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Improving seabird species identification in electronic monitoring applications using machine learning systems

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SUMMARY

Electronic Monitoring (EM) systems have been used in many fisheries for a variety of purposes, such as compliance monitoring and characterizing catch or bycatch. Accurate and precise enumeration of catch and bycatch using video imaging has been a challenge whether it is for commercial fishery management or research fishery cruises. Scientists in the U.S. Pacific Northwest, including National Marine Fisheries Service (NOAA Fisheries) staff in collaboration with University of Washington have been exploring technology that addresses this challenge. The success with accurate fish species identification led to this proof of concept research applying this technology and methodology to seabird species identification. In a laboratory setting, a multi-spectral camera chute was set up and birds collected for necropsy were presented to the imaging cameras. Training images (1,837) of a variety of species were used to support feature extraction by the camera systems. Test images (213) of 16 species or species groups were then examined. Overall accuracy was 93%, with some species (Black-footed and Laysan Albatross) at 100% accuracy. With the favourable results of the proof of concept, further research, development, and testing will be conducted.

1. BACKGROUND AND INTRODUCTION

Electronic Monitoring (EM) systems have long been tested for use in commercial fishery monitoring applications (Wallace et al., 2015). They offer a broad suite of attributes that include the ability to determine locations, provide vessel tracklines, sensors to turn systems on and off, images for a variety of uses, oceanographic sensors, and others. Applications are used both for compliance features and enumeration of catch and bycatch. Of the many challenges faced when developing EM to suit the needs of specific fishery management and fleet characteristics, viable enumeration of catch and bycatch is perhaps the most challenging. Our experience in having worked on this problem for the past 18+ years (Ames et al, 2005. McElderry et. Al., 2004) is that it is especially difficult to identify seabird bycatch to acceptable species or species group levels that allow for reliable estimation of both rare species of concern and relatively common species in the bycatch.

The performance attributes of EM for fisheries monitoring continues to improve as technology advances and programs are implemented to test systems in various fishery applications. The U.S. North Pacific Fishery Management Council, for example, has adopted a strategic plan (Loefflad, 2014) and formed an Electronic Monitoring Working Group to address a broad suite of uses and challenges to deploying EM systems that produces data similar to fisheries observer data that is used in real time for fishery management. The NOAA Fisheries Alaska Fisheries Science Center has been experimenting with a variety of technologies including digital versus analog video, stereo cameras, automated review systems, and others. While EM can never fully replace an onboard fishery observer and the many things they do, EM can often supplement coverage or complement on-board work. For example, to enter limited access fisheries in Alaska in some cases requires either 2 fisheries observers or an observer and an approved EM system that meets performance standards. Fisheries management for Alaska groundfish and halibut fisheries are prosecuted and managed in a real-time basis, with observer data being transmitted to the Alaska Fisheries Science Center. Some data quality control is completed onboard at-sea advisors working with observers to correct errors, and a weekly transmission of data to the Alaska Regional office where estimation (Cahalen et al. 2014) and quota management are completed. The goal of EM system deployment is for EM to have the capabilities to match this data stream with dependable reliable data. Another goal is to use automated image-based fish identification in scientific fisheries surveys using machine learning a type of artificial intelligence. To that end, much work has been done to improve automated fish species identification from images (Wallace, et al. 2015, Tsung-Wei Huang et al., 2018, Wang, G., et al, 2016, 2017 and 2018). The results of these efforts for fish identification were promising enough that we designed and conducted a proof of concept research project to develop best methods to identify seabirds that may be applied to the remote monitoring systems deployed to North Pacific fisheries. The research methods and results are described in this paper.

2. METHODS/CURRENT EFFORTS

2.1. Multi-Spectral Chute

To increase reliability of species identification to accepted species or species group levels, over 2,050 images have been taken using a multi-spectral camera chute system. This system was originally designed for fish species identification and has periodically been deployed on commercial longline vessels in Alaskan waters. The system collects data (images) with eight cameras, one full spectrum RBG and seven others that have 50 nm (nanometer) filters on them that range between the light frequencies of 375 nm to 810 nm. The filters ensure that for each image we only see what is reflected in that light band. This includes the ultraviolet range (375 nm) that birds can see but we cannot. Initial work on fish species identification using this system were positive (Wallace et al., 2015 and Williams et al., in progress). Managers were also dealing with reliable species identifications of seabirds for standard EM systems providing oversight on select longline vessels in SE Alaska so we began testing of this system.

Improved species identification via the multi-spectral chute system depends on a large number of images as part of the machine learning training protocol (Wang et al., 2019). While the chute system was deployed to commercial vessels for fish species identifications, where many individual fish on each haul could be imaged, seabird bycatch is so rare that we could not use the system in that way for improving seabird identifications. However, fisheries observers were collecting large numbers of bycaught seabirds as part of the NOAA-Oikonos Pacific Seabird Necropsy Program. Specimens collected in Alaska are first sent to the Alaska Fisheries Science Center before being delivered to Oikonos for necropsy. We were able to set up the multi-spectral chute in a laboratory setting and bring our study, or learning specimens, to the chute system. Protocols were developed where large birds (albatross and large gulls) were presented to the imaging cameras in 12 poses showing all features of the specimen while smaller birds (fulmars, shearwaters, etc.) typically were posed in 4 different ways (dorsal, head to right, ventral head to left, and then focus on the head and bill, right and left sides), although in some cases additional poses were taken. To date we have processed 56 Laysan Albatross (*Phoebastria immutabilis*), 58 Black-footed Albatross (*Phoebastria nigripes*), 131 Northern Fulmar (*Fulmaris glacialis*), 115 shearwaters (all Sooty or Short-tailed (*Ardenna grisea* and *A. tenuirostris*)), 21 gulls (*Larus* spp.), and a variety of other birds available.

2.2. Image Processing

Images from the multi-spectral camera chute system and the associated data from a variety of specimens and poses were provided to project partners at the University of Washington Information Processing Lab, Electrical Engineering Department, led by Dr. Jenq-Neng Hwang. There, they used 1,837 images composed of all species collected as the training data for machine learning. Convolutional Neural Network (CNN) processes were used to identify key features to support identification to the species level.

Using these key features, each image was then scrutinized using a Support Vector Machine (SVM), which provides a classifier in a manner similar to random forest analysis. Initial analysis has recently been completed where the system had 16 species or species group possibilities, based on how we coded (annotated) the bird specimen. In some cases, a group code represents a specimen being one of two or three similar species (e.g., sooty vs short-tailed shearwater) or represents a level of species identification that a person cannot go beyond (e.g., unidentified juvenile gull). Continued work will address some of these anomalies.

3. RESULTS AND CONTINUED DEVELOPMENT

3.1. Species Identification

Of the 213 test images representing 11 species (including Laysan Albatross, Black-footed Albatross, and Northern Fulmar) and 6 species groupings (although one was anomalous), the overall performance of the CNN alone was 93.0% correct and CNN + SVM was similar at 92.9% correct identifications. However, the number of training images available appeared to affect accuracy rates. For example, the system examined 53 Black-footed Albatross and 52 Laysan Albatross test images, and achieved 100% accuracy. We had a high number of training images (over 500) for each species. We also had high numbers of training images for Northern Fulmar, Short-tailed Shearwaters, and both Common and Thick-billed Murres (*Uria aalge* and *U. lomvia*). Fulmar species identification scored at 97.8% accuracy, Short-tailed Shearwaters at 92.3%, and both murre species at 100%. We had fewer Sooty Shearwater images in the training set and the resulting test yielded only 50% accuracy of the 6 test images used.

3.2. Ongoing research and development

Although these results are promising, the accuracy level can be improved and the results only reflect work done under well-managed laboratory conditions. At the same time, while the multi-spectral chute system has a proven track record at sea when fish species identification trials were being conducted, seabird bycatch is fairly rare in the fleet. Even Northern Fulmars, the most common species captured, were shown to only occur in 1.2% of 4,439 examined sablefish fishery hauls and 2.5% of 35,270 examined cod fishery hauls (Dietrich and Fitzgerald, 2010). Conducting sea trials for birds will require approaches similar to that used in Ames et al., 2005, where a line is set with pre-hooked birds and then retrieved with an active camera chute system in place. Continued access to seabird necropsy specimens will be important for this work. During the EM studies conducted by the Alaska Fisheries Science Center in 2002 (Ames et al, 2005, McElderry et al, 2004) the problems with reliable species identification for seabird bycatch using EM was documented. At that time, we believed that technology should at some point be able to monitor all gear retrieved, capture each seabird bycatch event, and automatically identify the specimen to an appropriate species or species group category supporting management and seabird conservation. Over the ensuing 16 years advances in technology and work by many scientist and technicians has brought us much closer to that goal (Wallace et al., 2015).

Citations

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