Building a platform for testing underwater navigation based on environmental sensor data

Lukas KLATT and Markus KRAFT and Harald STERNBERG, Germany

Key words: AUV, autonomy, hydrography, pipeline inspections, positioning

SUMMARY

Autonomous underwater vehicles (AUVs) holds a significant promise for hydrography and deep-sea exploration. The CIAM research project (Comprehensive Integrated and Fully Autonomous Subsea Monitoring), funded by the German Ministry of Economy, is dedicated to developing various AUVs for monitoring critical infrastructure, particularly deep-sea pipelines. These vehicles are equipped with a range of acoustic and optical sensors to monitor pipeline conditions, enabling the detection of damages and leaks. Employing a port-to-port concept allows for additional cost savings by directly following the pipeline without the need for a mothership. Traditionally, AUV navigation leans on inertial navigation, but to enhance long-term stability, updates are incorporated from a surface accompanying leading vessel or a network of installed underwater beacons providing extrinsic pose estimation through acoustic modems. However, this method is considered costly and under certain circumstances less robust due to expensive technology and the challenges posed by error-prone acoustic communication technology. With the CIAM project it is investigated how sensors actually intended for monitoring pipelines can be used to support inertial navigation. The research in this paper focuses on the development of an Extended Kalman Filter (EKF) integrating Inertial Navigation System (INS) sensor data for navigation using a-priori knowledge as well as visual and acoustic odometric methods. Recognizing the expensive and labor-intensive nature of underwater testing, a test platform has been created to evaluate these algorithms on land, utilizing sensors with specifically transferable characteristics to underwater environment. This platform includes a camera-based solution capable of identifying continuous features and computing velocity. Identified landmarks by the camera serve as references for updating the position estimation; potentially involving unmistakable geometries, labels, or purposefully placed markers, providing distinctive references with absolute coordinates to reinforce inertial navigation. Utilizing a line-laser-camera triangulation scanner, the study reconstructs the point cloud that is generated underwater with a multibeam echosounder carried by an AUV. The analysis of this point cloud occurs a few seconds after data capture, introducing temporal discontinuity, which aids the pose estimation in a closed-loop or cascaded EKF. This approach develops the possibility of guaranteeing not only precision but above all robustness. It further aims to improve navigation accuracy in challenging underwater environments and forms a basis for further advancements in this field.

Building a platform for testing underwater navigation based on environmental sensor data

Lukas KLATT and Markus KRAFT and Harald STERNBERG, Germany

Key words: AUV, autonomy, hydrography, pipeline inspections, positioning

1. INTRODUCTION

In recent years unmanned hydrographic systems have increasingly been used to monitor pipelines, which as supply lines are part of the critical infrastructure. The autonomous deployment allows for savings in personnel, an improved data basis, and a reduction in costs. Applying a port-to-port concept, further costs can be saved by following the pipeline. Conventionally, the navigation of Autonomous Underwater Vehicles (AUVs) has been based on inertial navigation. To ensure the reliability it can be coupled with updates from the accompanying escort vessel via an Ultashort Base Length modem (USBL) or an array of installed underwater antennas that provide extrinsic pose estimation via Long Base Length (LBL). This methodology can be considered expensive and not robust due to the high value inertial sensor technology and the challenging and error-prone acoustic communication technique. To address this issue the objective of this paper is developing an improved navigation concept with extrinsic sensors to ensure the collected data to be geo-referenced and a robust control of the AUV. For monitoring the pipelines, the versatile sensors are used to generate 3D models of the pipeline. In addition to the actual data evaluation and damage recognition in postprocessing, the methods for mapping the environment are also applicable for odometry, SLAM-based navigation and mission planning control. Hence, in the context of this paper, alternative concepts for navigation solutions are elaborated that use the detection of features in the AUVs operational environment to support the dead reckoning and bound the uncertainty. For this purpose, methods of environment representation are used by evaluating sensor data via machine learning and deterministic analysis to detect features. Possibly, this algorithmic improvement facilitates the replacement of the common and high-quality FOG inertial systems with lower-cost MEMS inertial systems.

This paper describes the possibilities of increasing the autonomy of an AUV through environment-based navigation and thus increasing the economic efficiency of AUV missions. For this purpose, the development of a test platform is described, which realizes the development of environment-based navigation in a less challenging environment then the deep sea.

2. MOTIVATION AND TECHNICAL CHALLENGE

The transportation of gaseous and liquid media by pipeline is an efficient solution that is much safer than by truck, ship or train. However, the consequences of an accident are dramatic. The damage to people and the environment is dramatic with long-term consequences. Faulty pipelines can occur intentionally or as a result of age-related processes; the causes are many and varied (see Figure 1: Sources of pipeline failure (Adegboye et al., 2019)). It is therefore virtually impossible to completely prevent accidents. However, comprehensive monitoring allows any damage or sabotage attempts to be detected in short time and countermeasures to be initiated (Adegboye et al., 2019).

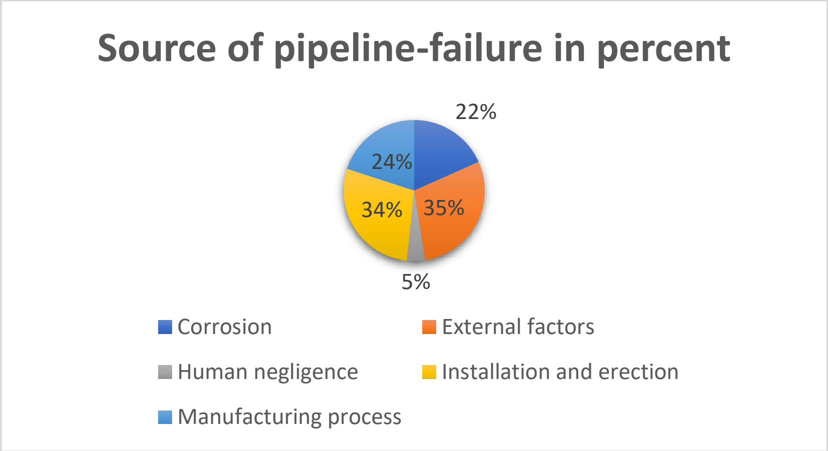


Figure 1: Sources of pipeline failure (Adegboye et al., 2019)

For deep-sea pipelines, so-called pigs are used alongside stationary methods to inspect the pipeline from the inside. Various hydrographic, acoustic and optical methods are used for external inspections.

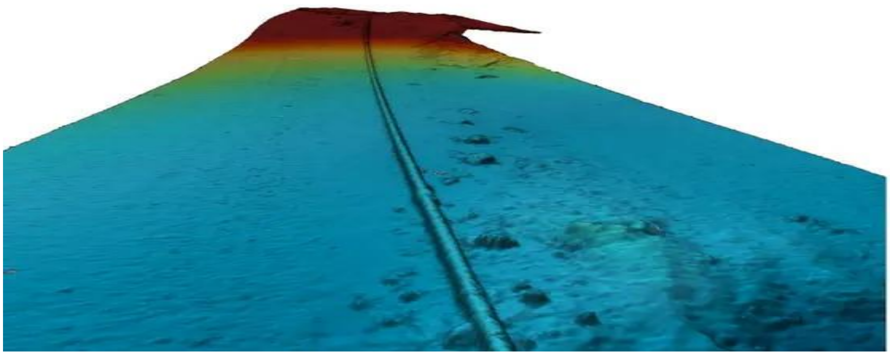


Figure 2: Bathymetrie-Plot of a pipeline, surveyed with a HUGIN AUV from Kongsberg (Offshore Engineer, 2018)

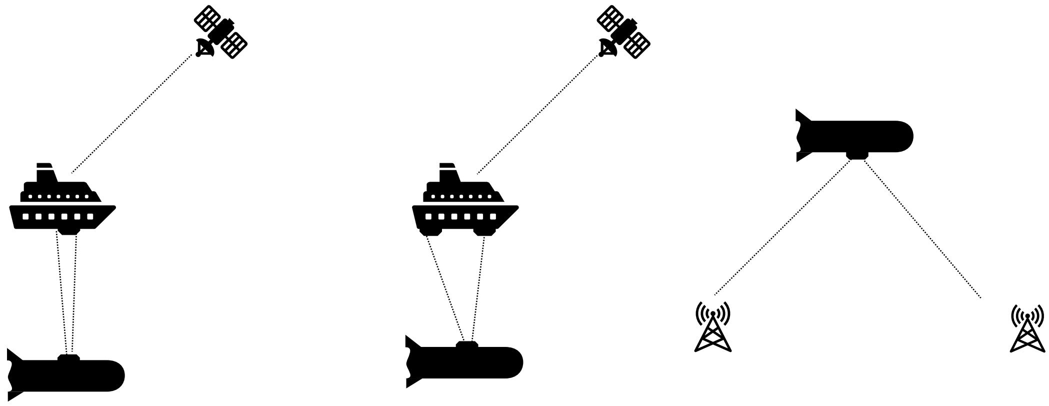
Traditional these inspections methods rely on large survey ships, which require significant fuel consumption and have a potential negative impact on the underwater environment. To mitigate these impacts, the research project CIAM (Comprehensive Integrated And Fully Autonomous Subsea Monitoring) is developing an autonomous underwater vehicle (AUV). This AUV will be equipped with various sensors and will perform an autonomous inspection of pipelines. 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 (Schild 2023).

ROVs (remote operating vehicles) have proven themselves capable as unmanned underwater robots. With a cable connection to a mother ship, they can carry out small-scale investigations and be controlled from there via a haptic control system. In recent years, autonomous underwater vehicles have increasingly been used to monitor pipelines on a large scale. The idea is that autonomy can save human resources and therefore costs. In recent years, the evaluation of AUV-borne sensors and damage identification has made great progress (Adegboye et al., 2019).

Navigation is a central component of an AUV. On the one hand, it serves to georeference the collected data. On the other hand, it is used for safe control in the underwater environment. One particular challenge is the inability to use GNSS, as electromagnetic signals cannot be transported through the water column. One possibility for underwater communication is via light signals, but this is severely limited in terms of range.

Acoustic signals are commonly used for communication with AUVs. However, they also have certain shortcomings, such as a narrow bandwidth and the associated low data rate. The high latency due to a low transport speed and high variability due to density differences in the water column also create a certain amount of uncertainty when communicating with acoustic signals. Nevertheless, acoustic signals via ultra-short baseline (USBL), short baseline (SBL) and long baseline beacons (LBL) are of central importance in the navigation of AUVs if longer mission times are to be achieved (Paull et al., 2018).

Inertial measurement units that provide dead reckoning are used as the backbone of navigation. The extension with a barometer provides a robust absolute determination of the water depth. Doppler velocity loggers are a common addition, which provides a further determination of the speed over the bottom of the water when the acoustic signal is connected. Successful sensor data fusion from these sources can also be used to cap to a linear error instead of a quadratic error. Depending on the cost class of the AUVs, MEMS and FOG IMUs are used. Due to the drifts that are common in dead reckoning and the technical characteristics of IMU technology, the commercial solutions sometimes differ significantly in their error over time, which range between 0.04% and 10 % in relation to their traveled distance without any external support.



SBL

USBL LBL

Figure 3: Acoustic communication to support navigation

In order to reduce this error propagation, the navigation is supported by acoustic signals during surveys with AUVs. USBL or SBL can be used for referencing to a GNSS-referenced mother ship. Other mobile underwater systems can also reference each other in this way. Stationary acoustic transmitters, so-called LBL beacons, can provide spatially limited support for the AUV, bounded by the acoustic range. Due to the high latency, this support is often included in the state estimation in the prediction, while the acoustic measurements are included in the updates (Paull et al., 2018). Even if robust navigation solutions are commercially available in the long term, they have the major disadvantage that they either require the installation of LBL beacons or need to be accompanied by a mother ship, which requires personnel and investment. The use of an autonomous surface vehicle is economically more favorable, but still costly.

3. Concepts for environmental based navigation

There are various approaches to using the environment for navigation. Similar to how humans can orient themselves to the environment. These can be individual features that are either available as a priori and provide the information. In urban areas, for example, these are landmarks such as well-known buildings or installations. In unfamiliar places, people use road or traffic signs to determine their own position. The environment is also used for small-scale location determination. These are, for example, continuous features such as traffic beacons on the highway or steps when climbing the church tower to determine the height. In places where people regularly pass, a map is built up using the geometric knowledge gained from the human sensorium. This map helps you to determine your own position.

3.1 Visual Odometry

Visual odometry is an important methodology in computer vision and is used in navigation and obstacle avoidance. It supports the robot's own state estimation, especially in areas where satellite-based fixed-point navigation is limited. By detecting features and the relative change in position or orientation of the robot. The features can be individual objects or, via Structure from Motion, almost the entire scenery to determine the robot's own state (Nister et al., 2004). In conventional AUV navigation, the DVL provides an odometry of the speed to the bottom of the water as well as the determination of surge, sway and heave. For this purpose, 4 pulses are usually emitted, which then determine the speed over the bottom and the current velocity by determining the Doppler effect (Paull et al., 2018). The DVL is the standard sensor for AUV navigation and provides a relative speed measurement. For this reason, it will not be considered further in this paper.

3.2 SLAM

Simultaneous Localization and Mapping (SLAM) refer to the process of the robot building a map of the environment and locating itself in this map.

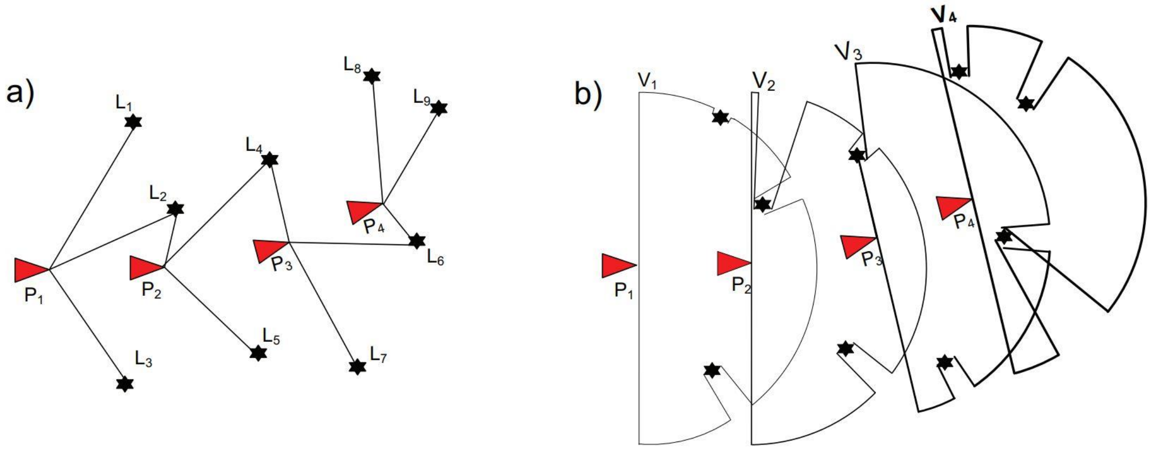


Figure 4:a) Feature based SLAM in comparison to a b) vision based SLAM approach (Paull et al., 2018)

The SLAM algorithm uses the current state to build up the posteriori state with the help of the constructed map. The state is often estimated using a Kalman filter (extended or unscented) or a particle filter. A SLAM implementation can either use the vision-based complete measurement to estimate its own state or use upstream feature detection for feature-based orientation (see Figure 4) (Paull et al., 2018).

4. CONCEPT OF NAVIGATION

In addition to the navigation systems that are conventionally carried by an AUV, the system in the CIAM project also carries many other sensors that are used to monitor the pipelines. In particular, this is a multi-beam echo sounder, which records the geometric features under the AUV. A camera captures images and, in conjunction with a laser line projector, forms a triangulation scanner. In addition, a forward looking sonar, a subbottom profiler and specially for the CIAM project developed new sensors are used.

4.1 Conventional Filterdesign

The classic filter setup for an AUV is shown in Figure 1Figure 5. As described in the introduction, acoustically communicated signals are used to compensate the drift of dead reckoning over time by direct or indirect coordinates. The high accuracy with low precision can be considered in sensor fusion (extended or unscented Kalman filter) with high covariances.

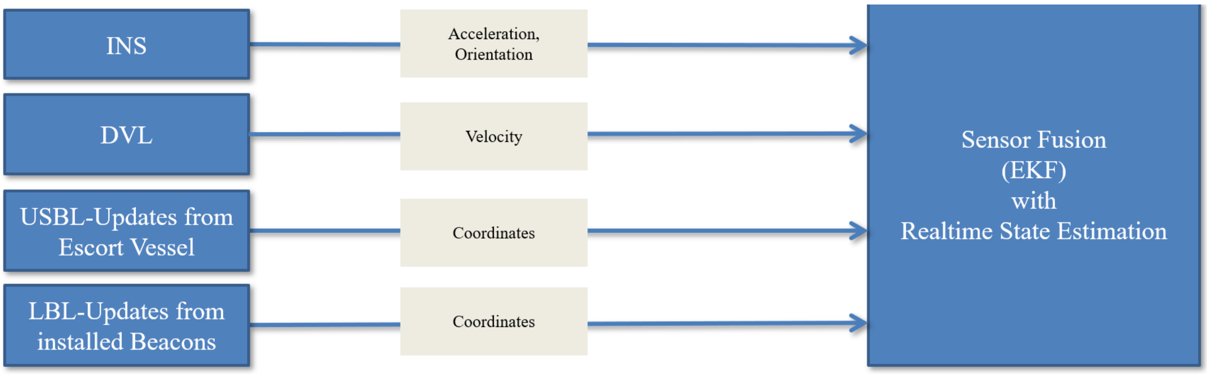


Figure 5: Conventional structure of AUV navigation

Even if robust navigation solutions are available, they have the major disadvantage that they either require the installation of LBL beacons or need to be accompanied by an accompanying mother ship, which requires personnel and investment. The use of an autonomous surface vehicle (ASV) is economically more favorable, but still costly.

4.1 Proposed Alternative Design

An alternative proposal was developed as part of the CIAM project. The backbone is still dead reckoning with IMU and DVL. However, in order to reduce costs and increase navigation, methods are to be added that make pre-installed LBL beacons or an escort vessel obsolete. The images from the AUV-mounted camera are used to analyze the detected pipeline. Curvatures are used to determine a change of rate. Continuous features on the pipeline (printed numbers, connection points) can be counted to provide an absolute distance traveled if the distance is continuously the same. Less common but still possible is the detection of unique landmarks or markers on the pipeline, which can be provided with global coordinates due to their uniqueness and can therefore provide an update to the sensor data fusion. The line scanner provides a geometric point cloud. Just like the point cloud of the multibeam echo sounder, which also contains backscatter information. This can be used in real time for the detection of continuous features and thus send an odometrical update to the sensor fusion.

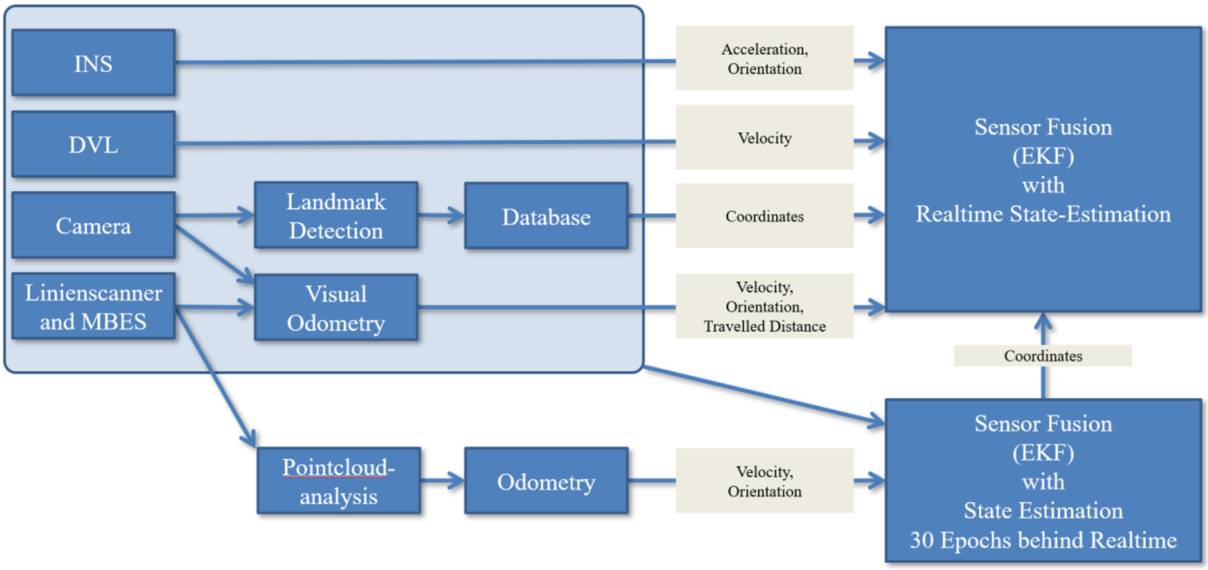


Figure 6: Structure of the proposed sensor data fusion based on the environment-based representation

The disadvantage of the point cloud is that the full benefit can only be derived from a holistic point cloud. For example, the absolute distance traveled by counting continuous features and also determining global coordinates by detecting unique hydromorphological features can only be determined after the fact. With a supporting additional temporal filter, either coordinates or possibly an estimated bias of the observations of the main filter can be transferred as observations or control input.

Caution is advised at this point, as the point cloud is created and processed partly on the basis of the inertial measurement unit and this may be included in the sensor data fusion several times, albeit via indirect paths.

5. SETUP OF A TESTPLATFORM AND DATA-ACQUISITION

The development of innovative robotic systems is complex. The development of a new type of navigation solution is particularly difficult in a challenging water environment like the deep sea. In addition, pipelines represent system-critical infrastructure and are only partially suitable as a test field for experimental purposes.
For this reason, a test platform was set up in the project that can be tested outside the water. A hand-drawn trolley and a linear comparator track are available for this purpose and have been set up accordingly. The IMUs used for navigation is the iNAT U200/RLD from iMAR Navigation and the DMU 41-02 from Silicon Sensing. In addition to LiDaR based total stations, the Nav RQH from iMAR Navigation is used as a ground truth, which as a ring laser IMU can demonstrate significantly higher precision and accuracy over longer observation periods compared to the both mentioned MEMS devices.
The systems were tested in conjunction with the environmental sensors in the geolaboratory of the HafenCity University in Hamburg, Germany, as precise georeferencing can be recorded here using totalstations. As a large amount of training data is required for the machine-learning-

based components of the algorithms, data was collected in urban areas. The handcart was moved in an AUV-like trajectory. Curbs and simulated data were trained as a pipeline replacement for image recognition. Metal profiles and pipes are used to create and analyze 3D point clouds with geometric similarities to pipelines.

Simulated data can only be used to a limited extent for training machine learning algorithms, as they quickly learn the simulated environmental parameters.

Table 1: The IMUs used for the tests and comparison for groundtruth (iMAR Navigation, 2021; Silicon Sensing, 2022; iMAR Navigation, 2012)

	iNAT-U200/RLD (MEMS-IMU)	DMU41-02 (MEMS-IMU)	Nav RQH (RLG-IMU)
Bias stability (AV) of Acceleration	< 0.1 mg	15 µg	< 10 µg
Bias stability (AV) of change of rate	2.5 °/hr	0.1°/hr	< 0.002 °/hr

Both the RPI v1.3 with 5 MP and the U3-3160CP from IDS with 2.3 MP are used as cameras for comparison. This is combined with a laser line projector from MediaLas, which uses a wavelength of 532 nm and therefore projects green light.

Figure 7: Hand cart with test setup and RLG-IMU as ground truth; the curb you can see is used as a pipeline replacement

The high-precision ring laser gyro is used in conjunction with GNSS as a ground truth to compare the coordinates determined on the basis of MEMS-IMUs.

5.1 Images Analysis

The deterministic evaluation of image data is very complex and often requires sophisticated adjustments to the parameters when environmental conditions change. For this reason, machine learning methods were used to provide targeted support for the entire navigation solution.

Ultralytics is a sophisticated library in Python, and it has introduced their new innovation, YOLOv8, which marks a leap forward in the realm of real-time object detection and image segmentation (Jocher et al., 2023). A new anchoring bottleneck has been introduced to increase the accuracy of the newly developed YOLO-V8 (Solawetz and Francesco, 2023). It stands as a powerfull tool in the fields of deep learning and computer vision and was therefore selected to achieve the needed speed and accuracy in these critical domains.
More than 300 simulated images of the seabed and pipelines were used in a first step to develop a model to detect pipelines. 173 and 75 images were used to train and validate the model, respectively, and labels were created based on the CVAT online tools, digitizing the pipelines. Training was implemented based on the Spyder Python platform using the Yolov8m-seg model with 1000 epochs. The training segmentation loss decreased to 0.25 after 200 epochs.

5.2 Landmark Detection

Different features can be used to distinguish pipelines. Some pipelines are numbered in sequential order or have texts. This unique characteristic can be used to possibly identify the location, if these features have been detected in prior mapping campaigns. The Cygwin terminal and Pytesseract module were used to detect numbers and texts. Certain filters in the Open CV library are used to increase the reliability of the recognized texts and numbers. Creating a mask from the numbers is the most important step in this case. Numbers and backgrounds can be differentiated. Different page segmentation modes (PSM) and OCR engine modes (OCR) were applied, and finally the --psm 6 and --osm 3 modes were selected considering the user requirements. It was found that the labels could be recognized with a high degree of reliability. A loop was developed with images taken at different resolutions and from different angles, also considering some artifacts to simulate the real environment.

Each label is stored in an SQLite database and provided with absolute coordinates. The metadata linked via an ID increases robustness, as a validity check can be used to prevent the observation from being passed on in the event of possibly incorrectly identified label.

5.3 Marker Detection

Fiducial markers can also be stored in a database, which can be uniquely assigned to their location using their ID. Various marker types are available for this purpose (e.g. ArUco markers, AprilTags).

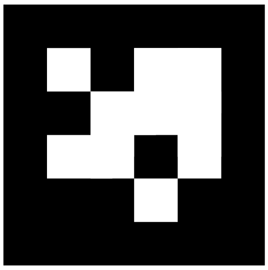


Figure 8: ArUco marker with an unique identifier

They also offer the advantage that the pose of the camera can be oriented in relation to the marker, although this is hardly necessary given the large-scale nature of navigation.

5.4 Odometric Observation in Images

In the deep sea, only a slight and gradual change in the geodetic height of the pipeline can be assumed. Based on the detected masks and the estimate of the orientation, the change in the course can be determined, which can be included as an observation in the sensor data fusion. The determination of the speed of passing continuous features (like joints and flanges) can also be used as a speed observation.

5.5 Triangulation Scanner

On land, the use of an acoustic multibeam echo sounder is not common. Therefore, only a triangulation laser scanner remains for the creation of a point cloud for testing purposes. The utilization of a green laser line projector serves therefore as a key element in this data collection process.

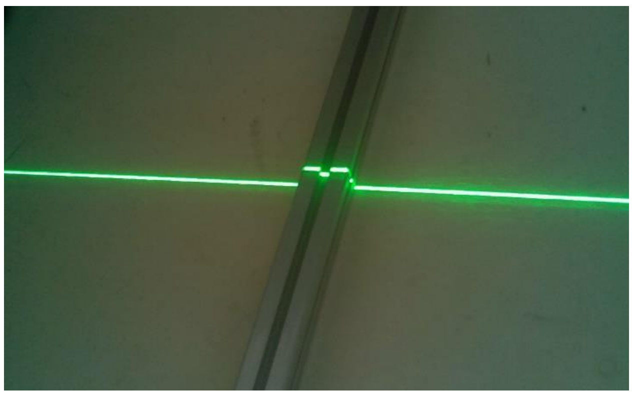


Figure 9: Image acquisition of projected laser line for triangulation-based creation of a point cloud

The python-module OpenCV is used to obtain the efficiency of the image analysis. This versatile tool facilitated the transformation of RGB images into the Hue, Saturation, and Value (HSV) stream. The reason behind this transformation lies in the superiority of HSV images over RGB images for image analysis purposes. This section outlines the rationale and the step-by-step process involved in this crucial transformation. The successful detection of pipelines relied heavily on accurate identification of the green values within the HSV images. To achieve this, the Hue range was incremental adjusted, utilizing intervals between 75 and 85. This adjustment not only facilitated the minimization of outliers but also contributed to a more precise identification of the green line.

5.6 Future Approaches for Point Cloud Analysis

Research is currently being conducted to increase the accuracy and test the program compatibility of the Linux-based system with the Robotic Operating System (ROS-2). Traditionally, complex algorithms such as RANSAC and Hough have been developed for the detection of linear features. However, recognizing the need for a more straightforward and less computing-intensive approach, a cascaded workflow is built up with a basic image processing algorithm upon the OpenCV framework. By masking the seabed based on the YOLO-V8 model described above, each image is reduced to the relevant areas and the point cloud is scaled down by a relevant proportion.

6. RESULTS AND DISCUSSION

The work steps described here reflect an interim status of the environment-based navigation in the CIAM project.

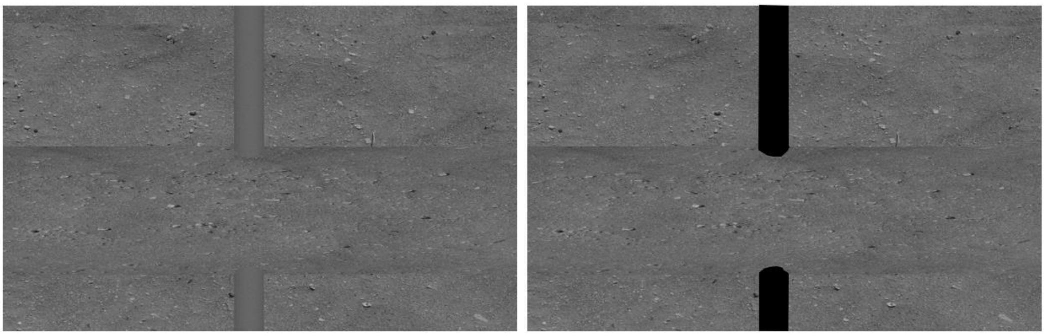


Figure 10: From ROS-Gazebo exported Image (left) and the segmented version (right), based on the trained model

The training of a neural network based on a simulated environment worked successfully. In the future, research will be carried out into recognizing features in the real environment rather than in the simulated environment. However, due to the changing environmental and weather conditions, extensive campaigns are required to collect training data.

Using the Cygwin terminal and Pytesseract module to recognize landmarks and text has proven effective in identifying numbered or labeled features on pipelines. The implementation in a ROS 2 environment works smoothly, while the geocoordinates retrieved from a database are sent to the main filter.

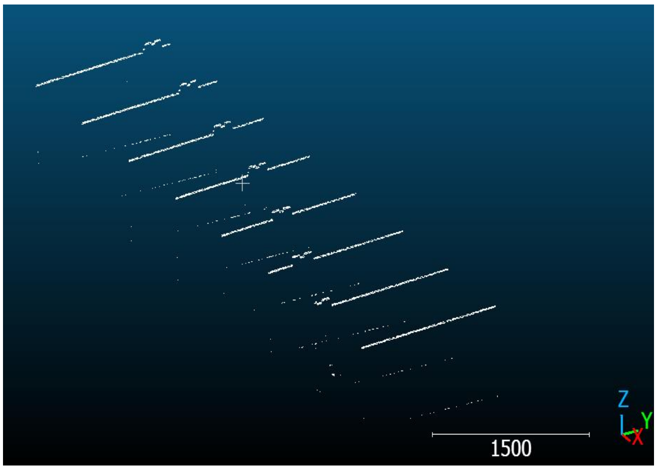


Figure 11: Point cloud of metallic profile created with triangulation scanner as benchmark

The triangulation laser scanner's role in creating a point cloud for environmental representation is a critical aspect of the navigation concept. Initial trials have already shown that a promising approach has been developed (see Figure 11: Point cloud of metallic profile created with triangulation scanner as benchmark). Tests with reference objects have successfully identified geometric features with a size of ~1 cm. Further adjustments promise further improvements here. This offers the possibility that singular features linked to a priori knowledge or continuous features can be successfully mapped.

The development of the main filter as a sensor fusion still requires effort, which can only be completed when a heuristic estimation of the covariances of each individual component can be carried out.

7. CONCLUSION AND OUTVIEW

Two main topics are presented and discussed in this paper. Firstly, the possibility of environment-based navigation in a very complex environment. On the other hand, the setup of a test platform to test and validate the elaborated methods.

If reliable navigation is achieved, the solution discussed here meets the condition of economic efficiency, as no further investment in hardware would be necessary without the escort vessel and LBL beacons. Only the need for additional computing power must be considered. When the AUV is determining its own position, however, the aim is not to achieve centimeter-precise positioning but rather to narrow down the possibilities of its own location according to the "bound the uncertainty" principle.

Acknowledging how complex the development of environment-based navigation solutions in the deep sea is, a suitable solution is in this paper with the handcart as a testing plattform proposed. The adjustment of a navigation-related state estimation is extremely extensive. Specifically, each building block requires special attention and understanding to correctly accommodate them with the respective error characteristics in the sensor data fusion. In all experiments, observations are recorded only during 2D movement of the handcarts, acting as AUV replacements. This setup is chosen for its simplicity in design. Furthermore, determining diving depth with a barometer as a sensor in the deep sea is favorable and easy.

The use of SLAM is currently not being considered in the context of this project, as the increased computing effort is disproportionate, especially since the added value of SLAM is achieved through loop closure, i.e. the multiple observations or identification of features, which is hardly achieved with an AUV that moves across a pipeline.

REFERENCES

Adegboye, M.A., Fung, W.-K., Karnik, A., 2019. Recent Advances in Pipeline Monitoring and Oil Leakage Detection Technologies: Principles and Approaches. Sensors (19).

2018. Autonome Unterwasser-Pipeline-Inspektion. https://de.oedigital.com/news/autonome-unterwasser-pipeline-inspektion-274313. Accessed 29 January 2024.

iMAR Navigation, 2012. iNAV-RQH-1003 Datenblatt, 2 pp.

Jocher, G., Munawar, M.R., Qaddoumi, B., Le Mentec, O., 2023. Comprehensive Tutorials to Ultralytics YOLO. Accessed 29 January 2024.

Nister, D., Naroditsky, O., Bergen, J., 2004. Visual odometry, 652–659.

Paull, L., Saeedi, S., Seto, M., Li, H., 2018. AUV Navigation and Localization - A Review.

Silicon Sensing, 2022. DMU41-02-0100 Datenblatt, 24 pp.

Solawetz, J., Francesco, 2023. What is YOLOv8? https://blog.roboflow.com/whats-new-in-yolov8/. Accessed 11 January 2023.

BIOGRAPHICAL NOTES

Lukas Klatt
Lukas Klatt is a studied environmental engineer (in RWTH Aachen University) and has several years of professional experience in the development of autonomous and unmanned hydrographic survey systems. Since April 2022 he is working in the CIAM project at

HafenCity University Hamburg on enhancing the navigation of autonomous underwater vehicles. In 2021, he set up his own business in the field of autonomous hydrographic measuring systems with the founding of the Start Up RiverDynamics. Before that, he worked at a research institute documenting climate change in inland waters. He is member of the German hydrographic association (DHyG).

CONTACTS

Title Given name and family name: Lukas Klatt
Organisation: HafenCity Universität Hamburg
Address: Henning-Voscherau-Platz 1, 20457 Hamburg
City: Hamburg
COUNTRY: Germany
Tel. + 49 40 428 27 - 5346
Email: lukas.klatt@hcu-hamburg.de
Web site: hcu-hamburg.de