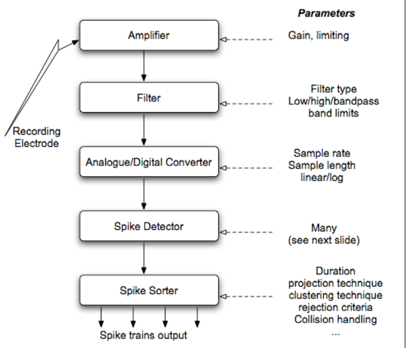
Testing spike detection techniques using synthetic data. 319.9

Leslie S. Smith, Shahjahan Shahid (University of Stirling, UK), Anthony Vernier (Univ. de franche comte,France)

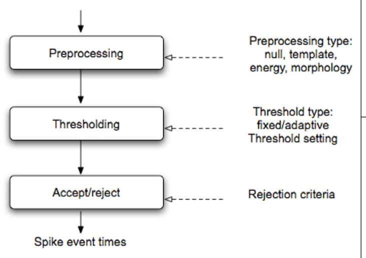
Abstract: Translating extracellular recordings into sets of spike trains requires spike detection and spike sorting. There are many techniques for each of these, and in earlier work we assessed some spike sorting techniques using synthetic noisy data generated from a biophysical model [Smith and Mtetwa 2007]. We report here using the same biophysical model to generate data with realistic noise at controllable levels to assess a variety of spike detection techniques. We assess simple thresholding, energy based techniques, a technique based in mathematical morphology, Nenadic and Burdick's wavelet based technique [Nenadic and Burdick 2005] and a blind equalisation based technique [Shahid et al in prep.]. Most of the techniques take the form of a preprocessing stage followed by thresholding. The techniques are all parameterised: the preprocessing part generally has at least one parameter, and the threshold parameter will require to be set. In simple thresholding, the preprocessing technique is null, so that only the threshold parameter requires setting. In energy based techniques, a parameterised instantaneous energy is computed, and this is then thresholded. In the mathematical morphology based technique we use a 1-dimensional opening where the structuring element size is a parameter, and this is again followed by a thresholding operation. In the wavelet based technique, we use Nenadic and Burdic's code which has a set of parameters. In blind equalisation technique, the Cepstrum of Bispectrum (CoB) (a higher order statistic), is used for spike shape estimation and to design an inverse filter. For each technique we adjust the parameters for best performance at each level of noise, and then assess the results on sets of data with different noise levels. The aim is to determine the effect of parameter selection for each technique in order to determine whether this can be made automatic without sacrificing performance.

1: Introduction

Extracellular electrodes record signals from a number of nearby neurons. In addition, they also record noise, partly from further-away neurons, and partly from extraneous signals etc. The aim of spike detection and sorting is to produce a set of spike trains from the extracellular electrode signal: each spike train should record the times of the spikes from one neurons which was near the electrode. The usual technique is to amplify the signals (normally < 1 mV), filter them, digitize them, then detect spikes. These detected spikes are then sorted into spike trains of spikes from different neurons.



Spike detection is usually a two stage process: in the first stage, the digitized signal is preprocessed in order to emphasize the spikes. This is followed usually by some form of thresholding, which then outputs a sequence of spike event times. This may be followed by an accept/reject stage (primarily because some techniques can output a pair of events when the recorded spike is biphasic). There are many different possible techniques for preprocessing, thresholding and acceptance/rejection. Each technique has parameters whose values define precisely how it operates.



This work is part of the UK EPSRC **CARMEN** project, which brings together the organizations below.

Society for Neuroscience Annual Meeting 2007, San Diego.

2: Techniques assessed:

We compare here a number of techniques for spike detection. The techniques are

Plain:
No preprocessing. Thresholding both positively at the median plus a number (parameter) of standard deviations and negatively at the median minus a (different) number (parameter) of standard deviations.

Wav:
Wavelet based preprocessing, as described in [Nenadic and Burdick 2005]. The following types of wavelet (parameter) were applied: biorthogonal spline wavelets (with of order 1 for reconstruction, and 3 and 5 for decomposition), Daubechies (order 2), Symlets (order 2), and Haar, all as supplied by the MATLAB toolbox. In addition, the parameter L was varied. The software used was provided by Z. Nenadic.

Morph:
The signal was turned into two positive going signals, by subtracting the median and (signal 1) setting negative values to zero, and (signal 2) inverting the signal, then setting negative values to 0. Both of these were then "opened" using a simple linear structuring element whose length is a parameter [Serra 1982]. The opened signal is then subtracted from the positive-going signal, and the resultant signal thresholded at some value (parameter). A related technique is used in [Zelniker et al].

Conv:
Template based technique in which a section of the signal found by simple thresholding was used as a template for a spike, and this template was then convolved with the signal. The threshold for determining spiking events is the parameter [Mtetwa and Smith 2006].

Sum:
This uses an averaging preprocessing technique which smooths the data from neighboring points, based on [Mariscotti 1967]. The threshold for determining spiking events is the parameter [Mtetwa and Smith 2006]).

Nced:
The cumulative energy in the signal is computed, and then differentiated. The threshold for determining spiking events is the parameter [Mtetwa and Smith 2006].

Neo:
This is also an energy based technique, and is an implementation of the technique described in [Kim and Kim 2000]. The threshold for spike detection is the parameter.

CoB:
This is based on the higher order statistical signal processing and uses Cepstrum of Bispectrum (CoB) based blind system reconstruction [Shahid and Walker, 2008] and the inverse filtering based blind equalization [Shahid et al in prep.]. A threshold (parameter) is used to discriminate the spike events.

3: The comparison technique.

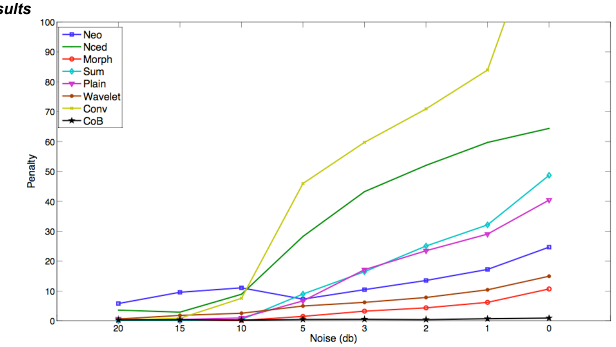
To compare the different techniques, we

(i) create a dataset of spike (event) times,
(ii) transform these events into the signal that would be detected,
(iii) add variable amounts of realistic noise (generated from uncorrelated spiking events transformed into detected signals) to this dataset,
(iv) apply each technique while varying the parameters for that technique.

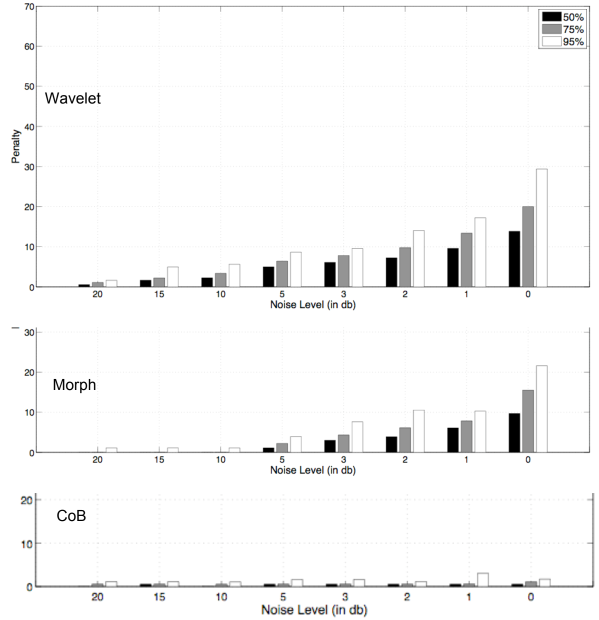
Each application results in a value for the penalty, which is set to be the number of missed spikes plus the number of inserted spikes. (Clearly, different weights could be applied to missing and inserted spikes.) The parameters are varied until the best performance is found.

Each synthetic dataset is 5 seconds long, sampled at 24 Ksamples/second, and contains data from two neurons plus noise generated from 15 uncorrelated spiking neurons. The penalty is calculated as a percentage of the total number of events (and can thus be greater than 100%). The test is repeated a 50 times for each technique to give a more reliable estimate of the penalty incurred. Different data and noise is used each time, always generated from the same distribution, and providing the same signal: noise level (measured peak:peak, as discussed in [Nenadic and Burdick 2005]). Since it may well be the case that the best values for these parameters will vary with the data and the noise level, we also recorded the parameters which gave rise to the best results for each test.

4: Results



The variation in effectiveness of the different techniques is clearest when the noise level is high. At high noise levels, CoB outperforms the other techniques, with morph second, and wav third.



CoB clearly outperforms all the other techniques. We note that this is only on simulated data: work is ongoing to examine how well each technique performs on real data from a variety of different sources, and on real data with additional noise.

References:
[Kim and Kim 2000] K. Kim, S. Kim, IEEE Trans Biomed Eng, 47(10): 1406—1411, 2000
[Mariscotti 1967] M. Mariscotti, Nuclear Instruments and Methods, 50: 309—320, 1967
[Mtetwa and Smith 2006] N. Mtetwa, L.S. Smith, Neurocomputing, 69(10-12): 1366—1370, 2006
[Nenadic and Burdick 2005] Z. Nenadic and J.W. Burdick, IEEE Trans Biomed Eng, 52(1): 74—87, 2005
[Serra 1982] J. Serra, Image analysis and mathematical morphology, Academic Press, 1982
[Shahid and Walker, 2008] S. Shahid and J. Walker, Signal Processing 88: 19-32, 2008
[Shahid et al in prep.] S. Shahid, L.S. Smith, J. Walker, in preparation.
[Smith and Mtetwa 2007] L.S. Smith and N. Mtetwa, J. Neurosci Meth, 159(1): 170—180, 2007
[Zelniker et al] E. E. Zelniker, A. P. Bradley, J. S. Castnet, H. J. Chenery, D. A Copland, P. A. Silburn, submitted to J. Neurosci Meth.