

Assessing New Techniques for Spike Detection on MEA Data

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Abstract

Spike detection and sorting on electrophysiological signals from MEA electrodes is demanding because noise levels are high, and many neurons may be simultaneously recorded by each electrode. In such data, there are always detection failures (false negatives and false positives). We present a new spike detection technique based on Cepstrum of Bispectrum (CoB) and assess it on real neural data. The technique is compared with four established techniques using simultaneously recorded intracellular and extracellular signals. The new technique outperforms existing techniques on detecting spikes in the extracellular signal which are due to recorded intracellular spikes.

1 Introduction

Detecting spike events (action potentials) in extracellularly recorded signals is a challenging task: there is a high probability of the presence of more than one dominant spike train, spikes appear randomly in the signal (due to natural behaviour), different shapes of spikes are present (due to additive neural noise), different phases of spike signal are found (due to different geometries of detector and neuron), neural noise is of high amplitude (the electrode is far from the target neuron), and others. Further, sometimes only spikes from distant neurons are present which can confuse spike detection algorithms.

Simple, popular detection techniques (e.g., plain amplitude thresholding *pln*) are applied directly to the signal after high pass filtering. But high pass filtering alone is not enough for noise treatment. Some algorithms (e.g., wavelet (*wav*) or nonlinear energy (*neo*) based techniques) use a denoising technique or use forms of noise suppression relying on spike signal characteristics. These techniques work well on a restricted range of signals, such as signals with high signal to noise ratio or signals where the spike shape is close to the predefined wavelet. The choice of signal conditioning technique is not optimal for processing general extracellular signals with spikes.

We propose a new algorithm (*cob*), based on Cepstrum of Bispectrum (CoB) [1] a new technique based on higher order statistics (HOS). This performs well on synthesized signals [2]. Here, we apply the new technique to real MEA data and compare the performance with other established techniques.

2 Spike Detection Techniques

pln employs no pre-processing. Amplitude thresholds (positive and negative) are applied to the signal. The threshold value is a function of the signal median and standard deviation.

wav [3] uses wavelet based signal processing. A predefined wavelet type (e.g. db2, bior1.3, bior1.5, haar, sym2, etc) is used for finding the wavelet coefficients which are relatively immune from noise effects.

mor [4] uses a structuring element based filter to enhance spike peaks and suppress noise. Amplitude thresholding is used to discriminate spike events.

neo [5] uses the product of the instantaneous amplitude and frequency of the signal to highlight spike events. Amplitude thresholding is used to discriminate spike events.

New Spike Detection Technique

The *cob* applies a technique based on blind deconvolution theory to the signal and estimates the spike events as a impulse sequence. Deconvolution needs an inverse filter which is estimated using CoB. Since CoB is based on HOS, it is immune to Gaussian noise. In addition CoB uses averaging in its estimation thus providing an average inverse filter. An error term is generated due to noise in the signal and/or estimation error. This error term can be suppressed by wavelet (coiflet) denoising and amplitude thresholding improving performance.

3 Results and Analysis

To observe the performance of *cob*, we apply it to real signals recorded from hippocampus [6] by the Buszaki Lab. Our first test signal is an intracellular signal recorded from dendrites (Fig.1: Top). This signal contains the neuron's internal spike trains plus some other secondary spike (spikelet) trains. There is a high level of noise due to the spikelets. We apply *cob* to this signal and show its pre-threshold output in Fig. 1 (bottom). Clearly, the algorithm suppresses the noise (spikelets) and at the same time it highlights the impulse train. Setting the threshold for this processed signal is relatively easy. Hence, it is possible to detect

spike events from this type of noisy signal with very few errors (either false positive or false negative).

cob performance is also observed from a pair of signals simultaneously recorded intracellularly and extracellularly (Fig. 2: top and second top) from Buzsaki's group [6]. Our aim is to observe the intracellular spike in an extracellular signal. The spikes are clearly visible in both signals because the noise level is low. We find that the extracellular signal records more than one spike train. We apply *cob* to the extracellular signal and show the output before applying a threshold (third top plot of Fig. 2), and after a suitably chosen threshold (bottom plot of Fig. 2). All visually observable spikes in the extracellular signal are detected by *cob*. All spike events in intracellular signal are found in *cob* detected spike events. In addition, it detects all other spike events even although they have different shapes.

	<i>cob</i>	<i>wav</i>	<i>mor</i>	<i>pln</i>	<i>neo</i>
True +ve	30	16	27	29	30
False -ve	0	14	3	1	0
False +ve	15	29	5779	189	139

Table 1. Confusion table. We show the number of correctly matched and missed spikes (with respect to the spikes in the intracellular signal (Fig. 2 top) for five algorithms applied to the real extracellular signal (Fig. 2 second from top).

To compare the performance of *cob* with other established techniques we use the same extracellular signal (Fig.2). We adjust the parameters of the respective techniques so that the maximum numbers of the intracellular spikes are matched (true positive) at minimum false positive (relative to the intracellular spike train). Table 1 shows the results from these techniques.

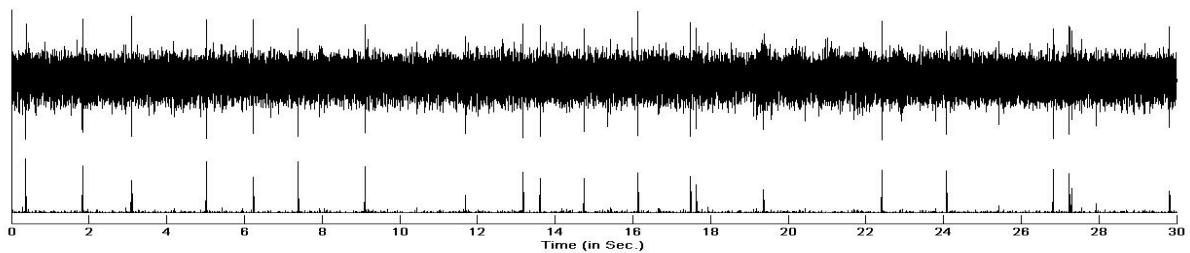


Fig. 1. Noisy intracellular signal (top) and noisy spike event train detected by *cob* (bottom)

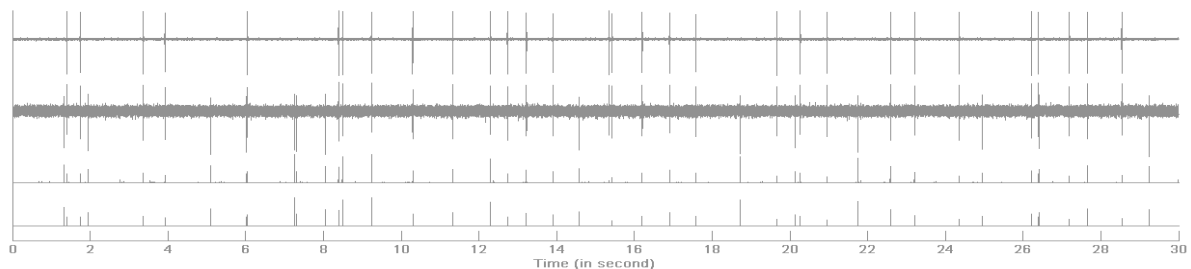


Fig. 2. Simultaneously recorded intracellular and extracellular signal (top 2 plots) and *cob* detected spike train: before and after threshold (bottom 2 plots)

Since our all observations are relative to the intracellular spike train, the spikes from other neurons are counted as false positives. Visually 30 intracellular and 45 extracellular spikes are detectable. *cob* and *neo* detect all intracellular spikes in extracellular signal while *wav* detects only 15 matched spikes. Since spike templates in this signal do not completely match with the available single wavelet, *wav* performs badly. On the other hand, the different techniques produce different number of false positives: *cob* produces fewest followed by *wav*, and *mor* produces most. Hence we conclude that *cob* detects spikes with fewest errors. Reducing the minimum inter-spike interval and spike timing accuracy from 0.5 to 1ms improves the performance of the other techniques.

5 Conclusion

cob is developed from HOS which extracts non-Gaussian terms from a distribution. The extracellular signal has a non-Gaussian distribution. Hence traditional techniques do not work as well. Thus the *cob* technique outperforms the others.

Acknowledgement

We acknowledge the support of the UK EPSRC, grant number EP/E002331/1 (CARMEN).

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