Quantitative Single-Neuron Modeling:

Competition 2008

Why such a competition?

How well are single-cell properties reproduced by the present-day neuronal models? Recently, several labs have approached this question by assessing the quality of neuron models with respect to spike timing prediction or characteristic features of the voltage trace. So far, every modeler used his own preferred performance measure on his own data set. The Quantitative Single-Neuron Modeling Competition offers a coherent framework to compare neuronal models with four different experiments on layer V pyramidal neurons of the somatosensory cortex under somatic and dendritic stimulation.

Participation

Participants can submit their prediction to one or more of the challenges A, B, C or D. Anyone can participate and any type of model is accepted.

Goal

This competition is an opportunity to bridge the gap between experimentalists and modelers (are there modelers who always dreamed of testing their theoretical model, and experimentalists who wondered which model to use for their specific case?). The Quantitative Single-Neuron Modeling Competition is an invitation to compare your methods and models to those of other people in the field. With good participation, the outcome of this competition will be of great interest to both experimentalists and network modelers.

Prizes

- 2nd prize: to the participant(s) providing best overall performance in one of the challenges A, B, C or D: 500 CHF*.
- 1st prize: to the participant(s) providing the best performance in at least 2 of the sub-challenges: 10 000 CHF*.

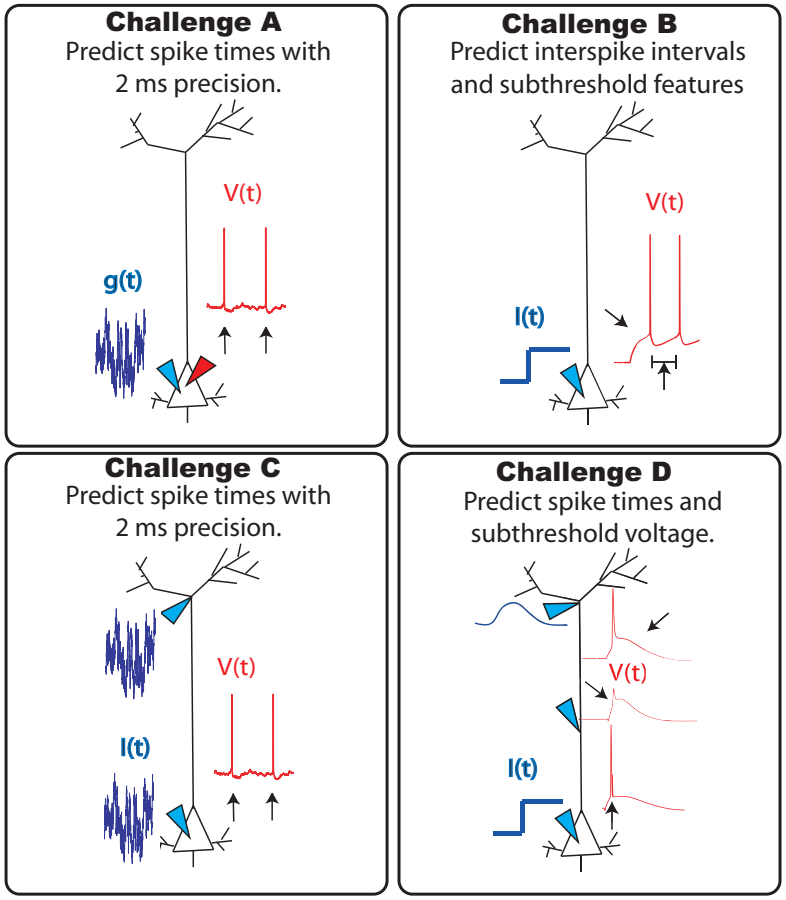
* Participants from the EPFL are not eligible to receive the money reward.

Important Dates

February 15th 2008 : submission deadline. March 3rd-4th 2008 : Presentation of the results at the modeling workshop taking place during Cosyne 2008 meeting, Salt Lake City, Utah.

Description

This year, the competition applies only to one neuron type. All of the experiments used in the sub-challenges below are from layer 5 pyramidal cells of the somatosensory cortex of young rats.



Organizers

Wulfram Gerstner - Thomas Berger - Arnd Roth

ChallengeA

Goal

Predict the spike timing of in vivo-like stimulation with a 2 ms precision.

How to Participate

We provide a set of data for training and a set of data for evaluating the performance. The training set contains the stimulation and the voltage recordings. The test set consists of a similar stimulation protocol but we keep the voltage recordings to later evaluate the performances.

Experimental methods

The neuron was injected with time-dependent conductance at the soma. The stimulation protocol was chosen to mimic the expected stimulation of these neurons in vivo. The net current injected in the dynamic clamp experiment is :

$$I(t) = g_{exc}(t)[V(t) - E_{exc}] + g_{inh}(t)[V(t) - E_{inh}] \quad (1)$$

Where gexc and ginh correspond to the magnitude of the excitatory and inhibitory conductance injected. These follow an Ornstein-Uhlenbeck process with fixed mean and time constant. The excitatory and inhibitory reversal potentials were fixed to -10 mV and -70 mV, respectively, and the time constant were 2 ms for the excitatory conductance and 10 ms for the inhibitory conductance. Nine different time series of excitatory and inhibitory conductance were generated, each with different standard deviation. These nine stimuli were injected in the soma of the pyramidal neurons multiple times to quantify the reliability of the neuron. Out of these nine stimuli, six are given for training and three are kept to evaluate the performances.

Evaluation methods

There are many methods to quantify how one spike train matches with another. In this challenge we want to assess the quality of the modeling based on spike timing only. For this we will use the gamma coincidence factor, Γ, which is a reliable measure of the fraction of spikes that are coincident notwithstanding the accidental coincidence to be expected from a poisson neuron (please see Jolivet et al. (2006) or Gerstner and Kistler (2002) for more information). A modeled spike is said to be coincident with the target spike if their occurence is separated by an time smaller than Δ. We provide a sample MATLAB code that computes Γ of spike-times with a precision of 2 ms. Spikes are defined as upward zero-crossings.

This measure of spike train similarity can also be used to estimate the internal reliability by averaging the coincidence factor across all N available repetitions (R). The neuron is said to be only partly reliable because on repeated injection of the same conductance time series, only about R of the spikes are

reproduced. Given the partial reliability of the neuron (here R 0.40 - 0.75), we do not evaluate the performance of the model on a single response of the real neuron. Instead, we average the coincidence factor across all N repetitions and scale it with the intrinsic reliability R:

$$A_1 = \frac{1}{N} \sum_{i=1}^{N} \frac{\Gamma_{mn_i}}{R} \tag{2}$$

If your model is probabilistic, you might want to submit multiple repetitions. You can submit up to 20 spike trains, which are averaged over all the repetitions to produce a single performance measure. To elect the winner, we compare the gamma coincidence factor of the different submission rounded off to the tenth of a percent.

Participate

You can download the training and test sets ChallengeA.zip. You should find inside the .zip with separate files containing the excitatory and inhibitory conductance injected, along with the recorded potential. Repetitions and different stimulations are stacked in different columns of the ASCII files, and the order of the columns is conserved throughout the associated .txt. The files are easily accessible, for instance you can load the potential recording in MATLAB with load V.txt -ascii. The potential measurements are in mV, the conductance injections in nS and the sampling frequency is 10 kHz.

The submissions should consist of 1 to 20 vectors of spike times in units of 0.1 ms, saved in tab-separated arrays (numbers only, ASCII). The file should be sent to : richard dot naud at epfl.ch in an email having the title Challenge A submission. We will analyze the submissions as fast as possible and display the results with the label Anonymous#xx until you allow us to display some details on the model used.

Submit to Thomas Berger.

References

Jolivet, R., Rauch, A., Lscher, H.-R., and Gerstner, W. Predicting spike timing of neocortical pyramidal neurons by simple threshold models. *Journal of Computational Neuroscience* 21: 35-49 (2006).

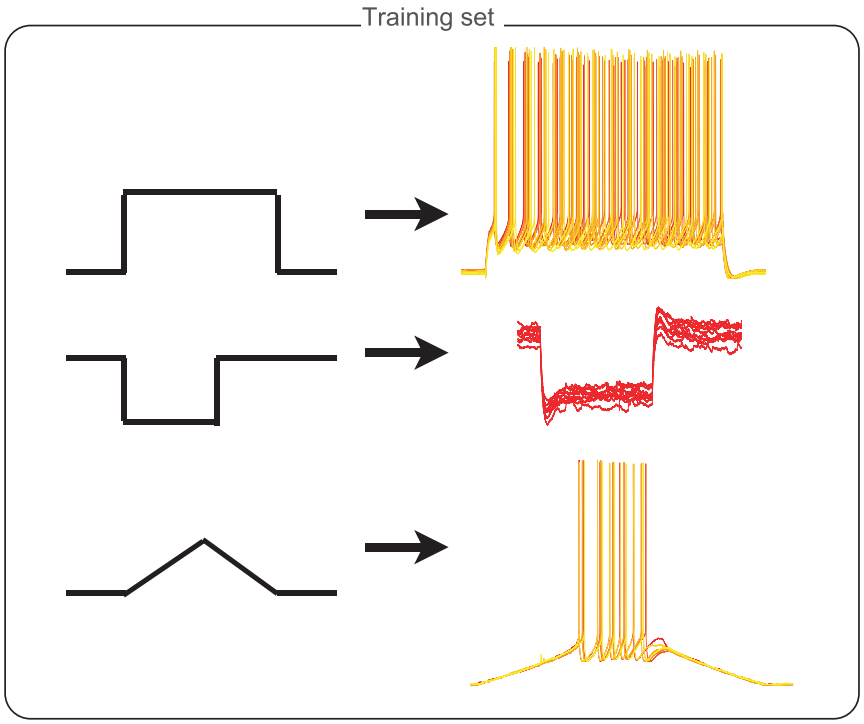
Gerstner, W., and Kistler, W., *Spiking Neuron Models*, Cambridge University Press (2002).

Challenge B

Goal Predict spike intervals and subthreshold voltage features of arbitrary step current stimulations.

How to Participate
We provide a set of data for training and a set of data for evaluating the performance. The training set contains the stimulation and the voltage recordings. The test set consists of a similar stimulation protocol but we keep the voltage recordings to later evaluate the performances.

Experimental Methods
For more details on the experimental protocol click Here. This experiment used single electrode stimulation of layer 5 pyramidal neurons from the somatosensory cortex of young rats. There are three different stimulation protocols: i) a suprathreshold current step of 1 sec, ii) a hyperpolarizing current step of 1 sec and iii) a combination of an ascending and a descending ramp.



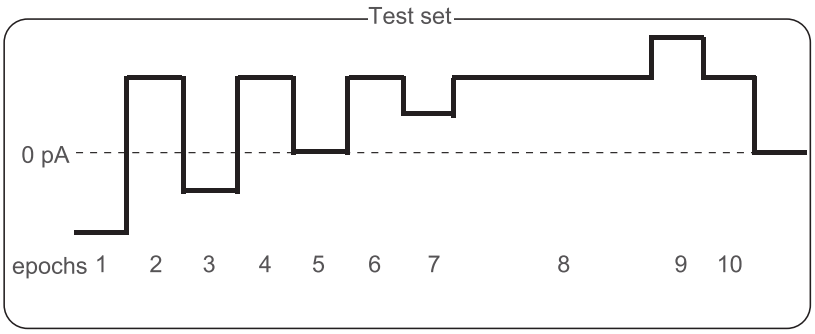
Evaluation Methods

We evaluate the performance of the models according to its voltage response to the test set shown below. The evaluation is performed on 18 different features. The features consist of total number of spikes, inter-spike intervals (ISI), first spike latency, subthreshold voltage and inter-spike potential depth (ISPD). Some of the features do not apply to all epochs, and it would be overly complicated to consider all the possible features of the neurons response. In this sub-challenge we focus on the restricted set of 18 features:

- f1: the total number of spikes,
- f2: the first spike latency in epoch 2,
- f3: the first ISI in epoch 2,
- f4: the second ISI in epoch 2,
- f5: the last ISI in epoch 2,
- f6: the mean ISPD in epoch 2,
- f7: the subthreshold voltage in initial segment of epoch 2,
- f8: the subthreshold voltage in epoch 3,
- f9: the first spike latency in epoch 8,
- f10: the first ISI in epoch 8,
- f11: the second ISI in epoch 8,
- f12: the last ISI in epoch 8,
- f13: the mean ISPD in epoch 8,
- f14: the subthreshold voltage in initial segment of epoch 8,
- f14: the first ISI in epoch 9,
- f15: the last ISI in epoch 9,
- f16: the mean ISPD in epoch 9,
- f17: the first ISI in epoch 10,
- f18: the last ISI in epoch 10.

For each feature, we compute the chi-square deviation in order to get the set of 18 performance measures. For example, the first performance measure writes:

$$B_1 = \sqrt{\frac{(N_m - \langle N_n \rangle)^2}{V[N_n]}} \tag{3}$$



where N_m is the number of spikes predicted by the model, N_n the number of spikes observed in the real neuron. The angular brackets stand for the average over all available repetitions, and V[.] stands for the variance across all available repetitions. Spikes are defined as upward zero-crossings. The ISI is simply the time difference between adjacent spikes and the ISPD is the minimum of the potential between two spikes. A slightly different procedure is used for the features concerned with the subthreshold voltage. We estimate the mean square difference between the voltage measured and the voltage modeled, from the onset of the current step to a time T. This is weighted by the average mean squared error across all combination of the six repetitions. The extent of the initial segment considered, T, is chosen to be the first spike latency minus three times its standard deviation. For probabilistic models, we compute the deviation on the average of each feature. Probabilistic models can submit up to maximum 20 voltage responses.

To determine the winner, we round off the performance measures, B_i, to the first decimal place and then compare the submissions. A submission is said to be better than another if and only if its performance measures are smaller or equal to the performance measures of the other solution. In this type of classification, there is not necessarily a overall best submission (2nd prize), see Druckmann et al. (2007) for more information.

Participate

You can download the training and test sets ChallengeB.zip. You should find inside the .zip separate files containing the different stimulation protocols and the recorded potential. Repetitions and different stimulations are stacked in different columns of the ASCII files, and the order of the columns is conserved throughout the associated files. The files are easily accessible, for instance you can load the potential recording in MATLAB with load StepV.txt -ascii. The potential measurements are in mV, the current injections in pA and the sampling frequency is 10 kHz.

For this challenge we accept submissions of the same format as for the training data set. The submission should consist of a potential waveform sampled at 10 kHz. If your model is probabilistic, you can submit an array where each column is a model output (numbers only, ASCII). The file should be sent to : richard dot naud at epfl.ch in an email having the title Challenge B submission. We will analyze the submissions as fast as possible and display the results with the label Anonymous #xx until you allow us to display some details on the model used.

Submit to Thomas Berger

References

Druckmann, S., Banitt, Y., Gidon, A., Schuermann, F., Markram, H., Segev, I., A novel multiple objective optimization framework for constraining conductance-based neuron models by experimental data. *Frontiers in Neuroscience* (2007) 1: 7-18.

Challenge C

Goal

Predict the somatic spike timing of current injection in both the soma and the dendritic tuft with 2 ms precision.

How to Participate

We provide a set of data for training and a set of data for evaluating the performance. The training set contains the stimulation and the voltage recordings. The test set consists of a similar stimulation protocol but we keep the voltage recordings to later evaluate the performances.

Experimental Methods

For details concerning the experimental preparation, please see Larkum et al. (2004). The data consists of noisy injections with ascending and descending mean current of various types: high standard deviation, low standard deviation, step increase in mean current, ramp increase, etc.

Evaluation Methods

Similar to challenge A, we will assess the quality of the model with the Γ coincidence factor. The absence of repetitions for the present experiments prevents us from scaling with the intrinsic reliability. However, we will test with Nstim different stimulation regime. Therefore the performance measure for challenge C is ;

$$D_1 = \frac{1}{N_{stim}} \sum_{i=1}^{N_{stim}} \frac{\Gamma_{m_i n_i}}{R} \tag{4}$$

where n_i corresponds to the ith recorded spike train and m_i to the modeled data. Probabilistic models can submit up to 20 spike trains for each stimulus regime. The resulting performance is an average of C_1 on the 20 spike trains submitted by the probabilistic model.

$$D_2 = \frac{1}{N_{stim}} \sum_{i=1}^{N_{stim}} \frac{1}{T} \int \frac{1}{1 + \frac{|V_{m_i}(t) - V_{n_i}(t)|}{2\,mV}} dt \tag{5}$$

Since there there are two cells, we obtain two performance measures: C_1 and C_2. We round off the value to the tenth of a percent before comparing the submissions. A submission can obtain the second prize only if its C_1 and C_2 are higher or equal to all other submissions.

Participate

You can download the training and test sets ChallengeC.zip. You should find inside the .zip with separate files containing the current injected and the potential recorded. The files are easily accessible, for instance you can load the potential

recording in MATLAB with load t7D1.txt -ascii. The potential measurements are mV, the current injections in pA and the sampling frequency is 10 kHz. You can refer to the README.txt for further details.

The submission should consist of 1 to 20 vectors of spike times in units of 0.1 ms for each test stimulation and each cell. The file should be sent to : richard dot naud at epfl.ch in an email having the title Challenge C submission. We will analyze the submissions as fast as possible and display the results with the label Anonymous #xx until you give us some details on the model used.

Submit to Arnd Roth

References

Larkum, M. E., Senn, W., Lscher, H.-R. Top-Down Dendritic Input Increases the Gain of Layer 5 Pyramidal Neurons. *Cerbral Cortex*, (2004) 14: 1059-1070.

Challenge D

Goal

Predict the spike timing and subthreshold voltage features for somatic and dendritic electrodes.

How to Participate

We provide a set of data for training and a set of data for evaluating the performance. The training set contains the stimulation and the voltage recordings. The test set consists of a similar stimulation protocol but we keep the voltage recordings to later evaluate the performances.

Experimental Methods

For details concerning the experimental preparation, please see Larkum et al. (2004) and Larkum et al. (1999). As in challenge B, the data consists partly of noisy current injection with different means and standard deviations (Larkum et al. 2004). In this challenge, the training and test sets also contain a special stimulation protocol used to study BAC firing (Larkum et al. 1999). The injection consists of a square current pulse in the soma and a delayed alpha-function injected in the distal dendrite.

Evaluation Methods In this challenge we test for two objectives. The spike timing is evaluated with the same technique as for challenge C:

$$D_1 = \frac{1}{N_{stim}} \sum_{i=1}^{N_{stim}} \frac{\Gamma_{m_i n_i}}{R} \tag{6}$$

where n_i corresponds to the ith recorded spike train and m_i to the associated model data. Here, in the test set we have $N_{stim} = 4$ different stimulations. Probabilistic models can submit up to 20 spike trains for each stimulus regime. The resulting performance is an average of D_1 on the 20 spike trains. The D_1 is rounded to the tenth of a percent for comparison.

The second objective consists of the prediction of dendritic to a precision of 2 mV. We use a measure related to the fraction of time the predicted voltage V_m is close to the measured voltage V_n: ? Where T is the total time of the stimulation, 70 ms. Nstim is the number of stimulation regimes used for testing, $N_{stim} = 8$. Here D_2 is evaluated with the distal dendritic potential. Similarly, D_3 can be defined as the performance of the model in predicting the proximal dendritic potential. Again the resulting numbers are rounded to the first decimal place for comparison. The best submission is the submission that is better or equal to the other submissions in all D_1 and D_2 and D_3.

Participate

You can download the training and test sets ChallengeD.zip You should find inside the .zip with separate files containing the current injected, and the potential recorded. The files are easily accessible, for instance you can load the potential recording in MATLAB with load t7D1.txt -ascii. The potential mea-

surements are mV, the current injections in pA and the sampling frequency is 10 kHz. You must refer to README.txt for further details.

The submission should consist of 1) 1 to 20 vectors of spike times in units of 0.1 ms for each test stimulation and each cell, 2) your prediction of the voltage recording in distal and proximal dendrites. The file should be sent to : richard dot naud at epfl.ch in an email having the title Challenge D submission. We will analyze the submissions as fast as possible and display the results with the label Anonymous #xx until you allow us to display some details on the model used.

Submit to Arnd Roth

References

Larkum, M. E., Zhu, J. J., Sakmann, B. A new cellular mechanism for coupling inputs arriving at different cortical layers, *Nature*, (1999) 398: 338-341.

Larkum, M. E., Senn, W., Lscher, H.-R. Top-Down Dendritic Input Increases the Gain of Layer 5 Pyramidal Neurons. *Cerebral Cortex*, (2004) 14: 1059-1070.