Theme Session H Report 2024

How can camera-based monitoring improve bycatch management?

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Background

Camera-based Electronic Monitoring (EM) is increasingly seen as a technology that can increase fisheries monitoring coverage worldwide, especially for monitoring bycatch of macrofauna. In many fisheries, these events can be rare and require a high level of coverage (either by observers or EM video review), which can be cost-prohibitive. EM programmes generally, but especially those designed for bycatch monitoring, should prioritise integrating artificial intelligence and machine learning (AI/ML) tools to expedite video analysis and reduce programs costs in meeting monitoring objectives. Most EM programmes collect and store images of catch for the development of AI/ML tools and there are a number of initiatives worldwide that promote the aggregation of such imagery in shared libraries to accelerate developments. This is particularly important for images of endangered, threatened, and protected (ETP) species, which due to the often-rare nature of these events, may be collected in low numbers, making a lack of training data prohibitive to the development of necessary tools. The ability to share imagery is often hampered by legal and jurisdictional constraints.

This session focused on the importance of integrating AI/ML tools in EM programmes for detecting rare events and identifying ETP species, and the advantages of sharing imagery. The objectives were to: 1) Identify existing datasets and initiatives to support the sharing of training datasets and promote the concept of developing common image libraries to rapidly advance AI/ML development; and 2) Share the ongoing progress made in EM programmes for bycatch monitoring, including the implementation practicalities, challenges, and/or opportunities for further integration of data collection to improve fisheries management.

Participants

Approximately 40 session attendees responded to an initial 3-question poll to identify the participants in the room. The majority represented Government Agencies followed by Academic/Independent research institutes. There was also a range of data ownership and access scenarios: in some cases, the data appears to be owned by the government and fishermen, or there was uncertainty as to who specifically owns it (e.g., Other). We found it interesting how much of the data is owned by the government and that no responses indicated that data is available to the public (Figure 1).

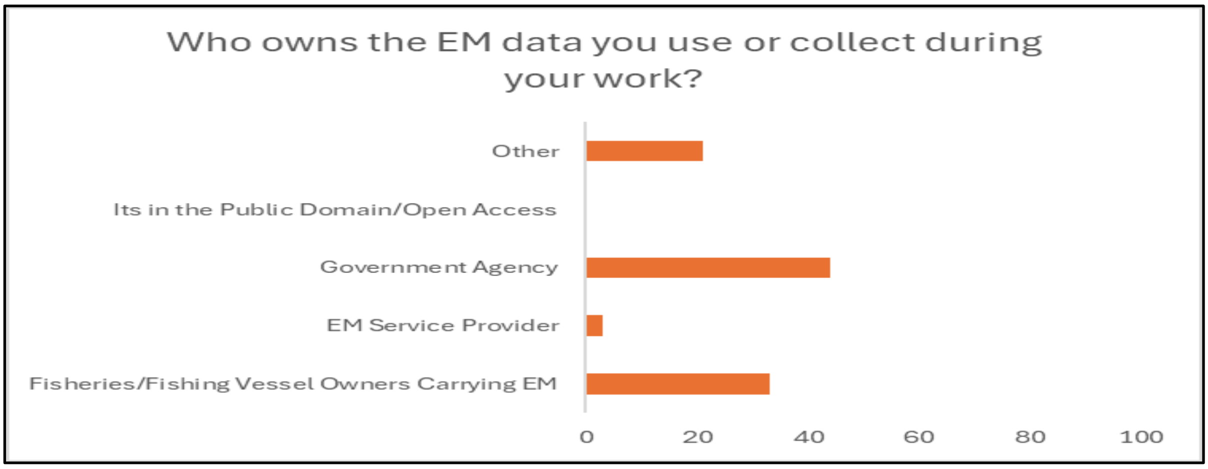

Figure 1. Responses to survey question on EM data ownership (n=39).

Summary of presentations

Several presentations covered a broad range of bycatch monitoring EM programmes, some of which have been operational for many years while others remain in a pilot-phase. A number of talks covered optimisation of EM using AI/ML to detect and identify bycatch events of ETP species. Set apart from the others, but relevant to all was also a presentation on submission of EM data to the ICES Regional Database Estimation System (RDBES). Demonstrating that the database can receive EM data, and showing the types/fields of data collected through EM programmes that can be used in bycatch assessments.

The EM programmes with bycatch monitoring objectives that were presented covered a range of geographical areas, from Australia to the UK, and both active and passive gear types. Most of these talks focussed on the utility of EM to enhance at-sea observer coverage and/or validate logbooks, training of AI/ML tools to optimise EM review, and how AI/ML can reduce the amount of time and associated costs needed to monitor for bycatch of ETP species. Tasks AI/ML tools had been used for included: detection of fishing activity, detection of bycatch events, identification of ETP species and masking of people for privacy.

The first was from Joshua Tucker of NOAA, who discussed the use of ML in the Hawaii Longline fishery to advance bycatch detection. This programme is training AI/ML for the detection of bycatch events to reduce human review time. So far, they have >200 000 annotations in their image library, and aim to have 10 000 annotations per class, which are either species or broad species groups. This demonstrates the vast amount of data required to train AI/ML. A talk by Vienna Saccomano demonstrated the utility of edge AI on vessels to detect and identify fishing activity periods, almost as well as a human reviewer, and trim the footage for upload to these periods. Reducing the time taken by human reviewers to find and watch the footage associated with fishing activity.

Summary of the panel discussion

Kate Wing and Ben Woodward led a discussion session on using AI/ML in fisheries and the challenges associated with it, with a specific focus on data sharing. Sharing imagery across libraries has featured as a potential aid to build training datasets of rare events (such as bycatch) for AI/ML tools. The aim of this discussion was to temperature check this idea with a wider audience and discuss the practicalities. A Slido poll allowed participants to provide input to set questions, which was then used by Kate and Ben to facilitate discussion.

If using AI/ML, what's working well?

Of the 30 respondents to the initial question regarding if they use AI/ML tools in their work, 27 responded yes. Following this, the room was asked what was working well in using AI/ML. Themes of the responses included collaborative working, allowing anonymisation of data and making other tasks easier (such as creation of further training data). There was a general feeling that tools in use were very much still in development and that this did not present a negative, but instead the opportunity for further growth.

If not using AI/ML, why not?

Approximately ⅕ of the room stated that they were not using AI/ML tools and this question aimed to find out why. Key responses included lack of in-house expertise to progress, training imbalances and lack of labelled training data. It was also felt that AI/ML tools were not developed enough to produce data of the same quality as manual human review, so the tools were not fulfilling a need. This echoed a point raised in Session J earlier in the conference. Potential solutions presented to these problems were centred around thinking of how the AI/ML tools are used, working with what they can do now, rather than waiting for a "perfect end product". For example, if training data has class imbalances, use the AI/ML models for the classes that have sufficient training data, to augment review and reduce the burden on human reviewers, rather than replace them completely.

Which of the following ideas would help advance your work?

The final discussion point aimed to discover what ideas could help to advance work with using AI/ML (e.g. sharing training data, coding sandboxes, more AI developers in fisheries, EM program design guidelines, policy experts working more with scientists and developers. The potential responses to this question were based on the topics in the recent paper published by Kate and Ben, but also invited other ideas. Of the ideas presented to the room, shared training data was the most popular chosen by 46% of respondents. However, a challenge identified with this was finding the right people to talk to about sharing data, but with the conference and sessions such as these as good opportunities to identify people working in similar areas. Further queries were raised around sharing data including at which point data should be shared (raw, processed, labelled/annotated) and how much images or video need to be anonymized before they can be shared.

Conclusions

The session presented a range of examples of EM being used for bycatch monitoring, both using AI/ML and not, as well as providing a space for discussions on how we can advance our use of AI/ML in fisheries. Most participants suggested they are "still developing" their programmes and AI/ML tools and it is perceived to be disappointing, but this perpetual improvement and progress should be seen as a success, not a negative.

This session brought back an old communication challenge, which we have seen previously when first implementing EM, but now for AI/ML. Observer data has been the yardstick for EM when using manual analysis for video, and now AI/ML outputs and data quality are being measured against human reviewers, instead of recognising and embracing the differences. AI/ML tools do not need to be perfect to augment manual review and there are many benefits to just getting started. The generation of data on ETP bycatch and rare events is difficult, and some data is better than no data, so we should encourage EM programmes to start somewhere and work towards improvement.

As a community of EM advocates and practitioners, we need to remain focused on the true purpose of data collection through EM systems while leveraging AI/ML. We are trying to more efficiently and accurately assess the impacts and bycatch of fisheries and integrate the data into stock assessments and science advice. We need to pursue standardisation of raw EM data, processed data, and other data systems so that stock assessment scientists and data analysts can do their work. We want them to maximise their time analysing data, and not combining or cleaning it.

The pursuit of sharing data across EM programmes and governments remains critical for all use cases of EM, but especially programmes with limited labelled data to train AI/ML models, and in particular, those with ETP bycatch. The challenges are partially technical due to the volumes of raw video and lack of standards for easily transmitting data across systems, but also a legal challenge due to the privacy protections by governments of all fisheries data and the on-the-water privacy of fishermen in view of cameras. Our initial session survey revealed that we did not have any attorneys in the room, but we will need to seek their engagement and support if we are to make progress in data sharing.