NetPSO: Gradient-free optimization method for the discovery of stimuli which drive specific network dynamics

Preprint · November 2018

DOI: 10.13140/RG.2.2.31712.53761

2 authors:

Jimin Kim
University of Washington Seattle

Eli Shlizerman
University of Washington Seattle

NetPSO: Gradient-free optimization method for the discovery of stimuli which drive specific network dynamics

Jimin Kim and Eli Shlizerman

Abstract— **We develop a novel method, NetPSO, for discovery of optimal neuronal network stimuli which enable the network to achieve given dynamics. NetPSO is a generalization of Particle Swarm Optimization (PSO), which is a gradient free biologically inspired algorithm designed to mimic swarm intelligence and operates with three steps, exploration, experience and mimicking. The steps guide a large set of particles to search for the optimal solution in collaboration with each other. To test the approach, we apply our method to an example Random Recurrent Neural Network with dynamic connectivity and excitatory/inhibitory neurons. We show that NetPSO is able to converge successfully on all trials to the inputs which give rise to the given dynamics. We also apply the NetPSO method to the neuronal network model of *Caenorhabditis elegans* (*C. elegans*) to investigate plausible stimuli which give rise to specific neural dynamics of the full somatic nervous system. In particular, we aim to discover constant input currents, within the locomotion sub-circuit, which trigger oscillatory dynamics in motor neurons associated with traveling wave propagating from anterior-to-posterior direction of the body. Our results show that we are able to recover stimuli that produce such dynamics. In addition, we observe that NetPSO can find alternative stimuli that lead to similar dynamics. Such functionality allows to explore stimulation of networks for which neural recordings are available, but their structure is unknown.**

I. Additional Detail

Particle Swarm Optimization (PSO) algorithm is a biologically inspired gradient free optimization routine designed to mimic the behavior of flocking birds or schooling fish [1]. The central concept is to define a set of particles which iteratively update their positions and velocities according to simple mathematical rule such that the particles search for the optimal solution in a collaborative manner. While all particles are trying to reach the same goal, they take distinct approaches. In each time instance, each particle has a chance to update its state according to its *directions of change*. The directions of change are determined by three main forces: Exploration, Experience and Mimicking. The weighted sum of the three forces determines final direction of change for the particle. More specifically, the forces are: **Exploration:** Keep the action the particle took in the previous time step with some randomness. **Experience:** Navigate toward the best action this particle has ever taken so far. **Mimicking:**

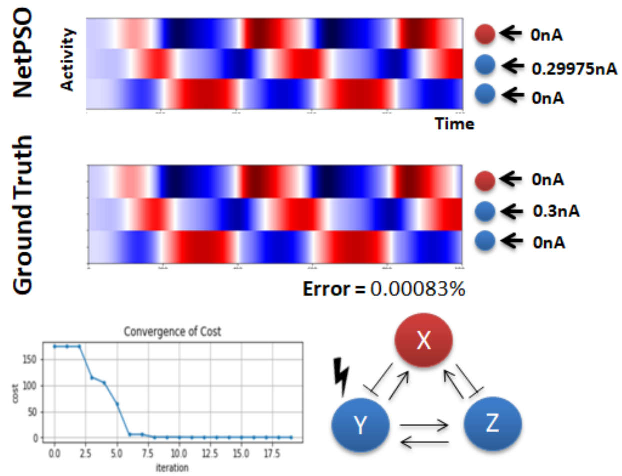

Fig. 1. **Application of NetPSO to 3-Node 2-Channel Random Recurrent Neural Network. Top:** Comparison of neural network activity generated by a network stimulated according to NetPSO (top) with Ground truth network (bottom). **Bottom left**: Convergence rate of the cost function used by NetPSO. **Bottom right**: connectivity structure of the network; blue nodes-excitatory, red nodes-inhibitory.

Follow the direction of the best performed "other" particle in the current time step. The above steps determine the following equations for the position and velocity update of each particle:

$$Position: x^i_{k+1} = x^i_k + v^i_{k+1}$$
$$Velocity: v^i_{k+1} = w_k v^i_k + c_1 r_1 \left(p^i_k - x^i_k\right) + c_2 r_2 \left(p^g_k - x^i_k\right)$$

where subscripts k and $k+1$ indicate the k-th and $(k+1)$-th time instances, the superscript i indicates the i-th particle out of the particle swarm, c_1 and c_2 are the two weighting values for balancing the local (experience) and global (mimicking) optimal force, w_k is the discounting weight indicating the probability of the particle to keep the previous state x^i_k, r_1 and r_2 are random floating point values to introduce randomness to the behavior of particles, and finally p^i_k and p^g_k are the local and global optimal states at time k. The fact that PSO does not include assumptions regarding the problem being solved and does not require the optimization problem to be differentiable makes it a viable method for discovery of functional stimuli of neuronal networks. In particular, we propose a generalization which searches the stimuli space, with each particle being a stimulus candidate and the cost is defined

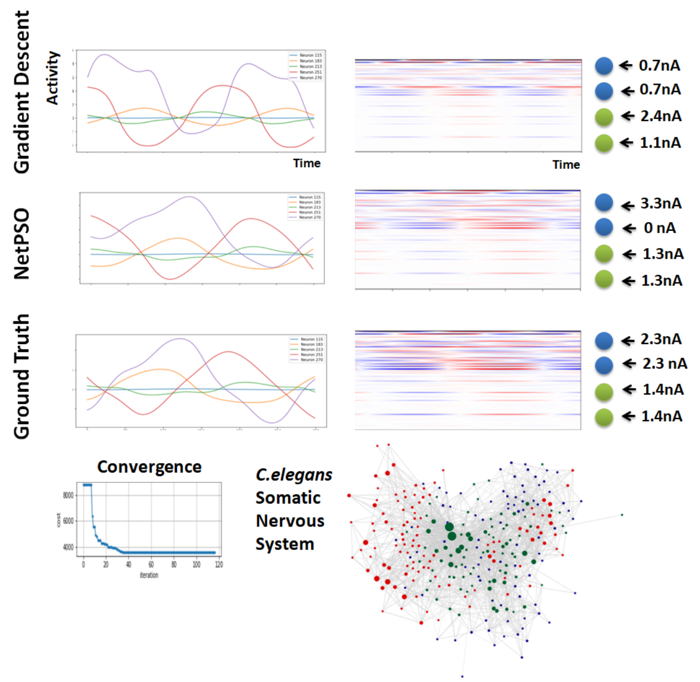

Fig. 2. **Discovery of stimuli in *C. elegans* nervous system model. Top**: Time series and raster plots of neural activity obtained from Gradient descent, NetPSO and Ground Truth . With 50 particles, NetPSO converges to $AVBL = 3.3nA, AVBR = 0nA, PLML/R = 1.3nA$ within ~ 100 iterations. **Bottom left**: Convergence rate of NetPSO. **Bottom right**: Visualization of *C. elegans* somatic nervous system network [3].

as the error between stimulated and given network dynamics. We call this variant of PSO, *NetPSO*.

A. Optimization of Input Parameters for Random Recurrent Neural Networks

To test the NetPSO approach, we first apply it to example Random Recurrent Neural Network consisting of 3 neurons (2- excitatory, 1-inhibitory) and 2 channels between neurons (synaptic and gap connectivity) for which we randomly choose constant stimuli, simulate the network and record its dynamics (the Ground Truth in Fig. 1). We then utilize NetPSO with 20 particles to find input stimuli which drive the network to produce the recorded dynamics. We observe that NetPSO successfully (up to error of 0.00083%) converges to stimuli used to produce the Ground truth dynamics. As expected, the dynamics of the network obtained by NetPSO indeed produces raster plots indistinguishable from the Ground Truth network dynamics, see Fig. 1. We obtain similar results for various connectivity weights and stimuli drawn randomly.

B. Discovery of Stimuli in the Somatic Nervous System Model of C. elegans

To test the performance of NetPSO on large networks we proceed and apply it to the dynamical model of *C. elegans* full somatic nervous system (279 neurons). To obtain the Ground Truth neural dynamics, we stimulate PLML and PLMR sensory neurons, and AVBL and AVBR inter neurons with constant stimuli (2.3nA to AVBL/R and 1.4nA to PLML/R). These stimuli are associated with the posterior touch response and trigger forward locomotion. The neural dynamics associated with it are expressed as traveling waves of neural activity from anterior to posterior along the body. The model indeed exhibits such characteristic oscillations and we record them as Ground Truth dynamics (Fig. 2). We then set the number of particles in NetPSO to 50 and utilize the method to recover the PLM and AVB stimuli. Optimization converges after approximately 40 iterations to stimuli values of (AVBL, AVBR, PLMR, PLML)=[3.3nA, 0nA, 1.3nA, 1.3nA] (Fig.2 NetPSO). The converged stimuli for PLM are similar to those in the Ground Truth scenario, while stimulus of AVB is significantly different. However, when we compare the similarity of neural dynamics obtained by NetPSO network with the Ground Truth we find remarkable similarity between the two activity profiles (Fig.2). Notably, when we attempt to find stimuli using the conventional Gradient descent method, such an approach fails to converge and the dynamics that the resulting network produces are substantially different in frequency amplitude and synchronization between different neurons' dynamics (Fig.2 top). Indeed, these results are consistent with the anatomical connectivity, since AVBR forms gap junction with AVBL, such that stimulation of AVBL alone can entrain AVBR and produce dynamics close to dynamics produced by the Ground Truth stimuli. Furthermore, these results indicate that NetPSO is applicable for discovery of novel stimuli, if such stimuli exist, and potentially characterize families of stimuli resulting in similar dynamics.

REFERENCES

[1] Kennedy J. Particle swarm optimization. InEncyclopedia of machine learning 2011 (pp. 760-766). Springer, Boston, MA.

[2] Kunert, J., Shlizerman, E. and Kutz, J.N., 2014. Low-dimensional functionality of complex network dynamics: Neurosensory integration in the Caenorhabditis elegans connectome. Physical Review E, 89(5), p.052805.

[3] Kim, J., Leahy, W. and Shlizerman, E., 2017. Neural Interactome: Interactive Simulation of a Neuronal System. bioRxiv, p.209155.

[4] Liu H, Kim J, Shlizerman E. Functional connectomics from neural dynamics: probabilistic graphical models for neuronal network of Caenorhabditis elegans. Phil. Trans. R. Soc. B. 2018 Oct 19;373(1758):20170377.