Using Deep Learning to Predict Locomotive Intention from Hippocampal Signals

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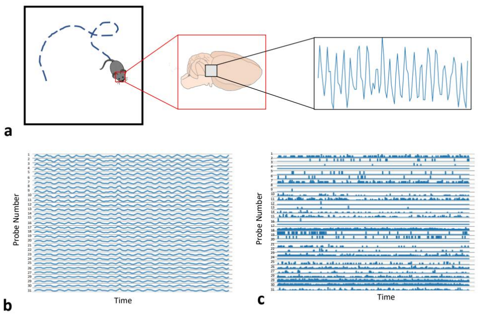
Abstract & Background

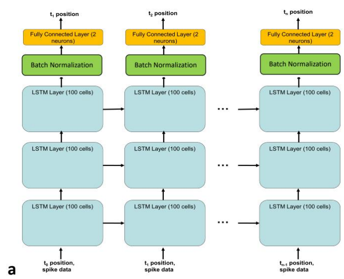
- Goal: Develop an LSTM model that inputs **local field potential (LFP) or neural spike data** from hippocampal neural recordings and **predicts X,Y position**
- Previous brain machine interface has been able to reconstruct motor intent for a limb using motor neurons.
- Hippocampus know to be involved in spatial navigation intent for the entire body -> important for controlling wheelchairs/walking
- Previous models have used control theory approaches such as Kalman filters to try to model Gaussian noise in neural data with limited success.
- Previous implementations of echo state networks worked well with cursor movement and eye motions.
- We seek to demonstrate a proof-of-concept LSTM model that can use hippocampal signals to decode movement intent.

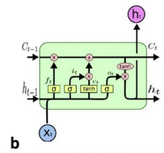
Dataset



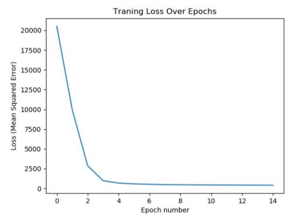
Data acquisition pipeline from open field foraging task. a. A Long-Evans rat explored a open field seeking water rewards while brain activity was electrical activity in the brain was monitored via shank probes. b. LFP from 32 probes plotted over 3 seconds. Characteristic 8 Hz theta waves were noted. c. Binned spike counts from probe locations over entire recording session.

Model





Overview of LSTM Model. a. A three layered LSTM model was constructed to process neural data with X and Y position predictions at each time point. b. Schematic version of a single LSTM node.



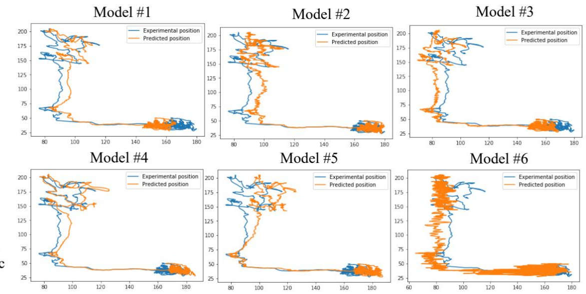
Loss declines over training. Mean squared error (MSE) was used for loss function as is common in BMI applications. Loss showed decline over training epochs.

Results

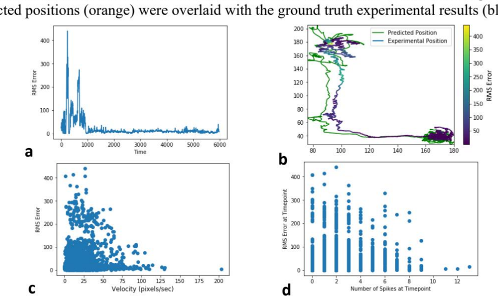
Model	Data Input	Layers	Sequence Length	Mean Squared Error	Avg Point Distance
1	Spike	3	100	78.852	0.288
2	Spike	2	100	20.803	0.465
3	Spike	1	100	101.076	0.734
4	Spike	3	20	40.577	0.243
5	Spike	3	5	49.257	0.4688
6	LFP	3	100	173.474	3.03

Summary of model architectures and results. Six models were constructed that varied the number of LSTM layers in the model, the sequence length (number of previous points inputted at each node), and data input (LFP or spike data). MSE and distance between points (measured of "jaggedness") were reported.

Results (cont'd)



Position Predictions from LSTM Models. Six models were trained and the resulting predicted positions (orange) were overlaid with the ground truth experimental results (blue).



Error Analysis from Model #2. a. MSE varied greatly over time. b. Error tended to occur along straighter potions. c. Inverse correlation between position and error ($R^2 = 0.4007$). d. Inverse correlation between spike at timepoint and error ($R^2 = 0.1401$)

Conclusions & Future Directions

- Model 2 and model 4 represented best accuracy as measured by RMS and "jaggedness" as measured by distance between points.
- Add term to punish jaggedness into loss function, use velocity instead of position
- Successful proof of concept for using hippocampal neural recordings for locomotive intent