Burst detection in neuronal activity

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***Abstract*— Neurons in the brain fire action potentials or spikes to encode information and communicate with each other. The firing can be in tonic mode, where individual spikes are emitted at relatively distant time intervals, and in burst mode, where neurons typically fire trains of spikes in short temporal succession. Functionally, neuronal bursts may be involved in reliable information transmission or specialized information encoding schemes. Understanding the dynamics of neuronal burst activity plays a crucial role in unravelling the complex mechanisms underlying neural information processing. However, detecting bursts in extracellularly recorded neural data is far from trivial. There are many methods for burst detection, but none was adopted universally, and they are based exclusively on the evaluation of spike times. This article aims to compare these burst detection algorithms against each other from several perspectives in order to establish the most suitable and robust one. Moreover, we propose a novel burst detection method considering additional features that contain as much information as possible from the recording.**

Keywords*— *burst, superlet, spectrogram, correlation.

I. Introduction

A. The detection of bursts

There are multiple approaches for burst detection, but none of them have been fully adopted in the field. This is believed to be due to the fact that many algorithms require the adjustment of multiple parameters and additional criteria to produce satisfactory results.

Some of the considered methods are: ISIn [1], ISI Rank threshold [2], Max Interval [3], Cumulative Moving Average [4], Rank Surprise [5], and Poisson Surprise [6]. These methods only utilize the timestamps at which action potentials occur, resulting in a loss of valuable information contained in the signal. Our goal was to develop a method that considers the criteria of burst characteristics established in the literature while also exploiting as much information as possible that is available in the recording. By considering additional features, we aim to increase the performance of distinguishing between bursts and superposed action potentials.

The main challenge lies in distinguishing between action potentials close in time originating from different neurons (also known as superposition in cases where there is no apparent refractory period) and consecutive action potentials generated by the same neuron within a small timeframe, called bursts. This problem can be addressed by attempting to differentiate between the shapes of action potentials of distinct neurons through frequency-domain correlation. Another challenge is to preserve as much information as possible from the signal in order to enhance the performance of burst detection.

A burst is defined as a short period of high-frequency occurrence of spikes, interspersed with periods of low-frequency tonic activity [1]. Burst detection algorithms can be divided into two main categories, however all of these methods make use of only the spike times in order to determine whether a burst occurred. The first type, based on rate-threshold, considers firing rates and involves setting a threshold to monitor whether the neuronal activity (measured by firing rate) exceeds the threshold and if it does, it is considered a burst. The second type, based on inter-spike interval (ISI), considers a specific time interval between consecutive action potentials. If the time interval is shorter than the set threshold, a burst is considered to have occurred. Therefore, these methods are based on the computation of statistical characteristics of the data and the use of manual or calculated thresholds to identify bursts.

In the next section we describe and analyze the most common burst detection methods and introduce a feature extraction method that adds information to the traditional time-based features used in burst detection. Furthermore, we propose a burst detection method that incorporates supplementary biological characteristics in the identification of bursting activity and a set of analyses based on correlation to assess the performance of a burst detection method.

B. The acquisition of data

In vivo electrophysiological data was recorded from the visual cortex of anaesthetised adult mouse using 32-linear probes (Cambridge NeuroTech) at 32 kSamples/s (Multi Channel Systems MCS GmbH) during a visual perception task with full-field drifting gratings. All animals subjected to in vivo extracellular recording experiments were anaesthetised using isoflurane and placed in the stereotaxic holder. Heart rate, respiration rate, body temperature and pedal reflex were monitored throughout the experiment. Multiple datasets were recorded over an interval of 4 to 8 hours from each animal to minimize the number of animals used and to ensure their welfare. This approach demonstrates a commitment to minimizing the number of animals needed for experimentation while ensuring the acquisition of reliable and meaningful data.

The experimental procedures and protocols underwent review and approval by the Local Ethics Committee (approval number 3/CE/02.11.2018) and the National Sanitary and Veterinary Authority (approval number

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ANSVSA 147/04.12.2018). The experiments were carried out in accordance with the ethical guidelines specified in the European directive, as well as the guidelines established by the Society for Neuroscience and the Romanian laws governing the protection of animals. The experiments were conducted in strict accordance with ethical guidelines and regulations, including the European Communities Council Directive 86/609/EEC, directive 2010/63/EU of the European Parliament, and Romanian Law 43/2014. These guidelines ensure the ethical treatment and protection of animals involved in scientific research.

II. Related Work

A. *Burst detection methods*

The ISIn algorithm takes as input data the timestamps sorted in ascending order. A number *n* of successive potentials is selected to be analyzed. For example, if *n* is equal to 2, the algorithm will analyze the time interval between the first and second action potential. This parameter determines the sensitivity of the algorithm. The algorithm can be adjusted through the parameter *n* and the threshold value. The ISIn method may struggle with multi-channel data that displays irregular activity [1].

The ISI Rank Threshold (IRT) takes as input data the timestamps that indicate the moments at which action potentials occur, sorted in ascending order. The threshold is set in such a way that the probability of observing a number of peaks greater than the threshold is lower than a specified limit probability. Bursts are detected when the rank of the ISI is below the threshold indicating a transition from the inter-burst period to the burst event. This method was introduced as a heuristic technique for unsorted spike data, and it was shown to have a poor performance in the detection of bursting activity of different types.

The Max Interval (MI) algorithm requires several parameters such as the maximum start interval of ISI, the maximum end interval of ISI, the minimum inter-burst interval (IBI), the minimum burst duration, and the minimum number of action potentials in a burst. These thresholds determine the characteristics of the bursts to be detected. The algorithm iterates through the timestamps and checks certain parameters. The last check is to iterate through these obtained bursts and check if they meet the conditions of the minimum burst duration and the minimum number of action potentials. If they do not meet these conditions, they will not be considered as bursts. The greatest disadvantage of MI is the large number of parameters which may be difficult to regulate, however the parameters can be easy to interpret biologically which eases their use.

The Cumulative Moving Average (CMA) method is based on the cumulative sum of the inter-spike intervals (ISIs) within a sliding window to identify bursts. The data consists of a sequence of timestamps indicating the moments at which action potentials occurred. The time interval between action potentials is calculated by subtracting consecutive timestamps. Parameters are defined for the size of the sliding window and the threshold. The CMA method may detect more bursting activity than it exists in recordings with unstable firing rates.

The Rank Surprise (RS) algorithm is based on the idea that bursts are characterized by an increased firing rate of a neuron, which can be detected by analyzing the probability distribution of ISIs. Rank Surprise is based on the values of the inter-spike interval rather than the firing rate. Using this distribution, a fixed threshold for a maximum value of ISI is computed and this threshold is used to find sequences of spikes that contain lower ISIs and that maximize the surprise statistic. Any sequences that rise above the given surprise value are considered bursts. The RS method may assign, independent of the spike distribution, the same amount of spiking activity [7].

The Poisson Surprise (PS) method is based on the idea that bursts are characterized by an increase in the firing rate of a neuron and that neuronal spiking follows a Poisson distribution. The algorithm computes the probability that a number of spikes can occur in a certain time interval given a Poisson process. Possible bursts are identified as sequences of spikes containing ISIs smaller than the mean ISI. These possible bursts are then modified to include neighboring spikes in order to maximize the surprise statistic, if any fall below the given threshold for the surprise value, they are discarded. The PS method may merge bursting activity that other methods consider to be separate or include more spikes than other methods [7].

These methods belong to the two types of detection algorithms, namely ISI or rate-threshold. Cumulative Moving Average, ISIn, ISI Rank Threshold, Poisson Surprise, and Max Interval are based on ISI, while Rank Surprise is based on rate.

The use of multiple burst detectors and comparing their results may be a robust approach to burst detection [8]. By analyzing the data with different burst detection methods and comparing their results, researchers can gain a better understanding of the bursting activity present in experimental data. The agreement of several detectors would increase confidence in the presence of bursting activity. This convergence of results across multiple methods provides a stronger validation of the identified bursts. However, major discrepancies between the methods may indicate areas of poor performance of certain detectors. These discrepancies can be further investigated by examining the specific spike trains of interest, allowing researchers to understand the reasons behind the variations and potential limitations of certain burst detection techniques. A more detailed analysis of the above-mentioned methods is provided in section IV.

B. *Superlet*

In [9] a new transform is introduced, namely the Superlet transform, that addresses the limitations induced by the Heisenberg-Gabor uncertainty principle to the Fourier Transform and Continuous Wavelet Transform. These methods optimize either temporal or frequency resolution, finding only a suboptimal trade-off between the two. To address these limitations, the Superlet transform was developed, which allows for super-resolution in both time and frequency domains. This transform geometrically combines a set of wavelets with progressively narrower bandwidths.

A Superlet was defined as a set of Wavelets with a fixed central frequency that covers a range of different cycles (progressively narrowing the bandwidth). It is defined in Equation (1), where f is the fixed central frequency, o is the order number, and $c_1, c_2, \ldots, c_o$ represent the number of cycles for each Wavelet. The order number corresponds to the number of Wavelets in the set. The number of cycles that define the Wavelets in the Superlet can be chosen in two ways: multiplicatively or additively. Typically, the multiplicative mode is used, meaning $c_i = i * c_1$ [9].

$$SL_{f,o} = \{ \Psi_{f,c} | c = c_1, c_2, \ldots, c_o \} \tag{1}$$

The response of a Superlet to a signal x is defined as the geometric mean of the individual responses of each Wavelet in the set. This response is mathematically described in Equation (2), where $R[\psi_{f,ci}]$ represents the response of Wavelet i to the signal and is described by Equation (3), where the * operator denotes the complex convolution operator [9].

$$\mathrm{R}[SL_{\mathrm{f,o}}] = \sqrt[o]{\prod_{i=1}^{o} R[\psi_{\mathrm{f},c_i}]} \tag{2}$$

$$R[\psi_{\mathrm{f},c_i}] = \sqrt{2}\, x * \psi_{\mathrm{f},c_i} \tag{3}$$

III. PROPOSED APPROACH FOR BURST DETECTION

In order to detect bursts and use as much of the information from the signal as possible, the steps that were followed are data preprocessing, finding burst candidates by using specific characteristics, applying the superlets and exploring their Pearson's correlation coefficients. The exact flow of steps of the proposed method is shown in Figure 1.

The data preprocessing extracts from the recorded signal the information of interest. The first step is to filter the signal in the range of 300 to 7000Hz where the spiking activity is found [10]. As bursts are composed of spikes, the next step is to identify singular spikes by an amplitude threshold, usually set to the standard deviation of the signal multiplied by a constant value between 3 and 5 [10]. By extracting the individual spikes, the detection and extraction of candidates for bursting activity can commence.

The Superlet transform provides the time-frequency power spectrum of a signal, transforming the one-dimensional information of the signal into two-dimensional information of a time-frequency spectrum.

Our hypothesis was that the statistical analysis of the correlation coefficient may provide the distinction between the sub-spikes of a burst and the tonic activity, due to the fact that the shapes of the sub-spikes in a burst are similar as they originate from the same neuron. Because of the similarities among spikes within the same burst, the expectation was for them to exhibit a higher correlation. This would allow the separation of bursting activity from tonic activity with the use of a threshold.

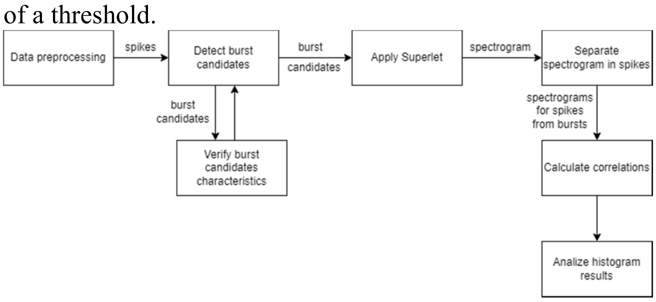

Figure 1. Diagram presenting the flow of operations used in the detection of bursts in the proposed method.

A. Burst characteristics

A burst represents a signal composed of multiple spikes fired in short succession by the same neuron. An important characteristic is the time interval between two consecutive spikes (action potentials) within a burst. This is used in ISI-threshold algorithms. In the literature, this interval varies between a minimum of 2-3ms and a maximum of 7-9ms [11]. The analysis of the time interval between spikes is therefore crucial in burst detection.

Several other characteristics are discussed in the literature, such as the neuron's inability to discharge spikes of the same amplitude within a burst, or the fact that the neuron does not return to the resting state. As a result, consecutive action potentials within a burst will lose amplitude [12]. One way in which bursts can occur is through a slow depolarizing mechanism that halts the repolarization of a neuron and the initiation of the refractory period in order to maintain the generation of consecutive spikes that constitute a burst. The slow depolarization can be caused by specific ionic currents, such as the T-type calcium current. Signals that do not meet these conditions will not be considered as burst candidates. There are many other characteristics that have not been addressed, such as returning to the resting state after the discharge of an action potential or the neuronal activity between consecutive action potentials.

In our approach, burst candidates are identified by iterating through the signal and finding peaks that exceed the threshold (usually in the negative potential direction). The distance between peaks is configurable. Based on the literature we have chosen the 2 to 7ms interval. In Figure 2, the red dots are the peaks, and they were extracted by finding local minima on a neighbourhood of ~0.3ms. In addition, we imposed that the values of the peaks of each subsequent sub-spike within a burst must have a higher value than the preceding one (decreasing amplitude).

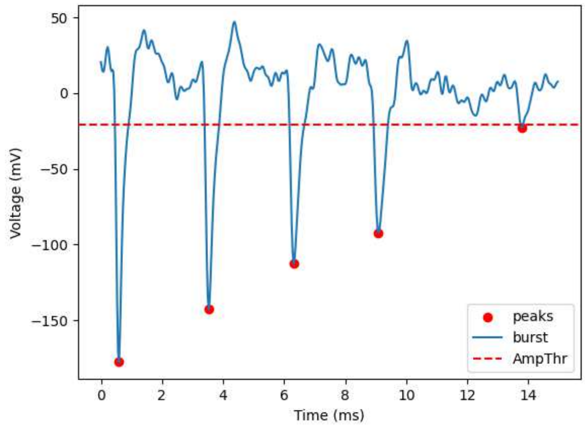

Figure 2. A burst candidate extracted from real data by the proposed method, the blue line represents the signal, the red dots show the peaks of spikes, and the dashed red line represents the amplitude threshold used in the detection of spikes.

B. Verifying requirements

Histograms were used to verify if the characteristics specified in section A are met by the detected burst candidates. To verify that the identified spikes are not noise, their duration was examined. It can be seen in figure 3 that their width is between 0.6 and 2ms, which are indeed the widths that spikes present in real data. Another condition for a burst is that it has to contain at least 2 spikes. In Figure 3 it can be observed that the burst candidates contain between 2 and 7 spikes. Additionally, in Figure 3 it can be observed that the inter-spike interval (ISI) ranges between 2 and 7ms.

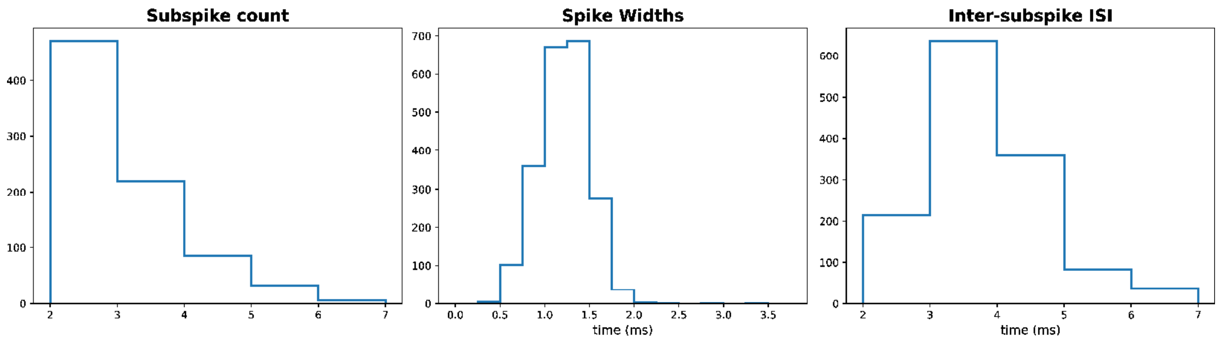

Figure 3. The left panel presents the distribution of sub-spike count of bursts, the middle panel presents the distribution of spike widths, whilst the right panel inter-sub-spike intervals of the sub-spikes present in detected bursts.

C. *The Superlet Transform*

This technique allows us to extract time and frequency information simultaneously and enables for a better characterization of a burst, burst candidate, or spike.

To obtain the spectrum, the following parameters were used: order 2, 1.5 number of cycles, and a sampling frequency of 32000. The spectrum is visualized within the frequency range of spikes of 300 Hz to 7000 Hz. These parameters were found to be optimal for the classification of spikes [13]. Figure 4 shows an example of the spectrogram obtained by the Superlet transform and its corresponding burst signal.

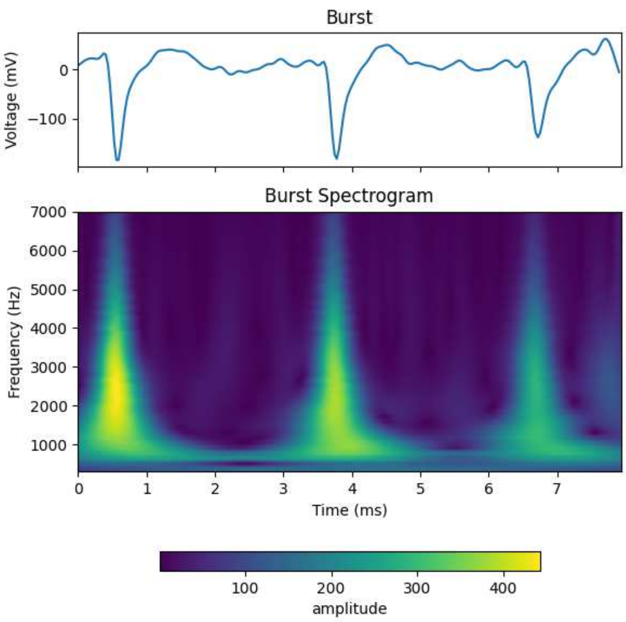

Figure 4. Spectrogram of a burst candidate, extracted from real data by the proposed method, containing three sub-spikes.

D. *Spectrogram separation into sub-spikes*

The burst candidate spectrogram needs to be divided into smaller spectrograms specific to each spike in order to allow the analysis of individual sub-spikes within bursts and enable the calculation of the correlation. By examining sub-spikes from the same channel and comparing with sub-spikes from different channels located at a relatively large distance, we computed the distributions of the expected correlations between spectrograms of spikes from the same and from different neurons. Because at a large distance, it is very unlikely to record spikes from the same neuron, across channel correlations give us the expected value of correlation between spike spectrograms of different neurons. The distribution of correlations between spectrograms of spikes within channels should in principle have a larger expected value than that of correlations across distant channels.

To split the spectrograms, our initial approach was to divide the signal first and then generate spectrograms for each segment. However, this approach is flawed because abrupt transitions at the edges of the signal can generate border effects that distort the spectrogram's edge. One solution to mitigate the border effects is to pad the signal with zero values or gradually transition towards zero from the last value. However, this solution is computationally more expensive compared to calculating the spectrogram for the entire signal, where there are no border effects, and then selecting the sub-matrices of interest afterward. In Figure 5, we show the separation of the burst candidate shown in Figure 4 into its sub-spikes.

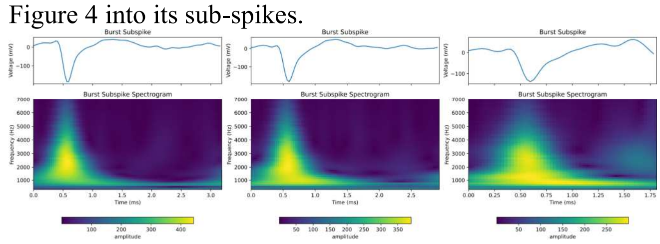

Figure 5. The separation into sub-spectrograms of the burst candidate shown in figure 4 for each sub-spike of the burst candidate.

E. *Correlation Analysis*

Another problem we had to solve is that the separation of burst candidates into spikes based on local minima results in action potentials of different lengths, which consequently leads to spectrograms of different lengths, leading to a different number of columns.

To calculate the correlation coefficient between two spikes, we need spectrograms of the same size so that the correlation will result in a single value. The method used to separate burst candidates based on the indices of action potentials results in spikes and spectrograms of different sizes. This problem is resolved by truncating the spectrogram of one or both action potentials. The duration from the beginning of the spectrogram to the column representing the peak of the action potential, as well as the duration from the peak column to the end, is calculated. The spectrogram(s) are then cropped accordingly, so that both have the shorter duration of either spectrogram before and after the peak. This ensures that the spectrograms being analyzed are of equal size, facilitating the calculation of correlation coefficients.

Several types of correlation analyses have been made on the sub-spikes of burst candidates from single-channel and multi-channel perspectives. We have considered the correlation as adequate to indicate the correctness due to the characteristics of bursts. Spikes of the same neuron will have similar shapes [10] and as bursts are the spiking activity of a single neuron in a small timeframe, it is to be expected that the correlation of intra-burst spikes to be higher than the correlation between intra-burst spikes and tonic spiking activity. Furthermore, the correlation coefficients were calculated for sub-spikes originating from bursts on the same channel, as well as from bursts on different channels at a distance. As distant channels will record the activity of different neurons, it is to be expected that the bursts found on a channel by any burst detection method will have higher correlation coefficients than the bursts of different channels as they present the activity of different neurons. After calculating the coefficients, the distribution of values is analyzed using histograms that have been normalized into Probability Density Functions (PDF) through division by their sum. The PDF was chosen as it provides comparable distributions.

IV. RESULTS

A. *Analysis of burst detection methods*

In order to compare the burst detection algorithms (ISIn, ISI Rank Threshold, MaxInterval, Cumulative Moving Average, Rank Surprise, and Poisson Surprise), two metrics were used: the true positive percentage (the number of action potentials correctly identified as part of bursts and labeled as bursts, divided by the total number of action potentials labeled as bursts) and the false positive percentage (the number of non-burst action potentials incorrectly identified as bursts, divided by the total number of action potentials in bursts).

These metrics measure how well the algorithms perform in terms of correctly detecting bursts (true positives) and incorrectly identifying non-bursts as bursts (false positives). The synthetic data [7] used to analyze these methods is comprised of labelled simulations of 300 seconds that allow for the measurement of correctness of the methods. Multiple types of data were created, the non-bursting and non-stationary types of data do not contain any bursts, while the regular, long, high frequency and noisy types contain bursts. Each data type contains 100 examples of spike trains. In Figure 6, we show one spike train of each data type.

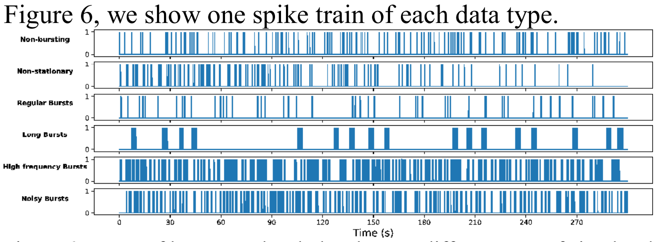

Figure 6. Types of bursts, each subplot shows a different type of simulated data indicated by the label on the left of each subplot. The data is composed of timestamps and as such 1s indicate activity and 0s no activity.

Each method was analyzed with the parameterizations suggested in the corresponding articles and the metrics were calculated for each type of data. In Figure 7, we present the true positives for each data type as a panel, and the x-axis indicates the method, the same layout is used for false positives presented in Figure 8.

By analyzing Figure 8, it can be observed that the methods do not, generally, misidentify non-bursting activity

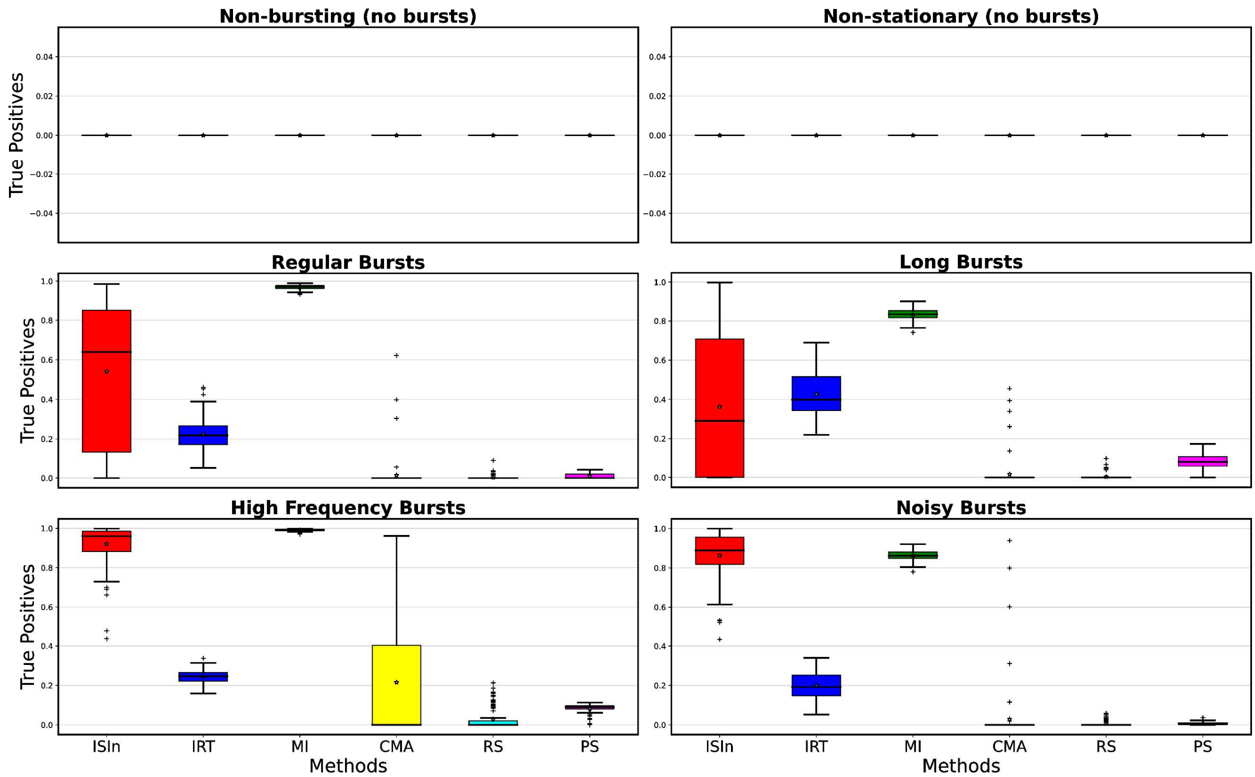

Figure 7. True positive percentage, each subplot shows the evaluation on the percentage of true positives (ranging from 0 to 1) found in a specified data type (indicated by the subtitle) by each method (indicated on x-axis labels).

as bursts. For high-frequency bursts, long bursts, and regular

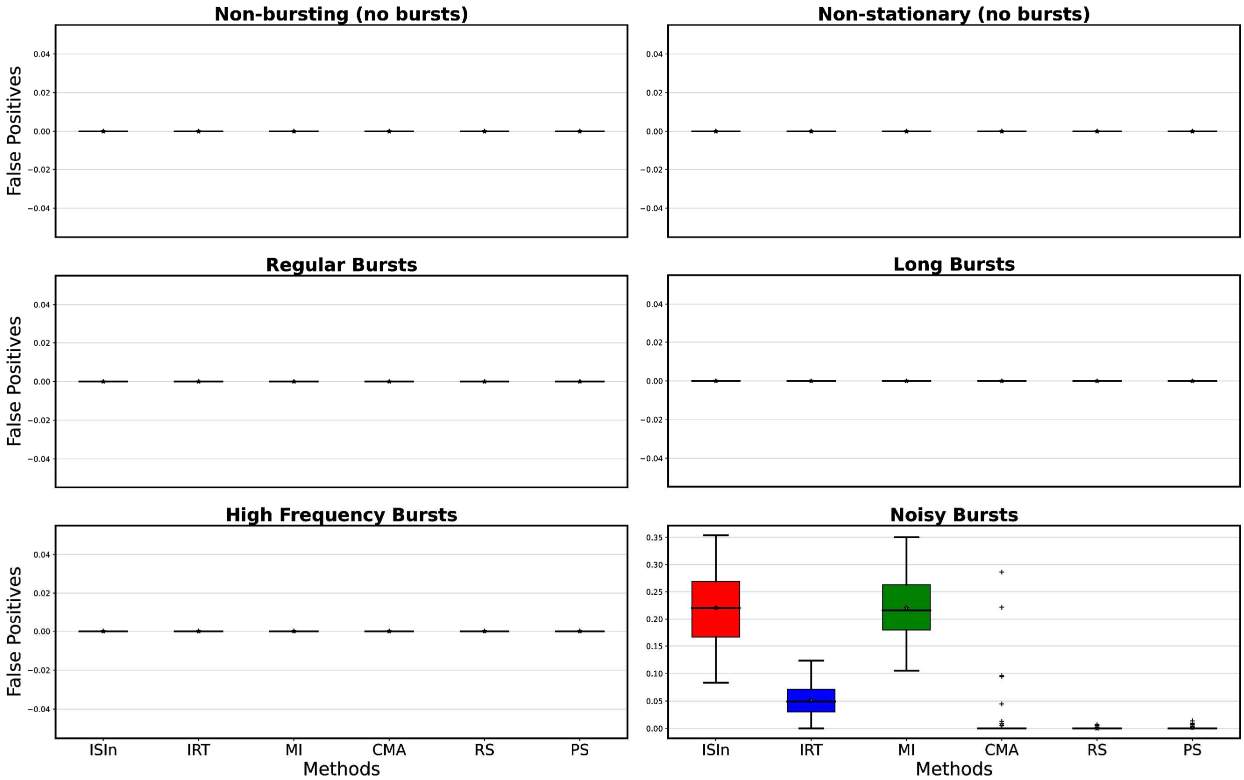

Figure 8. False positive percentage, each subplot shows the evaluation on the percentage of false positives (ranging from 0 to 1) found in a specified data type (indicated by the subtitle) by each method (indicated on x-axis labels).

bursts, the percentage of elements misidentified as bursts is 0. This suggests that the parameterization of the data for these algorithms is very good, as the elements identified as bursts are clearly bursts due to the lack of false positives.

The only case in which misidentification is present is for noisy bursts, which are the hardest to identify. The Rank Surprise, Poisson Surprise, and Cumulative Moving Average algorithms rarely misidentify a non-burst as a burst. ISI Rank Threshold falls in the middle, identifying more errors, while ISIn and MaxInterval misidentify bursts more frequently than the other methods. Although ISIn and MaxInterval have more false positive identifications, the overall error rate, as seen in the figure, is not very high, averaging around 22%.

Although Rank Surprise, Poisson Surprise, and Cumulative Moving Average algorithms have a very low rate of false positives, as seen in Figure 8, they also have a very low rate of true positives as can be seen in Figure 7. The ISI Rank Threshold algorithm performs slightly better in burst detection than the previous two. On the other hand, ISIn and MaxInterval, despite having an approximate 20% false positives rate, but only in the case of noisy bursts, also have the highest rates of correctly identifying bursts.

Analyzing the perspective of correctly identified burst types by these two algorithms, for high-frequency bursts, MaxInterval has an average identification rate of almost 100%, compared to ISIn which has an identification rate of approximately 96%. From the perspective of long bursts, as seen in Figure 7, MaxInterval performs much better, correctly identifying approximately 82%, compared to ISIn which only identifies about 30%. This significant difference can also be observed for regular bursts, with MaxInterval providing an identification rate of approximately 97%, compared to ISIn which has around 62%. However, in the context of noisy bursts, ISIn performs slightly better than MaxInterval, with the former having an approximate 90% identification rate, while the latter has approximately 85%.

B. *Analysis of correlation values on real data*

The MI burst detection method offers promising results for the simulated data. This subsection analyses its performance on real electrophysiological data, that has no ground truth, through the correlation coefficient. We have analysed the performance of the MI method using the parameterization suggested by the authors of the method and also using empirically chosen parameters. Here, we will compare the proposed method against the two previously mentioned options for the MI method. In Figure 9, we present a burst extracted the MI method using the suggested parameterization.

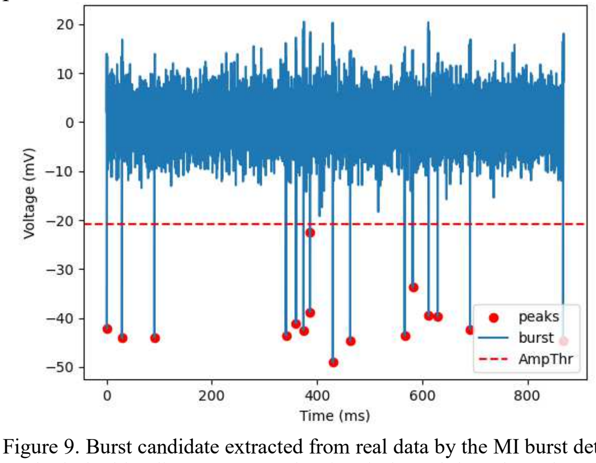

Figure 9. Burst candidate extracted from real data by the MI burst detection method, the blue line represents the signal, the red dots show the peaks of spikes, and the dashed red line represents the amplitude threshold used in the detection of spikes.

An initial hypothesis was that the correlations would be higher for action potentials originating from bursts on the same channel compared to those from different channels at a distance. This would aid in the problem of burst detection, as the identification of the source of action potentials, whether from a burst or an individual discharge, could be based on a simple correlation threshold. If the action potentials originated from different neurons, they would not form a burst. This analysis is shown in Figure 10 for the both the proposed method (left) and the MI method with the suggested parameterization (right). The correlations resulted from the sub-spikes of bursts identified by the proposed method on a single channel are much more concentrated towards values of 1 than those of the MI method, indicating that the sub-spikes identified are more similar. Furthermore, there is a visible disparity between the distributions of the same channel versus different channels for the two methods, indicating that the bursts detected by the proposed method are more distinctive across channels. As mentioned previously, it is to be expected that the sub-spikes of bursts from different channels to have lower correlation values as they originate from different neurons. In Figure 11, we show the comparison between the correlation PDFs for the same channel across the three methods on the left and for distant channels on the right. The highest correlation values for the burst sub-spikes are given by the proposed method, however the suggested parameterization of MI results in the most skewed distribution towards lower values for the burst sub-spikes of different channels. For this analysis, the correlations provided by the chosen parameterization of MI results in a distribution with its peak between the two methods.

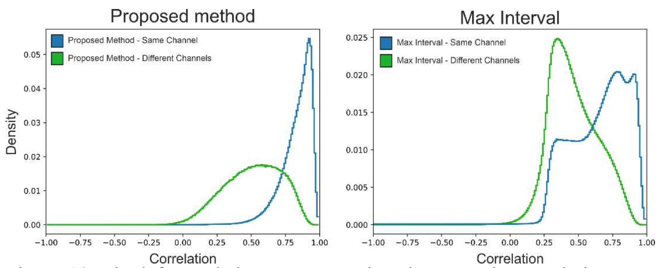

Figure 10. The left panel shows a comparison between the correlation PDF between burst sub-spikes of a single channel versus the burst sub-spikes of distant channels for the proposed method, the right panel shows the same analysis for the MI method with the suggested parameterization.

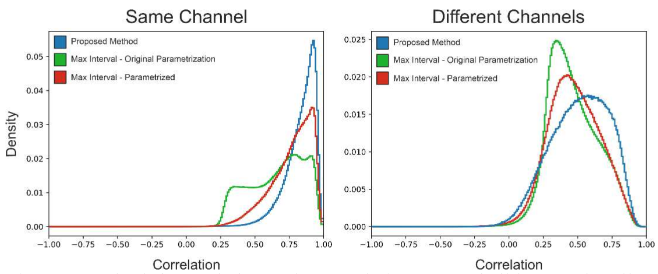

Figure 11. The left panel shows the correlation PDF of all burst sub-spikes against each other of a single channel for each of the methods, the right panel shows the correlation PDF between burst sub-spikes of two different distant channels.

Another hypothesis was that the correlations between intra-burst sub-spike would be higher than the those between burst sub-spikes and the tonic activity of the same channel because burst sub-spikes will have more similar waveform shapes than tonic activity as the sub-spikes originate from the same neuron. This analysis is shown in Figure 12, for the both the proposed method (left) and the MI method with the suggested parameterization (right). The correlations resulted from the intra-burst sub-spikes identified by the proposed method are much more concentrated towards values of 1 than those of the MI method, indicating that the sub-spikes identified by the proposed method are more similar. Our hypothesis was partially confirmed as the correlation values of intra-burst sub-spikes are indeed overall higher than those between burst sub-spikes and tonic activity, however not by a significant amount regardeless of the burst detection method. In Figure 13, we compare the correlation PDFs for the intra-burst sub-spikes across the three methods on the left and for bursting against tonic activity on the right. In spite of the noticeable difference between the distributions on intra-burst sub-spikes of the three methods, the comparison across methods between burst sub-spikes and tonic activity shows no significant difference across the three methods.

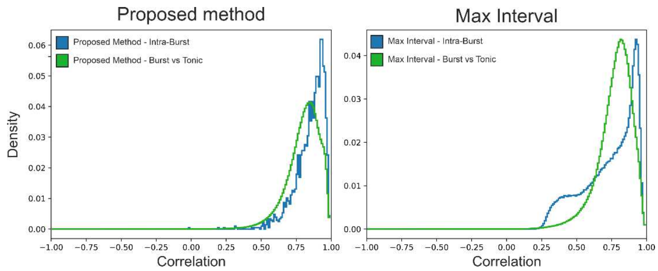

Figure 12. The left panel shows a comparison between the correlation PDF between intra-burst sub-spikes of a single channel versus the burst sub-spikes and tonic spiking activity for the proposed method, the right panel shows the same analysis for the MI method with the suggested parameterization.

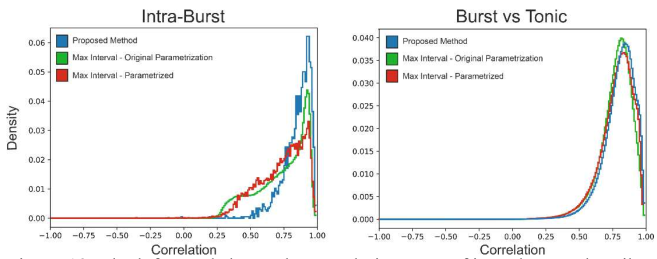

Figure 13. The left panel shows the correlation PDF of intra-burst sub-spikes of a single channel for each of the methods, the right panel shows the correlation PDF between burst sub-spikes and the tonic spiking activity of a single channel.

Upon these explorations, a clear differentiation point in the distribution peak could not be found for each case and for some cases the values are distributed quite similarly and close to the value of 1. Therefore, it is not possible to find a simple threshold that would produce separation for every situation. Consequently, a more suitable similarity metric on correlation is available for exploration and other correlation functions could be investigated. Nevertheless, the comparative analysis of correlation values can offer insights into the performance of detection methods for a variety of conditions.

V. CONCLUSION

Regarding the ability of burst detection algorithms to identify bursts, although it is desirable to have as few incorrectly identified bursts as possible, we also need a large number of correctly identified bursts. Analysing the overall results, we can say that the ISI Rank Threshold, Cumulative Moving Average, Rank Surprise and Poisson Surprise, and algorithms do not provide satisfactory results. The most performant algorithms for the identified data are MaxInterval and ISIn, with MaxInterval consistently achieving correct identification for all types of bursts, while ISIn's identification capability varies depending on the types of bursts. In conclusion, MaxInterval offers high performance for all types of bursts for the analysed synthetic data.

Several conclusions emerge, significant research has been conducted on bursting activity and its detection yielding promising results. Nevertheless, the quest for a golden detection method remains unfulfilled. With the advancement of experimental technologies, the future will require the development of more performant burst detection and analysis techniques.

A comparison between the proposed method and other burst detection methods is difficult. Firstly, these detection methods make use of only the spike times as while the proposed method requires more information from the recording. Secondly, the comparison between burst detection methods was made on synthetic data containing the ground truth, however for the analysis of performance in a real environment no ground truth is available. Thirdly, a comparison between methods that require a different amount of information would bias the results to favour the more complex algorithm resulting in an inequitable comparison. Furthermore, the criteria used in the detection of bursts of the proposed method is stricter than just the timing of neuronal activity, taking into account criteria such as the decreasing amplitude of the intra-burst spikes. These considerations are not quantizable in their impact throughout a comparison between existing methods and the proposed approach.

With these limitations in mind, our comparative analysis is based upon the evaluation of correlation values across a variety of conditions between the proposed method for burst detection and the Max Interval method that obtained the highest results on synthetic data. In this study, we have analysed whether correlation can be used to differentiate between the bursting activity of different channels by comparing the results to the values obtained for the bursting activity of the same channel across these burst detection methods. We have also analysed whether the bursting activity detected by these methods can be separated from tonic activity through an evaluation of correlation values.

Our exploration of correlation as a potential measure for differentiation revealed certain limitations. Despite initial expectations, the correlation values obtained from various cases were remarkably similar, making it challenging to establish a clear threshold for separation. Consequently, correlation alone proved inadequate for distinguishing between burst and non-burst cases. It would be unfair to exclude from contemplation the possibility that correlation might be an adequate tool and it is the burst detection methods that hinder its efficiency. However, this is a question that can only be answered as a deeper understanding of the bursting phenomenon is achieved in the domain.

Alongside a novel burst detection method, we propose correlation as a viable analysis tool for the comparison of performance of burst detection methods and for the validation of correctness of these methods as we show that even though MI displayed promising results on synthetic data, its performance on real data is debatable as its bursts are hardly differentiable across conditions. Nevertheless, exploration of other correlation functions and other metrics is one of the possible directions for further investigation in the domain of bursting activity detection.

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