



Aalborg Universitet

AALBORG UNIVERSITY
DENMARK

Fault Tree Analysis of Sensor Technologies for Autonomous UUV Navigation

Sørensen, Fredrik Fogh; von Benzon, Malte; Pedersen, Simon; Liniger, Jesper; Mai, Christian

Published in:
IFAC-PapersOnLine

DOI (link to publication from Publisher):
[10.1016/j.ifacol.2022.10.474](https://doi.org/10.1016/j.ifacol.2022.10.474)

Creative Commons License
CC BY-NC-ND 4.0

Publication date:
2022

Document Version
Publisher's PDF, also known as Version of record

[Link to publication from Aalborg University](#)

Citation for published version (APA):
Sørensen, F. F., von Benzon, M., Pedersen, S., Liniger, J., & Mai, C. (2022). Fault Tree Analysis of Sensor Technologies for Autonomous UUV Navigation. *IFAC-PapersOnLine*, 55(31), 484-490.
<https://doi.org/10.1016/j.ifacol.2022.10.474>

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal -

Take down policy

If you believe that this document breaches copyright please contact us at vbn@aub.aau.dk providing details, and we will remove access to the work immediately and investigate your claim.

Fault Tree Analysis of Sensor Technologies for Autonomous UUV Navigation

Fredrik Fogh Sørensen **, Malte von Benzon,
Simon Pedersen, Jesper Liniger, Christian Mai

*AAU Energy, Aalborg University, Niels Bohrs Vej 8, DK-6700 Esbjerg,
Denmark*

*** Corresponding author. E-mail: ffso@energy.aau.dk.*

Abstract: Autonomous unmanned underwater vehicles (UUVs) are increasingly used for inspection and cleaning tasks. While automating these tasks could greatly reduce the cost, it requires reliable feedback from position and surroundings. Both internal effects and different physical properties affect sensors, resulting in inaccurate feedback if not handled correctly by the navigation system. In this study, an overview of these effects and properties are examined for the most common sensor technologies used for underwater navigation. A fault tree analysis (FTA) is conducted to get knowledge about how the sensor faults, as a result of these effects, affect automated near-structure and off-structure missions, respectively. Moreover, experiments are carried out with a high-resolution sonar and stereo camera to compare the measurement accuracy at different distances. The sensor comparing test shows that cameras can, in some cases, be insufficient to use as the only sensor for obstacle avoidance. It is concluded that the sensor criticality is case-specific; in general, especially faults on attitude feedback are severe for an acceptably-working navigation system and should therefore have high priority when selecting the robotic sensors.

Copyright © 2022 The Authors. This is an open access article under the CC BY-NC-ND license (<https://creativecommons.org/licenses/by-nc-nd/4.0/>)

Keywords: Sensors, Underwater Robotics, Maritime robotics, Automated Navigation, Fault Tree Analysis, UUV, ROV, AUV

1. INTRODUCTION

Underwater navigation with unmanned underwater vehicles (UUVs) is a widely researched topic; see Paull et al. (2014); Vickery (1998). The offshore industry suspects that automation of the remotely operated vehicles (ROVs) used for maintenance tasks will greatly reduce operating costs (Pedersen et al. (2022); Tena (2011)), while autonomous underwater vehicles (AUVs) potentially can improve inspection tasks even further (Mai et al. (2016)). To achieve autonomy, good control performance is required, which again requires accurate and reliable feedback (Kinsey et al. (2006)).

Several studies examine different methods of navigation. In Kinsey et al. (2006) an overview of different sensors and some of their challenges, such as distortions, are given. In Paull et al. (2014) a review of different methods in regards to navigation is given, especially Simulation Mapping and Localization (SLAM) is presented. However, none of the previously mentioned studies clearly show how the sensor challenges described potentially can affect the overall navigation system. In Xu et al. (2013) a fault tree analysis (FTA) based on a TM4500M AUV is used to evaluate whether the AUV is reliable enough to use for a specific time span. This article is case-specific for the chosen ROV; combining the knowledge about sensor distortions and FTA could make a more general view of sensor faults.

In many fields, FTA is made to give a clear overview of the safety and reliability of a complex system (Lee et al. (1985)). Furthermore, failure mode effects analysis (FMEA) is widely used in safety-critical industries like nuclear plants, aviation, and automotive (Ruijters and Stoelinga (2015)). One example of how FTA can be used to find the critical components in a system can be seen in Liniger et al. (2017). Risk priority numbers are calculated for different components, concluding that valves and accumulators are the most critical components in wind turbines' hydraulic pitch system.

This study presents some common operation types conducted by UUVs, including inspection and marine growth removal. These operation types are used to present different kinds of operation-specific sensor distortions, which in this study are defined as faults if the distortion results in sensor inaccuracies violating a threshold. Then, faults are defined as events that lead to sensor inaccuracies or errors, eventually causing a mission failure. An FTA is made to give an overview of how different faults affect the overall navigation system. The FTA is evaluated in terms of which sensors are most critical and should have the greatest concern in the design phase. Moreover, the sensor faults are investigated from experiments with a high-resolution sonar and a stereo camera conducted in Port of Esbjerg for realistic conditions.

2. NAVIGATION SYSTEM

To achieve autonomous operation for UUVs, it is required to have a navigation system to give feedback, such as the UUV’s position and dynamic surrounding (Bjerkeng et al. (2021)). An example of such navigation system can be seen in Fig. 1.

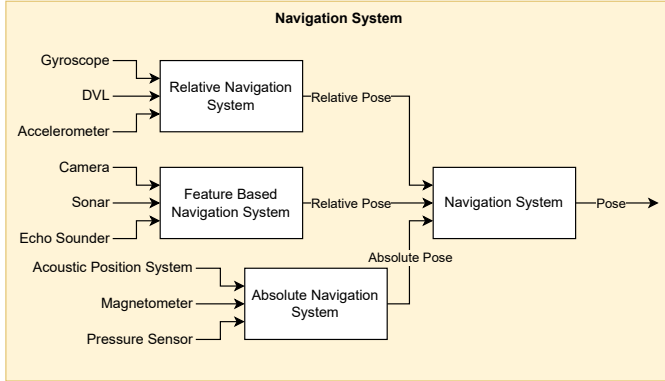


Fig. 1. Diagram of navigation system for an Underwater vehicle

In the navigation system example, three sub-navigation systems are constructed, relative navigation system (RNS), feature-based navigation system (FBNS), and absolute navigation system (ANS).

The RNS takes measurements from inertial sensors, such as inertial measurement unit (IMU) and doppler velocity log (DVL). The FBNS requires some sort of feature to track. Features could be the sea-bottom, rock formations, or man-made structures. The measurements are relative distances between the UUV and the feature tracked. Lastly, the ANS includes sensors such as acoustic position system (APS), magnetometer, and pressure sensor. These sensors give a measurement in the world frame, which means they are unaffected by the attitude of the UUV.

Table 1. Sensor Technologies used for underwater navigation (Kinsey et al. (2006); Falkenberg et al. (2014))

Sensor Technology	Motions*
IMU (9 DOF)	$x_b, y_b, z_b, \phi, \theta, \psi$
Pressure sensor	D
DVL	x_b, y_b, z_b
SBL**	N, E, D
LBL**	N, E, D
Camera	$x_b, y_b, z_b, \phi, \theta, \psi, d$
Sonar	$x_b, y_b, z_b, \phi, \theta, \psi, d$
Echo sounder	d

* The motions follows the frames defined in Fig. 2.

** These are referred to as acoustic positioning systems (APS).

In table 1 different sensor technologies are shown. All sensors shown are used in the navigation systems shown in Fig. 1, but they might not all be used in the same application, as some of the sensors are redundant. However, to give a wide overview of the potential faults, all sensors listed are used in this study.

The sensors are affected by many different distortions, which have to be considered carefully while designing

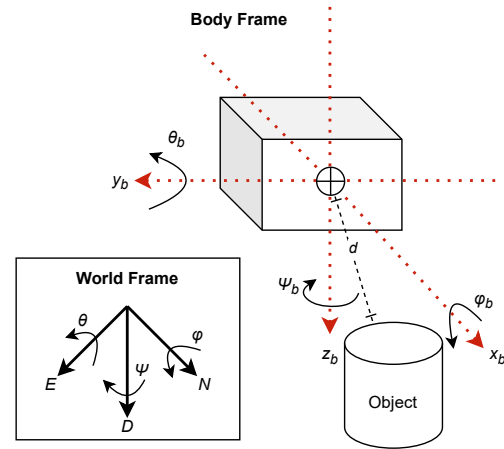


Fig. 2. Frames for the UUV, world frame follows the standard NED-frame, body-frame a local NED-frame, and d illustrates the distance to an object

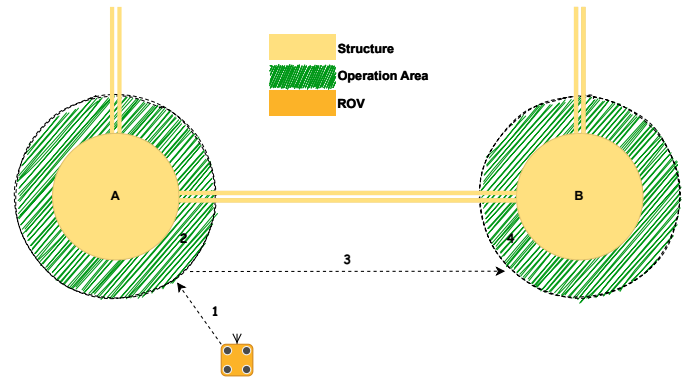


Fig. 3. Illustration of inspection and cleaning mission

an UUV. Some disturbances are case-specific such as ferromagnetic materials in man-made structures. To give a better idea of the disturbances acting on the sensors, this study will be based on an inspection and cleaning mission for an offshore installation.

3. INSPECTION AND CLEANING MISSION

The inspection and cleaning mission used as an example for this study is illustrated in Fig. 3. The operation areas define where inspection and cleaning take place, while the dashed line illustrates how the UUV moves between the operation areas. Thereby the mission can be described as four tasks.

Task 1: The UUV moves to pillar A. Task 2: The UUV does an inspection operation followed by a cleaning operation. Operation 3: The UUV navigates off-structure to pillar B. Task 4: An inspection operation and cleaning operation are performed at pillar B.

Task 1 and 3 can both be described as off-structure navigation operations. While operations 2 and 4 can be divided into two sub-operations, inspection and cleaning. These two operations are near-structure operations, which therefore have the possibility to utilize measurements relative to the structure.

3.1 Inspection

Inspection operations are conducted periodically to ensure structural integrity; today, these inspections are often done by ROVs. The inspection can be for cracks and assessment of marine growth (Liniger et al. (2022)). As the inspection is done on structures, these can also be used as features for SLAM. When using cameras for SLAM, two concerns must be considered: turbidity and light (Jian et al. (2021)). However, the structure also introduces some disadvantages regarding the navigation system. Man-made structures can be ferromagnetic and disturb the Earth's magnetic field (Menon et al. (2013)), affecting the magnetometer and resulting in inaccurate measurements of the UUV's heading. Another disadvantage is the lack of line of sight for acoustic positioning systems (APS), which decreases the accuracy or even makes the measurement unavailable Vickery (1998).

3.2 Marine Growth Removal

Marine Growth Removal has many similarities to inspection. It is also close to structures, which could result in magnetic disturbances. However, in contrast to inspection operations, the visibility could be decreased due to particles from the removed marine growth. Also, the cleaning tool itself could cause higher turbidity as seen on Fig. 4; therefore, cameras' placement must be considered carefully if visual SLAM is intended as part of the feedback system.



Fig. 4. Example of induced localized turbidity increase from high-pressure cleaning

3.3 Off-structure Navigation

Open water navigation differs from the previous operations types as this does not necessarily guarantee nearby objects, which can be used in SLAM algorithms. In contrast to near-structure operations, open water navigation is well-suited for APS; however, these systems also have some disadvantages. They require careful placement of transponders, and accurate knowledge of sound velocity and are limited by the speed of sound in water, resulting in noticeable time delays over long distances Kinsey et al. (2006)

4. SENSOR FAULTS

In this study, a fault is defined as unwanted behaviors and disturbances affecting the sensor, which results in

misreadings/incorrect measurements. In the following sections, different faults for the sensors considered for the navigation system are described. The sensors considered are gyroscope, accelerometer, DVL, camera, sonar, echo sounder, APS, magnetometer, and pressure sensor.

The gyroscope has two faults that affect the measurement: bias offset and drift (O-larnnithipong and Barreto (2016)). Bias offset is the value that the gyroscope reading provides when the sensor is stationary, which ideally should be zero. One solution to account for this bias offset is by using the measurement, when there is no angular movement by the ROV, as a bias offset estimate as proposed in O-larnnithipong and Barreto (2016). Drift is a constant angular rate change; one way to minimize drift is to compare a calculated gravity vector with the one measured by the accelerometer when the robot is not moving. This method is also presented in O-larnnithipong and Barreto (2016); however, it was not able to eliminate the drift.

The accelerometer can be used to estimate the position of the ROV; however, this requires a good knowledge of the orientations of the sensor. Some calibration can account for the misalignment of the sensors frame and body frame. However, as the rotation matrix between the body frame and the world frame can drift, the attitude drift can result in incorrect estimates of position in the world frame (Troni and Whitcomb (2012)). As with the gyroscope, accelerometers can also be affected by an offset bias; this can be removed by measuring the gravitational acceleration as shown in Ibrahim and Moselhi (2016).

The DVL measures velocities in the body reference frame; therefore, this is also affected by the attitude drift. The DVL is an acoustic sensor, which means that deviations in the speed of sound also impact the accuracy of the DVL. The sound velocity in water is affected by properties such as water temperature, salinity, and pressure (Bardakov et al. (2010)). The DVL also requires bottom lock, which can occasionally fail (Troni and Whitcomb (2012)).

Both camera and sonar are feature-based sensors that measure geophysical objects; these sensors have some shared faults, including a lack of features and long-term attitude drift. The position of the extracted features must be estimated in the world reference; however, it is measured in the sensor frame, and there has to be adjusted for the UUV's attitude. However, once again, this rotation matrix tends to drift. The lack of features can be due to missing geophysical objects from which to detect features. The lack of features can also be due to high turbidity in the environment in front of the camera. Cameras are also affected by the light settings as described in Jian et al. (2021). Sonar is not as affected by turbidity or light; however, it has the downside that it is affected by deviations in the speed of sound.

The echo sounder has the same working principle as sonar but sends a single acoustic beam in one fixed direction. Therefore it has the same faults as the sonar: deviation in sound velocity, lack of geophysical objects, and attitude drift.

The APS is like the previous two acoustic sensors, also affected by variations in the speed of sound. Another

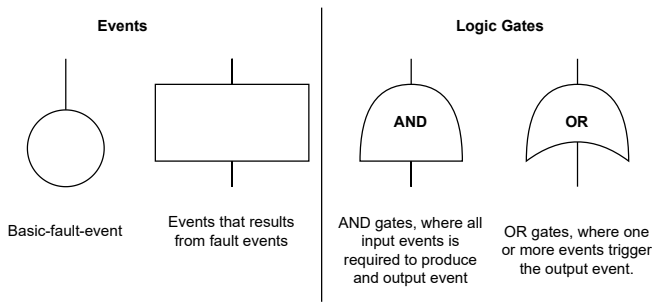


Fig. 5. Fault tree event and logic symbolism

requirement for APS to work is the line of sight between the locator and receiver (Miller et al. (2010)).

The Magnetometer is an excellent way to measure the heading of the ROV as the Earth's magnetic field is not weakened by water Tyren (1987). However, other magnetic fields affect the sensor as well. An iron calibration can be used to remove the static fields in the ROV; however, ferromagnetic materials in the surrounding environment, like man-made structures, cannot be accounted for in such calibration.

The pressure sensor can be used to estimate the current depth of the ROV. However, the sensor accuracy can be affected by temperature, resulting in temperature drift (Balavalad and Sheeparamatti (2015)).

To give a better view of how the faults affect the overall inspection and cleaning mission, an FTA is conducted.

5. FAULT TREE ANALYSIS

A fault tree is used to translate a physical system into a structured logic diagram and connects root causes to system failure. The analysis will be based on the definitions in Lee et al. (1985). The diagram consists of events and logic symbols. The symbols used in this study can be seen in Fig. 5, while a more complete list of symbols can be seen in Lee et al. (1985).

The fault tree seen in Fig. 6 is constructed to capture the general operating scenario of UUVs so that it can be easily transferred to more specific applications. The first event to define is the top event, an undesired or failed state of the system. In this case, the top event is an automated mission failure, which means that the automated inspection and cleaning mission cannot be completed without pilot intervention. This means that the UUV could still be recovered, or the inspection and cleaning could still be completed with the aid of a pilot.

The top tree structure following the top event depicts the two main operational modes of the UUV, namely, near-structure operation fault or off-structure operation fault, as described in section 2. The off-structure operation fault relies on the absolute and relative navigation systems and, as explained in section 3.3 does not rely on feature-based navigation. The absolute positioning system is broken down into each motion in the world frame, which can be seen on Fig. 2. Each motion will trigger the absolute navigation system to fail; however, this should be reconsidered for each mission. Some missions only require feedback in

the down position, not the horizontal movement or vice versa.

The near-structure navigation fault is triggered by the occurrence of both feature-based navigation system fault and relative navigation system fault, which are further connected to specific motion estimations.

The motions are then broken down into sensor faults. Recall from section 4 that a fault is defined as unwanted behaviors and disturbances affecting the sensor, which results in misreadings. Note that some sensor faults are affecting multiple events. For simplicity, the same sensor fault is for some sensors present multiple times as for gyroscope faults.

In Fig. 7 a further breakdown from sensor faults to effects acting on the sensors can be seen. These effects act as basic events. For DVL, an incorrect attitude measurement, an inaccurate estimate of the sound velocity, and a lack of bottom lock all result in misreadings from the DVL sensor. Depending on the application and the precision needed, short periods of misreadings can be permitted before triggering a fault in the navigation system. These thresholds for when an effect has been present long enough to trigger a basic event are case-specific and depend on the navigation system's estimator.

An estimator using dead-reckoning can enhance the time span under which a faulty signal or no signal can be present without triggering a fault in the relative navigation system. The estimators can also estimate the drift and counter these errors by combining the relative and absolute sensors, like using a magnetometer to estimate gyroscope drift. By using estimators for dead-reckoning and to counter drift, the occurrence can be lowered for the faults in the navigation system without making hardware changes; however, this can only be done to a certain point depending on the type of estimator, and the quality of the sensors used (D et al. (2022)).

The fault tree analysis can be used to find critical components by investigating the severity and occurrence of different intermediate events. However, this requires a good knowledge of the case and UUV's specifications, including sound knowledge about the chosen sensors.

Even though this is a general fault tree without comparable values for the different events, they can still be compared in terms of safety priority. E.g., if the collision avoidance fails, it can cause damage to the ROV. Therefore this system should have higher severity than the near-structure and off-structure navigation systems.

From the FTA, it can be seen that only FBNS provides information to the collision avoidance system. Therefore, the sensors related to the FBNS will also have high severity. To better understand the possibilities of using these sensors, an experiment has been conducted at Port of Esbjerg (See Fig. 8), where a ZED2i stereo camera and an Oculus imaging sonar from Blueprint Subsea have been compared. The echo sounder has been disregarded for this test because the narrow field of view would not be suitable for obstacle detection.

The test results are the RGB image from one of the stereo lenses and the distance map from the sonar, which

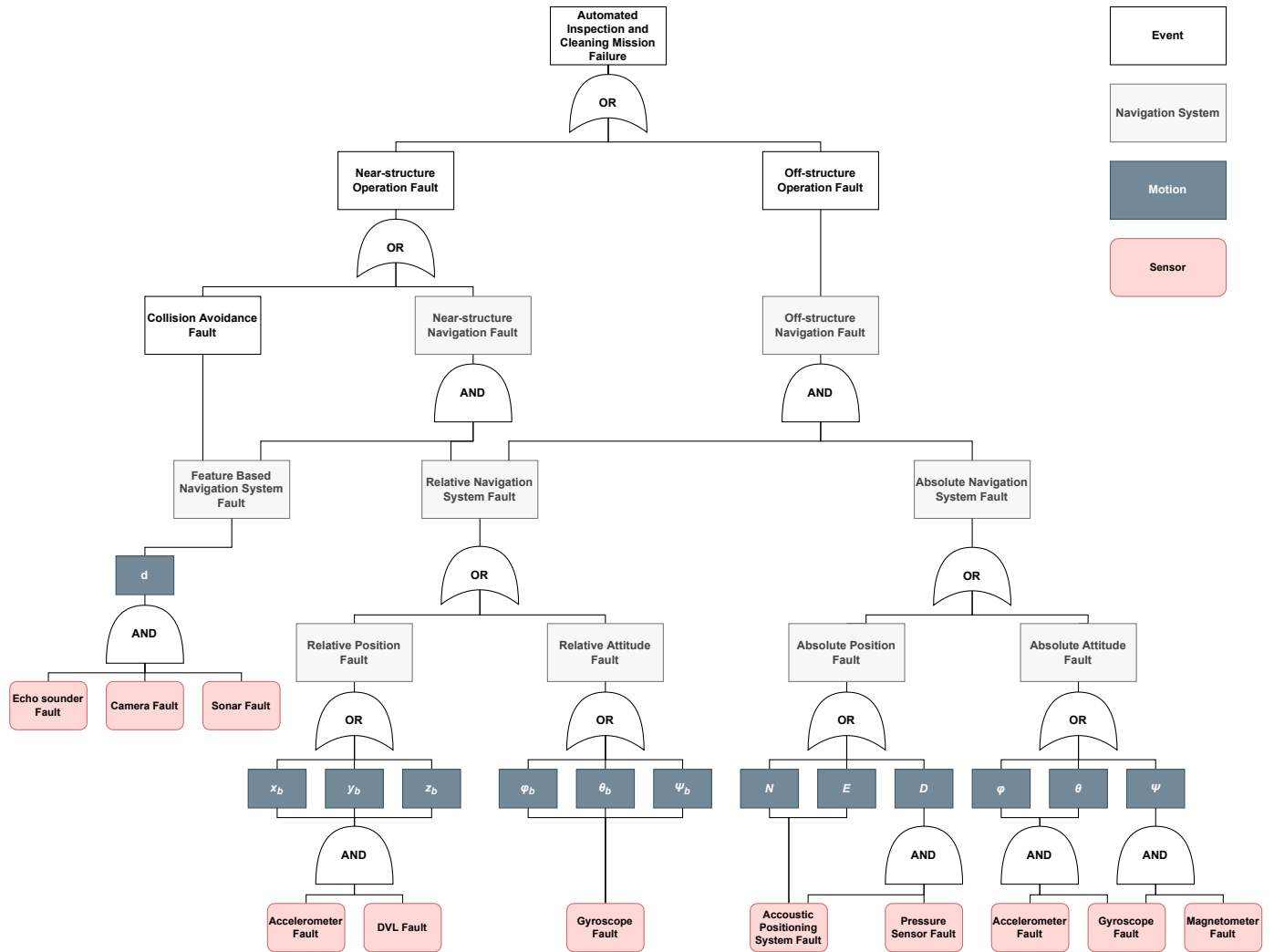


Fig. 6. Fault tree for sensors in relation to automated inspection and cleaning mission

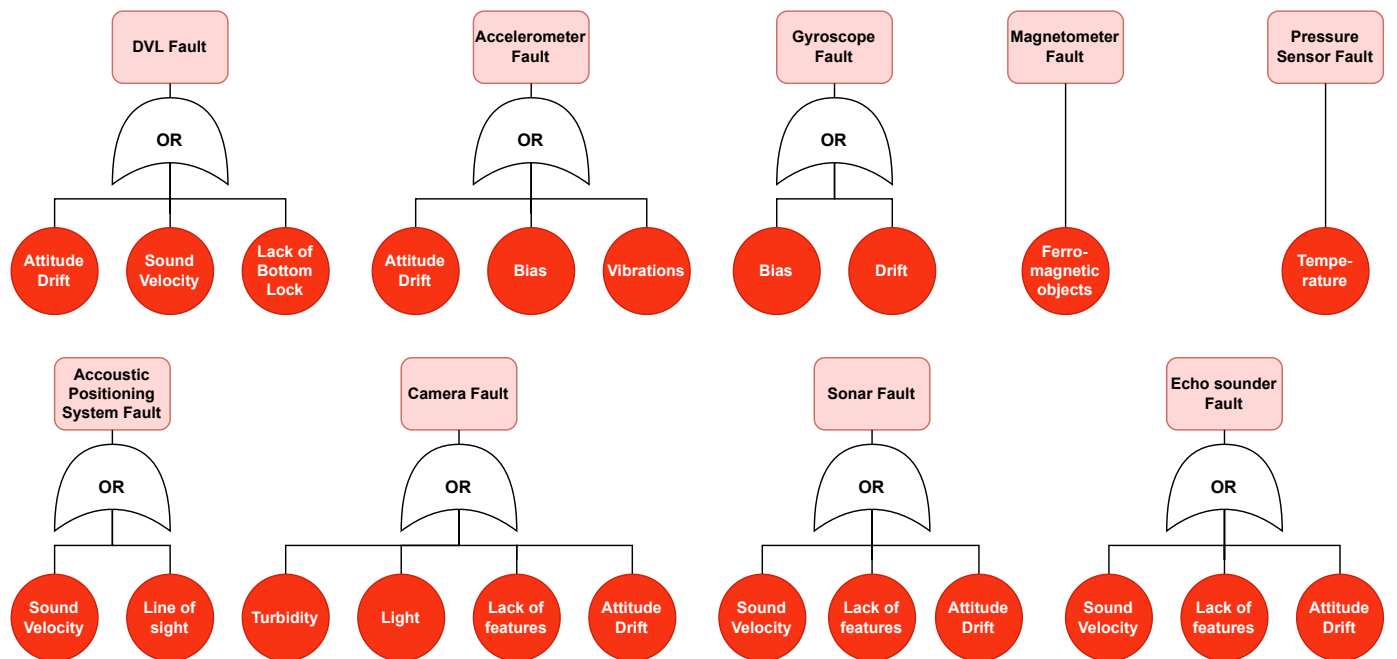


Fig. 7. Fault tree for sensor faults

means that no feature extraction has been done, as the experiment's goal was to test the quality of the raw measurements.



Fig. 8. Photo of the harbour wall at Port of Esberg above sea level where the sensor tests were conducted

The water has high turbidity in the water clearly seen in Fig. 9. When the camera and sonar are both placed close to the wall, as seen in Fig. 9a and Fig. 9d, both sensors give good measurements of the wall; however, when the sensors are moved away from the wall, the walls texture becomes unclear as seen in Fig. 9e and Fig. 9f. In contrast, the sonar keeps giving distance measurements to the wall (See Fig. 9b and Fig. 9c).

The experiment shows the importance of knowing the conditions within which the UUV should work. If collision avoidance were based on cameras exclusively, an obstacle would not be detected before being in a range of 0.2 m to 0.6 m, which could violate the allowed threshold and therefore result in an event failure.

6. CONCLUSION

This paper examines how the most typical sensor faults propagate through the navigation system, eventually becoming a system failure for the autonomous navigation system. This is done through an FTA. The top event is an automated inspection and cleaning mission failure; it is broken down through different events to end up in basic events, based on various sensor distortions that trigger these basic events if an allowed threshold is violated. Even though no risk priority numbers (RPNs) are calculated, the obstacle avoidance system has been considered a higher priority than the relative and absolute navigation systems. Two of the sensors in this system, sonar, and camera, have been tested to examine how they perform under turbid conditions. Tests at Port of Esbjerg highlight the importance of knowing how different sensor faults migrate through the system. It is shown that the camera is challenged by high turbidity. The FTA shows that this could easily result in a fault for the collision avoidance system. Therefore, cameras are not usable in operation cases where high turbidity can be expected. The tests also demonstrate that the imaging sonar is not as affected by the high turbidity, meaning that the possibility of faults in the obstacle avoidance can be reduced by adding sonar to the collision avoidance system. Furthermore, the FTA indicates that 4 out of 9 examined sensors utilize the attitude of UUVs for absolute positioning, which means

reliable attitude measurements must be of high priority when selecting sensors for the UUVs.

It is concluded that few sensors can greatly impact the overall reliability; therefore, good redundancy or robust and reliable sensor measurements are important for reliable control of UUVs. Future works will focus on finding RPNs for specific missions to determine more accurate severity levels for the different navigation systems. The fault tree can also be extended to include filter algorithms for sensor fusion. Furthermore, the FTA can be used in the development of fault-tolerant control.

ACKNOWLEDGEMENTS

Thanks to our project partners SubC Partner, Sihm Højtryk, Mati2ilt, Total E&P Denmark and Siemens Gamesa Renewable Energy, and our colleagues from Aalborg University, for many valuable discussions and technical support. The research is part of the ACOMAR project which is funded by the Energy Technology Development and Demonstration Program (EUDP), journal number 64020-1093.

REFERENCES

- Balavalad, K.B. and Sheeparamatti, B.G. (2015). A critical review of mems capacitive pressure sensors. *Sensors & Transducers*, 187(4), 120–128.
- Bardakov, R.N., Kistovich, A.V., and Chashechkin, Y.D. (2010). Calculation of the sound velocity in stratified seawater based on a set of fundamental equations. *Oceanology (Washington. 1965)*, 50(3), 297–305. doi:10.1134/S000143701003001X.
- Bjerkeng, M., Kirkhus, T., Caharija, W., T. Thielemann, J., B. Amundsen, H., Johan Ohrem, S., and Ingar Grøtli, E. (2021). Rov navigation in a fish cage with laser-camera triangulation. *Journal of Marine Science and Engineering*, 9(1). doi:10.3390/jmse9010079.
- D, N., D, K., and Murugan S, S. (2022). Localization systems for autonomous operation of underwater robotic vehicles: A survey. In *OCEANS 2022 - Chennai*, 1–8. doi:10.1109/OCEANSChennai45887.2022.9775325.
- Falkenberg, T., Gregersen, R.T., and Blanke, M. (2014). Navigation system fault diagnosis for underwater vehicle. *IFAC Proceedings Volumes*, 47(3), 9654–9660. doi:10.3182/20140824-6-ZA-1003.00774.
- Ibrahim, M. and Moselhi, O. (2016). Inertial measurement unit based indoor localization for construction applications. *Automation in construction*, 71, 13–20. doi:10.1016/j.autcon.2016.05.006.
- Jian, M., Liu, X., Luo, H., Lu, X., Yu, H., and Dong, J. (2021). Underwater image processing and analysis: A review. *Signal Processing: Image Communication*, 91, 116088. doi:https://doi.org/10.1016/j.image.2020.116088. ID: 271519.
- Kinsey, J.C., Eustice, R.M., and Whitcomb, L.L. (2006). A survey of underwater vehicle navigation : Recent advances and new challenges. *IFAC Conference of Manoeuvring and Control of Marine Craft*, 88, 1–12. URL https://www.whoie.edu/cms/files/jkinsey-2006a_20090.pdf.
- Lee, W.S., Grosh, D.L., Tillman, F.A., and Lie, C.H. (1985). Fault tree analysis, methods, and applications

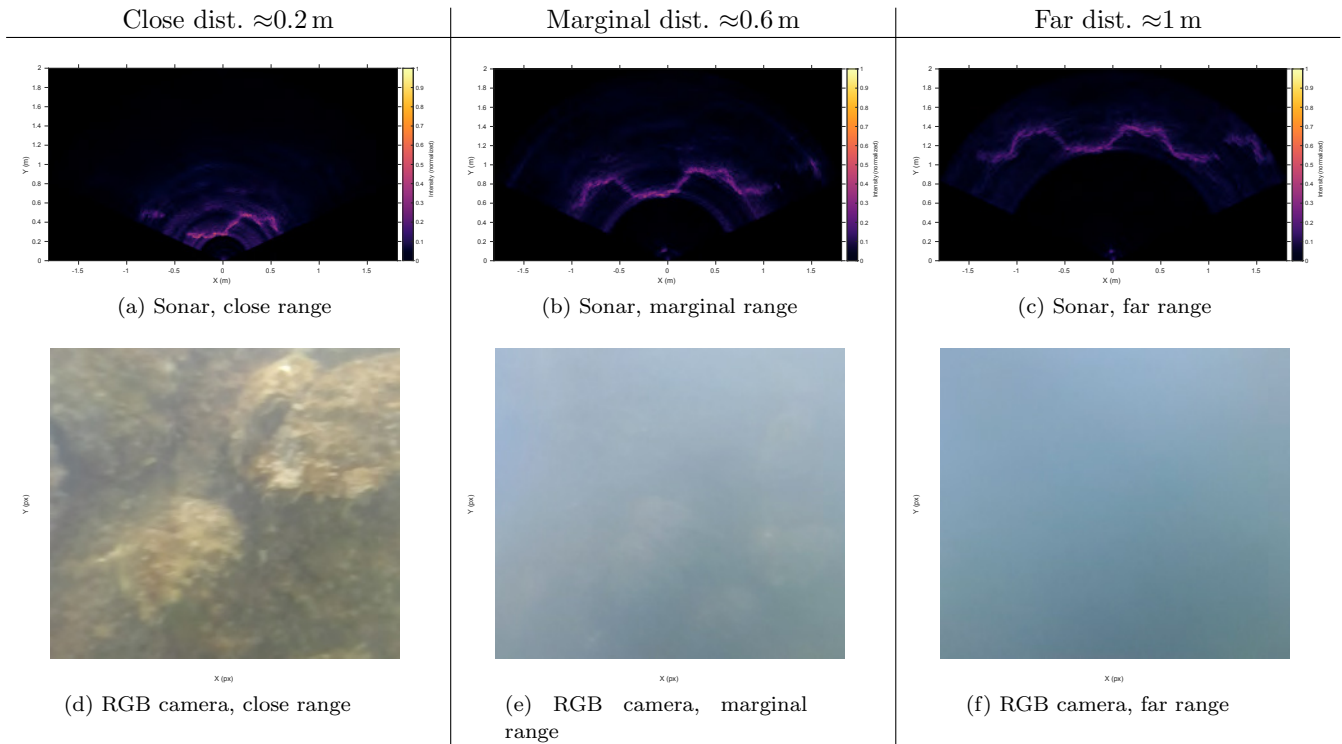


Fig. 9. Results from sensors at different ranges (close, marginal, far), acquired from a retaining wall of Port of Esbjerg, 55°28'32.8"N 8°25'26.9"E

- a review. *IEEE transactions on reliability*, R-34(3), 194–203. doi:10.1109/TR.1985.5222114.
- Liniger, J., Jensen, A.L., Pedersen, S., Sørensen, H., and Mai, C. (2022). On the Autonomous Inspection and Classification of Marine Growth on Subsea Structures. In *Proceedings of the IEEE OCEANS 2022 conference*, 1–6. Chennai.
- Liniger, J., Soltani, M., Pedersen, H., Carroll, J., and Sepehri, N. (2017). Reliability based design of fluid power pitch systems for wind turbines. *Wind Energy*, 20(6), 1097–1110. doi:10.1002/we.2082.
- Mai, C., Pedersen, S., Hansen, L., Jepsen, K.L., and Yang, Z. (2016). Subsea infrastructure inspection: A review study. In *2016 IEEE International Conference on Underwater System Technology: Theory and Applications (USYS)*, 71–76. doi:10.1109/USYS.2016.7893928.
- Menon, M., Dixon, T., and Tena, I. (2013). Resolving subsea navigation, tracking and positioning issues by utilising smart roV control system software. In *2013 MTS/IEEE OCEANS - Bergen*, 1–8. doi:10.1109/OCEANS-Bergen.2013.6607965.
- Miller, P.A., Farrell, J.A., Zhao, Y., and Djapic, V. (2010). Autonomous underwater vehicle navigation. *IEEE journal of oceanic engineering*, 35(3), 663–678. doi:10.1109/JOE.2010.2052691.
- O-larnnithipong, N. and Barreto, A. (2016). Gyroscope drift correction algorithm for inertial measurement unit used in hand motion tracking. In *2016 IEEE SENSORS*, 1–3. doi:10.1109/ICSENS.2016.7808525.
- Paull, L., Saeedi, S., Seto, M., and Li, H. (2014). Auv navigation and localization: A review. *IEEE Journal of Oceanic Engineering*, 39(1), 131–149. doi:10.1109/JOE.2013.2278891.
- Pedersen, S., Liniger, J., Sørensen, F.F., and von Benzon, M. (2022). On Marine Growth Removal on Offshore Structures. In *Proceedings of the IEEE OCEANS 2022 conference*, 1–5. Chennai.
- Ruijters, E. and Stoelinga, M. (2015). Fault tree analysis: A survey of the state-of-the-art in modeling, analysis and tools. *Computer science review*, 15-16, 29–62. doi: 10.1016/j.cosrev.2015.03.001.
- Tena, I. (2011). Automating roV operations in aid of the oil & gas offshore industry. Technical report. URL <https://www.unmannedsystemstechnology.com/wp-content/uploads/2013/10/White-Paper-Automating-ROV-Operations.pdf>.
- Troni, G. and Whitcomb, L.L. (2012). Experimental evaluation of a mems inertial measurements unit for doppler navigation of underwater vehicles. In *2012 Oceans*, 1–7. doi:10.1109/OCEANS.2012.6405003. ID: 1.
- Tyren, C. (1987). Magnetic terrain navigation. In *Proceedings of the 1987 5th International Symposium on Unmanned Untethered Submersible Technology*, volume 5, 245–256. doi:10.1109/UUST.1987.1158556. ID: 1.
- Vickery, K. (1998). Acoustic positioning systems. a practical overview of current systems. In *Proceedings of the 1998 Workshop on Autonomous Underwater Vehicles (Cat. No.98CH36290)*, 5–17. doi:10.1109/AUV.1998.744434.
- Xu, H., Li, G., and Liu, J. (2013). Reliability analysis of an autonomous underwater vehicle using fault tree. In *2013 IEEE International Conference on Information and Automation (ICIA)*, 1165–1170. doi:10.1109/ICInfa.2013.6720471.