A face individual North Atlantic right whales

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Abstract: Accurate monitoring of individuals in a threatened species is of upmost importance to conservationists and researchers. Human observation is expensive and autonomous ariel photography is becoming an increasingly useful technique regarding animal biometrics [1, 2]. Fewer than 500 North Atlantic right whales are left in the world's oceans. As with many animal biometric inspection processes, tracking and monitoring individuals is an extremely time consuming process. Advances in the implementation and performance of deep learning algorithms have drastically improved performance in object detection and recognition tasks [3]. We employ a wide range of interesting techniques to build a "face-identification" algorithm for ariel photos of 447 unique. We follow a conventional modern face recognition pipeline consisting of the stages: detect, align, represent and classify [4]. We use deep learning algorithms to both detect and classify. A fully convolutional network [5] is employed to semantically segment a given image to detect the location of the whale's head and body, we then use PCA on the resulting image to normalize for the whale's direction. A significant amount of hand labelled masks are needed to generate enough supervised training data to make this work effectively [6]. We tackle this issue by employing semi-supervised learning techniques and histogram matching between images to improve our localization algorithm and find a significant improvement in our results.

1. Introduction

We entered the 2015 Right Whale Recognition online competition issued by Kaggle. Data consists of aeriel images, the vast majority containing a single Right whale. The training set contains 4543 labelled images and the test set 6925 unlabelled images. Evaluation is based on the multi-class logarithmic loss

$$\text{logloss} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{i=1}^{M} y_{ij}\log(p_{ij}), \tag{1}$$

where N is the number of images in the test set, M is the number of whale labels, log is the natural logarithm, y_{ij} is 1 if observation i belongs to whale j and 0 otherwise, and p_{ij} is the predicted probability that observation i belongs to whale j.

The data was collected and labelled over a 10 year period by NOAA (National Oceanic and Atmospehric Administration) scientists via numerous helicopter trips over the northern Atlantic. The 447 whales are

1.1. Related work

Subsection text here.

2. Whale alignment

It is helpful to remove variation in inputs before giving them to a deep learning algorithm and specifically with faces, the success of a learned network is highly dependant on an alignment step [**?**, 4].

2.0.1. Results:

3. Whale classification

3.0.2. Results:

4. Conclusion

Sample equations.

5. Enunciations

6. Figures & Tables

The output for figure is:

Fig. 1. *Insert figure caption here*
a Insert Sub caption here
b Insert Sub caption here

The output for table is:

Table 1 An Example of a Table

One	Two
Three	Four

7. Conclusion

The conclusion text goes here.

8. Acknowledgment

Thanks to Christin Khan and Leah Crowe from NOAA for hand labeling the images. Kaggle for competition.

9. References

[1] L. Koh and S. Wich, “Dawn of drone ecology: low-cost autonomous aerial vehicles for conservation,” 2012.

[2] J. Martin, H. H. Edwards, M. A. Burgess, H. F. Percival, D. E. Fagan, B. E. Gardner, J. G. Ortega-Ortiz, P. G. Ifju, B. S. Evers, and T. J. Rambo, “Estimating distribution of hidden objects with drones: From tennis balls to manatees,” *PLoS One*, vol. 7, no. 6, p. e38882, 2012.

[3] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[4] Y. Taigman, M. Yang, M. Ranzato, and L. Wolf, “Deepface: Closing the gap to human-level performance in face verification,” in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2014, pp. 1701–1708.

[5] J. Long, E. Shelhamer, and T. Darrell, “Fully convolutional networks for semantic segmentation,” in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2015, pp. 3431–3440.

[6] S. Hong, H. Noh, and B. Han, “Decoupled deep neural network for semi-supervised semantic segmentation,” in *Advances in Neural Information Processing Systems*, 2015, pp. 1495–1503.

10. Appendices

Appendices are allowed but please be aware that these are included in the overall word count.