Deep Corals, Deep Learning: Moving the Deep Net Towards Real-Time Image Annotation

Lea-Anne Henry[1], Sankha S. Mukherjee[2], Neil M. Roberston[3], Laurence De Clippele[4], J. Murray Roberts[1]

[1]School of GeoSciences, University of Edinburgh, UK; [2]Institute of Signals, Sensors and Systems, Heriot-Watt University, UK; [3]Institute of Engineering, Communications and Information Technology, Queen's University of Belfast, UK;[4]School of Energy, Geoscience, Infrastructure and Society, Heriot-Watt University, UK

Challenge

The mismatch between human capacity and the acquisition of Big Data such as Earth imagery undermines commitments to Convention on Biological Diversity (CBD) and Aichi targets. Artificial intelligence (AI) solutions to Big Data issues are urgently needed as these could prove to be faster, more accurate, and cheaper. Reducing costs of managing protected areas in remote deep waters and in the High Seas is of great importance, and this is a realm where autonomous technology will be transformative.

Human V Machine

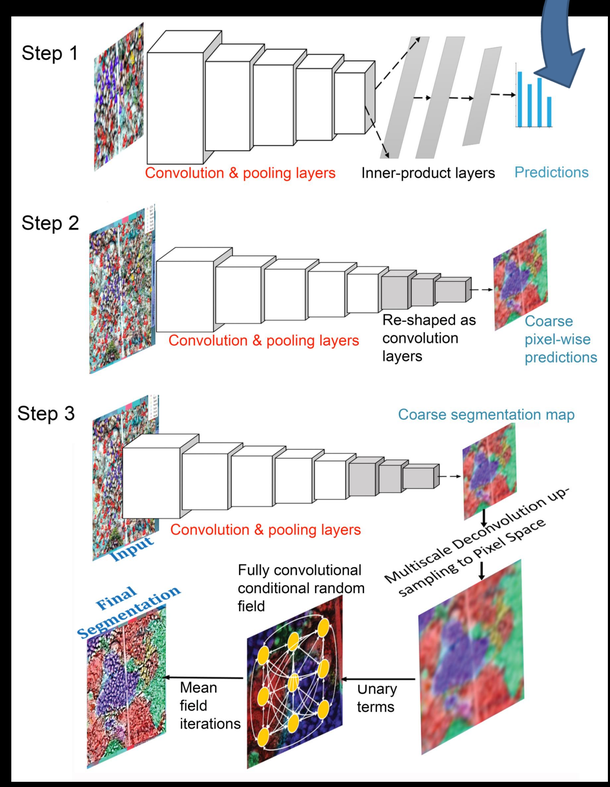
Our new integrated FCNN-DCRF surpassed human and other machine-learning performance benchmarks in speed and accuracy.:

- expert annotation of 159 images took an average of 30 minutes per image, that's 286200 seconds for 159 images;
- ***the deep net takes less than 1 second with 93.4% accuracy.***

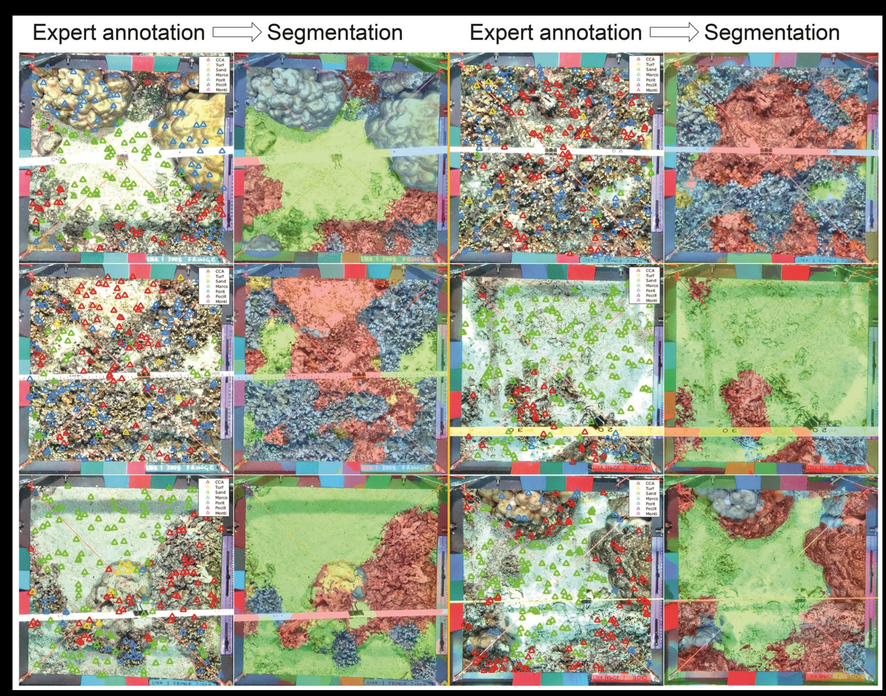
Deep Learning

Since the first deep convolutional net (CNN; LeCun et al., 1998), deep learning has reached the forefront of AI in medical, military and engineering applications.

The power of CNNs is in their ability for end-to-end learning of multiple layers from the original image ***using linear and non-linear operators that are learned together from the data itself*** in a supervised manner.



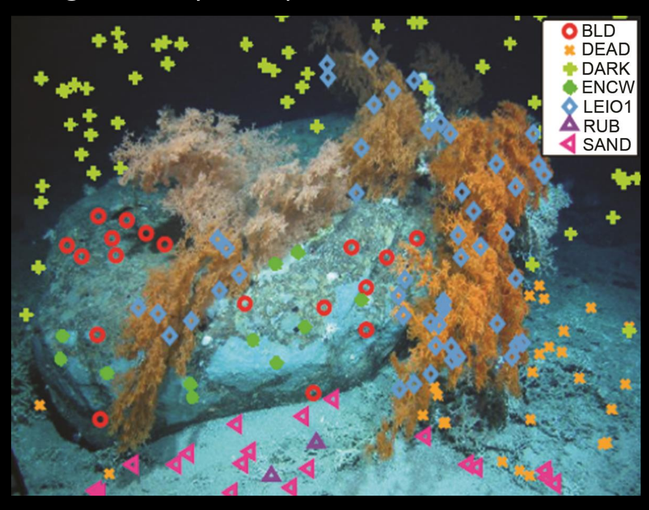
We started exploring CNN potential using the Moorea Labelled Corals (MLC) benchmark dataset of tropical coral diversity (Beijbom *et al.*, 2012). The pre-trained vanilla classification network (**Step 1**) was transformed into a fully CNN (FCNN, **Step 2**) that increased efficiency of feedforward and backpropagation computation more efficient. FCNN output was post-processed with dense conditional random fields (DCRFs, **Step 3**) that significantly improved fine-grained image segmentation accuracy and localisation of objects.



Deep Nets for Deep Corals

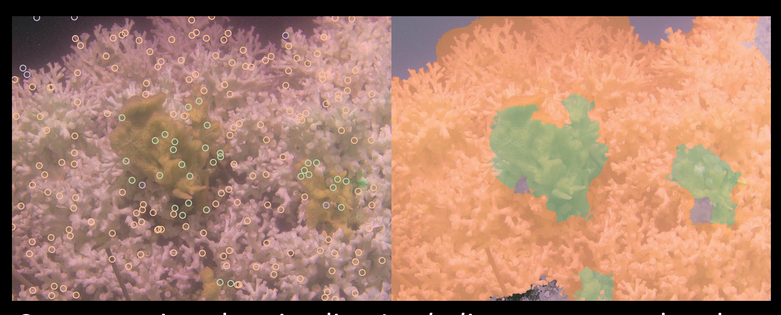
1 – The Dataset

The net was trained and validated on 159 images (size 2592 x 1944) of cold-water coral habitats obtained by remotely operated vehicle (ROV) from the Logachev Mound Province and the Mingulay Reef Complex off western Scotland during the *Changing Oceans Expedition 2012*. Each image was overlaid with 200 random points using the software Coral Point Count (Koehler and Gill 2006) and annotated into classes of substrata and megafauna by an expert.

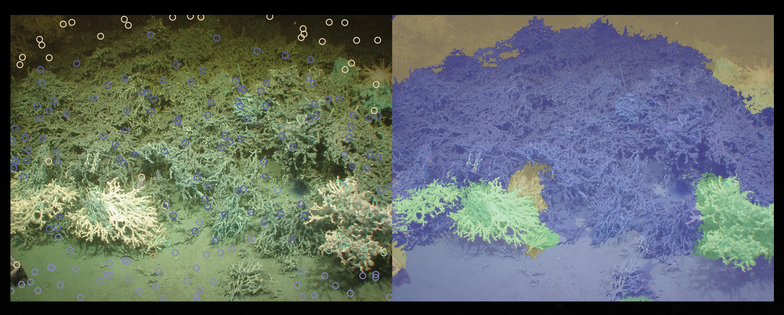


2 – Data Augmentation

Images were split 90:10 (training:validation). A central crop size of 224 x 224 was extracted for each image. A patch size of 200 x 200 had the best classification and fastest convergence rate. Geometric transformations (translation, scaling, homography, flipping and rotation) were used to overcome imbalance in class sample size.



Segmentation showing live *Lophelia pertusa* coral and the sponge *Mycale lingua*



Segmentation of live versus dead *Lophelia pertusa*

3 – Patch-Based Training

Three types of pre-trained classification nets were used: GoogleNet trained from scratch, GoogLeNet fine-tuned using ImageNet, and VGG-16 (Simonyan & Zisserman 2015) fine-tuned with ImageNet. All training was conducted in the Caffe toolbox. VGG-16 had the highest classification accuracy of the test images, at 97.1%.

4 – Classification and Localisation

The crop size of 224 x 224 often contained more than one class of substratum or megafauna, which degrades classification performance. Our deep nets overcame this challenge by making them fully convolutional (FCNN). Output of the FCNN was used as input into a dense conditional random field (DCRF) for the segmentation classifications as final outputs.

5 – Next Steps

Future plans are to trial the FCNN-DCRF method on other deep-sea coral image databases, and making the computations operational in real-time in order to allow the method to be used for autonomous underwater vehicle (AUV) on-board computing.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No. 678760 (ATLAS). This output reflects only the authors' views and the European Union cannot be held responsible for any use that may be made of the information contained therein. The Marine Alliance for Science and Technology in Scotland (MASTS) provided funding to launch the pilot deep corals, deep learning study.

THE UNIVERSITY of EDINBURGH

Queen's University Belfast

HERIOT WATT UNIVERSITY

Marine Alliance for Science and Technology for Scotland
a marine partnership for Scotland

atlas

References

Beijbom *et al*. (2012) IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Providence, Rhode Island, June, 2012
Kohler KE, Gill SM (2006) Computers and Geoscience 32:1259 – 1269
LeCun *et al*. (1998) Proceedings of the IEEE 86:2278–2324
Simonyan K, Zisserman A (2015) ICLR Conference Paper, 2015