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On the robustness of EC–PC spike detection method for online neural recording

Yin Zhou [a,b], Tong Wu [a], Amir Rastegarnia [c], Cuntai Guan [d], Edward Keefer [e], Zhi Yang [a,*]

[a] Department of Electrical and Computer Engineering, National University of Singapore, 117583 Singapore, Singapore
[b] Institute of VLSI Design, Zhejiang University, Hangzhou 310027, China
[c] Department of Electrical Engineering, Malayer University, Malayer 95863-65719, Iran
[d] Department of Neural and Biomedical Technology, Institute for Infocomm Research, A*STAR, 138632 Singapore, Singapore
[e] Nerves Incorporated, Dallas, TX 75206, USA

HIGHLIGHTS

- We evaluate the performance of EC–PC spike detection method under different firing rates, SNRs.
- Both simulated and experimental data are used in the performance evaluations.
- Results show that the EC–PC detection method is the most robust in comparison with some popular detectors.
- We show that the detection Precision can be derived without requiring additional user input parameters.
- We also report a hardware implementation based on a 0.13 μm CMOS chip.

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ABSTRACT

Background: Online spike detection is an important step to compress neural data and perform real-time neural information decoding. An unsupervised, automatic, yet robust signal processing is strongly desired, thus it can support a wide range of applications. We have developed a novel spike detection algorithm called "exponential component–polynomial component" (EC–PC) spike detection.
New method: We firstly evaluate the robustness of the EC–PC spike detector under different firing rates and SNRs. Secondly, we show that the detection Precision can be quantitatively derived without requiring additional user input parameters. We have realized the algorithm (including training) into a 0.13 μm CMOS chip, where an unsupervised, nonparametric operation has been demonstrated.
Results: Both simulated data and real data are used to evaluate the method under different firing rates (FRs), SNRs. The results show that the EC–PC spike detector is the most robust in comparison with some popular detectors. Moreover, the EC–PC detector can track changes in the background noise due to the ability to re-estimate the neural data distribution.
Comparison with existing methods: Both real and synthesized data have been used for testing the proposed algorithm in comparison with other methods, including the absolute thresholding detector (AT), median absolute deviation detector (MAD), nonlinear energy operator detector (NEO), and continuous wavelet detector (CWD). Comparative testing results reveals that the EP–PC detection algorithm performs better than the other algorithms regardless of recording conditions.
Conclusion: The EC–PC spike detector can be considered as an unsupervised and robust online spike detection. It is also suitable for hardware implementation.

1. Introduction

Neurons in the brain form closely connected networks and use action potentials to transfer information (Gerstner et al., 1997; Buzsaki, 2006). To study information generation, representation and propagation, action potentials need to be extracted from the raw data, a process known as spike detection (Lewicki, 1998).

* Corresponding author.
E-mail address: eleyangz@nus.edu.sg (Z. Yang).

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So far different spike detection algorithms have been reported in the literature (Chandra and Optican, 1997; Harrison, 2003; Gibson et al., 2009; Quiroga et al., 2004; Kim and Kim, 2000, 2003; Mukhopadhyay and Ray, 1998; Choi et al., 2006; Semmaoui et al., 2012; Gosselin and Sawan, 2009; Maragos et al., 1993; Goodall and Horch, 1992; Mtetwa and Smith, 2006; Kaneko et al., 1999; Gozani and Miller, 1994; Kim and McNames, 2007; Harris et al., 2000; Henze et al., 2000; Zouridakis and Tam, 1997; Nenadic and Burdick, 2005). In the methods that rely on amplitude thresholding (Chandra and Optican, 1997; Harrison, 2003), spikes are detected when neural data exceed a pre-determined threshold, usually 3–6 times the root mean squared (RMS) value of the data. Because of the computational simplicity, the amplitude thresholding detection is suitable for on-line implementation (Gibson et al., 2009; Quiroga et al., 2004). However, its performance is not reliable at moderate or low SNRs conditions. The other candidates for on-line implementation are the nonlinear energy operator (NEO) based methods (Kim and Kim, 2000; Mukhopadhyay and Ray, 1998; Choi et al., 2006; Semmaoui et al., 2012; Gosselin and Sawan, 2009). In these methods, both instantaneous amplitude and frequency are taken into account to improve the detection accuracy. However, these methods provide satisfactory results only when the background noise can be described according to the undamped oscillator model (Maragos et al., 1993), which may not be valid in many situations. Another popular spike detection method is template matching, where spikes are detected according to the similarity between neural data and candidate spike template (Goodall and Horch, 1992; Mtetwa and Smith, 2006; Kaneko et al., 1999; Gozani and Miller, 1994; Kim and McNames, 2007). It is effective given appropriately trained templates and stable neural signals; however, neural spikes may have both short-term and long-term variations that can cause false detection (Harris et al., 2000; Henze et al., 2000). In addition, cross-bin similarity measure and globally searching for the best match can be slow (Kim and McNames, 2007). Wavelet-based detectors are also used in spike detection (Kim and Kim, 2003; Zouridakis and Tam, 1997; Nenadic and Burdick, 2005). Similar to template matching, they require well-shaped mother wavelets to form suboptimal matched filters (Shalchyan et al., 2012). This approach requires the user to specify threshold at each individual layer followed by a joint decision making mechanism. Also the algorithm requires a considerable amount of computation for implementation (Nenadic and Burdick, 2005).

In our previous work (Yang et al., 2012), a new EC–PC framework for in vivo spike detection has been proposed. It is shown that neural data are a combination of two components including noise and detectable spikes. After Hilbert transform, the noise forms an exponential component (EC) and spikes form a polynomial component (PC). By using online trained EC and PC from raw data, the detector can output a probability map for spike detection. In this paper, we briefly introduce the EC–PC detection method, and evaluate its performance under different conditions (firing rates, SNRs), and in comparison with other methods. Both simulated and experimental data are used in the performance evaluations, showing that the EC–PC detection method is the most robust in comparison with some popular detectors.

However, the main contribution of this paper is to show that regardless of the recording condition, the numeric value of the probability threshold of the EC–PC detector is approximately equal to the expectation of *detection Precision*. In other words, we prove theoretically that the detection Precision can be quantitatively derived without requiring additional user input parameters. This new feature allows directly mapping a detection threshold to a point on the probability of false alarm (PFA) curve. As a result, the user can pick operation points from the receiver operating characteristic (ROC) curve, and the algorithm will automatically adjust the threshold accordingly. We also report a hardware implementation based on a 0.13 μm Complementary Metal Oxide Semiconductor (CMOS) chip, where an unsupervised, nonparametric operation has been demonstrated. The chip takes 2.5 s for training from the raw data (not requiring any user specified parameter), where once trained a real-time performance has been obtained.

The rest of this paper is organized as follows. Section 2 gives the algorithm formulation. Section 3 describes data preparations and testing protocols. Experimental results are presented in Section 4. Algorithm implementation in ASIC and testing results are summarized in Section 5. Discussions and concluding remarks are given in Section 6.

2. Robustness of the EC–PC detection algorithm

2.1. Algorithm overview

Extracellularly recorded neural data consist of neural spikes (300 Hz–5 kHz), field potentials (<250 Hz, Belitski et al., 2008), and noise. After applying highpass filtering on the raw neural data at 300 Hz, the filtered signal contains the following components

1. Activities of neurons within the recording radius, where spike power is much stronger than the noise power.
2. Activities of neurons in an extended radius (up to a few hundred μm), where spike power is comparable to the noise power.
3. Noise produced by different sources including unresolved synaptic activities, firing of distant neurons, and recording hardware.

To examine the recorded neural data distribution, let denote by $V(t)$ and $HV(t)$ the neural data sequence and its Hilbert transform respectively.[1] They together form a strong analytic signal as

$$V_{st}(t) = V(t) + jHV(t) = V(t) + j\frac{1}{\pi}\beta\int_{-\infty}^{\infty}\frac{V(\tau)}{t-\tau}\ d\tau \tag{1}$$

where $j^2 = -1$ and β in front of the integral denotes the Cauchy principal value. The instantaneous power of the analytic signal $V_{st}(t)$, is then given by

$$Z(t) = |V_{st}(t)|^2 \tag{2}$$

It is shown in Yang et al. (2012) that for recordings with less visually detectable spikes, the probability density function of $Z(t)$ (denoted by $f(Z)$) is an exponential function as

$$f(Z) \approx f_n(Z) \approx \frac{1}{2\sigma^2}e^{-(Z/2\sigma^2)}, \quad Z \geq 0 \tag{3}$$

where $f_n(Z)$ denotes the probability density function of noise term and σ is the data standard deviation. For moderate and high SNR recordings, the tale of $f(Z)$ is mainly contributed from spikes and follows a polynomial function as (see Appendix A for more details)

$$f(Z) \approx f_d(Z) \approx Z^{-((3+2x)/2x)} \tag{4}$$

where x is real number within 1–2. Both expressions in (3) and (4) together suggest that $f(Z)$ is a combination of an exponential component (EC, $e^{-\lambda_1 Z}$, generated by noise) and a polynomial component (PC, $Z^{-\lambda_2}$, generated by spikes), as illustrated in Fig. 1.

Now, let assume that $\tilde{f}_n(Z)$ and $\tilde{f}_d(Z)$ are the exponential component and the polynomial component, trained in real-time respectively. Then, the *spiking probability*, i.e. the probability that

[1] The Hilbert transform is used for two reasons. First, extracellular spike could have significant variation in shape. In comparison with data sequence, the corresponding analytic signal has less variation in shape and only require a single threshold for different shaped spikes. Second, as to be derived here, background noise has a simple representation in Hilbert space.