Multi-layer fields enable more complex neural dynamics

Gregor Schöner
... so far we assumed

that a single population of activation variable mediates both the excitatory and the inhibitory coupling required to make peaks attractors

\[ \sigma(u) \]

Activation field \( u(x) \)

- Local excitation: stabilizes peaks against decay
- Global inhibition: stabilizes peaks against diffusion

Dimension, \( x \)
But: Dale’s law

- says: every neuron forms with its axon only one type of synapse on the neurons it projects onto
- and that is either excitatory or inhibitory

This is not actually possible!
2 layer neural fields

Inhibitory coupling is mediated by inhibitory interneurons that
- are excited by the excitatory layer
- and in turn inhibit the inhibitory layer
2 layer Amari fields

\[
\tau_u \dot{u}(x,t) = -u(x,t) + h_u + s(x,t) + \int k_{uu}(x-x') g(u(x',t)) dx' - \int k_{uv}(x-x') g(v(x',t)) dx'
\]

\[
\tau_v \dot{v}(x,t) = -v(x,t) + h_v + \int k_{vu}(x-x') g(u(x',t)) dx'
\]

with projection kernels

\[
k_{uu}(x-x') = c_{uu} \cdot \exp\left(-\frac{(x-x')^2}{2\sigma_{uu}^2}\right)
\]
simulation
Implications

the fact that inhibition arises only after excitation has been induced has observable consequences in the time course of decision making:

- initially input-dominated
- early excitatory interaction
- late inhibitory interaction

[figure: Wilimzig, Schneider, Schöner, Neural Networks, 2006]
time course of selection

early: input driven
intermediate: dominated by excitatory interaction
late: inhibitory interaction drives selection

[figure: Wilimzig, Schneider, Schöner, Neural Networks, 2006]
early fusion, late selection

Figure 16 Wilimzig Schneider Schöner
[figure: Wilimzig, Schneider, Schöner, Neural Networks, 2006]
fixation and selection

[figure: Wilimzig, Schneider, Schöner, Neural Networks, 2006]
2 layer fields afford oscillations

- => simulation

- (oscillatory states for enhanced coupling among fields)

- (generic nature of oscillations)
mathematical basis of oscillations: limit cycle attractors

Amari 77

\[ \tau \dot{u} = -u + h_u + w_{uu}f(u) - w_{uv}f(v) \]
\[ \tau \dot{v} = -v + h_v + w_{vu}f(u), \]
u (solid), v (dashed)

(a)

(b)
mathematical basis of oscillations

\[ \tau \dot{u} = -u + h_u + w_{uu}f(u) - w_{uv}f(v) \]
\[ \tau \dot{v} = -v + h_v + w_{vu}f(u) , \]

- linearize dynamics in each quadrant
- compute fixed point
- if it lies in same quadrant: fixed point attractor
- if it lies in next quadrant: part of a limit cycle

Amari 1977
two-neuron simulator
Limit cycle oscillators

- are source for stable, autonomously generated time structure in neural dynamics
- used in movement generation
- and coordination...
- “liquid state machines” or “echo-state networks” are an expansion of that idea (not very well defined mathematically)
Active transient arises when the stable resting state is briefly pushed by input into the fourth quadrant: return on a temporally structured trajectory.
start active transient: blue => red
then fall back to blue
self-stabilized state

on: blue => red

on: red => green
set intention: blue => red

detection CoS: blue => green
Transient detector

2

\( v_{\text{inh}} \)

1

\( u_{\text{exc}} \)

onset

blue => red

\( \frac{3}{4} \)

\( \frac{1}{3} \)

\( \frac{2}{4} \)
Change detection

three layer field => simulation
Conclusion

by taking into account Dale’s law, reach much richer neural dynamics that includes

- oscillations: time course generation
- active transient: preserve oscillatory time structure in single-shot time course
- switching an activated node of with a finite/well defined amount of time before switch is achieved: Condition of Satisfaction
- transient detection: make a single, well defined time course from a step change
- change detection