Machine Learning and Unmanned Aerial Systems for Analysis of Whale Health and Identity in the Field

Bryn Keller[1]*, Javier Turek[1], Ted Willke[1], Iain Kerr[2], Andrew Rogan[2], and John Graham[2]

[1]Intel Labs [2]Ocean Alliance

sUAS for Visual Data

Improved cameras and flight time have made small Unmanned Aerial Systems (sUAS) practical for capturing high-quality images of cetaceans in their natural environment. Researchers use such data for a variety of photogrammetry tasks, but these efforts are limited by the need for manual processing. We believe machine learning can help, despite obstacles.

Data Starvation

The effectiveness of machine learning has been limited by the lack of large, high-quality, labeled datasets. We present a pair of new image analysis techniques for whale identification and morphometry that use methods specifically designed to deal with this *data starvation* challenge and process data in real-time. For both methods, we report initial results from trials conducted in Southeast Alaska in 2017, a location which offers difficult conditions in terms of lighting, reflectance, and turbidity.

Whale Identification

We used computer vision techniques and a small neural network to compute a signature for humpback whale flukes based on the distinctive pattern of the trailing edges and grayscale shade variations across them. Together, these features allow us to accurately rank matches against a database of known individuals (n=176) with as little as one example per known individual.

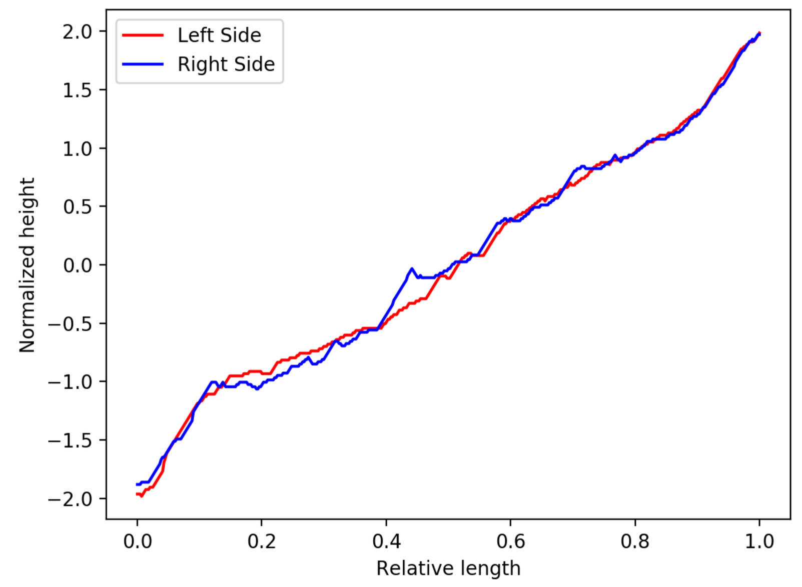
Identification Challenges

Identification suffers heavily from data starvation: whale image databases are typically small compared to many of the image datasets used to train today's machine learning models. It's also not unusual to have only a single image of an individual. Additionally, images are often unusable due to low resolution, lighting, or obscuration.

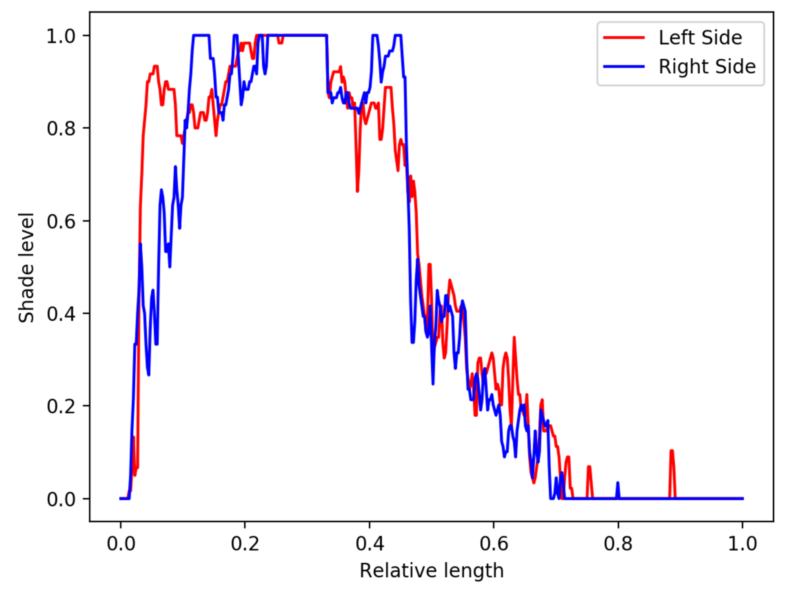
Identification Methods

We select the left and right fluke tips and the notch as keypoints. We use an affine transformation to correct for angle and distance. Then we capture fluke edge and patchwork features into 4 vectors. A k-NN search of the database yields close matches. The distance metric compares the vectors, using Dynamic Time Warping to deal with small photographic and physical distortions.

Edges & Grayscale

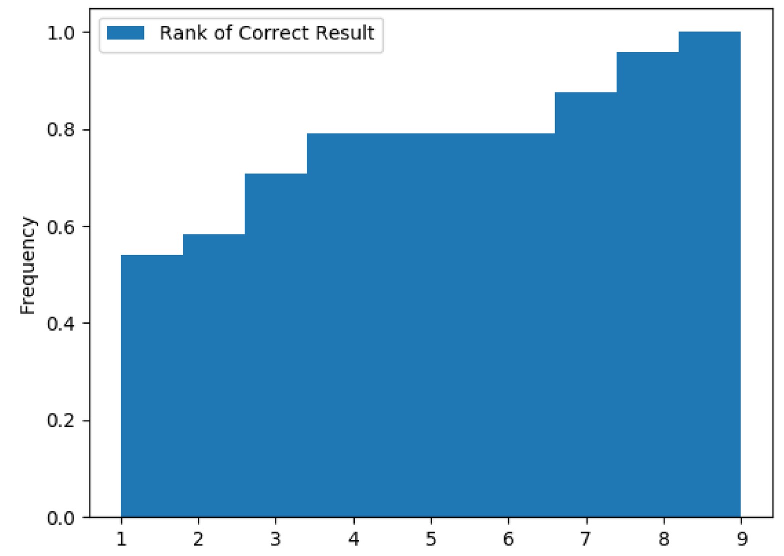


Fluke signatures are 4 vectors; two capture the shape of the trailing edges (above) and two the grayscale variations along notch-tip lines (below).



We train a small neural network to learn the optimal feature weightings. By limiting the amount of learning the network has to do, we reduce the amount of data needed.

Query Ranking

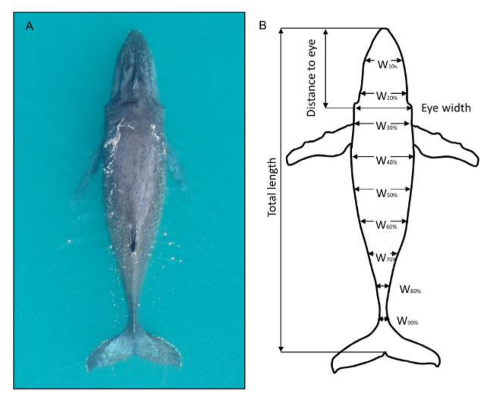


On 24 unique image queries on a database of n=176 (no query duplicated any image in the database), we measured the rank of the correct match in the results. In all cases, the correct match was in the top 9, 79% of the time it was in the top 5, and 54% of the time the correct result was returned first.

Body Condition Estimation

Migrating adult humpback whales (*Megaptera novaeangliae*) build up energy reserves (extra girth) during the feeding season, which they later use to pay the energy cost of procreation. We use machine learning based morphometry on sUAS images to quickly assess energy reserves.

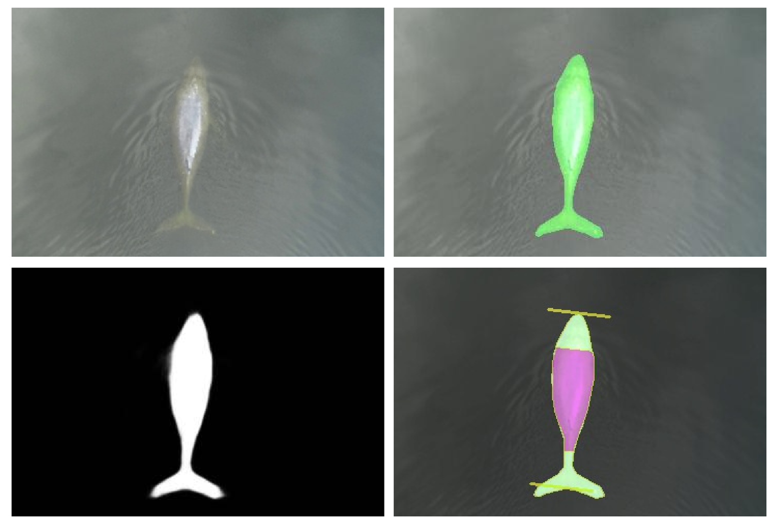
Body Condition Index



F. Christiansen et al. 2016 defined the measure of a whale's energy stores as $BCI = \sum_s A_s$, where A_s is the area of each trapezoid in the diagram, from the eyes to just before the tail flukes, excluding the pectoral fins.

Morphometric Methods

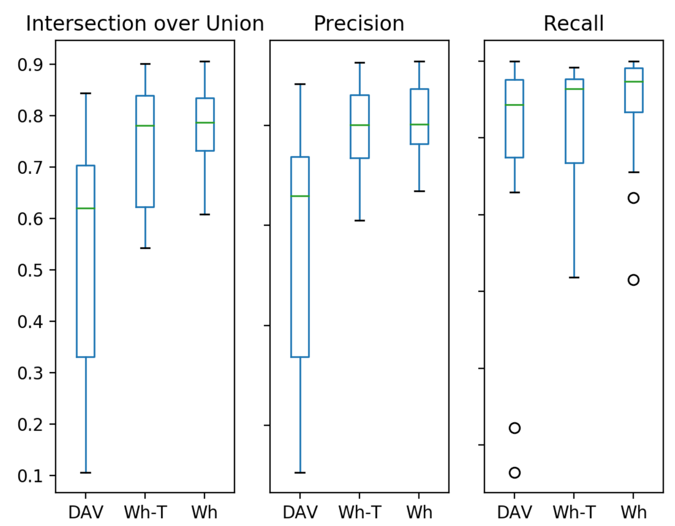
We use a deep learning model called One-Shot Visual Object Segmentation (OSVOS), described in (Caelles et al. 2017) to estimate A_s. OSVOS takes a *base network* trained in object detection (on ImageNet) and repurposes it (via transfer learning) into a *parent network* trained in image segmentation on the DAVIS video dataset. OSVOS-DAVIS fine-tunes a *test network* for each test video using a manually-segmented first frame. In our research, we train the parent network on whale images taken by sUAS (9 clips, 217 frames), creating OSVOS-Whales. To lower the burden of manual segmentation further, we apply *one-shot transfer learning*, only segmenting a single frame for a set of videos taken under similar ambient conditions.



The model segments the whale as foreground (above). It then removes the areas that are unrelated to energy storage using simple heuristics.

Segmentation Accuracy

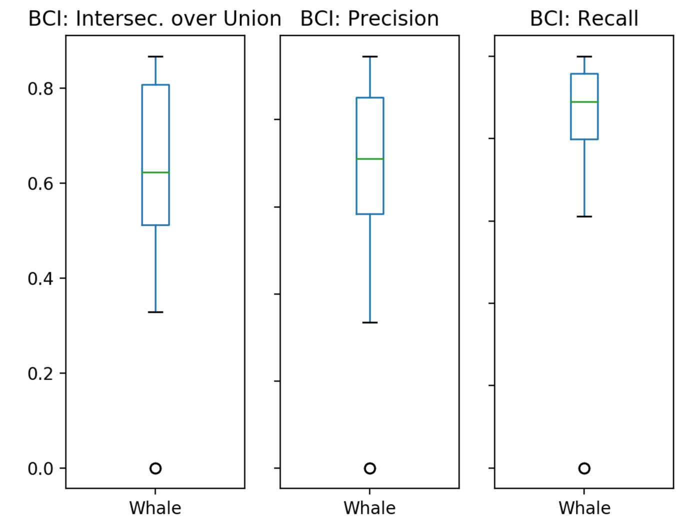
We tested two new models. **Wh** is OSVOS-Whales, fine-tuned in the same manner as OSVOS-DAVIS (**DAV**). **Wh-T** uses OSVOS-Whales with one-shot transfer learning. We compare both to **DAV** using human-annotated ground truth images, withholding 27 images from the training set (a 10% random sample) for testing.



Both of our models significantly outperform OSVOS-DAVIS (e.g. **DAV** 53%, **Wh-T** 74%, **Wh** 77% mean IoU), confirming the importance of training with whale images. **Wh-T** was nearly as effective as **Wh** (3% difference), demonstrating that one-shot transfer learning is effective.

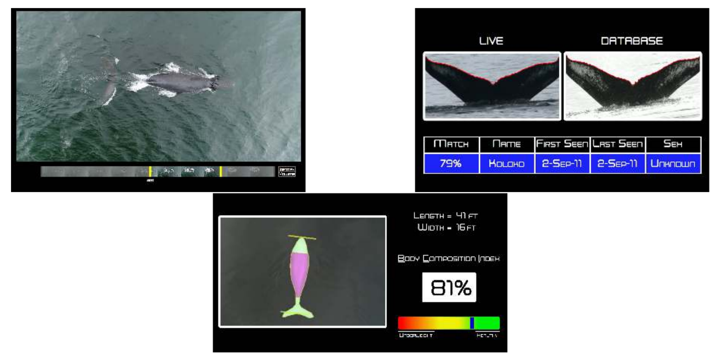
BCI Computation Accuracy

We assessed the impact of segmentation accuracy on BCI computation accuracy. We compared the BCI calculated on manual segmentations with that using OSVOS-Whales segmentation. A 77% mean IoU for segmentation resulted in 60% for BCI, indicating high sensitivity.



There's an App for That

We developed a set of applications in order to make our work more broadly useful to the cetacean research community.



Snapper is a tool for capturing salient information from live video feeds, such as those produced by sUAS. **Identifier** matches fluke images against a database. **Morphometer** computes the BCI from short video clips.

Conclusions & Future Work

- Limiting or transferring learning reduces data starvation
- Edge and grayscale patterns are effective fluke signatures
- One-shot transfer deep learning is effective for morphometry

We plan to combine our fluke signatures with a deep learning model to improve identification accuracy. We also plan to extend the morphometry model with deep learning based keypoint identification.

Whale images obtained under NMFS #18636

*Corresponding author: bryn.keller@intel.com