

Universiteit Utrecht

Department of Earth Sciences, Universiteit Utrecht, The Netherlands. ² Department of Earth Sciences, University of Oxford, UK.

| xample — Atlantic Ocean | | Picking discrete seamounts: current challenges |
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| | We repeat the analysis for a $10^{\circ} \times 10^{\circ}$ region in the Atlantic Ocean, including part of the spreading ridge (<i>left</i>). Conventional seamount-detection algorithms have typically found the Atlantic challenging, recording high false-positive rates due to 'seafloor roughness'. Topography of the region is shown <i>below left</i> ; seamounts identified by Kim & Wessel (2011) are shown <i>below right</i> . | For some applications, the error surfaces as shown in the two examples may be useful in their own right. However, in many cases it is desirable to reduce this to a set of discrete seamount locations. Essentially, this involves identifying the locations of minima in the error surface; It is unrealistic to expect any automated algorithm to perform 'perfectly'—even experts |
| -35° -25° 40° | 40° -25° 40° -25° 40° -25° | picking 'by hand' are unlikely to make identical decisions; There will always be a tradeoff between numbers of 'false positives' (picks placed at non-seamount locations) and 'missed |



seamounts'. The correct balance between the two may differ between applications;

Right: Results from picking all minima inside the E=30 contour for Pacific (upper) and Atlantic (lower) regions (red crosses).

- ▷ Most visible seamounts are picked (78%) match with handpicked seamounts in Pacific; 79% Atlantic)—but there are significant numbers of false positives (52% of automatic picks do not correspond to a handpicked seamount in Pacific; 60% Atlantic);
- Picking inside a lower contour would reduce false positives at expense of 'good' identifi- 35° cations;
- Many false positives appear to be due to small depressions on the sides of large minima (e.g. Pacific at $141^{\circ}W 24^{\circ}S$);

Can we improve results by eliminating these depressions?

First approach: spatial (frequency-domain) filtering





Grid of reconstruction error computed by autoencoder is shown above left, using identical colour palette as for the Pacific (left). Contours of this error surface are shown overlain on bathymetry *above right*. See Pacific example for further details.

Outlook

Neural network–based methods show promise for use in constructing large-scale catalogues and analyses of topographic data. The main advantage of this approach is that the user only has to assemble a set of examples of the feature of interest; they need not develop a mathematical description of it.

Here, we have used the encoder-decoder network as a 'filter' for identifying seamount-like topography. It may be possible to gain further insight by analysing the encodings themselves—what aspects of topography is the network sensitive to? Do different classes of seamount cluster in the encoding domain?

Within the neural network framework, it is straightforward to incorporate multiple datasets simultaneously. This may allow different sensitivities to be exploited,

Above; above right: seamount identifications by picking all minima inside the E=30 contour for error grids filtered using a secondorder Butterworth low-pass filter, wavelength 30 km. Whilst many false positives are eliminated, some 'desirable' seamounts are lost. (Match with handpicked: 71% Pac., 71% Atl.; False positives: 43% Pac., 52% Atl.)

Second approach: removal of picks with low 'energy barrier' to adjacent minimum





Below left; below: seamount identifications by picking all minima within the E=30 contour, discarding any that have an energy barrier of $\Delta E=2$ or less from an adjacent minimum.



leading to better results: for example, gravity data may be used in conjunction with the topography when searching for seamounts.

References

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This approach leads to significantly better results in the Pacific: 71% match to handpicked, 33% false positive. However, Atlantic results

are slightly worse: 66% match, 53% false positive. Different choices for parameters may lead to some improvement on these figures.