Overlapping spatio-temporal spike patterns in macaque motor cortex

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Spiking neural networks that perform on spike-time-based coding and computation schemes have been attracting interest of researchers [1, 2], since they are expected to enable faster, sparser and more energy-efficient information processing than the conventional, non-spiking neural network architectures. In computational neuroscience, the synfire chain [3, 4] was suggested as a model for spike-time-based brain processing. Since this model exhibits stabily propagating packets of synchronized spikes, the search for timed spiking activity in form of synchronous activity or spatio-temporal spike pattern (STP) in biological spike train data was initiated. However, due to a lack of a standard method to detect such signatures, previous reports are limited [5, 6, 7].
Here we suggest a STP detection and evaluation method that extracts the quality of STPs in terms of the unlikeliness of STPs based on the firing rates of individual neurons [**?**]. A formula for its computation is derived for stationary spike trains, and, in more general cases of non-stationary spike trains, it can be estimated from stochastic simulations or surrogate samplings of the original data. In this contribution, we report the application of this measure to datasets of $\sim$100 spike trains simultaneously recorded from the macaque motor cortex while the animal performed a reach-to-grasp arm movement task [9]. We found that the STPs of highest quality values are composed of only a small subset of the recorded neurons. Furthermore, these patterns often occured at the same timing overlapping each other, with spikes shared among different patterns.
We found such frequent occurrences of overlapping patterns intriguing and we are currently in the process of understanding the mechanisms underlying this phenomenon. We will also discuss their implications for spike-time-based computation, which may provide insights into the information processing in spiking neural networks, both biological and artificial.

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