Miniscope Pipeline: A Processing Pipeline for Analysing Behavioral and Brain-Imaging Data

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Introduction

Objectives of the Pipeline

What drives behavior? Understanding the relationship between neural mechanisms and behaviors is key to answer this question. The miniscope pipeline is specifically constructed to process and quantify both brain-imaging and behavioral data in a consistent and efficient manner based on open-source equipment and software packages. The pipeline first quantifies the neural activity and the behavior separately and then extracts possible patterns and correlations from the quantified output.

The Miniscope

The miniaturized microscope (i.e., "the miniscope") is a small microscope that is mounted on the head of a mouse during behavioral experimentation. The miniscope attaches to a small lens implanted in the region of study to allow for the acquisition of cortical or subcortical data at a cellular level in a free moving mouse. Prior to this technology, data could only be collected either at a cellular level or in a free moving animal but not both at the same time.

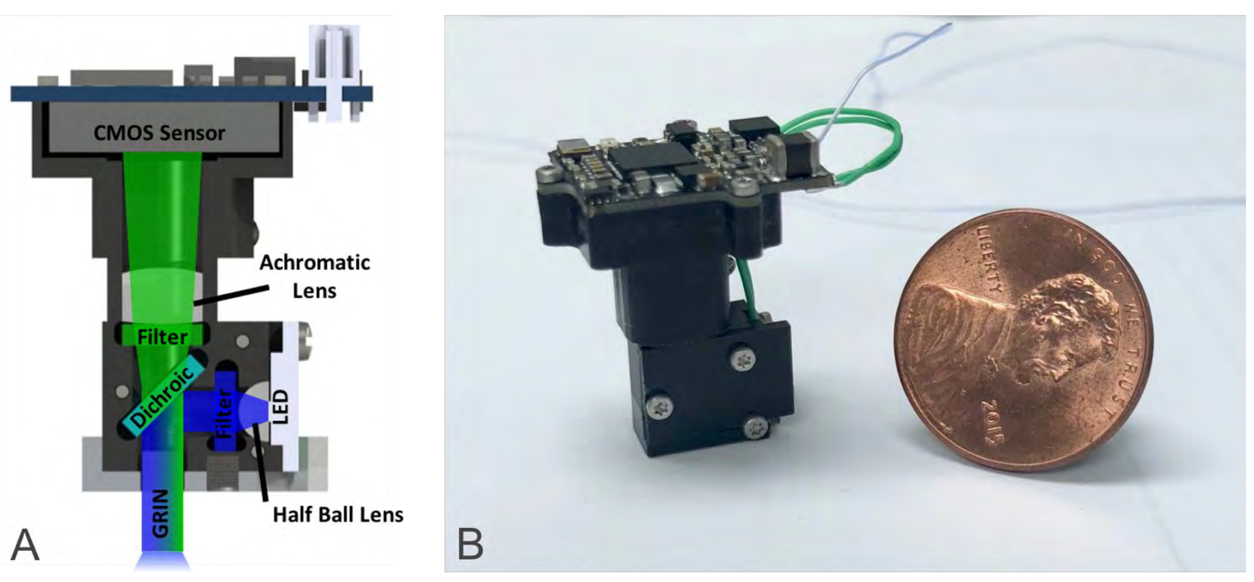

Figure 1: (A) Depiction of the miniscope's path of light. The blue represents excitation light and the green represents emission light (from Miniscope.org). (B) Assembled miniscope (penny used as size reference).

The Pipeline

MiniAn, DeepLabCut, and Hopper

To derive both neural and behavioral data from high-dimensional video samples, the pipeline draws from adaptations of two open-source Python packages; MiniAn and DeepLabCut. MiniAn identifies and traces neural signals from videos taken by the miniscope while DeepLabCut traces agents in their environments to assess different described behaviors[2,3]. Additionally, the Vassar computing cluster Hopper was used to efficiently process the high-dimensional video data.

Miniscope Workflow

The adapted MiniAn scripts were constructed to solve a series of problems that arise from using complex video data as shown in Figure 2.

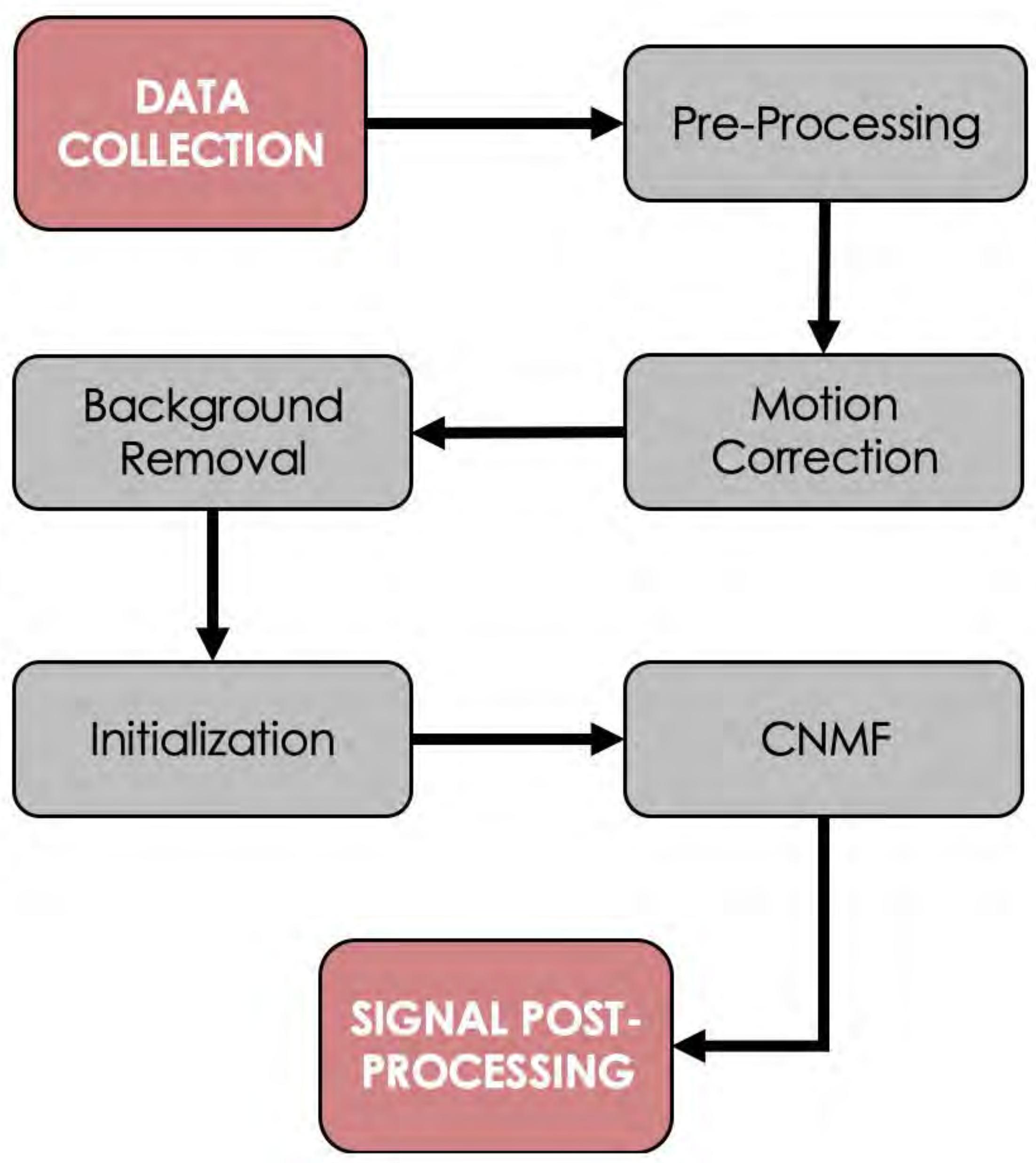

Figure 2: The Workflow for Processing Miniscope Data. The videos are cleaned first, and then series of bright points in the videos are stitched together into spatial footprints. A neural network is then trained to reliably identify neurons within the video data.

Visualizations of this workflow are shown in Figure 3. Up until the constrained nonnegative matrix factorization (CNMF) steps which employ the neural networks, most of these steps require fine parameter tuning for each set of videos to provide coherent results.

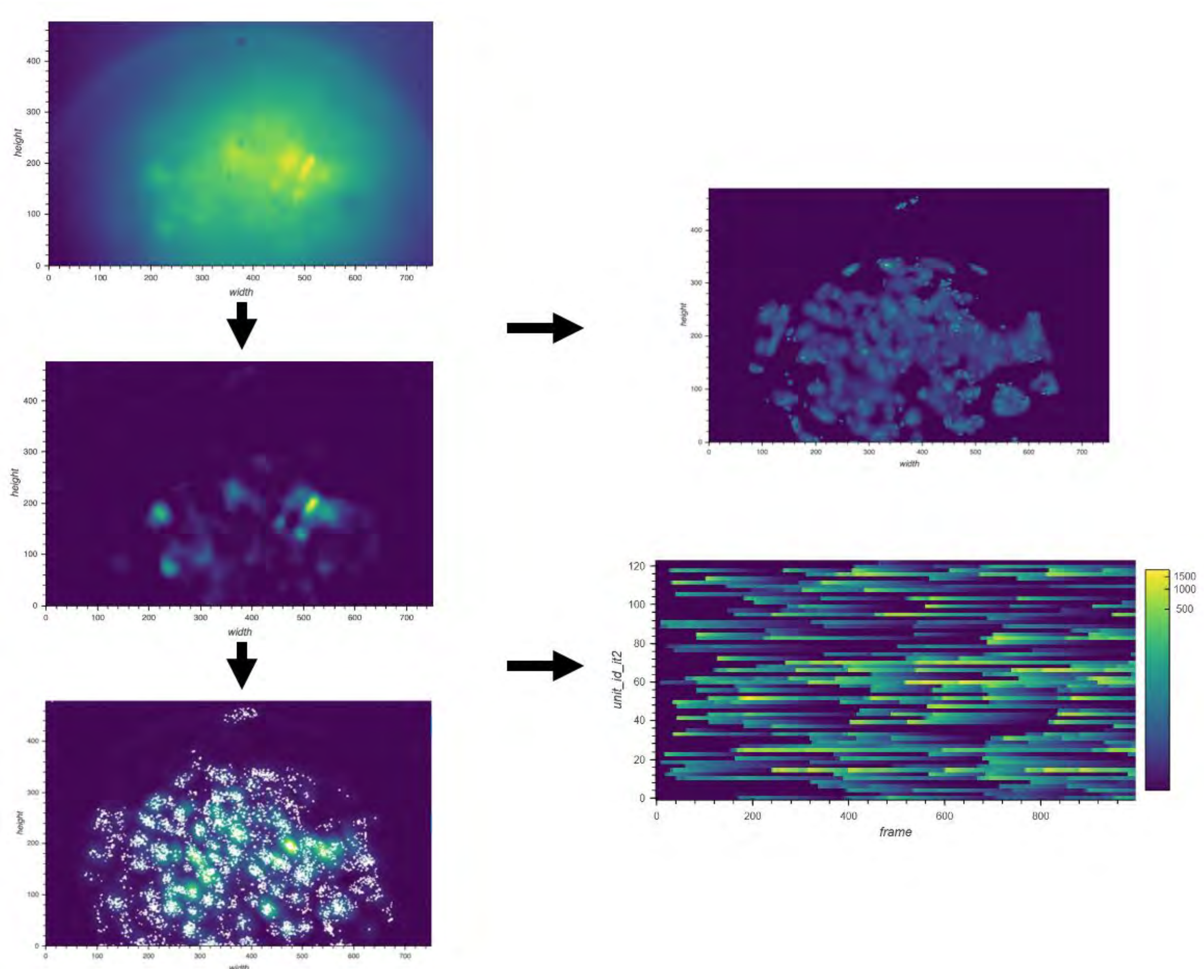

Figure 3: Visualizations of the Miniscope Pipeline output. After the pre-processing and initialization steps shown on the left, the pipeline yields both the spatial footprints in the top right and the temporal traces of those footprints in the bottom right.

Behavioral Workflow

The DeepLabCut scripts were adapted to perform quantification of behavioral recordings following the steps in Figure 4. Compared to manual labeling body parts in each frame of the videos, this method utilizes machine learning to achieve similar accuracy in a more consistent and efficient way (Figure 5). Subsequent analyses were then conducted in R to extract behavioral patterns of interest and to search for possible neural activity patterns that are expected to occur simultaneously with the behavioral patterns.

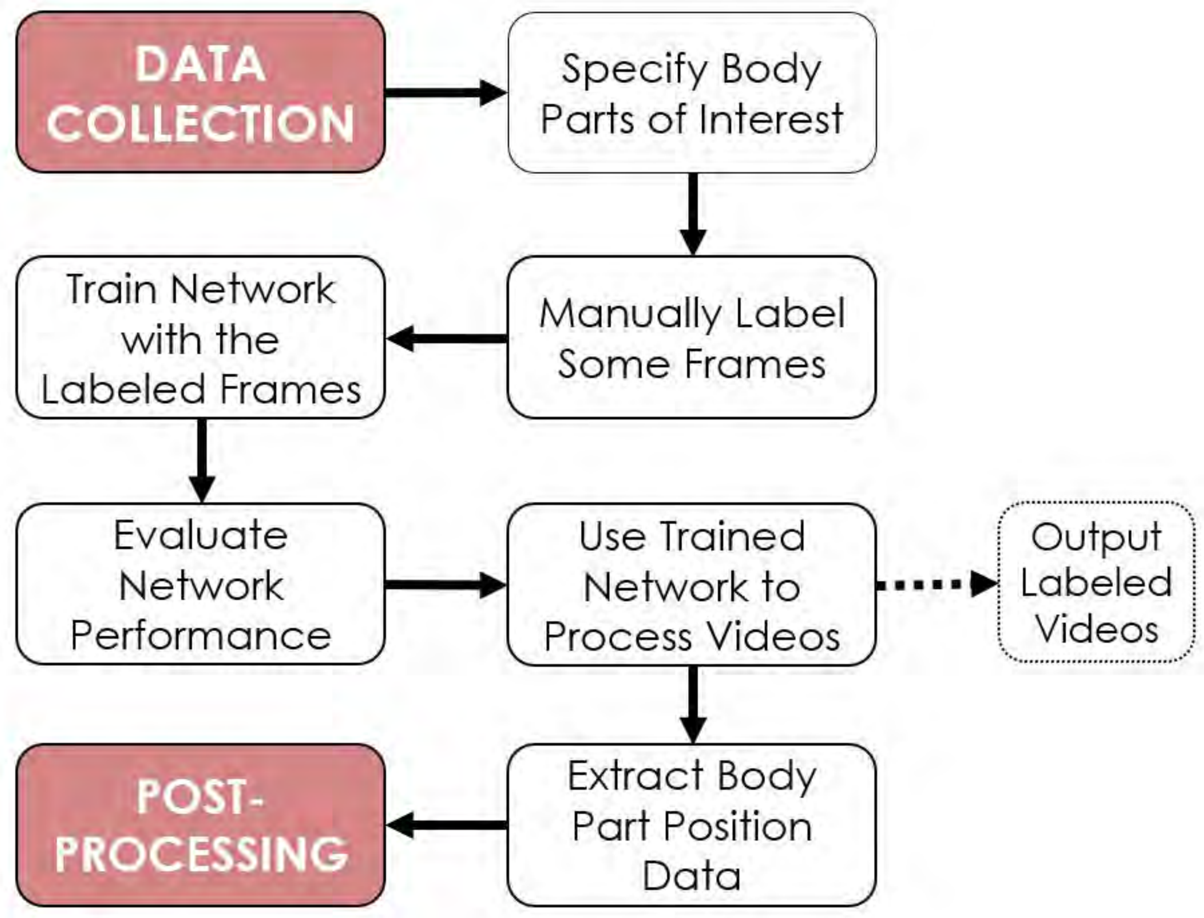

Figure 4: The Workflow for Processing Behavioral Data. A neural network is trained using a selected number of manually labeled frames and is then used to identify body part positions in videos. The network can also generate labeled videos for illustration purposes.

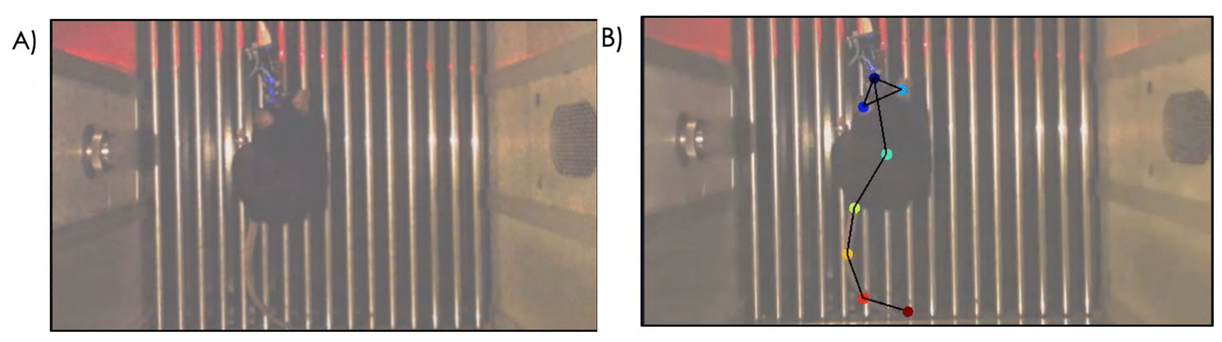

Figure 5: Examples of a frame A) in the original video and B) in the labeled video.

Discussion/Future Directions & Uses

We aimed to correlate brain-imaging data with behavioral data to understand what drives behavior. The MiniAn pipeline and DeepLabCut packages allowed us to derive clear neural traces from brain-imaging videos and track the movement of labeled body parts. We achieved great accuracy in identifying both neural activity and behavioral patterns using the pipeline; however, we struggled to achieve high accuracy when comparing different sessions using the cross-registration function of the MiniAn pipeline. In the future, we plan to work on increasing accuracy with the cross-registration function and identifying and analyzing different behavioral patterns.

Acknowledgements and References

A special thank you to Matt Tarantino and the CIS office. Thank you to Susan Painter and Brian Daly for running URSI this summer. We would also like to thank the creators of Minian and DeepLabCut, the open source packages used for our project.

1. Resendez, S. L., Jennings, J. H., Ung, R. L. *et al.* (2016). Visualization of cortical, subcortical and deep brain neural circuit dynamics during naturalistic mammalian behavior with head-mounted microsopes and chronically implanted lenses. *Nature Protocols, 11*(3), 566-597. https://doi.org/10.1038/nprot.2016.021
2. DeniseCaiLab. (2020). *minian*. Github. https://github.com/DeniseCaiLab/minian
3. Mathis, A., Mamidanna, P., Cury, K. M. *et al.* DeepLabCut: markerless pose estimation of user-defined body parts with deep learning. *Nature Neuroscience*, 21, 1281-1289. https://doi.org/10.1038/s41593-018-0209-y