A Rodent Paw Tracker Using Support Vector Machine

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The observation of both human and animal kinematics has proven to be of tremendous scientific value for both understanding biological phenomena and development of medical treatments. Rodents, in particular, are widely used as a model for human disease. Unfortunately, they are also notoriously difficult to use in experiments requiring the use of motion capture (MoCap) for kinematic analyses. Current commercially available technology for rodent MoCap (e.g. Digigait [1, 2], Motorater, Noldus Catwalk [3, 4]) requires either frequent anaesthesia for shaving and tattooing of anatomical landmarks , or retroreflective markers known to agitate rodent subjects. Less automated methods require the use of high speed video capture and manual tracking, which both time and data intensive.

In an attempt to overcome these challenges, we developed a "markerless" approach to tracking rodent paws for kinematic analyses that uses the HSV color space to segment images and identify paws based on hue channel values [6]. In addition, the application of hue thresholding is presented for segmentation in wireless capsule endoscopy frames [7]. While this approach initially showed promise in a single subject, it was not generally applicable to all mice, and was unable to recover from classification errors. Here, we present a modified version of this approach that includes the use of a support vector machine (SVM) to more robustly identify and track paws without the use of conventional marker based or manual approaches.

All data shown here was collected on a computer vision controlled treadmill with integrated high speed (250Hz) synchronous video capture across 5 cameras [8]. Each collection consisted of 1000 frames of 2048x700 images. Data shown here used two camera views and 16 videos (for a total of 32,000 frames) from 5 C57BL/6 mice. In overview, three principal stages were used to track paws automatically based on color, kinematic, and texture information. First, images were segmented based on color [6] (Fig. 1) to identify candidate paws. Next, the vertical and horizontal speed of the paws from the preceding two frames (for a total of four kinematic features) and the average intensity and entropy (to quantify texture), of the paw regions were used to create a feature matrix. This feature matrix was by an initial SVM to determine whether candidate regions were paw or non-paw. Then, a second SVM used the same feature matrix to classify paws as front or hind. Finally, we applied a checking protocol that handled collisions and occlusions based on knowledge of paw motion in rodent gait (Fig. 1). This approach successfully identified the front paw in 99.75% of the video frames in the test data set. For the hind paw the success rate was 99.97%.

Our approach to automated feature/paw tracking in rodents performed as well or better than conventional marker-based approaches to automated tracking. By combining multiple synchronized camera views with 3D reconstruction methods (i.e. Direct Linear Transform), we are now able to track paw position through time with high fidelity (Fig. 2). This sort of spatiotemporal information is of tremendous value for understanding fundamentals of robust locomotion and adaptation in pathological gait in rodent models. Because we are able to capture locomotion kinematics without the use of sticky markers, we can minimize agitation, and insure a more naturalistic gait in rodent subjects. First and foremost, we hope to expand this approach and make it more robust to both camera position and variability in presentation of anatomical landmarks. We also hope to apply it to tracking of paw and body kinematics in studies of perturbed healthy gait, as well as rodent models of disease to characterize features of gait pathology. To compare our method, we will try to use other methods like deep learning and sparse decompositions [9].

References

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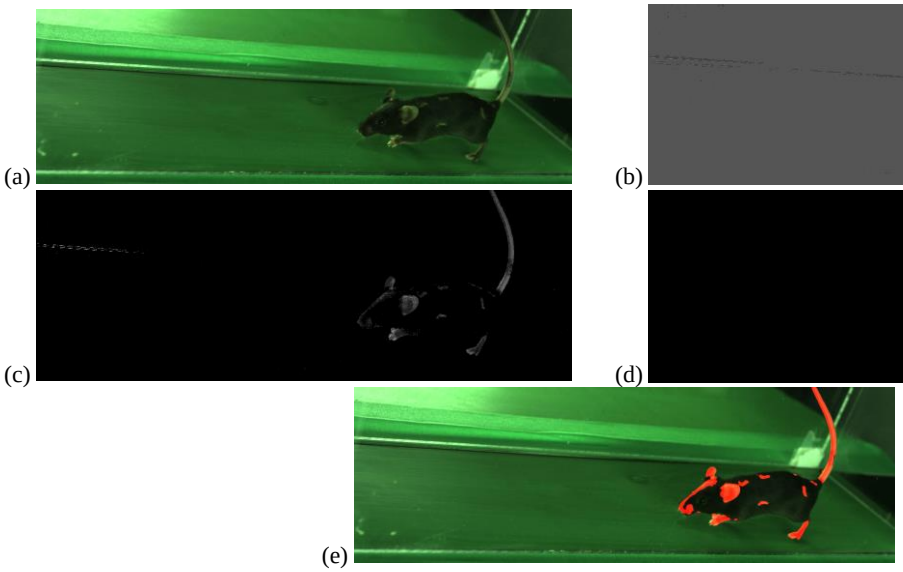

Fig 1. The segmentation process for a sample frame. (a) Original frame, (b) the hue channel, (c) thresholded hue channel, (d) after median filtering of (c), and (e) the final segmented regions transferred in colored images.

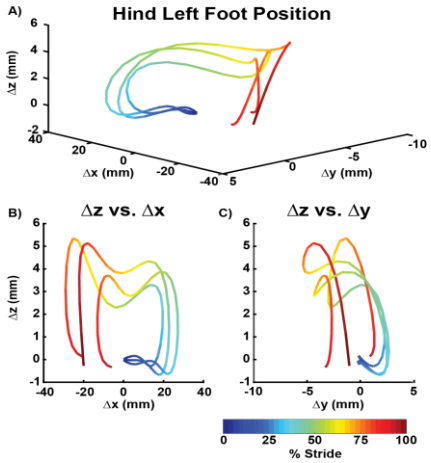

Fig 2. The 3D coordinates of segmented hind left paws for three strides using Direct Linear Transform (DLT). (A) 3D coordinates extracted using DLT coefficients, (B) 2D the coordinates in xz plane, and (C) 2D the coordinates in yz plane.

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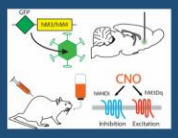
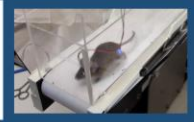
Introduction

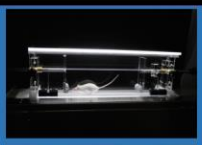
- Examining locomotion and study animal kinematics
- Why Mice? C57BL/6
- Perturbation, DREADDs, and Optogenetics
- Using high speed multi-camera system = High frame rates





Background

- Available systems:
  - Digigait
  - Motorater
  - Nodus Catwalk



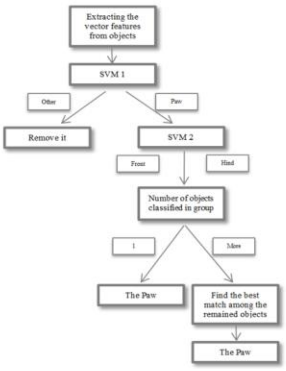
- These methods relied on:
  - Shaving fur and then drawing markers on the skin
  - The attachment of retroreflective markers
  - The use of optical motion capture systems
- Drawback:
  - Anesthesia
  - Multiple handlings
  - Applications of markers
  - Removing the attached markers

The Camera Setup

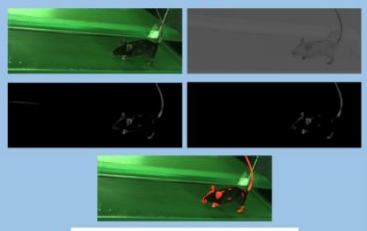
- Video data were gathered at 250 frames per second with a resolution of 2048×700 pixels.

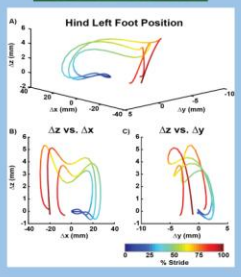
The Method

- In overview, three principal stages were used to track paws automatically based on color, kinematic, and texture information.
- Steps for the method in simple words:
  - First, images were segmented based on color
  - Next, four kinematic and two texture features were extracted. Two SVMs were used.
  - Finally, a checking protocol



A Sample Frame in Different Steps





Results

- This approach successfully identified the front paw in 99.75% of the video frames in the test data set. For the hind paw the success rate was 99.97%.
- This study shows the feasibility of the method; future work will be expanding the test sample for further videos from different mice.

Acknowledgements

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