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Sparse coding and dictionary learning for spike trains to find spatio-temporal patterns

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In biological neural networks, it is widely accepted that the spikes are the fundamental building blocks of information representation [1]. In contrast, whether such building blocks exist at a higher level in terms of time and in a population of neurons is a topic of ongoing debate. One approach for finding candidates for such building blocks is to seek for frequently appearing spike patterns in a population. These sequences are often called spatio-temporal patterns, cell assemblies, or unitary events [2-4]. They could metaphorically be considered as an “alphabet” of neural information processing [5,6]. Some patterns have already been found and are related to functional roles such as memory consolidation and gating of sensory inputs [7,8].

One difficulty in finding spatio-temporal patterns arises from observed spike trains being a superposition of multiple patterns. In signal processing, one commonly used method for decomposing the signal into patterns is dictionary learning for sparse coding [9-11]. Sparse coding expresses the input signal as a linear combination of a few template vectors taken from a matrix called a dictionary or codebook. In terms of linear algebra, sparse coding corresponds to finding a sparse vector x, which fulfills $y = Dx$, where y is the observed signal vector and D is a dictionary. When the dimension of × is much larger than that of y, it is possible to find sparse x. Each column of D is called an atom, which represents a template vector. A good dictionary decomposes the most of the observed signals into a small set of template vectors. In other words, D must sparsify not just one input vector y but many others as well. This is represented by using matrix Y whose column vectors are observed signals. In this case, sparse coding is represented by equation $Y = DX$. The goal is to find sparse matrix × given Y and D. Whether input matrix Y can be transformed into sparse × or not depends on dictionary D. The goodness of D depends on Y. The task of finding optimal D given Y is called dictionary learning. In this work sparse coding and dictionary learning were applied for finding spatio-temporal patterns from multivariate spike trains. Spike trains were transformed to vectors using binning, that is, converted to vectors of short-time firing rates. The methods were tested using different bin sizes. The results obtained for biological data showed possible candidates of spatio-temporal patterns in neural activity.

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