BMC Neuroscience

Poster presentation

Is the Langevin phase equation an efficient model for stochastic limit cycle oscillators in real neurons?

Keisuke Ota*[1], Toshiaki Omori[2,3], Shigeo Watanabe[4], Hiroyoshi Miyakawa[4], Masato Okada[2,3] and Toru Aonishi[1,3]

Address: [1]Dept. of Computational Intelligence and System Science, Tokyo Tech., Yokohama, 2268502, Japan, [2]Dept. of Complexity Science and Engineering, Univ. of Tokyo, Kashiwa, 2778561, Japan, [3]Brain Science Institute, RIKEN, Wako, 3510198, Japan and [4]Dept. of Life Science, Tokyo Univ. of Pharmacy and Life Science, Hachioji, 1920392, Japan

Email: Keisuke Ota* - keisuke@acs.dis.titech.ac.jp

* Corresponding author

from Eighteenth Annual Computational Neuroscience Meeting: CNS*2009
Berlin, Germany. 18–23 July 2009

Published: 13 July 2009

BMC Neuroscience 2009, **10**(Suppl 1):P236 doi:10.1186/1471-2202-10-S1-P236

This abstract is available from: http://www.biomedcentral.com/1471-2202/10/S1/P236

Background

The Langevin phase equation $d\varphi/dt = 1 + Z(\varphi)(G(t) + \sigma s(t))$, where φ is the phase, which is disturbed by a perturbation G and Langevin force s of intensity σ, and Z is the phase response curve (PRC), has been deemed to be a good model for stochastic limit cycle oscillators [1], and it has been extensively used in theoretical neuroscience as a model neural oscillator [2]. Inspired by the theoretical research, experimental researchers have measured PRCs, but none of them have identified the Langevin phase equation for real neurons directly. In fact, biological experiments have yet to show whether this equation is a good model for neural oscillators.

Methods

Here, we demonstrate that the Langevin phase equation is a good model for neural oscillators in rat hippocampal CA1 pyramidal neurons, through two steps in the same neuron. (A) Estimation step: We estimated the parameters of the Langevin phase equation, i.e., a PRC and the intensity of the Langevin force, from physiological noisy data (phase shifts disturbed by one-shot rectangle pulses 20 pA, 5 msec) by using the MAP estimation algorithm, from our previous study [3]. Figure 1 shows the estimated PRC (a) and the hyper parameters (b). The estimated PRC was fully positive, which indicates that hippocampal CA1 pyramidal neurons could be classified as Type I excitability neurons, while the estimated Langevin force intensity suggests that the inherent noise in the recording neuron is 9.0 pA. (B) Prediction step: We injected two different periodic perturbations, consisting successive rectangular pulses. One consisted of 20 pA, 5 msec pulses (the same values used in the PRC estimation), the other 10 pA, 20 msec pulses. We obtained histograms of phase differences between spikes and pulses for each perturbation. Then we ascertained whether the Fokker Planck equation (FPE) derived from the Langevin phase equation with the esti-

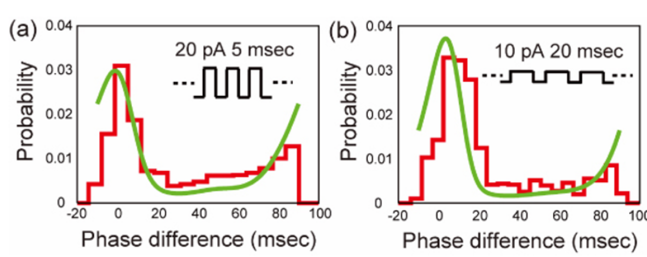

Figure 1
(a) Estimated PRC (solid line) from the phase shifts (crosses) disturbed by one-shot perturbations (20 pA, 5 msec) in a pyramidal neuron of rat hippocampal CA1. (b) The landscape of the marginal likelihood, where the maximum represents the estimated values of hyper parameters.

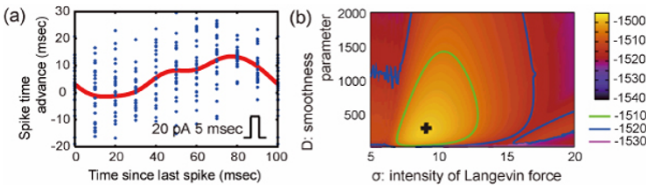

Figure 2
Comparison of distributions predicted by the Langevin phase equation (green line) and phase difference histograms calculated from physiological data (red line). The upper right of each graph displays the shape of the periodic perturbation, (a) 20 pA, 5 msec and (b) 10 pA, 20 msec.

mated PRC and Langevin force intensity could predict these histograms.

Results and discussion

The distribution derived from FPE was in good agreement with the experimental histogram (Fig. 2), even when the shape of the perturbation was not the same as the one used in the PRC measurement (Fig. 2b). This result suggests that the Langevin phase equation can describe the stochastic dynamics of neural oscillators, no matter what perturbation disturbs them.

References

1. Nakao H, Teramae J, Ermentrout GB: **Comment on "phase reduction of stochastic limit cycle oscillators".** [http://arxiv.org/abs/0812.3205].
2. Ermentrout GB, Galan RF, Urban NN: **Relating neural dynamics to neural coding.** *Phys Rev Lett* 2007, **99:**248103.
3. Ota K, Omori T, Aonishi T: **MAP estimation algorithm for phase reponse curves based on analysis of the observation process.** *J Comput Neurosci* in press.