

# EyeSea: Automated underwater video analysis for ecological monitoring around marine and hydrokinetic energy sites

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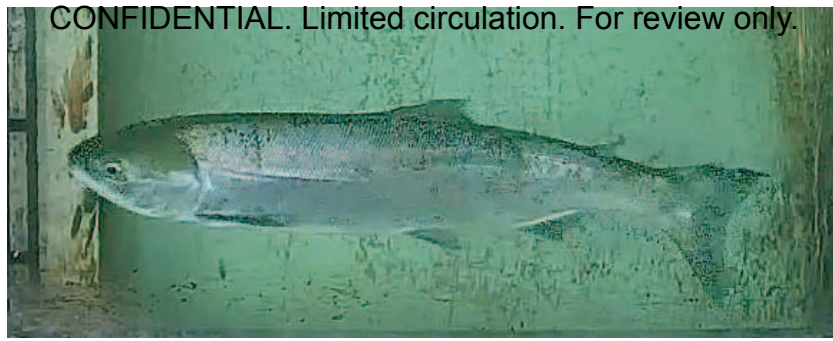
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## Abstract

Optical video provides a natural way to observe underwater areas because it is easy to interpret, in contrast to acoustic sensors that have traditionally been used for fishery research. Nonetheless, reviewing and annotating large volumes of optical video is time-consuming and costly. We are developing software for automated processing to speed the analysis of underwater video, and ultimately, to detect events of interest in real-time. The EyeSea software is a user-friendly application for analyzing under water video using a combination of human and machine intelligence. The automated algorithms include unsupervised video segmentation for event detection and convolutional neural networks pretrained on ImageNet data for fish recognition (Figure 1). The machine-detected events can be used to guide human reviewers, who can then add details to stored events. Both human and machine detected events are stored in a common database that can be used to generate reports for further statistical summarization.

One challenge with deep learning methods is the need for large amounts of data, and there is a risk that models trained on one data set will not be effective on new data acquired in a new location, maybe using different video recording equipment. To address this challenge, we have obtained six diverse data sets that represent a range of species and video quality (Figure 2.) Here we compare the results of the deep learning methods with our previous results using background subtraction and statistical classification methods [1] in terms of accuracy, computational cost and robustness of performance.



Results:

coho, coho, coho salmon, blue jack, silver salmon,  
*Oncorhynchus kisutch* (score = 0.65140)  
barracouta, snoek (score = 0.06516)  
electric ray, crampfish, numbfish, torpedo (score = 0.05649)  
sturgeon (score = 0.02146)  
terrapin (score = 0.01794)

Figure 1: The pre-trained convolutional neural network Inception recognizes the fish in an image from a fish passage viewing window at a hydroelectric dam.

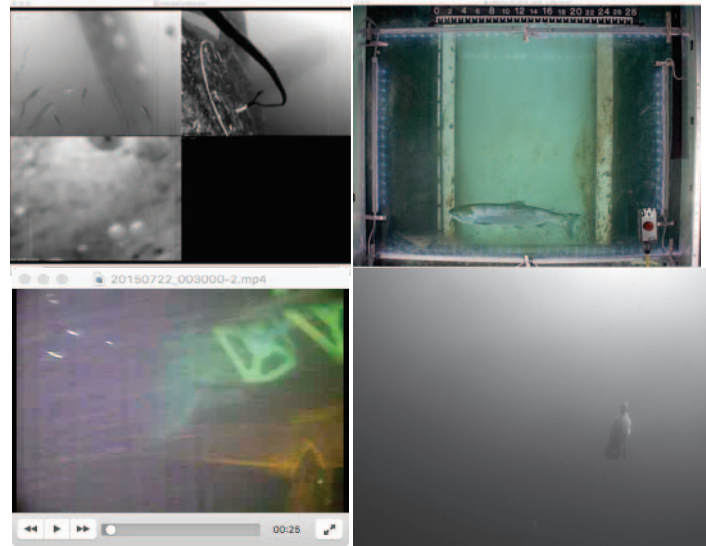


Figure 2: Underwater video data examples, clockwise from upper left: fish near a tidal turbine, salmon in a hydroelectric dam fish passage, diving bird, fish near an in-stream turbine.

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## References

- [1] S. Matzner, R. E. Hull, G. Harker-Klimes, and V. I. Cullinan. Studying fish near ocean energy devices using underwater video. In *OCEANS 2017 Anchorage*, pages 1–7, Sept 2017.