WASP-SE-Assignment 1

My Research Area

My research topic is localization, navigation and perception for underwater robots. Bathymetric surveys are essential to many industrial operations, such as installing pipelines and wind farms, because it is important to know the topology of the seafloor before the installation. Traditionally bathymetric surveys are done by surface vessels equipped with multibeam echo sounders. One of the limitations is that the resolution of the bathymetry worsen as seabed gets deeper due to the beam footprints get larger as range. Autonomous underwater vehicles (AUVs), on the other hand, could dive and get much closer to the seafloor thus obtaining bathymetric data with much higher resolution. Furthermore, AUVs can access to places where surface vessels could not, for examples, under ice[^1] or inside of an underwater cave[^2].

The challenges coming with AUVs are lack of high accuracy positioning, since AUVs will lose GPS signals once diving, and even with very good inertial sensors and Doppler Velocity Logs, the drift errors of dead reckoning (DR) estimates are unbounded. The very high end commercial AUVs, Hugins[^3], will drift a couple of meters or tens of meters during a very long mission (e.g. 24 hours). Small and low-cost AUVs equipped with much worse sensors will drift even more with the positioning. Localization and navigation for AUVs are extremely important to its autonomy ability and the usefulness of the collected data since most of the data need geo-referenced. With drifts in the DR, the bathymetric data for example will be locally consistent but not globally consistent. There are many approaches to address such issue, for example, acoustic positioning systems including long baseline (LBL) acoustic positioning systems or ultra short baseline systems (USBL) can be used for accurate positioning. But they require deploy and installation before AUVs can survey an area, which is expensive and cumbersome. Recently, simultaneous localization and mapping (SLAM) techniques[^4] have been drawn a lot of attention academically and industrially. SLAM use autonomous robots to sense the unknown environment and construct and update the map simultaneously localize themselves within the map. Terrain-aided navigation, formulates AUV surveys as a SLAM problem and utilizes the features on the seafloor to reduce the DR errors. My research focus on using sonars for underwater SLAM, where the challenges include that 1. most of the time the seafloor is featureless 2. sonar data are usually highly geometric-distorted and hard to interpret 3. it is very difficult to collect ground truth trajectories for evaluation. But there are some recent works that addresses this problem from different perspectives, including automatic data association[^5], graph-based SLAM[^6], filtering-based SLAM[^7].

As for the perception, my research mainly focus on utilizing imaging sonar to help bathymetric reconstruction. Multibeam echo sounders are the defacto sensors for bathymetric mapping, but they are huge and expensive, for small and low-cost AUVs, they are always suitable or feasible to equip. Imaging sonars (e.g. sidescan sonars) are similar to optical cameras in the sense of they project 3D environment into 2D data, where the information of one dimension is missing due to projection. The difference is that with optical camera images, the azimuth and elevation angles are known but not the range, while with imaging sonars, the azimuth angles and range are known but not the elevation angles. But it is possible to reconstruct this missing information with multi-view geometry given some regularization for imaging sonars, especially with the advances of deep learning, similarly as optical cameras[^8], due to the fact that the sonar backscatter data encodes the information of seafloor slopes. Even for high-end AUVs equipped with multibeam echo sounders, I believe fusing multibeam echo sounders with imaging sonars would help not only navigation but also perception, since they do compensate for each other. Sidescan sonars, for example, have wider coverage than multibeam echo sounders and higher resolution while multibeam echo sounders can measure 3D information about the seafloor. Wide coverage from sidescan sonars will be extremely helpful in the front-end of SLAM, while multibeam echo sounders would be very helpful in the back-end of SLAM and also serve as control points when estimating the bathymetry and sidescan sonars' high resolution will help to improve the bathymetry resolution.

ML Engineering - Data

ML engineering, integrating ML into Software Engineering, is still an iterative process similar to Software Engineering, but also includes many activities that involve with data, for example, data collection, data validation, data annotation. Data annotation, especially, is a extremely cumbersome process, which usually takes a lot of time, money and man power. In specific fields, one needs to hire experts to annotate data since the data is difficult to interpret and requires special knowledge. How to semi-automate data annotation[^9] and still keep human in the loop, is a interesting research topic for both academia and industry. However, [^9] utilizes the high frame rate camera images in videos, where two consecutive frames have very little movements, which makes tracking possible. However, for neither sidescan sonars nor multibeam echo sounders, two consecutive sonar scans have overlaps, which means tracking is not possible. Besides, being active sonars, the sound sources change as the sonars, making the sonar data from different views vastly dependent on the viewpoints, which adds another layer of difficulty for automation of data annotation. Thus, for sonar data annotation, we still rely heavily on human annotation, but it would be very helpful to make it semi-automatic in the future.

ML Engineering - Explainability

There are many non-functional requirements (NFRs) for machine learning, where explainability is one of the important ones. In general, people are reserved to adopt techniques that are not transparent, tractable and interpretable. Besides, when it comes to decision-making, people prefer explainability over performance, after all if the explanation behind a critical decision is not comprehensible to humans, no one would like to take a risk and just decide to trust the ML model. Explainable Artificial Intelligence (XAI)[^10] is a very popular research topic, especially when ML has been adapted and applied into different fields, where many of them require transparency. In underwater robotics, explainability is also extremely important for ML models if they are to run on-board, since one has to be able to trust the logic behind the decision-making before deploying them on AUVs to explore in the unknown environments. However, if the ML models are only used for post-processing of the data collected by AUVs, explainability is not the most important requirements, for example, bathymetry reconstruction from sonar data.

Continuous Integration

Continuous Integration (CI) is the practice of committing small changes from distributed developers to the same codebase repository and automating builds and self-testing. The aim is to avoid potential conflicts from different developers working on their branches without merging to mainline for too long. Research has been also conducted recently on several aspects of CI, including Continuous Deployment (CD) and software quality[^11]. In my PhD project, we have also tried to adapt more CI practices into our software development, including control, mission planning, navigation and perception systems for AUVs. We have created a simulation environment, which has the same interfaces as the real AUVs that can be used for self-testing. Once our own branch has been merged into the mainline, the builds are automately running and a pre-define mission is going to be executed in the simulation environment to test every core aspects of the system. However, we need more research on CI to understand more about for example, how many benefits we can gain from the different CI practices, and what are the challenges we face during implementation.

Plus, any ML-based control or perception systems are very difficult to self-test in terms of the cost, time, and its verification difficulty, which is also a very interesting topic for research.

Quality Assurance

Quality assurance (QA) is the process to ensures the software implementation meets the requirements and specifications, including verification and validation. Static techniques include linting, code review, code analysis and so on, while dynamic techniques mostly involve different ways of testing. One of the research topics on QA is to improve the quality of a software from the user's prospective[^12]. I think this is certainly a aspect that neither academia nor industry has deeply researched upon. Similarly, in our group, the QA of the software development for our AUVs is usually from the developer's perspective. For example, usually the post docs are responsible for the code review, and as mentioned before, a pre-designed mission is carried out for self-testing. And for future testing, it relies on the people whose research is highly correlated to the commits. All of the personal involved are very familiar to part not even all of the codebase, which is usually not the case for users, aka some other research group who are starting to use our open-sourced implementations. This means that there are many things that are trivial to us, are probably not documented or commented well enough to understand for users, even they are also doing research on underwater robotics. Not to mention there are marine biologist, oceanographers who are not very particularly familiar with the software and robotics, but still want to use our platform for their own research.

Boundary Testing

Boundary testing is to make sure the software functions properly at boundary conditions, which is important for obvious reasons, however, since the input space for testing is usually huge and some boundary cases are not always obvious to find out, especially there are many cases where one does not know what to expect for the output. [^13] has been focused on such cases by leveraging program derivatives with search-based software engineering. It could be quite helpful for my research since many parts of my program have neural networks and traditional BVA approaches have limitations when dealing with programs that are less transparent.

Measure Productivity

It is very difficult to measure productivity in software engineering and performance, quality, efficiency of the work are generally tricky to measure, especially in a shirt amount of time. Research on guidelines for measuring productivity in different contexts[^14] are useful in many industries, however, in my opinion, it is not trivial for research in universities. Because most researchers in universities focus more on publications, and one can be very productive in terms of publishing papers but not necessarily in software, even for researchers doing research in SE, ML, robotics and so on. In my PhD project, I have rarely seen requirements or guidelines in terms of increasing productivity of writing codes, and I am not sure they are going to be prioritized a lot more in the future.

All About the Future

In relation to underwater robotics, I think more ML Engineering will be involved, not only at the academical level, but also at industry. Nowadays, most of the ML-based SE in industry, for underwater robotics are still at research phase, with very little going into production. But as the development of ML in general, I am certain the future will be different. I have been to several conferences, like Oceans, AUVs, ICRA and discuss

AI's role in marine robotics, and most people share similar views that we need to push for open dataset, benchmarks, open source software so that the AL development for marine robotics could grow rapidly. I am planning to go to industry after graduation, and their AI research/production and their roles on the company's roadmap is definitely a key factor to me. I think ML Engineering is very important considering the cost of AUVs, risks, and the scale of ocean and its data. I would forecast that in the coming 5-10 years, more people in this industry would realise ML Engineering's importance.

[^1]: Wåhlin, Anna, et al. "Warm water flow and mixing beneath Thwaites Glacier ice shelf, West Antarctica." EGU General Assembly Conference Abstracts. 2020.

[^2]: Rahman, Sharmin, Alberto Quattrini Li, and Ioannis Rekleitis. "Sonar visual inertial slam of underwater structures." 2018 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2018.

[^3]: Énonsen, Kjetil Bergh, and Ove Kent Hagen. "Recent developments in the HUGIN AUV terrain navigation system." OCEANS'11 MTS/IEEE KONA (2011): 1-7.

[^4]: Thrun, Sebastian. "Probabilistic robotics." Communications of the ACM 45.3 (2002): 52-57.

[^5]: Zhang, Jun, et al. "A Fully-automatic Side-scan Sonar SLAM Framework." arXiv preprint arXiv:2304.01854 (2023).

[^6]: Fallon, Maurice F., et al. "Efficient AUV navigation fusing acoustic ranging and side-scan sonar." 2011 IEEE International Conference on Robotics and Automation. IEEE, 2011.

[^7]: Ruiz, I. Tena, et al. "Concurrent mapping and localization using sidescan sonar." IEEE Journal of Oceanic Engineering 29.2 (2004): 442-456.

[^8]: Tewari, Ayush, et al. "State of the art on neural rendering." Computer Graphics Forum. Vol. 39. No. 2. 2020.

[^9]: Naik, Hemal, et al. "3D-POP-An automated annotation approach to facilitate markerless 2D-3D tracking of freely moving birds with marker-based motion capture." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2023.

[^10]: Das, Arun, and Paul Rad. "Opportunities and challenges in explainable artificial intelligence (xai): A survey." arXiv preprint arXiv:2006.11371 (2020).

[^11]: Elazhary, Omar, et al. "Uncovering the benefits and challenges of continuous integration practices." IEEE Transactions on Software Engineering 48.7 (2021): 2570-2583.

[^12]: Kassie, Nigussu Bitew, and Jagannath Singh. "A study on software quality factors and metrics to enhance software quality assurance." International Journal of Productivity and Quality Management 29.1 (2020): 24-44.

[^13]: Feldt, Robert, and Felix Dobslaw. "Towards automated boundary value testing with program derivatives and search." Search-Based Software Engineering: 11th International Symposium, SSBSE 2019, Tallinn, Estonia, August 31–September 1, 2019, Proceedings 11. Springer International Publishing, 2019.

[^14]: Sadowski, Caitlin, and Thomas Zimmermann. Rethinking productivity in software engineering. Springer Nature, 2019.