Cell assembly dynamics of sparsely-connected inhibitory networks

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Striatum and the Basal Ganglia

- Motor control
- Action Selection / Learning by Reward
- Diseases

Inhibitory
Excitatory
Dopamine

[Fino and Venance, 2010]
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  - Parkinson
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Some Morphological Aspect of MSNs

- 90% Medium Spiny Neurons
- Sparse connectivity $\sim 10$
- Inhibitory (GABA) synapses
  - Weak $\sim 0.2 \text{ mV}$ (respect to the FS neurons)
  - Duration $\sim 20 \text{ ms}$

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- Highly variable firing rate
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Encoding Information

- Alternating activity of assemblies of neurons

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- Families firing synchronously
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Leaky Integrate-and-Fire (LIF) model

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\begin{align*}
\dot{v}_i &= a_i - v_i - \frac{g}{K} E_i \\
\dot{E}_i &= P_i - \alpha E_i \\
\dot{P}_i &= -\alpha P_i + \alpha^2 \sum_{n|t_n<t} C_{i,j} \delta(t - t_n)
\end{align*}
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- Inhibitory Post-Synaptic Potentials (IPSP) strength
- Inverse IPSP time decay
- Random sparse connectivity 5%
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Choosing Optimal parameters

$Q_0$ metric

$Q_0 \equiv \langle CV \rangle_N \times \sigma(C(\nu_i, \nu_j)) \times n^*$

- Variability in the firing rate
- Interplay of correlated / anticorrelated activity
- Many Active neurons (WLC paradigm)
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Maximizing $Q_0$
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![Graph showing $\sigma^*$ vs. $g$ with a peak at low/middle value of synaptic strength.](image)
Maximizing $Q_0$

Graphs showing the relationship between $Q_0$ and $g$, indicating a low/intermediate value of synaptic strength.

Graphs also show the relationship between $\langle CV \rangle$, $\sigma(C)$, and $n^*$ with $g$, illustrating how these variables change as $g$ increases.
Maximizing $\mathcal{Q}_0$

- Low/intermediate value of synaptic strength
- Long tailed synapses
Maximizing $Q_0$

- Low/intermediate value of synaptic strength
- Long tailed synapses

- Graphs showing the relationship between $Q_0$ and $1/\alpha$ (ms)
- Graphs showing the relationship between $Q_0$ and $g$
- Graphs showing the relationship between $\langle CV \rangle^2$, $\sigma(C)$, $n^*$, and $g$
Optimal $Q_0$ / Poissonian Network.

*Two input encoding*

Optimal $Q_0$: $1/\alpha = 20$ ms

Non-optimal $Q_0$: $1/\alpha = 2$ ms
Optimal $Q_0$ / Poissonian Network.

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Conclusions

• A simple model of LIF neurons is capable to reproduce the most significant aspects of the MSN dynamics
  • The new metrics $Q_0$ is able to measure the effect of the parameters in the model
  • The selected parameter values maximize $Q_0$
  • The dynamics of our network exhibit the same features of more complex models of the striatum [Ponzi and Wickens, 2013]
• We were able to reproduce at a qualitative extent some experimental finding [Carrillo-Reid et al., 2008]
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Angulo-Garcia, D., Berke, J. D., and Torcini, A.
Cell assembly dynamics of sparsely-connected inhibitory networks: a simple model for the collective activity of striatal projection neurons.
Manuscript submitted for publication.

Encoding network states by striatal cell assemblies.

Spike-timing dependent plasticity in the striatum.
Frontiers in synaptic neuroscience, 2.

Dichotomous anatomical properties of adult striatal medium spiny neurons.

Dysregulated information processing by medium spiny neurons in striatum of freely behaving mouse models of huntington’s disease.

Fast algorithm for detecting community structure in networks.

Optimal balance of the striatal medium spiny neuron network.

Gabaergic microcircuits in the neostriatum.
Thank you

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Mean vs. Fluctuation Driven Activity

- Low $g$ neurons are all active - Mean Driven
- By increasing $g$ the number of active neurons $n^*$ decreases
- $n^*$ has a minimum
- The number of active neurons increases again at large $g$ due to current fluctuations
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Computation capability

Principal Component analysis of the network firing response for three different inputs

- Black $\tau_\alpha = 20$ ms
- Red $\tau_\alpha = 2$ ms
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Pattern Separation

Dissimilarity in the firing response of the network when affecting a fraction \( f \) of the inputs

\[
d_f(t_m) = 1 - \frac{R^c(t_m) \cdot R^f(t_m)}{||R^c(t_m)|| \cdot ||R^f(t_m)||} - R(t) \text{ state vector of the instantaneous firing rates}
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- Black \( \tau_\alpha = 20 \text{ ms} \) – Red \( \tau_\alpha = 2 \text{ ms} \)
Chaos or not chaos?

Presence of weak chaos at optimal parameter values

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ISI Statistics

Slow synapses allows for a continuum of possible ISI

$CV > 1$
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Slow synapses allows for a continuum of possible ISI
CV > 1
- Peaks in the percentage of neurons bursting within a time window are identified as Bursting Events (mean + 2 std).
- The indices of the neurons participating in the $i^{th}$ event are recorded in a N dimensional binary vector $x_i : 1$ (0) if the neuron participate to the event (otherwise)
- The similarity between synchronized events are calculated as the normalized scalar product between $x_i$ and $x_j$, thus defining the matrix $R_s$
- Optimal algorithm for clustering is applied to $R_s$ to find the number of clusters [Newman, 2004]
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