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Remote Awareness of Image Quality for Multi-week Shore-launched AUV Surveys

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ABSTRACT Visual seafloor imaging using autonomous underwater vehicles (AUVs) has become an established method for seafloor mapping and monitoring. With AUVs now achieving multi-week endurance and several hundred kilometres of range on a single charge, image quality assessment on-board vehicles in the field is necessary for robust data acquisition given the sensitivity of underwater imaging surveys to environmental conditions. This research develops a metric to assess seafloor image quality in situ, and demonstrates its use for quality assurance during a 21-day, shore-launched AUV campaign that visited 3 sites up to 170 km from shore. The metric was transmitted via satellite communication along with vehicle telemetry to shore-based AUV operators during regular surfacing intervals without relying on physical vehicle recovery. The method was implemented on the seafloor laser scan and strobed imaging system BioCam, deployed on the Autosub Long Range AUV (a.k.a. Boaty McBoatface) in the North Sea. Several tens of hectares of seafloor imagery were collected, and image quality scores were transmitted. This information was used to re-task the AUV and maximise the quality of acquired images within operational constraints. Data products generated from the collected imagery show the improvements achieved that would otherwise have been missed. This highlights the importance of remote awareness of data quality to facilitate longer and consecutive mapping missions without reliance on physical vehicle recovery.

INDEX TERMS Autonomous underwater vehicles, environmental monitoring, image quality, low-bandwidth communication, photogrammetry

I. Introduction

The past ∼40 years have seen the development of various AUV mapping techniques [1], [2] to enable large-scale, high-resolution monitoring of seafloor environments. In particular, camera-equipped AUVs operating several metres off the seafloor can gather millimetre-resolution images in which human-made objects and benthic organisms can be identified, over multi-hectare regions of the seafloor. These are valuable for surveying marine protected areas (MPAs) that require regular monitoring of their ecosystem health, and for inspecting the increasing amount of seafloor infrastructure that exists, with growing recognition of the need to monitor their environmental impacts. The push towards offshore renewables, demand for subsea cables to support the internet and legal requirements for decadal monitoring of decommissioned offshore oil and gas infrastructure suggest the need for seafloor imaging surveys will continue for the foreseeable future [3]. While traditional methods using sampling and drop cameras provide information that cannot be replicated using AUVs, they do not scale well to large-

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area surveys as they rely on ships and manual labour. Seafloor imaging lends itself better to automation, where images gathered by AUVs can be post-processed to generate products such as mosaics [4], [5] and 3D reconstructions [6]–[8] that show areas larger than a single image footprint. Further analysis by human experts or machine learning algorithms [9], [10] can determine seafloor substrate type, taxonomy and distributions of seafloor organisms, as well as detect anthropogenic influences such as litter, sabotage or degradation of infrastructures. High-resolution imaging surveys can also capture temporal changes through precisely targeted repeat area surveys that are non-invasive and achieve sufficient cover to guarantee spatial overlap despite navigational uncertainties [11]. Laser scan microbathymetry is an effective complement to strobed colour photography as it can simultaneously map topography at millimetre-order resolution alongside visual features to capture fine details such as cables, natural depressions and trawl marks that often are hard to spot in strobed colour images [12].

Offshore AUV surveys typically deploy from crewed ships that use several orders of magnitude more energy than an AUV, accounting for most of the cost, logistical challenges and carbon footprint of monitoring. AUVs have also been deployed from autonomous surface vehicles (ASVs) [13], [14], with recent investments in full ocean-going lean crewed ships with AUV payloads [15]. However, autonomous launch and recovery adds complexity and limits operations to relatively calm weather windows. Recently, long-range and endurance AUVs have demonstrated shore-launched offshore surveys without the use of a support vessel for transport [16]–[19]. Such AUVs open the opportunity for ship-free seafloor visual mapping of sites hundreds of kilometres offshore. In addition to cost and carbon savings, shore deployed long-range AUVs are more robust to poor weather conditions. Close to shore the wave height and wind speed are generally lower than on the open sea, and once deployed, AUVs can shelter at depth if necessary to avoid strong winds and waves that can prevent traditional ship-based deployment and recovery operations. However, such missions introduce several new challenges for data acquisition, analysis and robust operation without physical intervention.

The impact of water turbidity on image quality makes camera surveys more sensitive to environmental conditions than acoustic survey methods (e.g., side-scan sonar, multibeam sonar). Typically, turbidity is not known before deployment and can vary locally and temporally, making the choice of observation altitude in long-range, long-endurance surveys a challenge. This is compounded by long-range flight-style AUVs being less manoeuvrable, and travelling faster than the hover capable AUVs typically used for detailed imaging surveys [20]–[26]. They therefore need to operate at higher altitudes to reduce the risk of collisions and cannot accurately follow complex terrains at a constant target altitude. Both factors increase the variability of image quality and sensitivity of data they acquire to environmental variables (i.e., terrain complexity, water turbidity).

Various approaches have been developed to correct for attenuation, colour shift and backscatter in underwater images [6], [10], [27]–[29]. Although these improve tolerance to image degradation, they cannot compensate for information that is lost through attenuation or masked by backscatter of the light from vehicle mounted strobes if the water turbidity and/or the mapping altitude is too high, or if the camera signal is weak or not resolved sufficiently high. With these requirements in mind, the University of Southampton and Sonardyne International developed the BioCam [30] mapping device with high-power strobes ($2 \times 200{,}000$ lumen) and line lasers (2×1 W), and cameras with a high dynamic range (79.7 dB). This allows data to be collected from higher altitudes than conventional imaging systems and improves robustness to the impact of the large range of altitudes expected when mapping from high-endurance flight-style AUVs such as the Autosub Long Range (ALR; also known as Boaty McBoatface) developed by the National Oceanography Centre (NOC) in Southampton, UK [18], [19].

In addition to hardware design, it is also necessary to modify operational workflows. During traditional ship-based AUV imaging, operators often assess the quality of images between deployment cycles and can adjust camera parameters (camera exposure, strobe intensity) and target altitude if navigational data indicates it is safe to do so. This also identifies hardware failures (e.g., of the illumination sources) to avoid taking unnecessary risk and effort by continuing to deploy a compromised setup.

To achieve similar goals with long-range AUV campaigns, it is necessary to assess the gathered data between dives and regularly feed it back to remotely located AUV pilots, who can in turn adjust mapping altitude or device settings, or navigate it back to shore early if there is any failure of hardware (e.g., illumination light sources). This also requires indicators about navigational performance to determine whether changes in observation altitude would be safe. While for ship-based missions or deployments close to shore full image and navigation data can be downloaded and assessed between dives, this is not possible in offshore missions without a support vessel. Data can be transmitted via satellite when the AUV is at the surface; however, with uplink speeds of pressure tolerant communication antennae typically in the order of kilobits per second and often intermittent connections, it is not practical to transmit entire uncompressed images and vehicle data.

Various approaches have been proposed for compressing underwater images for transmission over low-bandwidth communication links, such as acoustic modems. Early on, [31] and [32] proposed using the discrete wavelet transform (DWT) for compressing subsea photos and videos for transmission over an acoustic uplink. [33] demonstrated an algorithm for selecting representative images while collecting seafloor photos to be sent to a surface vessel, along with semantic maps. [34] presented broadcasting of automatically selected, progressively compressed photographic and SONAR images, as well as sensor data over networks of underwater acoustic relays. [35] demonstrated image selection and dropout-resistant image compression using a reduced-size colour palette for transmission over acoustic links. These methods enable adaptive, remote-supervised missions for mapping particular types of substrates or objects of interest on the seafloor, as seafloor images are available to operators in near real-time. While these show what has been observed, the quality of the gathered imagery can be difficult to assess, due to the effects of compression, and the number of transmitted images can be low in case of slow or intermittent communication. For applications where the area to be mapped is defined from the outset, or if the communication throughput is very low or unstable, transmitting the quality of the gathered imagery together with compressed navigational data is more suitable.

Traditionally, the Mean Opinion Score (MOS) based on the judgment of several human observers has been regarded as the best method for assessing the quality of images [36]. However, apart from being time consuming and not suited to autonomous applications, the MOS is subjective and therefore not generally repeatable. To overcome these limitations, various image quality assessment (IQA) algorithms have been developed. Some of these, so-called full-reference IQA algorithms, compare images to a perfect, not distorted version of the image as reference, while blind or no-reference IQA algorithms compute a score without such reference, only based on a single image.

The Blind Image Quality Index (BIQI) [37] is a two-stage no-reference IQA algorithm that identifies the types of distortions in an image and combines their respective impacts on quality based on natural scene statistics (NSS). Distortion Identification-based Image Verity and INtegrity Evaluation (DIIVINE) [38] extends BIQI with a larger set of NSS, demonstrating comparable correlation with human perception to full-reference IQA algorithms. The Learning based Blind Image Quality measure (LBIQ) [39] uses machine learning to map natural image measures and texture statistics to subjective image quality scores, achieving good correlation with human judgment based scores. The popular Blind / Referenceless Image Spatial QUality Evaluator (BRISQUE) algorithm [40] computes statistics of pixel intensity distributions and determines how natural an image is by comparing its coefficients to those of a model generated from training images. The Natural Image Quality Evaluator (NIQE) [41] like BRISQUE also uses a space domain NSS model, but does not rely on human judged images for training or modelling of image distortions. Perception-based Image Quality Evaluator (PIQUE) [42] is an opinion-unaware no-reference IQA method that estimates the quality for blocks of pixels while also computing and over-all score by pooling the separate block scores. While these algorithms were developed considering degradation influences characteristic for images taken in air, underwater images also suffer from shifts in colour balance, changing lighting across the scene depending on the distance from the camera, haze from backscatter, and marine snow. These influences are often stronger than image compression artefacts, sensor noise and blur of objects outside the depth of field, typically considered in conventional IQA algorithms. For this reason, IQA algorithms specially for underwater images have been developed.

Many earlier underwater IQA algorithms are based on feature engineering, where a combination of features designed by humans are assessed and combined to generate a score. The Underwater Color Image Quality Evaluation (UCIQE) algorithm [43] combines statistical measures of chroma, contrast and saturation to compute a score. The Underwater Image Quality Measure (UIQM) [44] and the Frequency Domain UIQA Metric (FDUM) [45] each define a quality measure using the colourfulness, sharpness and contrast of underwater images. The Colorfulness, Contrast, Fogdensity (CCF) [46] algorithm further accounts for backscatter. The No-reference underwater IQA based on Multi-feature Fusion in Color Space (NMFC) [47] method uses morphological and statistical parameters of distributions of intensity and colour, and the Contrast, Sharpness and Naturalness index (CSN) method [48] uses multiple contrast, sharpness and locally mean subtracted contrast normalized coefficients to determine image quality. More recent methods have used feature learning, where features are algorithmically identified from patterns in the data. The cross-spatial feature interactions and the cross-scale information complementarity (SISC) [49] method uses the ResNet CNN to analyse underwater images at different resolutions to compute a quality score. Prior-Based Underwater enhanced Image Quality Assessment (PBUIQA) [50] uses a convolutional neural network to estimate ambient light, water depth, absorption and scattering coefficients, as well as the object-camera distance map from a raw image to assess the quality of the colour image obtained after colour correction.

Many underwater IQA algorithms assess the quality of images after colour correction, rather than raw images [43]–[50]. This leads to a coupling between raw image quality and the performance of the colour correction algorithms, which is undesirable for real-time applications where the aim is to maximise the quality of raw data being acquired. Many algorithms are also geared towards the typical scenes a diver would photograph; often naturally lit and taken from oblique perspectives with an animal or object as its subject. However, images acquired using AUVs typically look vertically down on the seafloor and are illuminated using vehicle mounted strobes. Such images may also lack distinct objects, showing just the substrate of the seafloor. This makes many established IQA methods unsuitable for systematically obtained wide-area photo surveys. In addition, marine snow increases the measured contrast and spectrum of intensities in artificially lit images, raising the issued score of many published methods, even though it degrades the quality of seafloor imagery.

To address these challenges, a simple but robust algorithm was developed that works with downward looking raw strobed and laser scan seafloor imagery. It aims to express image quality information of such images with a few bytes of data. We demonstrate its use when sent via satellite communication along with filtered navigation data to provide sufficient information for making informed decisions for AUV piloting. Baseline data was collected using the ALR AUV equipped with the BioCam seafloor imaging system during the DY152 cruise in the Celtic Sea in July 2022 [12]. The image assessment algorithm was first used to inform decisions on a shore-launched science campaign as part of the AT-SEA project in September and October 2022 in the North Sea, where two decommissioned oil exploration sites and one MPA were mapped. The campaign comprised two deployments of the same setup as during the DY152 cruise, each lasting approximately 10 days, covering a total distance of over 1000 km with no support vessel.

In the remainder of this paper the image quality metric is described in section II and data post-processing algorithms are explained in section III. The seafloor mapping device and AUV used to demonstrate the effectiveness of the proposed image metric are introduced in section IV, along with details on the software integration and the data flow. Results from the 21-day shore-launched campaign are provided in section V, followed by a discussion and conclusions in section VI.

II. In-situ image quality metric

A. Considerations of light propagation in water

The limiting factor for the quality (and so largest range) of strobe-lit underwater images is typically backscatter, which is optical noise from light scattered towards the camera in the volume of water where the camera's field of view and the light cones from the strobes overlap, as shown in figure 1. Scattering occurs when light interacts with water molecules or suspended particles, where the latter can have a much larger contribution to the total amount of scattering. This is typically the case in waters near continents where particle density is high due to sediment influx from river run-off, industrial discharge or ship traffic in shallow waters. Light is scattered in all directions, at varying proportions depending on the particle size and wavelength. For imaging applications the impact is three-fold: Light scattered out of the light source-object-camera path (out-scatter) does not reach the camera and so leads to a reduction in the direct signal. Light scattered towards the camera before reaching the seafloor (backscatter) is added to the image of the scene, appearing as haze or fog; or bright spots if reflected off large particles of marine snow. Light scattered at small angles (forward scatter) also contributes to the image of the scene, however, due to the change in direction of the light path it blurs the

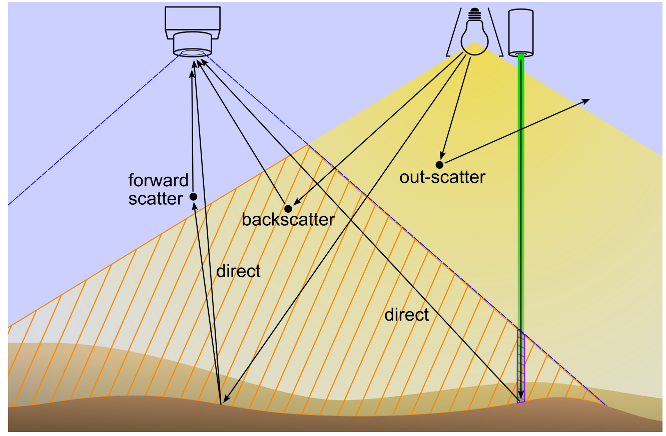


FIGURE 1. Illustration of various paths emitted light from an underwater strobe or sheet laser can take to the lens of a camera. The rays from the direct light path project the underwater scene on the camera sensor, whereas backscatter adds spurious light, reducing the signal-to-noise ratio of the image. Backscatter occurs where the camera's field of view and the volume illuminated by a light source overlap. The orange hatched area marks the overlap of the camera's field of view with the light cone of a strobe and the purple area shows the overlap with the volume of water illuminated by a sheet laser.

image. From that follows the image formation model for the irradiance at the camera [51]:

$$E_{total} = E_{direct} + E_{forwardscatter} + E_{backscatter} \quad (1)$$

While blurring from forward scattering limits the achievable optical resolution and can impact the performance of high-resolution camera systems, the reduced signal-to-noise ratio from the decreased direct signal compared to haze from backscatter is the more limiting factor for most imaging systems unless the water turbidity is very low. The intensity of the direct signal decreases with increasing distance to the seafloor due to absorption and out-scattering in water, but also due to the spreading of light according to the inverse square law.

Underwater laser scanners, where a laser line is projected onto the seafloor and observed from a camera separated by a certain distance, are also subject to the effects of scattering. However, because of the smaller overlap of the camera's field of view with the laser light sheet as opposed to the light cone in case of strobed photos (see figure 1), the relative amount of backscatter is significantly smaller. For setups where both types of images are taken sequentially, strobed images are more sensitive to environmental factors, and so constrain the maximum altitude from which sufficient quality data can be acquired.

B. Definition of metrics

To estimate the image quality, we propose a laser projection image derived quality metric. We assume that the line laser projector(s) is/are aligned with the the camera as shown in figure 2a, so that the laser line projections appear as horizontal lines across the images when scanning a flat area of seafloor. Because turbidity affects the laser line images mainly through out-scatter and less through backscatter, the brightness of the laser line is representative of the water turbidity and reflectivity of the seafloor. It is therefore an indicator for the expected quality of strobed images, as well as the laser line images themselves that can be acquired by a given system and mapping altitude. In contrast to optical backscatter (OBS) point turbidity sensors, the proposed method measures the direct rather than the backscattered component of light reaching the sensor. Although these properties are related, they depend on the particle size, which is normally not known. In addition, OBS sensors do not take the reflectivity of the seafloor into account, which also influences the signal-to-noise ratio in seafloor photos.

We define the quality score for the laser-projection-based Underwater IQA (LUIQA) as the maximum value in a region of interest (ROI) covering the entire height and the central d pixel columns in an image of a raw (unprocessed) laser line projection image I_{laser}:

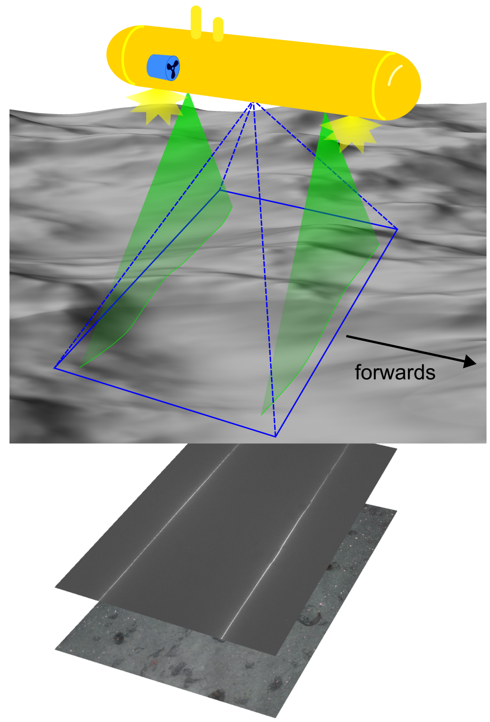
$$q = \underset{\substack{u \in [\frac{w-d}{2}, \frac{w+d}{2}] \\ \forall v}}{max} (I_{laser}(u, v)), \tag{2}$$

where w is the width of the image (aligned with the across-track direction of the vehicle), d the width of the ROI, and u and v designate the pixel coordinates across and down relative to the top left corner of the image, as shown in figure 2. While the vertical position of the laser line in the images depends on the vehicle altitude and the bathymetry, using the entire height of the image guarantees that the laser line is captured (as long as it is not occluded, e.g. due to steep terrain features). This provides a direct quality estimate of laser images and indirectly also of strobed images taken at roughly the same time (for the system considered in this research there is a laser line image taken within 0.1 s for every strobed image). However, the quality score does not pick up on potential physical problems with the strobed image collection, such as saturation or failure of the strobes to trigger. To convey this type of information for remote operations, an engineering score e for strobed images is defined as

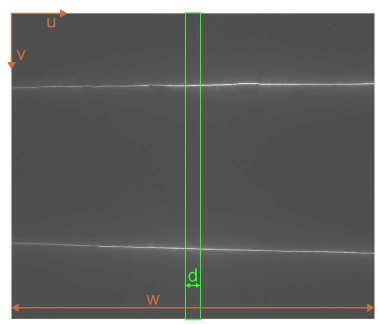
$$e = \underset{\substack{u \in [\frac{w-d}{2}, \frac{w+d}{2}] \\ \forall v}}{mean} (I_{strobed}(u, v)), \tag{3}$$

where $I_{strobed}$ is a raw strobed image, assumed to have the same dimension as images of the laser projection.

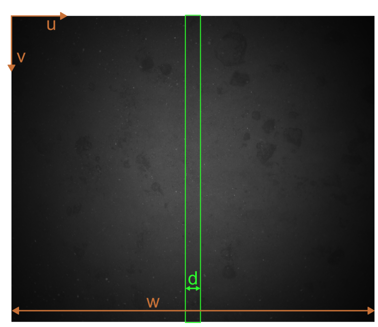
While the ROI covers the entire height of the image, the width is limited to the d columns in the centre, as the area below the vehicle's axis is illuminated most evenly and so leads to a uniform performance across different altitudes, and to reduce the computational load. The impact of the width of the ROI on the quality measure was investigated using a set of randomly sampled images acquired by the AUV-camera system described in section IV in the Greater Haig Fras MPA during RRS *Discovery*'s DY152 cruise whilst maintaining a constant altitude from the seabed. With the



(a)



(b)



(c)

FIGURE 2. Considered mapping system setup with examples of a laser line image and a strobed image. (a) Configuration of image acquisition system with the camera field of view shown in blue, the laser projections in green, and strobes in yellow, as well as an example of a monochrome image of the laser projections and an example of a strobed colour photo (after debayering and colour correction). (b) Monochrome image of the laser line projections with a ROI with $d = 100$ indicated in green and the image coordinate system and dimension in brown. (c) Raw strobed image (colour image prior to debayering) with a ROI with $d = 100$ indicated in green and the image coordinate system and dimension in brown.

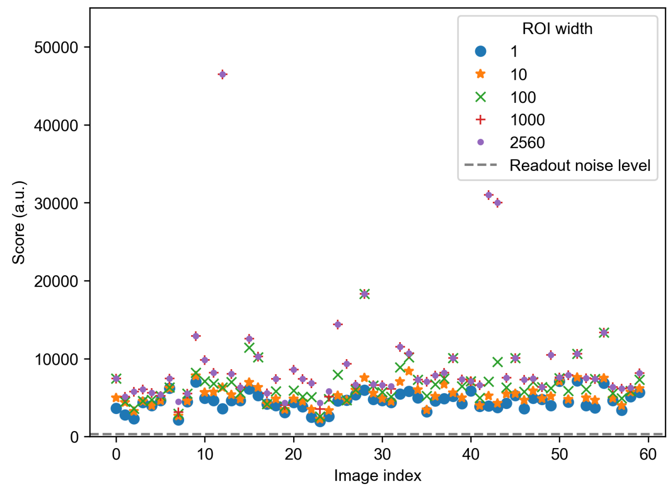
quality score q defined as the maximum brightness inside the ROI, it is designed to identify the brightness of a pixel showing the laser line projection. If the ROI is narrow, chances of particles suspended in the water occluding the laser line projection are increased. On the other hand, larger particles in the water can also appear as bright spots in the image if they happen to be in the plane illuminated by the laser, and in the camera's field of view (FOV). Widening the ROI increases the chances of picking up such outliers. Figure 3a shows that the quality scores are stable for narrow ROI widths of around 10 pixels (i.e., covering 0.32° across), with outliers appearing increasingly for widths larger than 100 pixels (i.e., covering 3.2° across).

As the engineering score e for strobed images is based on the average brightness within the ROI, it is less sensitive to outliers but as figure 3b shows, changing the width of the ROI leads to a scaling effect. The reason for the reduction in the mean brightness and so of the engineering score when widening the ROI is that lens vignetting causes the brightness of the images to fall off with increasing distance from the centre of the image. However, the shape of the result is the same within reasonable approximation, and as long as the same ROI width is used for reference and real-time collected data, the conclusions that can be drawn are not affected. For these reasons the width d of the ROI was set to 10 pixels for both types of score, as it reduces the probability of picking up bright outliers in the laser line images while also being robust against occlusions and keeping the computational load low for real-time computation.

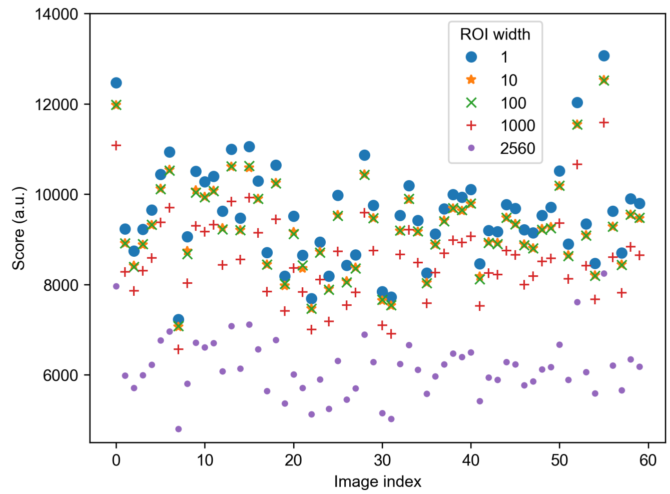
While the strobed images are in general uniformly illuminated, the laser line projections are narrow visual features originating from a point source. This makes them susceptible to occlusions, e.g. due to fish or large particles in the water column blocking part of the light path, or terrain features obstructing the view of the camera onto the laser projection. Such occlusions often only affect part of the laser projection. By applying the maximum operator on the entire ROI, the score picks up on the unobstructed part of the laser line in the event that part of it is blocked, whereas a measure using an averaging operator (e.g. mean-of-maximum-per-column) would lead to conflating brightness values from obstructed and non-obstructed areas. While it can still happen that the laser projection is not visible at all or an object in the water column leads to a bright spot inside the ROI, the unexpectedly low or high scores would stand out clearly as outliers in a time series and so could be ignored by operators.

C. Reference scores

Reference data from two locations in the Southwest Approaches with different water turbidities was collected with the ALR-BioCam setup during the DY152 research cruise in the Greater Haig Fras MPA with medium[1] level of water turbidity and South West Deeps (East) MPA with a low level of turbidity. Figure 4 shows the image scores from both sites plotted against the image acquisition altitude above the seafloor. For both types of scores there is a clear trend for decreasing scores with increasing altitudes, as expected, as light spreads and gets attenuated with increasing light path length and so reduces the signal from the seafloor. However, the level of turbidity strongly influences the rate at which images degrade with increasing altitude, as is apparent in the images from the different sites and which is correctly reflected in the quality scores. Meanwhile the engineering scores are indicating that the strobes were working correctly, without overexposing the photos, as all scores are well above readout noise levels (approximately 300 for the cameras used), yet far from saturation (65535). Unlike the laser line image based quality scores, the strobe based engineering scores are not as distinctly different in water of different



(a)



(b)

FIGURE 3. Quality and engineering scores for a set of images using different widths d of the ROI used to compute the score. (a) Image quality scores based on laser line images. (b) Image engineering scores based on strobed images.

[1]For the sake of simplicity we refer to the different turbidities at the surveyed sites discussed in this paper as "low", "medium" and "high". These are used as relative classifiers.

clarity, because in turbid waters where the direct signal is lower, increased backscatter adds to the average brightness.

The photos in the lower half of figure 4 show that images taken at the same altitude (A and D) have vastly different image qualities depending on the turbidity of the water with sharp, bright laser line projections (A) and clear views of sand ripples and shells in one location, but at the same altitude in a different location faint blurred laser line projections (D) and strobed images which are bright on average, but dominated by marine snow and turbidity throughout the image. On the other hand, images taken from different altitudes (B and C) but in waters of different clarity can be similar in quality with intermediate brightness of the laser line projections and strobed colour images that despite some marine snow, appearing as bright dots, offer relatively clear views of the seafloor. Hence the laser-based image quality metric is an effective indicator of image quality for both strobed and laser line illuminated images.

While the method generalises to any seafloor mapping system collecting laser projections and strobed imagery, the correlation of image score to image quality is characteristic for each setup. Based on the scores for the data collected during the DY152 cruise, these values were determined for the BioCam on ALR setup used to demonstrate the proposed method. Figure 5 shows strobed images with the corresponding quality scores indicated. The figure shows that for values around 500 the images are very turbid and so are not usable to identify any objects or creatures in them. For values around 700 structures can be recognised, in particular around the centre of the image, but marine snow is dominant. For scores around 1000 structures such as sand ripples and objects such as rocks are clearly visible across the entire image. Small objects such as shells can be recognised, but marine snow is also present, in particular around the borders of the image. For scores around 2000 structures and objects are well visible across the entire image, with some marine snow. For scores around 5000 and above images are clear with negligible effects of turbidity. The images in the figure were colour corrected with the algorithm described in section B.

III. Data post-processing

A. Generation of digital 3D reconstructions of the seafloor

While images are assessed for quality in real time, they are processed to generate data products in post-processing. The algorithm described in [8] is used to generate digital 3D reconstructions of the scanned seafloor based on the laser line and the strobed colour photos. It uses the images of the laser line projection to compute high-resolution bathymetry and the shape of objects on the seafloor, and therefore relies on the line projections being sufficiently clear. After converting the raw strobed photos to colour images with the algorithm described below, they are used to map the colour information to the 3D reconstruction of the seafloor. While the algorithm itself does not depend on the quality of the strobed colour photos, it is important for users of those reconstructions that the strobed photos are of sufficient quality for organisms, objects and properties of the seafloor substrates to be discernible in the texture maps that the algorithm generates.

B. Colour balancing of strobed photos

The colour images are debayered, attenuation corrected and colour balanced based on the method described in [52]. It applies the grey world assumption over the entire image dataset while accounting for the individual distance to the seafloor for every pixel using the 3D reconstructions to compensate for wavelength dependent attenuation over the distance the light has travelled in water.

C. Automatic classification of strobed images

In order to automatically classify the mapped areas into areas of same types of substrate, demersal communities, or areas with similar types of artificial objects, the colour photos are classified using the algorithm described in [9]. It ingests the colour balanced seafloor photos and is tolerant to limited amounts of image noise, but its ability to reliably classify images degrades with decreasing quality of photos that it is presented with. The algorithm identifies clusters in the latent space representation of the images resulting from applying a convolutional neural network CNN, and based on this prompts the user to label a number of images that allow it to best delineate the boundaries between classes of similar images. Provided with this information it trains a kernel support vector machine (SVM) with a radial basis function (RBF) to assign labels to all images based on their latent space representation [53].

IV. Seafloor mapping device and AUV

A. BioCam

The seafloor mapping device “BioCam” described in [30] with specifications noted in table 1 and pictured in figure 6 was used to demonstrate the algorithms. It consists of a main housing, two LED strobes, two sheet lasers and a laser safety float switch. It is designed to be mounted to an AUV supplying power and communication for sending start and stop commands, while strobed images and images of the laser line projection are recorded internally. During data collection the lasers are triggered simultaneously at 10 Hz and the projected lines are captured by a monochrome camera. The strobes are triggered every 3 s and the images are recorded with both mnochrome and colour cameras. During exposures when the strobes fire, the lasers are not triggered to avoid the laser projections appearing in the strobed images. The high dynamic range cameras make it possible to correct for strongly varying lighting conditions in post-processing without having to adapt the exposure or gain during image collection. The duration of both the strobes and lasers can be varied to adapt to different operating

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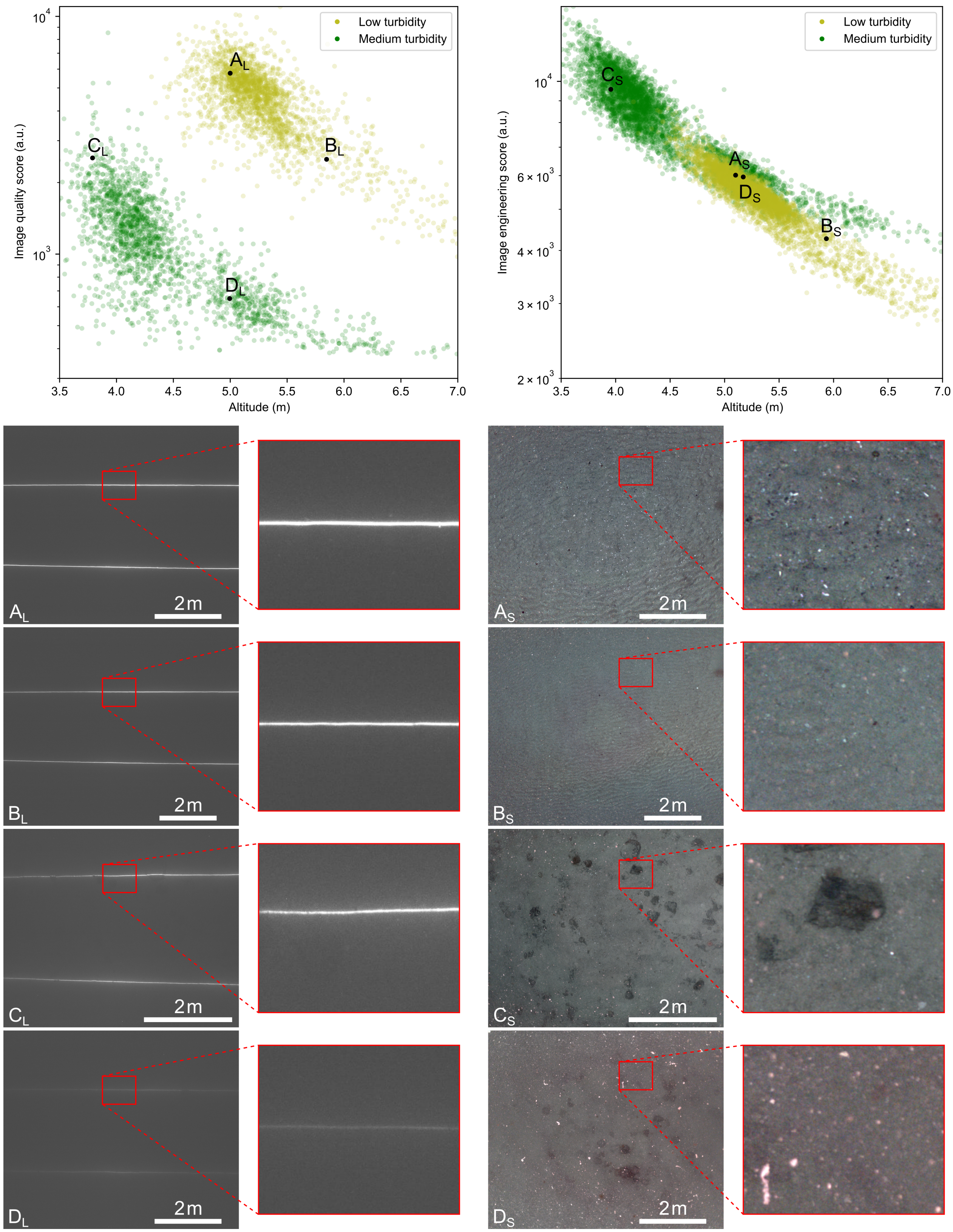

FIGURE 4. Quality and engineering scores from two different sites (medium turbidity: Greater Haig Fras MPA and low turbidity: South West Deeps (East) MPA). The images below the plots show examples from 4 locations, where neighbouring laser line and strobed images are from the same location. The enlargements of the strobed photos show the varying levels of marine snow appearing as blurred white or reddish spots, with a high density in image D_S and lower densities in B_S and C_S. The sharp white spots in A_S are fragments on the seafloor, rather than floating particles.

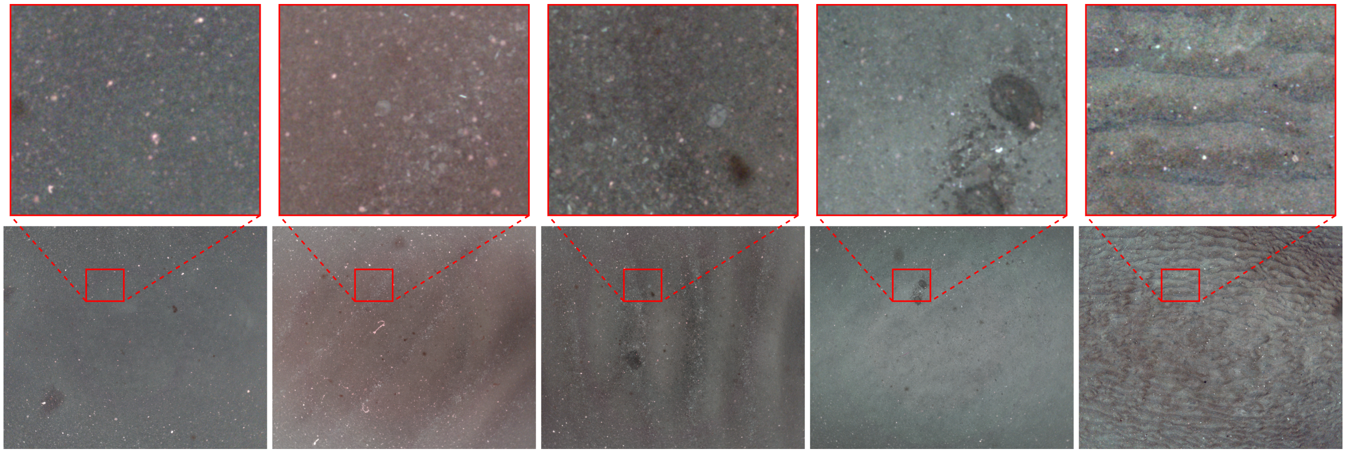

FIGURE 5. Examples of strobed colour photos taken under different conditions. The quality scores when these images were taken were 502, 710, 1007, 2025, 5020 (from left to right). The enlargements show decreasing levels of blurred bright spots from marine snow with increasing quality scores.

FIGURE 6. BioCam setup on ALR. The main housing containing the the cameras and electronics is mounted centrally. Sheet lasers and LED strobes are mounted one each at front and the back of the vehicle.

conditions. BioCam communicates with the AUV either via serial (RS232) communication or Ethernet to receive commands, send status updates, and synchronise clocks. The status update that is sent once a minute contains the latest image scores, as well as the number of images, current mode, remaining disk space, and the CPU and camera temperatures. This information can be used by the AUV, or forwarded to AUV pilots during communication windows, to ensure correct operation of the camera system and monitor data quality.

B. Autosub Long Range

Autosub Long Range is a class of ultra-long range AUVs developed at the National Oceanography Centre, that can operate for weeks to months in the ocean, depending on their payload. There is a 6000 m depth rated variant, ALR6000, with up to two months' endurance [18] and a 1500 m depth rated variant, ALR1500, with an endurance of up to 6 months [19]. The vehicles are 3.5 m long, 0.8 m diameter and weigh approximately 1.2 tonnes. The ALR6000 is built around two 0.71 m outer diameter forged aluminium pressure vessels, the forward of which houses the batteries and the aft contains the primary electronics. Surrounding the pressure vessels is a polypropylene boat frame skinned in a free flooding glass-reinforced plastic fairing, to provide a hydrodynamic shape. In the free flooding areas forward, aft and between the pressure vessels there is volume available for science payloads.

C. Mechanical integration of BioCam into ALR

BioCam was integrated into the 6000 m rated version of ALR. The polypropylene boat frame was redesigned to permit the BioCam camera unit to be installed centrally in the floodable space between the two main pressure spheres, in order to maximise the separation between the main housing and the strobes and lasers. To maintain the stiffness characteristics of the ALR replacement and additional syntactic foam was designed to counteract the low slung mass of the BioCam. Bespoke hydrodynamic fairings were produced to minimise drag penalties associated with the installation of the BioCam. In addition, an ADCP was mounted in a forwards looking configuration, to provide information on terrain in front of the AUV. Fairings installed between the forwards looking ADCP and the forward strobe assembly, on the ALR abort drop weight, and a Perspex cover over the rear strobe reduce the total drag by almost 10%, compared to not having the fairing, which is important to enable large range deployments to be planned with the desired contingency margin.

With minimum hotel load the 6000 m rated ALR has a range of up to 1800 km and an endurance of 2 to 3 months. Equipped with BioCam these values are reduced, but by turning BioCam on only when ALR has reached the area

TABLE 1. **BioCam specifications.**

Weight (in air / in water)	35.9 kg / 20.2 kg
Depth rating	4000 m
Power consumption (typical)	1.2 A at 48 V
Communication	RS232 and Ethernet
Cameras	pco.edge 5.5 (1 × monochrome, 1 × colour)
Lens	2 × ZEISS Dimension 2/12, Focal length: 12 mm
Camera FOV in water (each)	$69.3° \times 60.5°$
Camera resolution (each)	2560 × 2160 pixels
Image acquisition frequency (typical)	Laser line projection: 10 Hz Strobed: 0.33 Hz
Mapping altitude	4–10 m
Storage	2 TB (60 h of continued data collection)
CPU	Intel Pentium N4200, 1.1 / 2.5 GHz
Strobe brightness	2 × 200,000 lumen
Sheet laser optical power and wavelength	2 × 1 W at 525 nm
Laser safety	Float switch (→ disabled out of water), Watchdog timer
Resolution of 3D reconstructions (for alt. = 5 m, v = 0.75 m/s)	75 mm along track, 2.8 mm across, 2.5 mm vertical

of interest, mapping sites several hundred kilometres from the launch and recovery location can be reached.

D. ALR onboard control system and integrtion with BioCam

The ALR onboard control system (OCS) has been developed using the Robot Operating System (ROS) middleware [54]. It adopts a conventional three-layer control architecture, comprising of a supervisory layer consisting of a mission executive, mission layer responsible for converting mission goals to instantaneous control demands and the vehicle layer which performs real time control and communicates with hardware devices.

ALR has been developed to support a range of science applications and has been successfully operated both from research vessels and launched from shore. To support this variety of operating modes the vehicle is equipped with three communication channels, WiFi for near operator command and control (C2) on the surface, acoustic communications for near operator C2 subsurface and Iridium satellite communications for over the horizon C2 when the AUV is on the surface utilising Iridium short burst data (SBD) messages. Iridium SBD messages are utilised for satellite communication because of their short transmission time, which makes them robust for AUVs operating in rough conditions where antenna wash over is a regular occurrence. However, reliance of SBD messages for over the horizon operation does restrict the available bandwidth; the ALRs 9522B modem provides 1860 bytes uplink and 1920 bytes downlink in a single message. For each communication method the human machine interface is provided by the Oceanids C2 system [55].

Across all communication channels four distinct message types are currently supported. While designed primarily for the Iridium channel, the size of the message can be tailored to match the available channel constraints:

- Instant commands (uplink): used to manage payload power and settings and trigger specific pre-programmed behaviours (e.g. surface, stop or abort).
- Mission scripts (uplink): contain a sequence of manoeuvres that the AUV will conduct sequentially. Typically a mission script will comprise of a dive, followed by a sequence of tracks defining a trajectory between two waypoints for the AUV to traverse at a specific depth/altitude followed by a surface manoeuvre.
- Status Messages (downlink): status messages provide an instantaneous snapshot of the AUVs state including parameters such as the pose of the vehicle or the distance to the current target during a mission. A limited amount of space can also be used to send deployment-specific payload data. Status messages are transmitted periodically by the vehicle on all the available channels (WiFi, acoustic, and satellite), with independently configurable transmission period and content for each channel.
- Mission Summary (downlink): this message is automatically generated and sent on completion of a mission. As the name suggests, it provides a summary of the behaviour of the AUV during a mission, and one of its main aims is to provide the operator with a quick and effective means to assess the performance of the vehicle during a mission when piloting over the horizon (i.e. when access to the complete onboard logs is not

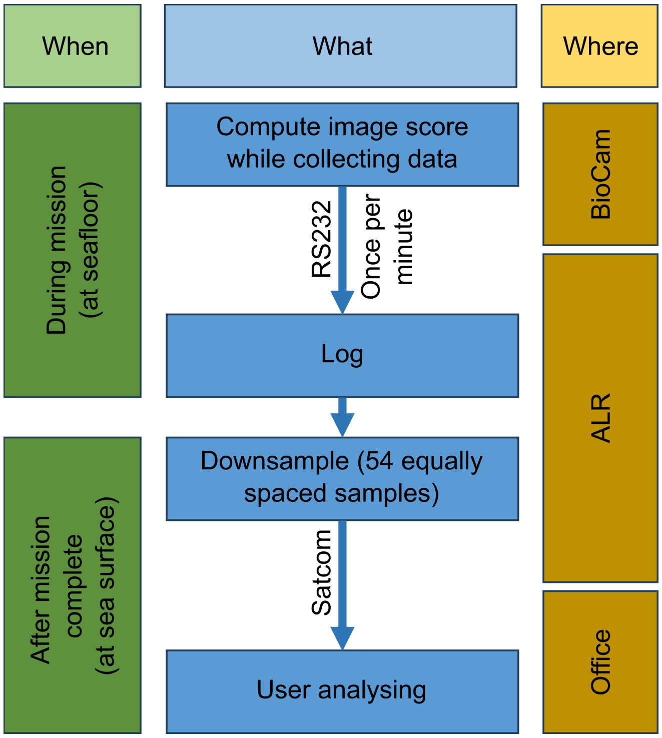

FIGURE 7. Flow of information for image scores transmitted via summary messages.

available). Mission summaries contain both statistics of engineering and payload data collected throughout the whole mission (such as the maximum depth or the average battery voltage), and an additional series of statistics computed over smaller time intervals obtained by subdividing the total mission into 54 sections of equal length. The number of sections was determined to maximise the data slices that can fit into a single Iridium message, which together offer sufficiently fine-grained resolution for simple remote analysis of the vehicle behaviour. Both the average and minimum altitude in each section are transmitted to facilitate efficient assessment of the safety of low altitude mapping operations. The altitudes are encoded in a custom format where the resolution is dropped to 10 cm, which is sufficient for safety-relevant assessment, but reduces the number of bits occupied in the transmitted bitstream. Fields are reserved to enable integration of deployment specific data. On missions where BioCam is used, these fields are populated with the latest BioCam image scores for each of the 54 time windows. These are retrieved from the logged scores that BioCam sends to ALR once per minute throughout the mission, and transmitted with the other vehicle data, as illustrated in figure 7.

E. Over horizon operation overview

During operations, the AUV is programmed to carry out a mapping dive, where the mapping altitude is set by identifying the most suitable trade-off between swath-width of the camera's field of view and resolution per pixel for the mission, factoring in expected visibility but also vehicle safety to ensure the AUV does not collide with the seafloor or objects on it. If after the dive the spread of the image scores received via satellite communication are at satisfying levels compared to the reference scores in section C and the minimum altitudes are close (within approximately 0.5 m) to the set altitude, the following dives can be carried out with the same settings. However, if the image quality scores are low, the mapping altitude may be lowered for the next dive, if there is sufficient margin in the altitude keeping and other information about the dive site suggests it is safe to do so. On the other hand, if the altitude data shows unexpectedly low values or if image scores suggest lighting hardware failure, the AUV may be sent back to shore early for analysis of the full data.

V. Results

In September and October 2022 ALR-BioCam was deployed on two shore-launched deplyoments from Lerwick on Shetland, UK, to monitor two decommissioned oil extraction sites and one MPA. The aim of the campaign was to demonstrate gathering data for environmental monitoring of offshore sites without a support vessel. The survey areas were up to 170 km from the launch site. The campaign was split into two legs, where the surroundings of the decommissioned rig at the North West Hutton oilfield was visited on the first leg and the decommissioned production site at the Miller oilfield, as well as the Braemar Pockmarks MPA in a second leg, as shown in figure 8. Multiple dives were carried out at each decommissioned site, between which ALR transmitted data via Iridium SBD packages while at the surface. Dives were planned based on multibeam echosounder (MBES) bathymetry maps collected during a survey by MRV *Scotia* operated by Marine Scotland Science in June 2021 and charts provided by BP. Since artificial structures still protruded from the seafloor in the areas of interest, missions were initially planned with a mapping altitude of 5 m above the seafloor. This was relatively high considering the expected visibility at the sites, but was set to minimise the risk of the AUV getting stuck with no ship in the vicinity to track the vehicle position underwater or salvage the AUV.

After being towed out of the harbour by a small boat, ALR transited at 30 m depth at an in-water speed of between 0.5 and 0.6 m/s towards the dive sites, and surfaced once per day to obtain a GPS fix, report telemetry to the pilots and take updates for the next waypoint. On leg 1 of the campaign it reached the remains of the North West Hutton oil platform after 4 days. After completion of the first 12-hour long mapping dive (M78), the mission summary containing the subsampled BioCam image quality and engineering scores

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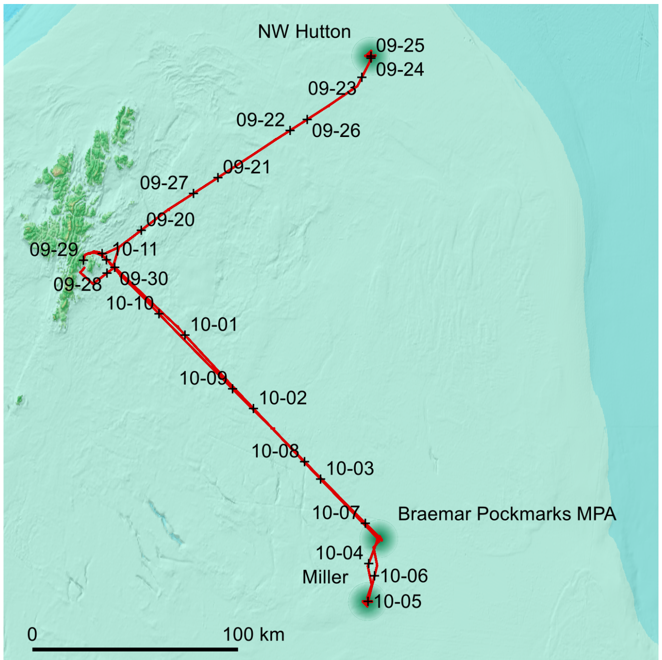


FIGURE 8. AUV track of the two-legged deployment out of Lerwick, Shetland. The crosses indicate where the AUV was at 0:00 of the indicated date (month-day in 2022).

as well as telemetry data of the AUV were transmitted by satellite communication, shown in the enlargement at the bottom left in figure 9. The telemetry data showed good altitude keeping with the minimum recorded altitudes within expected bounds, giving confidence in the performance of the AUV. The image scores showed that the lasers and strobes were working fine, but that the image quality was below ideal levels. If possible, the mapping altitude would be lowered in such a case. However, because of the presence of artificial objects protruding vertically from the seafloor in the area, the same mapping altitude was kept for the remaining dives at that site (M79 to M82) for safety reasons.

After successfully completing all three planned grid mapping dives, ALR returned to Shetland after 8 days and 18 hours of continuous operation and 453 km of distance travelled. It was recovered, recharged and the full AUV navigation and BioCam imagery data was downloaded. Figure 10a shows the image quality scores transmitted via satellite communication while at site, which are consistent with the scores from the full dataset downloaded after recovery of the AUV (also shown in table 3 discussed further down). It also shows that for a given mapping altitude the quality scores are in general lower than for the medium turbidity reference data and significantly lower than those for the low turbidity reference data. Water turbidity at a given location changes due to influences such as weather and tidal currents, which explains why the average quality scores change between dives despite the dive sites and the data acquisition altitudes being the same. The full AUV navigation data were also downloaded, which showed good altitude keeping throughout all dives, confirming what the heavily downsampled data transmitted via satellite had already indicated.

ALR-BioCam were then deployed on the second leg where they first mapped another former oil exploration site at the Miller oilfield, before mapping several transects in a single dive in the Braemar Pockmarks MPA. At the time of deployment a large storm with predicted 100 km/h wind speeds and 7 m wave height was approaching Shetland. The AUV was deployed before the weather window shut while the sea was still calm and programmed to head towards the survey site, but to stay at depth while the storm passed. The dark blue shaded area in figure 9 highlights the time window of the storm, with the depth-below-sea surface measurements varying slightly during this period, due to the large waves at the surface. The summary of image scores received via satellite communication after the first dive (M93) from an altitude of 5 m at Miller shown as blue crosses in figure 10b again reported lower than ideal image quality scores. As the navigation data confirmed reliable altitude keeping, with the lowest recorded distance over ground consistently larger than 4.4 m as the purple markers for dive M93 in figure 9 show, the mapping altitude was set to 4.6 m for the second dive (M94) and to 4 m for the third dive (M95) at the site. While the first reduction in altitude did not lead to a noticeable difference in reported image quality, which could be due to small changes in the water turbidity, the second, bigger reduction in altitude led to a clear improvement as the pink markers in figure 10b show.

ALR was then piloted to a third site, Braemar Pockmarks, where it conducted another dive (M97), mapping at a 5 m requested altitude. The AUV ended the dive early, and the satellite transmitted data showed the AUV had flown below the minimum acceptable altitude for longer than the 10 s persistence triggering an early surface, which, as became clear after downloading the data post recovery, was due to the sudden change in topography at a deep pockmark. The satellite-transmitted compressed navigation data showed good altitude keeping and performance up until the sudden altitude underrun. The limited data at the spatial and temporal resolution that could be transmitted by satellite communication did not provide sufficient detail to remotely identify the cause of the unexpected behaviour and no further dives were conducted at the site, as per the protocol outlined in section E. ALR was piloted back to Shetland where it was recovered after having covered 560 km in 12 days and 19 hours and conducted 4 dives, on top of the 5 dives from the first leg, as listed in table 2, bringing the total mapped area to over 89 hectares.

Table 3 shows the means (μ) and standard deviations (σ) of the quality and engineering scores when the AUV was at depth during the main mapping dives (not including M79 and M81, which were transits between grid-survey areas). The Student's t-test values (t) show that the distributions

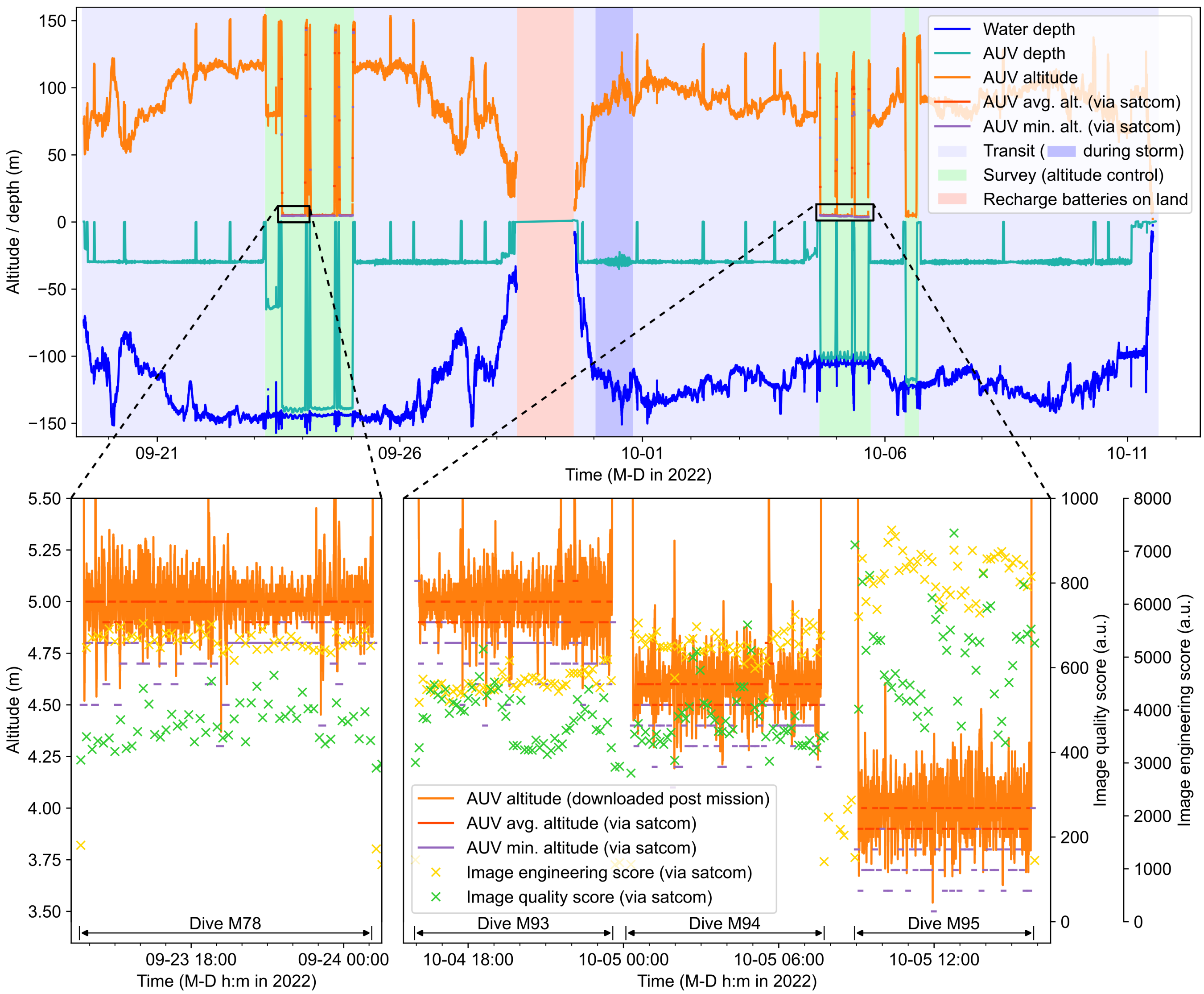
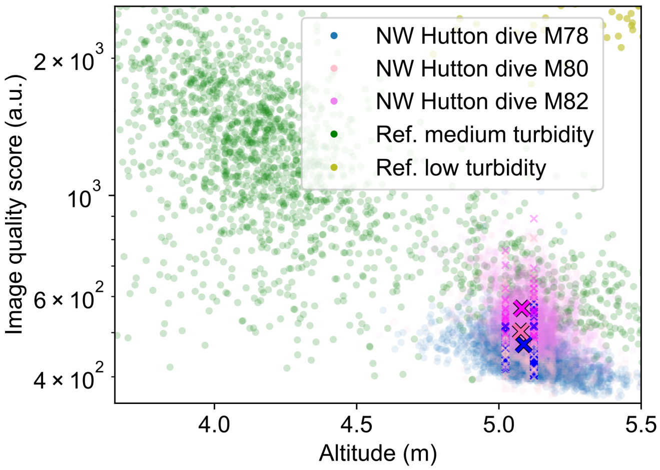


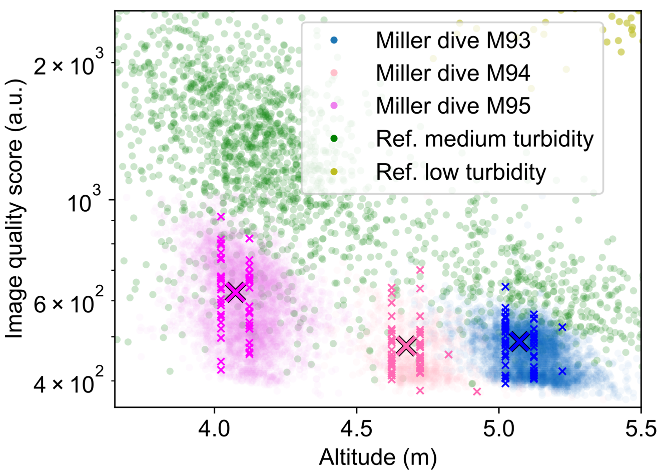
FIGURE 9. Plot of navigational data and image scores transmitted by the AUV over satellite communication and full data downloaded post recovery of the vehicle. The enlargement on the left shows details of the first dive at the NW Hutton site and the enlargement on the right data from the 3 dives at the Miller site.

TABLE 2. Statistics of ALR-BioCam dives. NWH: North West Hutton, MIL: Miller, BPM: Braemar Pockmarks MPA.

Dive	Location	Duration	No. strobed images	No. laser line images	Mapping alt. (m)	Mapped area (m^2)
M78	NWH	12h 16min 48s	13198	386681	5	190672
M79	NWH	1h 47min 24s	947	27758	5	11344
M80	NWH	12h 37min 48s	13655	400014	5	186404
M81	NWH	1h 39min 36s	660	19363	5	8165
M82	NWH	7h 22min 12s	7325	214711	5	98277
M93	MIL	8h 10s	8684	254534	5	118270
M94	MIL	7h 44min 37s	8456	247771	4.6	111348
M95	MIL	7h 46min 48s	7776	228112	4	93796
M97	BPM	6h 52s	6049	177263	5	73062
Total	-	**65h 16min 15s**	**66750**	**1956207**	-	**891338**



(a)



(b)

FIGURE 10. Laser image scores for two sites mapped during the INSITE AT-SEA deployment. The crosses are the values transmitted via satellite communication, with the larger crosses indicating their average. The dots are the full data downloaded post recovery of the AUV. (a) Scores from 3 dives at the NW Hutton site. (b) Scores from 3 dives at the Miller site.

of the transmitted score samples align with the distributions of the much larger number of scores logged on the device. Although the standard deviation of the transmitted score samples is in general higher than for the logged scores, this is expected, as the standard deviation decreases with increasing number of samples. While a narrow distribution of image scores implies uniform conditions, a high variance is indicative of diverse seafloor cover or multiple substrate types that are well visible in the camera images. For example, scattered shells on a silty seafloor as observed at the Miller site (figure 11) can lead to this. This effect is more pronounced for the quality score, as only a small area of seafloor is illuminated by the sheet laser, and presence or absence of bright objects in this area has a significant influence on the score for a particular image. It is also more pronounced in clearer imaging conditions, as turbidity has the effect of lowering the image contrast. Provided that the transmitted scores show no obvious signs of outliers, its average score is therefore a reasonable indicator even when the variance is relatively high.

Figure 11 shows a top view of the reconstruction of the Miller site generated based on the data from the 3 dives at the site, generated from the full data downloaded after recovering the AUV. Photos taken of the same location from different mapping altitudes show the change in image quality reflected in the level of detail visible and the amount of marine snow in the final processed images, highlighting the importance of ensuring the raw collected data is of sufficient quality.

While the strobed colour photos from the NW Hutton dive site suffered from higher levels of noise than at the Miller site, its strong visual features, including artificial structures, pipes and large organisms found at the site are clearly discernible also in the less optimal conditions as figure 12 shows. Additionally, the 3D relief of the seafloor and the objects on it was more pronounced and was mapped by the laser line based 3D reconstruction algorithm in high detail, virtually undisturbed by the higher level of turbidity, as the laser line images are less affected by it. The 3D reconstruction shows a guide base from the decommissioned oil and gas infrastructure, as well as several tens of metres of pipes, but also scores of $\sim$1 m length common ling (*Molva molva*) nesting in the area. While it is not obvious from the photos alone, the 3D reconstruction shows that the fish live in burrows with diameters up to 1.5 m and depths of up to 20 cm. Other features observed at the site were boulders from rock dumps, discoloured sediments and seafloor cables, among others.

As an example of automated information extraction from mapping data, the algorithm described in section C was used to automatically classify the seafloor photos. The geo-referenced results are shown at the top-centre of figure 12 with representative images for each class shown below. This enables further data analysis and statistics of the mapped area. The pie chart in the top-right of the figure shows an example where the relative distribution of identified classes at different distances from a point (in this case the former location of the oil platform) are identified. Data is split into bands of distance, each of which covers a range of 400 m and is represented by one ring of the chart. The orange and light green classes, which both represent sediments, are dominant in the entire mapped area, but closer to the former location of the platform the algorithm identified a significantly higher ratio of images belonging to the black class representing discoloured sediments, as well as images belonging to the blue and turquoise classes, representing boulders and man-made objects such as pipes, respectively. It has previously been shown that the ability of CNN-based image classifiers to correctly label data degrades with increasing image noise [56]–[58]. This highlights the importance of quality-controlling the imagery during data collection to generate these kind of results.

TABLE 3. Comparison of transmitted image scores to those logged on the device.

Dive	Quality scores					Engineering scores				
	$\mu_{transm.}$	$\sigma_{transm.}$	μ_{logged}	σ_{logged}	t	$\mu_{transm.}$	$\sigma_{transm.}$	μ_{logged}	σ_{logged}	t
M78	469.0	46.4	467.8	38.2	-0.2	5237.2	571.1	5315.2	188.0	1.0
M80	500.4	89.2	500.7	86.8	0.0	5173.1	606.6	5232.6	219.4	0.7
M82	558.2	80.3	568.3	71.0	0.8	5048.9	606.4	5129.7	150.9	0.9
M93	485.7	60.5	484.5	58.9	-0.1	4452.6	510.4	4512.4	172.7	0.8
M94	474.2	67.7	479.7	67.2	0.6	5145.4	627.9	5232.1	241.2	1.0
M95	626.8	112.1	629.1	125.0	0.1	6489.9	873.3	6642.0	369.0	1.2
M97	N/A	N/A	433.5	38.4	N/A	N/A	N/A	4893.0	274.8	N/A

During the 21-day-long campaign covering 1013 km in total, the AUV consumed 21.3 kWh of battery power, corresponding to approximately the energy contained by 2 litres of diesel. An equivalent survey deploying an AUV from a research vessel (2000 to 4000 tonne class) would complete the survey faster, approximately 5 days including transit between sites provided the weather conditions are favourable, but at the same time would use in the order of 10,000 litres of fuel per day [59] to power the ship. The shore-launched deployment reduced the fuel consumption and CO_2 emissions by approximately 3 orders of magnitude, and while this reduced the ability for real-time data assessment, the satellite transmitted stats were sufficient to make the correct mission-critical decisions.

VI. Conclusions and discussion

Data from the 21-day-long seafloor mapping campaign demonstrates how the image quality score defined in section II and forwarded to AUV pilots via the workflow explained in section IV provides a robust way to make informed over-horizon operational decisions for following dives to acquire raw data in the quality suitable for extracting usable and useful information in post-processing. The proposed measure adds minimal computation overhead and a small amount of payload data that needs to be transmitted via satellite communication, but provides sufficient information to adjust mission parameters and at the same time provides information about the correct functioning of lighting and cameras. As the algorithm directly works on the raw images, it does not conflate the image quality with the performance of the image reconstruction algorithm or its parameters. Compared to transmitting compressed or uncompressed images, the image scores reduce both the time an AUV needs to spend at the surface for transmitting data, as well as the energy consumed for that, as table 4 shows. AUV mission planners and pilots take many factors including vehicle dynamics and sensor properties into consideration for balancing the quality and amount of collected data with potential risks to the mission. The in-field vehicle performance details and payload data quality information provided by the proposed method delineates how well this balance is kept. It assists remote piloting of AUVs by providing the necessary feedback for making informed decisions, which with traditional approaches to AUV surveys used to be available only after recovery of the vehicle. It enables multi-week offshore campaigns without a support vessel to collect similar quality data as previously done on surveys with a research ship to support AUV operations.

Collecting data in the North Sea at sites up to 170 km from the launch site without a support vessel led to significant savings of fuel and emitted greenhouse gases, as well as reducing operational logistics and cost. Additionally, the AUV could be deployed despite a large storm approaching and make progress on its way to the survey site without being affected – by staying at depth during the time window when the storm passed, something that would not be possible with a small surface vessel. To the best knowledge of the authors this was the first time that a former offshore drill site has been visually mapped without a support vessel. The collected imagery gave valuable insights on the distribution of seafloor organisms, infrastructure and seafloor sediments in the mapped areas. Acting upon the transmitted scores led to a clear improvement of the raw data, reflected in the clarity of the processed images from the Miller site, where the transmitted data after the first dive showed good vehicle performance, but flagged low image quality. The decisions taken by the AUV operators based on this led to the collection of better raw data and ultimately to higher quality output from the survey. While the method has been demonstrated with sheet lasers, it could potentially also be applied in a similar fashion on camera systems with laser pointers, such as scaling lasers. However, the narrower beam would make it more susceptible to occlusions, and further studies would have to be conducted to determine potential applications.

Pressure to save costs and to progress towards the net zero goals motivate the development of non-invasive, economical and environmentally sustainable survey practises. While these are not likely to fully replace traditional survey methods, increasing the range of ship-free data acquisition methods that can gather useful information can reduce the duration or frequency of traditional surveys. While satellite communication has seen the coverage and communication speed increase, the significantly higher data acquisition rate

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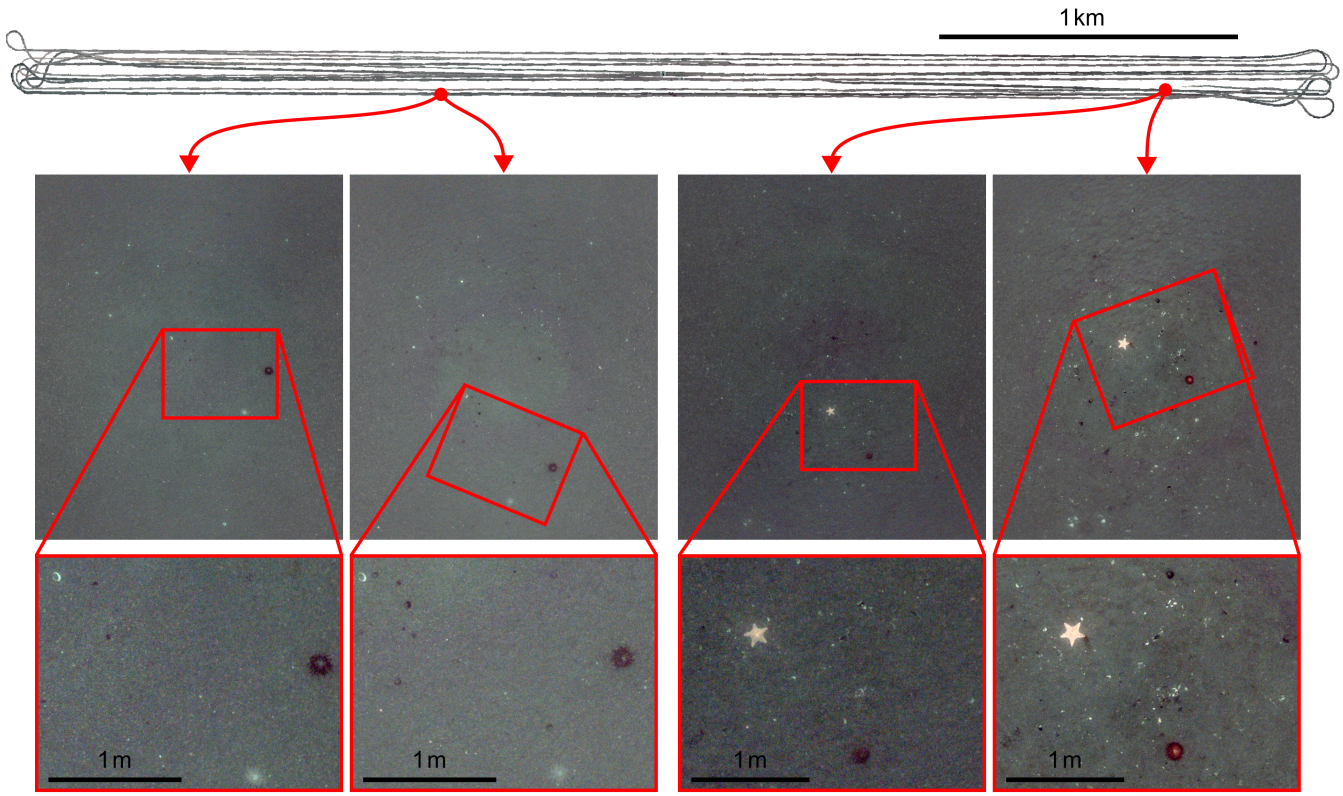

Altitude	5 m	4.6 m	5 m	4 m
Image quality score	464	506	498	780

FIGURE 11. Top view of the reconstruction of the Miller dive site with strobed colour photos from different altitudes (5 m: dive M93, 4.6 m: dive M94, 4 m: dive M95) showing the same areas. There is a clear reduction in image noise and improvement of image detail in the photos taken from the lower altitudes, which is reflected in the image score.

(8.3 MB/s for the system used in this research) compared to satellite transmission rate (1.1 kB/s for the system used in this research) for compact, deep dive compatible antennae means that full, uncompressed data cannot be transmitted in the foreseeable future and methods for compressing data will continue to play an important role. The proposed method also has potential real time applications where the AUV could change the altitude or lighting and camera settings as a function of the returned score, without the human in the loop.

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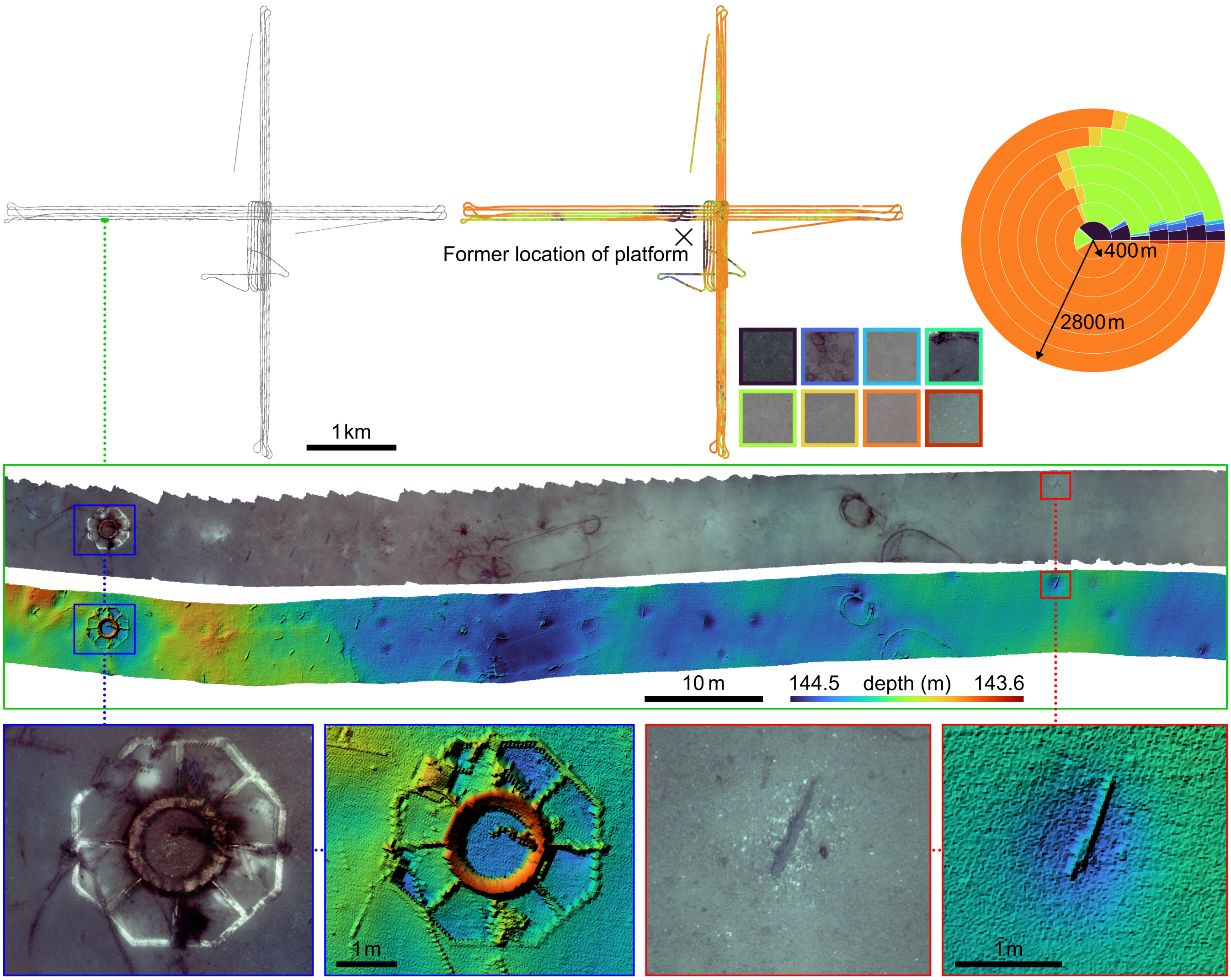

FIGURE 12. **3D reconstruction of the seafloor at the North West Hutton site mapped during dives M78 to M82 with texture and microbathymetry maps at different zoom levels. The image in the centre at the top shows the georeferenced classification of the seafloor photos and the pie chart to its right the portion of each class within the mapped area for different distances from the former location of the platform.**

TABLE 4. **Comparison of data volume and theoretical transmission time and associated energy consumption per image for different formats. The JPG and JPEG XL data size were determined for a quality setting of 40, and the BPG data size for a quality setting of 30 applied on set of images from the DY152 cruise. The transmission times assume Iridium SBD messaging with one 1960 byte SBD message being sent every 20 s (optimistic estimate in ideal conditions). The associated energy consumptions assume a power consumption of 10 W for the satellite modem and does not account for the power consumption of any other sensors or actuators.**

Data format	Data size	Transmission time	Energy (J)
Raw (16 bit per pixel)	10.5 MB	1 day 7 h 23 min 49 s	1130286
PNG (lossless compression)	9.2 MB	1 day 3 h 15 min 26 s	981265
JPG (lossy compression)	328.2 KB	57 min 10 s	34297
BPG (lossy compression)	283.7 KB	49 min 24 s	29640
JPEG XL (lossy compression)	181.6 KB	31 min 37 s	18975
Image scores	4 B	0.041 s	0.408

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