

Cepstrum of Bispectrum Spike Detection applied to Extracellular Signals with Concurrent Intracellular Signals

Shahjahan Shahid and Leslie S. Smith
Dept. of Computing Science and Mathematics
University of Stirling, Stirling, FK9 4LA, Scotland



Abstract

The new Cepstrum of Bispectrum based spike detection technique (cob) has shown excellent performance on simulated extracellular signals. However with real extracellular signal cob sometimes does not perform as well as we demand. In this research, we propose iterative application of the cob technique which improves the spike detection capability. We assess the performance of iterative cob on 3 types of real extracellular signal whose ground truth was estimated from concurrent intracellular signals from the same target neuron. It is observed that the iterative cob detects a higher number of target neuron's spikes from the extracellular signal even if the average quality (SNR - signal to noise ratio) of the extracellular recording is nearly 0dB. This technique does not make much difference if the SNR of extracellular signal is less than 0 dB.

Introduction

Detecting and sorting of spikes from extracellular recordings is demanding, because of the large number of neurons near the electrode. The extracellular signal acquired contains spikes from the target neuron (i.e. the neuron from which the intracellular signal is recorded concurrently) and neighbouring active neurons, as well as additional noise.

Thus the neural noise originates from many neurons; the noise contains spike-like components (in amplitude, structural shape and spectrum) which often mislead the detection procedure, as well as other noise (thermal noise, plus other extraneous non-spiking neural noise). Discriminating spikes from noise is a challenge in many ways [1, 2]: (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) shape of spikes varies due to neural noise (sum of signals from distant neurons); (f) nearby neurons' spikes are an element of the noise in the extracellular signal and hence the noise shape may be similar to the target neuron's spike shape.

There are many spike detection techniques ranging from simple thresholding to wavelet based techniques [1, 2]. Virtually all techniques apply some form of signal preprocessing, followed by thresholding. In our recent work [3-5] on spike detection, we process the extracellular signal using Cepstrum of Bispectrum [6]. CoB is a higher order statistics technique. CoB is followed by wavelet transformation. Finally the resultant signal is thresholded. The proposed technique (cob) was assessed by using simulated signals and gave outstanding performance compared to four other established methods: more than 99% of spikes were detected from simulated extracellular signals at 0dB SNR. In this research we seek the performance of cob with real extracellular signals.

Real signals and Concurrent spikes at extracellular signal

We use signals recorded simultaneously intracellularly and extracellularly from a target neuron in rat hippocampus from the Buzsaki Lab (signals are publicly available at <http://www.crcns.org/>). Since the extracellular signal contains many neurons' spikes, we setup our experiment to observe the performance of cob on detecting the target neuron's intracellular spike events in the extracellular signal. Performance was assessed from 64 data files (using 1 intra- and 1 extracellular signals) from different rats.

Both signals are first high-pass filtered (cut-off frequency is 300Hz; Butterworth filter of order 8) then assessed visually for signal quality and presence of artifacts. Intracellular spikes are simply thresholded (the SNR is high). Marker events were discarded. Detected intracellular spikes are the target neuron's spikes (ground truth).

First we examine the extracellular signal visually seeking a consistent template for spikes corresponding to ground truth. We examine extracellular signal for ± 1 ms from the time of the ground truth spikes. We classify the extracellular signal into 3 categories - (Type 1) where the amplitude of ground truth spike is higher than neural noise; (Type 2) where the amplitude of ground truth spike is equal or less than the amplitude of neural noise; and (Type 3) where there is no consistent shape from the ground truth spike.

Here (unlike in [3, 5]) we use an iterative cob process (3 iterations) [4] - where before each iteration of cob, we modify the test signal by setting the signal to zero for 1.5ms around identified events. We apply cob on 5s of the signal at a time, segmenting the original long signal. In the iterative cob process, the threshold level is set to 5% of the peak 'cob processed signal'.

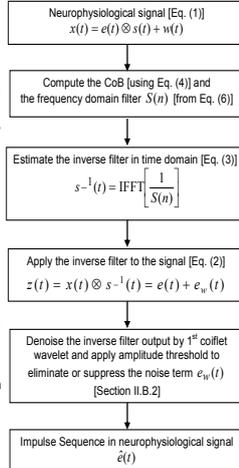
The CoB Technique

The technique is based on higher order statistics which suppress the noise (Gaussian and/or I.I.d. signal) and finds spikes even at high levels of noise. The technique uses the blind deconvolution theory to restore the system input signal from an unknown LTI system output signal thus targeting the specific system. 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) [6] is a recent 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) [3-6] for neurophysiological spike event detection is illustrated in block diagram form.

(Note that equations and references refer to reference [5], available from the presenter)



The Iterative CoB Technique

The primary free parameter in CoB is the threshold. An alternative to picking a single threshold is to pick a (high) threshold that selects what are undoubtedly spikes, then replace these with quiet, and re-analyse the dataset iteratively. A block diagram for this is shown at the top of the next column.

This technique allows relatively difficult to determine spikes to be found even in the presence of much clearer spikes.

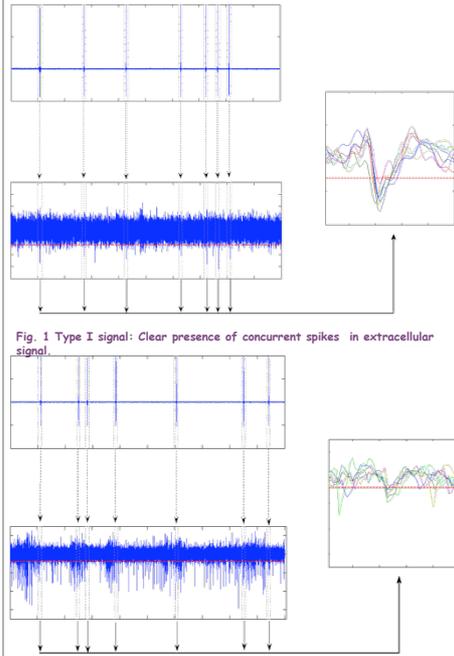


Fig. 1 Type I signal: Clear presence of concurrent spikes in extracellular signal.

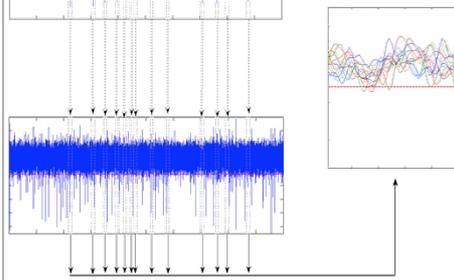


Fig. 2 Type II signal: Concurrent extracellular spikes are close to background noise.

Table 1 Description of considered intracellular signal: these spikes are considered as known ground truth of extracellular signal.

Signal	Duration of Signals in sec.			No. of spikes in the intracellular signal		
	Mean	Min.	Max.	Mean	Min.	Max.
Type 1	296	5	740	589	14	1468
Type 2	250	15	750	1539	145	5066
Type 3	437	125	750	1177	120	6083

Fig. 3 Type III signal: Concurrent extracellular spikes mask the intracellular spikes

Table 1 Description of considered intracellular signal: these spikes are considered as known ground truth of extracellular signal.

A New Iterative Algorithm for Spike Detection

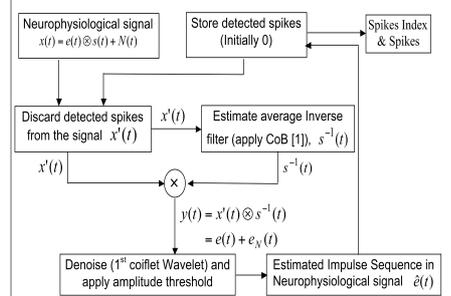


Fig. 4 Block diagram of iterative Cepstrum of Bispectrum based spike detection technique.

Result

Threshold level used is 5% of denoised cob signal $y(t)$

No. of correctly detected spikes from extracellular signal (True Positive)

Accuracy = $\frac{\text{No. of actual intracellular spikes to be detected from extracellular signal (True positive + False Negative)}}{\text{No. of actual intracellular spikes to be detected from extracellular signal (True positive + False Negative)}}$

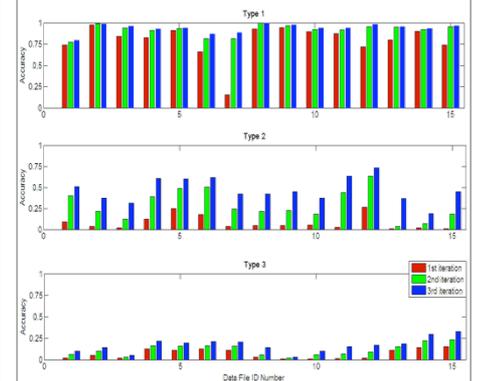


Fig. 5 Application of repetitive-cob based spike detection technique

Discussion and Conclusion

Spike detection techniques which include a nonlinear preprocessing step prior to setting a threshold can benefit from an iterative technique such as the one proposed. Applying this form of iteration to linear techniques (e.g. wavelet based techniques or pure thresholding) would give the same result as simply lowering the threshold. With CoB, however, re-estimating of the inverse filter after replacing detected spikes with an appropriate 'null' signal will result in a different inverse filter $s^{-1}(t)$. As a result, the inverse filter output, and hence the detected impulse sequence will be different to that which would have been detected by simply lowering the threshold.

The effect of this can be seen in figure 5: in all cases (even where the SNR is very poor) the accuracy of the spike detection increases as the number of iterations increases. We note that this iterative way of applying CoB is not restricted to this type of signal. Indeed, it can be applied to other types of signal altogether. One particular case of interest is using it to remove certain types of interfering signals specifically where the spectral characteristics of the interfering signal are reasonably constant and differ appreciably from those of the signal of interest. We are examining this possibility in the context both of extracellular neurophysiological recordings and EEG recordings.

References

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