**Methods**

**Kinematic Data Collection**

Rats reached for food pellets through a vertical slit in a custom plexiglass enclosure (**Figure X;** similar to Ellens et al., 2016). Two high-speed (250 frames/sec) USB3 cameras (Ximea XiQ series) captured each reach. Due to the large effect size observed, we found that a 2D kinematic analysis from one camera was adequate to demonstrate the effect of our treatment across groups for this proposal. Future work will utilize both cameras and a calibration object to reconstruct 3D trajectories, as is routinely done in the Spence lab (Maghsoudi et al., 2019), using a framework written in Python under the Robot Operating System (ROS) in Ubuntu Linux.

**Kinematic Data Analysis**

For the preliminary data presented here (**Figure X**), the shoulder, elbow, and wrist (**Figure XA, B**: blue, green, and red dots, respectively) were tracked in the raw videos using the deep learning algorithm DeepLabCut (Matthis, 2018). Individual reach attempts were compiled manually through identification of the peak x coordinate and extraction of the surrounding 400 ms in time, verified by consulting the video.

For the proposed work, the detailed kinematics of rat reaching will be analyzed using cutting edge techniques from the motor control literature (Mathis et al., 2017) and developments thereof as needed. The Spence lab has extensive experience in the relevant methods, from applying dynamical systems models to kinematic data (Wilshin et al., 2017ab), to the utilization of filtering methods, e.g. Kalman filters (Haji-Maghsoudi et al., 2019; Spence et al., 2013). Briefly, operational criteria are first applied to objectively select valid trials; a start position will be defined as the point where the wrist centroid crosses a plane in front of the animal, when moving towards the pellet; trials will then be temporally averaged by alignment of the Savitzky-Golay (>20Hz cut-off) filtered trajectories at this plane crossing point, and will be spatially aligned by baselining to the point of crossing the “start” plane. After alignment, population average trajectories will be computed, and distance metrics such as average Euclidian norm distance between individual trajectories and the population average computed, to give a reaching pattern error metric; these may require a normalized time to be computed. Distance versus time trajectories will be baselined to the start plane crossing point. Average speed and acceleration plots and subsequent metrics will be computed as derivatives of the temporally aligned Savitzky-Golay filtered trajectories. We will explore the ability of generative models to explain the observed changes in trajectory structure with cognitive excitability (Mathis et al., 2017; Berniker and Kording, 2008; Izawa and Shadmehr 2011), and if appropriate exploit them to quantify how cortical excitability influences reaching dynamics.

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