Deep-Sea Robotic Survey and Data Processing Methods for Regional-Scale Estimation of Manganese Crust Distribution

Umesh Neettiyath, *Member, IEEE*, Blair Thornton, *Member, IEEE*, Mehul Sangekar, *Member, IEEE*, Yuya Nishida, Kazuo Ishii, Adrian Bodenmann, Takumi Sato, Tamaki Ura, *Fellow, IEEE*, and Akira Asada, *Member, IEEE*

***Abstract*—Manganese crusts (Mn-crusts) are a type of mineral deposit that exists on the surface of seamounts and guyots at depths of >800 m. We have developed a method to efficiently map their distribution using data collected by autonomous underwater vehicles and remotely operated vehicles. Volumetric measurements of Mn-crusts are made using a high-frequency subsurface sonar and a 3-D visual mapping instrument mounted on these vehicles. We developed an algorithm to estimate Mn-crust distribution by combining continuous subsurface thickness measurements with the exposed surface area identified in 3-D maps. This is applied to data collected from three expeditions at Takuyo Daigo seamount at depths of ∼1400 m. The transects add to ∼11 km in length with 12 510 m^2 mapped. The results show that 52% of the surveyed area is covered by Mn-crusts with a mean thickness of 69.6 mm. The mean Mn-crust occurrence is 69.6 kg/m^2 with a maximum of 204 kg/m^2 in the mapped region. The results are consistent with estimates made from samples retrieved from the area, showing more detailed distribution patterns and having significantly lower uncertainty bounds for regional-scale Mn-crust inventory estimation.**

***Index Terms*—Aquatic robots, deep-sea survey, manganese crust (Mn-crust), mineral exploration, subbottom acoustics, unmanned underwater vehicles, visual reconstruction.**

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Umesh Neettiyath and Mehul Sangekar are with the Institute of Industrial Science, The University of Tokyo, Tokyo 113-8654, Japan (e-mail: umesh@iis.u-tokyo.ac.jp; mehul@iis.u-tokyo.ac.jp).

Blair Thornton is with the Centre for In Situ and Remote Intelligent Sensing, Faculty of Engineering and Physical Science, University of Southampton, Southampton SO17 1BJ, U.K., and also with the Ocean Perception Laboratory, Institute of Industrial Science, The University of Tokyo, Tokyo 113-8654, Japan (e-mail: b.thornton@soton.ac.uk).

Yuya Nishida is with the Frontier Research Academy for Young Researchers, Kyushu Institute of Technology, Kitakyushu 804-8550, Japan (e-mail: ynishida@iis.u-tokyo.ac.jp).

Kazuo Ishii is with the Department of Human Intelligence Systems, Kyushu Institute of Technology, Kitakyushu 804-8550, Japan (e-mail: ishii@brain.kyutech.ac.jp).

Adrian Bodenmann is with the Maritime Robotics Laboratory, Southampton Marine and Maritime Institute, University of Southampton, Southampton SO17 1BJ, U.K (e-mail: adrian.bodenmann@soton.ac.uk).

Takumi Sato is with the Offshore Advanced Technology Department, National Maritime Research Institute, Tokyo 181-0004, Japan (e-mail: sato-t@nmri.go.jp).

Tamaki Ura, retired, was with the Institute of Industrial Science, The University of Tokyo, Tokyo 113-8654, Japan (e-mail: ura@iis.u-tokyo.ac.jp).

Akira Asada, retired, was with the Institute of Industrial Science, The University of Tokyo, Tokyo 113-8654, Japan (e-mail: asada@iis.u-tokyo.ac.jp).

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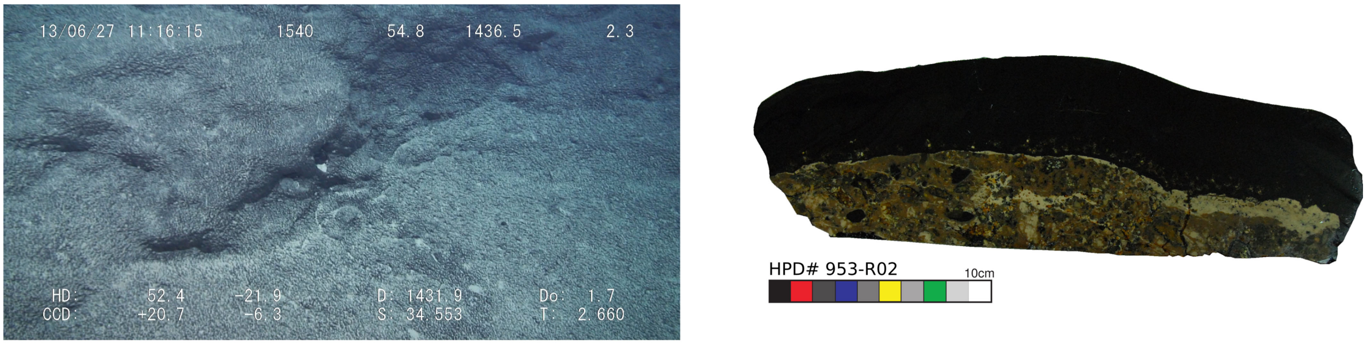
I. Introduction

COBALT-RICH manganese crusts (Mn-crusts) form on the slopes and shoulders of seamounts and guyots in geologically stable regions. The Mn-crust layer grows over millions of years by precipitation from the ambient seawater, as seen in Fig. 1 [1], [2]. The northwestern Pacific ocean is known to have large Mn-crust deposits spread over several hundreds of square kilometers [3]–[5]. Mn-crusts vary from 10 to 250 mm in thickness and are found between a depths of more than 800 m, with reports of Mn-crusts as deep as 5700 m. These deposits contain cobalt, nickel, platinum, and various rare-earth elements, making them a potential target for mining [6]–[9]. However, the thickness of Mn-crust varies due to slope, seawater conditions, depth, historical landslides, and sediment cover [2]. This makes reliable estimation of quantitative Mn-crust distribution difficult.

The survey requirements of Mn-crusts are different to manganese nodules (Mn-nodules), found in basins between 3500- and 6000-m depth [7], [10]–[12], where noncontact methods such as shipboard multibeam [13], [14], photogrammetry, and sidescan surveys [15]–[17] from autonomous underwater vehicles (AUVs) and remotely operated vehicles (ROVs) have been applied. Mn-nodule distribution can be accurately estimated from such data sets, since their distribution can be determined from surface appearance and shape alone. Accurate estimates of Mn-crust distribution requires both the subsurface thickness of the crust layer and their lateral percentage cover to be known. Dredging surveys are often used to survey the thickness of Mn-crusts, but samples recovered using this method are often damaged, and the method is biased toward loose rocks and edges that are more likely to be snagged. Core drilling and sampling from ROVs is effective to collect information about the thickness and elemental composition of samples, whose context is understood from camera footage [2], [3], [18]. However, obtaining samples is time consuming, and the spatial resolutions achieved are limited to just a few samples every kilometer [2]. The lateral distribution of exposed crusts can be surveyed using video or still cameras mounted on towed sleds or ROVs, where the footage is manually labeled by human experts into categories such as



(a) (b)

Fig. 1. Mn-crusts at the Takuyo Daigo seamount in the northwestern Pacific ocean. (a) Continuous Mn-crust deposits as seen from the video feed of ROV Hyper-Dolphin. (b) Cross section of a Mn-crust sample, showing crust (black color) deposited as a layer over a substrate rock (brown with intrusions).

TABLE I
SPECIFICATIONS OF THE PLATFORM (AUV BOSS-A)

Vehicle	
Dimensions	3.0 m x 0.7 m x 0.7 m
Mass	600 kg
Operating velocity	0.2 kn (0.1 m/s)
Operating altitude range	1.5 ± 0.5 m
Depth rating	3000 m
Endurance	7 h
Payloads	
Parametric acoustic probe:	
Frequency	2 MHz (carrier) , 200 kHz (signal)
-3 dB footprint	<2 cm (dynamic focusing)
Mounting	2-axis gimbal
Gimbal roll, pitch range	15° ± 45°
Ping rate	20 Hz
3D visual mapping system:	
Type	Monocular vision and structured light using sheet laser
Illumination	2 x LED panels (20 000 lm/panel)
Laser power, wavelength	120 mW, 532 nm
Camera resolution, FOV	1328 x 1048, 65° x 53°
Camera frame rate	15 fps
Laser to camera baseline	1.22 m
Swath, resolution	1.5 m, 1.4 mm
Bathymetry resolution (at 1.5 m)	1.4 mm (cross-transect)
	6.7 mm (along-transect)
	3.0 mm (depth)

Mn-crusts, nodules, or sediment deposits, which are compiled into estimates of distribution [4], [6]. However, manual labeling is time consuming, making it difficult to scale the operations to larger regions.

High-resolution scalable estimation of Mn-crust requires automated methods to determine the lateral distribution and thickness of Mn-crusts without physical sampling. Acoustic methods can be used to measure Mn-crust thickness as long as the Mn-crusts and their substrates have different acoustic impedances [19]. However, it can be difficult to determine if acoustic signals are of Mn-crust from their acoustic signature alone. For this, visual methods can be effective if reliable automatic classification methods can be developed [20]–[25].

This article presents a scalable way to determine the continuous mass distribution of Mn-crust over hectare-scale regions of the seafloor using visual and acoustic sensors. This builds on the work described in [19], describing modifications to the data acquisition hardware, and presenting novel data processing methods that scale to the hectare-scale regions now surveyed using this system. This overcomes previous limitations, where, in [19], the seafloor was segmented into regions of crust, sediment, and a mix of the two using Gaussian mixture models, and acoustic measurements within each segment were used to estimate the abundance of crust in each region. The high computational cost of segmentation does not readily scale to larger regions. While previous work analyzed small volumes of ROV data, the majority of data in this article have been collected using an AUV, described in [26], with modifications made to the data acquisition system. This includes real-time control of a double-gimbal system that orients the acoustic probe to be normal to the seafloor by analyzing the 3-D visual mapping data [27]. This allows acoustic measurements to be made on steep slopes and complex terrains. The advances in the sensor, platform, and novel algorithms described in this article allow estimates of Mn-crusts to be made over hectare-scale regions of the seafloor for the first time.

II. SYSTEM OVERVIEW

A. AUV BOSS-A

The specifications of the AUV "BOSS-A" [26], used to collect the data analyzed in this article, are shown in Table I, and the position of various sensors are shown in Fig. 2.

The acoustic probe is a parametric subsurface sonar that records subsurface reflections of the seafloor. The probe consists of a five-channel annular array of 2-MHz piezoelectric transducers for transmission and a 200-kHz piezoelectric transducer to record reflections. It is dynamically focused on the seafloor at

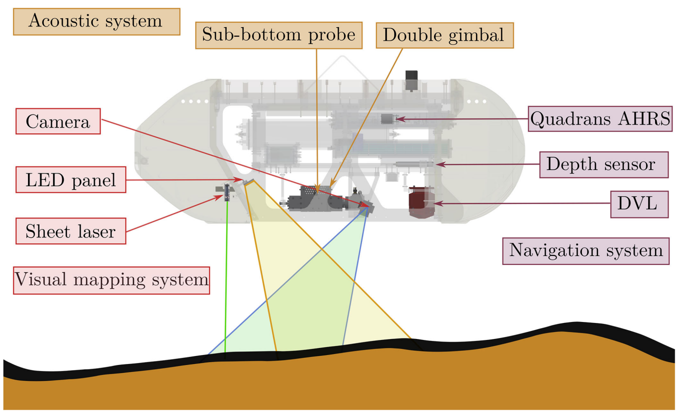


Fig. 2. Schematic representation of BOSS-A surveying Mn-crust using visual and acoustic subsystems.

ranges from 0.5 to 2.5 m [19]. Since measurements require the probe to be orthogonal to the measured surface for best results, the probe is mounted on a two-axis gimbal. The relative slope of the seafloor is calculated in real time, and the gimbals are oriented normal to the seafloor [27]. The signals are analyzed to find reflections from the crust-substrate boundary, and thickness values are calculated, as described in Section III-B.

The visual system generates 3-D color maps of the seafloor using a light sectioning method using a single camera, a sheet laser, and LEDs for illumination, as described in [28]. The deformation of the laser line, which corresponds to the bathymetry of seafloor, can be used to calculate the xyz coordinates of the points that fall on the line. As the AUV moves, these points will come in the illuminated region of the image; the RGB color values of the point can be identified based on the motion of the AUV.

B. Data Analysis Workflow

For processing, the seafloor is divided into sections of 10-m length, processed separately, and the results are compiled. The workflow for processing each section is shown in Fig. 3. Visual data are classified into sections of crust, nodule, and sediment, as described in Section III-A, to calculate the percentage cover of the exposed crust. The acoustic measurements over noncrust regions are discarded, and reflections are processed to make thickness measurements, as described in Section III-B. These thickness values are extrapolated to the crust areas, and the results are integrated to calculate the total volume of crust in the region, as described in Section III-C.

III. Algorithms

A. Seafloor Classification

The different seafloor types present in the survey area can be classified into continuous Mn-crust deposits, Mn-nodules, and sediments [6]. Examples of each type are shown in Fig. 4.

In terrestrial applications, researchers have used a support vector machine (SVM) for classifying 3-D point clouds [29]. Although neural networks are widely used in image classification tasks [30], [31], the SVM was found to perform better with

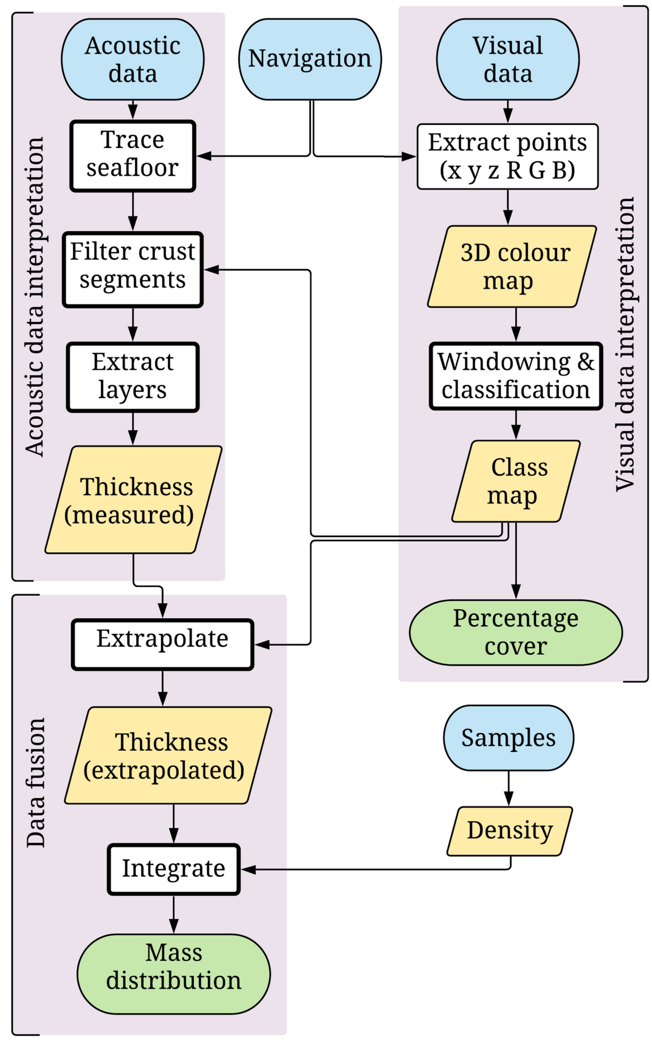


Fig. 3. Flowchart of the data processing framework. Contributions of this article are highlighted in bold outlines.

a small number of well-defined classes and large training data sets [32], [33].

The authors built an SVM classifier with a polynomial kernel for identifying Mn-crust from seafloor bathymetry and color maps [34], [35]. To make the classification scale to large areas, the seafloor was sampled into uniform sections called kernels and classified, reducing the processing times to be linearly proportional to the area of seafloor being classified. Two data sets (seeTable III for details) were selected as training and testing and cross-validation (CV) sets to ensure that robust classification is achieved.

Each kernel is an independent 3-D point cloud with each point described by its features (see Table II) derived from color (RGB) and location (xyz) values and has no overlap with adjacent kernels.

Bathymetric features describe the shape of the point cloud. The standard deviation in the vertical direction is a measure of the spread of the point cloud (f_2). The slope of the seafloor, independent of the direction it is facing, is represented by f_1 (measured as the altitude angle or elevation angle) and is

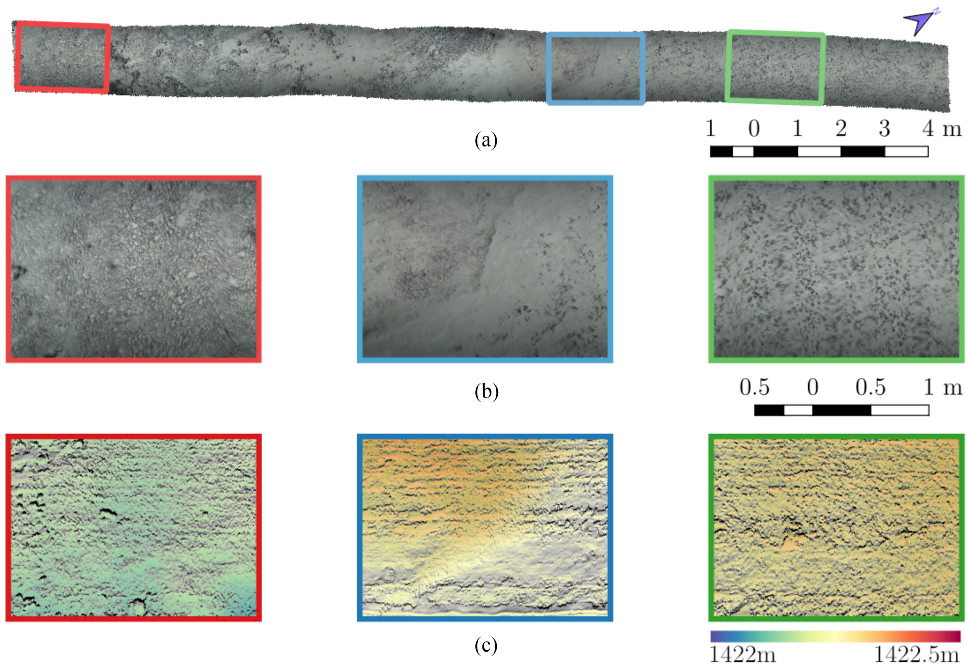


Fig. 4. Different types of seafloor present in the area. (a) Top view of a 21-m section, with insets showing different types. (b) Detailed views of each type. (c) Bathymetric maps. The frames are colored as follows: (red) continuous Mn-crust deposits; (blue) sediment-covered areas; and (green) nodules of varying sizes.

TABLE II
FEATURES CALCULATED WITHIN EACH KERNEL

Bathymetric Features		Image Features	
$\boldsymbol{f_1}$	**Slope**	f_5	Luminosity mean
f_2	Vertical standard deviation	$\boldsymbol{f_6}$	**Luminosity standard deviation**
$\boldsymbol{f_3}$	**Roughness mean**	$\boldsymbol{f_7}$	**Luminosity entropy**
$\boldsymbol{f_4}$	**Roughness standard deviation**	$\boldsymbol{f_8}$	**Red intensity mean**
		f_9	Green intensity mean
		$\boldsymbol{f_{10}}$	**Blue intensity mean**
		$\boldsymbol{f_{11}}$	**Red intensity standard deviation**
		f_{12}	Green intensity standard deviation
		$\boldsymbol{f_{13}}$	**Blue intensity standard deviation**

Bold font indicate the features chosen for use in the final classifier based on the F_1 scores calculated; see Fig. 7.

TABLE III
STATISTICS OF MANUALLY LABELED DATA SETS USED IN BUILDING THE SVM CLASSIFIER

Dataset	1. Training and testing	2. Cross validation
Dive number	BSA038	BSA031
Collected on	2017 January 21	2016 January 24
Crust area (m^2)	140	179
Sediment area (m^2)	164	107
Nodules area (m^2)	285	162

calculated as the deviation of the normal to the seafloor $\mathbf{N}$, as follows:

$$f_1 = 90 - \cos^{-1}(\mathbf{N} \cdot \mathbf{V}) \quad (1)$$

where $\mathbf{V} = [0, 0, -1]^T$ is the unit vector along the Z-axis facing away from the seafloor.

The seafloor is relatively smooth in sediment-covered areas and is more rough for crusts and nodules. This surface roughness is captured in two features, as defined in the ISO 4287:1997 standard: mean and standard deviation of the deviation from the plane of the kernel in the normal direction. Assuming that the kernel consists of n points, with each point i being $(x_i, y_i, z_i, R_i, G_i, B_i)$, the deviation of each point is calculated as

$$h_i = |\mathbf{N} \cdot [x_i, y_i, z_i]^T|. \quad (2)$$

f_3 and f_4 are then calculated as the mean and the standard deviation of all the points within the kernel, respectively.

Image features represent the features calculated from the color of the seafloor. The simplest image features include the mean RGB values of the kernel (f_8, f_9, and f_{10}) and their standard deviation (f_{11}, f_{12}, and f_{13}). Since crusts and nodules appear darker than the sediment areas, a luminosity image of the kernel is constructed. Luminosity of a point i is a measure of brightness of the point and is calculated as

$$I_i = 0.21R_i + 0.72G_i + 0.07B_i. \quad (3)$$

The mean and standard deviation of luminosity for each kernel are calculated as f_5 and f_6, respectively. Entropy (f_7) is calculated from the luminosity image using the following equation:

$$f_7 = -\sum_j P(I_j)\log(P(I_j)) \quad (4)$$

where $P(I_j)$ is the probability that a random point j will have a luminous intensity I_j.

The normalized values of all features are compared using Fig. 5, where a kernel size of 10-cm edge length is found to

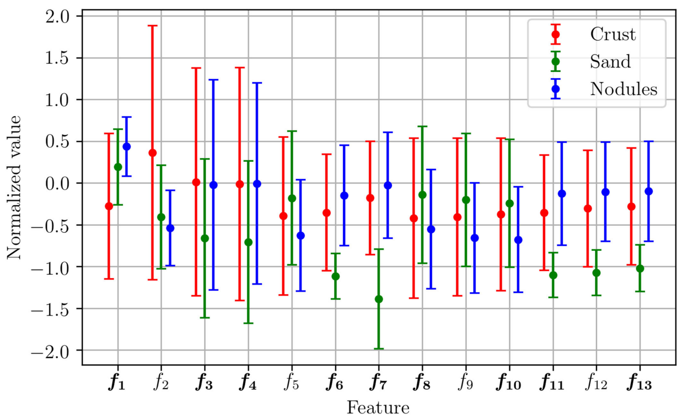


Fig. 5. Features used and their variation w.r.t. seafloor types. The values are normalized to approximately zero mean and unit variance across the whole training data for a kernel size of 10 cm. The bold font indicates features chosen for use in the final classifier based on the F_1 scores calculated; see Fig. 7.

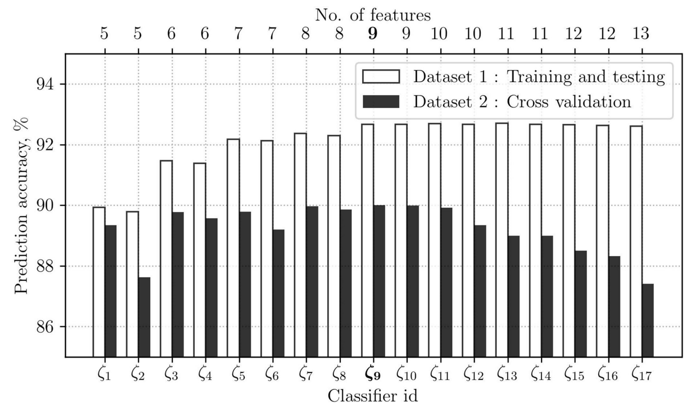


Fig. 7. Performance of the feature vector size on classification. Beyond seven features, increasing the number of features increases scores by a minimal amount. However, on CV, the higher results turn out to be due to overfitting. The selected classifier (ζ_9) is highlighted.

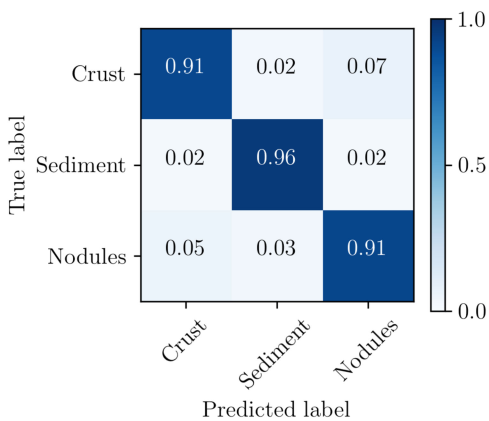


Fig. 6. Confusion matrix of classifier after optimization.

be appropriate for discriminating between the different types of seafloor.

To identify the optimal feature vector, optimize the hyperparameters, and train the classifier, two data sets are selected and manually labeled. A summary of the two data sets is shown in Table III. Data set 1 consists of 58 860 kernels and data set 2 consists of 44 830 kernels. The training data are constructed by randomly selecting 5000 kernels from data set 1. The testing data for the classifier, whose results are used to tune the SVM, are constructed by randomly selecting a different set of 5000 kernels from data set 1. The entire data set 2 is used as the independent CV data set and is used in the final step for selecting the best performing feature set.

Fig. 6 shows the confusion matrix of the classifier after optimization, where the crust kernels are double weighted during training to ensure the algorithm prioritizes identifying Mn-crusts. The final performance is measured using the F_1 score [31], [36]. The feature set with the best classification performance is identified by doing an extensive search under three categories—image features only (C_1), bathymetric features only (C_2), and a combination of both image and bathymetric features (C_3). Feature vectors from C_3 performed better than others. Fig. 7 shows the accuracy values for the best two classifiers for each feature vector length with the CV accuracy plotted alongside. The classifier ζ_9, with nine features (f_1, f_3, f_4, f_6, f_7, f_8, f_{10}, f_{11}, and f_{13}), has both the highest CV scores of 90% accuracy and 87.7% F_1 score. This feature vector was selected for the SVM classifier and is highlighted in bold in Fig. 7. The decision boundary of the classifier ζ_9 shows that crust is more prevalent in steeper areas. The mean roughness value is higher than the standard deviation of roughness for nodules indicating an undulating texture.

The classifier is further tuned by optimizing the hyperparameters, which influence the SVM decision function. Values are optimized using a random search over a large range of parameter values followed by an extensive grid search about the best performing parameter values [37].

B. Acoustic Data Interpretation

Acoustic reflections made over seafloor sections classified as crust are used to estimate a thickness value [38]. The acoustic measurements are corrupted by noise generated by scattering, multipath reflections, and local inclusions in the crust layer. To identify a continuous layer of Mn-crust from successive measurements, the algorithm carries out filtering of individual pulses, extracting signal boundaries, reframing the signal into a distance based grid, and identifying secondary reflections to calculate thickness.

Initially, each recorded signal is filtered by removing the spectral components that fall away from the transmitted frequency of 200 kHz. In extracting signal boundaries, the signal region of interest is identified using binary thresholding using Otsu's method [39] to identify the first reflection, i.e., the top surface of the seafloor.

In the third step, the reflections are bundled into a single image frame, with adjacent signals lined up with their first reflection matching and subsequent values as pixel intensities below. The signals are sampled into a uniform 2-D grid.

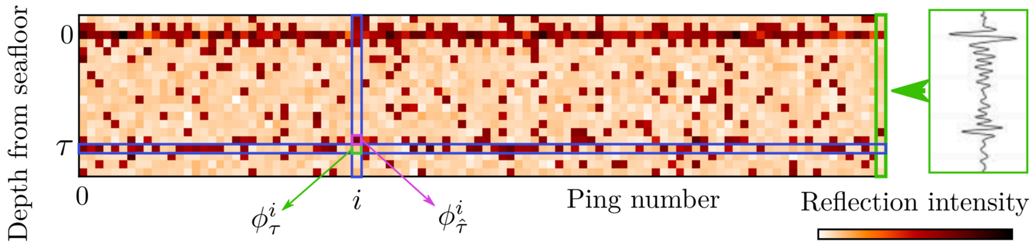


Fig. 8. Illustration showing acoustic thickness estimation. The reflections are arranged as an image aligned w.r.t. the top reflection. A cost function is calculated for each potential thickness [see (5)].

An illustration is shown in Fig. 8, where darker colors indicate stronger reflections. The image is filtered using a median filter to reduce noise. The signal intensities are then corrected for attenuation in crust.

Since the top surface has been identified as Mn-crust by the SVM classifier, a near continuous secondary reflection is assumed to exist, and the best candidate is selected using an integral function that calculates the strength of reflections at each distance from the top surface. The entire acoustic frame is denoted as Φ and an individual point in the image as ϕ_τ^i, where i denotes the X coordinate (ping number) and τ denotes the Y coordinate (depth from seafloor). A cost function is calculated for each potential thickness value of τ

$$\Gamma_\tau = -\sum_{i \in X} |\phi_{\hat\tau}^i| \tag{5}$$

where $\phi_{\hat\tau}^i$ is the point with highest intensity within a threshold distance to τ, for each ping i. For example, in Fig. 8, the point directly above τ is used ($\hat\tau = \tau - 1$). This is done to account for minor local variations of thickness within the layer. The mean thickness is identified as τ having the lowest cost Γ_τ and the secondary layer, which is the crust–substrate interface, is calculated as $\phi_{\hat\tau}^i$, for each ping i. Thus, the thickness becomes

$$t_i = \hat\tau_i. \tag{6}$$

This results in a thickness value, which is consistent over the range of several meters, yet accommodates for the local minor variations in crust thickness.

C. Data Fusion and Crust Volume Estimation

The thickness measurements made in the previous step lie along the 2-D path, where each acoustic ping struck the seafloor within the 1.5-m-wide 3-D map. Since the thickness of Mn-crusts is assumed to change gradually over the range of several meters, the measured thickness values are extrapolated into all crust kernels, and the volume of crust present in the area is calculated by integrating over all kernels.

To extrapolate thickness measurements, for a kernel i, a window of influence J_i is defined as the set of all kernels within a threshold distance d_{th} from the center of i (set to 2 m). The number of kernels in set J_i is calculated to be N_{J^i}, and the number of crust kernels is calculated to be C_{J^i}. Assuming $\hat{J}_i$ to be the set of all kernels inside J_i, where a thickness measurement is made, the thickness of the crust at i is calculated as a weighted sum of thickness values of $\hat{J}_i$

$$t_i = \begin{cases} \frac{\sum_{j\in\hat{J}_i} w_j t_j}{C_{\hat{J}_i}}, & \text{if } C_{\hat{J}_i} > 0 \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

where $C_{\hat{J}^i}$ is the number of crust kernels within $\hat{J}_i$. The weight w_j of each measurement t_j is calculated as an inverse function of Euclidean distance from kernel j to kernel i (d_{ij})

$$w_j = 1 - \frac{d_{ij}}{d_{th}}. \tag{8}$$

The local percentage cover of exposed Mn-crust deposits (Ψ_i) about i is calculated as

$$\Psi_i = \frac{C_{J^i}}{N_{J^i}} 100. \tag{9}$$

Using the density of Mn-crust (ρ) calculated from samples collected in the area, the local mass coverage per unit area of Mn-crust about i is calculated as

$$M_i = \frac{\rho \sum_{j\in J_i} t_j}{N_{J^i}}. \tag{10}$$

The window of influence J_i is then moved to the next point, where a thickness measurement was taken and the calculations are repeated, to estimate the distribution of crust along the entire mapped area.

TABLE IV
SUMMARY OF FIELD EXPERIMENTS CONDUCTED AT TAKUYO DAIGO SEAMOUNT IN THE NORTHWESTERN PACIFIC OCEAN

Vehicle	Number of dives	Lateral distance surveyed (m)	Observation speed (m/s)	Observation time (min)
Hyper-Dolphin (ROV)	1	3636	0.15	312
BOSS-A (AUV)	5	7217	0.1	931

IV. Analysis of Field Surveys

Field trials of the system were conducted at the southern shoulder of the Takuyo Daigo seamount. In a span of over five years, several dives were made to depths between 1350 and 1600 m below sea level. A summary of the dives is given in Table IV.

A. Continuous Flat Mn-Crust Deposits

The steps in analyzing a seafloor section to estimate crust distribution are shown in Fig. 9. They show a seafloor section

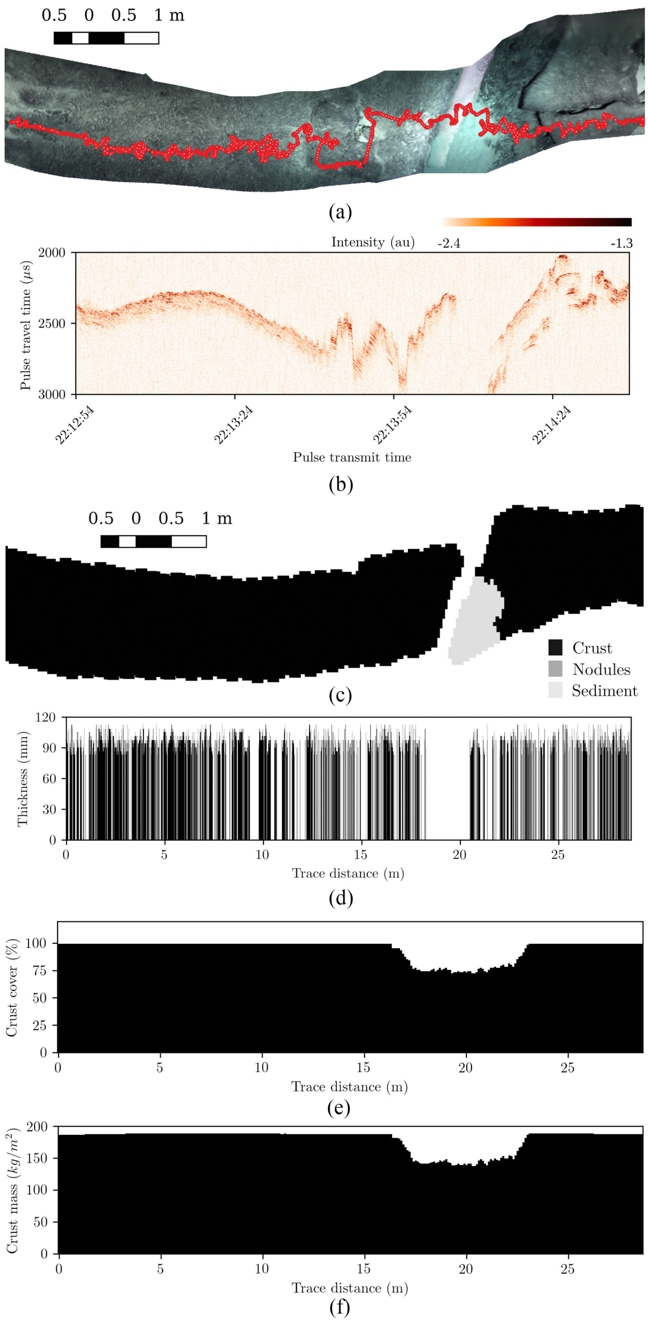


Fig. 9. Steps in processing the data collected over a flat crust section. The crust layer breaks toward the right, and the broken pieces can be seen at the extreme right. A short vertical drop and a small section of sediment separates the two. (a) Top view of the seafloor section with locations of acoustic measurements shown as dots. (b) Acoustic signals recorded. (c) SVM classification. (d) Estimated thickness values. The horizontal axis denotes the interpolated trace distance along the red dots in (a) and is significantly longer than the length of the seafloor section. (e) Percentage cover. (f) Mass coverage of crust.

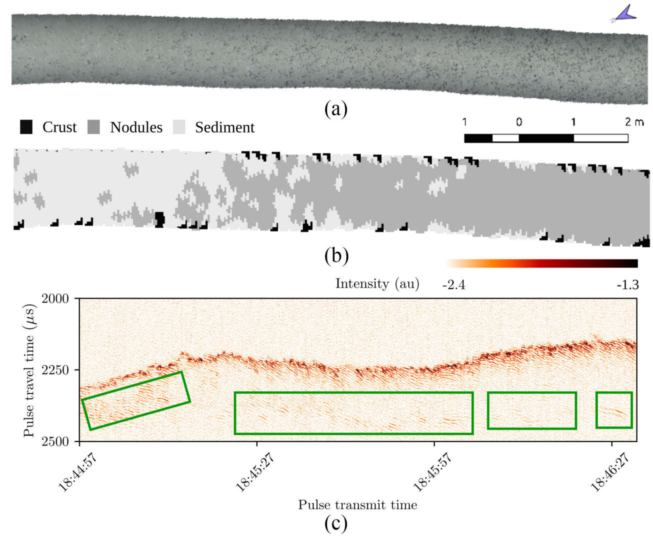


Fig. 10. Sediment section transitioning into a nodule section. Because no crust kernels were found, thickness values are not calculated. (a) Top view of the 3-D reconstruction. The trace of acoustic measurements [see Fig. 9(a)] has been omitted for clarity of visualization. (b) SVM classifier output. (c) Acoustic signals recorded by the probe, showing no consistent layer of crust. The image shows weak second layers of reflections in areas shown in boxes, presumably from a buried layer of crust.

consisting of a flat continuous Mn-crust layer, which is 6 m in length and 1.5 m in width. Fig. 9(a) shows the top view of the 3-D reconstruction with the red dots showing the locations of acoustic measurements. Toward the right, a short vertical drop, seen in the reconstruction as a white vertical strip, is present, where the crust breaks off and the broken slabs are seen immediately afterward. The acoustic reflections recorded by the probe are shown in Fig. 9(b). The classification results are shown in Fig. 9(c); other than a small section in the middle, all measurements are made over Mn-crust. A thickness value is calculated for points [red dots in Fig. 9(a)], which lie on kernels classified as crust, and is shown in Fig. 9(d). The horizontal axis of the plots represents the distance corresponding to the trace of the acoustic measurements on the seafloor. Due to the gimbals continuously orienting the acoustic probe so that the pulse is normal to the seafloor, the trace is longer than the length of the 3-D reconstruction. The percentage cover calculated using (9) is plotted in Fig. 9(e). The graph shows a dip in coverage in the middle due to the sediment-covered area. The estimated mass coverage is shown in Fig. 9(f), with ~180 kg/m^2 of crust.

B. Sediment to Nodules Transition

Fig. 10 shows a 12-m section that transitions from full sediment cover to full nodule cover. The acoustic signals also show a clear change from a weak top reflection in sediment-covered areas to sharper reflections with change in the type of seafloor. Since no crust is present, no thickness values are calculated. However, in the acoustic reflections, a weak second reflection can be seen indicating the presence of a buried layer. It is seen that some edge kernels are misclassified as crust due to the limitation of the color correction method used in generating the 3-D maps. In the presented example, this creates a 2.7% error in the percentage cover estimates. However, since the acoustic data are collected along the middle of the transect, which is classified correctly as sand/nodules, no error in thickness measurements and final mass calculations is incurred.

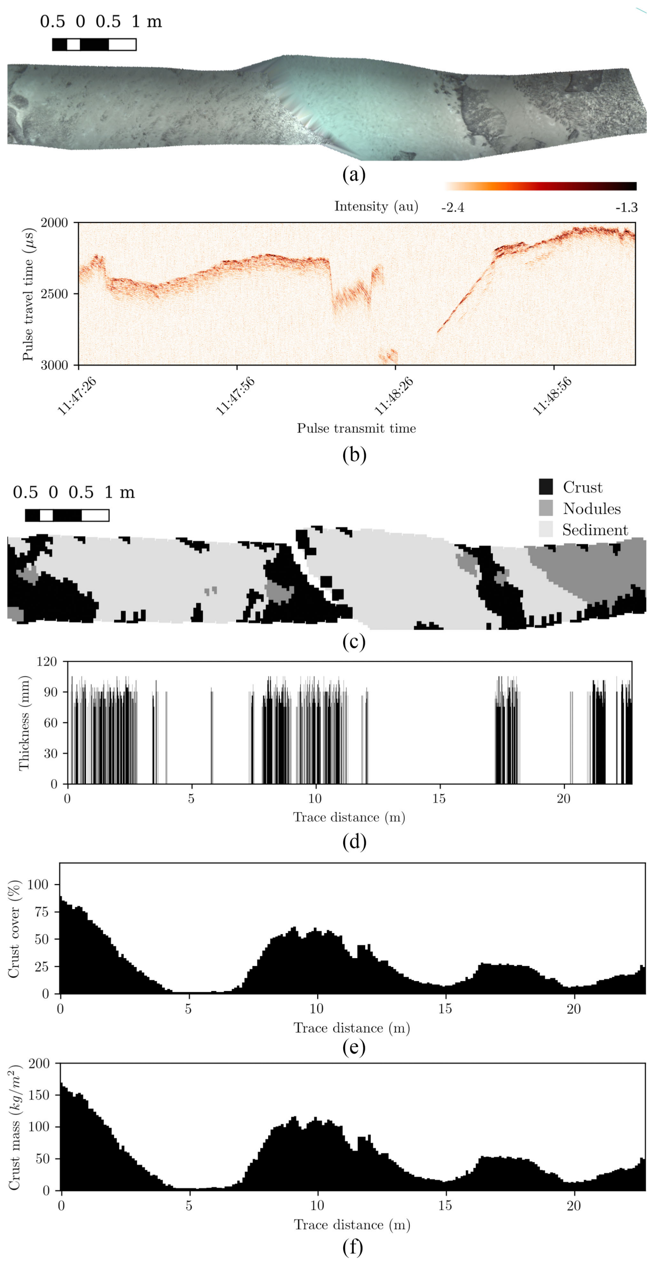


Fig. 11. Seafloor section containing a variety of types. Toward the left, the layer of crust is partially covered by sediment and gets broken in the middle. Farther to the right, the sections are covered by nodules. (a) Top view of the seafloor section. (b) Acoustic signals recorded by the probe. (c) SVM classification of the seafloor section. (d) Thickness values estimated. (e) Percentage cover of crust. (f) Mass coverage of crust. Toward the left side, although it is nearly 100% covered by crust, the layers are thin, and hence, the mass coverage is only about 75% of the maximum coverage expected in the area.

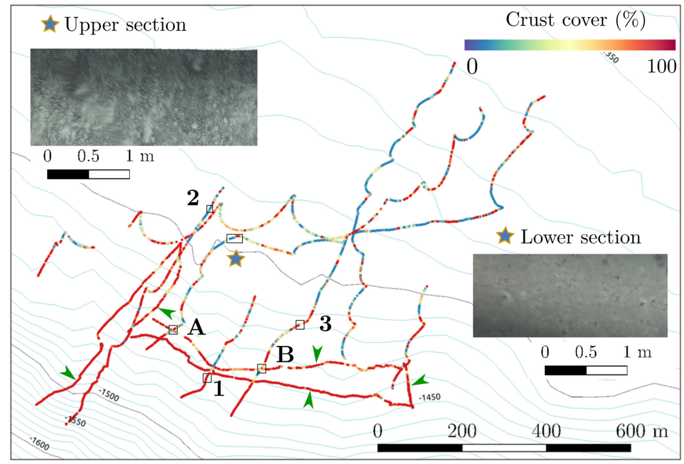


Fig. 12. Percentage cover of Mn-crust along mapped transects. The four ROV transects (shown by arrows) have a higher percentage cover as regions with exposed crusts were followed manually by the ROV pilots, whereas the AUVs used for all other transects followed preplanned trajectories. Crust coverage can vary rapidly such as in the area marked by ★, with very different landscapes only 10 m apart (3-D maps shown in insets).

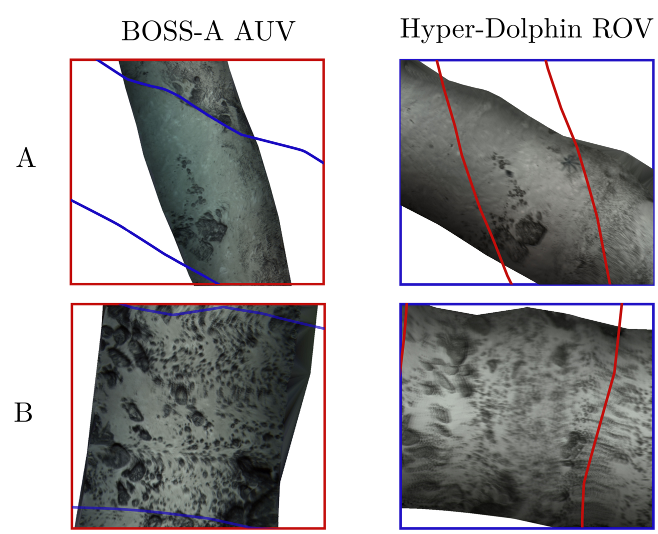


Fig. 13. Two locations where the transects intersect are selected for intercomparison between AUV and ROV collected data (see Fig. 12 for the locations). The blue outline shows the ROV transects, and the red outline indicates the AUV transects.

C. Sediment-Covered Flat Mn-Crust Near a Ledge

Fig. 11 shows a 12-m section of various types of seafloor. It is centered on a ledge of flat Mn-crust and partially covered by a layer of sediment. Below the ledge, a thick layer of sediment is visible, followed by broken slabs of Mn-crust. Since Mn-crusts are exposed partially, the coverage estimate oscillates between near zero and 80%. Toward the left, the sparse and weak acoustic reflections indicate a sand layer, and a second layer becomes clear, where the crust is exposed. Toward the right, the seafloor is covered in nodules, and it shows in the acoustic reflections as strong reflections, but with no secondary layer visible. To the left of the nodules, where a sand section of about 0.8 m is present, a secondary layer beneath the sediments is visible in the acoustic reflections; however, the type of the layer cannot be determined with the proposed techniques.

D. Compiled Results From All Dives

The data collected from all the dives are analyzed and combined, and the distributions for a 50-cm edge window are shown in Figs. 12–15. Since the ROV transects followed a crust layer,

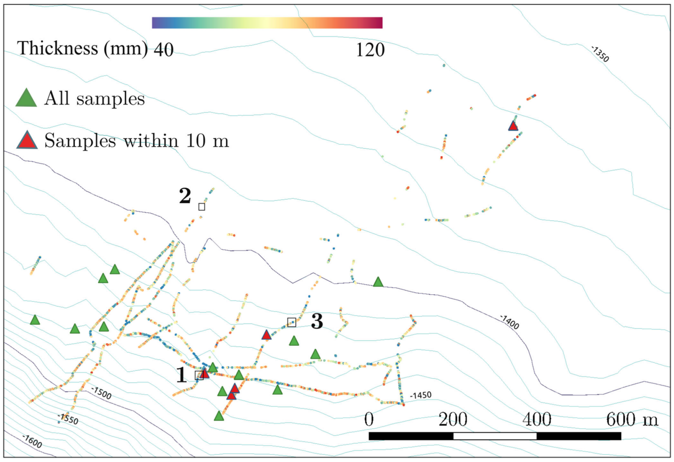


Fig. 14. Thickness of Mn-crust along mapped transects. The thickness is higher in deeper and steeper sections of the seamount (left bottom area). The samples collected from the visible area and the samples that are close to the mapped area are shown as green and red triangles, respectively.

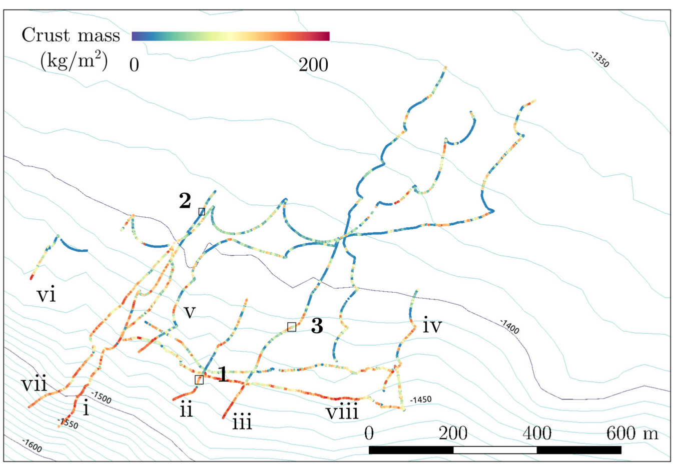


Fig. 15. Final volumetric coverage estimate along mapped transects. The results vary from nil to 204 kg/m^2, with the maximum crust coverage found in the steeper lower sections of the mapped region.

the results show a high percentage cover throughout. These four transects were mapped during a single dive and are indicated using green arrowheads. The remaining transects, mapped by AUVs, shows a varying landscape that has anywhere between 0% and 100% crust coverage. It is seen that the lower sections of the seamount, which are also steeper, have a high crust coverage. In some areas, the cover is seen to vary rapidly. The section marked by ★ has flat continuous Mn-crust deposits in the upper section, whereas the lower section, only 10 m away, shows a sediment-covered seafloor. This high variability in the seafloor classes indicate the need for a continuous measurement system to assess the crust volume accurately. Locations A and B in Fig. 12 are intersects of ROV and AUV transects, with closeup views in Fig. 13 showing consistency between the transects. Crossing A is a sand-covered crust area (exposed crust is seen to the right and top of the intersection) with some rocks. Crossing B is covered with nodules of various sizes.

TABLE V
ESTIMATED MN-CRUST AT TAKUYO DAIGO SEAMOUNT MEASURED ALONG A TOTAL TRANSECT LENGTH OF 10.9 km (SEE TABLE IV FOR SURVEY DETAILS), WITH UNCERTAINTY VALUES IN BRACKETS

Parameter	Proposed method		Samples N=7	
	Mean ($\pm\sigma$)	Variability ($\pm\sigma$)	Mean ($\pm\sigma$)	Variability ($\pm\sigma$)
Total area mapped (m^2)	12 510 (±1150)	-	-	-
Percentage cover (%)	52.0 (±5.20)	±39.0 (±3.90)	-	-
Thickness of crust (mm)	69.6 (±4.25)	±18.7 (±1.14)	63.3 (23.9)	29.5 (11.2)
Crust per unit area (kg/m^2)	69.6 (±12.5)	±59.7 (±10.7)	63.2* (±31.4)*	22.1* (±10.1)*
Amount of crust (t)	870 (±237)	-	791* (±466)*	-

The variability of estimated values indicates the contrasting nature of the Mn-crust deposits. An indicative estimate using only samples collected from the same area is compared.
*Visual mapping data for area estimates are used to calculate this value.

The thickness values measured and the samples collected from the area are shown in Fig. 14. The relative abundance of crust in the upper and lower sections of the map and the lack of crust in the central regions is observed. The thickness varies from about 40 mm to a maximum of 114 mm, with a mean thickness of 69.6 mm. A total of 26 samples were collected in the past in the area covered; their locations are shown as green triangles. Although there is no exact overlap between the samples collected and the surveyed regions, seven samples are within 10 m of the transects. These samples, shown as red triangles, are used for further analysis for comparing the results of the present survey with sampling-based methods in Section IV-E.

The final volumetric estimates are shown in Fig. 15, which shows the unit crust mass coverage for every part of the mapped regions. The results vary from zero up to a maximum of 204 kg/m^2. As observed from Figs. 12 and 14, the lower steeper sections of the seamount contains maximum coverage of crusts, even though the coverage can vary abruptly in a short range of a few tens of meters.

E. Discussion

Quantitative estimates of Mn-crust abundance are obtained over large areas using the instruments and methods described. A summary of the results along with the variability and estimates of uncertainty for each measurement is provided in Table V. The variability is calculated as the one-sigma deviation from the mean value. The uncertainty is estimated as the error in measurements on the mean and variability values.

The sources of error in the measurements are propagated as systematic errors depending on the thickness, the density of crust, the area, and the classification. The 3-D mapping

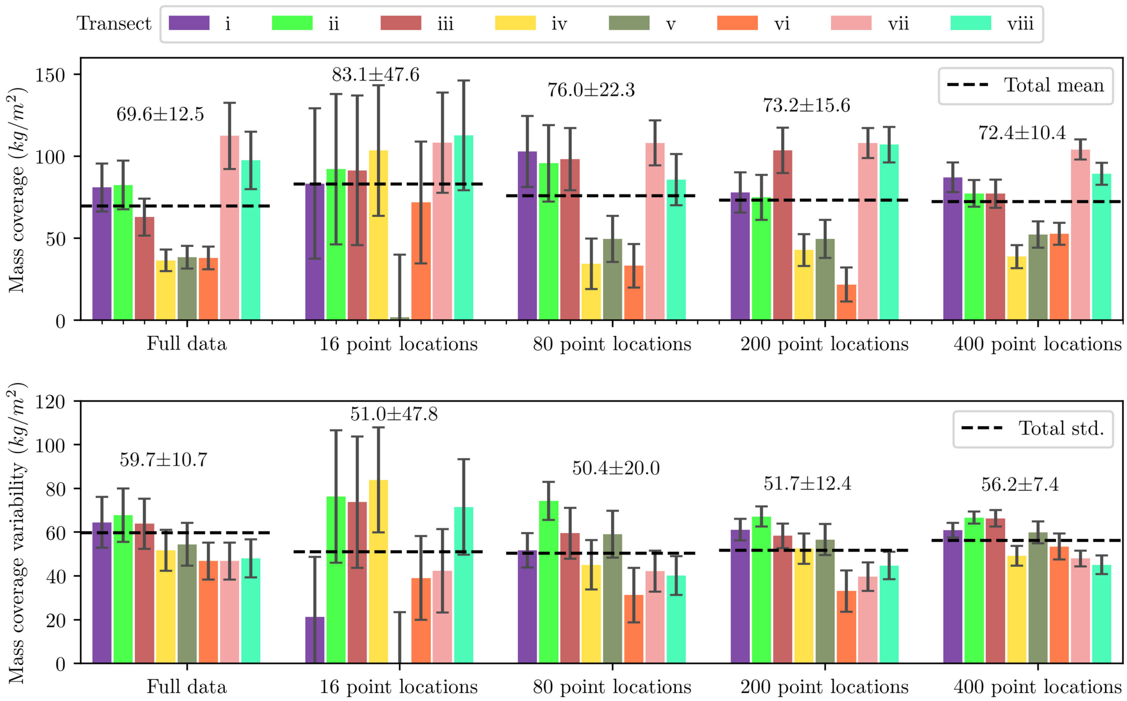


Fig. 16. Mass coverage of each transect shown in Fig. 15 and its variability. This is compared with a simulated sampling scenario, by randomly selecting points from the surveyed data. Mean value and error for each data set are written above the bars. Variations among transects show that extrapolating the results from a single transect to the whole area can result in erroneous estimates. The error values indicate that >200 random samples are required for getting an accuracy comparable to the proposed method.

system has a one-sigma uncertainty of 9.17% affecting the total mapped area. The thickness measurements are subject to a 6.1% variability in the velocity of sound (2932 ± 179 m/s) in Mn-crusts [19]. The percentage cover has 10% uncertainty from classification (CV accuracy—see Section III-A). In calculating the total amount of Mn-crust present in the area, a 1.9% variability in the density of crust (1920 ± 36 kg/m^3) is also considered [19], resulting in a total uncertainty of 27.2%. It is estimated that there is 870 t of Mn-crust in the mapped area, with an uncertainty of 237 t. Error in mass coverage is calculated to be 18%, and the calculations show the amount of crust per unit area to be 69.6 kg/m^2 with an uncertainty of 12.5 kg/m^2. However, particularly notable is the variability of 59.7 (±10.7) kg/m^2, which is 85.8% of the mean value. This is consistent with the observation that crust deposits are highly variable and, therefore, require continuous measurements to accurately map their distribution and indicates that high-resolution measurements are required for accurate portrayal of crust distribution and inventory survey.

A comparison of the results is made with estimates made using only samples taken within 10 m of the mapped region and is included to show the advantages of the proposed method. Since a percentage cover estimate cannot be calculated from ROV sampling dives, percentage cover estimates calculated in the previous step are used instead. Samples taken in an area within a distance of 10 m of the mapped region was considered, which show a mean thickness of 63.3 mm with a standard deviation of 29.5 mm. A total of seven samples are selected, which are collected from five locations, as indicated in Fig. 14. The limited number of samples constitutes a large statistical error of 37.8% in sample thickness measurements. Since percentage cover cannot be calculated from samples, the estimates made in the previous step are used to illustrate the advantages of continuous measurements. It is seen from Table V that the final estimated crust mass per unit area and the total amount of crust in an area equal in size to the mapped area have an uncertainty of 49.7% and 58.9%, respectively.

The high uncertainty in surveys based on sampling, as compared to AUV surveys, arises due to the significantly smaller number of measurements. In acoustic surveys from an AUV, there are over one million measurements, and thus, the statistical error is negligible. Only the 6.1% systematic error, due to the variability in the speed of sound, needs to be considered. On the contrary, the thickness of physically recovered samples can be measured with high accuracy, making the systematic error almost zero. Nevertheless, the statistical error is high and can be reduced only by increasing the number of samples in the given area. Producing an uncertainty less than the systematic error in the acoustic measurements requires a minimum of 268 samples to be collected for an equivalent surveyed area. Since sampling using ROVs takes approximately 40 min–1 h [2], collecting so many representative samples is not practical. Furthermore, the continuous local variability of crust cover indicates that pointwise sampling alone is not suitable for accurate survey of Mn-crust distribution.

To study the spatial distribution of Mn-crust over the scale of hundreds of meters, crust per unit area and its variance for each transect (see Fig. 15 for transect numbers) are compared in Fig. 16. These transects are roughly parallel in most places and are spaced between 100 and 250 m in the lower sections. The bar charts to the right show estimates made by randomly selecting a fixed number of points, equally from each transect, to simulate sampling where the total number of points considered is shown. The error bars indicate the systematic error for the full data and the standard deviation of 50 iterations for each random selection of point locations. The systematic error is not shown in the random point samples to illustrate the level of uncertainty that would be expected if an equivalent number of samples was recovered. A larger number of points provide a more representative estimate of the crust coverage, where the statistical error levels become comparable to the systematic errors in the proposed method after 200 random points. Even with 200 locations sampled, which would take approximately eight days of bottom time for ROV sampling, the spatial variability still influences the estimates (e.g., transect iii), indicating that further sampling is required to capture the variability between adjacent transects. The variation in estimates among transects indicates that extrapolating results from a single transect over the entire mapped area can lead to highly inaccurate results. Multiple surveys at different locations are required to accurately estimate crust coverage and volume.

V. Conclusion

1) *In situ* measurements of the distribution of Mn-crust in hectare-scale regions have been demonstrated for the first time by using machine learning tools to analyze visual 3-D maps and acoustic subbottom sonar measurements. The results were combined to calculate the total mass and distribution of the Mn-crust in the region. The measurements were validated using samples collected from the survey area, which indicated a comparable total volume of crust.
2) SVM methods can achieve a high level of classification accuracy (90%), where it has been demonstrated that combining both shape and visual features improves the performance over classifiers that consider only shape or visual features. Furthermore, this article showed that using too many features leads to overfitting, and that a relatively small number of combined features have better generalization.
3) The proposed method is advantageous over sampling with a nearly 50% lower uncertainties in crust estimates. It is shown that it is not practical to achieve a similar uncertainty level using sampling and video surveys, since $>$200 samples would be required. Also, the proposed method avoids the inherent biases of sampling toward samples that are easy to collect, and not characterizing regions with no samples, such as nodules and sediments.
4) The surveyed region of the Takuyo Daigo seamount has an average Mn-crust distribution of 69.6 kg/m^2 for a 12 510 m^2 mapped region, with occurrence ranging between 0 and 204 kg/m^2. The region has a variability in distribution of 85.8%, indicating that continuous measurements are needed to accurately characterize Mn-crust distribution.

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Umesh Neettiyath (Member, IEEE) received the B.Tech. degree in electronics and communication from the University of Calicut, Malappuram, India, in 2008, and the M.S. by Research degree in underwater robotics from the Department of Engineering Design, Indian Institute of Technology Madras, Chennai, India, in 2013.

He is currently a Project Researcher with the Institute of Industrial Science, The University of Tokyo, Tokyo, Japan. His research interests include the design and development of field robotics systems for environmental observation. His current research interests include large-scale data collection and analysis of manganese crust deposits using underwater robots.

Blair Thornton (Member, IEEE) received the B.Eng. degree in ship science and the Ph.D. degree in underwater robotics from the University of Southampton, Southampton, U.K., in 2002 and 2006, respectively.

He is currently an Associate Professor with the University of Southampton. He is also with the Ocean Perception Laboratory, Institute of Industrial Science, The University of Tokyo, Tokyo, Japan. His research interests include the development of *in situ* sensors and data processing techniques for integrated acoustic, visual, and chemical survey of marine minerals and environment monitoring. He is dedicated to fielding real systems in real environments and overcoming bottlenecks in the flow of information from data collection to human interpretation.

Mehul Sangekar (Member, IEEE) received the M.Sc. degree in underwater robotics and the Ph.D. degree in ocean technology from The University of Tokyo, Tokyo, Japan, in 2010 and 2014, respectively.

He is currently a Project Researcher with the Thornton Lab, Institute of Industrial Science, The University of Tokyo. His current research interests include techniques for intelligent multilayer resolution mapping of the seafloor using autonomous underwater vehicles. He is also working on developing algorithms for analysis of high-resolution seafloor bathymetry and correlating it with other measured seafloor parameters.

Yuya Nishida received the Ph.D. degree in engineering from the Kyushu Institute of Technology, Kitakyushu, Japan, in 2011.

He is currently an Assistant Professor with the Kyushu Institute of Technology. He is working on development of autonomous underwater vehicles and underwater instruments for surveying the marine resources. His research interests include the automation of marine survey and inspection conducted by humans.

Kazuo Ishii received the B.S. and Doctor of Engineering degrees the from Department of Naval Architecture and Ocean Engineering, Faculty of Engineering, The University of Tokyo, Tokyo, Japan, in 1991 and 1996, respectively.

He is currently a Professor with the Department of Human Intelligence Systems, Kyushu Institute of Technology, Kitakyushu, Japan. His research interests include field robotics, underwater robotics, and neural networks.

Adrian Bodenmann received the M.Sc. degree in microengineering from the Ecole Polytechnique Federale de Lausanne, Lausanne, Switzerland, in 2009.

He is currently a Senior Research Assistant with the University of Southampton, Southampton, U.K. His research interests include the development of camera systems for high-altitude seafloor mapping and algorithms for generating 3-D seafloor reconstructions based on photos of the seafloor. He also works on quantifying the certainty in these reconstructions and identifying correlations between identified objects in reconstructions and data from acoustic and chemical sensors.

Takumi Sato received the B.S. degree in engineering from the Tokyo University of Agriculture and Technology, Tokyo, Japan, in 2011, and the M.S. degree in environmentology from the University of Tokyo, Tokyo, in 2013.

In 2016, he joined the Offshore Advanced Technology Department, National Maritime Research Institute, Tokyo, as a Researcher. He is involved in the research of underwater observation systems for marine resource consisting of autonomous underwater vehicles.

Tamaki Ura (Fellow, IEEE) received the graduate and D.Eng. degrees from the Department of Naval Architecture and Ocean Engineering, Faculty of Engineering, The University of Tokyo, Tokyo, Japan, in 1972 and 1977, respectively.

He retired as a Professor Emeritus of the University of Tokyo and has held positions as the Director and Distinguished Professor of the Center for Socio-Robotic Synthesis, Kyushu Institute of Technology, Kitakyushu, Japan, and the Director of the Underwater Technology Center of the National Maritime Research Institute, Tokyo. He has developed various types of autonomous underwater vehicles (AUVs) and related application technologies, including navigation methods, a new sensing method using a chemical sensor, precise seafloor mapping methods, a precise seabed positioning system with a resolution of a few centimeters, and a new sensing system of the thickness of cobalt-rich crust. Finally, he exemplified using these technologies that AUVs are practicable and valuable tools for deep-sea exploration.

Akira Asada (Member, IEEE) received the graduate degree from the Department of Electronic Engineering, Faculty of Science and Engineering, Waseda University, Tokyo, Japan, in 1977, and the D.Sc. degree from the University of Tokyo, Tokyo, in 1995.

He retired as a Professor and the Director of the Center for Integrated Underwater Observation Technology, University of Tokyo. His research interests include the development of acoustic observation systems, including interferometric and synthetic aperture sonar systems, subbottom sonars, and 3-D acoustic imaging systems for marine survey, fishery, and underwater security applications.