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Extracellular spike detection from multiple electrode array using novel intelligent filter and ensemble fuzzy decision making

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HIGHLIGHTS

- Neuronal data are used in many scientific and clinical applications.
- Spike detection methods are needed to estimate the time instants of action potentials.
- We suggest utilizing a novel approach to choose the filter parameters automatically.
- Hilbert transform is employed as a pre-processing step.
- We propose two novel approaches to combine some existing spike detectors.

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ABSTRACT

Background: The information obtained from signal recorded with extracellular electrodes is essential in many research fields with scientific and clinical applications. These signals are usually considered as a point process and a spike detection method is needed to estimate the time instants of action potentials. In order to do so, several steps are taken but they all depend on the results of the first step, which filters the signals. To alleviate the effect of noise, selecting the filter parameters is very time-consuming. In addition, spike detection algorithms are signal dependent and their performance varies significantly when the data change.
New methods: We propose two approaches to tackle the two problems above. We employ ensemble empirical mode decomposition (EEMD), which does not require parameter selection, and a novel approach to choose the filter parameters automatically. Then, to boost the efficiency of each of the existing methods, the Hilbert transform is employed as a pre-processing step. To tackle the second problem, two novel approaches, which use the fuzzy and probability theories to combine a number of spike detectors, are employed to achieve higher performance.
Results, comparison with existing method(s) and conclusions: The simulation results for realistic synthetic and real neuronal data reveal the improvement of the proposed spike detection techniques over state-of-the art approaches. We expect these improve subsequent steps like spike sorting.

1. Introduction

Multiple electrode array (MEA) is a usual tool in neuroscience that records simultaneous activity of several neurons in a piece of neural tissue. The electrode may be intracellular, although it is more commonly extracellular. The recorded signals are small, and they frequently arise from electrical activity in some nearby neurons (Azami and Sanei, 2014; Smith et al., 2007).

The majority of techniques for the analysis of neural activity begin with spike detection to identify the time instants at which action potentials occurred from one or several neurons. The quality of the spike detection algorithm notably influences the performance of the subsequent steps, such as spike sorting (grouping the recorded spikes into clusters based on the similarity of their shapes). Errors in detecting the number and location of spikes will

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inevitably propagate through all later analyses (Azami and Sanei, 2014; Martinez et al., 2009; Nenadic and Burdick, 2005).

There are a number of reasons that make the spike detection a challenging task. First, extracellularly recorded spike trains are unavoidably corrupted by the superimposed activity of multiple neurons and the noise from the recording hardware. Second, implanted microelectrodes usually pick up the concurrent electrical activities with various sizes and shapes from an unknown number of local neurons. Third, the activity of distant neurons may emerge as noise that is highly correlated with the useful signal (Nenadic and Burdick, 2005; Liu et al., 2012).

Few decades ago, spike detection was being performed by using simple amplitude thresholds. This method detects events, like spikes, by considering a peak that is higher than a threshold defined by a user or a statistical property of a signal, such as mean, standard deviation, or median. The threshold can been selected manually by visual inspection or automatically. Although this kind of spike detection method is appropriate for intracellular recordings, extracellular recordings from high-density MEAs and low-impedance microelectrodes frequently have low signal-to-noise ratio (SNR), and the problem becomes far more complex (Kim and McNames, 2007; Maccione et al., 2009).

Another widespread method to detect spikes is based on template matching, a technique used in signal and image processing. In this method, templates representing a typical waveform are utilized as benchmarks. The initial stage of this method is to select a waveform that represents a typical spike shape as template. In the second stage, the method locates possible events in the signal that "closely resemble" the template. Finally, there is a thresholding stage. Early template matching methods often started with the experimenter identifying a couple of high-quality spikes, and using them to train a filter. However, this is unfeasible, especially when there are a large number of electrodes (Azami and Sanei, 2014; Kim and McNames, 2007; Shahid et al., 2010). Even though the template matching algorithm often detects spike events better than simple threshold algorithms, its performance depends on a priori knowledge of the spike shape to create the template. In addition, since the automatic selection of a template in a noisy neuronal data is very complicated, the performance of the method decreases in poor SNRs (Azami and Sanei, 2014; Kim and McNames, 2007; Shahid et al., 2010).

In Liu et al. (2012), an automatic spike detection method based on piecewise optimal morphological filter is suggested. The interesting benefit of this method is that the piecewise optimal morphological filter can highlight the spikes categorized by their structural elements and successfully reduce the background noise. However, the method missed spike events with dissimilar morphological characters from most of spike events presented in data window. This increased the false detection rate of the algorithm notably. This problem was, at least partially, due to the fact that the burst of one or two types of spikes makes the rest type of spikes uncommon within the data window, which leads to the bias of optimal structuring elements to bursting spikes.

A model-based algorithm to detect the spikes by taking into account the distributions of spike amplitudes, widths and frequencies was suggested in Takekawa et al. (2014). Quiroga showed that spike shapes can be distorted significantly by the causal filters frequently used for online spike detection. He illustrated this impact using elliptic filters, but similar results were obtained with Butterworth or Chebyshev causal filters (Quiroga, 2009).

There are also a number of approaches based on wavelet transform to detect the spikes in neuronal data (Nenadic and Burdick, 2005; Yang and Shamma, 1988). In Yang and Shamma (1988), a spike detection method using discrete Haar transformation, which does not need a priori assumptions about spike shape or timing, was proposed. However, the approach assumed white noise and required an unnecessary inverse transformation from wavelet domain to time domain (Nenadic and Burdick, 2005). To overcome this problem, Nenadic and Burdick combined wavelet transforms with basic detection theory to enhance an unsupervised method for detecting spikes in extracellular neural recordings robustly (Nenadic and Burdick, 2005). The most important advantage of this approach is its ability to separate signals from noise by thresholding the wavelet coefficients and, therefore, this method performs well even in poor SNR. However, its main disadvantage is the need to assume a single spike shape resulting in the wavelet choice that is suboptimal for other spikes (Shahid et al., 2010).

Another well-known approach uses signal transformations such as nonlinear energy operator (NEO or NLEO). This is a powerful tool for spike detection. However, when the signal contains multiple frequencies or components, the output of the method includes a DC part and a time-varying part, called cross-terms. The cross-terms and the presence of noise reduce the accuracy of this spike detection algorithm (Azami and Sanei, 2014; Kim and McNames, 2007; Shahid et al., 2010). To overcome these problems, Azami and Sanei employed the smoothed NEO (SNEO) and some filters to detect the spikes in noisy neuronal data (Azami and Sanei, 2014).

Mtetwa and Smith have presented five spike detection algorithms and three thresholding criteria for spike detection (Mtetwa and Smith, 2006). Among them, the best method was based on normalized cumulative energy difference (NCED). This method, inspired by the fact that the energy in a spike (either positive or negative) should be greater than that in noise of the same length, can be followed by multi-template-based spike sorting.

In Azami and Sanei (2014), three new methods to detect the neuronal spikes buried in noise and interferences based on SNEO, fractal dimension (FD) and standard deviation were proposed. In order to overcome the impact of noise and to overcome the low speed of discrete wavelet transform (DWT), singular spectrum analysis (SSA), Kalman filter (KF) and Savitzky–Golay filter were used as pre-processing steps. In addition, since DWT, SSA, KF and Savitzky–Golay filter have several tunable parameters, Azami and Sanei proposed to use the residual signal obtained by empirical mode decomposition (EMD) as a filtered signal (Azami and Sanei, 2014).

To sum up, there are still two outstanding problems in spike detection: (1) usually, choosing appropriate parameters for each noise reduction method is a time-consuming task and needs to be done in many trials. (2) Generally, each spike detection approach is only suitable for a limited number of signal types and applications.

In order to overcome the first problem, we now propose an intelligent approach to set appropriate filter parameters automatically by two powerful evolutionary algorithms, namely genetic algorithm (GA) and new particle swarm optimization (NPSO). In addition, we suggest using an ensemble EMD (EEMD) method as a pre-processing noise reduction step. EEMD is a powerful new algorithm to decompose a complex time series into a number of intrinsic mode functions (IMFs) and a residual signal and it achieves better performance than EMD (Mandic et al., 2013). After using an intelligent filter or an EEMD to increase the accuracy of the existing methods, we propose to employ the Hilbert transform (Beniteza et al., 2001).

In order to tackle the second problem and achieve much better performance compared with those of the conventional neuronal data spike detection methods, we also propose two approaches based on the probability and fuzzy concepts that combine some existing approaches.

In the following section, the proposed intelligent filter and two methods to combine the existing algorithms are explained. Section 3 provides describes the dataset employed in this paper. Then, the results of the proposed methods and the conventional ones