A Self-Learning Approach for Beggiatoa Coverage Estimation in Aquaculture

Yanyu Chen[1], Yunjue Zhou[2], Son Tran[3], Mira Park[3], Scott Hadley[3], Myriam Lacharite[3], and Quan Bai[3]

ABSTRACT

Beggiatoa is a bacterium that is associated with anoxic conditions beneath salmon aquaculture pens. Assessing the percentage coverage on the seafloor from images taken beneath a site is often undertaken as part of the environmental monitoring process. Images are assessed manually by observers with experience in identifying Beggiatoa. This is a time-consuming process and results can vary significantly between observers. Manually labelling images in order to apply visual learning techniques is also time-consuming and expensive as deep learning relies on very large data sets for training. Image segmentation techniques can automatically annotate images to release human resources and improve assessment efficiency.

This paper introduces a combination method using Otsu thresholding and Fully Convolutional Networks (FCN). The selflearning method can be used to estimate coverage and generate training and testing data set for deep learning algorithms. Results showed that this combination of methods had better performance than individual methods.

INTRODUCTION

Beggiatoa is a bacterium which percentage coverage in the benthic area beneath salmon pens indicates the anoxic and polluted level [1]. Image segmentation technique could help score images, but it usually requires massive data and expert annotations. In addition, it is a challenge to label images comprehensively and correctly, especially Beggiatoa with sparse distribution or less-obvious on the seafloor in poor light condition.

This paper aims to develop a new self-learning AI framework to estimate coverage, or produce mask for next step of deep learning, based on less data application in image segmentation. We propose to highlight the optical characteristic apparent in the Beggiatoa region. In practice, the highlighted regions always belong to the Beggiatoa regions. The motivation is to find the highlighted regions in an underexposed images.

This method helps aquaculture researchers and companies reduce labour costs and increase efficiency of Beggiatoa assessment, and provides practical proof of the usefulness of this technique. This technique potentially could be applied to other areas of research in benthic impacts in salmon aquaculture. Primarily however it will be put into practice for developing a bacteria assessment tool.

METHODS AND MATERIALS

Self-learning annotation module contains two parts, namely image processing and unsupervised initial annotation. Otsu's threshold is used to generate initial annotation data for Beggiatoa segmentation based on the self-learning segmentation approach.

Otsu's algorithm subdivides the image into two major classes, namely foreground and background. A binary segmentation mask for two regions can be generated through Otsu's threshold.

Transfer-learning annotation data generated by self-learning is used by an FCN model for Beggiatoa region segmentation. This model adopts the training weights of VGG-16, and the dataset supplied by ImageNet. As Beggiatoa is a bacterium, with a morphology of a bacterial mat and a non-microscopic substance, transfer learning adopts the weights based on ImageNet.

RESULTS

- **Self-learning Annotation Approaches Comparison**

Otsu's threshold method performs best among these methods acrossboththe absolute error or the precision measures.

- **Transfer-learning Approaches Comparison**

FCN8 performed best according to the absolute error perspective, while FCN16 performed best when using the precision error. This result indicates that more results from FCN16 are within the ground truth range ie. more images are predicted correctly, while the results from FCN8 are closer to the ground truth range.

- **Self-learning AI Framework**

Model performance when combining the Ostu threshold with FCN-8 to segment the image is summarised in Table 1.

	Center Absolute Error	Lower-bound Absolute Error	Upper-bound Absolute Error	Minimum Absolute Error	precision
Otsu Threshold	15.58	8.86	24.55	8.86	73.84%
Simple Threshold	30.16	19.69	40.63	19.69	6.84%
Adaptive Threshold	27.72	38.01	20.50	20.50	68.85%
Regional Growth	15.82	8.86	25.34	8.86	72.50%
K-means	17.60	13.55	23.84	13.55	60.25%
FCN8	19.99	14.34	27.31	14.34	59.81%
FCN16	35.59	43.85	30.37	30.37	62.99%
FCN32	56.36	66.84	45.89	45.89	48.27%
FCN + Otsu thresholding	24.46	30.60	22.84	22.84	74.35%

Table 1. Results of Each Method.

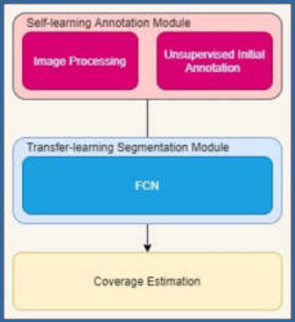

Figure 1. Self-learning AI Framework.

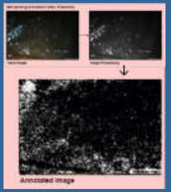

Figure 2. Self-learning Annotation Scheme.

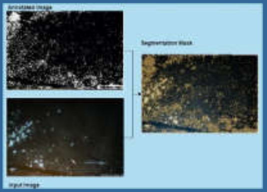

Figure 3. Flowchart of FCN Segmentation.

DISCUSSION

The Otsu's thresholding method scores 73.84% for the precision and the lowest Minimum Absolute Error, which indicates its worth for future use, because of its good performance in sparsely distributed objects and objects with optical properties. When an FCN model is trained with the predicted results from Otsu's threshold, the precision is improved by 18.03%. The results showcase the possibility to combine the unsupervised methods with the transfer-learning methods when trying to avoid expensive training dataset preparation.

But there are three key limitations in this Self-learning AI Framework. Firstly, the model can only deal with two labels and cannot learn more types. The other limitation is in transfer-learning segmentation module. Because weight selection and dataset similarity will influence model performance, these depend on human experience. The last one is caused by the ground truth scope. Due the large-scale range of ground truth, the result error will increase.

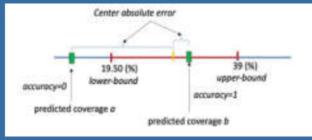

Figure 4. Explanation of Absolute Error.

CONCLUSIONS

In future work, the entire image could be divided into grids and each grid could be classified as a specific type, with image segmentation methods applied to small regions rather than the whole image. For each grid cell, binary classification is possible because only the corresponding (dominant) type for that cell needs to be segmented. For the whole image, the predicted results for grid of the same type could be gathered together, and the entire coverage percentage for different types could be calculated more accurately.

REFERENCES

1. Crawford, C., Mitchell, I., Macleod, C.: Video assessment of environmental impactsof salmon farms. ICES Journal of Marine Science 58(2), 445–452 (2001)
2. Goyal, M., Oakley, A., Bansal, P., Dancey, D., Yap, M.H.: Skin lesion segmentationin dermoscopic images with ensemble deep learning methods. IEEE Access 8, 4171–4181 (2019)
3. Yang, X., He, X., Liang, Y., Yang, Y., Zhang, S., Xie, P.: Transfer learningor self-supervised learning? a tale of two pretraining paradigms. arXiv preprint arXiv:2007.04234 (2020)

CONTACT

Yanyu Chen
Email: yanyu.chen@utas.edu.au