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Automatic tracking and analysis of fish trajectories for developing a bio-inspired robot controller

Claudio Massimo Coppola*‡, Lissa O'Reilly*†‡, Sarah Dalesman†§, Otar Akanyeti*§

*Department of Computer Science, Aberystwyth University, Wales, UK
†Department of Life Sciences, Aberystwyth University, Wales, UK

‡shared first authorship §corresponding author: sad31@aber.ac.uk, ota1@aber.ac.uk,

***Abstract*—Bio-inspired controllers may help robots better adapt to dynamic and unpredictable environments. In this paper, we present work in progress towards developing an automated tool for tracking and analysis of fish trajectories. These trajectories will be used to develop a bio-inspired robot controller through learning by demonstration paradigm.**

***Index Terms*—bio-inspired robot controller, deeplabcut, fish tracking, learning by demonstration**

I. Introduction

Learning by Demonstration (LbD), whereby a teacher guides a robot to acquire new skills without explicit programming, is a powerful paradigm to improve robots' autonomy and performance [1]. While previous LbD research exclusively featuring humans as the demonstrator (e.g., [2]), very few attempts have been made to learn from other animals in an automated fashion, although many studies have shown that controllers inspired from non-human animals can help robots better adapt to dynamic environments (e.g., [3]).

In this project, we work towards developing a conceptual framework to enable a robot to learn from a fish, and present an automatic fish tracking and analysis software. To demonstrate the utility of the software, we analysed a set of video recordings obtained from one individual fish (three-spined stickleback, *Gasterosteus aculeatus*) across 42 trials. In these trials, the fish was learning to associate a landmark with the food chamber in two-choice experiments. We are hoping that deciphering how fish encode information in this novel environment will help design new bio-inspired learning algorithms for robots.

The videos were recorded at 30 FPS and at 720p, and the duration of the videos varied throughout the trials depending on how quickly the fish entered the correct food chamber. From each video, we manually digitised 5 minutes of data at 5 FPS. This data was used to train an artificial neural network for automatic fish tracking and evaluate its performance.

II. Manual tracking

A two-dimensional manual tracking program was created using Python (version 3.7.11) and OpenCV (version 4.2.0). The program first prompts the user to enter the desired number of tracking points (along the body) and then allows the user to go through the video frame-by-frame to manually annotate these points. The program also has the options of skipping frames, re-annotating frames and choosing start and stop frames. The program outputs a .csv file which consists of frame number, timestamp and x and y coordinates of each point of interest. In this study, the first author used the manual tracker to digitise the fish videos. Two points along the head were chosen: the most anterior point (snout point) and the middle point between the eyes (i.e., base point). Both points were used to recover the position and orientation of the fish relative to the tank, which were then used to estimate the angular and linear velocity of the fish. The base point was used to train and evaluate the performance of the automatic tracker. To evaluate inter-coder reliability, one video (trial 1) was additionally annotated by a second researcher, and the agreement between two annotators were measured.

III. Automated tracking

The automatic tracker was created using a DeepLabCut (DLC) toolbox [4], whereby artificial deep neural network model was trained using 300 annotated frames from trial 1 over 200,000 iterations. Google Colab was used to train the network, and evaluate its performance. The performance was reported as the percentage of frames where the pose estimation of the DLC network was within 10% of the fish body length, *BL*, (3.7 cm). For frames that met the 10% *BL* threshold, the distance between actual (manually annotated) and predicted (by the DLC network) point was also measured.

IV. Analysis of fish trajectories

The inter-coder reliability was 100% (percentage of frames) and 0.02 *BL* (distance). The average performance of the DLC network was 86±9% and 0.04±0 *BL* (±standard deviation of the mean) (Fig. 1a). The DLC network performed best in trial 4 (97% and 0.03 *BL*) (Fig. 1b-c) and worst in trial 37 (47% and 0.03 *BL*) (Fig. 1d-e). In trial 37, the DLC network often confused the fish with the landmark (stone) which had a similar shape and colour to the fish (Fig. 1e).

The comparison of fish movements from trial 1 and trial 42 demonstrate that the fish learned to associate the landmark with the correct food chamber (Fig. 2). In the first trial, it took the fish 805.6 seconds to find the food (Fig. 2ai) which was 786.2 seconds longer than trial 42 (Fig. 2bi). In both trials, fish exhibited a range of angular (-180 and 180 degrees s^{-1}) and linear velocity (0 - 5 *BL* s^{-1}) (Fig. 2aii and bii). As

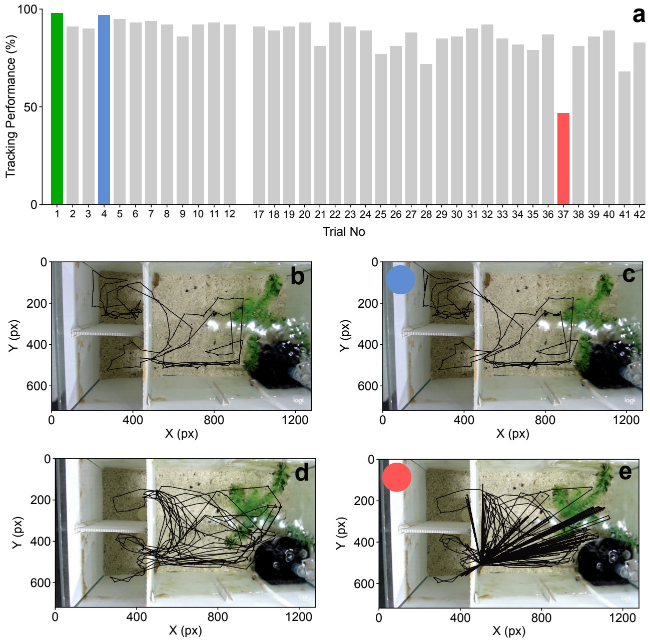

Fig. 1. Comparison between manual and automated tracking. **a.** Automatic tracking performance across fish trials. Video recordings from trials 13 to 16 were corrupted and omitted from the analysis. The performance was evaluated as the percentage of frames where the error between predicted and actual fish position was less than 10% of fish body length. Trial 1 (green) was used to train the DLC network, and trials 2-42 were used to test the model. **b**. **c**. Actual and predicted fish trajectories (black) from trial 4 (blue) for best case scenario. **d**. **e**. Actual and predicted fish trajectories (black) from trial 37 (red) for worst case scenario.

learning progressed, the fish had a lower tendency to stay near the walls (i.e., thigmotaxis), and its movements became more direct (fewer stops) often exhibiting simultaneous turning and forward movements (Fig. 2aiii and biii).

V. Conclusion

We present a work-in-progress automatic tracker for estimating the position of a fish while swimming in a laboratory setting. The performance of the tracker in unseen trials was promising but needs to be further improved to provide accurate results. Our preliminary results from one manually annotated individual show improved decision making over learning trials as indicated by the change in fish velocities and trajectories.

VI. Limitations and Future Work

Manual tracking is a laborious and time consuming process which does not allow continuous fish tracking over extended periods of time. Automated tracking is quicker but less accurate due to light reflecting off the water, ripples from the filter (distorting the fish silhouette) and occlusions (e.g., the fish was partially (or not) visible to the overhead camera while passing through the doorway or hiding under the plant or the water filter). In addition, our initial investigation using preliminary data suggests that the DLC network had poor generalisation performance when used to analyse videos from other fish.

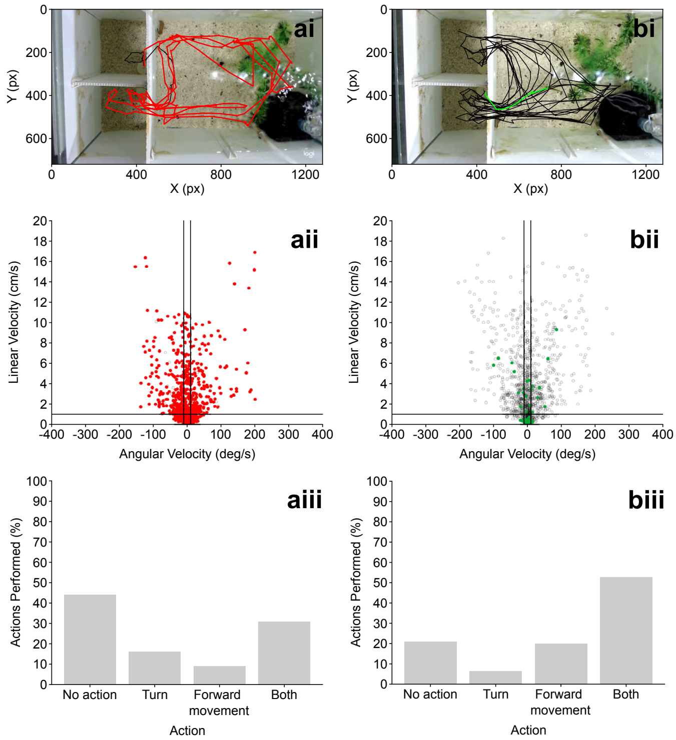

Fig. 2. Comparison of fish behaviour before (**a**) and after learning (**b**). **ai**. **bi**. The red and green trajectories show incorrect and correct decisions made until food was found. **aii**. **bii**. Fish instantaneous angular velocity (positive values corresponding to turn right) and linear velocity (positive values corresponding to forward movement). Grey markers correspond to individual data points. Red and green markers correspond to individual data points until food was found. **aiii**. **biii**. Distribution of fish actions split into four groups: 1) No action, 2) Turn, 3) Forward movement and 4) Both movements at the same time.

We are currently working on a new outlier detection and imputation method to post-process data generated by the automatic tracker. We are also developing a semi-automated, human-in-the-loop fish tracking program to combine the best features from the manual and automated tracking methods. This will speed the process for collecting fish trajectories and provide accurate and reliable data to use for researchers. By collecting more data it will increase the progression towards developing a bio-inspired robot controller through LbD.

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