Quantifying the power of light-controllable molecular motors: Tracking velocities of individual actin filaments using (R)-CNN facilitated labeling

Nina Hooper, Cooper Galvin | CS 230, 21 March, 2018

Problem:

- Light controllable molecular motors (myosins) have been engineered to vary their speeds and direction upon exposure to blue light, but quantifying their speeds in lit and dark states has proved difficult [1.2.]
- A method to determine the polar filament orientation and position must be developed in order to track the signed velocity [3] throughout a movie of filaments moving

Figure 1. The theory and structure behind an engineered, light-controllable myosin motor [1]

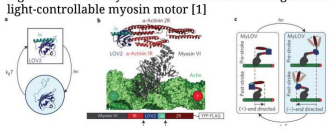
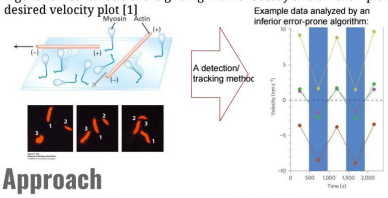


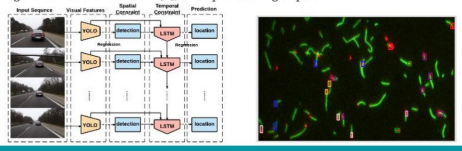
Figure 2. A schematic of the gliding filament assay and an example of the desired velocity plot [1]



Approach

We first aim to implement a YOLO CNN algorithm to identify polar filaments position and orientation by labeling random frames throughout the videos of gliding data and training on those data. If we can achieve that approach prior to the project deadline, we will also attempt to implement an LSTM into our method, creating a R-CNN, which can make use of the information of previous and future frames to better detect filaments (Figure 3).

Figure 3. Model of a R-CNN [4]; example labeling of polar



Context

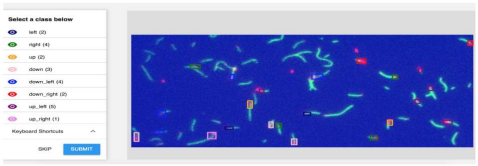
Cytoskeletal motors perform the functions of force generation and transport throughout eukaryotic cell species and types, from the beating of cardiac myocytes to the long-range transport of neurotransmitters or nutrients in plants. The Bryant lab has designed motors that can be optically controlled in order to test our understanding of protein structure-function relationships and in order to develop new tools for controlling cellular processes in vivo.

Data generation

We worked with a post-doctoral scholar in the Bryant lab, Paul Ruijgrok, to collect videos of the myosin motors sliding actin filaments in the lit and dark states and converted those videos into 8-bit RGB jpeg files.

We then used labelbox an online image labeling toolkit to create a training and test set of labeled images with filament positions and orientations labeled.

Figure 4. Example labeling of polar filaments in the lit state using using labelbox



Model training

We chose to apply the YOLO9000 algorithm,[5] which has been shown to be effective in cases where limited labeled pictures are available for training. To do this, we needed to write a variety of python scripts to convert our labeled file outputs to that which could be interpreted by the NN implementation.

We broke up our labeled data such that 10% was reserved for dev/testing and 90% was used for training. We chose not to have a separate dev set for this case.

We also ensured that our test set had adequate lit and dark state examples to be representative of the target population of images.

Evaluation metrics

We tracked the rate of training on a lab-quality personal computer in order to get some understanding of the rate at which we can expect raining to occur with our given model. We found that each iteration takes approximately 5 minutes, so to get through 100 iterations would take several hours. Therefore, we have moved on to using the AWS cluster to train on our dataset.

(Preliminary) conclusions

- Training was very slow, even with my NVIDIA GeForce GTX 1070/PCIe/SSE2, so we moved to an AWS deep learning-ready image processing server today
- Once one hundred iteration of training have been completed, we will test our model on the rest of the labeled frames and evaluate their efficacy both quantitatively (accuracy) and qualitatively (does it roughly label the correct filaments?) to determine if our model will be useful for determining signed velocities.

We do hope to provide the Bryant lab with some idea of how difficult a deep learning strategy would be to implement to solve their filament tracking problem. More will be annouced by the end of the course!

References

1. Nakamura, M et al. **Remote control of myosin and kinesin motors using light-activated gearshifting, 2014,** Nature Nanotechnology,, 9, 693-697
2. Chen, L. **Engineering controllable bidirectional molecular motors based on myosin, Nat Nanotechnol.** 2012 Apr; 7(4): 252–256
3. Aksel, T. **Ensemble force changes that result from human cardiac myosin mutations and a small-molecule effector.**Cell Rep. 2015 May 12;11(6):910-920
4. Ning, G. **Spatially Supervised Recurrent Convolutional Neural Networks for Visual Object Tracking,** arXiv:1607.05781 [cs.CV]
5. Joseph Redmon, Ali Farhadi, **YOLO9000: Better, Faster, Stronger,** arXiv:1612.08242 [cs.CV]