Investigating Social Communication of Mormyrid Weakly Electric Fish using Machine Learning Algorithms

Rachel Miller, Leo Farber, Krista Perks
Department of Biology, Wesleyan University

Introduction

Mormyrids are pulse-type weakly electric fish that emit and receive electric organ discharges (EODs) in order to communicate and locate objects in their environment. These EODs are pulsed electric fields. EOD waveforms are stereotyped, but the fish are able to vary the interval between EODs (inter-pulse-intervals – IPIs). The IPIs differ depending on social context, and the timing of EODs are coordinated during behaviors such as mating, hunting, and aggression.

Much of the past research on Mormyrid social behavior has examined this coordination within individual and pairs of fish. For example, Worm et al. (2017) demonstrated that fish coordinate their pulsing with a dummy fish that emits electrical signals.[1] Investigations on the social dynamics of larger groups of fish have been done by manually identifying EOD fish pairs in recordings. In 2005, Arnegard and Carlson found EOD acceleration and synchronization during hunting in a wild group of Mormyrids.[2]

However, the timescale and spatiotemporal resolution that these researchers could achieve with manual methods do not enable the investigation of social behavior at a resolution that can be integrated with studies of the underlying neural mechanisms. Our research utilizes machine learning algorithms to conquer this obstacle. This enables us to finally tackle long-standing questions about how the coordination of communication signals enables group cohesion in dynamic social environments by leveraging Mormyrid fish as a model system.

Research Question

What are the mechanisms of coordination in social behavior?

How can machine learning algorithms be leveraged to enable the investigation of social coordination in Mormyrid weakly electric fish?

Methods: Motion Tracking

DeepLabCut is an open source package used for pose estimation tracking of animals.[3] A network must be trained for a specific animal, in this case Mormyrid fish. Once well-trained, the network will generalize to track the fish in unlabeled videos (and across a variety of environmental conditions).

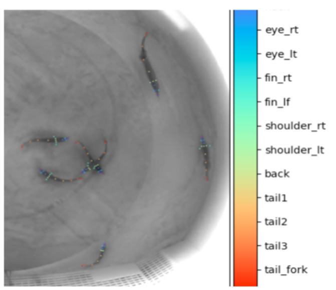

Figure 1: A sample manually-labeled frame from a video recorded under IR light in the behavioral arena. Twenty frames were extracted from this ten second video of freely swimming Mormyrids. Thirteen body parts were chosen to be labeled on each fish in each frame.

DeepLabCut Development Process

- First, we optimized the video recording setup to enable the acquisition of video under IR light. This serves two purposes: 1) fish are nocturnal so they are more comfortable interacting in the dark, 2) sheltering is a significant part of their social ecology and under IR light, we could make shelters that did not obscure visual access.
- We extracted a subset of frames from a video and labeled all fish in each extracted frame with easily determined body parts. We chose body parts to label to balance identifiability with numerosity.
- To train the network, DeepLabCut splits labeled frames into train and test groups. The training frames are used for the network to learn how to predict the labels. The test frames are used to check the accuracy and generalizability of the network after being trained.

Results

Network Evaluation

Train error(px)	Test error(px)	p-cutoff used
2.01	4.58	0.6

Table 1: DeepLabCut network analysis showing error measured in Pixels. Train error shows the number pixels off DeepLabCut was when labeling frames used in training. Test error shows the number of pixels off when labeling frames not used in training. The p-cutoff is the set p-value at which DeepLabCut does not place a label. The next stage of network evaluation involves a bootstrap procedure in which we quantify how well the network can generalize.

Labeled Video and Tracking Data

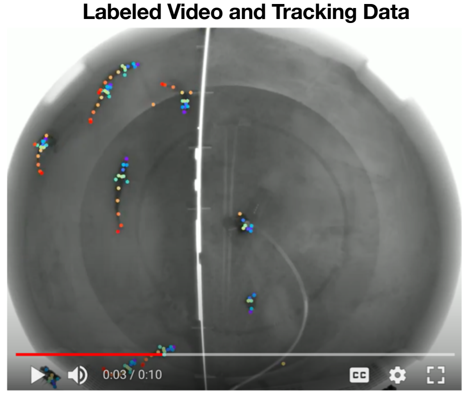

Figure 2: Labeled video created by the trained network.

individuals	ind1					
bodyparts	snout			head		
coords	x	y	likelihood	x	y	likelihood
0	NaN	NaN	NaN	NaN	NaN	NaN
1	681.963	564.650	0.99935	660.649	538.879	0.99379
2	681.856	565.254	0.99981	675.760	565.164	0.98910
3	681.835	565.120	0.99977	659.858	539.657	0.98701
4	681.244	564.918	0.99996	660.410	538.659	0.99356

Table 2: Example of the data acquired by the analysis of the novel video (Figure 2) by the trained network. Coordinates created with the labeled video. Shows the x and y coordinates for each body part on each fish in each frame.

After the initial training, we are working on reiterating the process to acquire more video from which to extract more frames to add to the dataset and retrain the network. Specifically we are focusing on improving performance on instances where the fish cross paths or the environment changes appearance.

EOD Recording Integration

To quantify the results of our behavioral assay, we need to integrate motion tracking with the recording of EODs. Leo Farber used a multi-channel electrode array to record EODs and we have integrated the visual and electrophysiological streams of data (see accompanying poster). We can calculate the angle of each fish at each moment in time from the data we acquire with DeepLabCut pose estimation. We can now utilize information about the angle of each fish to assign individual fish identity to each EOD (by comparing the fish orientation with the polarity and amplitude of each EOD recorded across channels of a multi-electrode array).

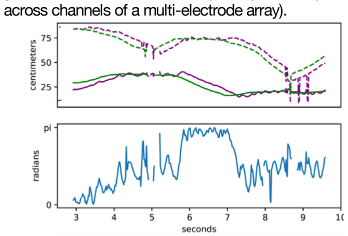

Figure 3: Top: X and Y coordinates of the tail_tip and tail2 positions of a single fish (sample data predicted from iteration1 of the trained network). Bottom: the angle of the fish over time, calculated from the X/Y data.

Discussion

The behavioral assay that we are developing will be used to investigate the mechanisms of coordinated communication in social behavior. Specifically, our assay focuses on the exploration of novel environments and how group size affects group cohesion and communication during exploration. In this assay, a tank with eight fish will be split into two compartments with all fish acclimated to one side. Groups of one, two, and five fish will be moved to the novel side, consisting of a single shelter. We will observe changes in time spent in the shelters and time spent exploring the novel environment across different group sizes. We will measure IPIs to assess overall levels of communication and movement kinematics to assess exploration. Critically, as group size increases, we expect to see increased coordination and cohesion among the fish. This will be quantified using higher-dimensional metrics.

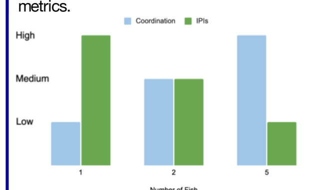

Figure 3: Experimental design and anticipated results. As group size increases, we expect the coordination of EODs between fish to increase and the length of the IPIs to decrease (EODs are closer together).

Recent advances in machine learning provide us with the tools to overcome past technical limitations and measure the social behavioral ecology of electric fish with high temporal and spatial resolution. From this data, we can better understand the coordination of communication signals that results when social environments place different demands on group interaction in Mormyrid weakly electric fish.

References and Acknowledgements

1. Worm, Martin, et al. (2017), "Social Interactions between Live and ARTIFICIAL WEAKLY ELECTRIC Fish: ELECTROCOMMUNICATION and Locomotor Behavior of Mormyrus RUME Proboscirostris towards a MOBILE DUMMY FISH."
2. Arnegard, Matthew E, and Bruce A Carlson. (2005), "Electric Organ Discharge Patterns during Group Hunting by a Mormyrid Fish."
3. Lauer et al. (2021), Multi-animal pose estimation and tracking with DeepLabCut

Thank you to The Baker '64 Collabria Fellowship which has funded my research this summer.