Automated Stitching and Spine Detection of Spiny Projection Neurons

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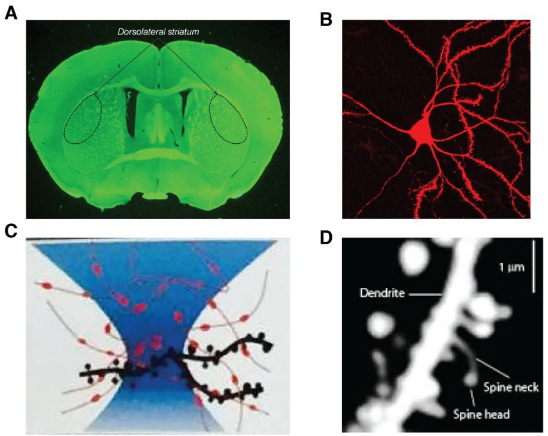
Background and motivation

A complex problem in neurobiology, and microscopy in general, is image processing of neuronal processes. Although some software exists to help extract imaging data, they are currently not sophisticated and neuroscientists are thus left to manually or crudely stitch together images of several compartments belonging to the same cell, in order to analyze cellular properties such as the number of dendritic spines.

Goal: Here we apply object recognition and machine learning techniques to approach this issue in order to process and analyze images more automatically and efficiently.

2-photon imaging (data summary)



A) Mouse coronal section depicting the area containing the neurons of interest
B) Spiny Projection Neuron (SPN) morphology (note the density of dendritic spines)
C) Cells were imaged with 2-photon microscopy (cells filled with fluorescent dye)
D) Example tile of dendritic process imaged (max projection of z-stack)

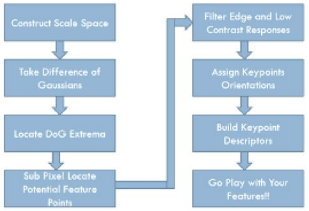
1092 image tiles (12 cells taken across 4 mice)
Tiles are 512 x 512 pixel projections of z-stack images

Project Outline

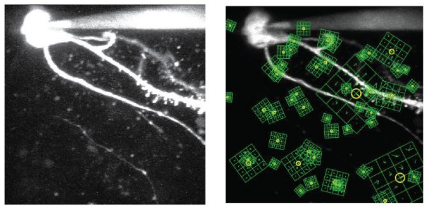
1. Pre-process the tile images
2. Extract features from tiled images (Scale-Invariant Feature Transform, SIFT)
3. Stitch tiles together based on matched features (Random Sample Consensus, RANSAC)
4. Detect dendritic spines using feature detection and random forest classifier (ilastik framework)
5. Compare results of automated spine counting with manually stitched and counted samples

Stitching Spiny Projection Neurons

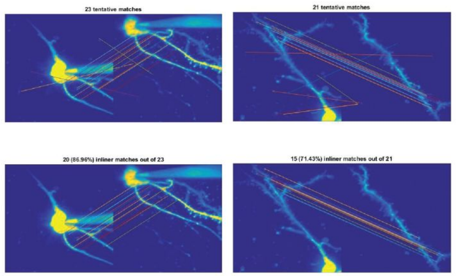
SIFT algorithm



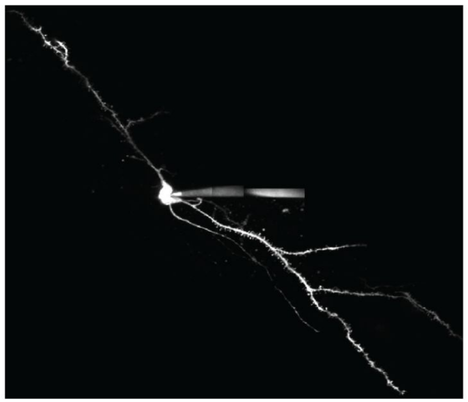
Feature detection and keypoint descriptor



Matching common features

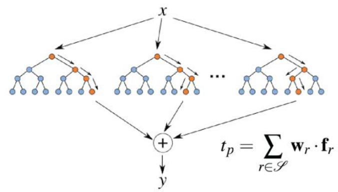


Stitched Image



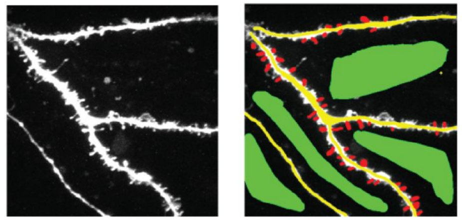
Avg error = 7 (across 12 cells)
Where error is sum of px offsets from manually stitched

Spine Detection with Random Forests



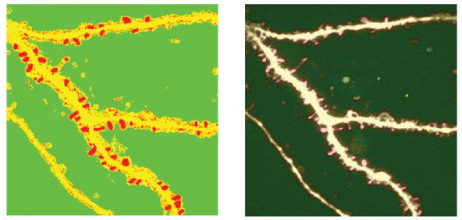
$$t_p = \sum_{r \in \mathcal{S}} \mathbf{w}_r \cdot \mathbf{f}_r$$

Training (image annotation)

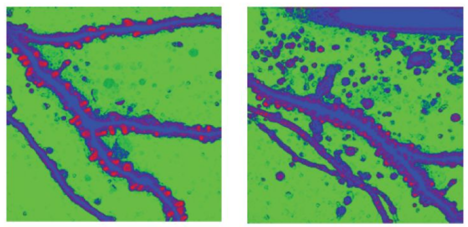


Raw tile image | Labeled image

Random forest learning

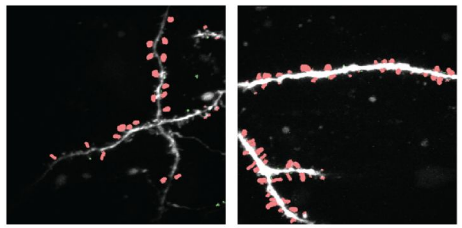


Segmentation of labels | Probabiliy map of training image



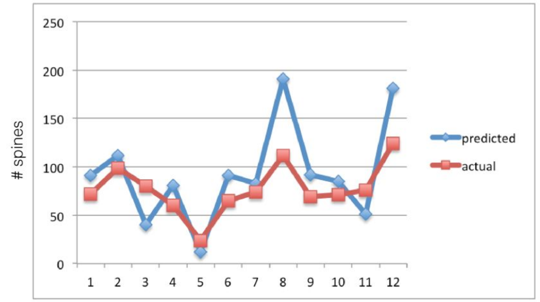
Probability map - training file | Probability map - testing file

Spine classification



Analysis and Summary

Spines Counted



Cell index (12 total)

Prediction error

Cell index (12 total)

Future Directions

1. Collect many more images (sample size is currently too small)
2. Try different forms pre-processing for the images (in order to emphasize different features such as edges)
3. Experiment with different multi-class classifiers (compare to random forest classification)
4. Combine Ca2+ imaging data in order to detect active spines, which could be used to determine upstream inputs to any given SPN spine.

Acknowledgments

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References

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