Extracellular spike detection using Cepstrum of Bispectrum

Poster No 498.13

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CARMEN ENHANCING COLLABORATION IN NEUROSCIENCE

UNIVERSITY OF STIRLING

Abstract

Detection and sorting of spikes from extracellular signals is a demanding task in extracellular electrophysiology. Extracellularly recorded neurophysiological signals contain spikes from the target and many other neighbouring active neurons as well as other noise. Discriminating spikes from noise is a challenge since the noise also originates from many neighbouring neurons and includes action potentials from these neurons. Detection of spikes in extracellular signals becomes harder when the signal to noise ratio is low. In this poster, we present a new spike detection technique based on Cepstrum of Bispectrum (CoB) which uses higher order statistics (HoS) techniques to find events of non-Gaussian nature in the extracellular signal. We assess the algorithm on several synthetic and real neural signals. Here we show some comparisons of spike detection performance using the new technique and four other established techniques. The comparative results indicate that the new technique outperforms the existing techniques on detecting spikes in extracellular signals.

Introduction

An extracellular signal is the sum of electrical signals from the neurons surrounding it. At any instant a set of neurons fires: some of these are relevant to the task under study whereas the rest of the neurons are not related to this task (known as neural noise). During an extracellular recording, the neurons closest to the electrode (target neurons) provide the largest signals at the electrode, but more distant neurons' action potentials are superimposed on the signal of interest and change its amplitude and shape. The activity of distant neurons appears as noise which may be highly correlated with the signal from target neurons. We seek to find action potentials from nearby neurons.

Difficulties inherent in spike detection in the extracellular signal :

(a) Neural spikes appear randomly.
(b) Spikes in an extracellular signal are not always of significantly higher amplitude than the noise.
(c) Extracellular electrode/target neuron geometry differs between neurons resulting in different shapes of spike.
(d) Different neurons' spikes may be superimposed.
(e) The overall shape of spikes changes due to neural noise (sum of signals from surrounding distant neurons)
(f) The surrounding neurons' spikes are an element of the noise in the extracellular signal and hence the noise may be similar to the target neurons spike shape (thus misleading the detection procedure).

Different Spike Detection Techniques

There many established spike detection techniques available which use simple or advanced signal processing algorithms. Some of these techniques are described below. These techniques are the best known to us so far.

Table 1 Different spike detection techniques

Methods	Brief Description	Applied Signal Processing Technique	Comments
Amplitude Thresholding (*pln*)	This technique detects spike events when the signal crosses a user-specified single (or pair of) amplitude levels. The threshold can be set automatically as a function of the median and standard deviation of the signal.	High-pass filtering for signal pre-processing	This is the simplest and most widely used technique . The performance of this technique deteriorates rapidly at low SNR.
Nonlinear Energy Operator (*neo*)	This uses the product of the instantaneous amplitude and frequency of the signal which enhances spike events in the signal.	High-pass filtering for signal pre-processing	This technique does not perform well on very noisy signals as it uses instantaneous amplitude which is already corrupted by high frequency noise.
Wavelet Transform (*wav*)	This employs wavelet coefficients. With a good choice of mother wavelet, higher value of wavelet coefficients are found at spike events.	High-pass filtering for signal pre-processing & Wavelet Transformation	A well balanced mother wavelet is necessary for the signals with multiple spike types. Inappropriate choices, may lead to poor performance even in high SNR.
Morphological Filter (*mor*)	This technique examines the shape and amplitude of the signal. The shape of a spike and any background noise are supposed to be different. Observing structure element of the signal the spike event can be identified.	High-pass filtering for signal pre-processing & Morphological filter	A morphological filter suppresses the low amplitude noise without specifically enhancing spike shape. Hence, it misjudges correlated and high amplitude of neural noise.
Template Matching	This technique defines templates from the signal, and matches the templates with the rest of the signal by comparing sum-of-squared differences, convolution, cross-correlation, or maximum likelihood.	High-pass filtering for signal pre-processing	The template definition is crucial. Performance decreases in low SNR due to the difficulty of automatic template definition.

A New Algorithm for Spike Detection

A single channel neurophysiological signal can be modelled as the output of a filtered point process. Mathematically,

$$x(t) = e(t) \otimes s(t) + N(t)$$

$e(t)$ is the input point process (spike event), $s(t)$ is the filter of the process (spike as received at electrode) and $N(t)$ is the noise which may contain both correlated and uncorrelated signals at different amplitudes. Correlated signals are also filtered point process from surrounding neurons. These normally appear at the same time of the signals of interest.

The proposed technique is based on higher order statistics which suppress the noise (Gaussian and/or i.i.d. signal) and finds spikes even at high noise levels. The technique uses blind deconvolution theory to restore the system input signal from an unknown LTI system output signal thus targeting each electrode's signal independently. Deconvolution requires a transfer function which is an estimate of the inverse filter. We estimate inverse filter of the system's output signal.

Cepstrum of Bispectrum (CoB) [1] is a recently developed higher order statistical measurement that provides average filter information (both magnitude and phase) blindly from any noisy triggered process. With a simple additional computation, an inverse filter can easily be estimated from CoB based estimated filter.

The new technique (*cob*) [2] for neurophysiological spike event detection is illustrated in the block diagram below

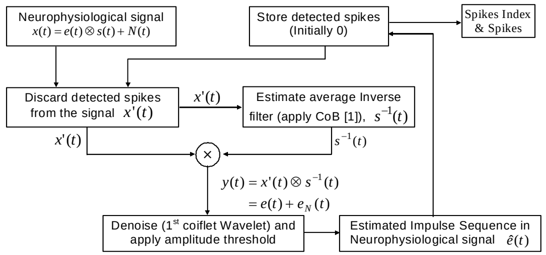

Fig. 1 Block diagram of new Cepstrum of Bispectrum spike detection technique.

Performance Observations & Comparison

On Synthetic Signals:

Considered Algorithms: *pln*, *neo*, *wav*, *mor* and *cob*

Signal description: Each observation was made from 50 synthetic signals [3] where each signal is 5 second long and sampled at 24KHz.

SNR levels: Amplitude ratio computed from peak to peak level (spike) / peak to peak level (noise). SNR levels used are 10dB, 5dB, 3dB, 0dB, -3dB, -5dB, and -10dB

Spike details: Each synthesized signal combines three dominant spike trains (with different spike shapes) The average spike rate in each spike train is approximately 60 (±5) spikes per second

Neural noise: 7 correlated and 5000 uncorrelated spike trains.

Evaluation Parameter: Hit rate (= 'number of correctly detected spike events' ÷ 'number of true spike events') and Precision (= 'number of correctly detected spike events' ÷ 'total number of detected spike events')

Assessing Procedure: Comparing detected (by an algorithm) spike events with the signal's ground truth (known) and computing the hit rate and precision for each algorithm. For each signal, the tuning parameters (e.g., amplitude threshold) of each technique have been set up to minimise the total error (i.e., true positive plus false negative).

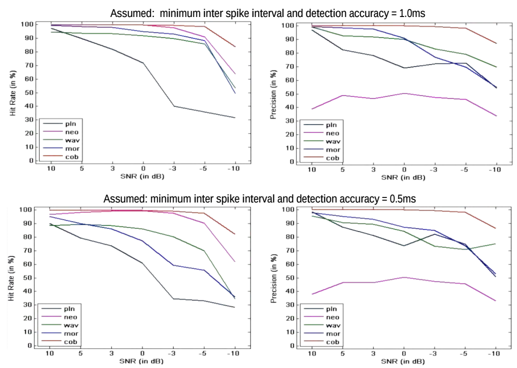

Fig. 2 Comparison of spike detection performance across the five algorithms.

The performances show (a) with a good choice of threshold level *cob* can detect the highest number of spikes with highest precision – more than 99% of spikes are detected (at precision more than 99%) from signal at SNR up to 0dB. *cob* performs best even when spikes are very close (<1.0ms). (b) spike detection by *pln* deteriorates with level of noise, (c) detection of spike by *neo* is unreliable as it has the worst precision value.

On Real Signals:

The proposed technique has been applied to some real simultaneously recorded intra- & extra- cellular signals [4]. Two results are shown here: (a) the intracellular signal has high level of spikelet content (Fig. 3) and (b) the extracellular signal shows clear presence of spikes (Fig 4). The result after applying the algorithm has been shown at two stages: before and after final thresholding. In both signals the algorithm highlights spike events and suppresses noise.

Since the extracellular signal was recorded to observe the effect of the intracellular signal, the spikes detected by the different techniques were compared with the spikes from the intracellular signal. Spike detections matching the time of intracellular spikes are assumed true positive. Table 2 compares the techniques. The technique *cob* detects all spikes with fewer errors (false positive and false negative).

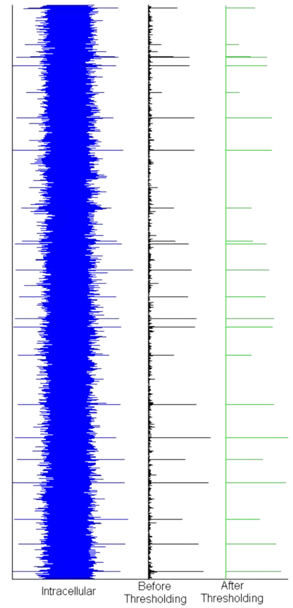

Fig. 3 *cob* Technique applied to intracellular signal recorded from dendrites

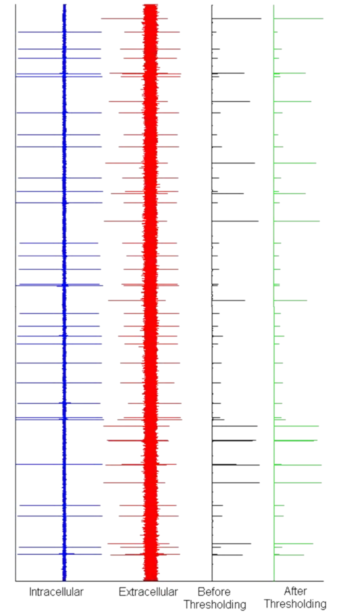

Fig 4. *cob* Technique applied to extracellular signal recorded simultaneously from inside and outside of the neuron

Table 2 Comparison of spike detection by the five algorithms.

Δt		*cob*	*wav*	*mor*	*pln*	*neo*
0.5ms	**True Positive**	30	16	27	29	30
	False Negative	0	14	3	1	0
	False Positive	15	29	5779	189	139
1.0ms	**True Positive**	30	30	30	30	30
	False Negative	0	0	0	0	0
	False Positive	14	14	88	79	112

Δt denotes the assumed minimum inter spike interval and detection accuracy

Discussion and Conclusion

Available techniques produce acceptable results if the signal has a high SNR: but this is not always possible. The result produced by these techniques becomes unreliable if the SNR is low. In addition, these techniques require a relatively long time between two successive neuron firings. The proposed technique uses an advanced and appropriate signal processing technique which highlights spike events by suppressing the noise. Hence *cob* detects spikes at low SNR (0dB or less) with low estimation error (false positive and false negative). The detection performance of *cob* on both real and synthetic signals is an improvement on the traditional techniques. We conclude that results from *cob* provide a better basis for further processing of spike trains.

References

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Acknowledgment: This work was carried out as part of the EPSRC CARMEN grant, EP/E002331/1