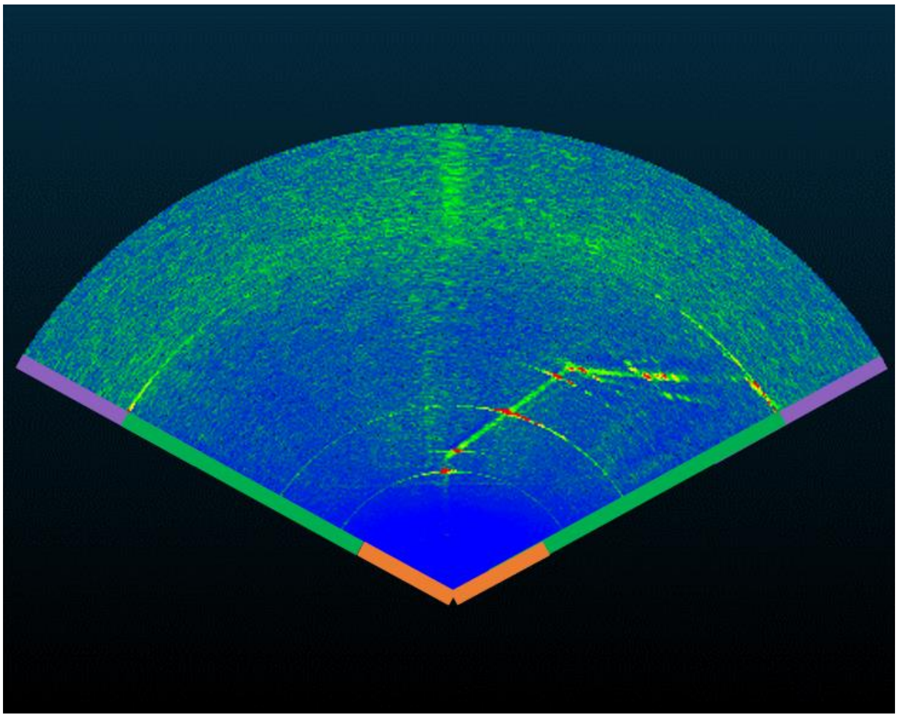


Figure 4: A measurement from an imaging sonar. In addition to the pipeline, the three areas are also visible. These are marked on the sloping sides of the measurement with the respective colors. The green area represents the measurement of the sea bottom, while the orange area indicates the space between the sensor and the sea floor. The purple area represents the theoretical measurement of the ground, which cannot be directly measured due to the non-penetrating signal.

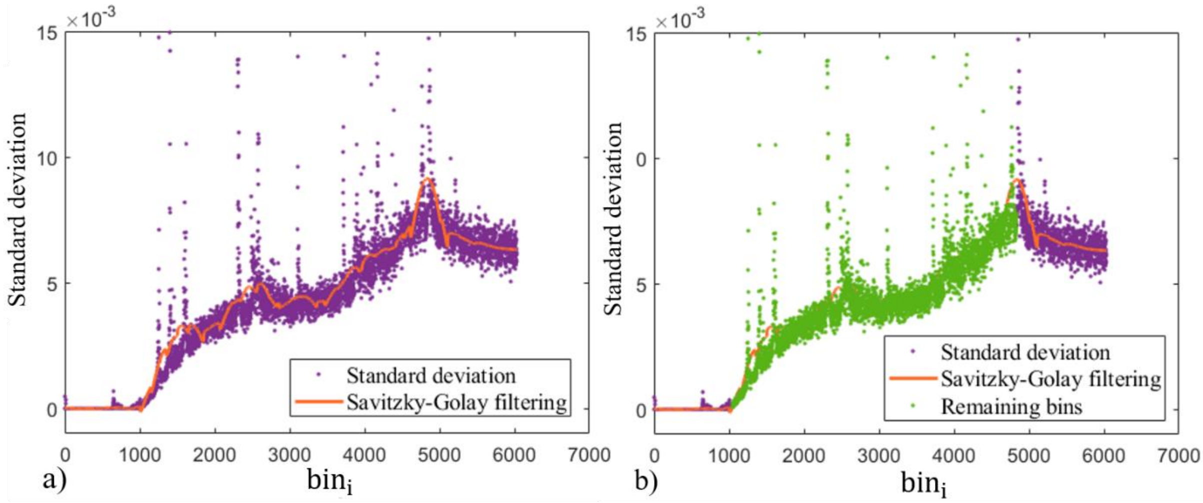
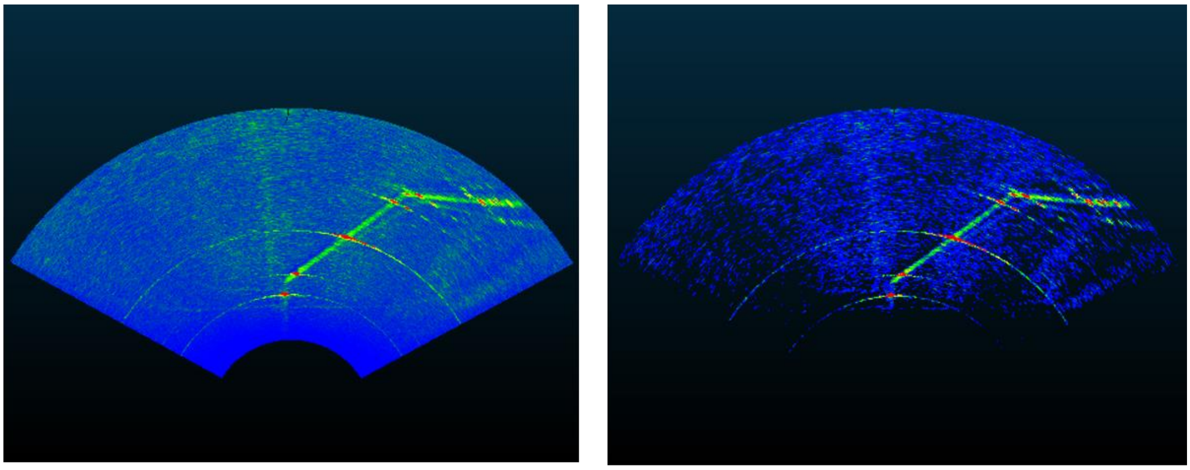


Figure 5: a) The standard deviation calculated for each of the 6032 bins, together with the result of the Savitzky-Golay filtering of order 2. b) Marked in green are the bins determined by the algorithm, which represent the ground measurements.



a) b)

Figure 6: a) Point cloud with ground measurements, where irrelevant areas were automatically filtered out using the standard deviation of the bins and the elaborated method. b) Point cloud after filtering out points with low measured intensity.

3.2. Segmentation of point clusters

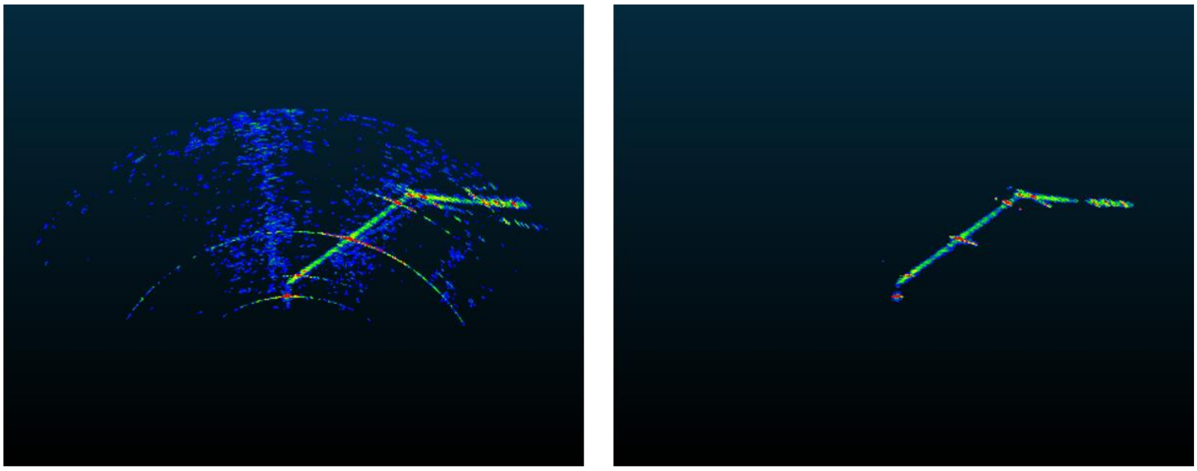
After the point cloud dataset has been automatically and appropriate reduced, the goal of segmentation is to identify and extract objects that could potentially represent a pipeline. This process involves searching for all contiguous point clusters within the dataset and then discarding any small point clusters that are unlikely to correspond to a pipeline.

Different segmentation algorithms were tested with the datasets and evaluated visually. The evaluation involved comparing the performance of various algorithms in terms of their ability to correctly segment and extract objects that resembled pipelines.

The combination of two specific algorithms - the statistical outlier removal filter and the radius outlier removal filter - produced the most promising results. The statistical outlier removal filter identifies and removes points that are considered outliers based on their statistical distribution within the dataset (Balta et al., 2018). This filter is also effective in imaging sonar measurements, as shown in Figure 7 a.

The radius outlier removal filter eliminates data points that do not have enough neighboring points within a specified radius (Prio et al., 2022). This method is particularly useful in removing small clusters of data points, which can be difficult to reliably detect as indicating the presence of a pipeline. By applying the radius outlier removal filter, these small clusters of data points can be removed, reducing noise in the data and facilitating the detection of pipelines and other patterns in the measurement (shown in figure 7 b).

By applying this specific combination of filters, it is possible to further reduce the size of the data set without eliminating any objects that could potentially be pipelines. This approach allows for a more refined data selection process, ensuring that all relevant data is retained while still achieving a significant size reduction.



a) b)

Figure 7: a) Point cloud after filtering out the essential measurement area and applying a statistical outlier removal filter. b) Point cloud after filtering out the essential measurement area and applying a statistical outlier removal filter and additionally a radius outlier removal filter.

3.3. Geometric analysis to determine the pipeline

To locate a pipeline within a point cloud and determine its orientation, a geometric analysis of all remaining point clusters is performed. This analysis is based on the assumption that a pipeline appears as an elongated, contiguous cluster of points in forward-looking imaging sonar measurements. Therefore, the algorithm searches only for elongated objects and discards the rest.

To ensure reliability, the algorithm searches for objects with a specific target width. This target width is estimated using the known diameter of a pipeline and the height above the ground of the AUV. The height above ground could be determined with a DVL, which measures the velocity of the AUV relative to the seafloor. The determined target width is used as input in a RANSAC algorithm to find the best possible line in the data (Fischler & Bolles, 1981).

The RANSAC algorithm randomly selects a subset of points in the point cloud, fits a line to them, and then checks how many points are within the pipeline's approximated target width. This process is repeated several times to obtain the best possible line based on the target width. If the best point cluster has more than 600 points, which indicates that it is not a small object, it is extracted as a pipeline candidate (shown in figure 8 a).

Based on the direction of the line and the starting point of the point cluster, the location and orientation of an object that is most likely a pipeline can be determined. The RANSAC algorithm is then repeated to determine if a pipeline segment is still present in the data (see Figure 8 b). This is particularly useful when a branch of a pipeline occurs and is essential for efficient route planning.

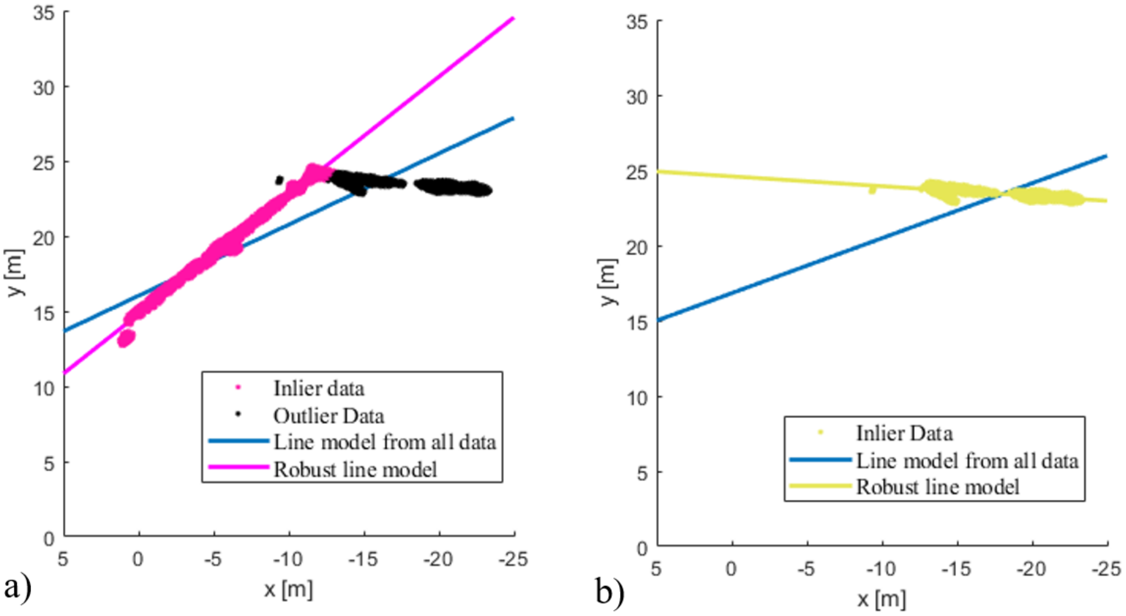
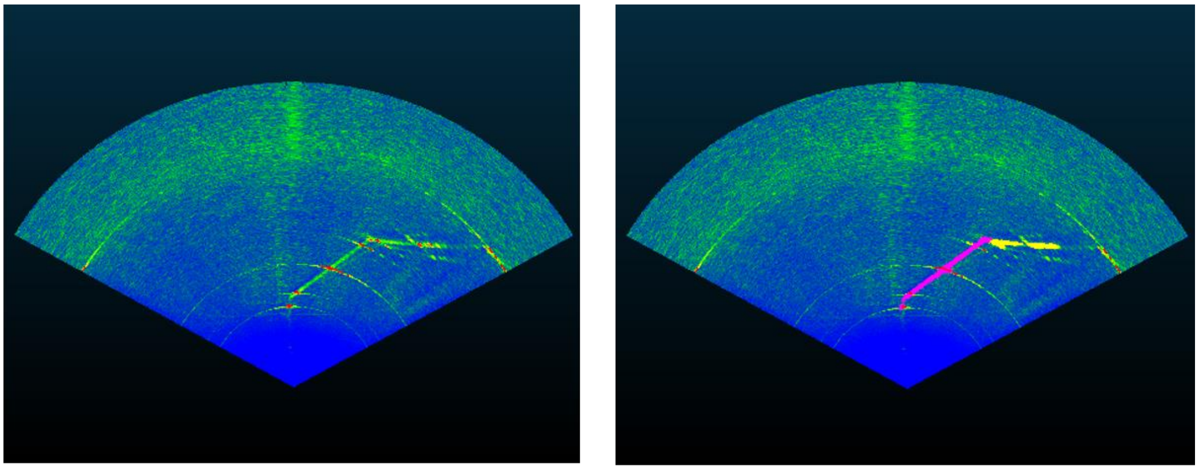


Figure 8: a) The pink line represents the line identified by RANSAC as the best fit, where the majority of the points (marked in pink) are within the specified width. All points outside this range, represented by black dots, are not selected by the algorithm. The blue line represents the result of a line fitting using the least squares method. b) After excluding the best result from the first run, the RANSAC algorithm was recalculated. The new result is now represented by the yellow line and the yellow points.

4. Results

Section 3 presented a method for automatically filtering a pipeline in imaging sonar data. The performance of this approach will be evaluated using a variety of measurement data.

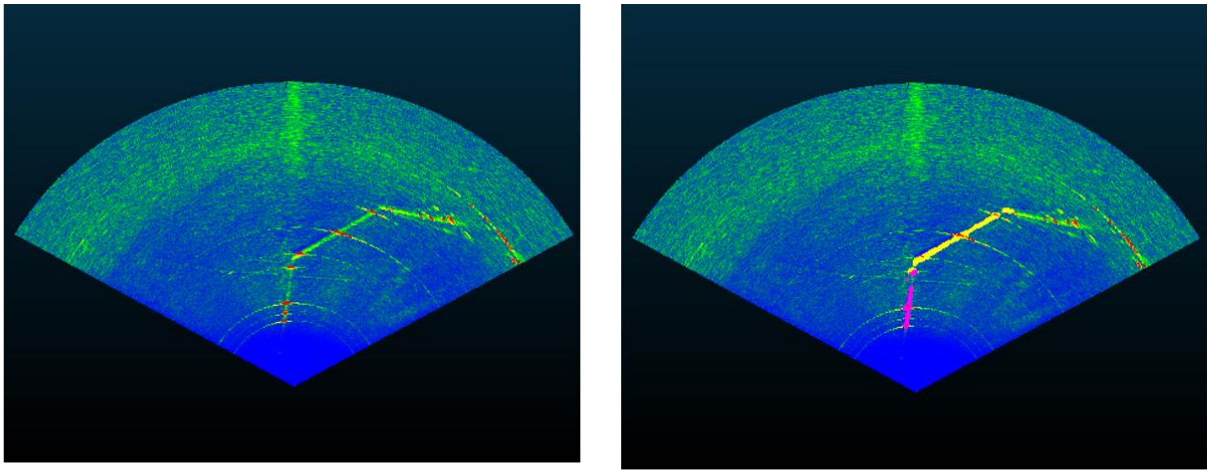
Figure 9 a shows an imaging sonar measurement in which a pipeline with a branch is included, while Figure 9 b illustrates the result obtained by the algorithm. Despite strong measurement noise and additional lines, the algorithm was able to detect both pipeline segments reliably. This demonstrates the success of the preprocessing, which includes noise reduction, and the subsequent RANSAC algorithm using input parameters, such as the approximate target width of the pipeline. By detecting both segments, the AUV can follow the pipeline and prepare for the upcoming change in the pipeline direction.



a) b)

Figure 9: a) Measurement of the seafloor with a pipeline using imaging sonar. b) The pink and yellow highlighted points are respectively segments that were successfully detected as a pipeline by the developed algorithm.

Figure 10 a shows an imaging sonar measurement that includes a pipeline with two branches. As can be seen in Figure 10 b, only one branch was detected, which is consistent with the reliability criteria of the algorithm. In the test data set, an octagonal pipeline mock-up was surveyed, as described in Section 2.2. However, it is uncommon for real offshore pipelines to have many branches in succession. Therefore, the algorithm was concluded to identify only a maximum of two pipeline segments and consequently just one branch. Furthermore, the information about the direction of the next two pipeline segments is sufficient to be considered for the route planning of the AUV.

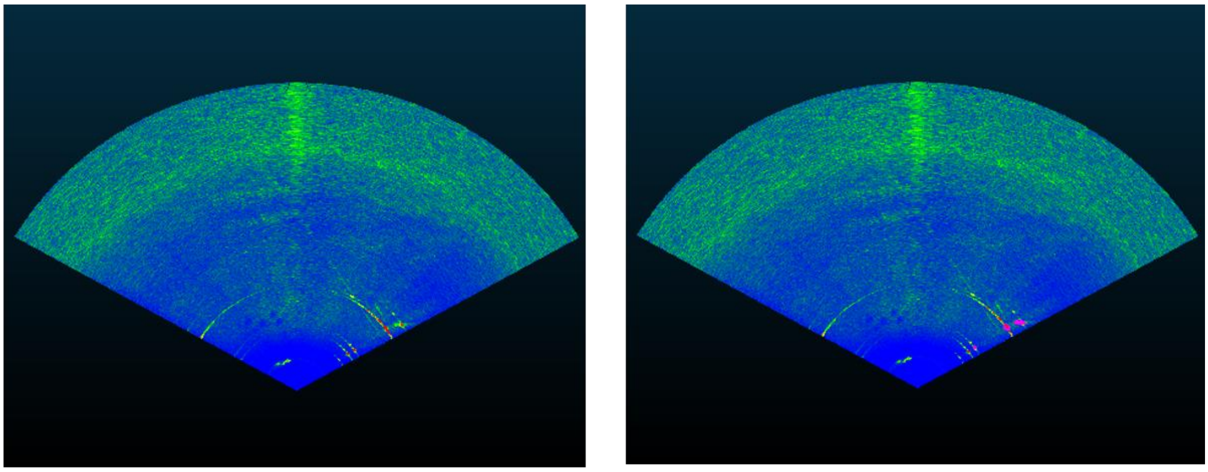


a) b)

Figure 10: a) Measurement of the seabed on which a pipeline with two branches runs, using imaging sonar. b) The pink and yellow highlighted points are the first two segments that were automatically detected by the algorithm.

Figure 11 a shows a measurement where no obvious pipeline is visible. However, a potential pipeline candidate has been identified (shown in figure 11 b). This segment still meets the requirements of the developed algorithm. It is an elongated cluster of points with enough points within the approximate nominal diameter of a pipeline.

Detecting potential pipeline candidates when no obvious pipeline is present helps find pipelines that are not currently being tracked. The AUV can investigate the segment further by heading in that direction to confirm if it is a pipeline. This will give the AUV additional clues to conduct a more detailed investigation and potentially discover a pipeline.



a) b)

Figure 11: a) Measurement of the seafloor without a pipeline. b) A possible pipeline segment was detected in pink. If a pipeline is searched for by the AUV, the segment can be investigated further by steering the AUV in the direction of the segment.

In the rest of the dataset, the pipeline was also confidently detected in real-time. The algorithm identified the points belonging to a pipeline and the location and orientation of the pipeline within the imaging sonar survey could be determined.

5. Conclusion

Monitoring existing subsea pipelines is extremely important given the enormous climate damage that can be caused by pipe ruptures. To reduce the impact on the underwater environment and ensure efficient surveying, the development, and deployment of an autonomous underwater vehicle (AUV) is a valuable solution. The use of an AUV minimizes CO2 emissions and impacts on marine life by reducing the water column that must be sonicated. It can also be deployed in all weather conditions, eliminating the need for hydrographers to go out to sea, which increases work safety.

To ensure the latter, the AUV must monitor the underwater pipelines completely autonomously. One step towards full autonomy is to automatically identify the pipeline in the measurements.

This paper presents an approach to reliably and efficiently track pipelines by using data from a forward-looking imaging sonar. For this purpose, a pipeline mock-up was sunk in a storage basin and surveyed by a test platform equipped with the Gemini 720is imaging sonar and other sensors.

The presented method provided promising results in test data sets and can continuously and reliably detect pipelines in real-time using forward-looking imaging sonar measurements. The algorithm is based on the assumption that a pipeline is an elongated, contiguous set of points in the point cloud. To automatically filter out these objects, the data set was first reduced to include only the seafloor and possible objects on it. In order to filter out this important range of measurements, a method was developed using the standard deviation of the bins. By combining two selected segmentation algorithms, the statistical outlier removal filter and the radius outlier removal filter, all single points and small groups of points are then removed. This ensures that only large point clusters are included in the remaining point cloud. This is necessary because small point clusters are not sufficient to reliably determine whether it is a pipeline.

In the final step, the remaining point clusters are geometrically analyzed and checked if a pipeline is present. For this purpose, the nominal diameter of a pipeline was used as a parameter for a RANSAC algorithm. Using the RANSAC algorithm with the defined input parameters, it is possible to filter out objects from the remaining point clusters that have a high probability of being a pipeline. The estimated line can also be used to determine the position and orientation of the pipeline, making it useful for navigation (Schild, 2022).

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BIOGRAPHICAL NOTES

After obtaining his master's degree in geodesy and geoinformatics from the Leibniz University of Hannover, Niklas-Maximilian SCHILD began working as a research assistant at HafenCity University Hamburg in 2021. Currently, he is involved in a research project focused on the development of an autonomous underwater vehicle.

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