Using Deep Learning for Mouse Pose Estimation and Motion Analysis in 3D

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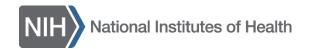
Background





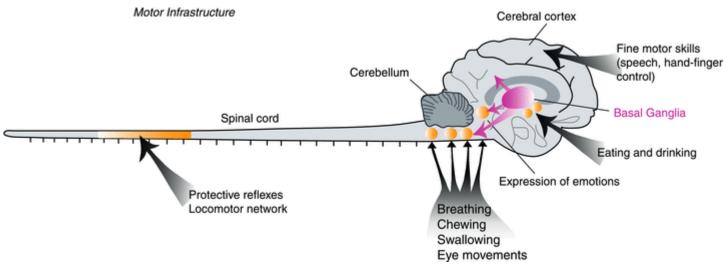
To understand the neural basis for jumping in mice.

- Core behavior used in many contexts
- How do different neural cell types contribute to the way a mouse jumps?



Neurology of Jumping

- Locomotor networks in the brain and spinal cord
- Manipulating locomotor network can affect movement
- How can we see if the jump has changed?



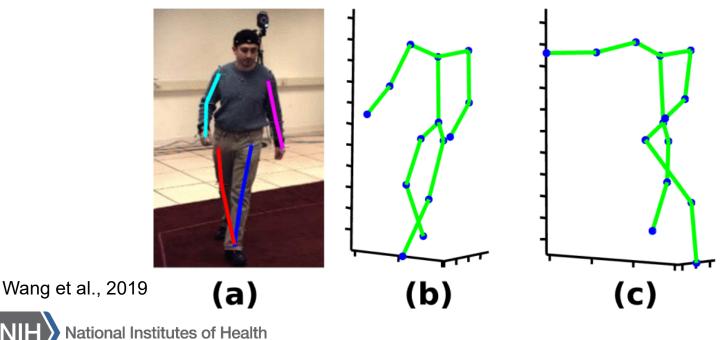


Pose Estimation



Pose Estimation

- Must quantify movement in order to analyze
- Articulated body pose estimation: automatically detect a body's pose in an image
- Complex but central problem in computer vision



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Deep Learning

- Machine learning algorithms modeled after human brain to "learn" information
- Two phases: training and analysis
- Training: critical process of learning parameters
- Analysis: apply trained network to new data
- Many applications, including *pose estimation*



DeepLabCut

- Public deep learning software for animal pose estimation
- Uses a pre-trained Residual Network (ResNet) to analyze videos and identify user-specified joints
- Basis for our quantification of mouse jumping behavior



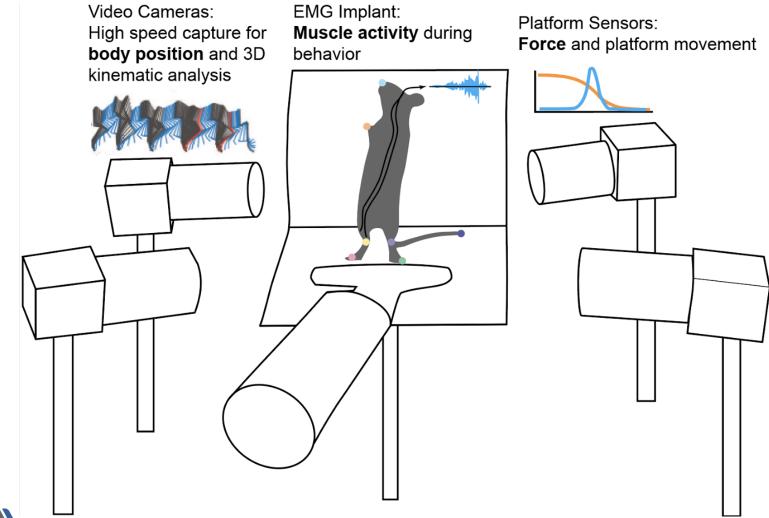
Nath et al., 2019



Experimental Methods



Apparatus





Software Environment

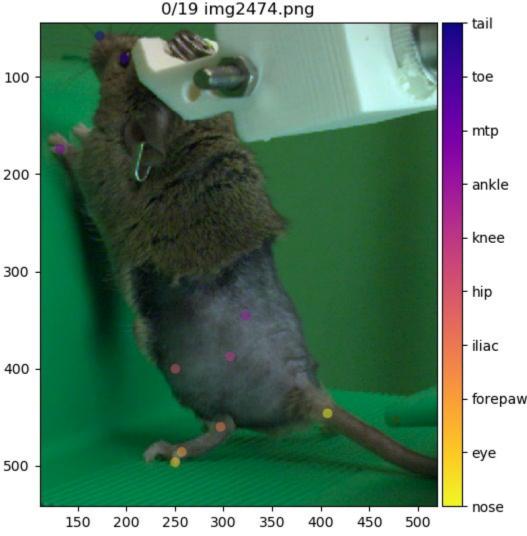
- Python 3.7 via Anaconda
- Graphics Processing Unit (GPU) and driver
- DeepLabCut (DLC) software and user interface

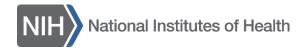




Body Part Labels

- DLC is designed for general use – requires user input
- For jumping behavior:
 - Nose, eye, forepaw, iliac crest, hip, knee, ankle, MTP, toe, tail base

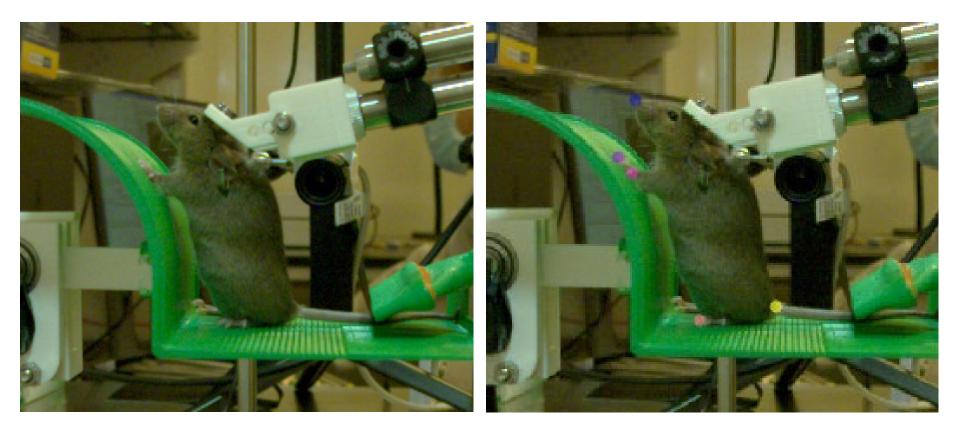




Data and Results



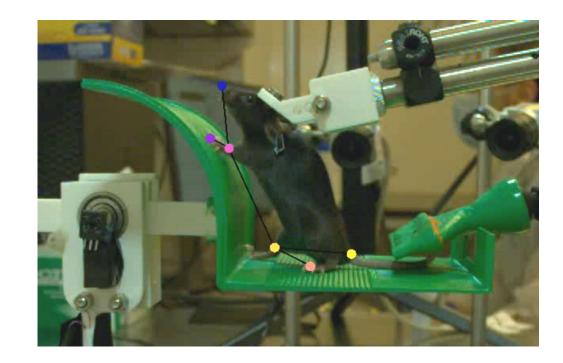
Proof of Concept – Data





Proof of Concept – Results

- Promising, clear indication that DLC is learning
- Issues: limb switching, low resolution, motion blur, noisy and dark image, inconsistent data

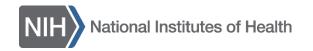




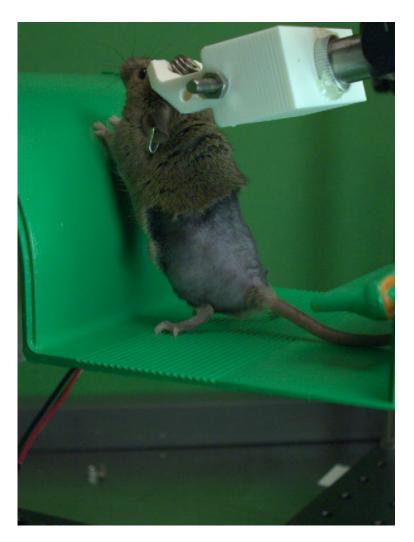
Design Adjustments

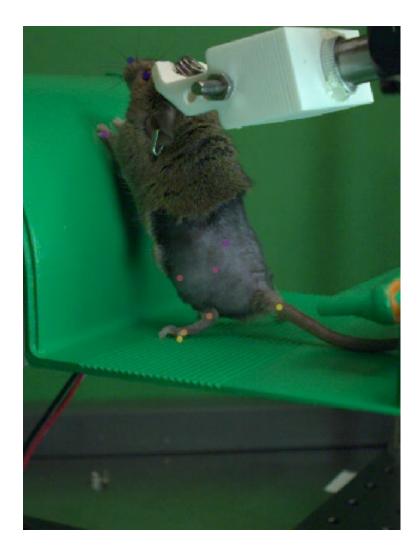
Issues: limb switching, low resolution, motion blur, noisy and dark image, inconsistent data

- Add more points
- Move camera closer
- Better lighting
- Increase video frame rate
- Shave mice, use same-colored mice
- Trim videos



Improved Data

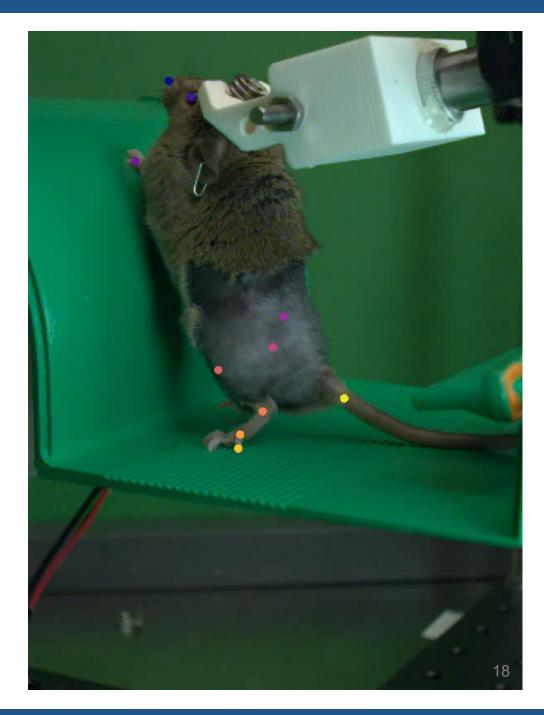






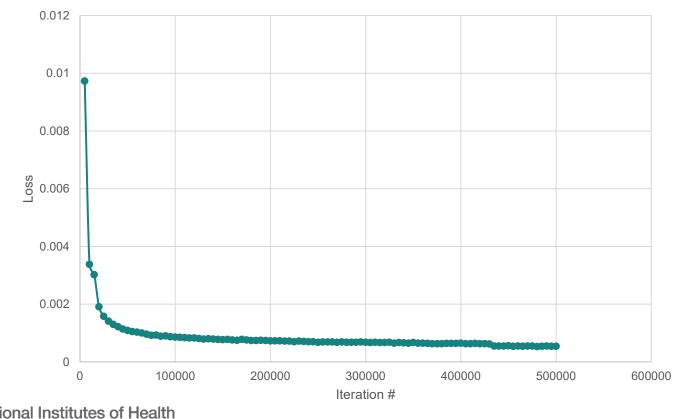
Improved Results

- Adjustments proved highly effective at addressing issues
- Data is easier to label and analyze, with more consistent and accurate results



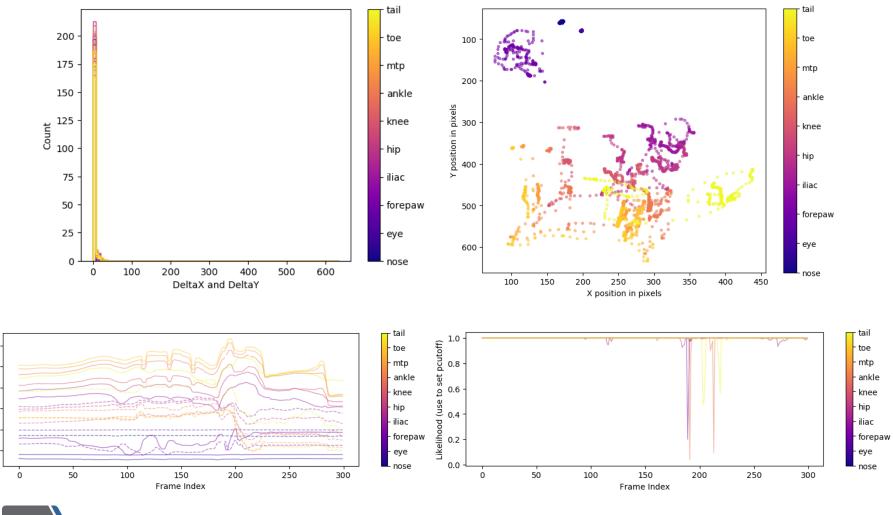
Additional Analysis – Training Efficacy

• Validation: train error = 0.8, test error = 1.57 (in pixels)



Training Loss Progression

Additional Analysis – Generated Plots



NIH National Institutes of Health

X-(dashed) and Y- (solid) position in pixels 00 00 00 00 00 00 00

Future Directions



Future Directions

- Refine the training parameters in DLC
- Generate four DLC models for four camera angles
- Collect more data and analyze from all angles
- Calibrate across multiple cameras to obtain 3D position
- Synchronize with EMG and platform data
- Perturb cell populations and quantify changes in jump



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References

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Questions? Feel free to email me at tara.m.tang@gmail.com!

