

Temporal Dynamics in an Attractor Model of the Songbird's Premotor Nucleus

Fjola Hyseni, Arthur Leblois, Nicolas P. Rougier

► To cite this version:

Fjola Hyseni, Arthur Leblois, Nicolas P. Rougier. Temporal Dynamics in an Attractor Model of the Songbird's Premotor Nucleus. COSYNE 2022 - Computational and Systems Neuroscience, Mar 2022, Lisbon, Portugal. hal-04443688

HAL Id: hal-04443688 https://hal.science/hal-04443688v1

Submitted on 7 Feb 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers. L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Temporal Dynamics in an Attractor Model of the Songbird's Premotor Nucleus

Fjola Hyseni, Arthur Leblois, Nicolas P. Rougier Univ. Bordeaux, CNRS, IMN, UMR 5293, F-33000 Bordeaux, France fjola.hyseni@u-bordeaux.fr

What do songbirds tell us about timing?



Temporal control is crucial for the generation of coordinated movements during sensorimotor tasks. Like human speech, birdsong relies on a tight muscle coordination, and songbirds have proven to outstandingly model the neural substrate of action timing. In songbirds, premotor nucleus HVC is responsible for the precise control of song tempo. Current computational models of HVC rely on synfire chains.

2. Modifing syllable duration

Relying on a reward covariance rule, we show that the duration of a syllable can be modified in response to a perturbed reward profile, as implemented in a widely used lab conditioning paradigm.



 γ : learning rate parameter, , R(t): the reward, η : noise at the postsynaptic neuron, $r_{j:}$ rate of the presynaptic neuron.



Synfire chains are however not robust to noise and function for a narrow range of feedforward weights (W, see figure below), requiring fine tuning during learning.



Propagation of activity in a synfire chain model

Attractors dynamics and timing

Here, we propose that HVC neuronal dynamics may be modelled by attractor

Changes in synaptic connectivity when the syllable is targeted for shortening vs lengthening





dynamics, where recurrent connections allow the formation of a travelling activity bump with robust functional properties.



Feature space (x: preferred timing during song)



 $W(x - x') = W_0 + W_2 \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{1}{2} \left(\frac{x - x' + bias}{\sigma}\right)^2}$ $I(x,t) = \sum_{x=1}^{n} \frac{1}{n} W(x - x')m(x',t) + I^{0}$ $\tau \frac{d}{dt} m(x,t) = -m(x,t) + [I(x,t) - T]_{+}$





Change in weights, averaged across the targeted syllables' presynaptic neurons



The behavior of the model when we locally inhibit mimicking a Muscimol injection and the effect on the bump formation and consequently the song.

Activity profile (bump) in the Feature space (left) and Physical space (right).

Activity profile in HVC

The width of the activity bump, and thus the duration of transient neuronal activation, can be decreased to reproduce the brief activity bursts of HVC neurons.



Conclusion

We propose that HVC neuronal dynamics may be modelled using the ring model.

The duration of a syllable can be modified in response to a perturbed reward profile and consistent with behavioral data, the change in duration is specific to the target syllable.

We derive a new prediction from the model. Following local muscimol (GABAa agonist) injection in HVC, in contrast to the synfire chain, a perturbation in the initial phase of the pattern formation would delay song initiation, but singing would be sustained.

Future perspectives:

A spiking network (with adapting LIF neurons) to replicate the behaviours acquired from the rate model, i.e 10ms bump width, learning and predicition.

References

- Hansel, D., & Sompolinsky, H. (1998). 13 Modeling Feature Selectivity in Local Cortical Circuits, 69.
- Ali F Pehlevan C and Olveczky. Nat Commun 9, 977, 2018.
- Williams, R. J. (1992). Machine Learning, 8(3).
- Zhang, K. (1996). Journal of Neuroscience, 16(6).
- Mauk, M. D., & Buonomano, D. V. (2004). Annual Review of Neuroscience 27(1).
- Hahnloser, R., Kozhevnikov, A. & Fee, M. *Nature* **419**,(2002)
- Brainard, M. S., & Doupe, A. J. (2002). Nature, 417(6886).