

Testing spike detection and sorting algorithms using synthesized noisy spike trains

Leslie S. Smith

Department of Computing Science, University of Stirling
Stirling FK9 4LA, Scotland, UK
contact: lss@cs.stir.ac.uk

1 The Problem

Neural signals recorded by extracellular electrodes (and in particular signals recorded from multi-electrode arrays at the bottom of culture dishes) often suffer from low signal: noise ratios. This makes spike detection and sorting of interest. There are many algorithms for detecting and sorting spikes in noise (reviewed in [2]). However, assessing their quality is difficult because one does not normally know the ground truth: that is, where the actual spikes are. Wood et al [4] report over 20% errors using semiautomated spike sorting.

2 The Solution

We have developed a noisy spike synthesizer which can generate signals for which the ground truth is known. This is an alternative to other techniques, such as selecting a spike-free period in a real recording e.g. [1, 5], providing more control over the signal produced. The synthesizer is based on an equivalent circuit for the transfer of charge from neurons to an electrode (see figure 1).

We describe three sets of spiking neurons: (1) target neurons, namely those for which we hope to detect and sort spikes, (2) correlated noisy neurons, namely neurons which generate spikes which are correlated with one of the target neurons, and (3) uncorrelated noisy neurons which generate spike trains uncorrelated with the target neurons. We emulate variations in the spike train shape and size (as recorded at a single electrode) caused by (i) variations in the distance of the different parts of the spiking surface from the neuron, (ii) variations in the mode of transfer of the signal to the electrode, and (iii) shape of intracellular spike. Signal transfer from neuron to electrode during spikes is based on analysis of the circuit model in figure 1, integrated over the spiking surface of the neuron. This provides justification for the techniques used for (i) computing the effect of the spatiotemporal distribution of the spike on the spiking part of the neuron membrane as a weighted sum of delayed spikes, and (ii) computing the effect of the transfer path as a weighted sum of the intracellular spike and its first and second derivatives (see figure 2).

Using a weighted sum permits variation in electrode/neuron distance within a single neuron to be modelled. For both the effect of the different delayed signals and the effects of differing transmission characteristics (implemented here using a weighted mixture of the intracellular signal, and its 1st and 2nd derivatives), the weights are user specified, permitting considerable variation in the

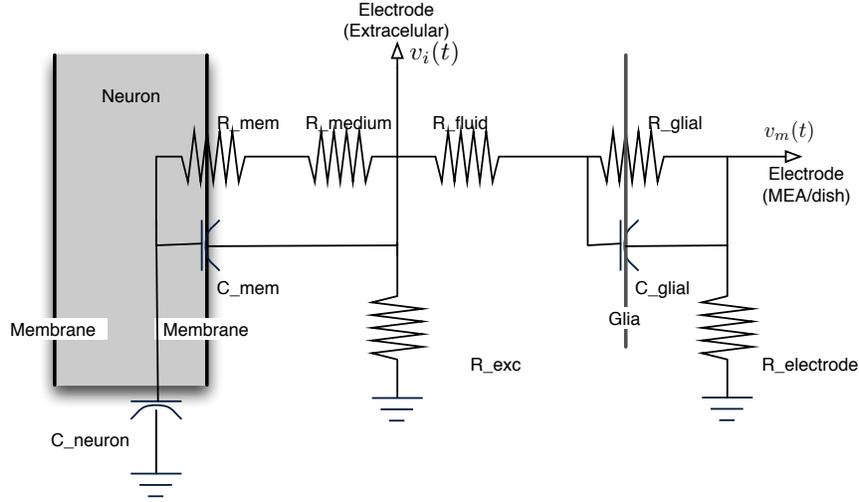


Figure 1: Electrical equivalent circuit for charge transfer from a patch of neuron to an electrode.

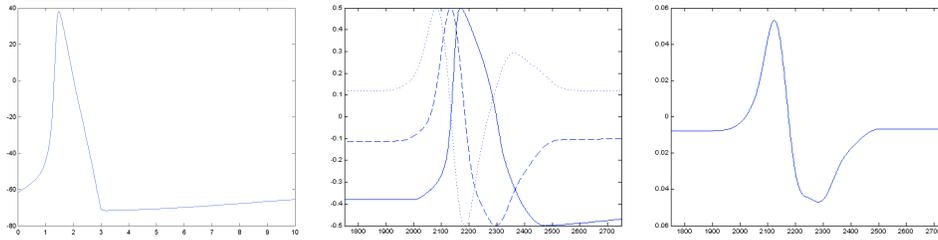


Figure 2: Left shows intracellular signal at a point (generated using [3]). Middle shows overall intracellular signal (integrated over spiking surface) (solid line), 1st derivative (dashed line) and 2nd derivative (dotted line). Right shows extracellular signal (for one particular parameter selection). X-axis is milliseconds (left) and samples (100KSamples/s) for others, adjusted so that they are the same. (Y-axis scale is millivolts (left), but is arbitrary for the others).

actual recorded spike shape as well as user determination of the relative strengths of the different components. The user can thus not only alter the shapes of the target neural signals, but also the relative strengths of all the different signals. One can then add in correlated and uncorrelated signals at an appropriate strength. For an appropriate parameter selection, the signal generated looks like a real electrode signal (figure 3).

The actual spike times for all the target neurons are recorded (and may be re-used), so that the results from different spike detection and sorting algorithms may be compared with the ground truth. The experimenter may vary the strengths of the signals and the noise.

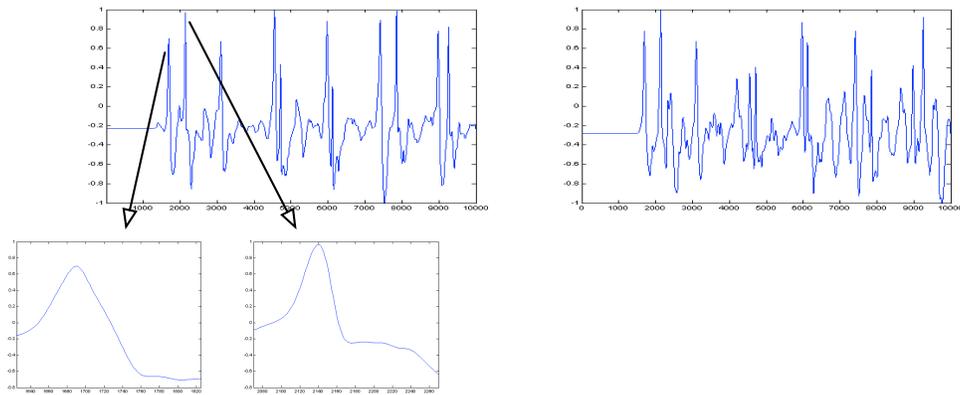


Figure 3: Upper left shows signal from two target neurons, plus 7 correlated and 45 uncorrelated (much weaker) neurons. There is an initial silent period. Right has same target spike times, but 3 times as much uncorrelated noise as the left. Lower images show 2ms of spike trace from each target neuron (centred on peak of intracellular spike). Signal from 1st neuron has a contribution from more of its spiking area than 2nd neuron, resulting in a wider peak: signal from 2nd neuron has a higher amplitude.

3 The Software

The software is a set of MATLAB .m files, currently version 0.3 (note: it needs the Statistics Toolbox), and is freely available from <http://www.cs.stir.ac.uk/~lss/noisyspikes>. It consists of a set of .m files, and a detailed user manual. A full paper describing the analysis that underlies the synthesis of these noisy spike trains is in preparation, but an early draft may be found on the web site. The software is still currently under test, but is usable.

References

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