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Analysis of spike train data: Discussion of results*

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Abstract: In this paper we summarize and comment on different techniques presented for analyzing spike train data.

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The neural spike train dataset makes for an interesting case study since the neural firing activity relates to underlying movement behaviors. Consequently, this dataset carries relatively more information in its phase components, compared to other datasets studied in this special section. This provides an opportunity for use of phase data as a dominant item, over the amplitude component, in driving inferences. The preceding data analysis papers display a wide range of techniques for: (1) phase-amplitude separation task, (2) clustering and classification of spike train data, and (3) modeling of separated phase and amplitude components. Noticeably, all the methods are able to successfully classify the spike trains into their respective action groups, highlighting the simplicity of the particular spike train dataset.

Patriarca et al. [4] solve a joint problem of alignment and clustering, focusing only on the affine group and its subgroups – shift and dilation – for alignment. More general nonlinear warpings are not allowed in this setup. The criterion for pairwise alignment is the coefficient of correlation between the given functions. They also provide a novel perspective on the problem by considering the data

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as periodic functions. In both the treatments, periodic and non-periodic, their method succeeds in classifying hand motion patterns.

Wu and Srivastava [5] describe a metric-based framework for alignment of signals using nonlinear warpings, and apply it to spike train data in two ways. (This metric is presented as an extension of the Fisher-Rao metric from the space of probability densities to larger function spaces.) First, they obtain phase-amplitude separation within each class and display the differences in components across classes. Second, they align functions across classes and use only the phase component to separate the classes. They also compare their alignment results with some other existing techniques.

Cheng et al. [1] extend this Fisher-Rao framework to *random* nonlinear warpings using a Dirichlet process model and set up a Bayesian inference problem that is solved using MCMC algorithm. This Bayesian perspective allows for a more comprehensive exploration of the alignment space and helps retains multiple solutions, and thus multiple interpretations, of spike train data.

Lu and Marron [3] also use the extended Fisher-Rao framework of [5] to separate phase and amplitude variability in two sets of spike train data – the real dataset used in this section and a simulated dataset taken from an earlier publication on this topic. After separating these components, the authors use functional principal component analysis (FPCA) and display top two coefficients for different classes. Using scatter plots, they show that the four classes are well separated in both the phase and amplitude space. They also highlight the ease of classification in this dataset by demonstrating the separation of classes in the original, unseparated data.

Hadjipantelis et al. [2] adapt an FPCA approach where they represent the phase and amplitude components by their coefficients with respect to functional principal bases, and impose a joint statistical model – a mixed effects model – on these coefficients. The problem of phase/amplitude separation is treated as a pre-processing step and is performed using the PACE library. The influences of principal components on individual paths are shown to be nicely separated into four classes.

We thank all the authors for their careful consideration and interesting analysis of the spike train dataset. We sincerely hope that this set of papers help create an interest in the statistics community for rich and novel data sources such as the neural spike train data studied here.

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