This paper describes a novel method for estimating the sparse dynamical model of neural functional connectivity. This method combines the group Lasso and Laguerre expansion techniques to achieve model sparsity. It has been applied to the identification of neural functional connectivity of hippocampal CA3-CA1. Results show that the sparse model out-performs the full model estimated with the standard maximum likelihood method in terms of out-of-sample prediction accuracy.

I. INTRODUCTION

Modeling the functional connectivity of brain regions using spiking data is an important problem in neuroscience and neural engineering. This type of model is typically under-determined due to the large number of coefficients associated with the multiple inputs and the input-output dynamics. In order to yield reliable estimation and avoid overfitting, we have developed and applied a novel estimation method combining group Lasso and Laguerre expansion techniques.

II. METHODS

In this approach, functional connectivity between neurons is represented with a nonlinear dynamical MIMO model of spike transformation [1, 2]. First, Volterra kernels of the MIMO model are expanded with Laguerre basis functions (Fig. 1, Right). Thus, the system input-output property is represented with Laguerre coefficients $C$. Secondly, $C$ are grouped with respect the inputs and then selected with a group Lasso method, which includes a penalty term ($P$) that shrinks the coefficients within the group (i.e., $L_1$-regularization) and selects the coefficients at the group level (i.e., $L_2$-regularization; Fig. 1, Left). The resulting sparse model contains only the coefficients of the inputs that have significant effect on the output [3].

III. RESULTS

We have applied this method to model the hippocampal CA3-CA1 functional connectivity using spike trains recorded from those two regions in rats performing a memory-dependent behavioral task [1, 2]. The sparse models are estimated and compared with the full models estimated with the standard maximum likelihood estimation (MLE).

![Figure 1. Group Lasso estimation and Laguerre basis functions](image1)

![Figure 2. Performance of the sparse hippocampal CA3-CA1 models](image2)

Results show that (a) the sparse model contains less than half of the total coefficients; (b) it out-performs the full model in terms of the out-of-sample (i.e., model estimation and prediction are performed with independent datasets) mean negative log-likelihood (NLL; Fig. 2); and (c) the improvement of model performance becomes more significant when the training data in short (Fig. 2). In summary, this method effectively mitigates the overfitting problem caused by the large number of model coefficient.

REFERENCES

