Analyzing Spike Train Similarity Measures: the Effects of Bursts and Silences

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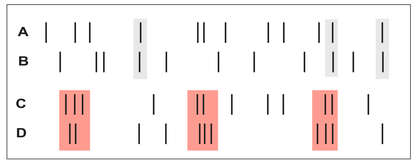
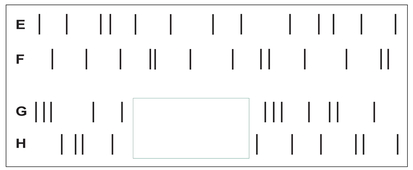
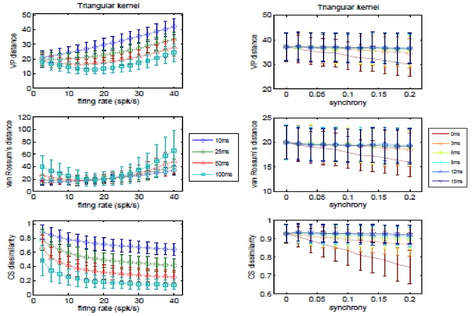
Introduction

- Spike train similarity measures address the question: How similar are two spike trains?
  - Why use them?
    - Quantifying reliability of single neurons
    - Identifying cell assemblies
    - Clustering, pattern discovery
- But what does it mean for two trains to be similar?





- Previous work has been shown the differences between some measures on the basis of firing rate and synchrony (figures reproduced from Antonio 2010):



- We utilize a different set of criteria for distinguishing between measures (bursts and silence), and propose a new technique for measuring spike train similarity

Methods

The following spike train similarity measures were analyzed:

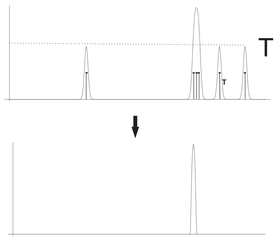
1. van Rossum metric [3] - convolve trains with exponential kernel, compute L2 distance.
2. Victor-Pupura Metric [1, 2] - cost based metric, costs assigned to adding/deleting spikes, moving spikes, distance between trains is the minimum cost.
3. ISI-Distance [6] - trains are mapped to functions that depend on the ISIs, Distance is the integral of the ratio of the ISIs over time.
4. Spike Correlation distance [8] - convolve trains with Gaussian kernel, compute correlation distance.
5. Event synchronization [7] - counts normalized number of synchronous spikes.
6. "Synapse-like" van Rossum variant [5] - van Rossum variant in which kernel width depends on the time since the last spike.

A New Similarity Measure

Burst Sensitive Component

Procedure:
1. Convolve trains with Gaussian kernel
2. Choose threshold T
3. Discard everything below T
4. Compute:

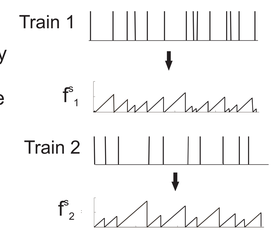
$$d_B(f_1,f_2) = 1 - \frac{\langle f_1,f_2\rangle}{\|f_1\|\,\|f_2\|}$$



Silence Sensitive Component

Procedure:
1. Map each train to a function that grows linearly between spikes but is reset to zero at each spike
2. Compute:

$$d_S(f^s_1,f^s_2) = 1 - \frac{\langle f^s_1,f^s_2\rangle}{\|f^s_1\|\,\|f^s_2\|}$$



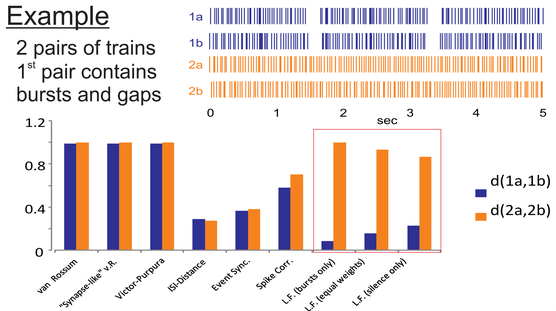
Combination

Combine into a single measure by taking the weighted average:

$$d_{Combined} = \frac{W_B * d_B(f_1,f_2) + W_S * d_S(f^s_1,f^s_2)}{2}$$

Example

2 pairs of trains
1st pair contains bursts and gaps

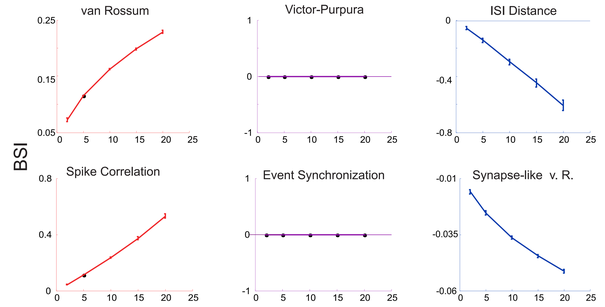


Testing Sensitivity to Bursts and Silences

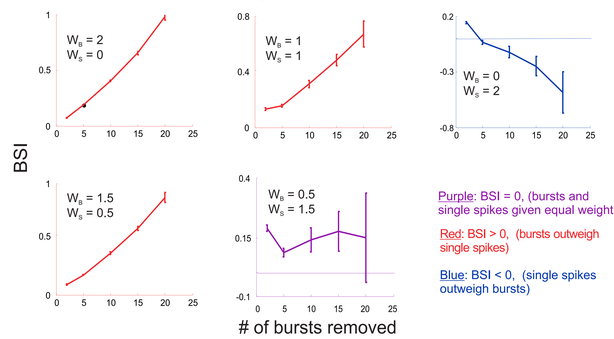
Measures responded to bursts vs. single spikes in 3 distinct ways

BSI = d(original, bursts missing) - d(original, spikes missing) (normalized)

Other similarity measures



New Measure (different weights)

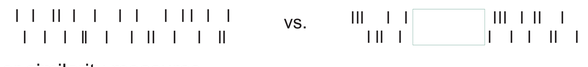


Purple: BSI = 0, (bursts and single spikes given equal weight)

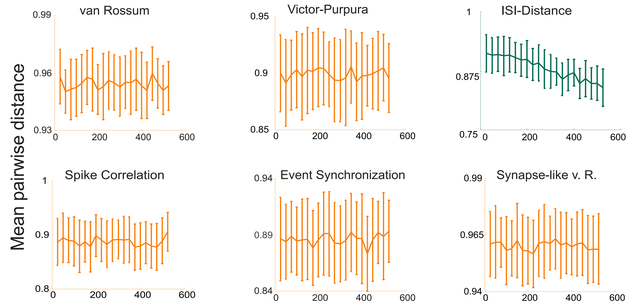
Red: BSI > 0, (bursts outweigh single spikes)

Blue: BSI < 0, (single spikes outweigh bursts)

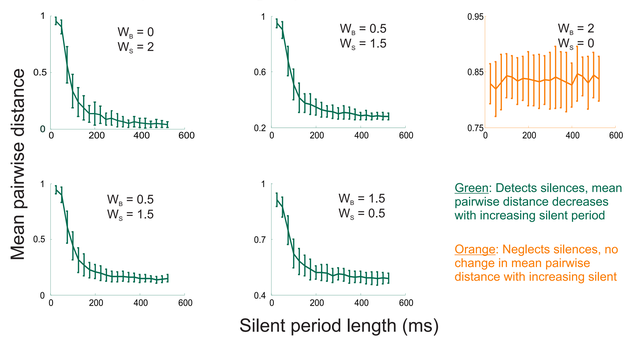
New measure is uniquely responsive to shared silence



Other similarity measures



New Measure (different weights)



Green: Detects silences, mean pairwise distance decreases with increasing silent period

Orange: Neglects silences, no change in mean pairwise distance with increasing silent

Conclusions

- We focus on bursts and silences because of their potential physiological importance, and the fact that their effect on spike train similarity measures has not been explored.
- Simple, empirical tests using surrogate data reveal important and intrinsic differences in the way existing spike train similarity measures respond to specific spike train features (bursts and silences).
- We propose a new spike train similarity measure that is sensitive to both bursts and silent periods.
- The parameters of our new measure are physiologically motivated and can be chosen based on the data.

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Acknowledgements

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