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An alternate burst analysis for detecting intra-burst firings based on inter-burst periods

David C. Tam*

Deptartment of Biological Sciences, University of North Texas, 76203 Denton, TX 76203, USA

Abstract

A time-scale invariant burst-detection algorithm for single-unit spike train is described. This burst analysis is an auto-adaptive algorithm that uses inter- and intra-burst intervals for identifying the burst itself. By using a self-adaptive algorithm, a burst is defined by the characteristic firing patterns within and between bursts. Bursts are detected by auto-adaptive method when the inter-burst periods (inter-spike intervals (ISIs) between bursts) exceed the intra-burst periods (the sum of ISIS within a burst). This adaptive method is time-scale invariant because bursts are defined by the firing patterns rather than the specific time scale of the bursts or ISIs.

Keywords: Spike train analysis; Burst firing; Burst detection

1. Introduction

In traditional spike train analysis, the focus is often placed on characterizing the statistics of spike timings and spike-to-spike interactions. There are many traditional spike train analyses that identify spike-to-spike interactions, such as the auto-correlation technique [1] and cross-correlation technique [2]. They establish the statistics based on interspike intervals (ISIs) and cross-intervals (CIs), respectively.

Yet, burst firing is often encountered in neural firings. Most spike train analyses often are not designed to characterize the statistics of bursts in relation to the spike-firing patterns. Although there are many burst-detection algorithms, the definition of bursts is often dependent on the detection algorithm itself. Thus, different burst-detection methods may characterize the system differently. So it is important to apply different

* Tel.: +1-940-565-3261; fax: +1-940-565-4136.
E-mail address: dtam@unt.edu (D.C. Tam).

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burst-detection methods to the spike train so that the significance of the burst patterns may not be missed by any analysis. Furthermore, "bursts" are often subjectively perceived traditionally, depending on the time scale of the bursts observed by the experimentalists. Thus, a time-invariant burst-detection algorithm is important for objective analysis.

Since there are many different types of bursts and burst patterns, it is also important to use a self-adaptive algorithm for the detection rather than using some pre-defined burst patterns as the criteria. This paper describes a self-adaptive spike train analysis that detects burst firing in neurons. Since burst firing is a phenomenon that is often defined qualitatively rather than quantitatively, because there are many different definitions of "burst" depending on the burst-detection method used. Thus, a burst extracted by one method may not be the same as the burst detected by another method, such as the "surprise measure" for identifying the spike intervals that exceed the chance occurrence of spikes and/or other ad hoc methods for defining bursts.

There are many different spike train analyses that are used to detect bursts. A correlation analysis was introduced to detect the interaction between spike firing in one neuron and the burst firing in another neuron [4], similar to the detection of the contribution of doublet firings in one neuron to the spike firings in another neuron [3]. This analysis is a cross-correlation analysis between two neurons' firing, while the present burst-detection analysis is a single-neuron analysis. Thus, this burst-detection algorithm is entirely different from the previous method by Tam (2001) in many respects. The inter- and intra-burst information is used to define the bursts rather than using the probability of consecutive firings as the criteria in previous methods.

2. An alternate definition of burst

This paper will provide an alternate self-adaptive statistical measure to detect burst firing. We use an alternate definition to define a "burst" based on the *sum of firing intervals within the burst*. Before we define a "burst" quantitatively, it is easier to define the *duration* of a "burst" by the sum of the ISIs within that burst (see Fig. 1). An ISI is defined as the time interval between consecutive spikes. This is the conventional definition of a "burst-duration" even though it seems to be a circular definition.

Given the above burst-duration definition, we can now define a burst based on the inter-burst interval (see Fig. 1). An inter-burst interval is basically an ISI in the conventional sense that is relatively long compared to the burst duration. This is the qualitative definition that most neuroscientists seem to adopt conventionally.

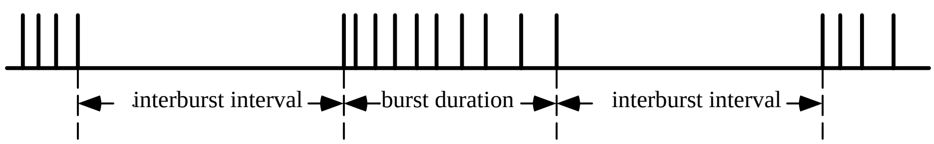

Fig. 1. Definitions of burst duration and inter-burst interval.

3. The alternate theoretical definition of burst

We will now quantify this qualitative definition quantitatively by the following:

Let I_i represents the ith interspike interval in a spike train (see Fig. 2). A burst is defined by the burst duration, $B_{i,k}$, as follows:

$$B_{i,k} = \sum_{k=i+1}^{j} I_k, \quad \text{if} \sum_{k=i+1}^{j} I_k < I_i \quad \text{and} \quad \sum_{k=i+1} I_k < I_{j+1}. \tag{1}$$

In other words, if the *burst duration* for any consecutive sum of j ISIs is *less than* the *preceding ISI* or the *succeeding ISI*, then a burst is defined within that burst duration. Otherwise, the consecutive sum of j ISIs does not define a burst, if the sum is greater than either preceding or succeeding ISIs. This provides a self-adapting algorithm independent of the number of spikes within the burst or other probability measures.

4. Advantages of this alternate burst definition

This alternate definition of burst becomes a *self-adaptive* measure in which the bursts (and burst durations) are defined by the delimiting ISIs (i.e., the inter-burst intervals before and after the burst).

It does not require any a priori or ad hoc burst-detection parameters, such as the number of spikes within a burst, the burst duration in millisecards or other "surprise measure" of unexpected deviation from chance occurrence of spikes within the spike train.

It does not require any specific firing pattern to determine the burst characteristics other than the criteria used to define burst duration based on the inter-burst intervals before and after the hypothetical burst. If the criteria are not satisfied, then the cluster of j spikes is not considered as a burst.

This burst definition is also time-scale invariant. That is, a burst is defined by the relative time intervals within the intra- and inter-burst intervals locally. No specific ad hoc ms time-scale parameter is imposed on defining whether it is a burst or not.

Furthermore, the total number of spikes within a burst is also a self-adaptive measure based on the local relative timing information rather than an artificial number of spikes (parameter) imposed by the observer used in the burst-detection algorithm.

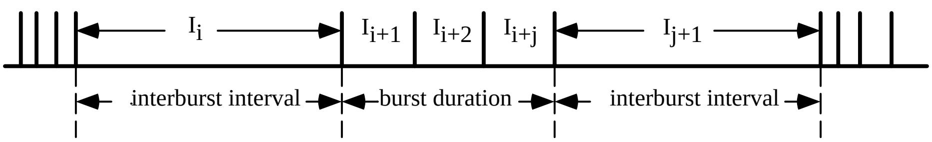

Fig. 2. Definitions of burst and (ISI).

5. Disadvantages of this alternate burst definition

As with other burst-detection algorithms, there are disadvantages for each method. This alternate definition of burst does not take into account the local firing pattern within a burst. In other words, the intra-burst spike patterns are degenerate using this algorithm. It is because only the *sum* of the ISI within the burst is used as the criterion rather than the intra-burst spike patterns.

Nonetheless, the specific intra-burst spike patterns are often ignored in other burst-detection algorithms. Most burst-detection methods detect the duration and presence of a burst, but not the intra-burst spike patterns, because the focus of interest is burst detection rather than burst classification.

It is beyond the scope of this paper to classify different burst patterns, since we are introducing a novel method for burst detection. We will address burst classification in our subsequent papers.

6. Results

To test the validity of our burst definition, we simulated a set of spike trains using different criteria for generating the burst-firing patterns. We applied this self-adaptive burst-detection algorithm to detect the presence of bursts (or non-bursts), the onset time and the duration of the bursts.

We also changed the time scale of the spike trains using the same sequential firing pattern to test if our burst-detection algorithm can detect bursts that span different time scales.

Simulation results show that this burst-detection algorithm can detect the presence of bursts, the onset time, and the duration of bursts in a self-adaptive manner without any externally imposed burst-detection parameters.

The results also show that the algorithm can detect bursts that span different time scales independent of the intrinsic spike-firing ISIs within the burst (intra-burst intervals).

7. Conclusion

The proposed burst-detection method and burst definition provide a robust way to detect the presence of bursts, onset time and their duration. This definition is consistent with the qualitative, intuitive definition of bursts used by most neuroscientists. This burst definition allows neuroscientists to quantify the presence of bursts that is consistent with the intuitive burst definition.

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David C. Tam is an associate professor at the University of North Texas. He holds a Ph.D. in physiology, and three B.S. degrees in computer science, physics and astrophysics, all from the University of Minnesota. His current research interest is developing statistical multiple spike trains analysis techniques and applying these analytical methods to both simulated and experimental neurophysiological data to understand the signal processing functions of the central nervous system (CNS) as well as extracting the encoding schemes used by the CNS.