AURORA, A multi sensor dataset for robotic ocean exploration

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Abstract

The current maturity of autonomous underwater vehicles (AUVs) has made their deployment practical and cost-effective, such that many scientific, industrial and military applications now include AUV operations. However, the logistical difficulties and high costs of operating at-sea are still critical limiting factors in further technology development, the benchmarking of new techniques and the reproducibility of research results.

To overcome this problem, this paper presents a freely available dataset suitable to test control, navigation, sensor processing algorithms and others tasks. This dataset combines AUV navigation data, sidescan sonar, multibeam echosounder data and seafloor camera image data, and associated sensor acquisition metadata to provide a detailed characterisation of surveys carried out by the National Oceanography Centre (NOC) in the Greater Haig Fras Marine Conservazion Zone (MCZ) of the U.K in 2015.

Keywords

Autonomous Underwater Vehicles, imaging camera, sidescan sonar, multibeam echosounder, underwater navigation

1 Introduction

Recent years have seen dramatic progress in the development of Autonomous Underwater Vehicles (AUVs) and the accompanying communication and sensor technology (Ferreira et al. 2019) (Ferri et al. 2017; Munafo and Ferri 2017; Ferri et al. 2018; Caiti et al. 2013). This in turn has allowed a significant advance in marine survey and science results (Caress et al. 2008). Recent examples include AUVs deployed under the ice-shelves of Antarctica collecting data that has changed our understanding of the under-ice environment (Jenkins et al. 2010), or the usage of a combination of AUV and ROV missions to obtain unprecedented high-resolution maps of marine vertical structures (Robert et al. 2017; Ribas et al. 2012).

It is likely that robotics will play a key role in the future of ocean research and exploration (Huvenne et al. 2018; Robison et al. 2017). Marine robotic systems can be deployed at depths and in environments that are out of direct reach for humans, they can work around the clock, for example, Autosub6000 (McPhail 2009) has a maximum battery endurance of 36h and Autosub Long Range 1500 (Roper et al. 2017) an endurance of more than three months. AUVs can carry out a range of pre-programmed operations (McPhail 2009), that can include adaptive behaviours (Yoerger et al. 2021; Ferri et al. 2018), freeing up resources to enable cost savings or to extend the scope of activities undertaken in a particular project. Despite these steps forward and undoubted achievements, the underwater environment remains one of the most challenging to operate in, being characterised by logistic difficulties and high cost activities. These issues exacerbate the already important difficulties in benchmarking new algorithms, and in reproducing research results (Peng 2011; Bradbury and Plückthun 2015).

A recent survey (Baker 2016) has revealed that more than 70% of researchers have attempted and failed to replicate another scientist's research results, and more than half have not succeeded to reproduce their own experiments. Top methodological failings range from low statistical power and poor analysis, to poor experimental design and insufficient replication in the original lab, with methodological improvements pointing strongly to a more robust experimental design and to stronger statistical analysis. All of this relates to long-understood aspects of good experimental / survey design. In this respect, from a scientific perspective, AUVs offer some key advantages, being uniquely positioned to greatly increase the size of the sampling unit and to greatly increase the level of replication. Being well instrumented they also have the ability to partition (stratify) the environment (sampling population) into relevant compartments by co-measurement of multiple parameters. From a marine robotics perspective, one of the main reasons for a general lack of reproducibility is often to be found in the lack of a clear experimental description and in the difficulties in accessing the original data. Sometimes, even when the data are made available, the lack of informative metadata makes its effective usage very difficult. The lack of time-synchronization among

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the sensors and the needs of pre-processing steps, often requiring proprietary software, on the acquired data are additional high-impact barriers. Moreover, in the underwater case, the logistic difficulties and the high costs typically associated with marine experiments and surveys usually make reproducing a mission practically infeasible. As a result, the available datasets may be seen to have a very high value, prompting researchers and institutions to become quite conservative when it comes to deciding on data access permissions. To overcome some of these issues, this paper introduces a multi-sensor dataset named AURORA (A multi sensor dataset for robotic ocean exploration) built by putting together multiple missions of the AUV Autosub6000 (McPhail 2009), with the aim of allowing other scientists to benchmark solutions, compare results, and hopefully help the overall reproducibility of the related research. The AURORA dataset groups together and makes available high quality AUV navigation data with sidescan Sonar (SSS), Multibeam EchoSounder (MBES) and camera images. The data were collected during the RRS *James Cook* cruise 125 (JC125) (Huvenne et al. 2016) and the non-curated version of the raw data are available from the British Oceanographic Data Centre (BODC). This article describes the AURORA dataset, a carefully curated and selected subset of sensor data and AUV navigation and sensor settings. To make it easily accessible and usable for algorithm development and benchmarking, the raw data have been carefully polished, organised, space and time synchronised and timestamped. Moreover, all sensor data have been converted to standard formats and all data logs to human readable form. When specific processing was necessary, this is described, documented and exemplary code is made available. In this respect, the dataset presented here provides a unique set of synchronised vehicle and sensor data prepared and made available to simplify test and reproducibility of control, navigation, and sensor processing algorithms, using data collected in the very dynamic and challenging offshore environments of the Celtic Sea. To maximise its potential impact as a benchmarking tool, AURORA includes both raw and processed data, navigation and positions of the vehicle together with all sensor settings and configurations. The authors hope that the information provided will make the dataset usable in many application areas such as ocean engineering, robotics, and computer vision.

Below, the paper gives an overview of some publicly available datasets that can be used to complement the information provided in this work (Section 2); provides a concise description of the AUV missions, of the area where the data were collected, and of the environment at the time when the missions were performed (Section 3); describes the characteristics of the vehicle and its sensors (Section 4); report the structure of the dataset (Section 5); presents conclusions and directions of future work (Section 6).

2 Related Work

Publicly available datasets are becoming the norm for algorithm comparison and benchmarking, thanks to a substantial pull from the machine learning and computer vision fields (Krizhevsky 2009; Cordts et al. 2016; Russakovsky et al. 2015). Terrestrial robotics is also witnessing a surge in the number of datasets made openly available. A dataset captured from a VW station wagon for use in mobile robotics and autonomous driving research is presented in Geiger et al. (2013). The paper describes six hours of traffic scenarios using a number of sensors, ranging from laser scanner to high precision GPS/IMU inertial navigation systems. Scenarios are diverse and they include freeways, rural areas, and inner-city scenes. The data are calibrated, synchronized, and timestamped. A large dataset gathered from a robot driving several kilometres through a park and campus is described in Smith et al. (2009). All data are carefully timestamped and all data logs are in human readable form with the images in standard formats. Tools are also provided to access the data. The data from 1000 km of recorded driving, collected over more than a year is reported in Maddern et al. (2017). The data were collected in all weather conditions, including heavy rain, night, direct sunlight and snow. In the underwater community several datasets have been published to compare methods and algorithms. Most of them are in the form of vision data (Kavasidis et al. 2014; Joly et al. 2015; Duarte et al. 2016; Radolko et al. 2016; Skinner and Johnson-Roberson 2017; Chavez et al. 2019). These datasets are task-specific and can be categorised as either image classification, image restoration, or underwater change detection. Synthetic datasets are used to create large sets of training data for deep-learning applications, for instance, WaterGAN (Li et al. 2018) uses a synthetic underwater colour image to train a colour correction dataset. The integration of multiple sensor data has allowed the generation of several datasets (Bryson et al. 2013; Lindemuth and Lembke 2013; Mallios et al. 2017) that open the way for the development of new solutions in various tasks. A particularly interesting dataset from a vehicle navigation perspective is that presented in Mallios et al. (2017). This dataset consists of sonar, doppler velocity log (DVL), inertial measurement units (IMUs), depth, and camera information. The mission, which explores an underwater cave, was performed in a very challenging environment but it was relatively short, with the vehicle running for approximately 500m. As in the case of the imaging datasets, these datasets have been built mainly to address the needs of one specific application (e.g. localization and simultaneous localization and mapping SLAM).

In contrast, AURORA, which collects data over more than 150 km of underwater navigation, aims at providing data that are normally collected during long range oceanographic missions and does not have the constraints of any specific application. The dataset consists of all the necessary data (from raw to processed) to allow users to use it and process it according to their specific needs. Moreover, additional information (metadata, sensors positions, navigation, etc.) are provided in human-readable form.

3 Mission Data

The data presented in this work were collected in the Greater Haig Fras Marine Conservation Zone (MCZ) area of the UK (Figure 1).

Greater Haig Fras MCZ is located around $120km$ west of Cornwall and it is considered a particularly significant

Figure 1. General location of the Haig Fras survey area in the Celtic Sea shown as a blue rectangle. The black line shows the position of the repeat Autosub6000 survey.

area as it encompasses all of Haig Fras, a geologically valuable, fully submerged outcrop of bedrock, surrounded by continental shelf seabed consisting of a wide range of sediment types. Autosub6000 was first deployed in the area in July 2012 (Ruhl 2013), with early results published in Wynn et al. (2014), with a detailed account of the environment and seafloor fauna of the survey area published later (Benoist et al. 2019).

In general terms, the survey area has a water depth of ca. 100m and only modest topographic range ($<$ 10m), it encompasses a broad range of seabed types from exposed bedrock to fine sandy sediments, that provide habitats for many species of fish and larger invertebrates, some having particular conservation interest (e.g. the ’ross coral’ *Pentapora foliacea*).

This work collates data obtained during the JC125 research expedition (Huvenne et al. 2016), to the Greater Haig Fras survey area in 2015. From the perspective of this work, two AUV missions are used:

1. Mission number 86 (M86), in which MBES, SSS and camera data were acquired. The MBES data acquisition was performed at an altitude of 50m from the bottom for the MBES survey, 15m from the bottom for the SSS data, 3m from the bottom for the camera work, and at the mean speed of approximately 1.1m/s. The mission lasted 20 hours (from 10th of October 2015 at 16:30 to 11th of October at 12:45) with a total distance travelled of 81.25 km. Only the MBES data set is included in AURORA.
2. Mission number 87 (M87), was carried out soon after to collect camera and sidescan sonar images. The SSS mission (a repeat of $M86$) was carried out at high frequency at two different altitudes (15m, 3m). However, the main SSS data have been acquired at 15m with an acoustic frequency of 410kHz. The photo mission was performed at an altitude of 3m and more than 40000 images were collected. The AUV reached a maximum depth of 107.7m. The mission had a duration of 15 hours. It started on 12th of October 2015 at 06:30 and ended on 12th of October at 22:00.

Note that this multi-altitude/ multi-sensor approach is a common mission profile for AUV operations, where the first dive is done to collect multibeam data to have a generic view of a large area, while subsequent dives are planned to collect data in specific regions using sidescan sonars and cameras (Ferri et al. 2017).

The trajectory of the AUV in the area of operation is shown in Figure 2.

During the cruise, the weather was relatively fair, with a calm sea and a light breeze on the first two days (9-10 August). For the following days conditions worsened, reaching up to a sea state 6.

4 Platform and sensors

The data presented in this work was collected using the Autosub6000 AUV (McPhail 2009). The vehicle measures 5.5m in length and 0.9m in diameter, having a weight in air of 1800kg (Figures 3, and 4). It is fitted with five pressure-balanced lithium polymer rechargeable batteries that can provide up to 54kWh. It can operate for $\sim$ 36 hours (McPhail 2009), which corresponds to about 230km at the maximum speed of 1.75m/s (McPhail 2009). It comes with control, collision avoidance and terrain following algorithms to operate well in different conditions and extreme environments. It has an IXSEA Photonic Inertial Navigation System (PHINS) and an RDI Teledyne Workhorse Navigator Acoustic Doppler Current Profiler (ADCP) to enable underwater navigation with an accuracy of about 0.05% of the distance travelled. The LinkQuest Tracklink 10000 acoustic device, is used to combine Ultra Short Base Line (USBL) and bi-directional acoustic messaging system (acoustic telemetry) for real time tracking of the AUV from the support ship.

Table 1 presents the specifications of the vehicle and of the sensors used to generate this dataset.

4.1 Navigation sensors

The main navigation system is the IXSEA Photonic Inertial Navigation System (PHINS) (IXBlue 2019). The PHINS has a position accuracy of 0.05% of travelled distance and a heading accuracy of 0.02^o secant latitude RMS, when DVL bottom lock is available. To enable high navigational accuracy the PHINS uses the RDI Teledyne Workhorse

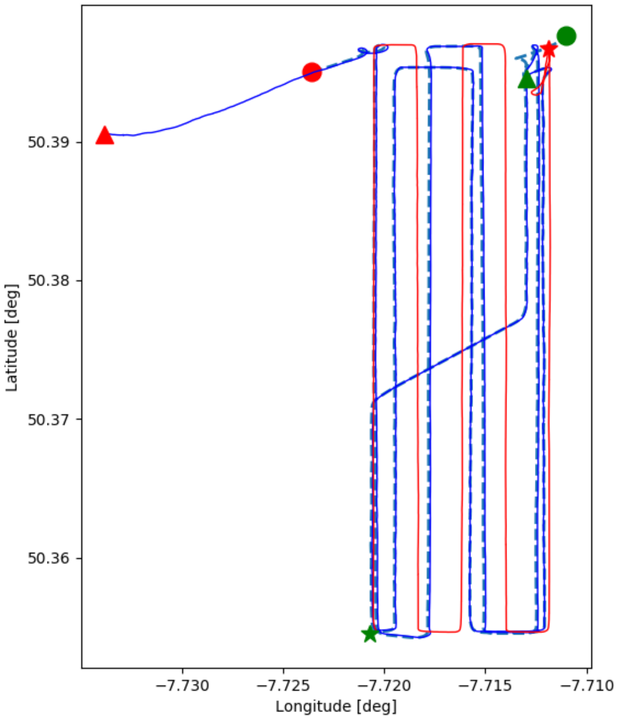

Figure 2. Autosub6000 trajectory during mission M86 from RRS James Cook cruise 125. Autosub6000 performed a multibeam survey first (red line), and then a sidescan sonar (SSS) (dashed blue line) and camera survey (continuous blue line). Green circle: start of camera acquisition, Red circle: end of camera acquisition; Green triangle: start of SSS acquisition, Red triangle: end of SSS acquisition; Green star: start of multibeam acquisition, Red star: end of multibeam acquisition.

Navigator DVL. The DVL, which has a 300kHz centre frequency, works within an altitude range of 1.0 - 200m from the seabed. The DVL has a bottom velocity resolution of 0.1cm/s and a long-term accuracy of ±0.2cm/s. The DVL also acts as an Acoustic Doppler Current Profiler (ADCP) to measure water velocities. The DS2806 HPS-A pressure sensor is used to measure the depth. It can measure with a range from 100mbar to 600bar.

4.2 Perception sensors

The vehicle carried a sensor suite which included: 300 kHz ADCP for water velocity measurements, an EdgeTech 2200M sidescan sonar with chirp sub-bottom profiler, a multibeam echosounder, and dual conductivity, temperature, and depth (CTD) sensors. In addition to these standard sensors, one vertical downward-facing camera, and one oblique forward-facing camera were also fitted. The AURORA dataset focuses on the data acquired from the downward-facing imaging camera, the sidescan sonar and the multibeam echosounder:

1. The FLIR, formerly Point Gray Research Inc. Grasshopper 2 camera used has a 2/3-inch sensor, comprising 2448 x 2048 pixels. The camera was equipped with a 12 mm focal length lens with resultant horizontal and vertical acceptance angles of 26.71^o and 22.65^o, respectively. The vertical camera was mounted in the forward section of the vehicle, at 90^o with respect to the longitudinal axis (Figure 4). With this geometry, and operating at a $3m$ altitude, the vertical camera captures an image of size 1.78m^2 seabed. An 11 J xenon strobe unit designed at the NOC was used with each camera (Figure 5), with a 1Hz repetition rate. The AURORA dataset includes more than 40000 images from the vertically oriented camera.
2. The Kongsberg EM2040 multibeam sonar system (Kongsberg 2019) operated at a 200kHz frequency with a maximum ping rate of 50Hz. The system provides 400 beams with an angular range of ±70^o across track and a 0.4^o bandwidth along track.
3. The Edgetech 2200M (Edgetech 2019) is a dual-frequency sidescan sonar (120/410kHz) and sub-bottom profiler. All missions used the high-frequency system with a 410kHz, 50kHz bandwidth, 2.4ms wideband pulse, together with a 2-13kHz 16ms sub-bottom chirp pulse running at 6Hz repetition rate (Huvenne et al. 2016).

Table 1. Main characteristics of the sensor suite specifications.

System	Specifications
Autosub6000	
Body Type	Torpedo
Size (L×W×H)	5.50m ×0.90m ×0.90m
Weight	2000 kg
Maximum Depth	6000m
Dynamic Buoyancy	No
Endurance (nominal load)	36 hours
INS - PHINS	
Position accuracy (with DVL)	0.05% of traveled distance
Heading accuracy (with DVL)	0.02 deg secant latitude RMS
Roll and pitch dynamic accuracy (no aiding)	0.01 deg RMS
DVL - RDI Teledyne Workhorse 300	
Frequency	300 kHz
Velocity Accuracy	± 0.4% ± 0.2 cm/s
Altitude	$1.0 - 200.0$m
Max ping rate	7 Hz
Depth DS2806 HPS-A	
Pressure range	100 mbar - 600 bar
Output span	4V ± 1%
Repeatability	± 0.25% of span
Grasshopper2 imaging camera	
Sensor	Sony ICX625AQ
Resolution	2448 × 2048
Sequence period	1000 ms
EdgeTech 2200M sidescan sonar and sub-bottom profiler	
Frequency	410 kHz
Altitude	15 m
Sub-bottom profiler Chirp Sweep	16 $ms, 2 - 13$kHz
Kongsberg EM2040 multibeam	
Frequency	$200 - 400$ kHz
Beam Count	256 and 400
Beam Angle (Degree)	140^o

The sensor data are then geo-referenced using the AUV navigation system (INS, DVL and CTD sensor) described in Section 4.1. Figure 3 shows the position of the various sensors on the vehicle and their offsets (see also Table 2).

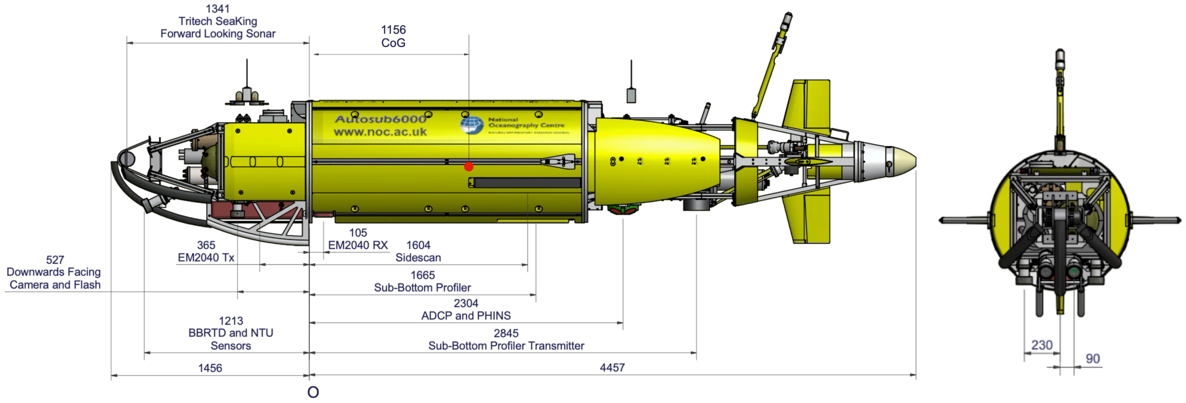

Figure 3. Autosub6000 sensors and their position on the vehicle during the Haig Fras surveys (dimensions are in mm). The centre-of-gravity (CoG) is represented with a red circle and it is located 1156mm from the reference axis O.

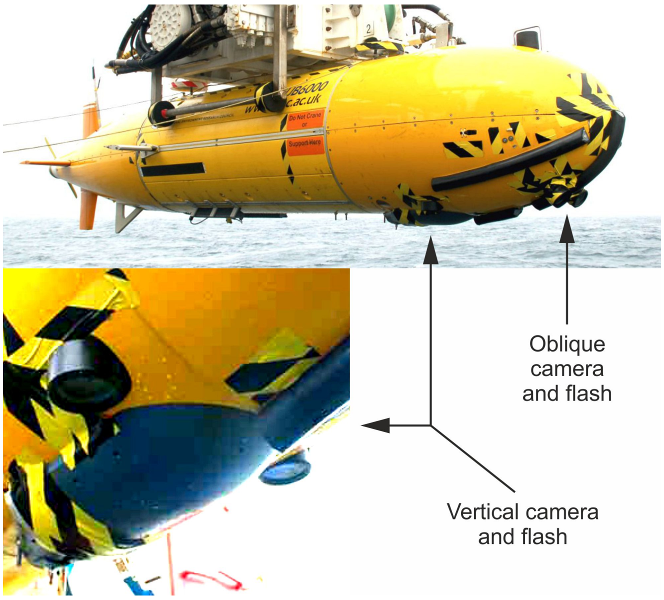

Figure 4. Autosub6000 showing camera locations and orientations on the vehicle. Note that the oblique camera was not used during this mission (adapted from Morris et al. (2014)).

Table 2. Sensor offsets with respect to the centre of gravity of the vehicle (COG) *.

Sensor	Value (mm) [x,y,z]
DVL/PHINS	[-1148, 0.0, -387]
Vertical Camera	[1683, 230, -407]
EM2040 (TX)	[1521, 0.0, -421]
EM2040 (RX)	[1051, 0.0, -421]
2200M (Sidescan)	[-448, ± 430, -156]

5 Data structure

The dataset is provided in raw and standard format so as not to constrain users by requiring a specific tool. All data have been synchronised and timestamped to make it easily accessible in both time and space. The general structure is shown in Figure 6.

The folder structure is based on the separation between the two vehicle missions. Within each mission one folder per sensor is used to store data. AUV navigation data are included together with the sensor data. Each folder includes one index file that can be used to easily access the data (or specific variables in the data) and to synchronize all sensors together. Along with the raw data, some preliminary post-processing have been performed to simplify usage such as colour conversion for camera data or format conversion for SSS data. The data are hosted and available at https://ieee-dataport.org/open-access/aurora-multi-sensor-dataset-robotic-ocean-exploration. Exemplar code and detailed instructions on how to process the data are available at https://github.com/noc-mars/aurora.

The following sub-sections go into the details of the processing performed and on the detailed structure of the metadata provided with the dataset.

5.1 Imaging camera

AURORA contains 45319 images of size 2448 x 2048 with four representive examples reported in Figure 7. The Grasshoper2 camera captures raw format images. To convert the raw format data into colour images, a demosaicking or debayering function is required. The result is stored as a jpeg image together with the raw image. The MATLAB and Python processing code is available to detail what operations have been performed. The images are accompanied by a comma separated (csv) metadata file that contains the position, depth and altitude, relative folder and availability of every frame taken by the camera.

5.2 Sidescan sonar data

The SSS raw data are stored in JSF format (Edgetech 2016). This file includes low and high-frequency sidescan data as well as the chirp sub-bottom profiler data all collated together. To ensure greater clarity when working with these files, two main issues had to be overcome. First, the JSF format is a proprietary format with no specific documentation. Second, the official document (Edgetech 2016) is not intended to be a complete description of this format. As a result those files were processed as follows. First, the raw data are converted into eXtended Triton Format (XTF) (Zhang et al. 2016) files through a

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* x is positive forward, y is positive to port, and z is positive upward.

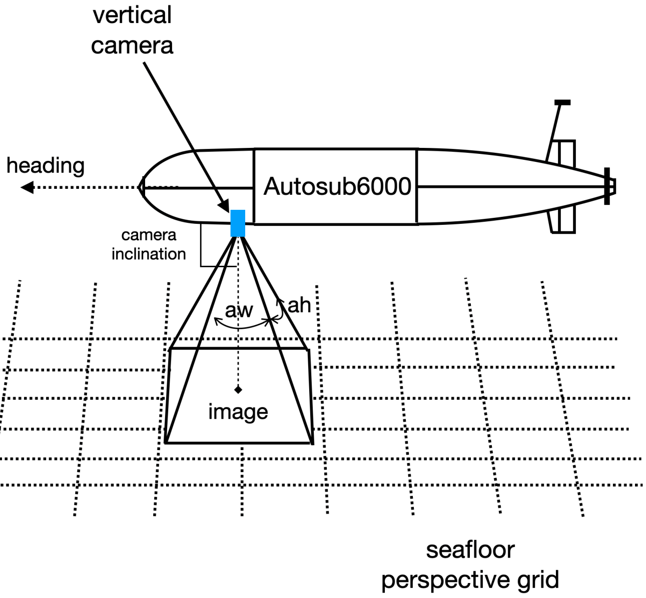
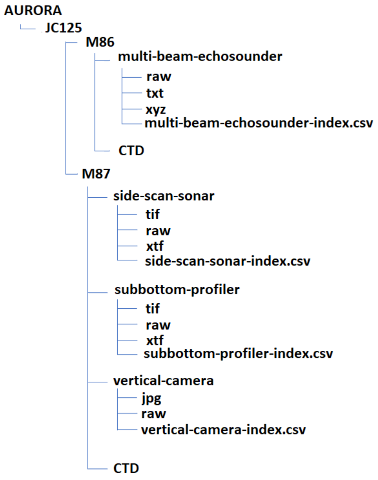


Figure 5. Schematic of the Autosub6000 in operational mode above the sea floor showing the camera locations and fields of view. aw = angle width; ah = angle height of vertical camera. Note. Autosub and the perspective grid are not to scale (adapted from Morris et al. (2014)).



```
AURORA
└─ JC125
   ├─ M86
   │  ├─ multi-beam-echosounder
   │  │  ├─ raw
   │  │  ├─ txt
   │  │  ├─ xyz
   │  │  └─ multi-beam-echosounder-index.csv
   │  └─ CTD
   └─ M87
      ├─ side-scan-sonar
      │  ├─ tif
      │  ├─ raw
      │  ├─ xtf
      │  └─ side-scan-sonar-index.csv
      ├─ subbottom-profiler
      │  ├─ tif
      │  ├─ raw
      │  ├─ xtf
      │  └─ subbottom-profiler-index.csv
      ├─ vertical-camera
      │  ├─ jpg
      │  ├─ raw
      │  └─ vertical-camera-index.csv
      └─ CTD
```

Figure 6. Structure of the AURORA dataset. Note that the AUV navigation files are included together with the sensor data. Each folder includes an index file to simplify and synchronize the data.

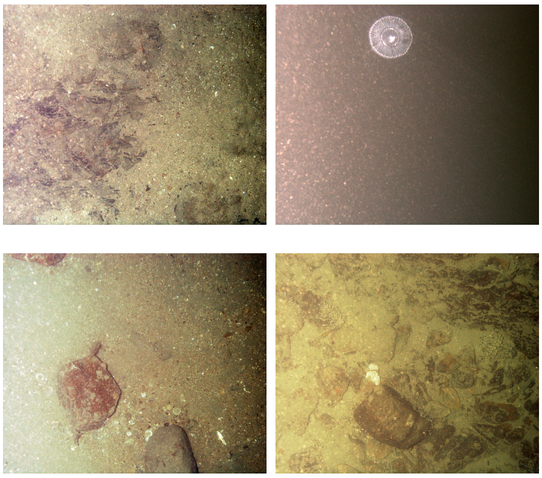


Figure 7. Camera images captured during the JC125 expedition (mission 87).

converter program provided into the SSS folder and set Gain 15dB TVG 0dB/100m . The next steps concern the extraction of image and ping information. To achieve this, the SonarWiz software (Technolog 2016) was used. Firstly, the navigation information are imported into each .xtf file. This is because, during the JC125 missions, the SSS navigation is obtained separately from Autosub data files. Then, the new .xtf file with navigation, which Autosub collects during its mission, were imported into SonarWiz and the images were extracted. Finally, individual pixel lines were processed in high-resolution into a greyscale mosaic. The mosaic has been stored in .tiff format. The SSS folders include both raw data and .xtf files (with and without navigation information). Finally, a metadata file was created with further information such as time, number of pings, navigation. An example of the sidescan sonar data is shown in Figure 8.

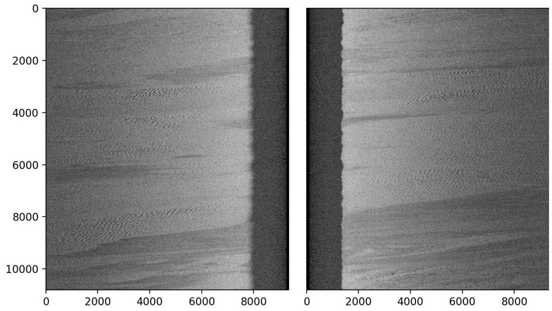


Figure 8. Sidescan sonar transect acquired during during Autosub6000 mission 87, port and starboard channels.

5.3 Multibeam echosounder sonar

The Kongsberg EM2040 stored its information in .all format (Kongsberg 2018). The provided multibeam files

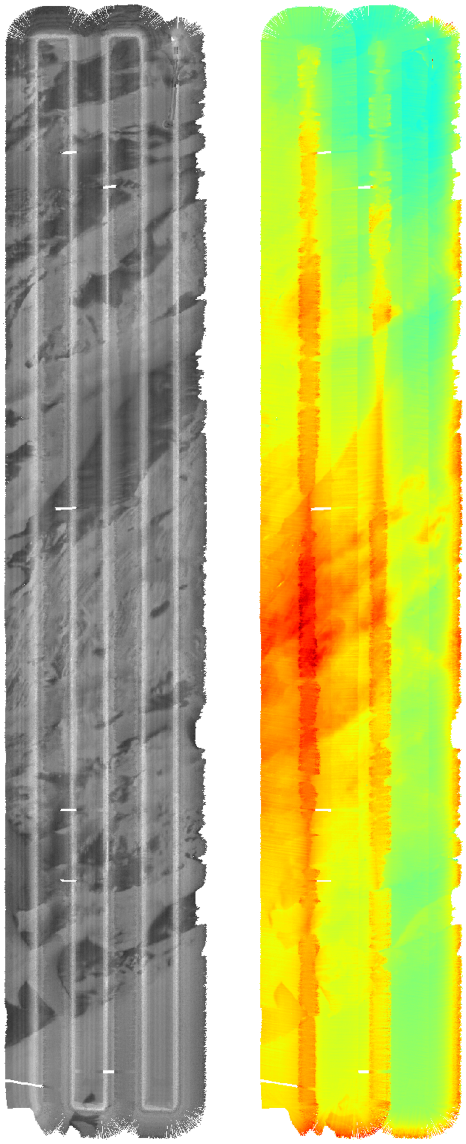


Figure 9. MBES backscatter (left) and MBES bathymetry data (right) acquired during the JC125 expedition, mission 86.

were partially pre-processed to simplify access. The following steps have been performed.

Due to an in-mission time desynchronization problem, to process the MBES data, all files had to be merged into a single file. This is not a standard procedure for multibeam processing but it was necessary for these data to maintain the correct metadata structure (only the first recorded file possessed the required header information). This has been done while maintaining the file in chronological order. The resulting file was imported to SonarWiz and navigation, and beam data were extracted. The collected multibeam data is reported in Figure 9.

6 Conclusion

This paper provides a comprehensive dataset of AUV navigation, sidescan sonar, multibeam, and camera images. The data were collected during two missions of the Autosub6000 AUV in the Greater Haig Fras Marine Conservation Zone in the Celtic Sea. The data have been carefully polished, timestamped and time and space synchronised, and are provided both in raw form and after a very light and preliminary pre-processing to make them more easily accessible. The ambition is to continue to update the dataset to include additional sensors and to add more missions as they become available.

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