JMLR: Workshop and Conference Proceedings 46:85–92, 2015 ECML 2014

Predicting Spiking Activities in DLS Neurons with Linear-Nonlinear-Poisson Model

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Editors: Demian Battaglia, Isabelle Guyon, Vincent Lemaire, Jordi Soriano

Abstract

Spike train generation in primary motor cortex (M1) and somatosensory cortex (S1) has been studied extensively and is relatively well understood. On the contrary, the functionality and physiology of the dorsolateral striatum (DLS), the immediate downstream region of M1 and S1 and a critical link in the motor circuit, still requires intensive investigation. In the current study, spike trains of individual DLS neurons were reconstructed using a Linear-Nonlinear-Poisson model with features from two modalities: (1) the head position modality, which contains information regarding head movement and proprioception of the animal's head; (2) the spike history modality, which contains information regarding the intrinsic physiological properties of the neuron. For the majority of the neurons examined, viable reconstruction accuracy was achieved when the neural activity was modeled with either feature modality or the two feature modalities combined. Subpopulations of neurons were also identified that had better reconstruction accuracy when modeled with features from single modalities. This study demonstrates the feasibility of spike train reconstruction in DLS neurons and provides insights into the physiology of DLS neurons.

Keywords: Spike Train Reconstruction, Dorsolateral Striatum, Motor Circuit

1. Introduction

1.1. Dorsolateral Striatum Single Body Part Neurons

Motor commands initiated by motor neurons in M1 descend to the spinal cord and result in the flexion or extension of their corresponding muscle groups. These motor neurons also send an efferent copy of motor commands to the DLS (corresponds to the dorsolateral caudate-putamen in human), the input structure for the basal ganglia. Similarly, the DLS receives inputs from S1. Information from the DLS is further relayed through globus pallidus, thalamus, premotor cortex and back to M1. This motor loop is thought to be involved in monitoring and providing feedback for ongoing movements (Alexander et al., 1986; Cohen et al., 2010). Moreover, a number of diseases involving motor or sensorimotor impairment, including Parkinson's and Huntington's disease, feature disrupted DLS function (Georgiou-Karistianis and Egan, 2011; Kordower et al., 2013). Thus, understanding DLS functionality

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may lead to new diagnostic and therapeutic methods for these diseases.
Previous studies discovered single body part correlated neurons (SBP neurons) in the DLS. These neurons are tuned to single body parts and specific movement features (e.g. distance, duration, velocity, and starting position) for that body part (Crutcher and DeLong, 1984; Crutcher and Alexander, 1990; Cho and West, 1997; Tang et al., 2007; Ma et al., 2013). Current methods for identifying movement correlates used in these studies involves defining movement features and categorizing movements according to those features. However, if movement features are incorrectly defined (i.e. not defined according to features the neurons are sensitive to), or if movements were categorized into categories that are too broad, a significant amount of information might be lost. To avoid this problem, the current study used the raw position data without arbitrarily defining movement features and applies a Linear-Nonlinear-Poisson Model to predict the neural activities in the DLS.

1.2. The Linear-Nonlinear-Poisson Model

The Linear-Nonlinear-Poisson Model (the LNP model) is commonly used to model the process of spiking activity. Ample studies have reported successes in predicting single neurons' activities in sensory neurons by the LNP model (up to 82% accuracy) (Schwartz et al., 2006; Pillow et al., 2008). The LNP model can simultaneously capture variables from different modalities that may influence the spiking activity of a neuron with high efficiency. Variables from two modalities are often considered when predicting spiking activities: (1) the extrinsic stimulus that the neuron may respond to or encode, (2) the spike history of the neuron. The LNP model first applies a linear filter (the linear part of the LNP) to the extrinsic stimulus and/or spike history. Then, the filtered responses are summed and exponentiated (the non-linear part of the LNP) to obtain an instantaneous spike rate. The instantaneous spike rate is the parameter of the Poisson distribution that determines spiking activity (Poisson part of the LNP). The parameters of the model were fitted with maximum likelihood estimation.
In the present study, head position record (extrinsic stimulus) and spike history data were used to predict spiking activities of individual neurons in the DLS, using the LNP model as classifier. The result of the study indicated that it is possible to predict spiking activity using the LNP model in the DLS, despite the fact that the DLS does not interact with extrinsic stimulus (the head positions) directly, but instead only receives information from primary motor and sensory areas. Also, results show that the head position record and spike history data contribute differently when predicting the spiking activities for individual neurons.

2. Methods

2.1. Data Collection and Preprocessing

The current study reanalyzed data previously published in Pawlak et al. (2010), where details regarding data collection can be found. Briefly, the dataset consists of extracellular single neural recordings of 47 neurons from 13 rats. All neurons were histologically confirmed to be located in the DLS. Recordings from these neurons lasted one hour, during which time the animals were walking on a treadmill and producing head movements primarily in the vertical direction. The position (x, y coordinates) of the animal's head was measured by

a video camera (60 Hz) facing the treadmill. The action potentials (spike train) were simultaneously recorded with 50 kHz sampling frequency.
The primary goal of the present study was to determine the feasibility of reconstructing the spike train, i.e. to predict whether or not a spike occurs in a short time interval, using head position and spike history data as predictors. An interval of 16.7 ms was used, since the position records of the head was obtained at a 60 Hz sampling rate. More specifically, the neural activity was binned into 16.7 ms intervals and then converted to binary and used as the outcome for prediction, such that equal number of observations for position record and neural activity were obtained for a given neuron.

2.2. Experimental Design

2.2.1. Predicting Neural Activity with Features from All Modalities

Firstly, features from both head position history ($\boldsymbol{hp}$) and spike history ($\boldsymbol{spkh}$) were used to predict neural activity at time t. For this analysis, position record m time bins before time t was used, i.e. hp_{t-m}, hp_{t-m+1},..., hp_{t-1}. Similarly, spike history data was used up to m time bins before, i.e. $spkh_{t-m}$, $spkh_{t-m+1}$,..., $spkh_{t-1}$. The LNP model is expressed as the following:

$$\lambda(t) = \exp(\boldsymbol{hp\_filter} \cdot \boldsymbol{hp}(t) + \boldsymbol{spkh\_filter} \cdot \boldsymbol{spkh}(t))$$

$\lambda(t)$ is the rate of the Poisson distribution that generates the spike at time t. $\boldsymbol{hp\_filter} \cdot \boldsymbol{hp}(t)$ is a linear projection of $\boldsymbol{hp}(t)$, the head position record m time bins before time t, onto the receptive field of the neuron, as defined by the linear filter for the head position $\boldsymbol{hp\_filter}$. Similarly, $\boldsymbol{spkh\_filter} \cdot \boldsymbol{spkh}(t)$ is $\boldsymbol{spkh}(t)$, the spike history m time bins before time t, convolved with the spike history filter.
Cross validation was utilized to select parameter m for individual neuron's individual data split. Data from individual neurons were split into splits of 10 minutes, resulting in 6 data splits that were consecutive in time. The model was first trained on data split s, performance was validated on split $s+1$, with $s \in [1, 2, 3, 4]$. Parameter m that resulted in the best performance, as measured by AUC, on the validation set was selected. AUC is the area under precision recall curve constructed by comparing the true occurrence of the spike vs. the instantaneous firing rate $\lambda(t)$. The LNP model was then retrained on data from split s and $s+1$. The resulting model was tested data split $s+2$. The average AUCs over the four testing sets was obtained for every neuron. In addition, permutation tests was conducted to determine whether the prediction performance on the testing sets were significantly better than random for every neuron.

2.2.2. Comparing Performances of Different Feature Modalities

The relative importance of different data modalities, i.e. head position and spike history, was then evaluated by constructing classification models with data from either modality separately. The training, validation and testing of the models was similar as described in Section 2.2.1. Permutation tests were conducted to determine whether the differences in AUCs between model using head position modality vs. model using spike history modality was significantly better than random.

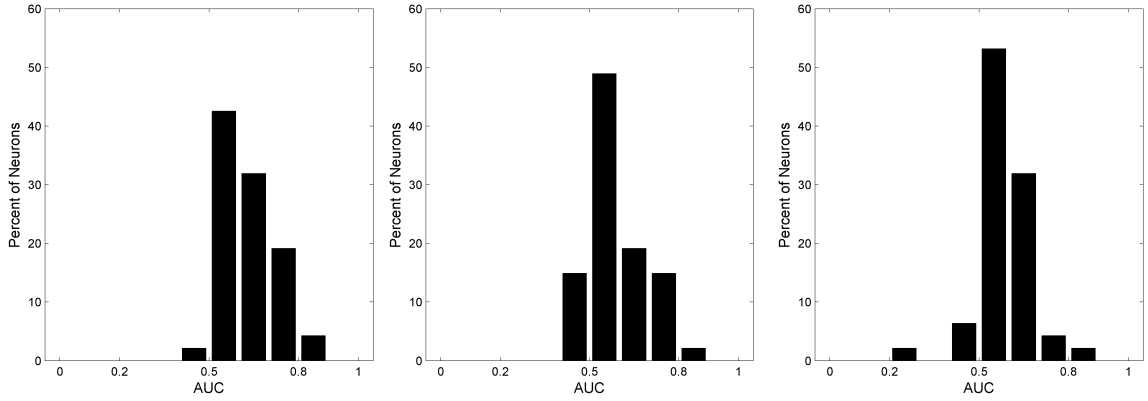
2.2.3. Comparing Performances of Single Modality vs. All Modalities

Lastly, the possible improvement of performance by combining features from multiple modalities was examined. AUC resulting from models using features from all modalities were compared with the best AUC resulting from models using features from any single modality. Permutation tests was conducted to determine whether the differences in AUCs was significantly better than random. The p values resulting from all permutation tests were FDR adjusted globally to correct for multiple comparisons.

3. Results

3.1. Predicting Neural Activity with Features from all Modalities

When using features from all available modalities, i.e. head position and spike history, significantly better than random AUCs were achieved in 44 out of 47 neurons. The distributions of average AUCs for individual neurons were shown in Figure 1(a). Notice that about 40% of the neurons have AUCs between 0.5 and 0.6, the majority of which were significantly better than random, indicating small yet significant signal.



(a) Head Position + Spike History (b) Head Position (c) Spike History

Figure 1: Distribution of AUCs predicted by Different Feature Modalities

3.2. Predicting Neural Activity with Features from Individual Modalities

In 32 out of 47 neurons, significantly better than random AUCs were achieved by models using features from head position modality. In 35 out of 47 neurons, significantly better than random AUCs were achieved by models using features from spike history modality. The distributions of AUCs for individual neurons were shown in Figures 1(b) and 1(c) respectively for models using head position features and spike history features.
The relative importance of the two feature modalities was also evaluated. This analysis was conducted in the 41 neurons that showed better than random AUCs predicted by features from either modalities. Out of the 41 neurons, 15 neurons showed significantly better performance predicted by features from head position modality and 13 neurons showed

significantly better performance predicted by features from spike history modality. The remaining 13 neurons did not show significantly different AUC between models using the two modalities (Figure 2).

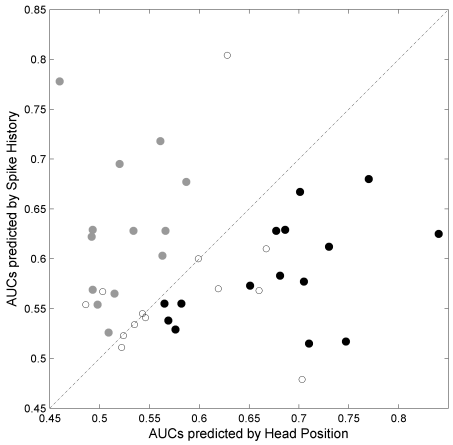


Figure 2: AUCs Predicted by Head Position Features vs. those Predicted by Spike History Features: Each dot represents one neuron. Open circles represent neurons with similar AUCs when predicted by head position features or spike history features. Grey dots represent neurons that have significantly higher AUCs predicted by spike history. Black dots represent neurons that have significantly higher AUCs predicted by head position.

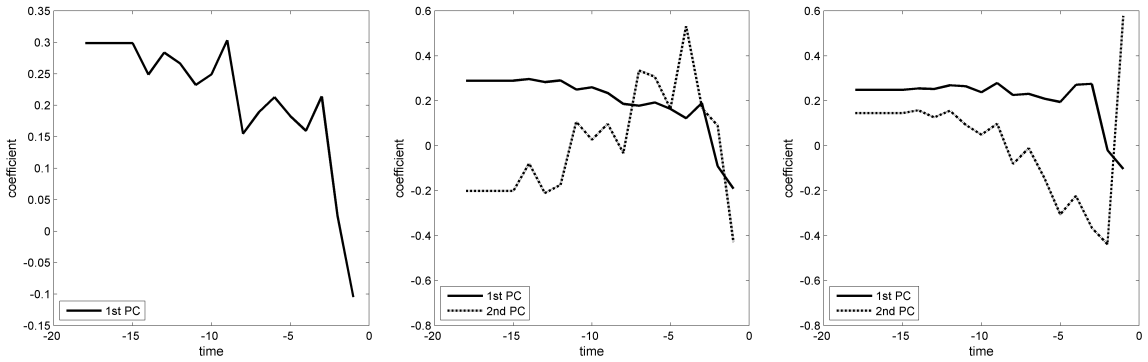
3.3. Comparing Performances of Single Modality vs. All Modalities Combined

There are a total number of 45 neurons that showed significantly better than random AUCs obtained from models using either single modalities or all modalities. Out of these 45 neurons, 9 of the neurons show a significant improvement in AUC when modeled with features from all modalities.

4. Discussion

The current study illustrated the feasibility of reconstructing the neural activity in majority of DLS neurons. One of the advantages of using the LNP model as classifier is that it implicitly keeps the temporal structure of the features, which is well-suited for time series data. Another advantage of the LNP model is that the linear coefficients of the model depict the typical sequences of head position or spike history leading to spikes. Principal component analysis was conducted on the linear coefficients of the LNP models for individual neurons to identify common patterns. Principal components (PCs) that explain more than 10% variability were plotted (Figure 3). The first PC for both horizontal (x coordinates) and vertical (y coordinates) head position indicates that one of the position sequence that triggers a spike is a abrupt movement in one direction (Figures 3(a) and 3(b)). For the vertical head position, the second PC indicates that a relatively slow movement with a change in

direction may trigger spikes(Figure 3(*b*)). For the spike history, the first PC indicates a relatively rapid change in spiking activity often precedes a spike, while the second PC indicates that a slow change in spiking activity followed by a rapid reversal in spiking activity often precedes a spike(Figure 3(*c*)).



(*a*) PC of Head Position Coef (x) (*b*) PCs of Head Position Coef (y) (*c*) PCs of Spike History Coef

Figure 3: The Top Principal Components of the Linear Coefficients

The current study identified subpopulations of neurons that primarily correlate with different feature modalities. The proportion of neurons that are identified to be correlated with head position history is higher (32 out of 47) when compared to traditional methods (less than 25%) which require categorizing movements according to some movement features (e.g. direction, distance, velocity, duration). Specifically, traditional methods examine neural activity for categorized movements and compare this activity to activity during both other movement categories or non-movement (baseline control). In this method, neurons are identified as movement related if their firing rates in one or more of the pre-defined categories are different when compared to the non-movement baseline. In contrast, the LNP model does not arbitrarily define movement features. Instead, the LNP model uses the raw data and maximun likelihood estimation to determine what head position sequences (i.e. movements) are most likely to result in spiking activity. Thus, the LNP model may be able to utilize head position data at its full resolution, leading to the identification of more head movement correlated neurons.

The current study failed to identify improvement in prediction performance in most of the neurons examined when using features from both modalities. It is possible that in some cases the two data modalities contain overlapping information (e.g. the spike history may encode the head movement history). Alternatively, it is possible that one of the modalities does not contain any information regarding the outcome (e.g. the neuron might not be related to the movement of the head, therefore incorporating the head movement history data does not help the prediction).

In conclusion, the current study demonstrated the feasibility of predicting the neural activity in DLS using the LNP model. Also, for individual neurons, the presnent data show that specific feature modalities contribute differently when predicting neural activity. The relative importance of feature modalities provide insights into the response characteristics of individual neurons.

Acknowledgments

The Authors thank Dr. Alexander Statnikov and Dr. Sara Solla for their constructive input in experimental design and Dr. Anthony Pawlak for providing the data. This work was partially supported by NRSA grant DA 032270 and Rutgers special study award.

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