**Comparison of Decoding and Encoding Methods for Motor Cortical Spiking Data**

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Experimental evidence suggests that external variables (such as position, velocity, forces, etc) are encoded in motor cortex.  One source of this evidence is the presence of cosine tuning during center out tasks where neurons are most activated when the subject is reaching towards a specific target.  This has been shown in several studies, including the study by Stevenson et al (2011), for which the neuronal activity of a monkey was recorded while performing a centre out reaching task.  Our study analyzed this data in order to further investigate the properties of the neural population.

Discrete Decoding:  Target location can be decoded from neuronal firing.  Here we present four methods (Bayesian and machine learning) and compare the success rates of each.

A Naïve Bayesian classifier (NB) predicted target location from neural firing rate following target onset. The firing rate in each direction for each neuron was assumed to be independent and Gaussian distributed.  The mean and variance for the probability of neural activity given direction were fitted to the training set and then, using Bayes rule and the assumption of independence, the probability of direction given neural activity was calculated. The NB had 70% prediction accuracy.

Three machine learning architectures were trained to predict the target location that the monkey was reaching toward using the firing rate of each neuron from each trial as input.  This involved the use of a Support Vector Machine (SVM), an Extreme Learning Machine (ELM), and an Echo State Network (ESN).  Each of these architectures project the input data onto a high dimensional state space which can be used to classify the firing rate input to its corresponding target location.  The SVM approach uses the kernel trick to transform the data to its state space, while the ELM and ESN are types of artificial neural networks whose hidden layer of neurons perform the transformation.  The ELM and ESN approaches use a simple and efficient training algorithm, where only the output weights are trained.  The SVM and ELM approaches contain no memory, while the recurrent properties of the ESN allow it to possess a short-term memory of the input it has been presented with.  All three architectures have been shown to offer high performance for a variety of tasks, hence the investigation of their performance for this neural encoding task.  Each architecture was trained on half of the trials and tested on the remaining trials.  The performance of the SVM, ELM and ESN were 85%, 67.5% and 64.5% respectively, indicating that the SVM was best suited for this task.  The short-term memory of the ESN may impede its performance for this task as the data contains little temporal current information (as the inputs are the spike rate).  Further investigation into the use of these techniques for this task as well as the use of spike trains or other temporal data as input data is the focus for future work.

Continuous Decoding:  Additionally, continuous trajectories can be decoded.  We fitted the parameters of a Kalman filter, assuming a Gaussian model of state space and error correction of observable parameters. For each of the of the test examples the Kalman filter decoded position and velocity of the trajectory.  The predicted kinematics are qualitatively similar to the actual hand kinematics.

Furthermore, electrode recordings with unsorted waveforms (multi-unit activity) improve the trajectory decoding of the Kalman filter.  Out of 196 recorded neurons 112 could not be reliably established as reliable single cell recordings.  To test if these signals made the Kalman filter less reliable the unreliable neurons were removed from the dataset and a Kalman filter with the remaining “good” neurons was constructed. Using this approach made the decoding less accurate. The accuracy was quantified as the mean squared error between predicated and true trajectory.  The mean squared increased with 50 percent with the exclusion of neural recordings from uncertain sources. Thus including neural data from ambiguous signals sources significantly improves the Kalman filter trajectory decoding.

Additionally, Kalman filter end position prediction is robust against change in the initial position. We observed that the predicted initial positions of the Kalman filter changed little between trials while the true initial position varied a lot. We tested the hypothesis that the trajectory decoding improved when the Kalmar filter had information about the true initial point. Simulations showed that even though the predictions of the modified and original Kalman filters started apart from each other, they converged to the same endpoint. Thus the endpoint prediction of the Kalman filter is robust against perturbations in initial position.

Neuronal Encoding: As well as decoding neuronal activity, we can explore what features are encoded in neuronal firing.  For the following analyses, the kinematic data were concatenated such that we had continuous position and spiking data.  The spikes were binned into 4ms bins so that each bin would contain either 1s or 0s, representing a Poisson process.  The position were fit with a cubic spline then resampled to 250Hz, and analytic first and second derivatives were found.

A Generalized Linear Model (GLM) was fit to three different sets of predictors: other neurons, kinematics, or other neurons and kinematics.  The spike trains of other neurons were convolved with a one-sided Gaussian (µ=1, σ=2) such that the receiving neuron could only receive spiking information from the past, and not the future.  The GLM outputs weights onto each of the inputs.  For training the GLM, the first 100000 bins (of 194602 bins) of continuous movement fitted to each neurons spiking.  The spiking was modeled as a Poisson process.  To estimate the quality of the fit, the GLM was used to predict firing patterns based on the second half of the data (94602 bins).  As expected, GLM outputs conditioned on spike trains contain high frequency components, and GLM outputs conditioned on kinematics relate the low frequency components.  Together, they can accurately predict a neuron’s firing.

Recent analysis of multi-electrode recordings in motor areas during reaches suggests the existence of stereotypic quasi-oscillatory population dynamics during movement following an extended preparatory phase. Here we investigated whether similar dynamics are present in the experimental data of Stevenson et al. (2011), in which monkeys performed less stereotyped reaches in the absence of an explicit extended preparatory phase. In a preliminary analysis based on the ‘jPCA’ method developed by Churchland et al. (2012) we find quite prominent rotational structure during reaches in M1 population dynamics, which disappears in a control analysis on shuffled neural responses. Hence, our results complement and extend the analysis of Churchland et al. (2012) and provide further evidence for a specific ‘rotational’ substructure in population dynamics during reaching.

Conclusion:  Thus, different methods can be used to answer different questions.  Bayesian and machine learning classification can decode which target the monkey is moving to with varied success.  Kalman filters are successful at decoding continuous position and velocity.  GLMs can explore which features a neuron encodes by predicting a neuron’s firing pattern from external covariates.  jPCA can be used to find higher dimensional structure in neuronal activity.  Each method has strengths and weaknesses, but here it is shown that they can be used a complementary techniques in order to further analyze the properties of neuronal behavior for a given task.  Further analysis of the results presented here is the focus of future work, as well as the use of related techniques which may reveal further interesting characteristics of the dataset under analysis.