UDT 2024 – Autonomous robotic monitoring of subsea communication cables

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Abstract — This paper describes technology for autonomous robotic inspection of subsea communication cables. The method uses camera equipped Autonomous Underwater Vehicles (AUV) and develops intelligent subsystems to find, track and generate surveillance summaries of cables without interrupting their service. We present an overview of the methods being developed and describe initial proof-of-concept of the intelligent subsystems. The methods are being integrated on an AUV with field trials planned in 2024.

1 Introduction

The socioeconomic function of all nations relies on a network of >500 subsea cables, totalling 1.4 million kilometres in length and transmitting over 95% of internet data [1]. 200 to 300 cable faults occur each year, with 80% caused by activities such as fishing and anchoring, and natural hazards accounting for most of the rest. Strategies to improve critical cable infrastructure resilience include:

- Reduce damage consequence via network redundancy
- Reduce downtime through rapid damage detection and repair
- Reduce damage risk through surveillance and preventative measures

This paper proposes the use of camera-equipped Autonomous Underwater Vehicles (AUVs) to efficiently gather high-resolution cable surveillance information and rapidly identify and report threats to cable integrity.

In shallow coastal areas, cables are buried to reduce accidental anchor and fishing damage risks. However, the majority of seafloor cables lay exposed on the seafloor far from shore. Surveillance presents significant challenges:

- Cables are narrow (diameters <30mm, Fig. 1) making them hard to detect. Condition inspection and identifying abnormalities requires sub-cm resolution
- Cable route knowledge is uncertain, typically with lateral offsets of 5 to 10% water depth excepted on the as laid location, with further displacement possible due to currents, landslides and accidental snagging

These challenges are compounded by the high cost of offshore surveys (with survey vessels costing £20k-£50k per day of operation), and navigational challenges of Global Navigation Satellite System (GNSS) denied subsea environments, where position errors accumulate at 1% distance travelled or 1% of vehicle depth with surface acoustic tracking using sensor aided inertial navigation [2].

Fig. 1. Cross section of subsea cable next to a coin for scale

The core of the problem is that the uncertainty in prior cable route knowledge far exceeds the narrow swath of the high-resolution sensors needed to detect and inspect the cables. This makes the traditional pre-programmed waypoint following used by AUVs ineffective. Furthermore, the large volumes of high-resolution data gathered makes manual analysis unacceptably slow and error prone in the context of surveillance where there is an inherent need to minimise delays to response.

2 Objectives

We propose inspection of in-service subsea communication cables using AUVs equipped with cameras, lasers and intelligent realtime processing. As with other forms of surveillance, we expect large volumes of high-resolution data, the majority of which will not show any abnormality or cause for concern. To improve efficiency, we aim to develop the following capabilities:

- Realtime AI-enabled cable detection: Robust cable detection based on self-supervised feature learning to detect cables on a wide range of seafloor types [3,4]
- Cable-relative navigation: Probabilistic navigation that leverages approximate cable route knowledge as priors, updating these on the fly using realtime observations to guide cable tracking and search
- AI-based anomaly flagging: Identification of anomalies on or near cables for rapid reporting of these through wireless communication channels [4]

The methods are being implemented on the University of Southampton's Smarty200 AUV (Fig. 2 and Table 1 for specification). However, the approaches are platform and sensor agnostics, and are compatible with any camera and laser scan equipped AUV with a Doppler enabled navigational suite (i.e., Doppler velocity log, inertial measurement unit, depth and altitude sensors). This includes deep-diving AUVs capable of covering up to 100km per day with more than a week of endurance, with recent demonstration of shore-launched long-range imaging surveys [5]. There are also numerous examples of multiple AUVs being simultaneously operated from a single support vessel [6]. The scalability in numbers allows for significant reduction of operational cost per length of inspected cable through the use of AUVs compared to tethered, remotely operated vehicles (ROVs).

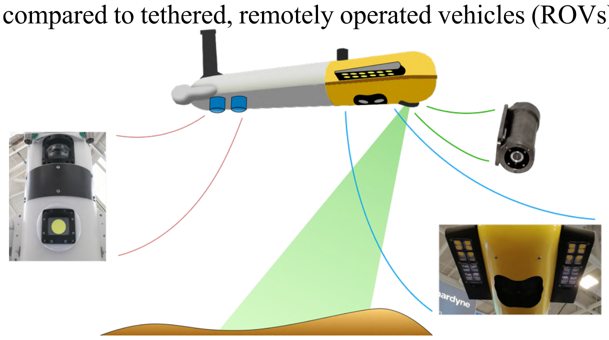

Fig. 2. Illustration of the Smarty200 AUV's imaging setup

Table. 1. Smarty200 AUV specification

Length, mass	2.0m, 70kg (in air)
Endurance, range, depth	12h, 12km, 200m (maximum)
Speed, altitude	0.3m/s, 1 to 3m
Swath, resolution	1.5 to 4.5m, <1mm
3D imaging	Recon LS 12MP camera with structured light line laser
Navigation, obstacle avoidance	Sprint Nav Mini DVL-INS USBL (Avtrak Nano), Micron scanning sonar
Communication	Acoustics (Avtrak Nano, in water) Wifi, Iridium (at surface)

3 Approach

Cable detection: Optical methods can achieve sufficient realtime resolution to resolve cables and determine their relative position and orientation to guide AUV navigation. While active and passive electro-magnetic (EM) sensors can also detect cables (including shallow buried sections) from up to 5m range with ~10m measurement footprint [7], they indicate bulk presence/non-presence of ferrous material and/or electrical currents, which is not ideal for guiding local autonomous navigation. The advantage of cameras over high-resolution acoustics such as Synthetic Aperture Sonar (SAS) is that although SAS can achieve large swaths ~200m, achieving cm-resolution requires processing of acoustic waveforms that cannot be achieved in realtime and so is unavailable for AUV navigation. Both EM and SAS have measurement swaths smaller than cable route uncertainties and cameras are still needed to identify anomalies, requiring a combined sensing approach.

Fig. 3 shows examples of images and structured light line laser-bathymetry from previous trials of our team, showing the varied appearance of cables and their background substrates, with intermittent local burial through natural processes. The sub-cm resolution bathymetry provides detailed context such as landing marks of an ROV skid next to the cable (centre image), which are hard to spot in images. Our detection is based on location-guided self-supervised feature learning methods developed in our previous research (Fig. 4) where we compare the location-guided autoencoder LGA [3] and geo-referenced contrastive learning of representation, GeoCLR [4]. An advantage of self-supervised methods is that they do not rely on human labelled training data to learn the features they use to describe images. Instead they learn features from unlabelled inputs directly. Location-guiding allows the methods to prioritise features that reoccur in nearby images, making these approaches effective at describing features that extend beyond the footprint of a single image frame. In marine applications, where light attenuation limits image footprints to <10m, this allows large scale spatial patterns and linear infrastructure to be efficiently described.

We analysed an AUV image dataset consisting of 113,658 image patches and paired laser-bathymetry maps. The dataset has 36,000 human ground truth labels, of which 1563 are of cables. The dataset was gathered during the FK180731 cruise of the RV Falkor, using a camera and laser scanning system similar to that on Smarty200. We assessed the algorithms' ability to detect cables, and the time taken to classify each image patch when using image only and combined image and laser-bathymetry.

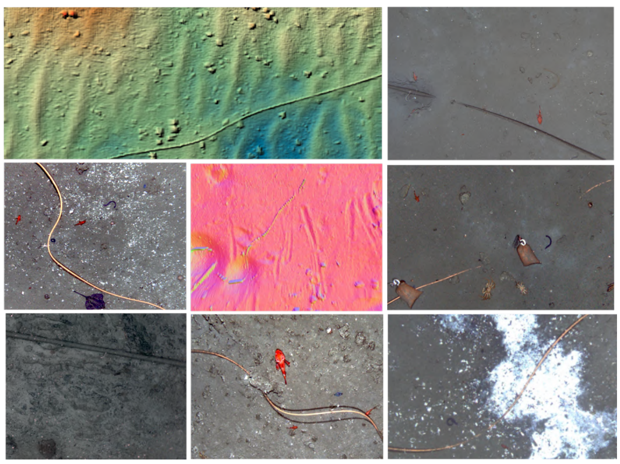

Fig. 3. Example images and laser-bathymetry of subsea cables

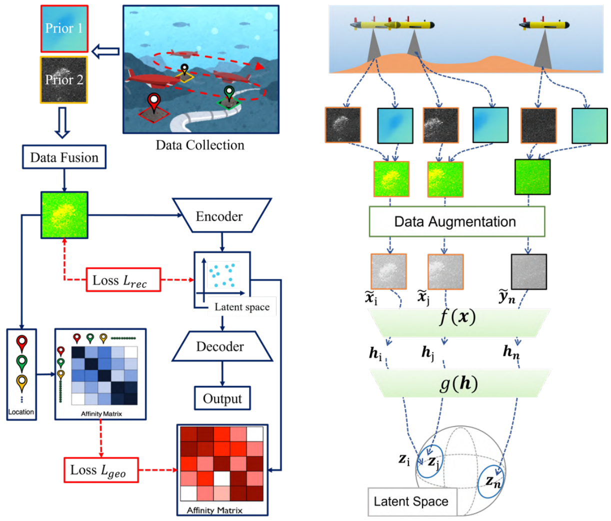

Fig. 4. Illustration of the self-supervised feature learning methods (left) LGA and (right) GeoCLR used in this work [3,4]

Navigation: A probabilistic navigation method is developed to guide cable search patterns using uncertain cable route maps as input. The method treats cable route estimation as a graph-based Simultaneous Localisation and Mapping (SLAM) problem [8], updating cable route estimates on the fly using realtime cable observations. This bounds the search space when detection is not possible, and back fills route estimates to unobserved regions.

Fig. 5 shows the concept. The cable search pattern is initially bounded by the cable route uncertainty. Search patterns are parameterised through the angle of incidence of the AUV relative to the cable route estimate, where the uncertainty envelope bounds search trajectories to form a zig-zag (dotted lines in Fig. 5). Once the cable is observed, it is tracked based on realtime cable detection (orange in Fig. 5). If cable detection is unsuccessful for any reason, the observation updated cable route estimate is used to guide the search trajectory. The updated uncertainty boundaries grow from the observed regions using cable catenary calculations that model the maximum divergence of cables based on assumed friction and cable load bearing calculations. Since the search envelope grows smoothly with range from successful detections, the method recovers quickly from momentary loss of cable tracking due to vehicle manouevring (e.g., obstacle avoidance) or local occlusion. We assess the method using simulated cable routes and uncertain route priors and investigate sensitivity to the steepness of the zig-zag search pattern.

Rapid remote awareness: To minimise the time from observation of an anomaly to human awareness, we have developed a flexible dataset query capability that can interact with large image datasets over available wireless communication channels without reliance on physical recovery of the AUV. AUV camera surveys typically gather images at a rate of ~1/s, resulting in >10,000 images being gathered in a single deployment. Since AUVs are often deployed at the same time as other AUVs and marine systems, reliance on physical recovery to access their data forms a bottleneck that can introduce significant delays to human awareness of threats (e.g., ROV operations, deployment or recovery of other assets can occupy ship cranes, crew and constrain manoeuvrability to recover AUVs by several hours). We assess the effectiveness of

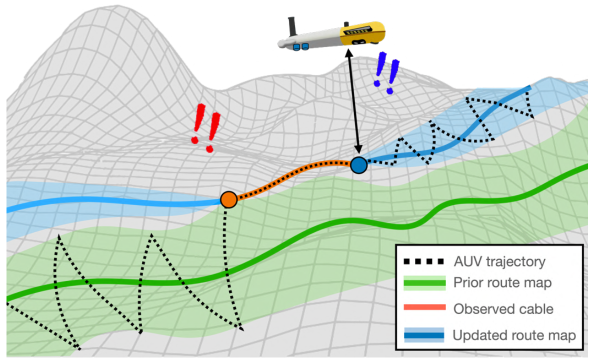

Fig. 5. Illustration of the probabilistic navigation method

enabling humans to flexibly interact with large image datasets using the same self-supervised feature learning used for cable detection as the AI back-end. The framework allows humans to present any query image, where the corresponding location of the image in the AI feature space is used to rank all images in the dataset according to their similarity to the query. Returning similar images together with their georeferences allows prioritised image subsets to be presented to humans. Since similarity can be determined from already computed image feature spaces, querying an entire dataset takes milliseconds, and can be done interactively over low-communication bandwidths to efficiently understand large datasets. Interaction can be over acoustic modems, typically available during missions if ships support AUVs for acoustic localisation, or via wifi from a nearby ship once an AUV has surfaced. Global interaction (e.g., to shore) is possible over satellite networks, where we have previously transmitted ~100kB summaries of >100GB raw image datasets over the Iridium network (~20min at the surface). Since the AUV navigation estimates used to georeferenced anomalies have order of magnitude lower uncertainty than the initial cable route estimates, subsequent operations can efficiently revist relevant seafloor locations.

4 Results and discussion

This section provides proof-of-concept demonstrations of each intelligent subsystems. Table 2 summarises cable detection results using the LGA and GeoCLR feature learners, with and without laser-bathymetry information. The performance is assessed against human-expert labelled ground truth using standard accuracy metrics. GeoCLR outperforms LGA, achieving an F1-score of 0.85 (max. 1.0). The precision (0.97) indicates a low false positive rate, and the recall (0.75) indicates some cables are not detected. Addition of depth information does not improve the results, where for the LGA it leads to confusion of the learning network. Both methods are realtime deployable from a standard AUV embedded CPU.

Fig. 6 shows a simulated example of the probabilistic navigation method applied with a search angle of 60^{O}

Table. 2. Cable detection performance and processing time on Smarty200's Intel Core i7 2.20GHz Dual Core, 8GB RAM

Precision: Recall: **F1**	RGB	RGB+D	Time per image (ms)
LGA	0.82:0.56:**0.67**	0.33:0.36:**0.35**	371.4
GeoCLR	0.97:0.75:**0.85**	0.94:0.73:**0.82**	376.5

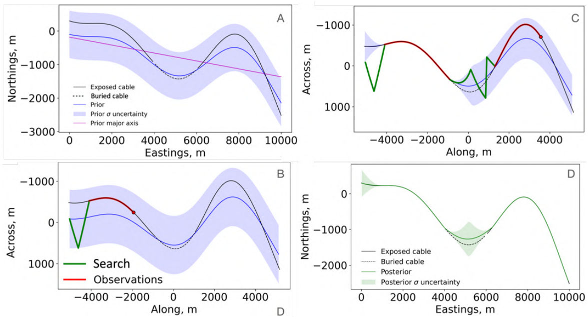

Fig. 6. Graph-SLAM based probabilistic cable route estimation using uncertain priors, observations and cable catenary models

relative to the estimated cable route. Panel A shows the initial cable route and uncertainty prior that guides the initial search. In Panel B, the AUV search finds the actual cable route on the second zig-zag leg and tracks the cable. Panel C shows the response to a region of buried cable, where the observation updated route estimate and uncertainty are used to bound the search. Panel D shows the final cable route estimate after all observations.

Fig. 7 shows query results on the 113,658 image dataset, where sandbags are used as a query example (these do not pose a threat). The dataset has 25 sandbags in total. The figure shows the 50 images judged to be most similar to the query (top left image) according to GeoCLR's feature space. Table 3 summarises the performance when each of the 25 sandbags was used as the query. The results indicate order-of-magnitude reduction in data that needs to be looked at compared to a random search.

Currently, the proposed intelligent subsystems are being integrated on the University of Southampton's Smarty200 AUV, where field trials are planned in 2024.

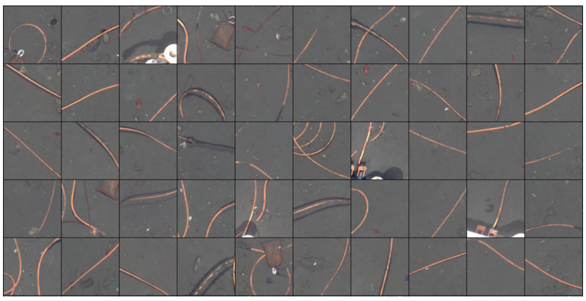

Fig. 7. Top 50 similarity return for a query image (top left)

Table. 3. GeoCLR driven query results (median performance)

% of 25 targets to find	60	80	96	100
% of dataset to check	1.0	2.3	6.0	7.3
% for random search	56.0	76.0	92.0	96.0
η gain over random	56.0x	33.0x	15.3x	13.2x

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References

[1] M.A. Clare, I.A. Yeo, L. Bricheno, Y. Aksenov, J. Brown, I.D. Haigh, T. Wahl, J. Hunt, C. Sams, J. Chaytor, B.J. Bett, L. Carter, Earth Sci. Rev. **237**, 104296 (2023)

[2] L. Paull, S. Saeedi, M. Seto, H. Li, IEEE J. Ocean. Eng. **39**, 131 (2014)

[3] T. Yamada, A. Prügel-Bennett, S. B. Williams, O. Pizarro, B. Thornton, Field Robotics **2**, 1134 (2022)

[4] T. Yamada, A, Prügel-Bennett, B. Thornton, J Field Robotics **38**, 52 (2021)

[5] A. Bodenmann, J. Cappelletto, M. Massot-Campos, D. Newborough, E. Chaney, R. Marlow, R. Templeton, A.B. Phillips, B.J. Bett, C. Wardell, B. Thornton, *IEEE Underwater Technology* (2023)

[6] U. Neettiyath, H. Sugimatsu, T. Koike, K. Nagano, T. Ura, B. Thornton, IEEE Robot Autom Mag. (2024)

[7] T. Szyrowski, S.K. Sharma, R. Sutton, G.A Kennedy, Underwater Tech. **31**, 133 (2013)

[8] R. Kümmerle, G. Grisetti, H. Strasdat, K. Konolige and W. Burgard, *IEEE International Conference on Robotics and Automation* (2011)

Author/Speaker Biographies

Prof Blair Thornton has 20 years experience developing sub-sea robotic platforms, sensors and data-processing. He has >500 sea days for exploration, infrastructure inspection and disaster monitoring. **Adrian Bodenmann** is a robotics engineer of 14 years, with experience building and deploying systems for seafloor visual mapping, and developing methods for 3D reconstruction and interpretation of large datasets. **Dr Miquel Massot-Campos** is a field robotics engineer and C++/Python developer. He works on remote awareness and interpretation for scalable understanding of robotically gathered imagery. **Sam Simmons** is a marine robotics technician with experience integrating and operating advanced navigation and imaging capabilities on AUVs. **Dr Hugo Putuhena** is a geospatial analyst, with experience in GIS analysis of multivariate geospatial datasets for offshore infrastructure. **Prof Susan Gourvenec** has 25 years of geotechnical engineering experience with particular interest in offshore geotechnics and is the RAEng Chair in Emerging Technology for Intelligent and Resilient Ocean Engineering. **Prof David White** is a geotechnical engineer who's work ranges from fundamental mechanical soil response studies to design of novel construction and monitoring technologies. **Tom Bennetts** has >20 years experience integrating technically pioneering systems into field deployable marine solutions, working across; robotics, positioning, acoustic and optical communications, sonar, Doppler inertial and multi-vehicle control over satellite communications. **Dr Darryl Newborough** has >20 years experience developing sub-sea technology and applications, including; acoustic and free-space optical communications, Doppler, imaging and inertial navigation. He partners academic groups to accelerate advances into commercial reality.