Inaccurate navigation, blurry images and too little samples

_How we nevertheless map the deep sea in high resolution and quantify Mn-nodule resources_

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Wishes, competences and reality

What we want is to:

• discover the seafloor, even in the abyss, as we can discover land

• map the seafloor in such a detail/spatial accuracy needed for meaningful (future) monitoring (-> data need to be digitized)

• derive quantitative data from all sorts of seafloor sensing techniques (visual, acoustical)

• find statistically valid correlations between spatial data sets (-> mapping) and point data sets (-> measurements) for extrapolating point observations
What we can is to:

• map the seafloor with various tools (MBES, towed side scan or cameras, ROVs, AUVs)

• sample the seafloor and perform sophisticated analyses on the recovered sample (sediment, water, rocks, …)

• Process data from mapping surveys and link them in a GIS environment

• Derive correlations between point and spatial data, extrapolate point observations spatially (-> machine learning)
Wishes, competences and reality

Reality is that:
• underwater navigation is often not as accurate (no GPS!) devices drift (-> DVL), have none constant time-legs (-> roll attitude vs. ping), … --> well planned surveys get data gaps

• water absorbs light, illumination is not enough, ‘long’ image exposure cause motion blur, … it always looks blue

• large volumes of data are acquired and need to be processed quickly for adaptive mapping/monitoring offline --> processing ideally online

• too little ground truth samples are taken at the wrong location
AUV bathymetry mapping
AUV bathymetry mapping

Roll, always an issue!
AUV bathymetry mapping

misaligned survey lines
AUV optical mapping
AUV image processing

Original fisheye image

“Light” image

Cropped & undistorted

Köser-enhancement, fSpice algorithm, ....
AUV image mosaicking

Detect significant features

Detect correspondences

Check geometric plausibility

Construct optical flow

Reconstruct movement & 3D point cloud
AUV image mosaicking
AUV image mosaicking

Digital Ocean
AUV navigational errors

Section of the photo survey of AUV Mission 168 (dotted green line); the highlighted spots mark the images which have been taken above the track line.

The offset to the plotted track varies from 31 – 37m.
Counting Mn-nodules

Figure 2. Two example images from $I^{(1)}$ (left) and $I^{(2)}$ (right). Both were acquired by an autonomous underwater vehicle (AUV). The left image was acquired by the Deep Survey Camera on board the GEOMAR AUV Abyss. Abyss flew in an altitude of ca. 8.9 m above the seafloor. Each image in $I^{(1)}$ shows a seafloor area of ca. 180 m². The right image was acquired by NOCS’ AUV Autosub6000. It flew in an altitude of ca. 2.6 m. Images in $I^{(2)}$ show a seafloor area of ca. 1.4 m². Red boxes mark sections that are shown as zoom-ins in following figures.
Counting Mn-nodules

Figure 3. Workflow of image processing steps for contrast maximisation in the first phase of CoMoNoD: a) shows a zoom-in of an input image from F(50) (ca. 1/10th of source image). b) shows the colour corrected version after applying the JSpice method. c) shows the contrast-maximised binary image $B_1$ after applying the heuristically tuned threshold $t_1$. d) shows a noisy result created by a threshold $t_2$ that was chosen too large (by erroneously setting $t_2$ too high).

Figure 5. Workflow of the nodule delineation steps in the second phase of CoMoNoD: a) Distance image $D$, computed from $B_1$ (see Figure 3 c). b) Peaks within the distance image constitute nodule candidate centroids (yellow markers). These are filtered to determine the regional maximum within a neighbourhood (purple markers). Shape bottlenecks between adjacent nodules are used to separate connected nodule candidates (red lines). c) Each nodule candidate blob is delineated by its convex hull. d) Convex hulls from c) are fit by an ellipsoid and shown as an overlay on top of the original image (green nodule delineations). The size of these delineations can be measured in cm$^2$ and provides the basis for statistical assessments of PMN abundance.
Counting Mn-nodules

**Figure 6.** Processing results for $f^{(1)}$. Shown are the zoom-ins to the original images (see Figure 2, a) source image, b) fSpice result, c) binary image, d) nodule delineations.

**Figure 8.** Nodule abundance map showing nodule coverage in percent. 34,200 images contributed to this map. It was computed in about 12h. The map represents an area of 500x400 m$^2$ size. It lies in the DISCOL experimental area in the Peru Basin, Pacific Ocean. Narrow linear structures, criss-crossing the area, are anthropogenic plough-marks (8 m wide) from a mining simulation conducted in 1989\textsuperscript{[3]}. The larger scale (ca. 100m), east-west facing wave pattern correlates with the seafloor micro-bathymetry. The striped horizontal pattern follows the AUV dive trajectory. It is likely an artifact of the data gridding method. AUV track lines are shown in the red box. Eighty horizontal lines were conducted at a spacing of 5m.
Counting Mn-nodules

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Example from the CCZ, a Mn-nodule mining area
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Random Forest machine learning
- take statistically representative sub-data set of the training data
- find optimum number of trees and runs
- check performance of the model results
- extrapolate best model results to a larger area
Example from the CCZ, a Mn-nodule mining area

Validation data set
Example from the CCZ, a Mn-nodule mining area
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