Tracking freely moving mice using computer vision, statistical inference and statistical learning techniques

Aishah Qureshi[1,2] and Dario Campagner[3,4] and Mitra Javadzadeh No[3,6] and Joaquín Rapela[4,6]

Abstract— **Tracking movements of animals is essential for understanding behaviours in natural environments, as well as for investigating their neural correlates. Here we describe and evaluate the computer vision, statistical inference and statistical learning methods that we used to estimate positions, velocities and accelerations from videos of mice freely moving in a large arena. We provide code and sample data to reproduce all figures in the poster.**

I. INTRODUCTION

A central aim of current neuroscience is to understand the relation between neural circuits and behaviours. Many important behaviours are only observed in naturalistic settings. Therefore, signal processing methods to accurately monitor behaviour in these settings are essential.

II. METHODS

Computer vision: We extracted the mouse position in each video frame using thresholding, dilation, contour finding functions in the OpenCV library.

Linear dynamical system (LDS) model: we used a linear dynamical system with a six-dimensional state space $\mathbf{x}(n) = [x(n), \dot{x}(n), \ddot{x}(n), y(n), \dot{y}(n), \ddot{y}(n)]^\intercal$ and mouse position measurements $\mathbf{y}(n) = [m_x(n), m_y(n)]^\intercal$. The state dynamics followed the Discrete Wiener Process Acceleration model [1].

Statistical inference: using the Kalman filter and smoothing algorithms[2] we inferred denoised positions, velocities and accelerations (i.e., $\mathbf{x}(n)$) from noisy position measurements (i.e., $\mathbf{y}(n)$).

Statistical learning: the linear dynamical systems model contained free parameters We set their values to those that maximised the likelihood of the position measurements under the LDS model [2], using the `optim` library of PyTorch.

Simulations: to assess the quality of the previous methods, we sampled states ($\mathbf{x}(n)$) and position measurements ($\mathbf{y}(n)$) from the LDS model and attempted to recover the states from the measurements.

III. RESULTS

Simulations Despite large amounts of noise introduced into the simulated measurements, and the missing observations, both the Kalman filter and smoother yielded accurate estimates of true positions. The Kalman filter and smoother provided more accurate estimates of velocities and accelerations than the baseline finite differences method. We also obtained more accurate estimates with learned than with manually set parameters. For missing observations, estimates by the Kalman smoother were more accurate than those by the Kalman filter.

Mouse tracking The interactive figure shows positions extracted with the computer vision functions and those inferred by the Kalman filter and smoother, for an example session. At times with missing observations (i.e., missing black dots) the Kalman smoother provided more natural position estimates than the Kalman filter, that sometimes went astray. As with simulated data, estimates of velocities and acceleration by the baseline finite differences method appeared noisy, and those from the Kalman filter and smoother were less noisy (data not shown). Extrapolating from the simulation results, we infer that Kalman filter and smoother velocity and acceleration estimates of behaving mice are more accurate than those from the finite difference method.

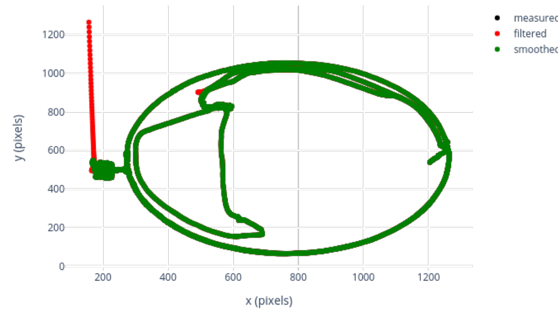

Fig. 1. Positions measured with computer vision functions (black) or inferred with the Kalman filter (red) or smoothing (green) algorithm. Parameters of the LDS used for inference were learned from data. Please refer to [3] for an interactive version of this figure, and double click on a trace legend to hide/show the corresponding trace.

[1] Queen Mary University of London
[2] Simons Collaboration on the Global Brain Undergraduate Research Fellow
[3] Sainsbury Wellcome Centre for Neural Circuits and Behaviour, University College London
[4] Gatsby Computational Neuroscience Unit, University College London
[6] Simons Collaboration on the Global Brain Undergraduate Research Mentor

REFERENCES

[1] Y. Bar-Shalom et al. Estimation with applications to tracking and navigation. John Wiley & Sons, 2001.
[2] R.H. Shumway and D.S. Stoffer. Time Series Analsys and its applications. Springer, 2016.
[3] interactive figure available at http://www.gatsby.ucl.ac.uk/~rapela/surf21/aishah/embc22/figures/fig.html

Manuscript 1882 submitted to 2022 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). Received April 8, 2022.