Guided self-organization and attractor meta-dynamics

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Multiple time scales are present in various forms in the brain. A single neuron is functionally equivalent to a relaxation oscillator driven by the interplay of slow and fast current dynamics. Fast neural dynamics and slow adaption processes can be distinguished on a network level. Adiabatic attracting states are defined, in this context, as the fixpoints of the fast dynamics when the present configuration of slowly adapting variables is frozen in. Adiabatic attractors have been postulated to be the guiding centers for ongoing brain dynamics and of central importance in decision making processes.

We consider the dynamics of the adiabatic attractors in autonomous slow-fast dynamical systems. In particular we investigate the correlations between the adiabatic phase diagram and possible types of attractor meta-dynamics. For the systems considered we can identify continuously morphing and discontinuously jumping adiabatic attractors and find that the corresponding adiabatic phase diagrams are characterized by second- and first-order phase transitions respectively.

Our systems are generated from objective functions implementing the principle of polyhomeostatic optimization. We consider a system to undergo guided self-organization when targets for the self-organizing process are given in terms of time-averaged statistical properties of the dynamical activities. This is a typical example of statistical time allocation optimization. For the case of the brain, neurons need to optimize their respective time-averaged firing statistics, in order to maximize information transmission. Minimizing the respective objective function, the Kullback-Leibler divergence, leads to polyhomeostatic adaption rates for the intrinsic neural parameters, like the threshold and the gain.

In addition we consider a new generating functional, the Fisher information with respect to the synaptic flux, which allows to derive self-limiting Hebbian learning rules. We discuss whether the resulting synaptic competition can be viewed as self-organizing process guided by the task to minimize, as an average over time, the synpatic flux.

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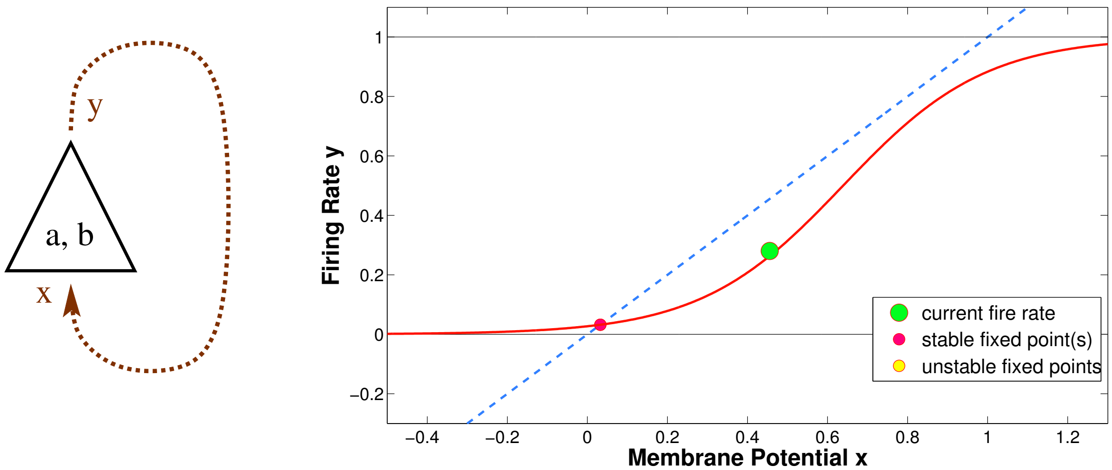
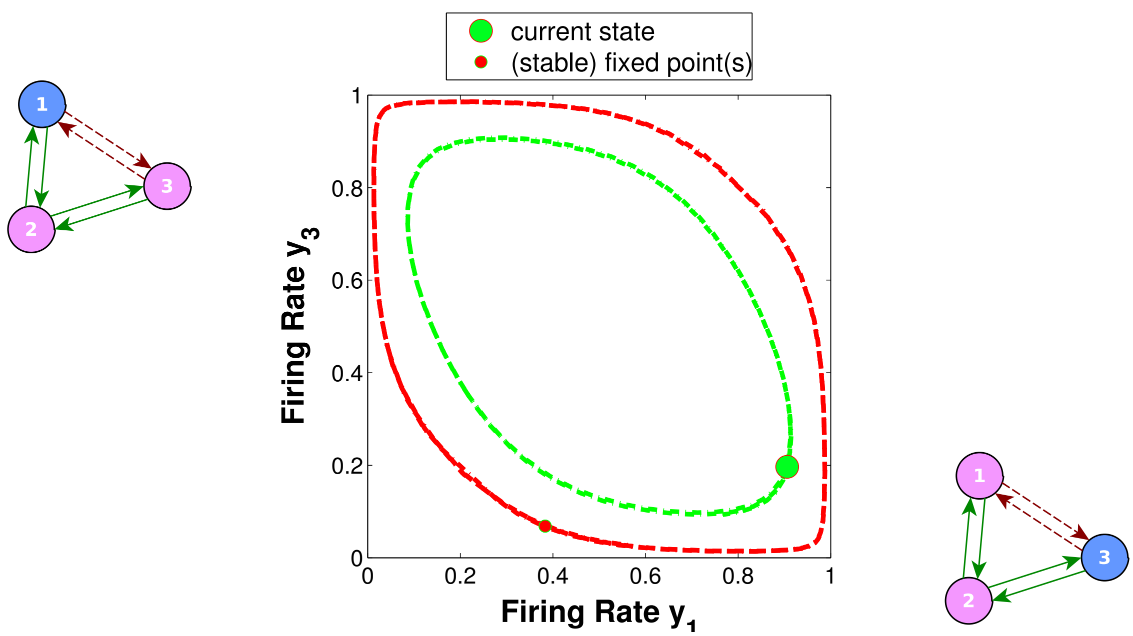


For a self-coupled neuron (autapse, left panel) the fixpoint condition (right panel). Shown is, as a function of membrane potential x, the actual neural firing rate y (green dot), being attracted by the actual adiabatic fixpoint (red dot). The adiabatic fixpoint jumps discontinuously in between the lower and the upper branch, upon adaption of the slow intrinsic neural parameters.



A three site network having excitatory (green arrows) and inhibitory (red arrows) synaptic weights. The network may have, depending on the configuration of slow variables, one or two attracting states, corresponding to (0,1,1) (left) or to (1,1,0) (right). The actual trajectory in the (y_1, y_3) plane (green dot, middle panel) of neural activities approaches a limiting cycle (green dashed curve) following at all time the adiabatic attractor (red dot, middle panel), which is continuously morphed by the slow adaption processes (red dashed curve).