Computational Modelling of Auditory Processing in the Brain

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Overview

- 1. The Problem: A Cacophony of Sound
- 2. Model of Auditory Cortex and Recent Results
- 3. Ongoing and Future Pursuits

1. The Problem: a Cacophony of Sound

The Complexity of Hearing

- The input signal to the auditory system is a set of two onedimensional time series, one hitting each ear drum.
- In natural environments, the time series represent the superposition of multiple overlapping sound sources.
- From this time series data the auditory system is able to extract vast amounts of information
 - Separation of sound sources
 - Location of each source in 3D
 - Assignation of meaning to each source



The Problem of Time

- Frequency is represented in tonotopic maps in the auditory system.
- Sound meaning is completely context-dependent.
- How is information integrated over time? Some kind of memory is required, but what?





Bartlett & Wang (2005) J. Neurophysiol.

P. May – MMS Days, Berlin, 27 Jan 2016

May et al. (1999) J. Comput. Neurosci.

T.T.

200

2. Model of Auditory Cortex & Recent Results

The Column: Computational Unit



- The cortex has granular, column structure.
- A column is a complex, local (vertical) collection of neurons which have similar response properties.
- We cut though the complexity, and model the column in the simplest possible way.

i: inhibitory population e: excitatory population W_{ee}, W_{ie}, W_{ie} connectivity matrices

Neural Dynamics

Equations describing neural interactions: LIN firing rate model Hopfield & Tank, 1986; May et al. 2010, 2013, 2015

Model Construction

- AC has multiple fields (each defined by tonotopic map)
- Multiple Core-Belt-Parabelt streams: feedforward activation progresses serially from core to belt to parabelt fields along many, parallel routes.
- This structure can be translated into the weight matrices W_{ee}, W_{ie}, and W_{ei}



Simulations

<u>Major advantage over real experiments</u>: Modelling allows us to simulate non-invasive MEG (summed activity of columns) and to simultaneously observe "invasive" activity on the single-column level.

Single-column (firing rate) observations:

- Forward masking: stimulus repetition leads to suppressed responses.
- Stimulus-specific adaptation (SSA): response recovery by stimulus change (i.e,. supression in not generalized).
- Two-tone facilitation: With AB tone pairs, response to tone B is enhanced if preceeded by tone A
- Temporal intergration: tuning to the temporal structure of tone sequences, speech stimuli, and monkey calls.

MEG (summed activity) observations:

- Adaptation: stimulus repetition leads to suppressed responses.
- Mismatch responses: Statistical structure of stimulation is reflected in response amplitude.
- Temporal intergration: mismatch responses also when tones are replaced by more complex stimuli.
- These MEG effects can be traced back to single-column behaviour

Temporal Binding of Tone Pairs

- Columns are tuned to the ٠ temporal structure of stimulation.
- Combination sensitivity (CS): selectivity to pair AB vs. (1) reveresed pair BA, (2) isolated tones (A or B).
- This phenomenon has mystified auditory neuroscientists.
- Explanation: CS is due to synaptic depression (adaptation) and the serial structure of AC (May & Tiitinen, 2013; May et`al. 2015).
- Similar CS for four-tone sequences, speech sounds, & monkey calls



Tone B

n

Non-CS columns

600

600

600

600

800

800

800

800

1000

1000

1000

1000



Tone A

MEG Examples

- Presenting a stimulus (A) repeatedly leads to attenuated MEG responses
- When the series of repeated stimuli is interrupted by a stimulus with a different structure (B), the MEG response is much larger.

AAAAABAAAAAABAAAABA...

- This phenomenon is the so-called mismatch response, and its neural origins have been hotly debated for two decades.
- Our computational approach has provided an adaptation-based explanation which replaces a previous, more complex, information-processing models (May & Tiitinen, 2010).



3. Ongoing and Future Pursuits

Analytical Approach

$$\tau_{\rm m} \frac{d\boldsymbol{u}(t)}{dt} = -\boldsymbol{u}(t) + A_{\rm ee}(t) \cdot W_{\rm ee} \cdot g[\boldsymbol{u}(t)] - W_{\rm ei} \cdot g[\boldsymbol{v}(t)] + \boldsymbol{I}_{\rm aff}(t)$$

Analytical Approach

Linearization (slow adaptation, quasi-static)

 $\ddot{\mathbf{u}}(t) + 2\Gamma\dot{\mathbf{u}}(t) + \Omega_0^2 \mathbf{u}(t) = \mathbf{q}(t)$

$$\begin{split} & \frac{\widetilde{W}_{\mathrm{ei}}\widetilde{W}_{\mathrm{ii}}\widetilde{W}_{\mathrm{ei}}^{-1} - \widetilde{W}_{\mathrm{ee}}}{2} = \Gamma \\ & \widetilde{W}_{\mathrm{ei}}\widetilde{W}_{\mathrm{ie}} - \widetilde{W}_{\mathrm{ei}}\widetilde{W}_{\mathrm{ii}}\widetilde{W}_{\mathrm{ei}}^{-1}\widetilde{W}_{\mathrm{ee}} = \Omega_0^2 \\ & \widetilde{W}_{\mathrm{ei}}\widetilde{W}_{\mathrm{ii}}\widetilde{W}_{\mathrm{ei}}^{-1}\mathbf{I}_{\mathrm{e}}(t) - \widetilde{W}_{\mathrm{ei}}\mathbf{I}_{\mathrm{i}}(t) + \dot{\mathbf{I}}_{\mathrm{e}}(t) = \mathbf{q}(t) \end{split}$$

Overdamp

Diagonalization & Uncoupling $\Upsilon\Gamma_{\rm d}\Upsilon^{-1}=\Gamma \quad \text{damping}$

$$\mathbf{u}_{\mathrm{d}}(t) = \Upsilon^{-1}\mathbf{u}(t)$$
 uncoupling

 $\Upsilon\Omega^2_{0_{\rm d}}\Upsilon^{-1} = \Omega^2_0 \ \ \text{normal frequency} \ \ \ \ddot{\mathbf{u}}_{\rm d}(t) + 2\Gamma_{\rm d}\dot{\mathbf{u}}_{\rm d}(t) + \Omega^2_{0_{\rm d}}\mathbf{u}_{\rm d}(t) = \mathbf{q}_{\rm d}(t)$

Solution: normal modes are damped oscillators

$$\begin{split} u_{\rm d}(t) &= \exp(-\gamma_{\rm d}t)(a_{\rm u_{d}}\sin(\delta_{\rm d}t) + b_{\rm u_{d}}\cos(\delta_{\rm d}t)) + f_{\rm u_{d}} \\ & \begin{cases} a_{\rm u_{d}} &= \frac{w_{\rm ei}\gamma_{\rm d}}{\omega_{0_{\rm d}}^{2}\delta_{\rm d}}I_{\rm i}(t) + \frac{\omega_{0_{\rm d}}^{2} + w_{\rm ei}w_{\rm ie}w_{\rm ii}^{2}}{2\omega_{0_{\rm d}}^{2}\delta_{\rm d}}I_{\rm e}(t) + \frac{w_{\rm ii} + w_{\rm eed}}{2\delta_{\rm d}}u_{0} - \frac{w_{\rm ie}}{\delta_{\rm d}}v_{0} \\ b_{\rm u_{d}} &= \frac{w_{\rm ei}}{\omega_{0_{\rm d}}^{2}}I_{\rm i}(t) - \frac{w_{\rm ii}}{\omega_{0_{\rm d}}^{2}}I_{\rm e}(t) + u_{0} \\ f_{\rm u_{d}} &= -\frac{w_{\rm ei}}{\omega_{0_{\rm d}}^{2}}I_{\rm i}(t) + \frac{w_{\rm ii}}{\omega_{0_{\rm d}}^{2}}I_{\rm e}(t), \end{split}$$

Coupling: linear combination of normal modes, can explain any waveform

 $\mathbf{u}(t) = \Upsilon \mathbf{u}_{\mathrm{d}}(t)$

Analytical Approach

- Fast, precise, memory efficient
- Well defined dynamical building blocks -> allows the study of damping, oscillations, resonances
- Coupling -> allows the study of hierarchical (core-belt-parabelt) activations on the single-column level







Other Ongoing Projects

- Working memory experiments: Linking human and monkey results in cognitive tasks
- Extension of the model to subcortical processing (using rat model) Spike rate (spikes/s
- Modelling auditory scene analysis: separating sound sources from each other



Conclusions

- We are studying the auditory system in a computational model based on the anatomical structure of auditory cortex.
- The motivation is to link single-cell observations with MEG
- The model provides explanations for several basic phenomena in auditory neuroscience which have lacked an explanation.
- Fast (firing rate) and slow (synaptic plasticity, adaptation) dynamics coupled with serial stucture of auditory cortex seems to be the explanation.
- We are still a long way from understanding what goes on at a cocktail party.

Thank You