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Detection of neuronal spikes using an adaptive threshold based on the max–min spread sorting method

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ABSTRACT

Neuronal spike information can be used to correlate neuronal activity to various stimuli, to find target neural areas for deep brain stimulation, and to decode intended motor command for brain–machine interface. Typically, spike detection is performed based on the adaptive thresholds determined by running root-mean-square (RMS) value of the signal. Yet conventional detection methods are susceptible to threshold fluctuations caused by neuronal spike intensity. In the present study we propose a novel adaptive threshold based on the max–min spread sorting method. On the basis of microelectrode recording signals and simulated signals with Gaussian noises and colored noises, the novel method had the smallest threshold variations, and similar or better spike detection performance than either the RMS-based method or other improved methods. Moreover, the detection method described in this paper uses the reduced features of raw signal to determine the threshold, thereby giving a simple data manipulation that is beneficial for reducing the computational load when dealing with very large amounts of data (as multi-electrode recordings).

1. Introduction

Deciphering neuronal spikes from background noises is essential for retrieving neural information hidden in neurological signals. Spike information is useful for correlating neuronal activity to various stimuli, finding target neural areas for deep brain stimulation, and for decoding intended motor command for brain–machine interface. Unsupervised neuronal spike detection is commonly used because it does not require *a priori* knowledge about neuronal spike waveforms. Conventional spike detection is made by comparing a signal's magnitude with a preset or an adjustable threshold depending on the root-mean-square (RMS) value of data in the running window (Guillory and Normann, 1999). The detection threshold is set to multiples of the RMS value. However, the RMS value is susceptible to bias induced by high-amplitude, high firing-rate neuronal spikes (Watkins et al., 2004), and often results in failure to detect lower-amplitude neuronal spikes.

Several methods were recently proposed to overcome this difficulty by adopting an unbiased estimate of the standard deviation (S.D.) of background noises. The median absolute deviation divided by the 75th percentile of the standard normal distribution (Donoho, 1995) is equivalent to the S.D. of background noises. In 2007, Thakur et al. developed an algorithm to estimate the S.D. of background noises by considering only the cap, which is the middle portion of the amplitude distribution (i.e., “cap-fitting” algorithm). As the demand of embedding spike manipulation in low-power chips or systems increases (Harrison, 2003; Zumsteg et al., 2005; Farshchi et al., 2006; Zviagintsev et al., 2006; Perelman and Ginosar, 2007; Sodagar et al., 2007), simple, efficient spike detection methods are needed. In 2003, Harrison developed an adaptive threshold detector that estimates the S.D. of background noises by keeping the duty-cycle (defined as the portion of data with larger magnitude than the estimated S.D.) at a desired value of 15.85%. Harrison's method can be implemented by a low-power analog integrated circuit.

Instead of directly manipulating the large-amount raw data, we propose employing a simple adaptive threshold based on the

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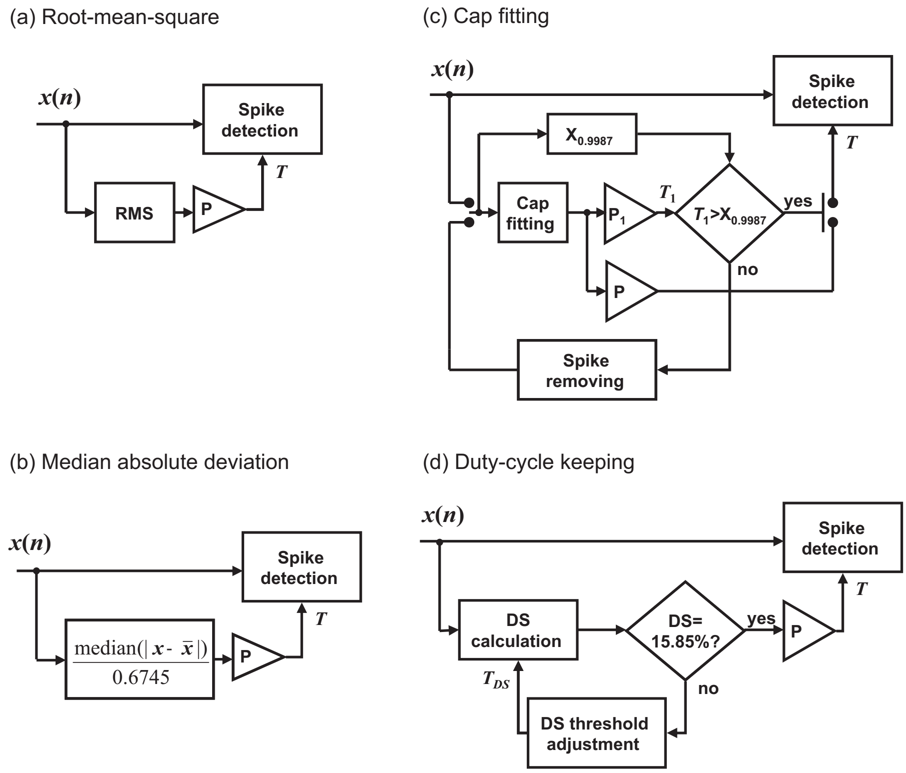

Fig. 1. The neuronal spike detectors incorporated with adaptive thresholds derived by (a) root-mean-square (RMS), (b) median absolute deviation, (c) cap fitting, and (d) duty-cycle (DS) keeping methods.

max–min spread (MMS) sorting method. With this approach, the signal in the running window is first divided into consecutive 2-ms bins with 50% overlap. The signal intensity in each bin is quantified by MMS, and the MMSs in the window are subsequently sorted. MMSs that are less related to neuronal spikes and small-magnitude backgrounds are averaged in order to determine the detection threshold. Various detection method performances were assessed based on the simulated signals composed of neuronal spikes with varying firing rates and different signal-to-noise ratios over Gaussian noises or colored noises. All data processing was performed in MATLAB 7.0 (The MathWorks, Natick, MA, USA).

2. Methods

2.1. Adaptive thresholds

Detecting neuronal spikes from background noises are commonly made by comparing signal's magnitude with thresholds. The RMS-based method is traditionally used to estimate the S.D. of background noises (Guillory and Normann, 1999). As shown in Fig. 1a, the detection threshold can be set to multiples of the running RMS value:

$$T = P \times \sqrt{\frac{1}{N}\sum_{1}^{N}(x_n - \bar{x})^2} \tag{1}$$

where $\bar{x}$ is the mean value. However, the threshold is susceptible to bias induced by large-amplitude, high firing-rate neuronal spikes (Watkins et al., 2004), thereby yielding large fluctuations in the derived thresholds (Fig. 2a). The fluctuation degree can be quantified by the threshold variation index (TVI) defined as the S.D. of thresholds divided by their mean value.

Several methods have been proposed to reduce the effect of neuronal spikes on the detection thresholds (Fig. 2b–d). The median absolute deviation (MAD)-based method (Fig. 1b) can be used to distinguish spikes from background noises (Donoho, 1995):

$$T = P \times \frac{\mathrm{median}(|x_n - \bar{x}|)}{0.6745}, \quad n = 1 \cdots N \tag{2}$$

All samples in the running window are subtracted by their mean value $\bar{x}$ and the absolute values of the subtracted samples are then sorted. The MAD is defined as the median value of $|x - \bar{x}|$. The S.D. of background noises is equivalent to the MAD divided by 0.6745 which is the 75th percentile of the standard normal distribution.

In 2007, Thakur et al. developed the cap-fitting algorithm to estimate the S.D. of background noises. This algorithm considers only the middle portion of the amplitude distribution, the cap. As shown in Fig. 1c, the cap-fitting algorithm is first applied to the input signal for estimating the S.D. of background noises. For a zero-mean Gaussian signal, it has a probability density function defined as

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{x^2}{2\sigma^2}\right) \tag{3}$$

The S.D. (σ) can be derived from the logarithmic form of Eq. (3)

$$Y(x) = -\frac{1}{2\sigma^2}x^2 - \ln\left(\sqrt{2\pi}\sigma\right) \tag{4}$$

by a least-square estimation:

$$A = \frac{\sum_{d=1}^{N_D} Y(x_d)x_d^2 - (1/N_D)\sum_{d=1}^{N_D} Y(x_d)\sum_{d=1}^{N_D} x_d^2}{\sum_{d=1}^{N_D} x_d^4 - (1/N_D)\sum_{d=1}^{N_D} x_d^2\sum_{d=1}^{N_D} x_d^2} \tag{5}$$

$$\sigma = \frac{1}{\sqrt{2\pi}}\exp\left(\frac{A\sum_{d=1}^{N_D} x_d^2 - \sum_{d=1}^{N_D} Y(x_d)}{N_D}\right) \tag{6}$$