Fluctuation-driven plasticity allows for flexible rewiring of neuronal assemblies

Alex Roxin, Centre de Recerca Matemàtica (CRM), aroxin@crm.cat
Federico Devalle, Universitat Pompeu Fabra (UPF), federico.devalle@upf.edu
Toni Guillamon, Universitat Politècnica de Catalunya, antoni.guillamon@upc.edu
Ernest Montbrió, UPF, ernest.montbrio@upf.edu
Marina Vegué, CRM and UPC, marinavegue@gmail.com

Cortical circuitry is shaped through ongoing synaptic plasticity. However, network models in which recurrent synaptic connections change via Hebbian plasticity rules are unstable: synapses become maximally potentiated or depressed, effectively erasing all nontrivial structure in the connectivity. One solution to this dilemma is to include additional mechanisms to offset Hebbian instabilities [1]. Here we consider an alternative scenario in which, given constant firing rates, the rates of potentiation and depression are equal and opposite. Net potentiation or depression only occurs when the firing rates of neurons covary in time. We show that standard heuristic STDP (spike-timing dependent plasticity) rules can have this property. Furthermore, we show how external time-varying signals can be used to flexibly control the network structure. As an example, neuronal assemblies can be strongly coupled, decoupled, or uni-directionally coupled by driving them with oscillatory signals with distinct phase lags. Alternatively, the connectivity between assemblies driven by stochastic inputs can be flexibly shaped via the covariance matrix of the inputs.

Specifically, we consider a system of coupled firing rate equations of the form

$$\tau \dot{\mathbf{r}} = (\mathbf{W} - \mathbf{I})\mathbf{r} + \mathbf{I}(\mathbf{t}), \tag{1}$$

where the connectivity matrix $\mathbf{W}$ is shaped via a pairwise spike-timing dependent plasticity rule (STDP) implemented by generating spikes stochastically in accordance with the underlying rates. In the limit in which plasticity occurs much more slowly than the firing rate dynamics, the evolution of the synaptic weights can be approximated as a continuous process [2]

$$\dot{W}_{ij} = \int_{-\infty}^{\infty} dT K(T) r_j(t) r_i(t+T), \tag{2}$$

where $K(T)$ is the plasticity rule and we take $K(T) = A_+ e^{-T/\tau_+}$ when $T > 0$ and $K(T) = -A_- e^{T/\tau_-}$ otherwise. We formalize the slowness of learning by introducing a small parameter ϵ such that $(A_+, A_-) = \epsilon(\tilde{A}_+, \tilde{A}_-)$ and then define a slow time $t_s = \epsilon t$. This separation of time scales allows to treat the connectivity $\mathbf{W}$ as a constant in Eq.1, solve for the rates exactly, and then calculate the self-consistent ODEs for the connectivity by performing the integral in Eq.2. In this way we can determine the evolution of the recurrent synaptic weights as a function of the feedforward inputs $\mathbf{I}(\mathbf{t})$.

Recent work [3] shows that model networks with hierarchically organized clusters can fit all relevant connectivity statistics reported in slice experiments from rat cortex [4]. Our work here suggests a mechanism to account for the formation of such a clustered network structure. Namely, when sensory stimuli drive a time-varying response in a network with heterogeneous feature selectivity, the recurrent connectivity will be shaped by the cross-correlation in the firing rates as in Eq.2. Our analysis indicates that neurons with similar time-varying response (selectivity) will form strongly interconnected clusters, while the connectivity between any pair of clusters will depend on the cross-correlation and time-lag in the sensory drive that each receives. Importantly, this rewiring only occurs due to stimulus-driven fluctuations of the neuronal activity about the baseline rates; constant rates result in no overall plasticity.

References

[1] F. Zenke, E. J. Agnes and W. Gerstner Diverse synaptic plasticity mechanisms orchestrated to form and retrieve memories in spiking neural networks, *Nat. Commun.*6:6922 doi: 10.1038/ncomms7922 (2015).

[2] R. Kempter, W. Gerstner and J. L. van Hemmen. *Hebbian learning and spiking neurons, Phys. Rev. E* 59(4):4498-4514 (1999).

[3] M. Vegué, R. Perin and Alex Roxin. *On the structure of cortical microcircuits inferred from small sample sizes, J. Neurosci.* 37(35):8498-8510 (2017).

[4] R. Perin, T. K. Berger and H. Markram. *A synaptic organizing principle for cortical neuronal groups, PNAS* 108(13):5419-5424 (2011).