Automatic Extraction of Thickness Information from Sub-Surface Acoustic Measurements of Manganese Crusts

Umesh Neettiyath^{1,2}, Blair Thornton^{3,1}, Mehul Sangekar¹, Kazuo Ishii², Takumi Sato¹, Adrian Bodenmann¹, Tamaki Ura⁴ ¹Institute of Industrial Science, The University of Tokyo, Komaba, 153-8505, Japan (E-mail: umesh@iis.u-tokyo.ac.jp)

²Graduate School of Life Science and Systems Engineering, Kyushu Institute of Technology, Kitakyushu, Japan ³Southampton Marine and Maritime Institute, University of Southampton, Southampton SO16 7QF, UK ⁴Center for Socio-Robotic Synthesis, Kyushu Institute of Technology, Kitakyushu, Japan

Abstract—Mapping and estimating the volumetric distribution of cobalt-rich manganese crusts (Mn-crust) is a challenging task that lies at the centre of deep-sea mineral prospecting. Acoustic methods are effective and capable of in-situ continuous measurements of Mn-crust thickness, providing much higher spatial resolutions compared to traditional methods involving sampling. However, processing acoustic signal in order to estimate thickness values is difficult due to low signal to noise ratios. This paper proposes a combination of image processing techniques in addition to acoustic signal processing in order to improve the accuracy of measurements. The advantage is the possibility of using the physical properties of Mn-crust, such as local continuity in order to recognize valid measurements. Testing the algorithm on data collected from sea experiments demonstrate that the reflected signals from the crust can be identified, resulting in spatially continuous thickness estimates.

I. INTRODUCTION

Manganese crusts (Mn-crusts) are mineral deposits that can cover several thousands of square kilometres of the seafloor in regions that have been relatively free of tectonic activity and sedimentation for tens of millions of years [1], [2]. Mn-crusts are seen as a potential source of minerals such as cobalt and tellurium by governments and industries internationally [3], [4]. This drives interest in the development of methods to quantitatively estimate their distribution and abundance.

Traditional methods of estimation, such as sampling from Remotely Operated Vehicles (ROV) [4], dredges or core drilling can obtain samples for detailed, pointwise measurements of thickness and composition. However, they fail to capture the continuous local variations of the deposits. This limitation can be overcome by in situ measurement techniques, which can significantly improve the spatial resolution of measurements. The Institute of Industrial Science of the University of Tokyo developed a high power parametric acoustic probe which uses a highly focused pulse to make measurements of the sub-surface structure of Mn-crusts from a close range of $1 \sim 2 \,\mathrm{m}$. The probe has a vertical spatial resolution of about 1.4 mm and penetrates approximately 30 cm below the top-surface of the crust, and is actively controlled by a

double gimbal that ensures the acoustic waves always enter the crusts normal to their surface [5]. This system is mounted on the purpose built AUV, BOSS-A [6], together with a highresolution 3D visual mapping device.

Using the data acquired by the probe, the thickness of the crust layer can be determined from the acoustic signals based on the acoustic velocity. However, automated and reliable extraction of this information in the presence of noise due to scattering, multi-path reflections, local inclusions inside the crust layer, fluctuating signal levels and signal attenuation is not trivial. In order to constrain the outputs of algorithms to extract the thickness of exposed crust layers, this work leverages the fact that the thickness of the layers is typically locally continuous. The proposed method uses a combination of image processing and acoustic signal processing, and instead of considering signals individually, translates successive measurements into a spatial frame and applies image processing techniques to find layers that are consistent.



Fig. 1. Picture of Mn-crust sample (thickness = 85mm)

The rest of the paper is organized as follows. The acoustic



Fig. 2. Principle of thickness measurement

probe and its principle of operation are described in Section II. Section III details the proposed method. In Section IV, implementation of the algorithm and results are presented. The results are discussed in Section V.

II. SYSTEM OVERVIEW

The acoustic probe emits a 2 MHz amplitude modulated signal, which generates a 200 kHz parametric wave that penetrates the seafloor. The beam is focused on the seafloor such that it projects a spot of 3 cm diameter at a distance of 1.5 m. The probe is an improved version of the probe developed in [7], which used a 100 kHz wave modulated on a 1 MHz carrier wave. The probe records the reflections of the wave at a sampling rate of 2 MHz. Figure 2 shows a typical measurement scenario on a Mn-crust sample. The recorded signal, in an ideal scenario, will consist of two major reflections, one from the top of the seafloor (i.e. top of the Mn-crust) and another from the interface between the Mn-crust and the substrate rock on which it is formed. The time delay between the reflections is twice the thickness of the crust multiplied by the velocity of sound in Mn-crust. Using the velocity measured in prior studies [7], the thickness is calculated.

The reliability of the calculation is affected by noise in the recorded signal arising due to scattering, multi-path reflections, and seafloor features such as local inclusions inside the crust [8]. In areas without Mn-crusts, there will not be a second reflection. The signal, therefore, may not contain two uniquely identifiable reflections. In such cases, misidentification of top and bottom reflections may occur or the identification might fail altogether. Since Mn-crusts are hydrogenetic deposits, the thickness can be assumed to not vary abruptly; this will be violated in noisy measurements, resulting in an output which is not locally continuous.

The measurements begin with the firing of a short amplitude modulated 2 MHz burst, and recording its reflections for 4.096 ms where measurements are repeated at a sampling interval of 50 μ s. The signal shown in Fig. 2 shows part of a single pulse. An arbitrary number of pulses (denoted as N) are stacked together to form a frame. N is decided by the user depending on the number of pulses to be processed. The frame is formed in such a way that each pixel is a signal value, each vertical line from top to bottom is the recording of a single pulse, and these are stacked consecutively from left to right. Each frame is treated as a 2-D grayscale image. Since the axes are aligned with respect to time, it does not always scale linearly to distance. In order to reconstruct the physical scales, the data are plotted on a distance scaled axes based on the vehicle's navigation data and the angle of the gimbals in later processing stages. This is described in detail in section III.

III. ALGORITHM AND PROCESSING WORKFLOW

The process of finding thickness of Mn-crust from the recorded data consists of four steps - filtering individual pulses, extracting signal boundaries, re-framing the signal into a distance based grid, and identifying reflections to calculate thickness. The complete algorithm is listed in Fig. 3.

The pulse transmitted from the acoustic probe is a parametric wave whose shape can be approximated into an exponentially decaying sine wave. By deconvolving this signal with the reflected signal, the exact instants where the reflections happened can be identified from the recorded signal. However deconvolution is highly sensitive to noise and noise levels are very high in underwater measurements. Therefore, an equivalent operation was performed by calculating the cross spectral density between the two signals. The recorded signal was cropped using a moving rectangular window and the cross spectral densities are calculated at regular intervals. An analysis of the resultant spectrum reveal that the strongest components in the spectrum occur around 200 kHz, the transmitted signal frequency, as shown in Fig. 4. The spectral components that fall within the 3 dB bandwidth - which was identified to be between 70 kHz and 300 kHz - are selected and a filtered pulse is reconstructed by adding these components to increase the signal to noise ratio.

The reconstructed signals are assembled into an image frame using the methodology explained in section II. This image is then filtered using a median image filter in order to remove shot noise without blurring the image. In the frame, the reflections from the crust are continuous regions having relatively high intensity values. They are selected by thresholding the image using an adaptive threshold value. Otsu's method is used for calculating the threshold value [9]. The adaptive threshold will ensure that variations in signal levels across different datasets arising due to changes in the underwater environment and changes in the system tuning does not affect the results. The resulting binary image will have several small disconnected peaks. In order to consider these into the signal region, a morphological closing operation is

- **Require:** For the selected area, identify the pulses to be processed
- **Require:** Calculate pose information for the robot and acoustic probe
- 1: for each pulse in the frame do
- 2: Calculate 3D location of each point
- 3: Pass the pulse through cross spectral density function and split the components
- 4: Discard values in noisier frequencies
- 5: Using selected components, reconstruct a filtered pulse6: end for
- 7: Assemble N pulses into a frame \triangleright N decided by the user
- 8: Run a median filter on the frame and remove noise
- 9: Threshold the image into binary image > Otsu's method
- 10: Using morphological closing, fill gaps in the binary image
- 11: Identify the top and bottom limits of the signal region
- 12: Trace a virtual line in 3D space along the top reflection
- 13: Integrate along the line to find distance traveled
- 14: Segment the trace distance into uniform intervals
- 15: Vertically offset each pulse based on depth
- 16: Interpolate pulses from step.5 into the new x-z space
- **Ensure:** A signal frame with time axes is converted to frame with distance axes; where signals can be spatially understood intuitively
- 17: Run a median filter on the frame
- 18: Compensate for attenuation in the region of interest
- 19: Run a canny edge detector to locate signal transitions
- 20: Discard edges outside the boundaries identified in step.11
- 21: On the edge image, run a progressive probabilistic hough
- transform to detect continuous lines
- 22: Discard steep lines and repeated lines
- 23: Discard pulses over non-crust areas ▷ if the classification information is available
- 24: Calculate strength of reflection for each line
- 25: Identify bottom reflection as the strongest line
- 26: Wherever reflections are available, calculate thickness **return** An array of thickness estimates

Fig. 3. Processing Steps

performed using a rectangular kernel of 6×11 pixels. The top and bottom boundaries of the signal region is then extracted as the first non-zero line with a minimum width (a value of approximately 7.5 mm was used) from the top and bottom of the image respectively. Further processing focuses only in this region to find the reflections and thickness.

The physical nature of Mn-crusts dictate a dependence on spatial scales and is independent of temporal aspects such as the frequency of measurement or the speed of AUV. Thus, for further processing, the signals are transformed into a spatial 2-D frame. A point in 3-D space is identified for each of the pulses as the highest point of the top line. The coordinates of these points are calculated using the localization information of the AUV and the pose of the acoustic probe using a coordinate transformation. A line is then traced through these



Fig. 4. Cross correlation spectrum. The 3 dB bandwidth is highlighted

points in 3-D space, which is considered as the top surface of the Mn-crust. The distance along the this line is calculated and is used as the horizontal coordinate for the frame. The trace distance is sampled at uniform intervals of defined horizontal resolution (the authors used a resolution of 0.01 m, which is the approximate average physical distance between two adjacent pulses). The vertical resolution was calculated using equation 1.

$$V_{res} = \frac{x_{shift} \cdot \nu_{sound}}{2 \cdot f_s} \tag{1}$$

where $\nu_{sound} = 2700 \text{ m/s}$ is the velocity of sound in Mn-crust [7], x_{shift} is the width by which the window is shifted while calculating the cross-correlation spectrum, and $f_s = 2 \text{ MHz}$ is the rate of sampling of the measured signal. Although this vertical resolution does not accurately describe all parts of the image due to the change in speed of sound, it is valid throughout the region of interest of the signal calculated in the previous step and thus can accurately describe the reflections inside the crust.

The signals are plotted similar to the previous frame, left to right and top to bottom, with the vertical axis of the frame compensated for each pulse separately based on probe's depth for each pulse. The horizontal location of each pulse is interpolated using a one dimensional nearest neighbor interpolation using k-D trees. The result is an image frame consisting of signal reflection intensities with physical locations to scale, from which the reflections and therefore the thickness can be determined.

The image is then filtered using a 2D median filter for removing noise using a square kernel of approximately 5 mm size. The filtered image is then corrected for attenuation, between the top and bottom boundaries of the signal's region of interest. Equation 2 shows the calculation performed.

$$\gamma_{\alpha}^{i}\left[z\right] = \begin{cases} \gamma^{i}\left[z\right] \times 10^{2\alpha_{f}\left(z-z_{top}\right)/20} & \text{if } z_{top} \le z \le z_{bot} \\ \gamma^{i}\left[z\right] & \text{elsewhere} \end{cases}$$
(2)

where $\gamma^i [z]$ denotes the pixel at vertical coordinate z and horizontal coordinate i. The signal's region of interest, as identified in step 11 is between z_{top} and z_{bot} . $\alpha_f = 1.266^{\text{dB}}/\text{cm}$ is the attenuation coefficient of Mn-crust at the measuring frequency, calculated using the value measured in [7].

The final steps of calculation consists of identifying the lines corresponding to the secondary reflections within the region of interest. The primary reflection is identified as the top of the signal region. Since each reflection indicates a transition of signal levels, a canny edge detector is used to extract edges in the frame. A progressive probabilistic hough transform then detects lines having a minimum length and continuity [10]. The probabilistic progressive hough transform is chosen over other line detection methods because it is able to detect line segments along with their start and end points with a specified minimum length. Among all lines detected, overlapping lines and steep lines are discarded (the authors used a threshold value of slope of 10° with respect to the top reflection). The secondary reflection, originating from the Mn-crust - base rock interface, is assumed to be the strongest of all reflections present in the signal. In order to determine the stronger reflections, the remaining lines are analyzed to calculate a strength of reflection, which was defined as the sum of intensities of all points lying on the line. The image is then scanned horizontally to find the secondary reflections. Wherever lines overlap, the line having highest intensity is selected as the secondary reflection. Finally, the thickness is calculated as the difference between the top and bottom lines.

IV. IMPLEMENTATION AND RESULTS

The proposed method is verified using the data collected during field experiments conducted at No.5 Takuyo seamount located in the northwest Pacific Ocean. Results from two research cruises, namely KR16-01 and NT13-13 are used. NT13-13 cruise was conducted in 2013 and performed survey of the Mn-crusts using the ROV HyperDolphin using the acoustic probe, at depths ranging between 1400 and 1700 metres. The ROV also collected a number of samples with a mean thickness of 60 mm, one of which with a measured thickness of 85 mm is shown in Fig. 1. KR16-01 research cruise used the research vessel Kairei and surveyed Mn-crusts using the AUV Boss-A in 2016. Visual 3D mapping systems on board the AUV and ROV collected data which is used for reconstructing the 3D colour maps of the seafloor.

The proposed method is verified on the data collected over a patch of seafloor of approximate length of 8.1 m, a visual 3D reconstruction of which is shown in Fig. 5. This data was collected during the BSA-032 dive using Boss-A. The initial processing steps are shown in Fig. 6. The acoustic data collected is shown in Fig. 6a as a colour-coded image frame. The values are scaled along a logarithmic axis with



Fig. 5. A snapshot of the seafloor showing the region from where acoustic reflections were obtained

lighter colours indicating a higher signal amplitude level. After filtering the individual pulses and the signals are arranged into an image frame as shown in Fig. 6b.

The image is thresholded into a binary image followed by a morphological closing operation resulting in Fig. 6c. The limits of the signal region are identified and are shown in Fig. 6d overlaid on Fig. 6b. The top boundary is plotted as a blue line and the bottom boundary is plotted as a green line. Tracing the top line in 3D space result in Fig. 7. The traced line has a length of about 22 m on a patch of about 8 m distance; this behavior arises due to the gimbals which causes the acoustic beam to move in a nonlinear fashion on the seafloor. The signals are then interpolated into a distance based axes resulting in Fig. 8a; the horizontal resolution of the axes is chosen to be 10 mm and vertical resolution is calculated to be about 1.9 mm.

After filtering and attenuation correction, a canny edge detector is applied on the signal region of the frame resulting in the black edges shown in Fig. 8b. On this edge image, within the limits identified in Fig. 6d, the potential secondary reflections are identified using progressive probabilistic hough transform. The calculation used a minimum line length of 60 cm and a maximum gap of 10 cm as parameters. These parameters ensured that long lines are detected despite smaller gaps, while small inclusions that result in pulses with ideal reflections are excluded. The resulting lines are plotted as red lines in Fig. 8b. Optimal candidates for the secondary reflections and thickness values are calculated. The estimated thickness values are shown in Fig. 8c.

The mean thickness of the crust in the region was calculated to be approximately 65 mm, which is consistent with the observations made during the cruise. The thickness values are plotted as a colour coded bar graph above the seafloor reconstruction in Fig. 9. The figure shows that the detection is consistent with the coverage of crust, with no reflections identified over sand section in the middle of the patch.

V. CONCLUSION

This paper proposed a method to estimate the thickness of manganese crust deposits from sub-surface acoustic reflections using techniques from image and signal processing. By assembling subsequent pulses into an image frame and interpolating



Fig. 6. Steps leading up to detection of the signal boundaries



Fig. 7. Integrated trace distance of the signal

them into a distance scaled image, the authors could identify reflections using probabilistic line detection algorithms. This allowed the locally continuous nature of Mn-crust deposits to be leveraged in detecting the sub-surface crust-substrate boundary. Improved thickness estimates can lead to higher reliability in estimating the volumetric distributions of Mncrust.

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Fig. 9. Colour coded output of thickness plotted over the 3D map