Wavenet identification and input estimation from single voltage traces

**OUTLINE**

- We present a computational procedure both to obtain a neuronal model and to estimate input parameters from single voltage traces.
- The procedure is based on an efficient use of artificial neural networks (ANN) built on wavelets (wavevnet). More precisely, a modification of wavevets aiming at decreasing the number of functions used.
- We identify (obtain a black-box synthetic equivalent model) by means of the wavevnet.
- By computing the inverse wavevnet, we are able to provide input estimations from voltage traces and further distinguish between excitatory and inhibitory input conductances.
- We test our procedure with the Morris-Lecar model as a proof-of-concept instantiated by conductance-based neuron models, but it has potential applications to experimental data.

**MODEL**

We consider the Morris-Lecar model:

\[
\begin{align*}
\frac{dV}{dt} &= -g_L (V - E_L) - g_w (V - E_w) - g_m m(V)(V - E_m) + I_{app}(t), \\
\frac{dw}{dt} &= \frac{w_w - w(V)}{\tau_w(V)},
\end{align*}
\]

(1)

(2)

Ultimate goal: estimating the input \( I \sim I_{app} \sim I_{app} \) from the voltage traces.

**FUNCTION APPROXIMATION USING WAVELETS THEORY**

Wavelets form a family of functions, constructed from expansions and translations of a basic function \( \psi (\cdot) \) called wavelet mother (here, a quadratic spline).

\[
\psi_{mn}(t) = \frac{1}{a} \psi \left( \frac{t - n}{a} \right)
\]

A standard particular choice (discrete wavelets family) is:

\[
\psi_{m,n}(t) = \psi \left( \frac{t - n}{a} \right)
\]

They can represent any function \( f(t) \in L^2(\mathbb{R}) \):

\[
|f(t) - f_m| = \sum |a_m,n|
\]

Series expansion is generally divided into 2 parts: non-refined information identified by an expansion in scaling functions \( \phi_{m,n} \) (quadratic spline) and details identified by wavelets \( \psi_{m,n} \). The complete signal is the sum of both parts:

\[
f(t) = \sum a_{m,n} \phi_{m,n}(t) + \sum c_{m,n} \psi_{m,n}(t)
\]

Modified wavelet

The proposed modification combines localized and global scaling functions unlike classical Wavelets, which only use localized wavelets and scale functions.

**Dynamical systems identification**

The identification of a dynamical system consists of:

1. Acquisition of data groups for fitting (training patterns): data obtained by solving the system of differential equations.
2. Determination of the best network structure: Studying what set of input variables better identifies the process. Simple criterion: the smaller number of variables giving the smallest quadratic error.
3. Simulation: Acquisition of a new data group (test), relating inputs to outputs, different from that used in training. The network performance is evaluated in relation to test data group (crossed validation).
4. Validation: Through dynamic prediction. In this case, the first point of the validation data group (initial condition) is used as an input to the network. In relation to the other points, only the information of perturbation variable is used, as external information, and a feedback of the output variables is made.

**IDENTIFICATION OF THE ML MODEL**

Inputs (5): \( I_{app}(t) \), \( v(t - h) \), \( w(t - h) \), \( v(t - 2h) \), \( w(t - 2h) \). 

Network: 1 level of activation functions; \( \rho \sim 10^{-7} \)

\( \rho \) - regularization parameter, composed by the quadratic error of the output and the weights of the network squared to penalize the excessive curvature of the surface.

**CONCLUSIONS**

1. Identification: From an appropriately designed input and the corresponding voltage trace, we obtain a black-box model the ANN identifies the neuron’s behavior with high accuracy. Interestingly, the interval of input currents used to train the wavenet includes both quiescent and spiking regimes, thus tracking also abrupt changes in the bifurcation diagram.
2. Estimation: We also show how the wavenet methodology can also be applied to the reverse situation, that is, to provide input estimations from voltage traces (inverse wavenets). Estimating the synaptic input (synaptic conductances) is the ultimate goal, an active research problem line with no complete solutions yet, see for instance [2].
3. Similar results obtained for more realistic conductance-based models (not shown here). Tailored training allows to generalize the method to the presence of multiple timescales.
4. The method is extendable to experimental data. These findings open new avenues to provide heuristic models for real neurons by stimulating them in closed-loop experiments using, for instance, dynamic-clamp. Unfortunately, we lose any biophysical meaning of the model.

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