ID16 NEW ADVANCES IN AI-BASED ELECTRONIC MONITORING (EM) TECHNOLOGIES FOR AUTOMATIC, REAL-TIME CATCH DATA COLLECTION: THE IOBSERVER2.0

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ABSTRACT

The implementation and fully compliance of the Common Fisheries Policy (CFP) of the EU depends largely on the ability to quantify total catches on board commercial fishing vessels. To this aim, the use of electronic devices is gaining relevance and vision-based electronic monitoring technologies have emerged as a more cost-effective and efficient way to monitor fishing activity. In this work, we present the iObserver 2.0, a device that uses Deep Learning image recognition to automatically identify and quantify in real time the entire catch on board fishing vessels. It builds upon two previous prototypes, improving image quality by using line scan technology. Two neural networks are used for fish species segmentation, identification, and length regression tasks. As main results of this disruptive technology, the iObserver 2.0 distinguishes more than twice the number of species than previous version, works with area scan and line scan camera images, and it is evaluated with a test set incorporating more complex images. An experimental fishing survey has been conducted to assess the system's performance in real-life conditions, showing promising results in terms of total catch registration of target and discard fish species.

Keywords - Electronic monitoring, deep learning, image recognition, fish species identification, fish length regression, line scan.

INTRODUCTION

Catch registration and reporting, as well as monitoring, control and surveillance (MCS) are extremely challenging in wild capture fisheries. Insufficient reporting and MCS have contributed to unsustainable fishing practices, caused data limitations in stock assessments and created opacity and unfair competitive advantage for those disobeying the rules. It is a fact that the successful implementation of the Common Fisheries Policy (CFP) (with an increasing level of compliance with the Landing Obligation) depends, to a large extent, on the ability to quantify total catches on board commercial vessels. So, major expenses and efforts are awarded to MCS, but effectiveness and coverage is generally limited. However, as improved technological solutions are fast emerging, the potential to significantly improve data collection, information accuracy and verification, automatic catch registration, reporting and MCS, while also reducing costs, is on the horizon. These solutions include Electronic Monitoring (EM), satellite detection, Vessel Monitoring Systems (VMS), Automatic Identification Systems (AIS), video monitoring (CCTV), computer vision, artificial intelligence (AI), and application of various sensors. Authorities, fishing companies and enterprises are already experimenting with these solutions, with some having implemented elements of these new techniques, with the aim of reaching Fully Documented Fisheries (FDF) towards sustainability of fishing activity.

In this work, we present the iObserver 2.0, an EM device that uses Deep Learning image recognition algorithms to automatically identify and quantify (fish ID) total catches on board fishing vessels. Located over the conveyor belt of catch processing deck (Fig. 1), it takes pictures of entire catch during fish sorting, and each picture is analysed to identify the species and length of each individual, from which weight is estimated, and then combined to generate a catch report for the entire haul. We present next the main characteristics of this new concept of automatic, AI-based EM system.

Fig 1. iObservers 2.0 installed on board R/V Miguel Oliver

HARDWARE

The iObserver 2.0 builds upon two previous prototypes: the first one used classic Computer Vision algorithms [1] and, the second one incorporated Convolutional Neural Network based recognition algorithms that greatly improved the fish ID results [2]. In this work, we present a new version of AI-based EM system where the size of the image capture unit over the conveyor belt is reduced by moving the processing hardware to an external computer, achieving increased power and flexibility. Image quality is also improved by replacing the area scan camera system with a line scan system. To this aim, two different versions of the iObserver 2.0 were developed: one based on the use of line scan cameras and the other one based on area scan cameras that work in linear mode aided by an optical flow analysis algorithm created ad hoc. The use of line scan technology allows to avoid the problems of image stitching of individual photos while providing a continuous capture of entire hauls. Moreover, it uses more focused light sources so the number of light bars is reduced and brightness is increased, allowing to reduce exposure time to just 1 ms, solving motion blur issues and reducing noise.

ALGORITHMS

The iObserver is based on two neural networks; i) for the fish species segmentation and identification task, the Mask R-CNN algorithm was adapted to the problem at hand and; ii) for the fish length regression task, a modified MobileNet Convolutional Neural Network was developed. Since both neural networks only work with single images, for the iObserver 2.0, a Multi-Object Tracking and Segmentation inspired algorithm was developed to provide a solution for the continuous identification and quantification of the fishing hauls. Moreover, to the catalogue of 14 target species recognized by the iObserver (corresponding to targets of Spanish trawlers operating in ICES areas 8c and 9a), 16 non-target species were added in the iObserver 2.0. Additionally, the new images obtained with the line scan version of iObserver 2.0 and over 3,000 new annotations were added to retrain the neural networks.

RESULTS

As main results for the detection task, a precision of 96% (percentage of correct identifications) and a recall of 92% (percentage of correct identifications among positives) was obtained for images that were not used to train the algorithms (test set). Regarding the length regression algorithm, the mean absolute percentage error was 3.1%, and the mean absolute error was 9 mm. Although these results are quantitatively similar to those obtained in the previous version of iObserver, qualitatively they represent a great improvement, since now the iObserver 2.0: i) distinguishes more than twice the number of species; ii) works both with area scan camera images and line scan camera images and; iii) it is evaluated with a test set that incorporates more complex images with multiple fish and overlap. The iObserver 2.0 was tested (on the framework of TIPES project) on the DESCARSEL0921 research campaign to assess its performance under close-to-real fishing conditions (Figure 1). Such research campaign was carried out by our colleagues of the Oceanographic Center of Vigo of the Spanish Institute of Oceanography on board the R/V Miguel Oliver, of the General Secretary of Fisheries of the Spanish Government. The fishing hauls were carried out under ordinary conditions simulating the activity of a commercial trawler. The fishery is a mixed bottom fishery, targeting different species, with various colours, sizes and shapes (rounded, plane or laterally compressed bodies). During the trials, the discharge of the fish from the hopper to the belt was controlled by the crew to avoid excessive fish clumps on the belt and occlusions whenever possible. Obtained results are very promising (Fig. 2). When calculating the catch weight by species, the Weighted Average Percentage Error (WAPE) for the target species was 49%. However, when grouping similar species such as gurnards and megrims, as in commercial classification, the value dropped to 20%. The model had some difficulty with species with few individuals or very similar appearance. When calculating WAPE per haul, it was 18%, dropping to 16% when grouping similar species. In this case, the weighted effect of the most abundant species improved the final result. For non-target species, weight was not estimated, so calculations were based on the number of individuals, resulting in a WAPE of 381%. In this case, the reduced number of annotations used in training was noticeable, although we expect to greatly improve these values for the most abundant species or by grouping the two species of flying squid.

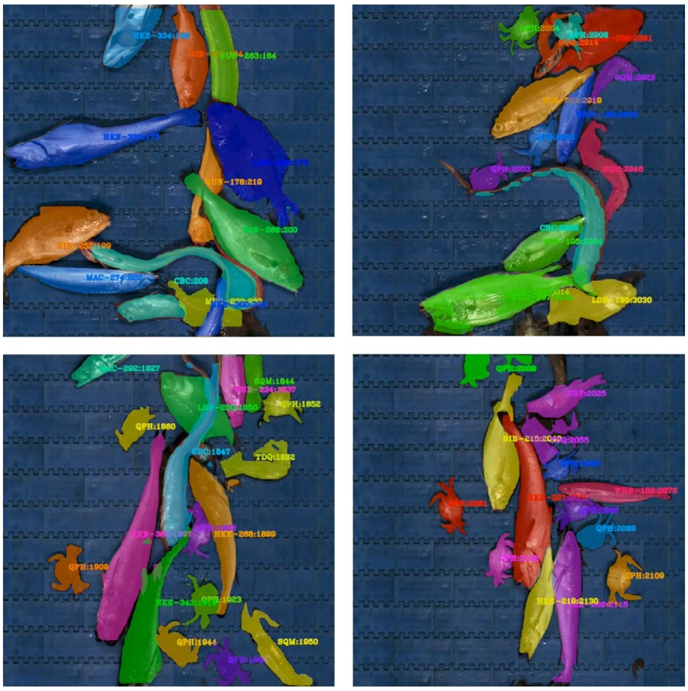

Fig 2. Example output of the algorithms for one haul of DESCARSEL0921. For each detection species FAO code, length in mm for target species and track-id are shown.

CONCLUSIONS

The trial results obtained when using the iObserver 2.0 for providing total catch estimates are promising, but further research is still needed, and research groups involved in this work are currently conducting it. The main obstacle lies in hauls with a high overlap of fish. To solve this, it will be necessary to install a mechanical fish separation system in the fishing parks (physical barriers, vibrating devices, conveyor belts with different speeds, etc.). In addition, and from the point of view of the software/algorithm, many of the observed problems could be alleviated by improving the annotation catalogue by incorporating specimens with a complete and balanced distribution by species and size. The implementation of recognition algorithms has considerable room for improvement, and new advances are published daily. Finally, more tests on commercial ships will be necessary to produce a device that can be used systematically for the entire fleet.

REFERENCES

[1 C. Vilas, L.T. Antelo, F. Martin-Rodriguez, X. Morales, R.I. Perez-Martin, A.A. Alonso, J. Valeiras, E. Abad, M. Quinzan, M. Barral-Martinez, "Use of computer vision onboard fishing vessels to quantify catches: The iObserver", Marine Policy, vol. 116, 2020. DOI: 10.1016/j.marpol.2019.103714

[2] Juan Carlos Ovalle, Carlos Vilas, Luís T. Antelo, "On the use of deep learning for fish species recognition and quantification on board fishing vessels", Marine Policy, vol. 139, 2022. DOI: 10.1016/j.marpol.2022.105015