Applying Image Recognition to Enhance Fisheries Management Capabilities

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How Many Herring?
Image Recognition Solution:
6 herring found in 0.01 seconds
Today’s Presentation

- Objective
- Background
- Current Technique
- Applying Image Recognition
- Results
- Conclusion
- Future Work
- References
Objective

- To automate the detection and counting of relevant fisheries species in image and video data through image recognition

- Relevant fisheries species:
  
  - Alewife Herring / Blue Back Herring *(Alosa pseudoharengus / Alosa aestivalis)*
  
  - Atlantic Sea Scallops *(Placopecten magellanicus)*
  
  - Skates *(Rajidae)*
  
  - Flatfish, such as flounder *(Pleuronectiformes)*
  
  - Various round fish species
Background

“The world’s finest wilderness lies beneath the waves …”
— Robert Wyland, Marine Life Artist

- Fisheries populations have a large impact on the U.S. economy
  - The U.S. fishing industry contributes about $90 billion and 1.5 million jobs to the U.S. economy [4]
  - In 2014, 17% of the U.S. fisheries were classified as overfished [4]

- Therefore, NOAA Fisheries Management is interested in monitoring relevant species populations
Current Technique:

**Gather**

1. *Gather [underwater photographs]*

- Habitat Mapping Camera System (HabCam)
2. Manually Annotate [underwater photographs]
3. Extrapolate [population estimates]

[1] Chang et al. 2017
Applying Image Recognition

- Can image recognition be used to accurately detect and count fisheries species?
- How many iterations of training are needed to yield accurate results?
- How does the quality of annotations used in training impact accuracy?
Appling Image Recognition:
Convolutional Neural Networks

- Loosely based on biological neural networks
Applying Image Recognition:

Methodology – Gather & annotate
Train YOLOv2 Real-Time Object Detection algorithm:

Original training set: 5,063 images

Adjusted training set: 5,063 images
Run trained YOLOv2 algorithm on 300 test images

- False positives?
- False negatives?
Results:

Metrics

- Intersection Over Union (IOU) (%)
  \[ \text{IOU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} \]

- Recall (%)
  \[ \text{recall} = \frac{tp}{tp + fn} \]

- Precision (%)
  \[ \text{precision} = \frac{tp}{tp + fp} = \frac{tp}{n} \]
Can image recognition be used to accurately detect and count marine species?
Results

How many iterations of training are needed to yield accurate results? \( \sim 2000 \)
How does the quality of annotations used in training impact accuracy?

IOU values averaged across all objects (N = 489) in both the adjusted and original training sets.

Results
Conclusion

- Image recognition is a viable solution to detecting and counting fisheries species in photographic data

- You Only Look Once (YOLO) v2: Real-Time Object Detection software can obtain as high as 93% average recall
  - According to [2] Chang et al. 2016, imperfect automated annotation can be combined with human annotation

- We recommend annotation guidelines be strictly followed

- Deliverables: training sets, trained weights, programs for counting fisheries species

Implications:

- NOAA Fisheries can use these techniques to optimize time and resource allocation
Future Work

- Continue applying image recognition to herring
  - Of interest to: NOAA Fisheries, state agencies, as well as regional fisheries councils and local municipalities
  - Image recognition is a novel approach
- Develop graphical user interface for end users
- Test other image recognition algorithms, such as Faster R-CNN and Mask R-CNN
References


