뇌파를 통하여 알아보는 뇌의 동역학

2023 생명물리 여름학교

포항공대
2023.07.03

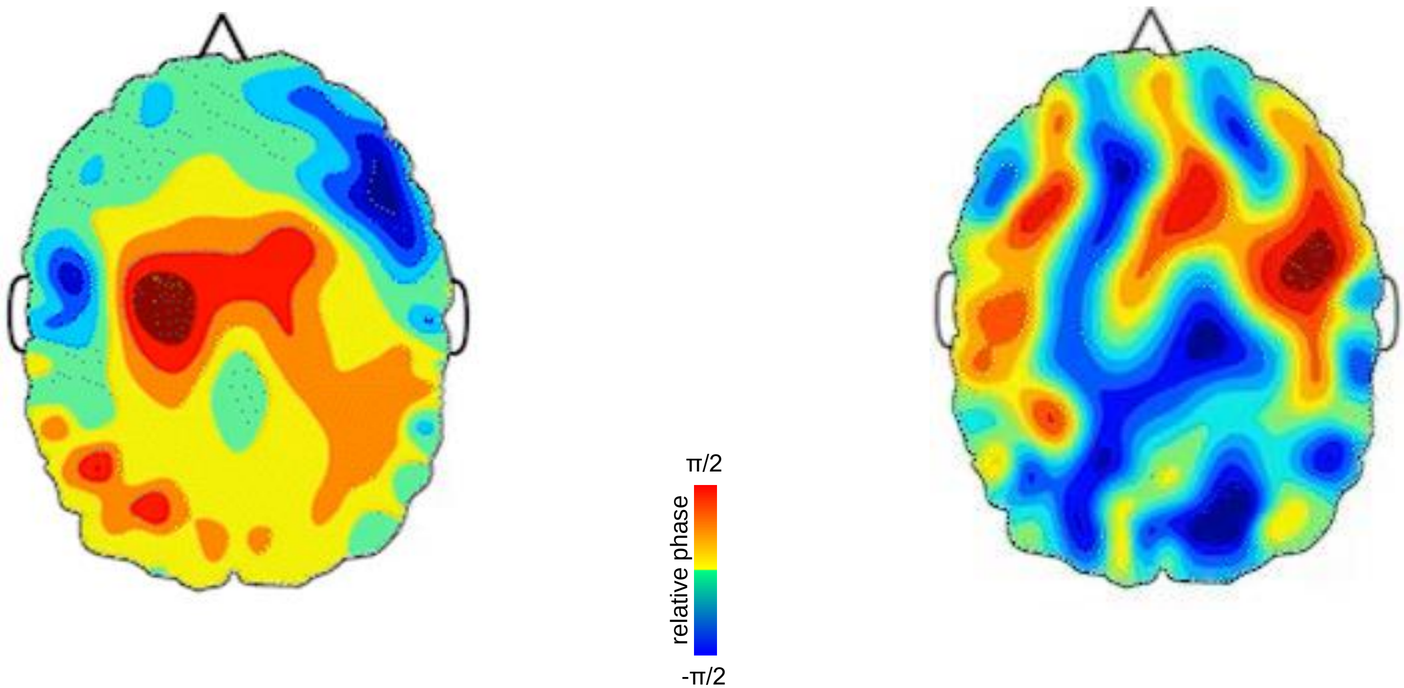
Joon-Young Moon

Brain State and Transition Lab,
Center for Neuroscience Imaging Research,
Institute for Basic Science/
Sungkyunkwan University

https://www.dropbox.com/s/8g99hgudw6n8ydt/JoonYoungMoon_SummerSchool_2023.pdf?dl=0

Research Motivation

Our work is motivated by the idea that understanding the dynamics of brain waves in the brain is critical to identify, monitor, and ultimately control brain states transitions.



Conscious state

Control state (unconscious state)

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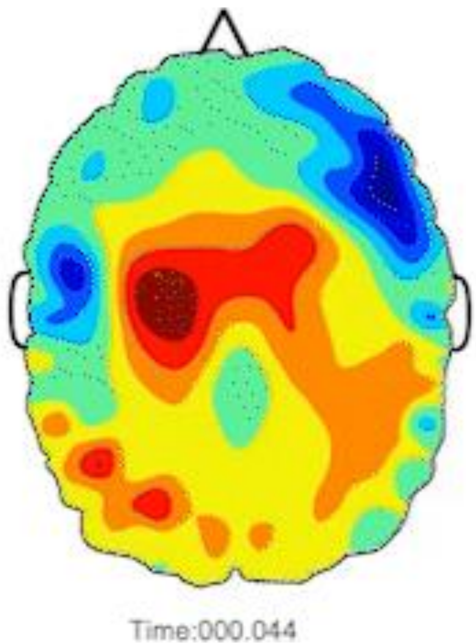

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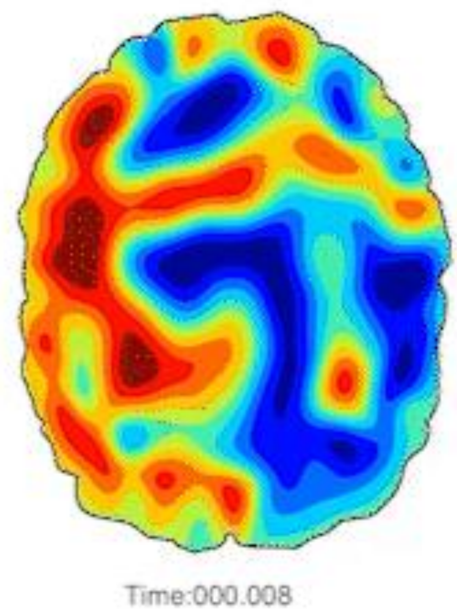


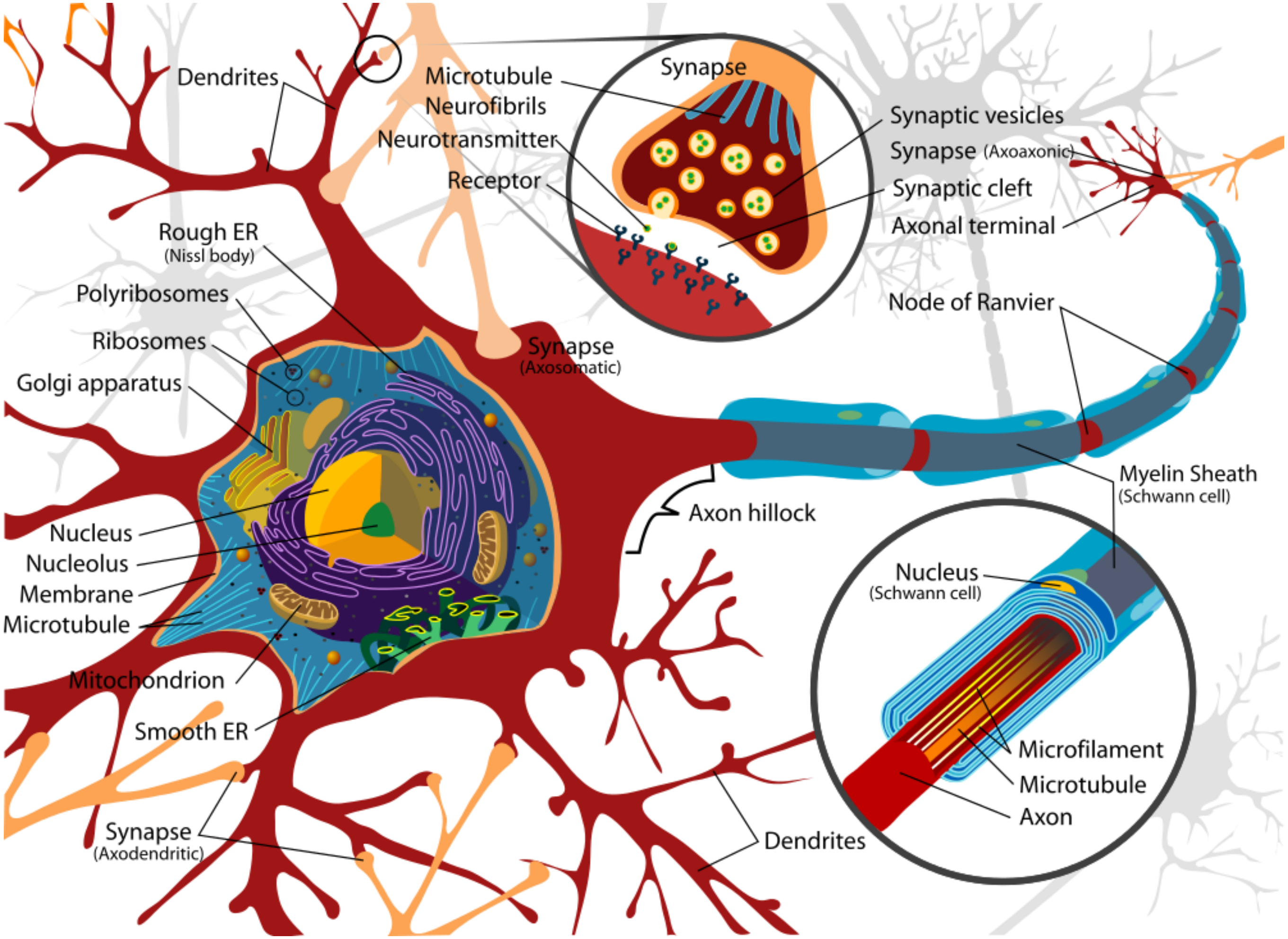
Control state (unconscious state)

Research Themes

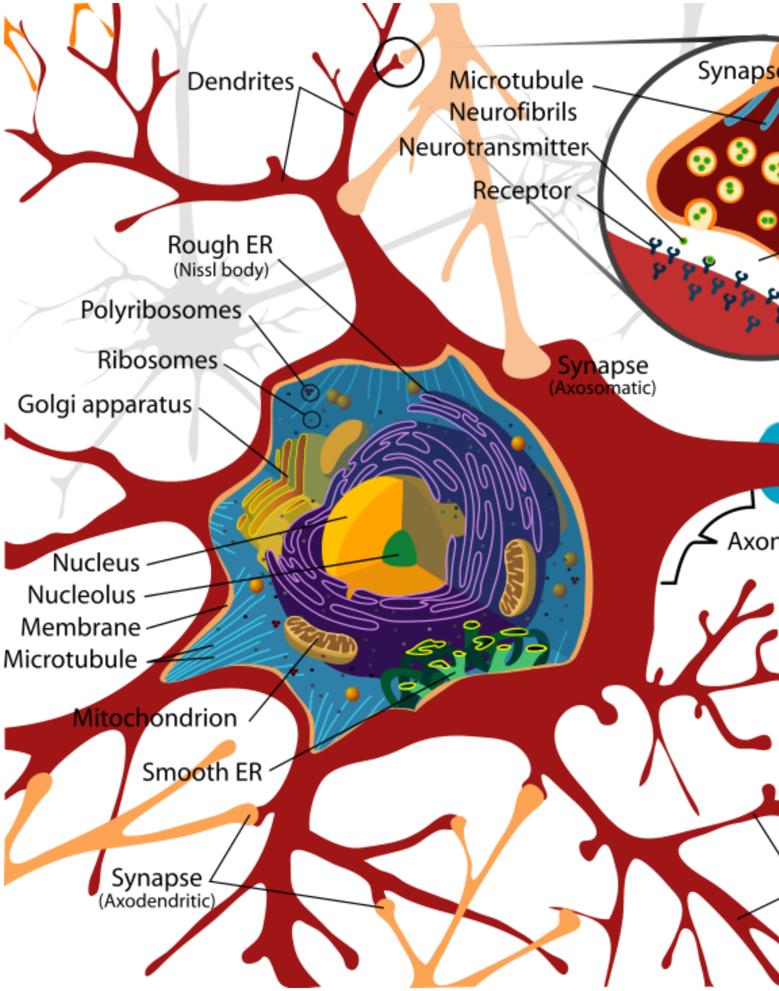
I. **Brain Waves**

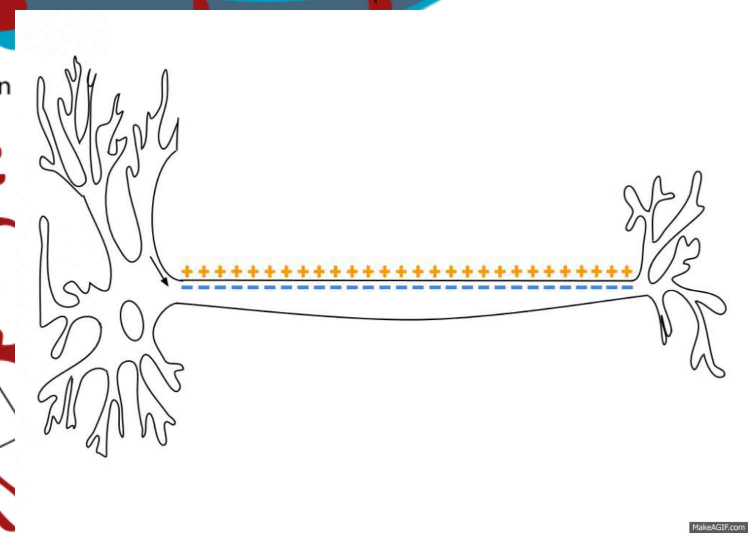
II. Phase Patterns in Brain States

III. Phase Dynamics of Brain States



~100 billion (~10^{11}) neurons and ~100 trillion (10^{14}) synapses in human brain. Recent estimate: 86 billion neurons, 16.3 billion in the cerebral cortex, and 69 billion in the cerebellum.





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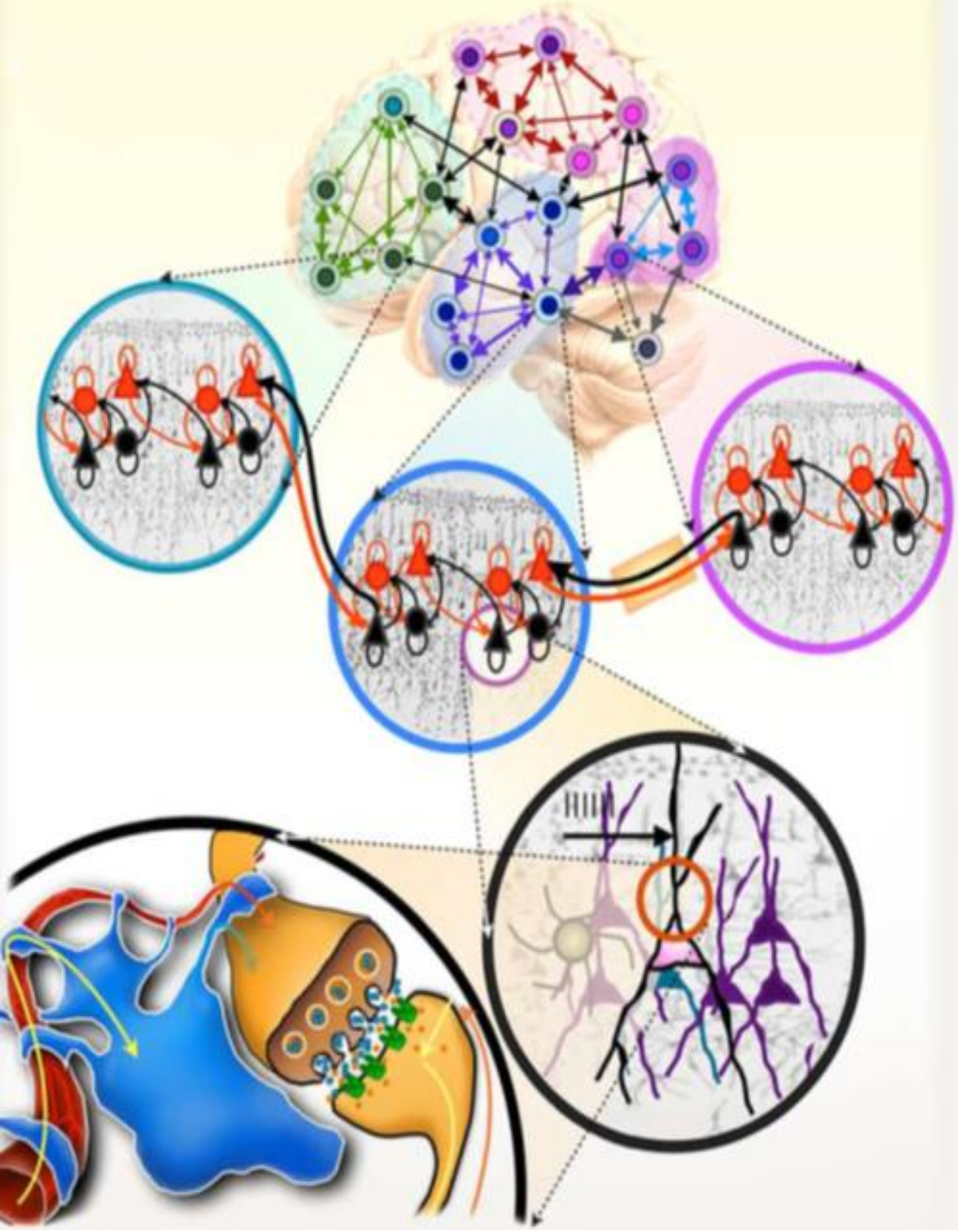
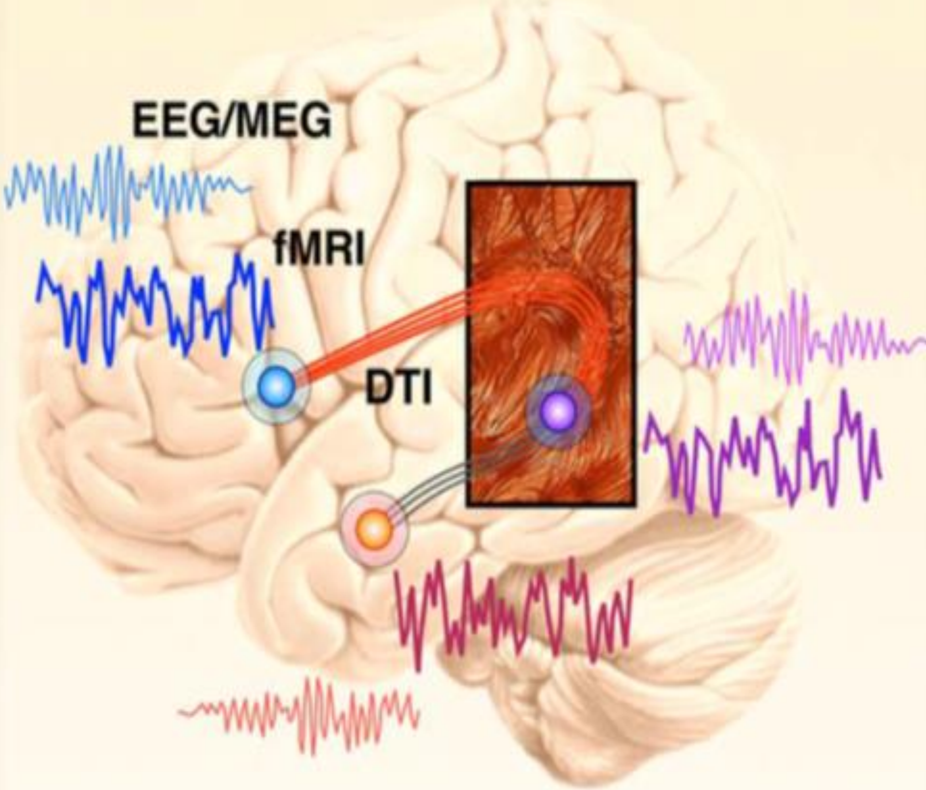
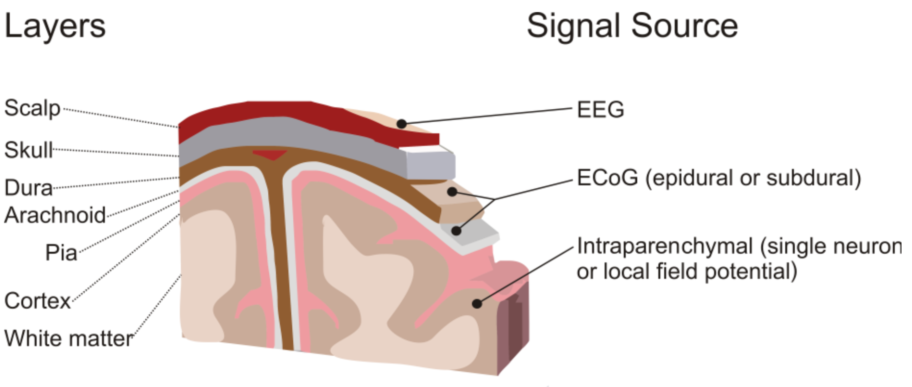


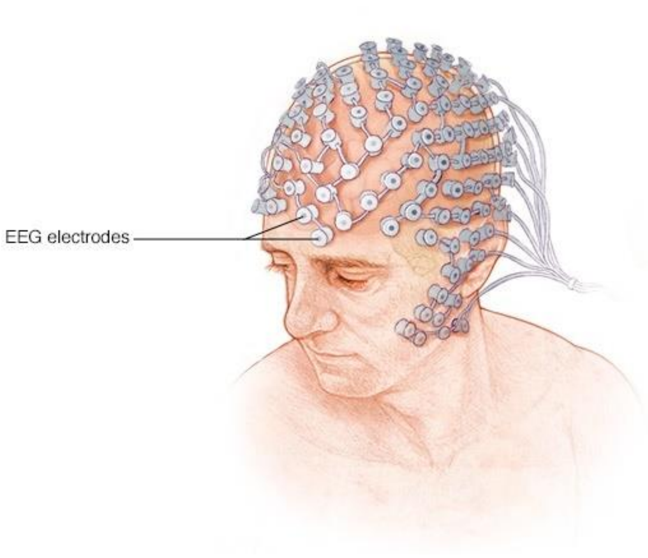

EEG/MEG
fMRI
DTI

EEG: electroencephalography

EEG is an electrophysiological monitoring method to record electrical activity of the brain. It is typically noninvasive, with the electrodes placed along the scalp, although invasive electrodes are sometimes used, as in electrocorticography (ECoG).



http://www.schalklab.org/research/brain-computer-interfacing



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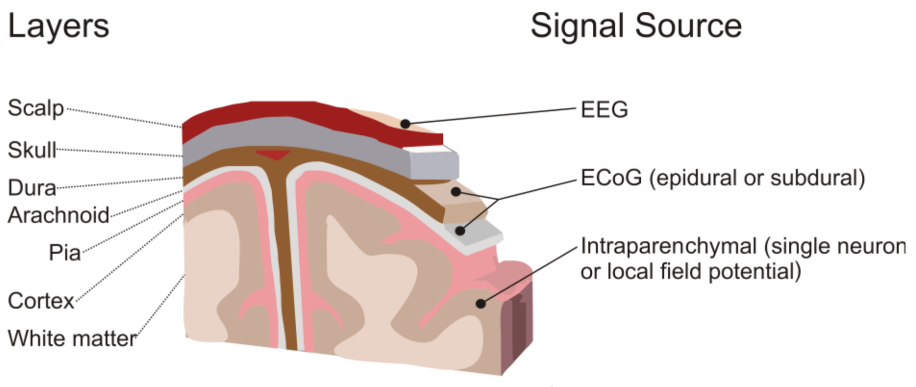
EEG measures voltage fluctuations resulting from neuronal activities of the brain.



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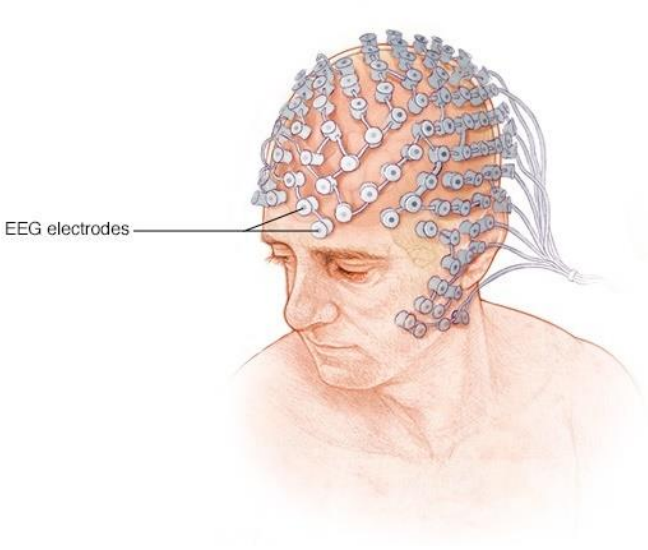

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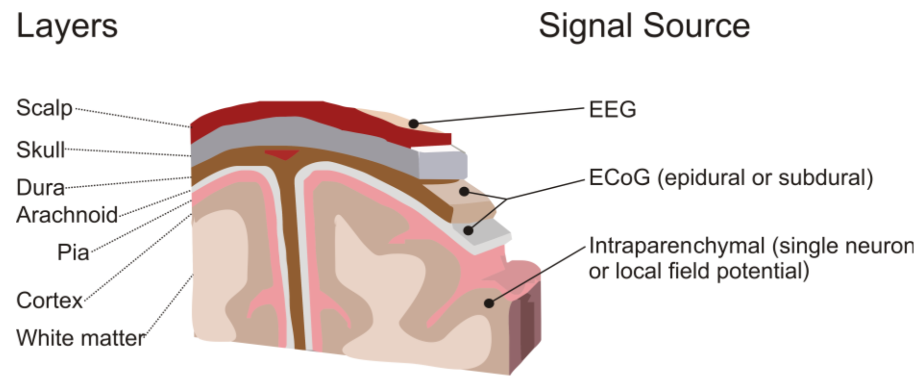

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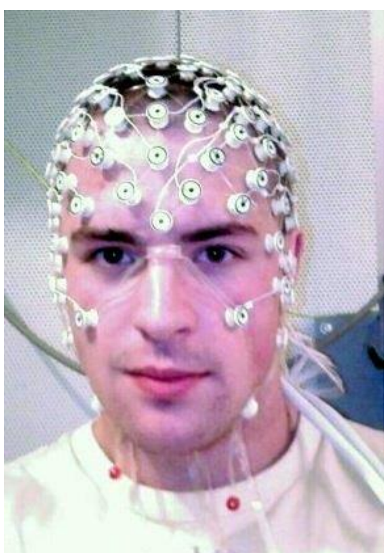
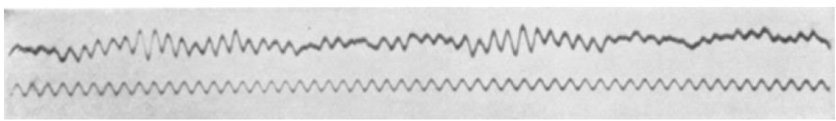


EEG: electroencephalography

Richard Caton (1875): reported electrical activities of rabbits' and monkeys' brains

Adolf Beck (1890): published electrical activities of rabbits' and dogs' brains

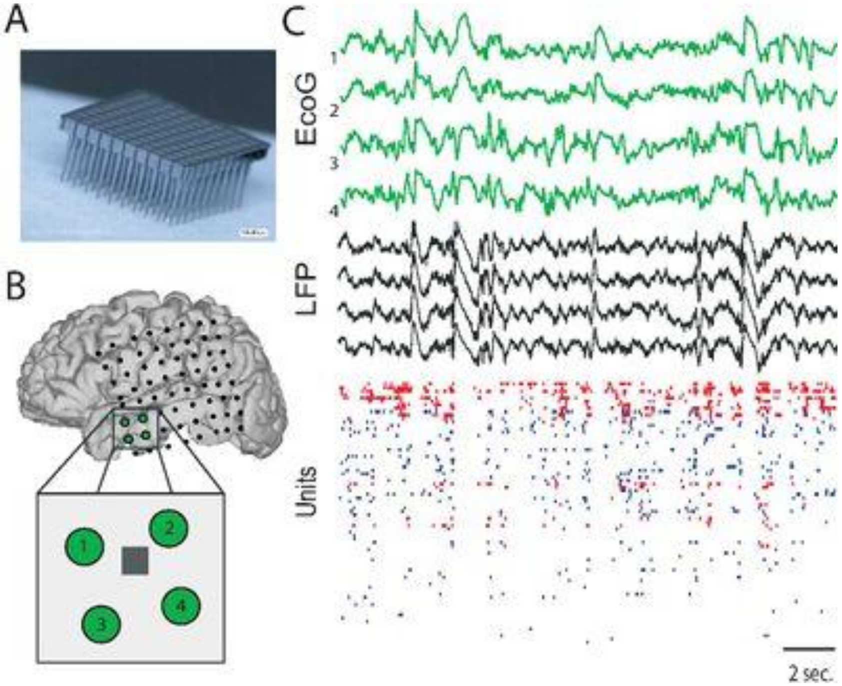
Hans Berger (1924): recorded the first human EEG.



Hans Berger (1873-1941)

LFP (local field potential)

The Local Field Potential (LFP) is the electric potential recorded around neurons, typically using micro-electrodes (metal, silicon, etc).



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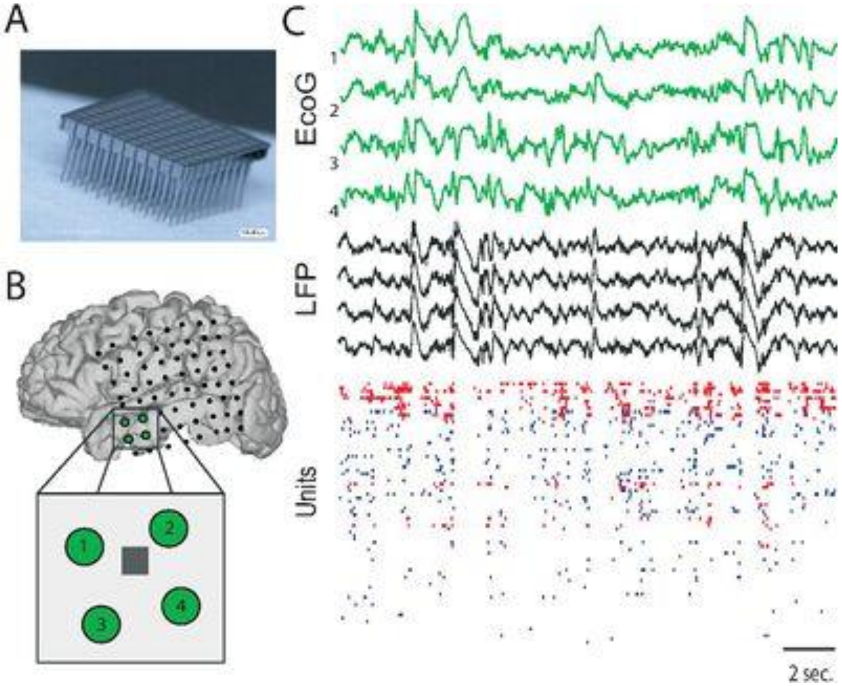
LFPs differ from the electroencephalogram (EEG), which is recorded at the surface of the scalp, and with macro-electrodes. LFPs are recorded in depth, from within the cortical tissue.



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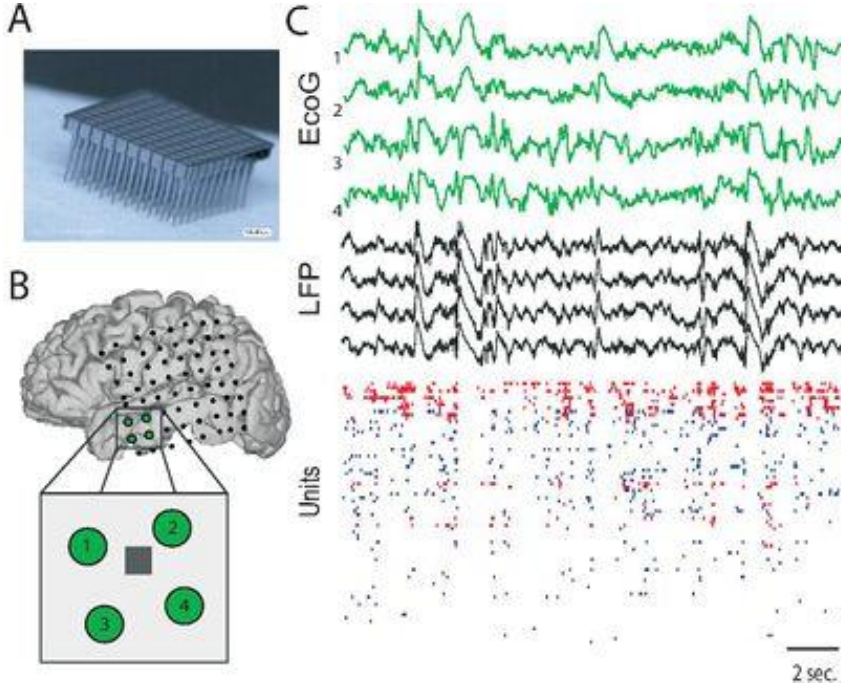
Besides their invasive aspect, LFPs also sample relatively localized populations of neurons, separated by a few hundred microns. In contrast, the EEG samples much larger populations of neurons.



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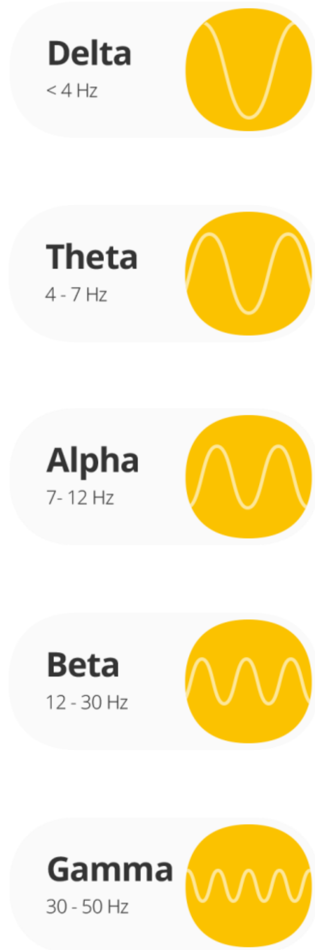
Brainwaves

The electric potential generated by an individual neuron is far too small to be picked up by EEG.

EEG therefore reflects the group synchronous activities of the neurons.

Scalp EEG shows oscillations at a variety of frequencies (Fourier transform can be applied).



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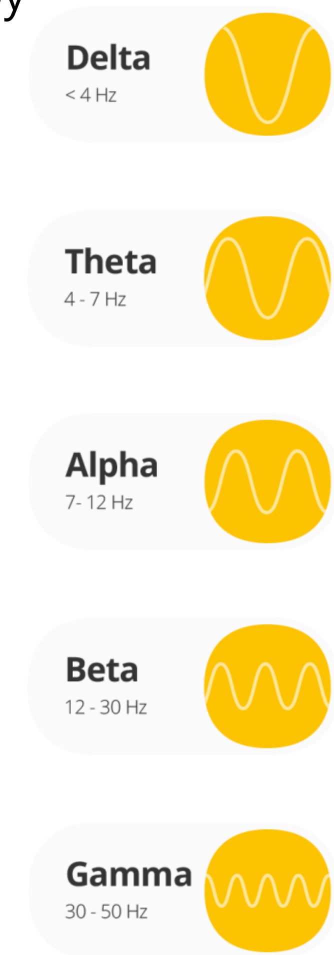
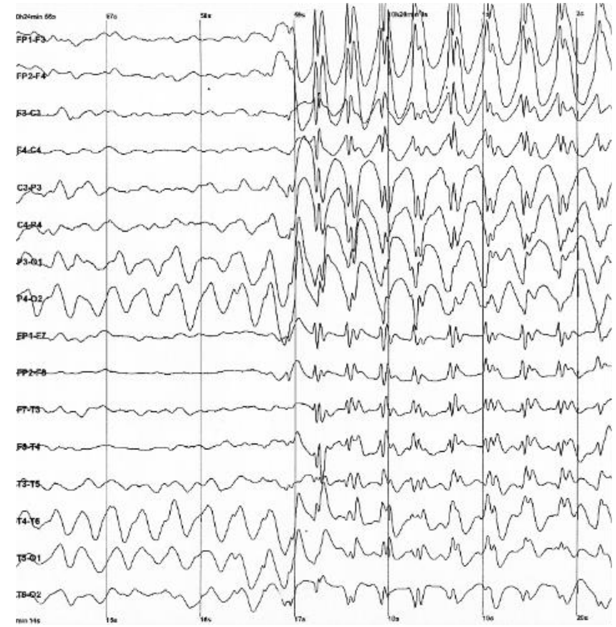
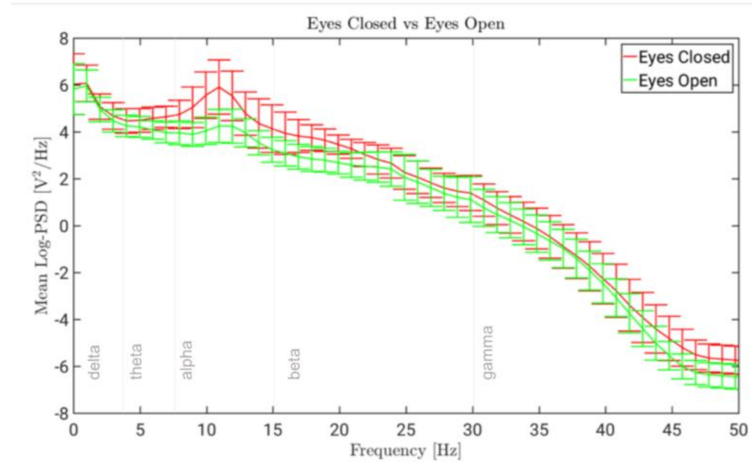


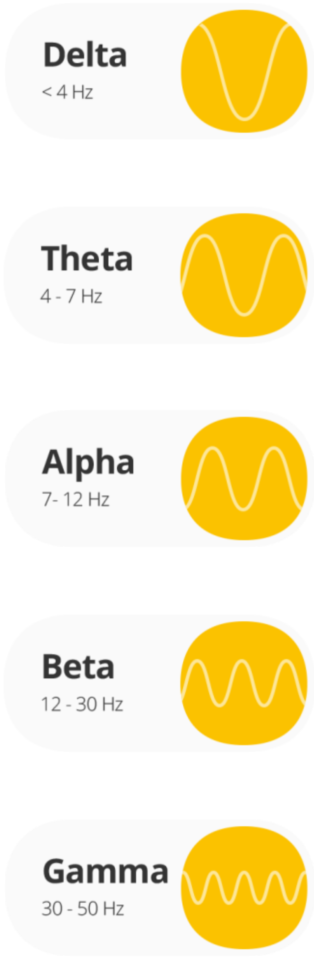




https://sapienlabs.co//eyes-open-eyes-closed-and-variability-in-the-eeg

Brainwaves

Delta: Deep, dreamless sleep (non-REM)

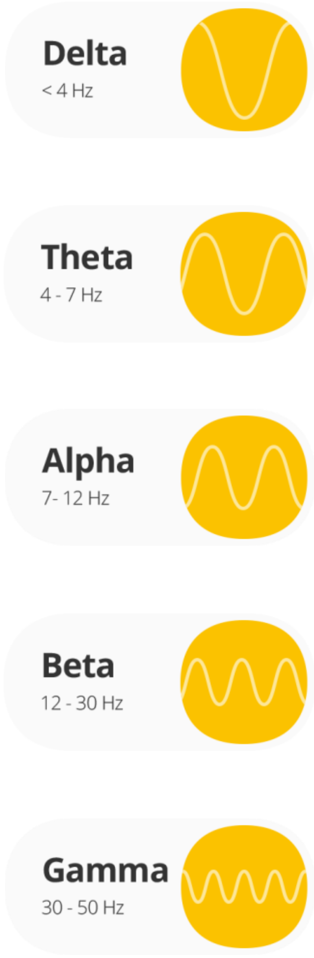


Ned Herrmann, https://www.scientificamerican.com/article/what-is-the-function-of-t-1997-12-22/

Brainwaves

Delta: Deep, dreamless sleep (non-REM)

Theta: Light sleep (REM), dream, deep meditation.
"A person who has taken time off from a task and begins to daydream is often in a theta brainwave state. A person who is driving on a freeway, and discovers that they can't recall the last five miles, is often in a theta state."



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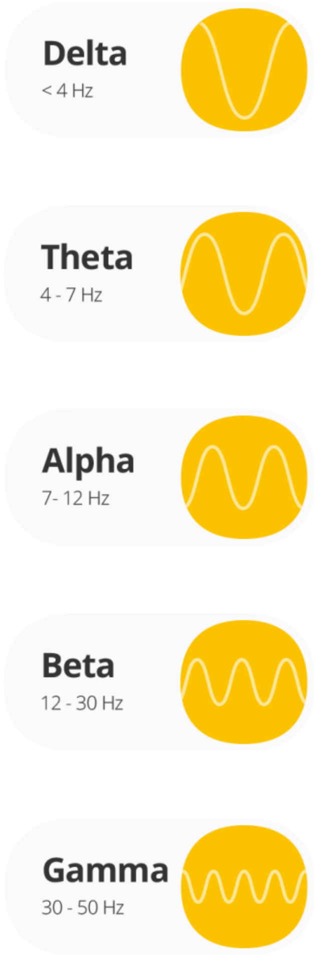
Alpha: eyes closed or brain not actively engaged to external stimuli, light meditation.
“A person who has completed a task and sits down to rest is often in an alpha state. A person who takes time out to reflect or meditate is usually in an alpha state. A person who takes a break from a conference and walks in the garden is often in an alpha state.”



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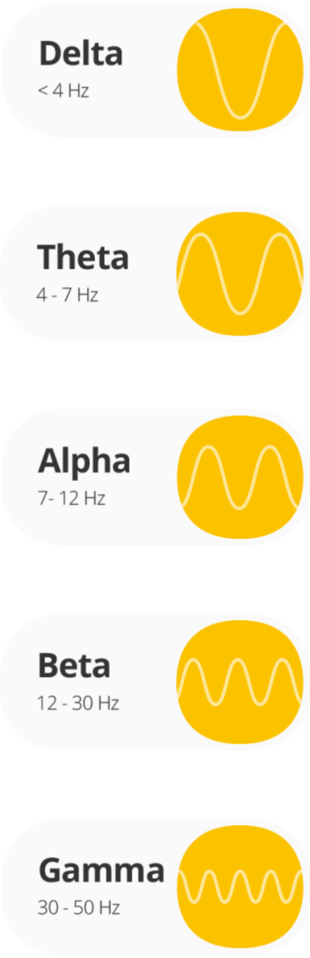
Beta: engaged state.
"A person in active conversation would be in beta. A debater would be in high beta. A person making a speech, or a teacher, or a talk show host would all be in beta when they are engaged in their work."



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Alpha: eyes closed or brain not actively engaged to external stimuli, light meditation. **May be a conduit for global brain communication.**
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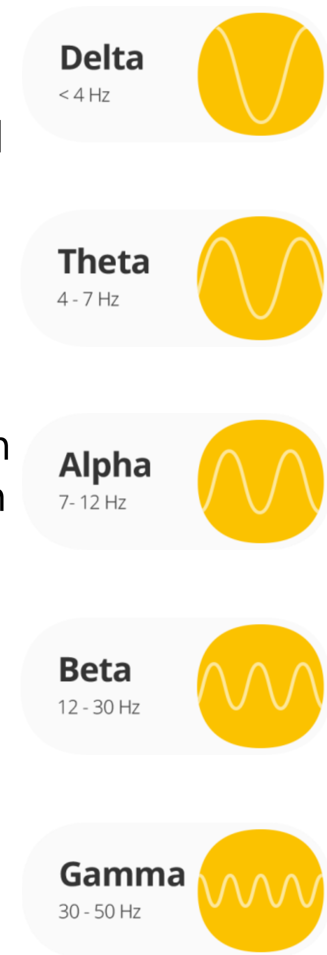
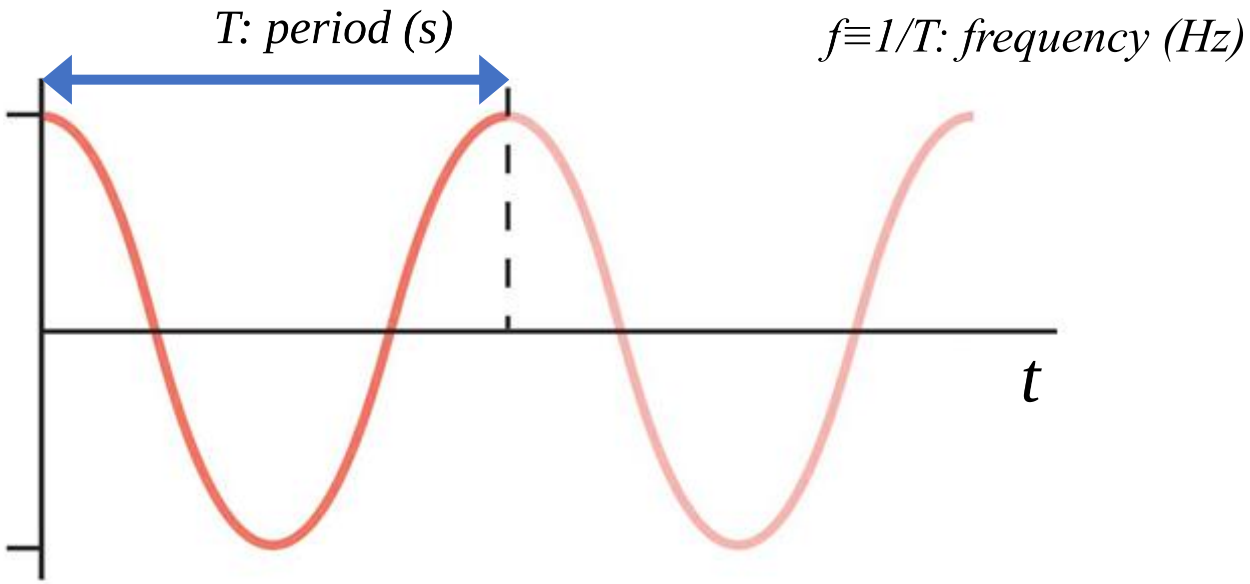
Gamma: sensory processing. **Local brain interaction.**



Ned Herrmann, https://www.scientificamerican.com/article/what-is-the-function-of-t-1997-12-22/

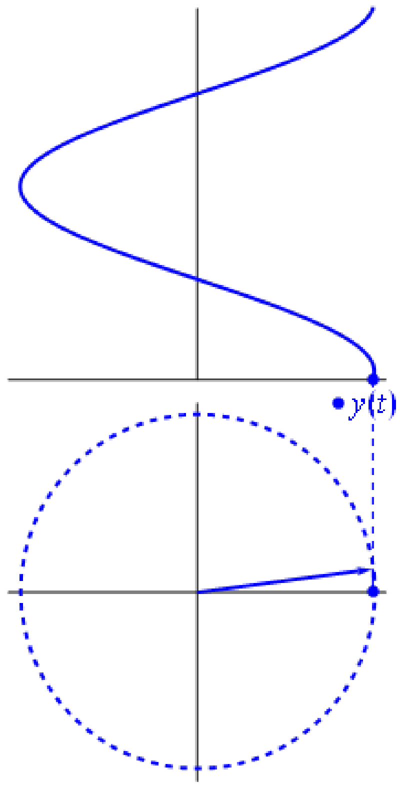
Oscillation and Wave

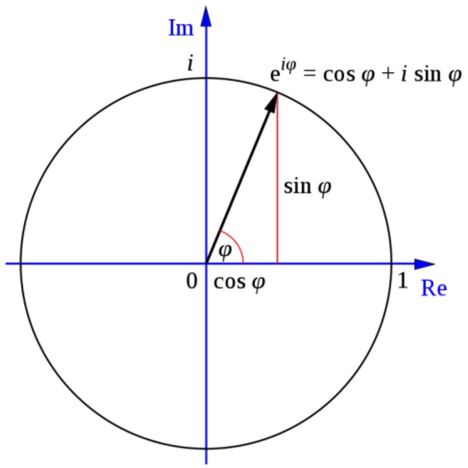


Amplitude and Phase

A wave (oscillating signal) can be mapped to a circle on a complex plane (Hilbert transform).

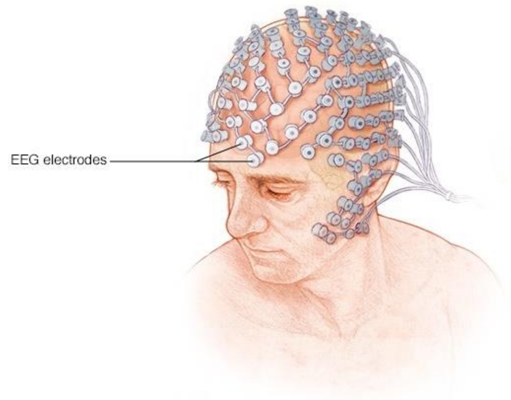
Θ is the phase of the oscillator, and |z| is the amplitude of the oscillator.





Research Themes

I. Brain Waves



II. **Phase Patterns in Brain States**

III. Phase Dynamics of Brain States

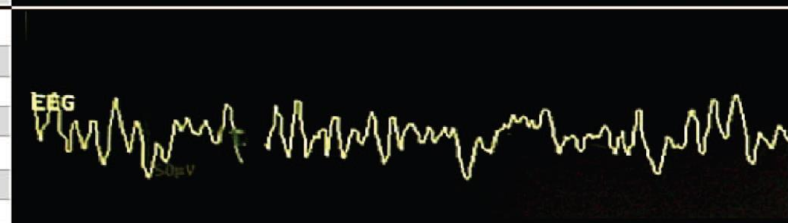
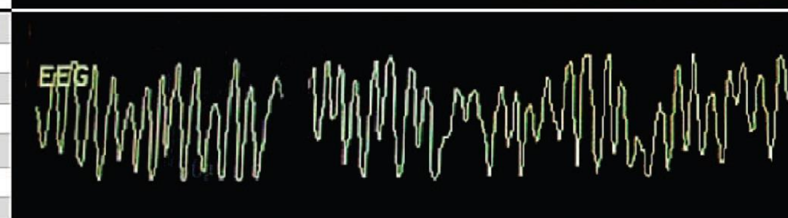
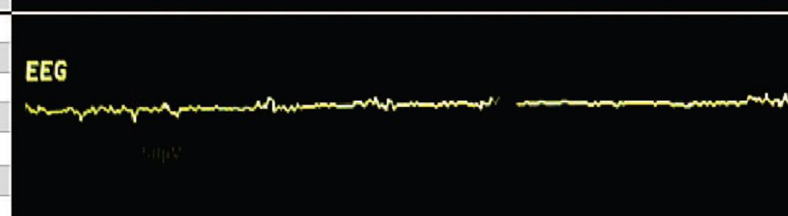
How to Distinguish Consciousness from Unconsciousness?

Center for Consciousness Science, University of Michigan

Lee, UnCheol

Mashour, George

How to Distinguish Consciousness from Unconsciousness?

Patient State	Device	Features	Reading	Frontal Electroencephalography (EEG) Trace
Wakeful	EEG	↑*f*, ↓Amp, blinks	↑γ,β,α↓θ,δ	
	SEF$_{95}$	Twenties	26 Hz.	
	BIS	High β ratio	96	
	Entropy	High entropy	97	
	AAI	↓lat, ↑Δamp	81	
	NI	EEG *f* band analysis	A	
	ETAG	Age-adjusted MAC	0 MAC	
Sedated	EEG	α oscillations	↓γ,β, ↑α,θ,δ	
	SEF$_{95}$	High teens	19 Hz.	
	BIS	Low β ratio	78	
	Entropy	High entropy	85	
	AAI	↑ing lat, ↓ing ΔAmp	45	
	NI	EEG *f* band analysis	B / C	
	ETAG	Age-adjusted MAC	0.4 MAC	
Unresponsive	EEG	Spindles, K, ↓*f*	↑α,θ,δ	
	SEF$_{95}$	Low teens	14 Hz.	
	BIS	Bispectral coherence	52	
	Entropy	Entropy drop	43	
	AAI	↑ing lat, ↓ing ΔAmp	30	
	NI	EEG *f* band analysis	D	
	ETAG	Age-adjusted MAC	0.8 MAC	
Surgically Anesthetized	EEG	Slow δ waves, ↓*f*	δ dominance	
	SEF$_{95}$	< 12 Hz.	10 Hz.	
	BIS	Bispectral coherence	42	
	Entropy	Low entropy	38	
	AAI	↑ing lat, ↓ing ΔAmp	22	
	NI	EEG *f* band analysis	E	
	ETAG	Age-adjusted MAC	1.3 MAC	
Deeply Anesthetized	EEG	BS, isoelectricity	Bursts & flat	
	SEF$_{95}$	< 2 Hz. (BS corrected)	2 Hz.	
	BIS	High BSR	9	
	Entropy	Burst suppression	8	
	AAI	↑latency, ↓Δamp	11	
	NI	EEG *f* band analysis	F	
	ETAG	Age-adjusted MAC	2 MAC	

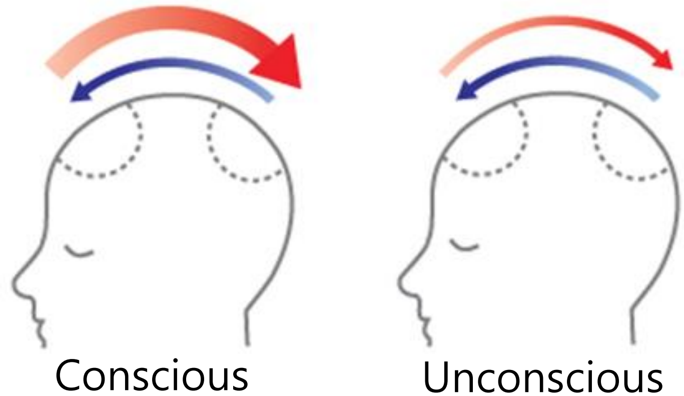
G Mashour et al., Anesthesiology (2011)

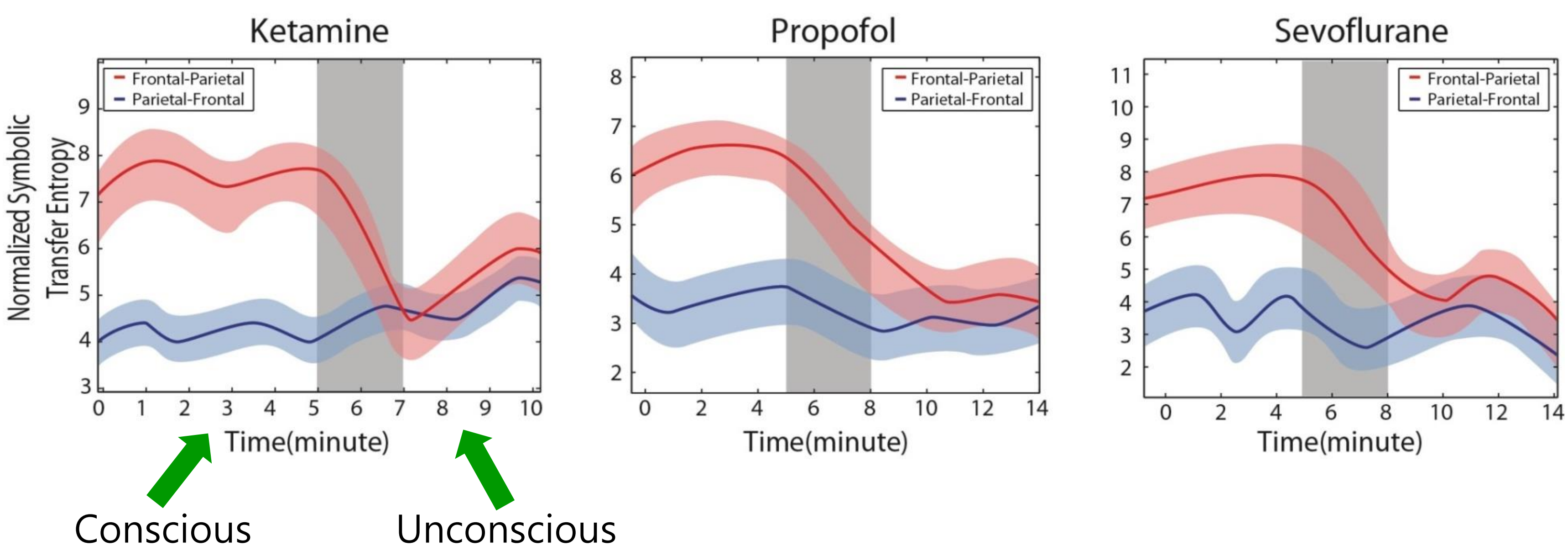
How to Prevent Intraoperative Awareness?

Anesthesia awareness rate may approach 1% in high risk patients.
BIS (Bi-Spectral Index) is a popular monitoring tool, but not always accurate.

Directionality Changes in EEG Functional Networks

Front-Back directionality may be a neural correlate of consciousness.





UC Lee et al., Anesthesiology 2013

Model: Brain as a Coupled Oscillator System

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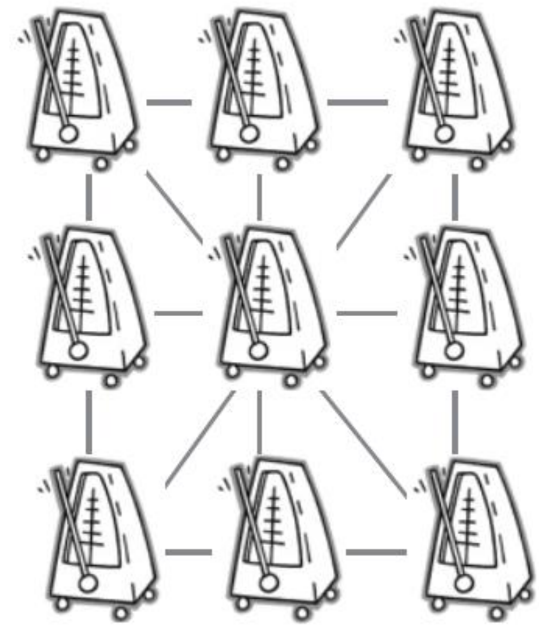
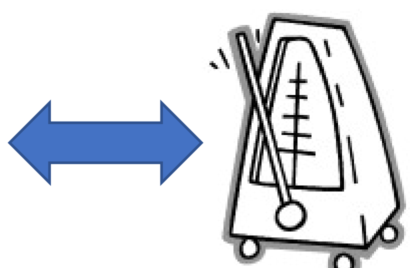
Coupled Oscillator System



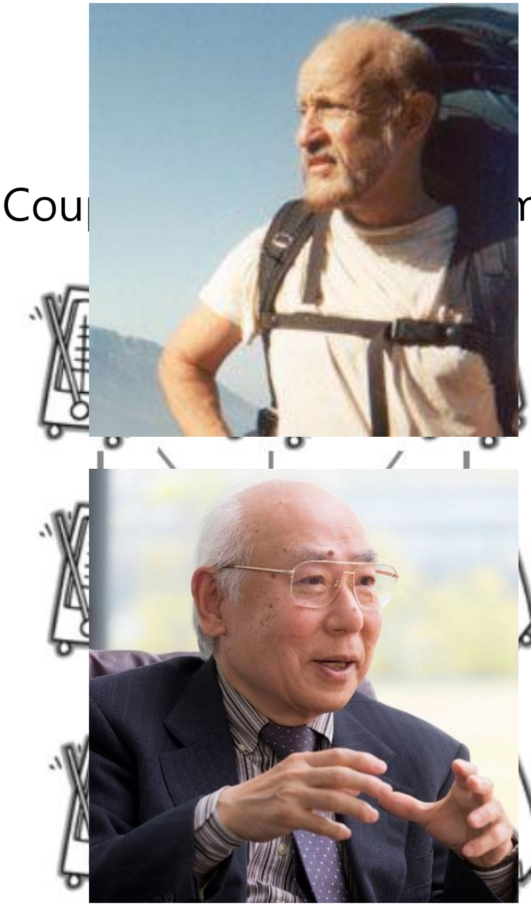
We consider neural masses as oscillators



Arthur T. Winfree, 1967
Yoshiki Kuramoto, 1975

Model: Brain as a Coupled Oscillator System

Cou m



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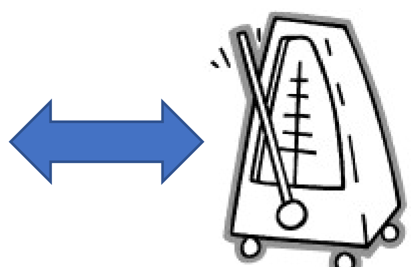

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非線形問題解決軍団
池口研究室
NONLINEAR DYNAMICAL SYSTEM

メトロノーム同期 (72個)

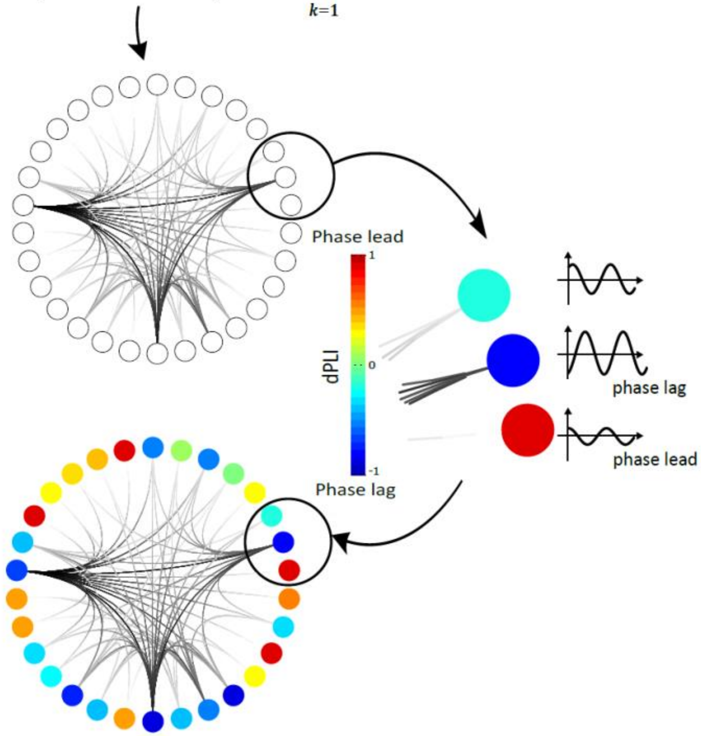
Synchronization of 72 metronomes

2014年2月8日，池口研究室にて撮影

Recorded by Ikeguchi Laboratory, on February 8, 2014.

Canonical Coupled Oscillator Models

$$\dot{z}_j(t) = \left\{\lambda_j + i\omega_j - \left|z_j(t)\right|^2\right\} z_j(t) + S\sum_{k=1}^{N} K_{jk} z_k\left(t-\tau_{jk}\right), \quad j = 1, 2, \ldots, N$$



Wilson-Cowan Model

$$\dot{E}_j(t) = -E_j + F\left[C_{EE}E_j - C_{IE}I_j + P_j + S\sum_{k=1}^{N} K_{jk}E_k\right]$$

$$\dot{I}_j(t) = -I_j + F\left[C_{EI}E_j - C_{II}I_j + Q_j\right], \qquad F[x] = (1 - e^{-x}), \qquad j = 1,2,\ldots,N.$$

Stuart-Landau Model

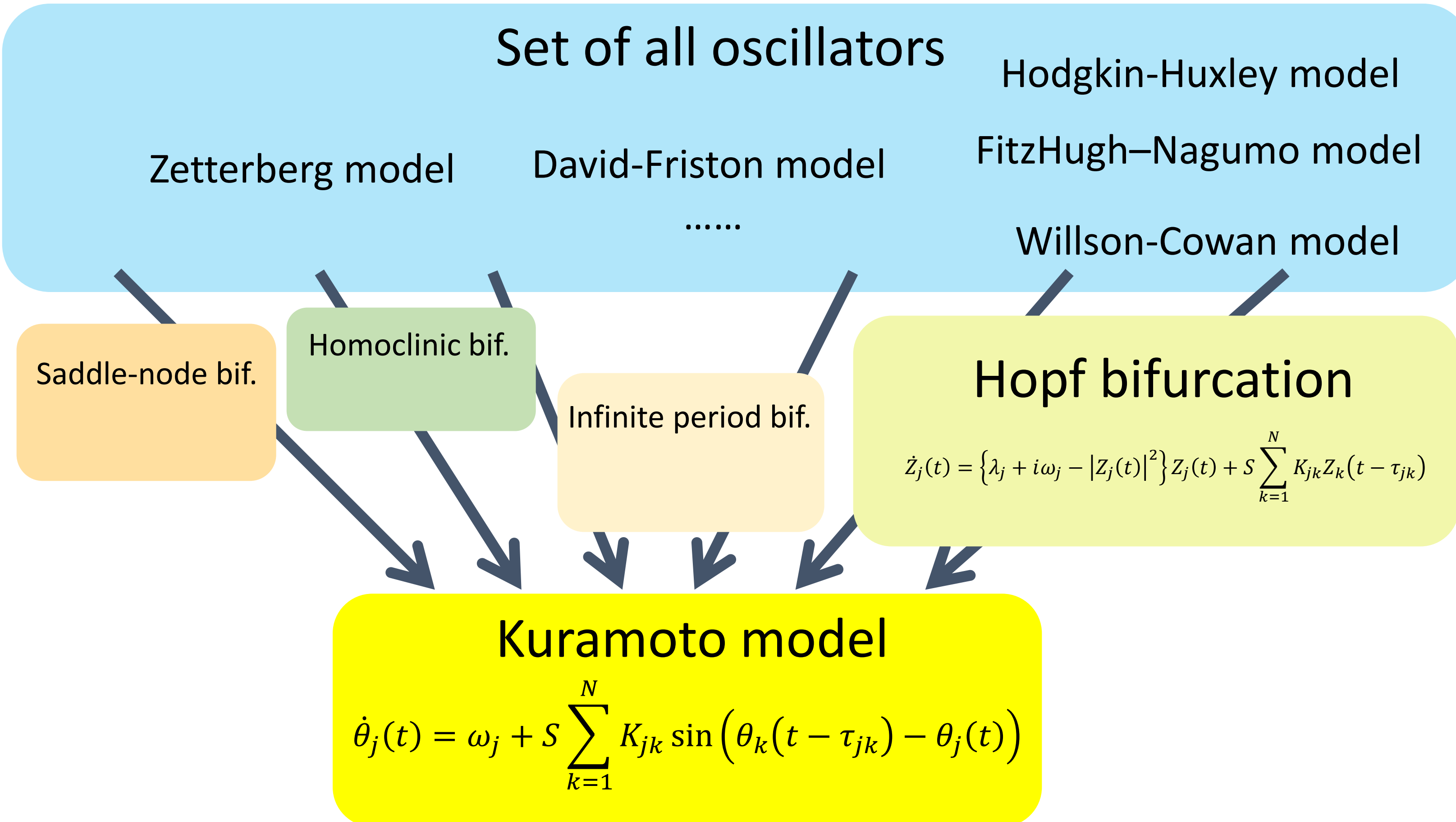
$$\dot{Z}_j(t) = \left\{\lambda_j + i\omega_j - \left|Z_j(t)\right|^2\right\} Z_j(t) + S\sum_{k=1}^{N} K_{jk} Z_k\left(t-\tau_{jk}\right), \quad j = 1,2,\ldots,N$$

Kuramoto Model

$$\dot{\theta}_j(t) = \omega_j + S\sum_{k=1}^{N} K_{jk}\sin\left(\theta_k\left(t-\tau_{jk}\right) - \theta_j(t)\right), \qquad j = 1,2,\ldots,N$$

Kuramoto/Stuart-Landau models are general/canonical models of the oscillators, and have general properties which more complex models also have.

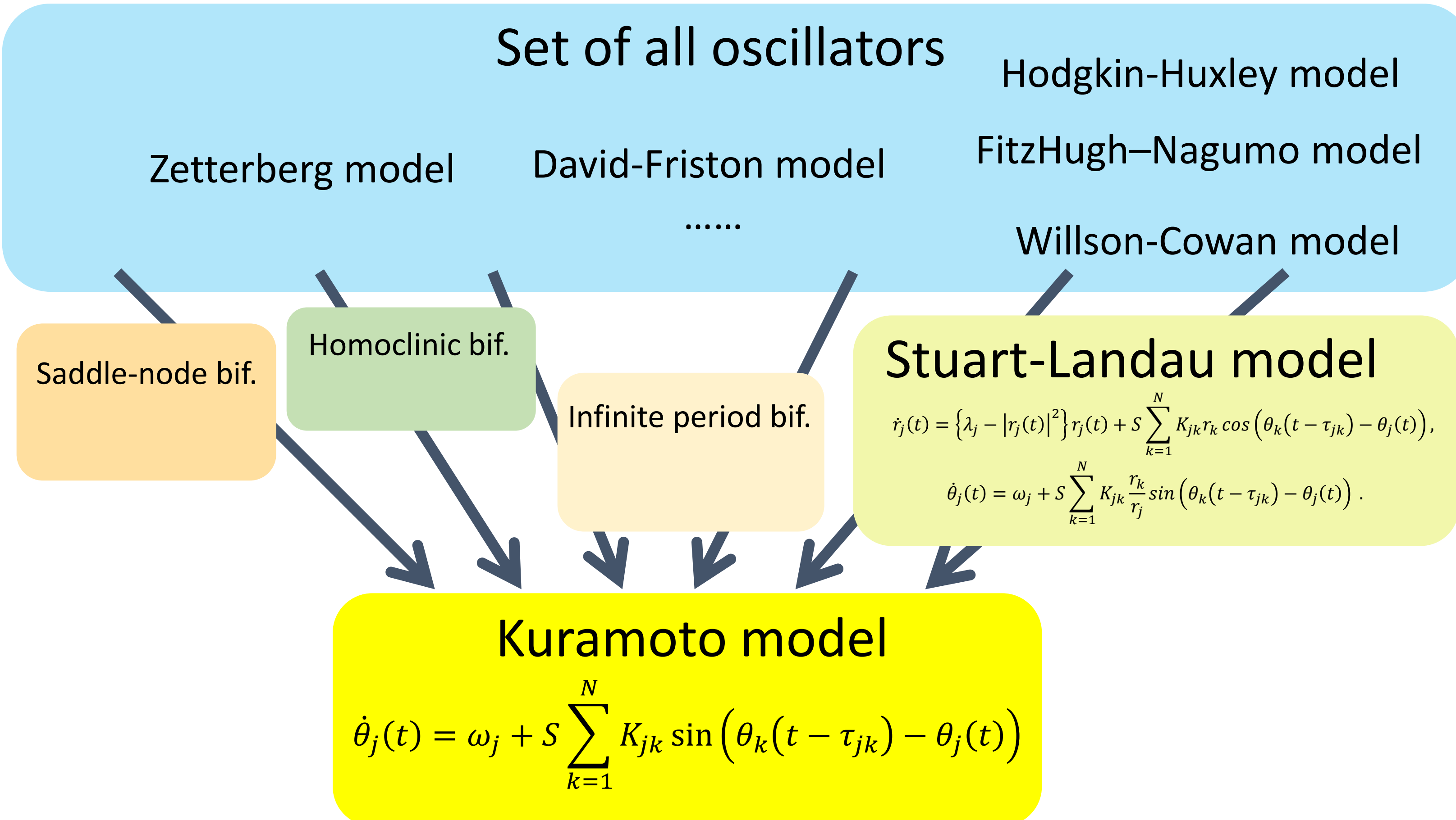
J-Y Moon, PLOS Comp. Biol. 2015



There exists mappings from all oscillators to the Kuramoto model, as a first-order approximation.
There exists mappings from some oscillators to the Stuart-Landau model, as the next-order appx.

Kuramoto/ Stuart-Landau model are the canonical models of oscillators.
If we can show that the K. model and S.-L. model yield *a specific property*,
it suggests that other oscillators can possibly yield *that property.*

Hoppensteadt and Izhikevich, Springer, 1997



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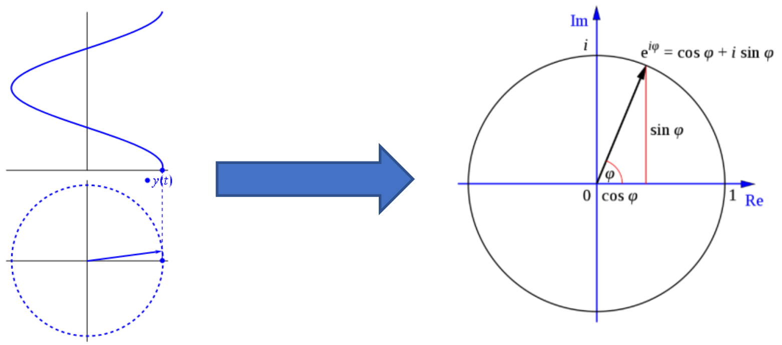
Kuramoto Model

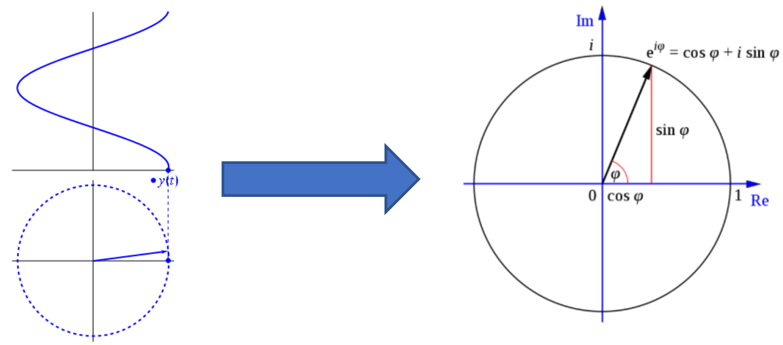


$$\dot{\theta}_j(t) = \omega_j + K \sum_{k=1}^{N} A_{jk} \sin\Big(\theta_k(t-\tau) - \theta_j(t)\Big), j = 1,2,\ldots,N.$$

https://hdietert.github.io/static/kuramoto-animation/kuramoto.html

https://gereshes.com/2018/02/26/modeling-fireflies-in-sync/

Kuramoto Model



coupling strength

$$\dot{\theta}_j(t) = \omega_j + K \sum_{k=1}^{N} A_{jk} \sin\left(\theta_k(t-\tau) - \theta_j(t)\right), j = 1,2,\ldots,N.$$

change of phase

frequency

connectivity matrix

phase of coupled node

phase

https://hdietert.github.io/static/kuramoto-animation/kuramoto.html

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Stuart-Landau Model

$$\dot{Z}_j(t) = \left\{\lambda_j + i\omega_j - \left|Z_j(t)\right|^2\right\} Z_j(t) + K \sum_{k=1}^{N} A_{jk} Z_k(t-\tau), \qquad j = 1,2,\ldots,N$$

$$\dot{r}_j(t) = \left\{\lambda_j - \left|r_j(t)\right|^2\right\} r_j(t) + K \sum_{k=1}^{N} A_{jk} r_k cos\left(\theta_k(t-\tau) - \theta_j\right),$$

$$\dot{\theta}_j(t) = \omega_j + K \sum_{k=1}^{N} A_{jk} \frac{r_k}{r_j} sin\left(\theta_k(t-\tau) - \theta_j\right), \quad j = 1,2,\ldots,N$$

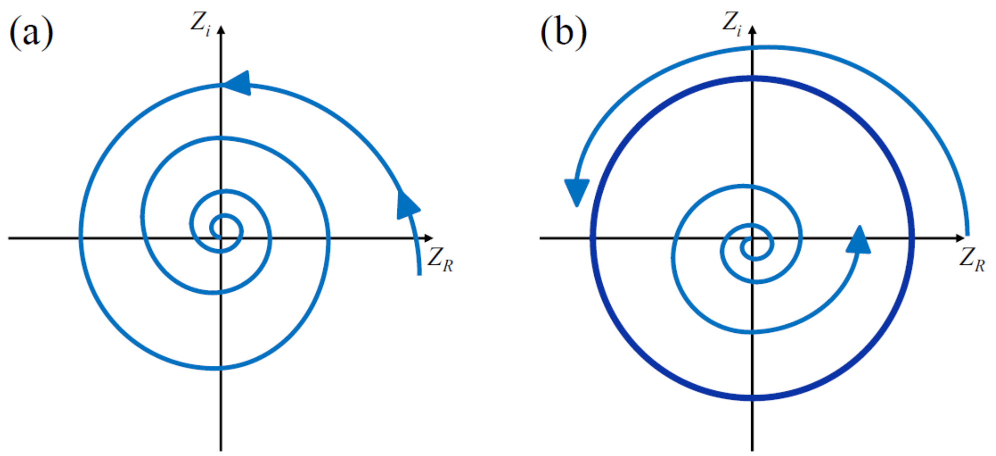
Stuart-Landau Model

$$\dot{r}_j(t) = \left\{\lambda_j - \left|r_j(t)\right|^2\right\} r_j(t)$$

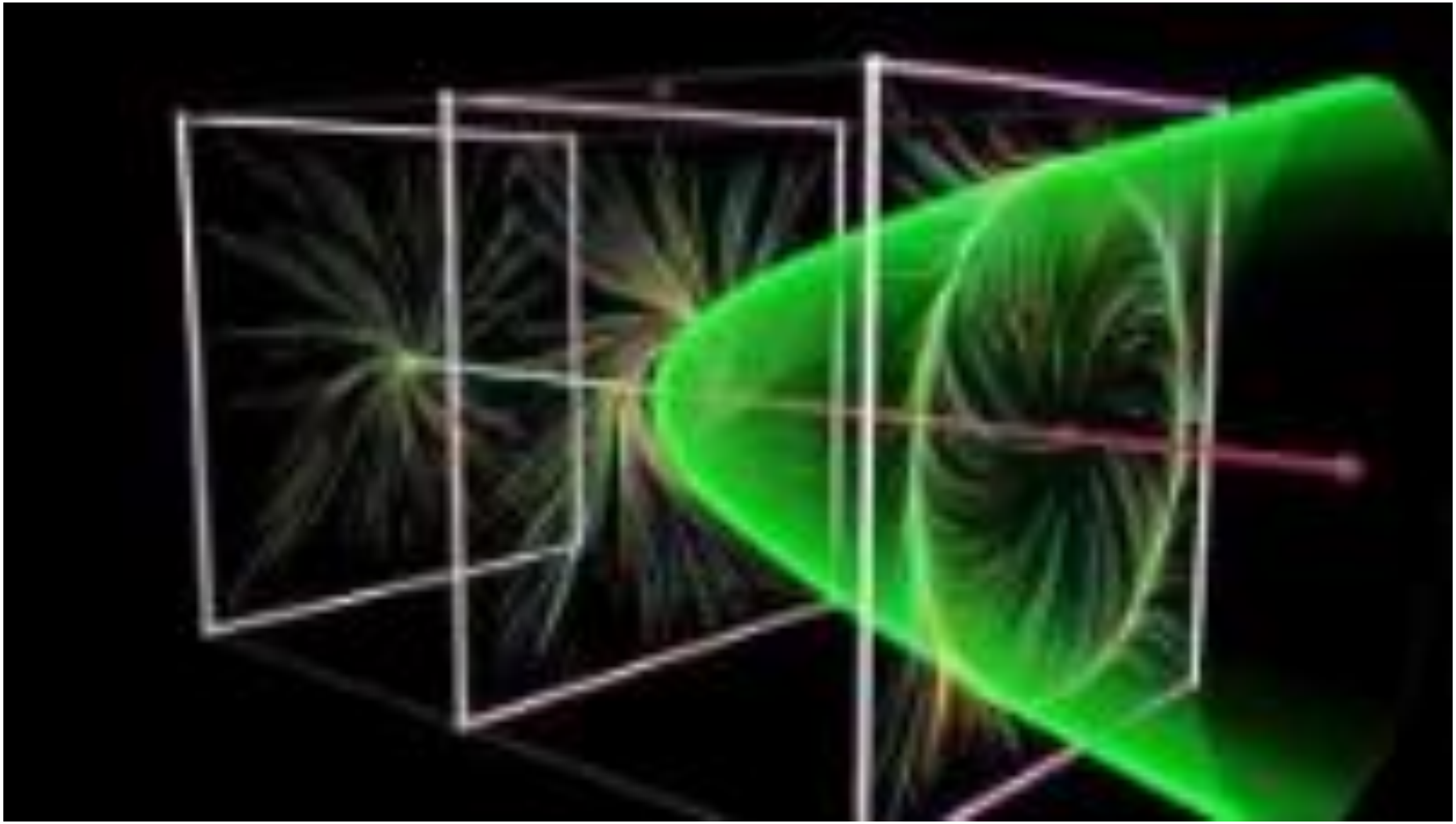
$$\dot{\theta}_j(t) = \omega_j$$

$$\dot{r}_j(t) = \left\{\lambda_j - \left|r_j(t)\right|^2\right\} r_j(t)$$

$\lambda_j > 0$ $\lambda_j < 0$



Moon et al., PLOS Comp. Biol. 2015



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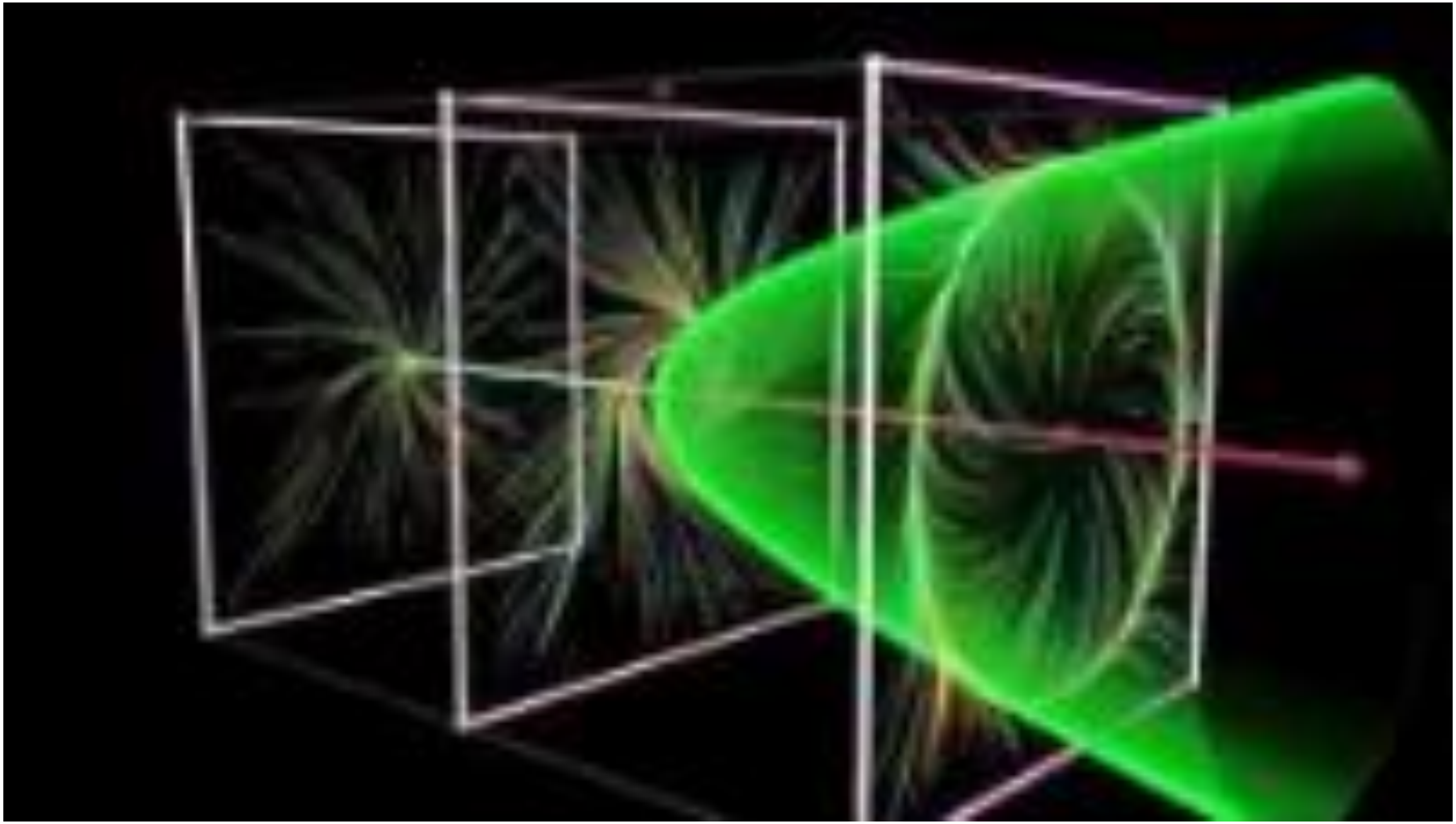
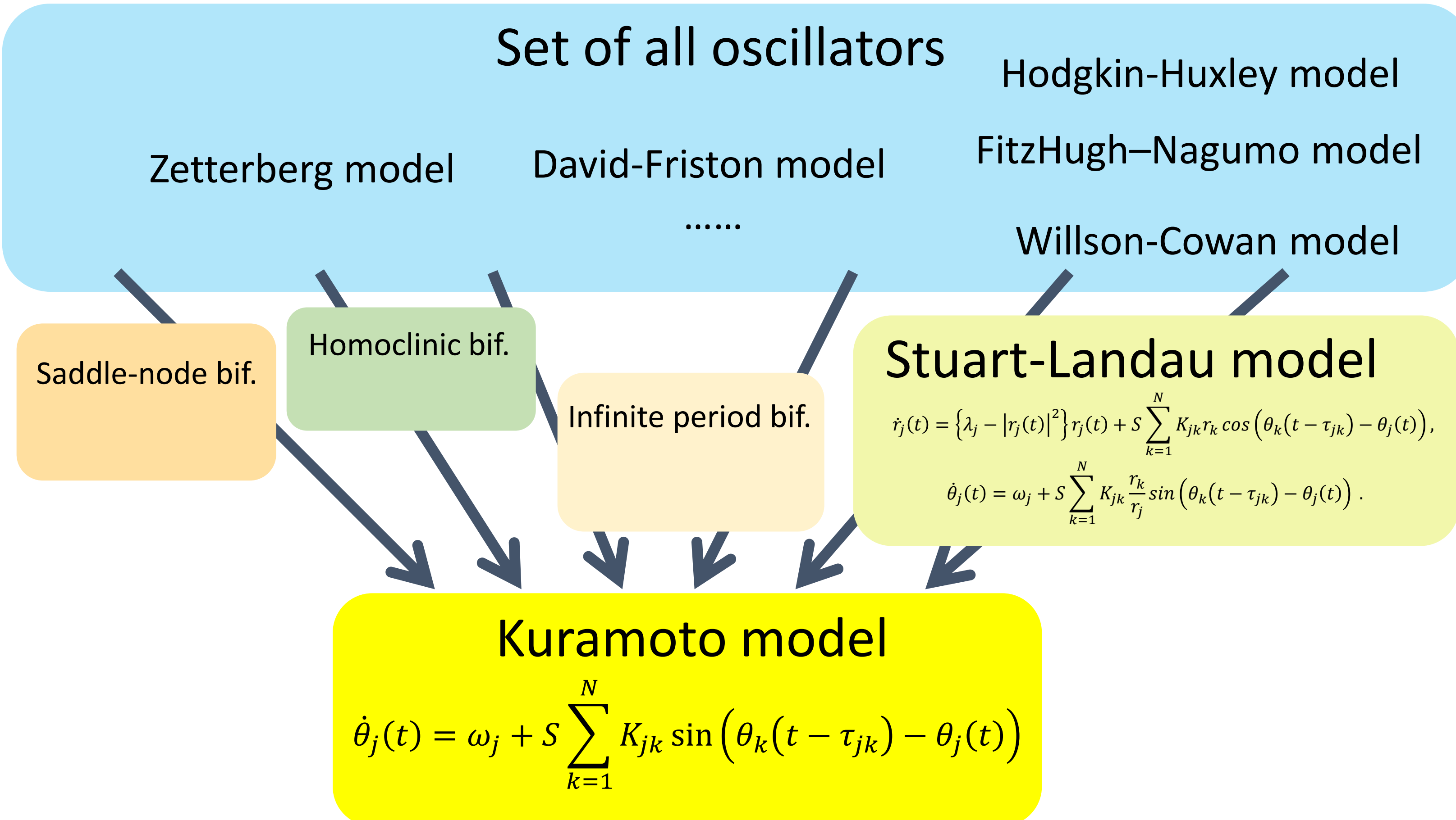


$$\dot{Z}_j(t) = \left\{\lambda_j + i\omega_j - \left|Z_j(t)\right|^2\right\} Z_j(t) + S \sum_{k=1}^{N} K_{jk} Z_k\left(t - \tau_{jk}\right)$$

$$\dot{r}_j(t) = \left\{\lambda_j - \left|r_j(t)\right|^2\right\} r_j(t) + S \sum_{k=1}^{N} K_{jk} r_k \, cos\left(\theta_k\left(t - \tau_{jk}\right) - \theta_j(t)\right),$$

$$\dot{\theta}_j(t) = \omega_j + S \sum_{k=1}^{N} K_{jk} \frac{r_k}{r_j} sin\left(\theta_k\left(t - \tau_{jk}\right) - \theta_j(t)\right) .$$

Moon et al., PLOS Comp. Biol. 2015



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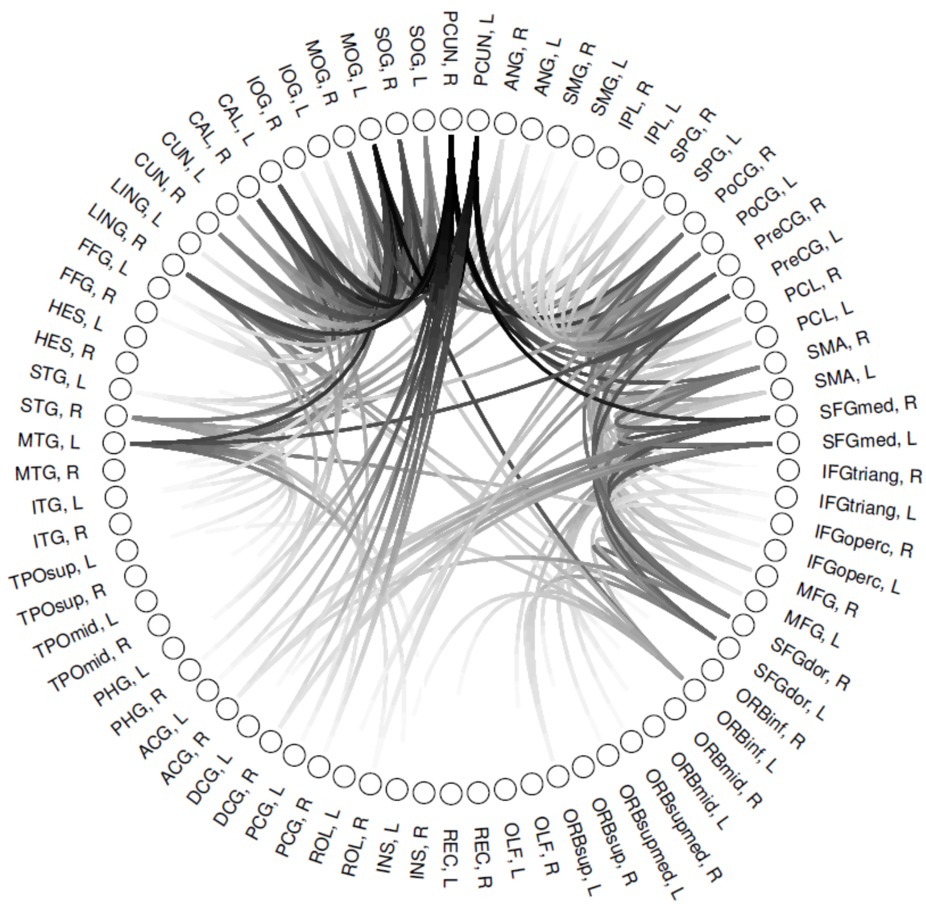
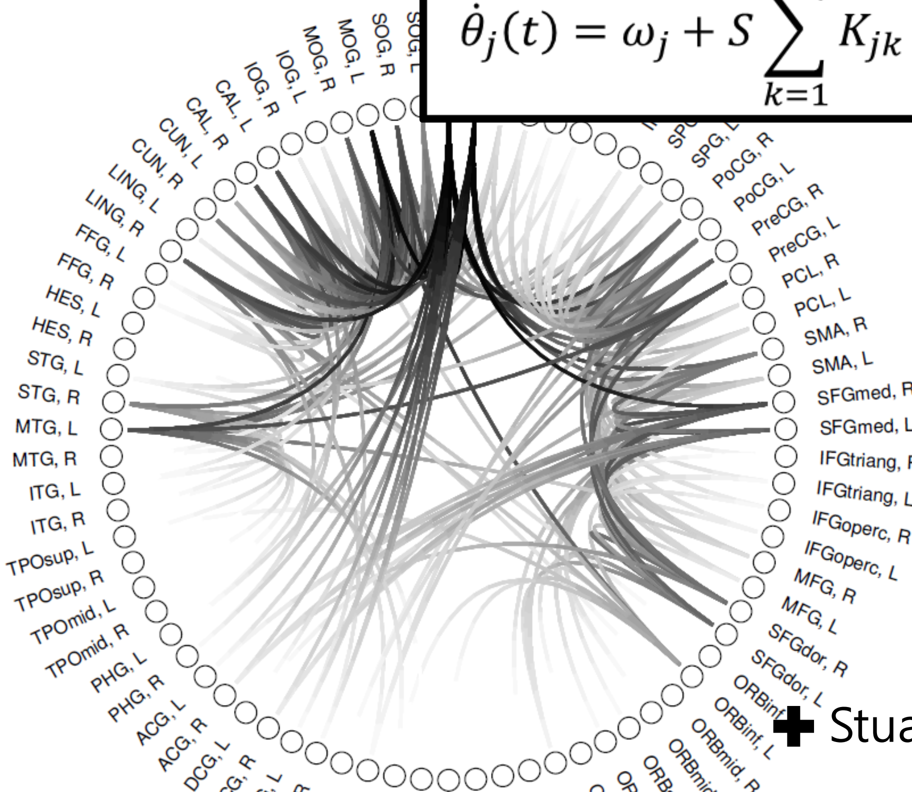
Model: Results on Human Structural Brain Networks



Model: Results on Human Structural Brain Networks

✚ Kuramoto Model

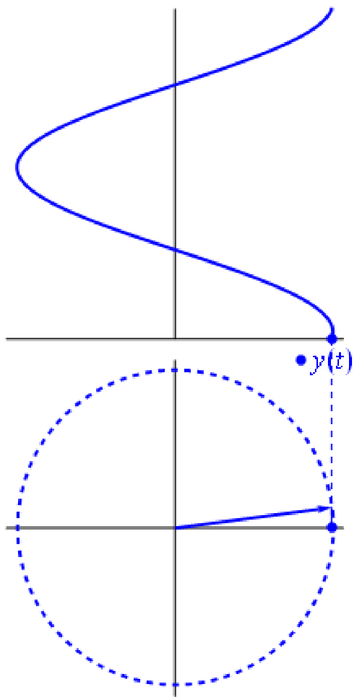
$$\dot{\theta}_j(t) = \omega_j + S \sum_{k=1}^{N} K_{jk} \sin\left(\theta_k(t - \tau_{jk}) - \theta_j(t)\right)$$

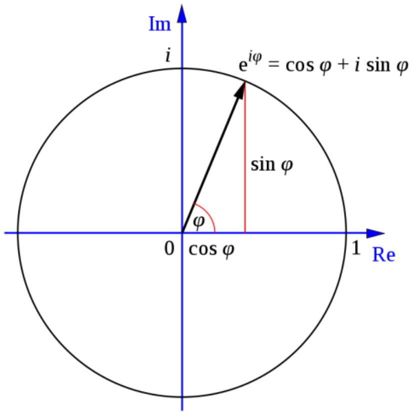


✚ Stuart-Landau Model

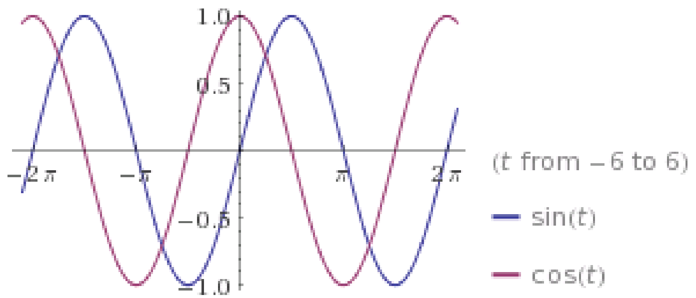
$$\dot{Z}_j(t) = \left\{\lambda_j + i\omega_j - \left|Z_j(t)\right|^2\right\} Z_j(t) + S \sum_{k=1}^{N} K_{jk} Z_k(t - \tau_{jk})$$

Every Oscillations Are Represented by Phase and Amplitude

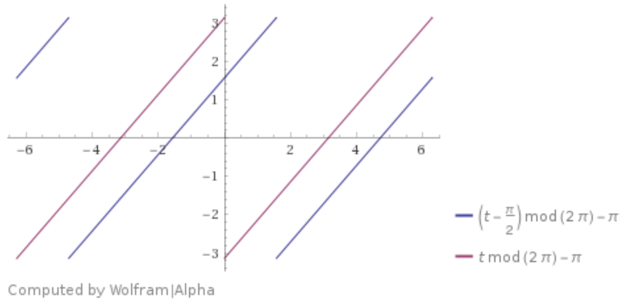




Oscillations



Phases



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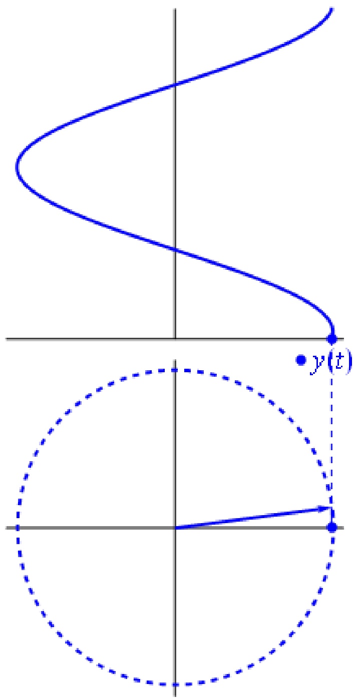

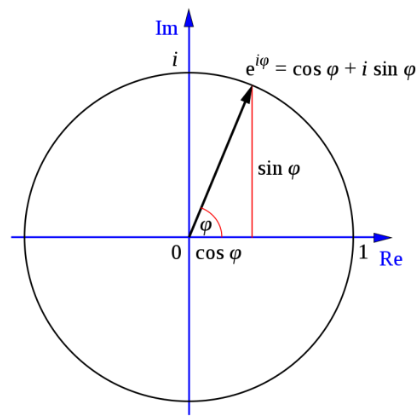

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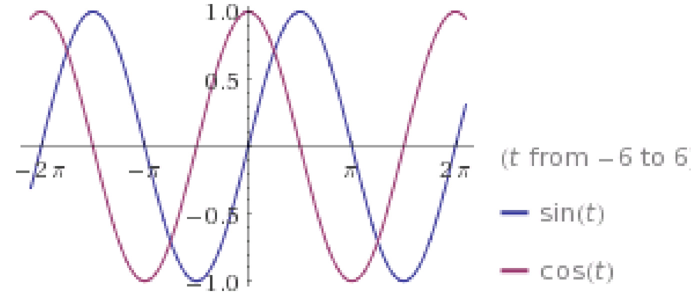
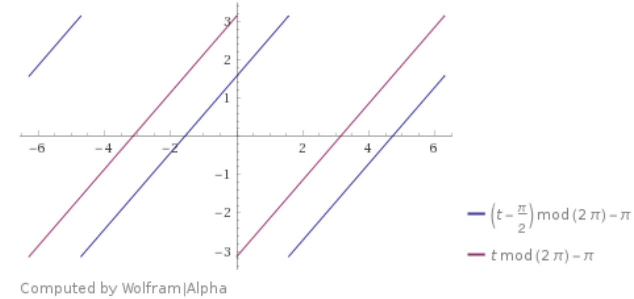


Phases



Relative Phase

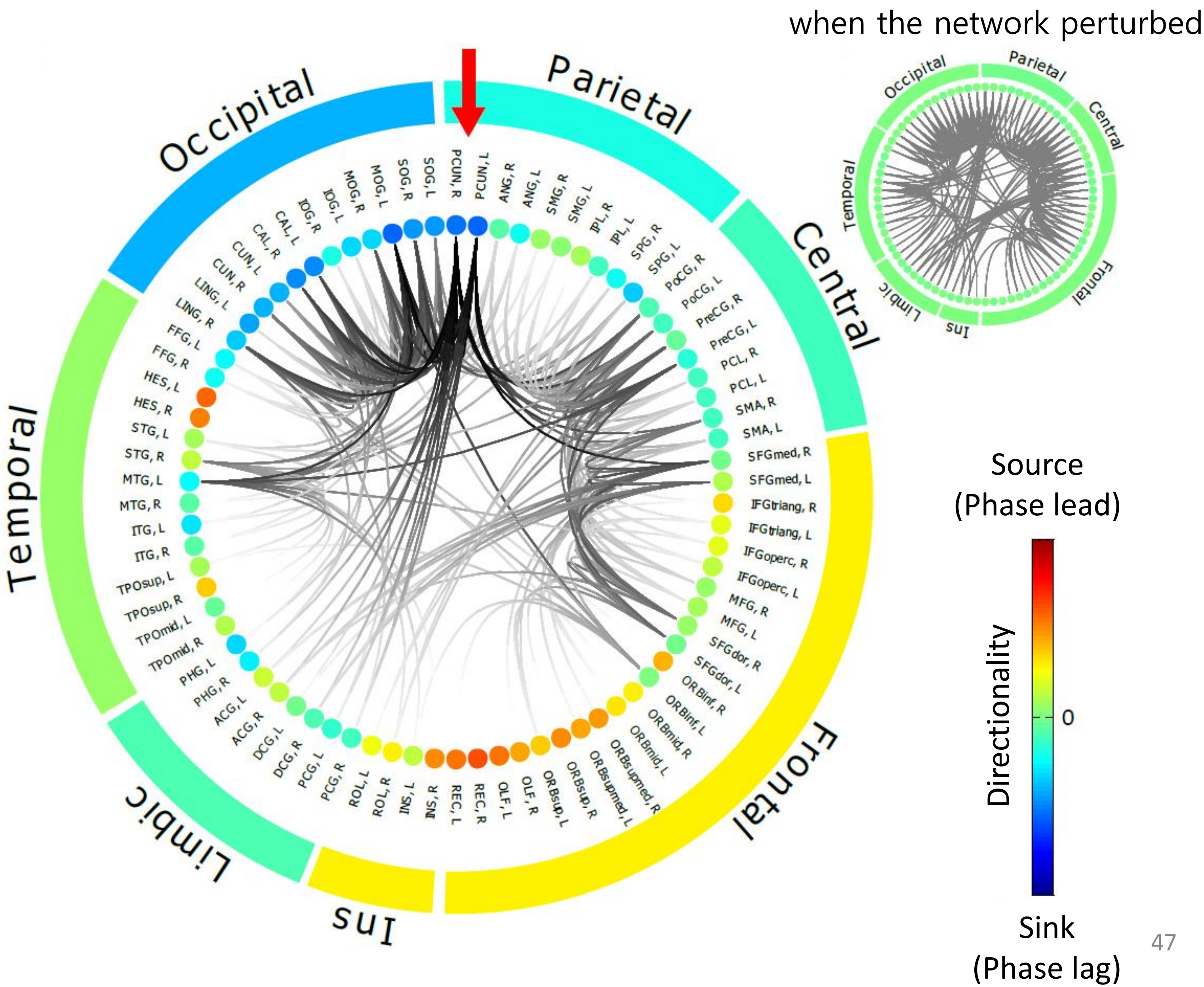
1. Summarize phase of each oscillator in the system and define the system’s phase Θ :

$$Re^{i\Theta} = \frac{1}{N}\sum_{j=1}^{N} e^{i\theta_j}$$

2. We subtract the system’s phase from each oscillator’s phase, and define it as relative phase φ_j :

$$\varphi_j = \theta_j - \Theta$$

Model: Results on Human Structural Brain Networks



Model Analysis, Simulations, and Experimental Confirmations

(a) Analytic study → (b) Simulations with model and brain networks → (c) Empirical validation from human EEG

$$\dot{z}_j(t) = \left\{\lambda_j + i\omega_j - |z_j(t)|^2\right\} z_j(t) + S\sum_{k=1}^{N} K_{jk} z_k(t-\tau_{jk}), \quad j = 1, 2, \ldots, N$$

For

$z_j(t)$ on networks with sufficient coupling strength S and small time delay τ_{jk},

if

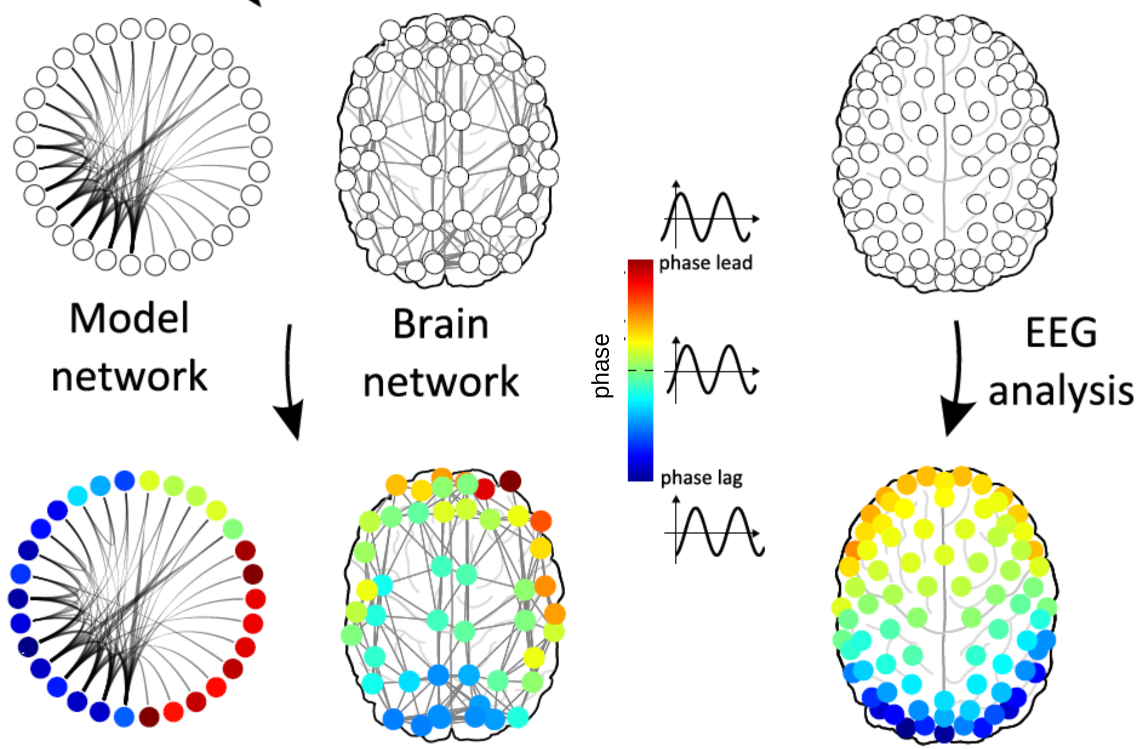
degree(m) > degree(n),

then

$|z_m| > |z_n|$,

and

phase(m) < phase(n).



J-Y Moon et al., PLOS Comp. Biol. 2015

Mathematical Results 1: Mean-Field Method

Using mean-field technique, we show the degree-phase relationship.

$$\dot{\theta}_j(t) = \omega_j + \frac{S}{N}\sum_{k=1}^{N} K_{jk} \sin\left(\theta_k(t-\tau_{jk}) - \theta_j(t)\right), \qquad j = 1,2,\ldots,N$$

$$\approx \omega_j + \frac{S}{N}\sum_{k=1}^{N} K_{jk}[\sin(\theta_k - \theta_j - \beta)]$$

$$\approx \omega_j + \frac{SK_j}{N^2}\sum_{k=1}^{N}[\sin(\theta_k - \theta_j - \beta)]$$

$$\because S(homogeneous) \rightarrow \frac{SK_j}{N}(inhomogeneous)$$

$$\boxed{\theta_j = sin^{-1}\left(\frac{N}{K_j}\frac{\Delta_j}{SR}\right) + \Theta - \beta}$$

$$\boxed{\Delta_j \equiv \omega_j - \Omega} \qquad \boxed{Re^{i\Theta} \equiv \frac{1}{N}\sum_{j=1}^{N} e^{i\theta_j}}$$

For

$z_j(t)$ on networks
with sufficient coupling strength S
and small time delay τ_{jk},

if

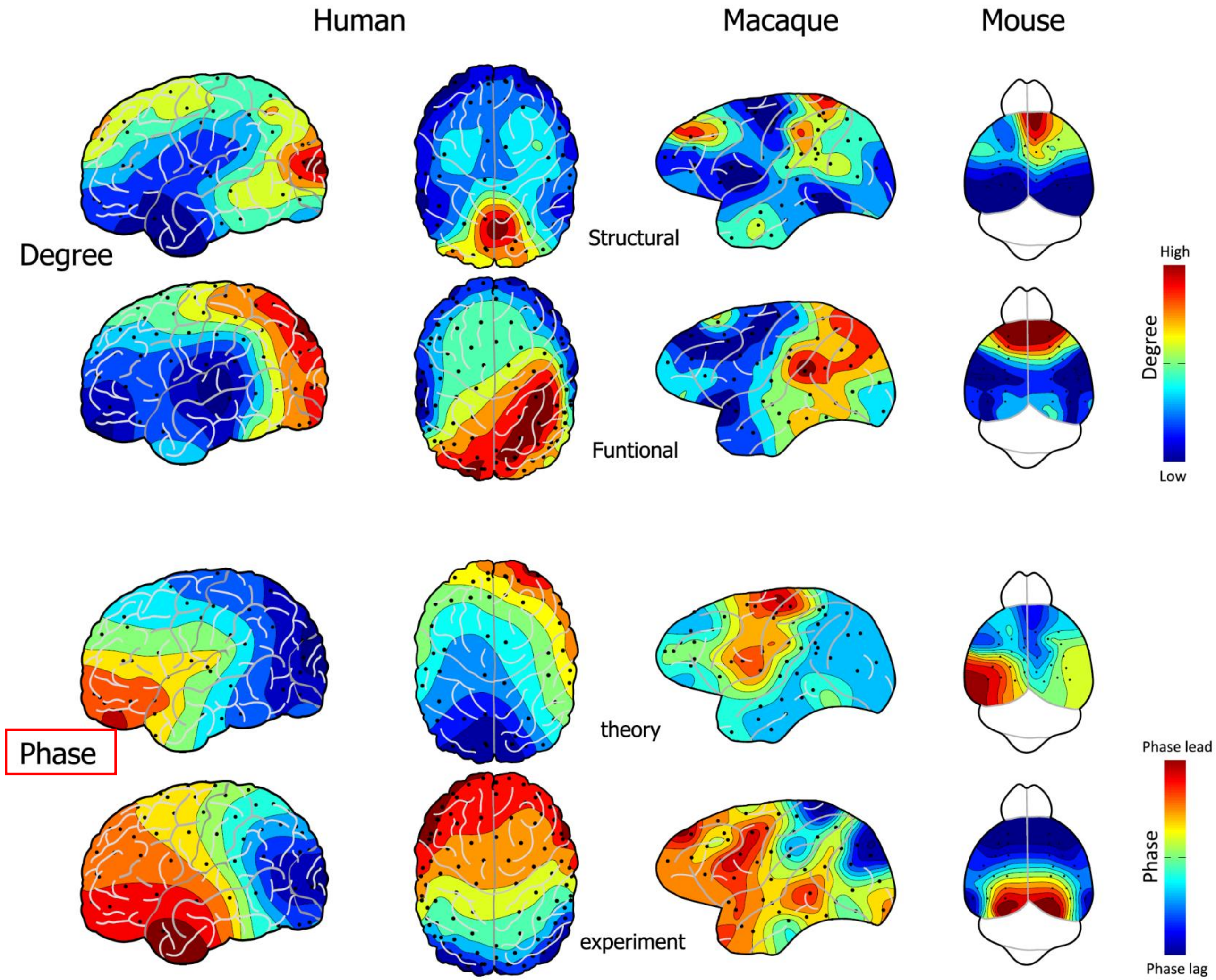
degree(m) > degree(n),

then

phase(m) < phase(n).

T-W Ko, PRE 2008.
J-Y Moon, PLOS Comp. Biol. 2015.

Information Flow Analysis across Different Species



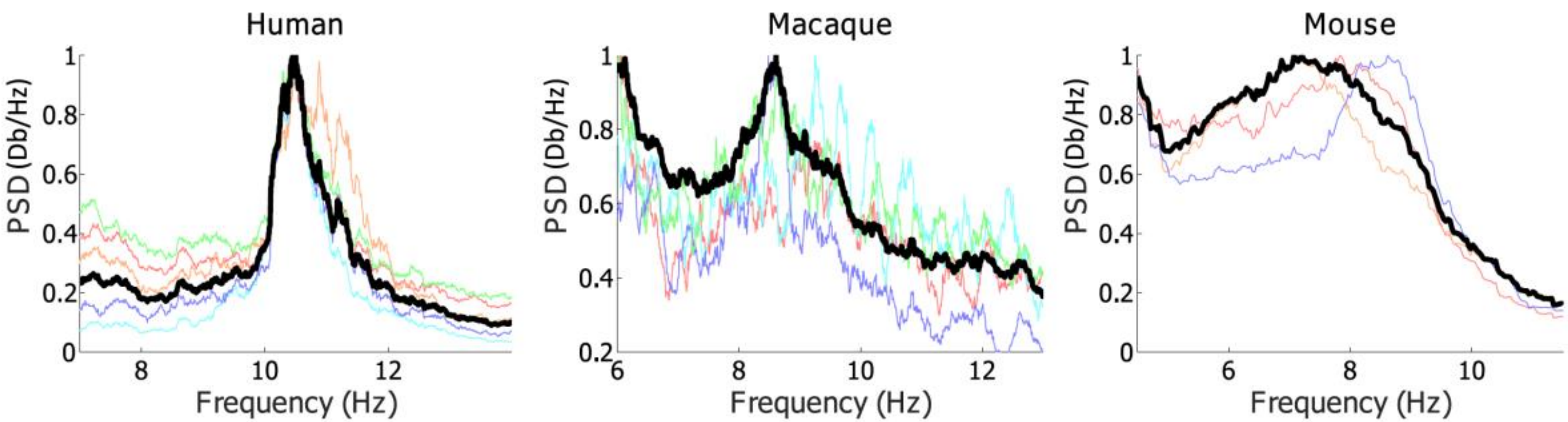
Human:
- 6 subjects
- 128 ch. EEG

Macaque:
- 4 subjects
- 128 ch. ECoG

Mouse:
- 9 subjects
- 38 ch. ECoG

J-Y Moon et al., Sci. Rep. 2017

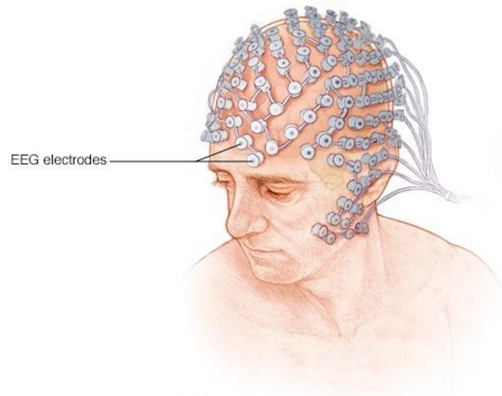
Patterns Strongest at the Peak Frequency

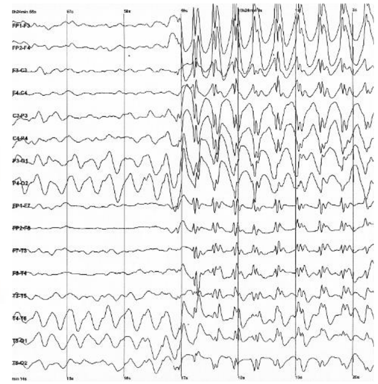


Each species has a peak in its frequency distribution: 10~11 Hz for human, 8~9 Hz for macaque, 7~8 Hz for mouse. The observed patterns were strongest at the peak frequency, suggesting that the global inter-regional communication may be strongest at the peak frequency of each species.

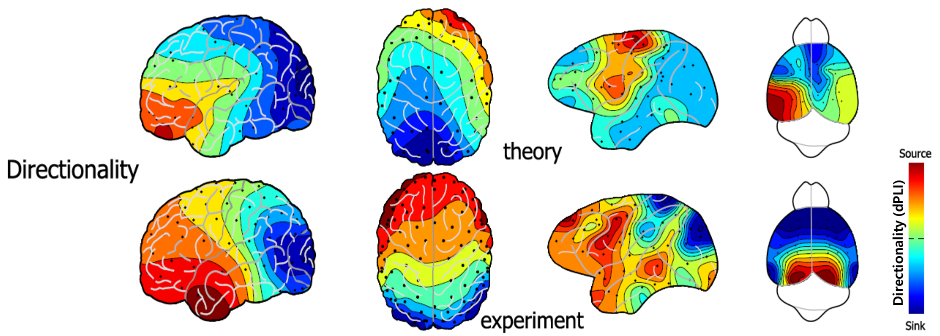
Research Themes

I. Brain Waves





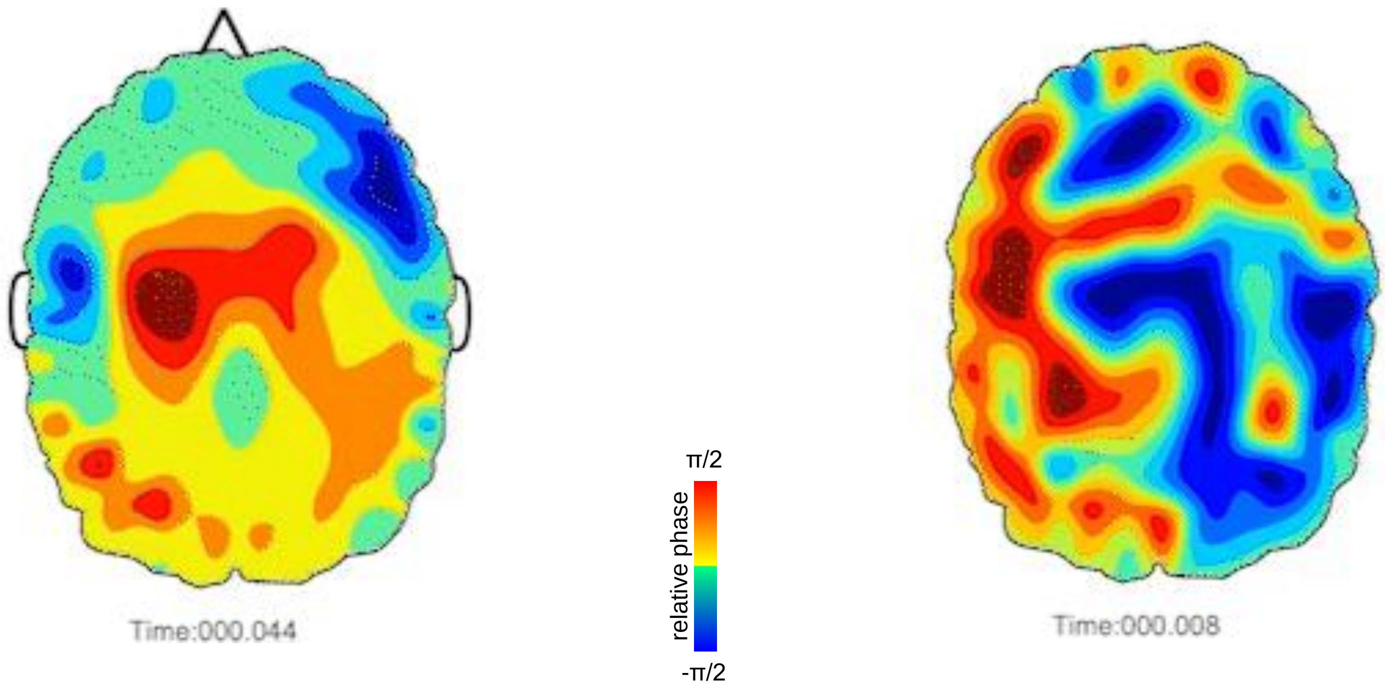
II. Phase Patterns in Brain States



III. Phase Dynamics of Brain States

Current Research: Identification of Internal/External Modes

Hypothesis: The majority of time windows will match the internal or external template.



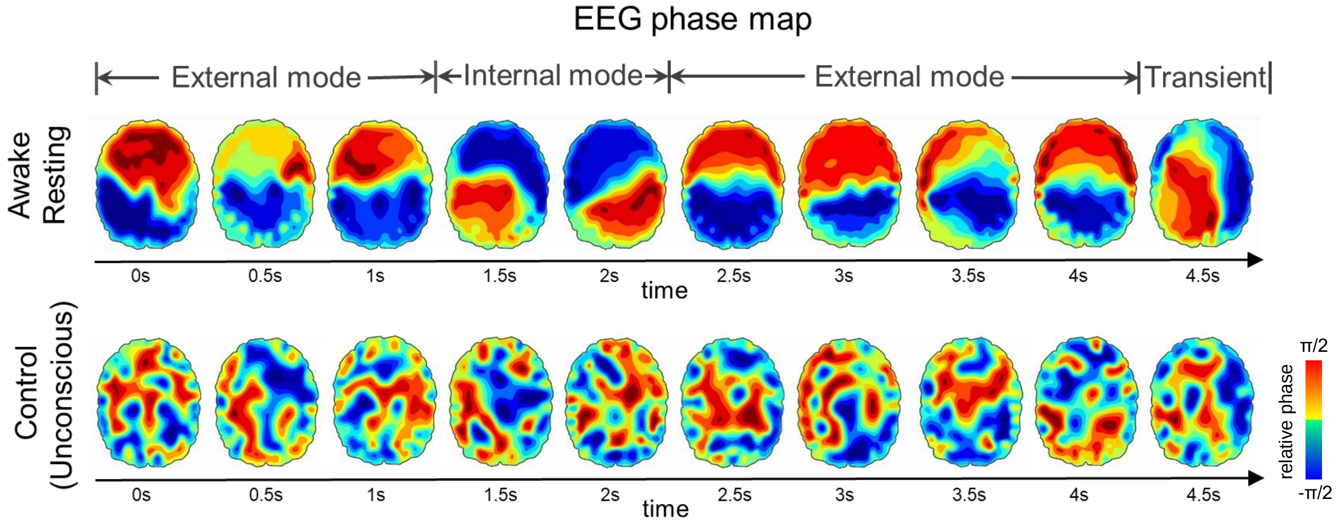
Conscious state

Control state (unconscious state)

Identification of Internal/External Modes in EEG and ECoG Recordings

Hypothesis: The majority of time windows will match the internal or external template.

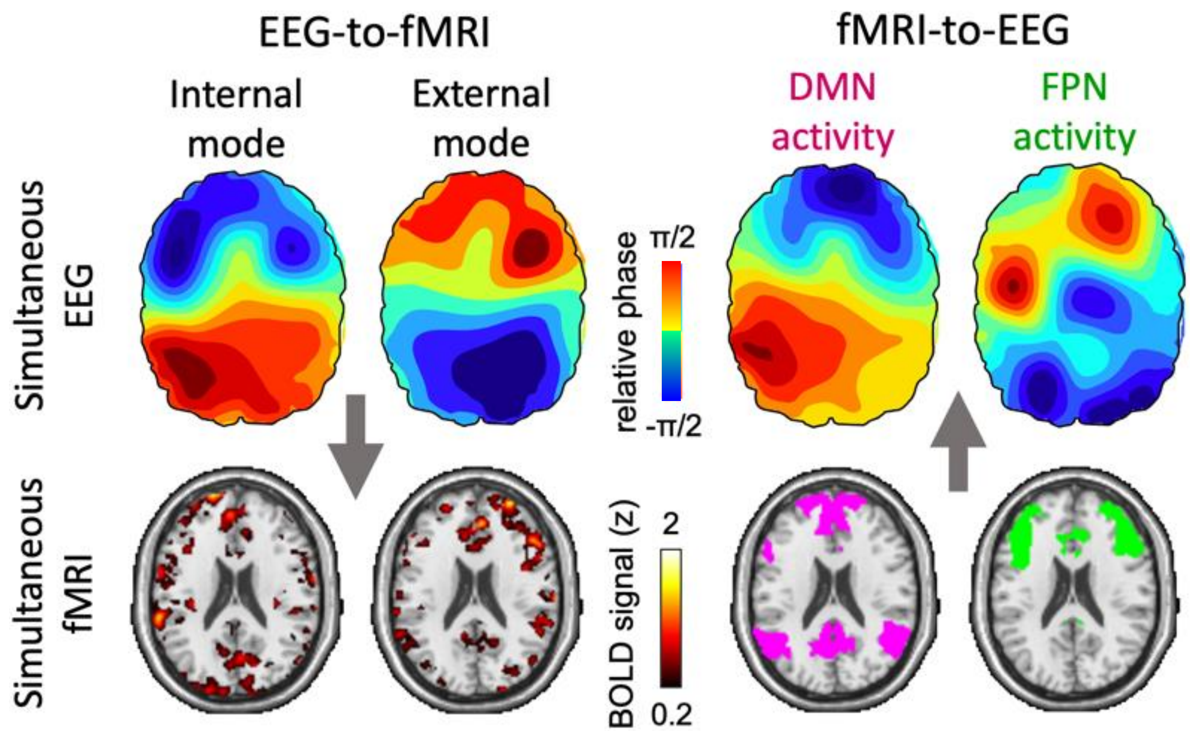
Park, YoungJae



Validate Electrophysiologically Defined Modes against fMRI Reference States

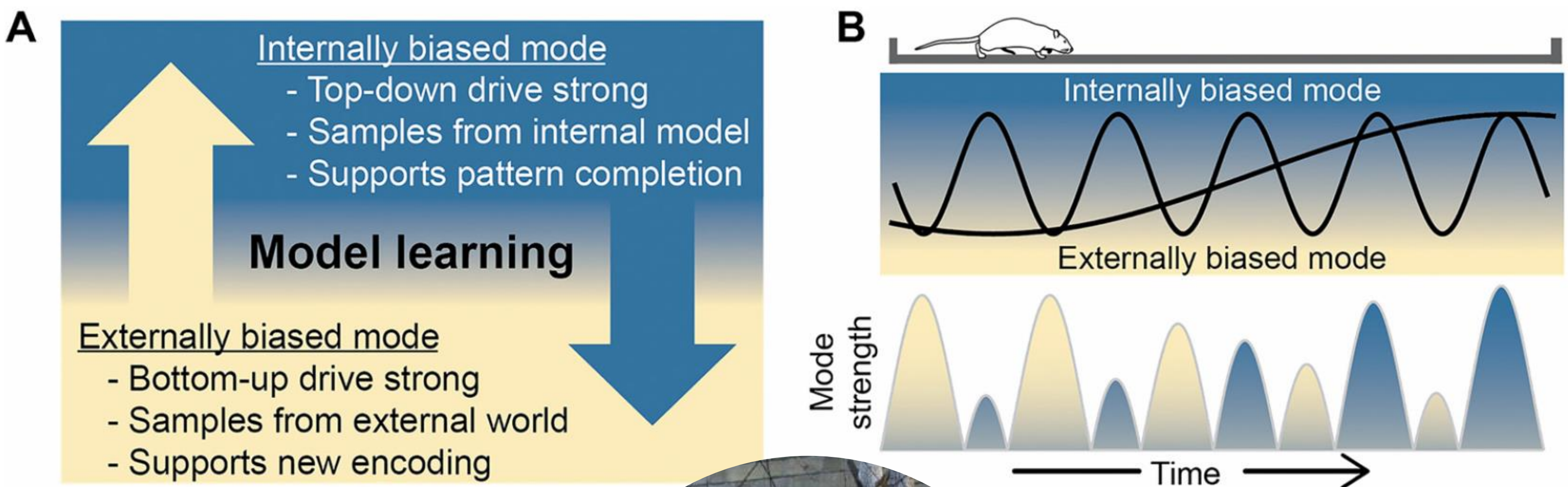
Hypothesis: EEG-defined modes are be associated with fMRI defined states

Kim, HyoungKyu



Internal/External Brain Modes Transitions May Be a Crucial Mechanism

Hypothesis: Transitions between two dominant modes, internal & external mode, can be the crucial mechanism facilitating learning and memory.



Honey et al., Network Neurosci. 2017

Honey, Christopher

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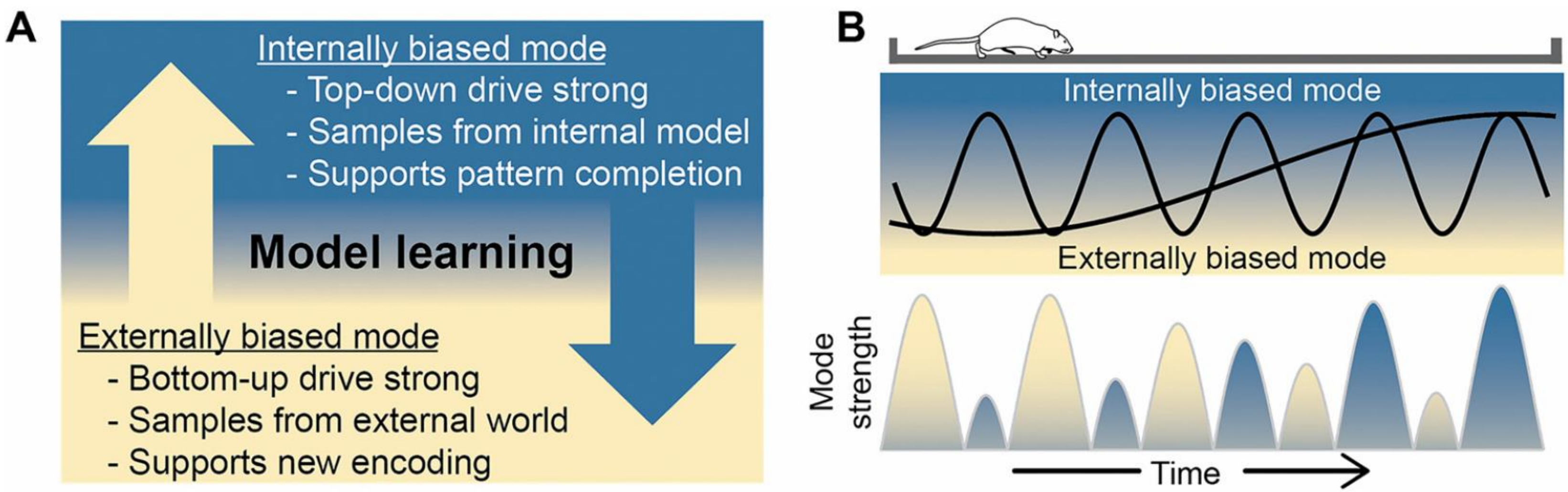

In external mode, we are biased towards external world.
In internal mode, we process information, and construct an internal model.

Honey et al., Network Neurosci. 2017

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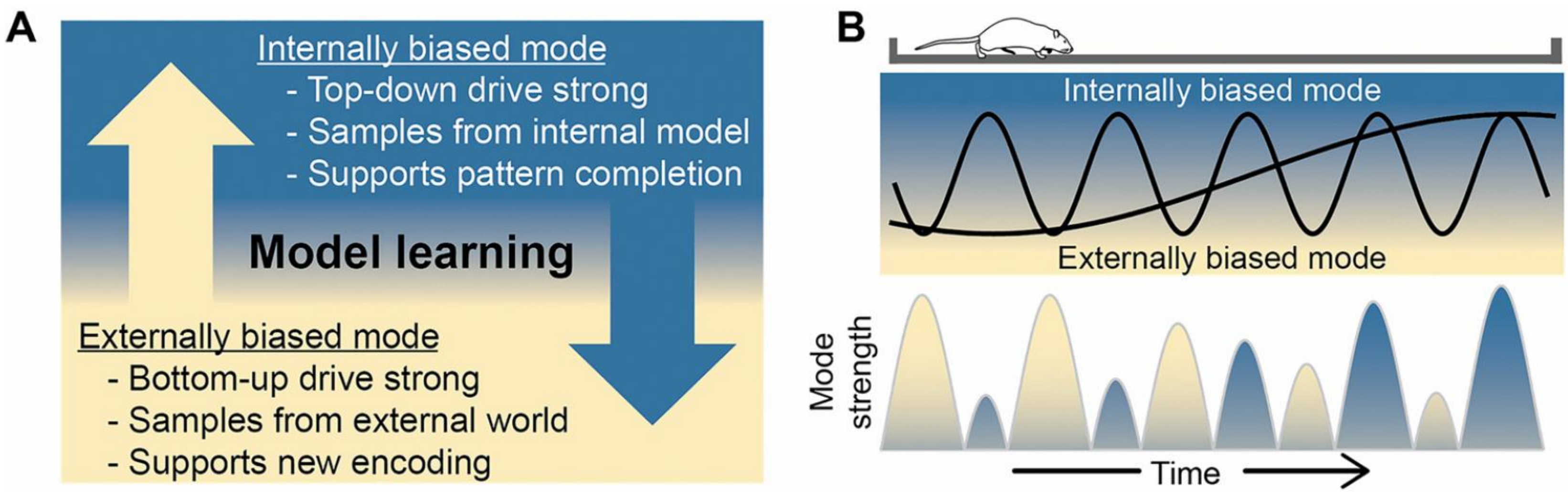


In external mode, we are biased towards external world.
In internal mode, we process information, and construct an internal model.

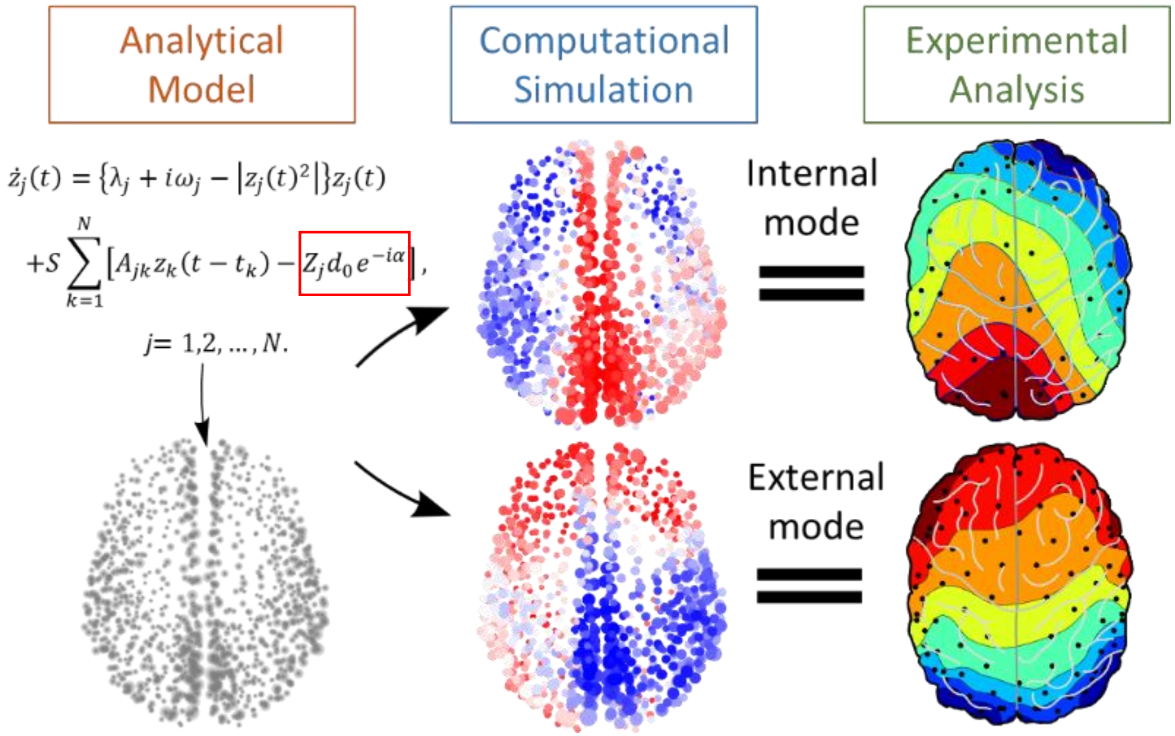
Again in external mode, we compare our model against external world.
Again in internal mode, we modify our model, triggered by the "mismatch".

⋮

Honey et al., Network Neurosci. 2017

Characterize Internal (top-down) /External (Bottom-up) Modes Using EEG

Hypothesis: Large-scale cortical dynamics transition between two dominant modes, internal & external mode.



Characterize Internal (top-down) /External (Bottom-up) Modes in Our Model

Idea: we can map how amplitude/phase dynamics are affected by diffusive coupling term in our model.

Lee, HaeSung

Stuart-Landau model with diffusive term

$$\dot{Z}_j(t) = \left\{\lambda_j + i\omega_j - \left|Z_j(t)\right|^2\right\} Z_j(t) + S \sum_{k=1}^{N} A_{jk}\left[Z_k(t)e^{-i\beta} - \boxed{Z_j(t) g e^{-i\alpha}}\right],$$

$$j = 1,2,\ldots,N$$

equivalent to

$$\dot{r}_j(t) = \left\{\lambda_j - \left|r_j(t)\right|^2\right\} r_j(t) + S \sum_{k=1}^{N} A_{jk} r_k \left[cos\left(\theta_k - \beta - \theta_j\right) - \boxed{r_j g \cos\alpha}\right],$$

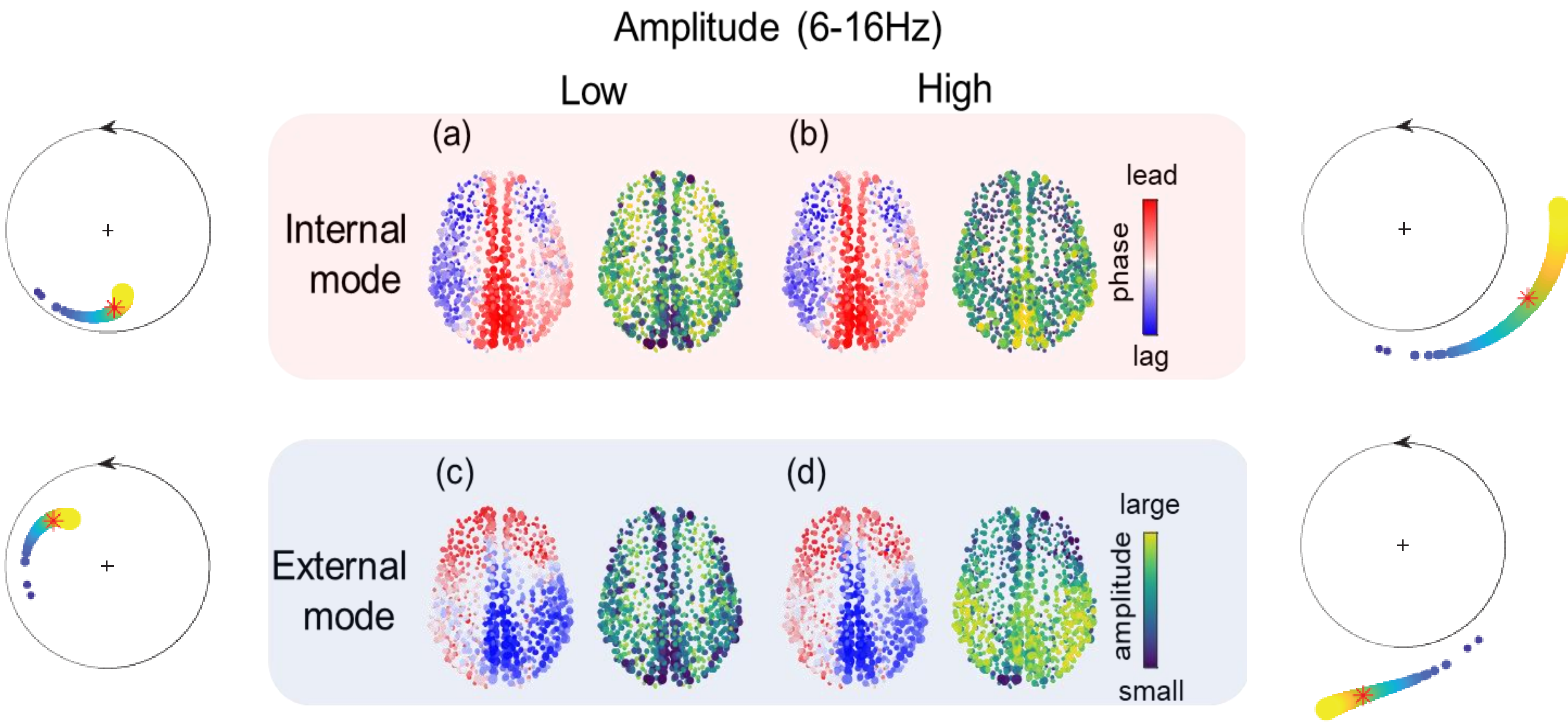
$$\dot{\theta}_j(t) = \omega_j + S \sum_{k=1}^{N} A_{jk} \frac{r_k}{r_j}\left[sin\left(\theta_k - \beta - \theta_j\right) + \boxed{g \sin\alpha}\right],$$

$$j = 1,2,\ldots,N$$

Woo et al., Chaos 2020

Characterize Internal (top-down) /External (Bottom-up) Modes in Our Model

Hypothesis: Both internal and external states will allow for both high & low-amplitude oscillations.

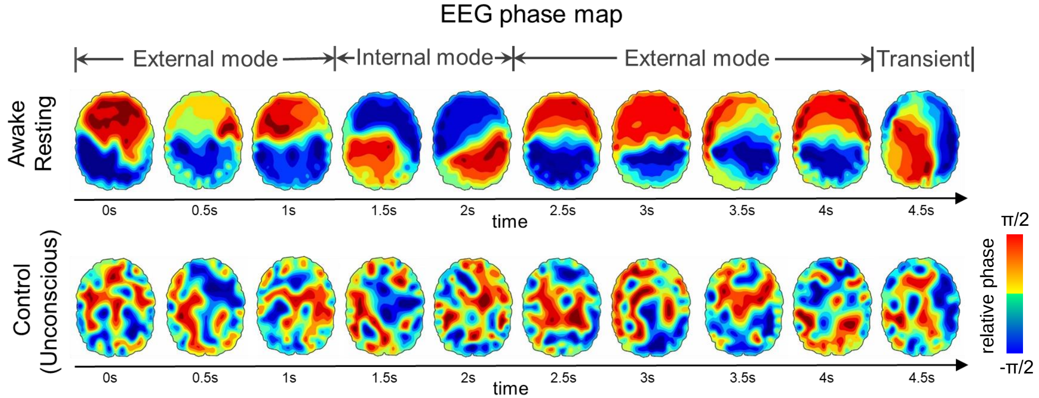


Woo et al., Chaos 2020

Current Research

1. Characterize Internal and External Brain Modes

- Characterize internal vs external modes in model
- Identify internal/external modes in EEG/ECoG, and against fMRI reference states



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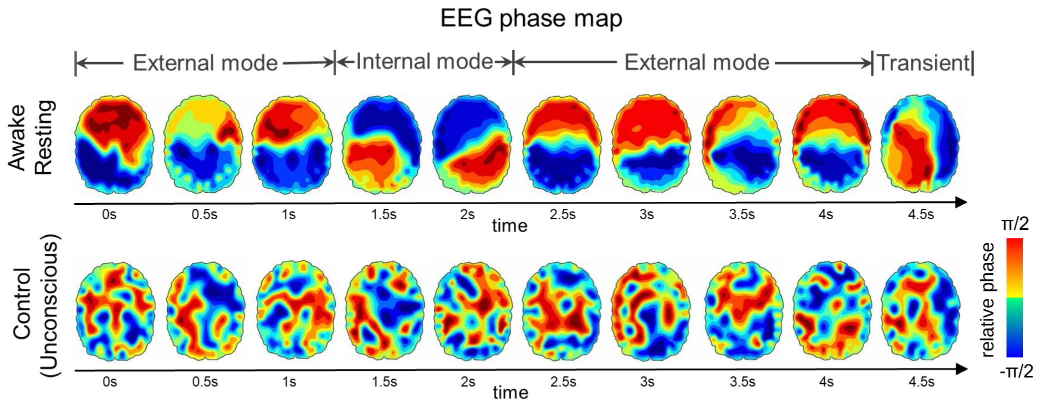

2. Determine Mechanisms and Targets for Triggering Mode Switches

- Determine conditions for mode transitions from model
- Determine triggers for internal-external mode transitions from experiments

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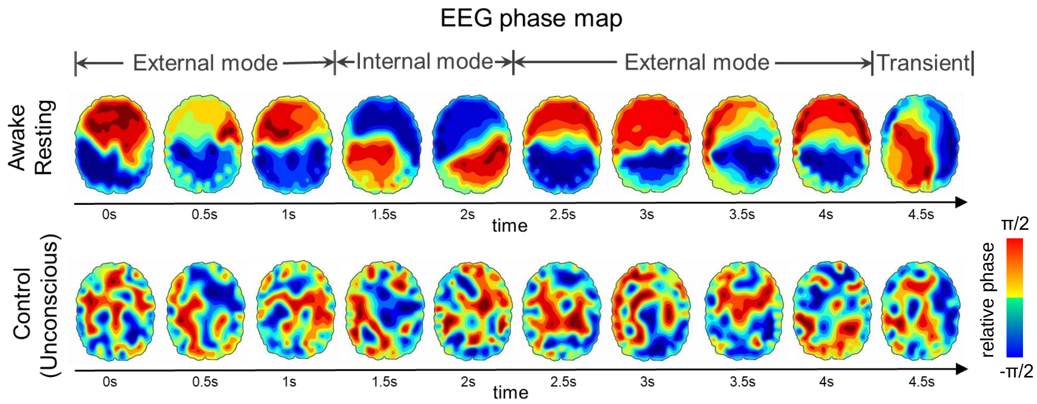

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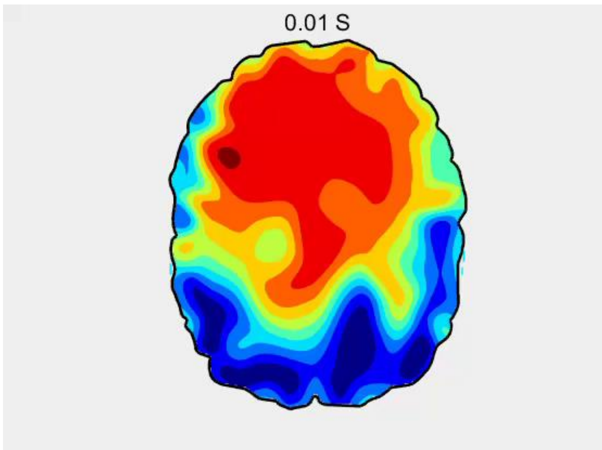
3. Compare Mode Transition Properties against Non-General Populations.

General Population vs. ADHD (inattentive type)

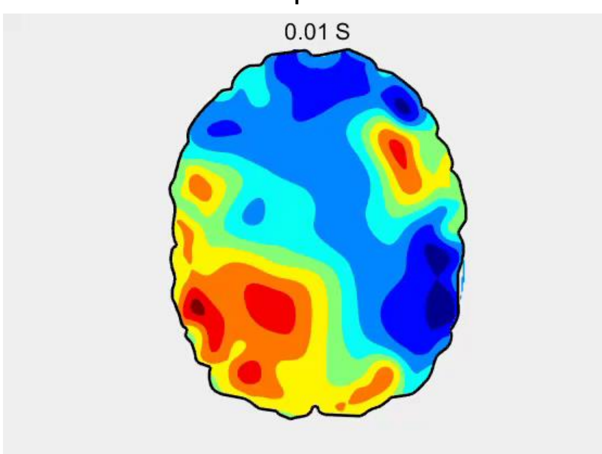
Cha, YoungHwa

General Population

Participant #1

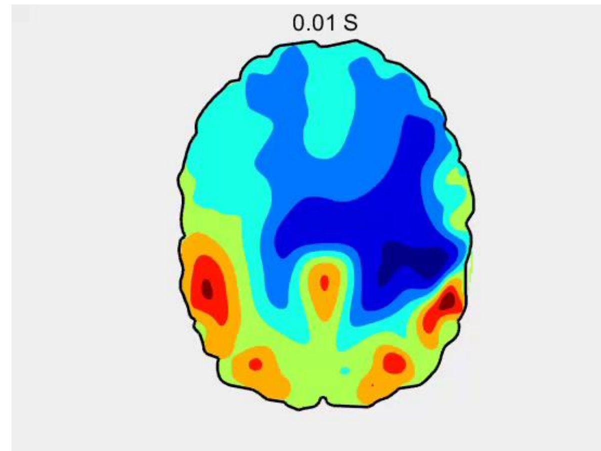


Participant #2

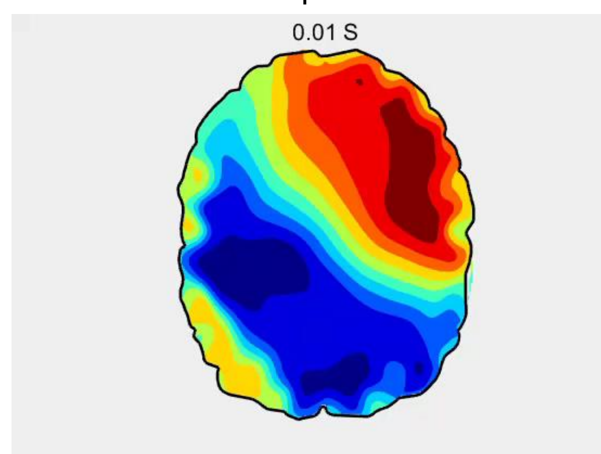


ADHD (inattentive type)

Participant #3



Participant #4



Experiments Utilizing Simultaneous EEG/fMRI


Kim, HyoungKyu


Park, YoungJae

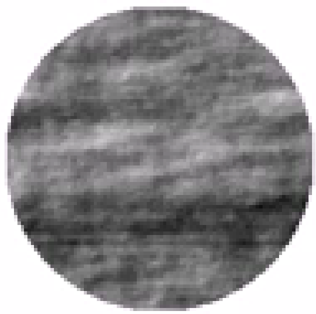

Lee, HaeSung

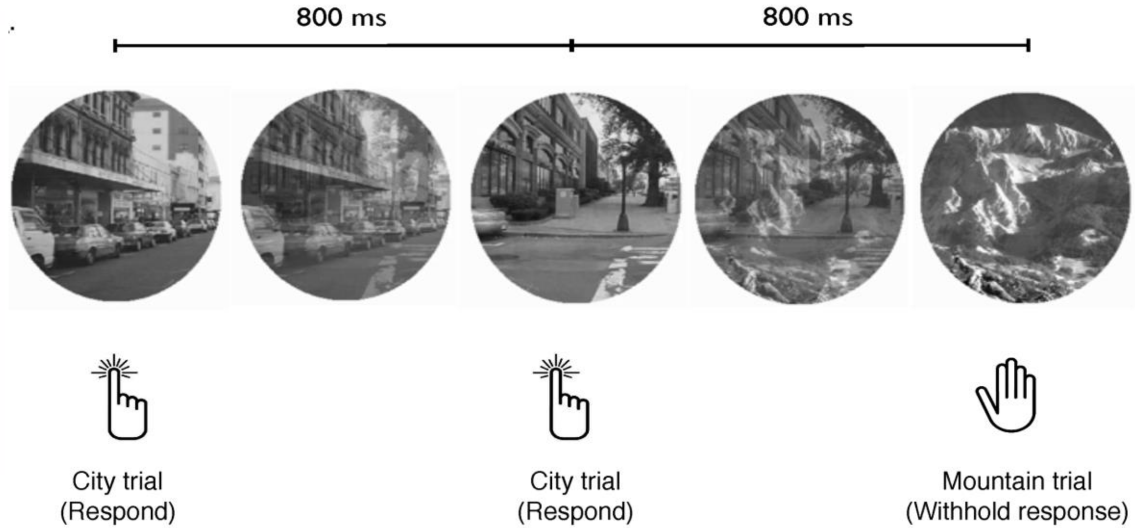

Cha, YoungHwa


Lee, YeJi


Cho, MinSeo

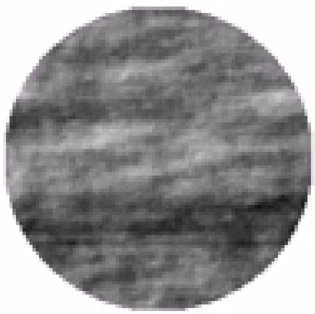
Experiments Utilizing Simultaneous EEG/fMRI: gradCPT

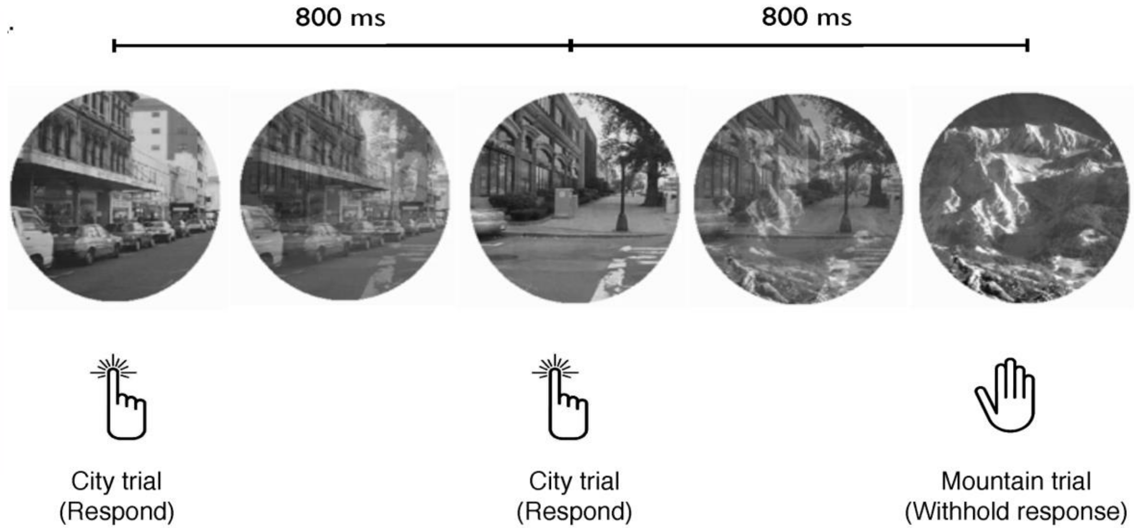


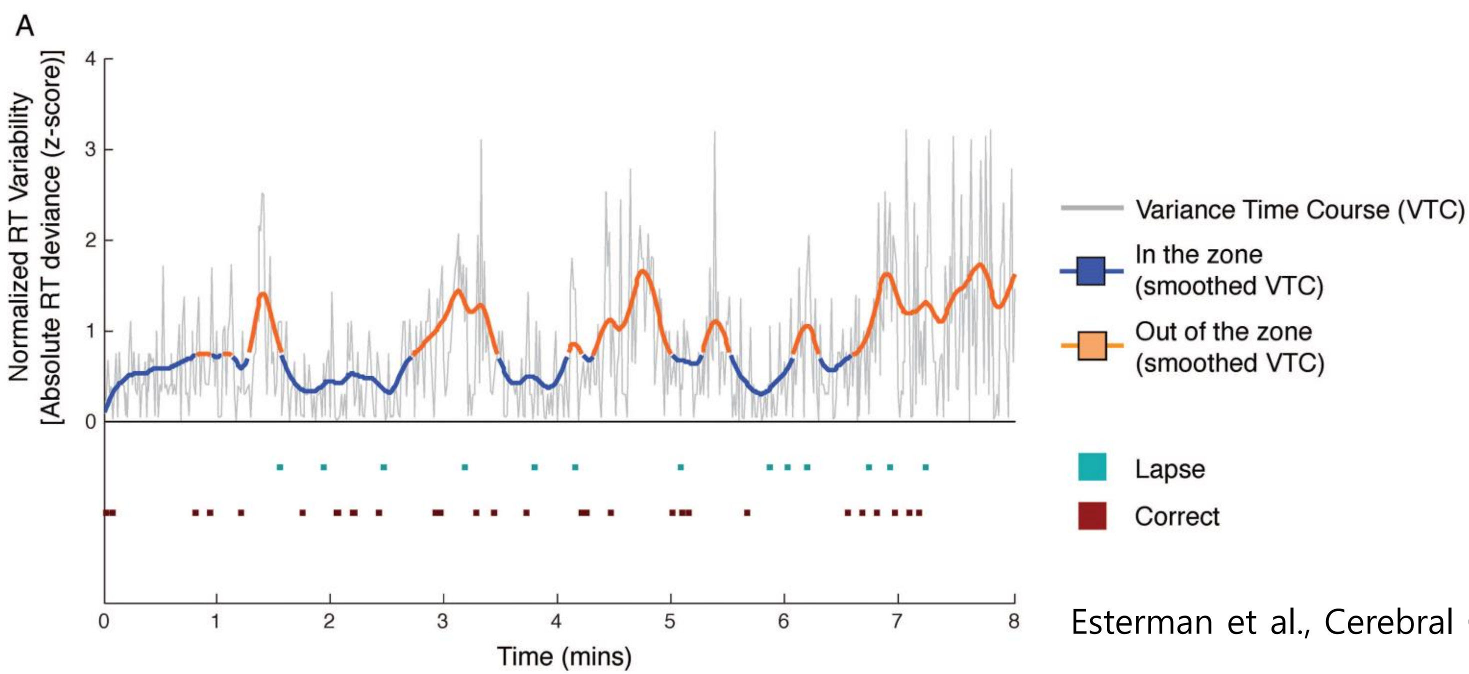


Esterman et al., Cerebral Cortex 2013

Experiments Utilizing Simultaneous EEG/fMRI: gradCPT

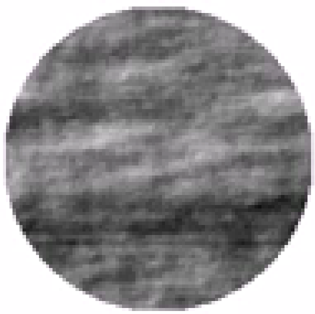


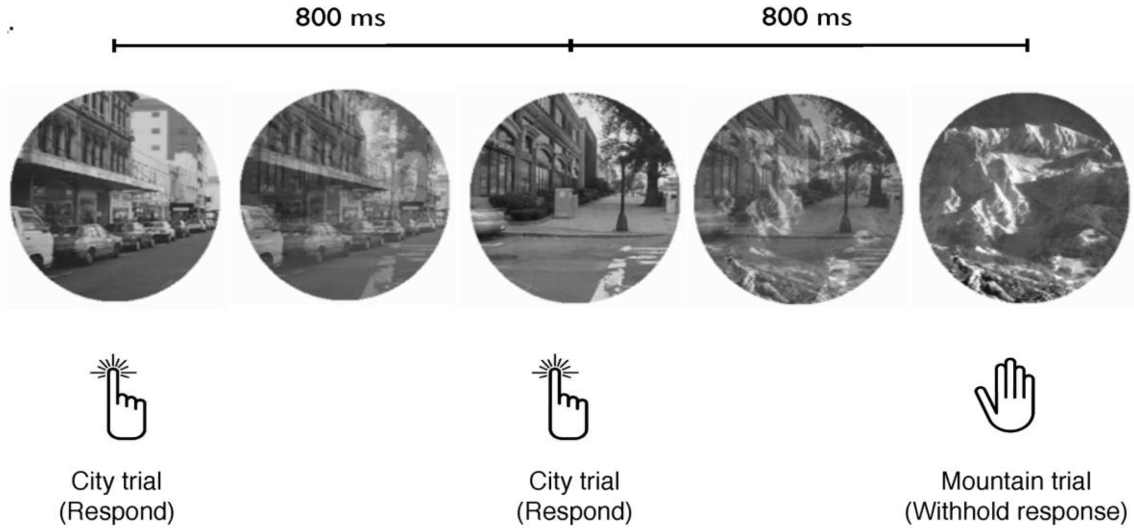




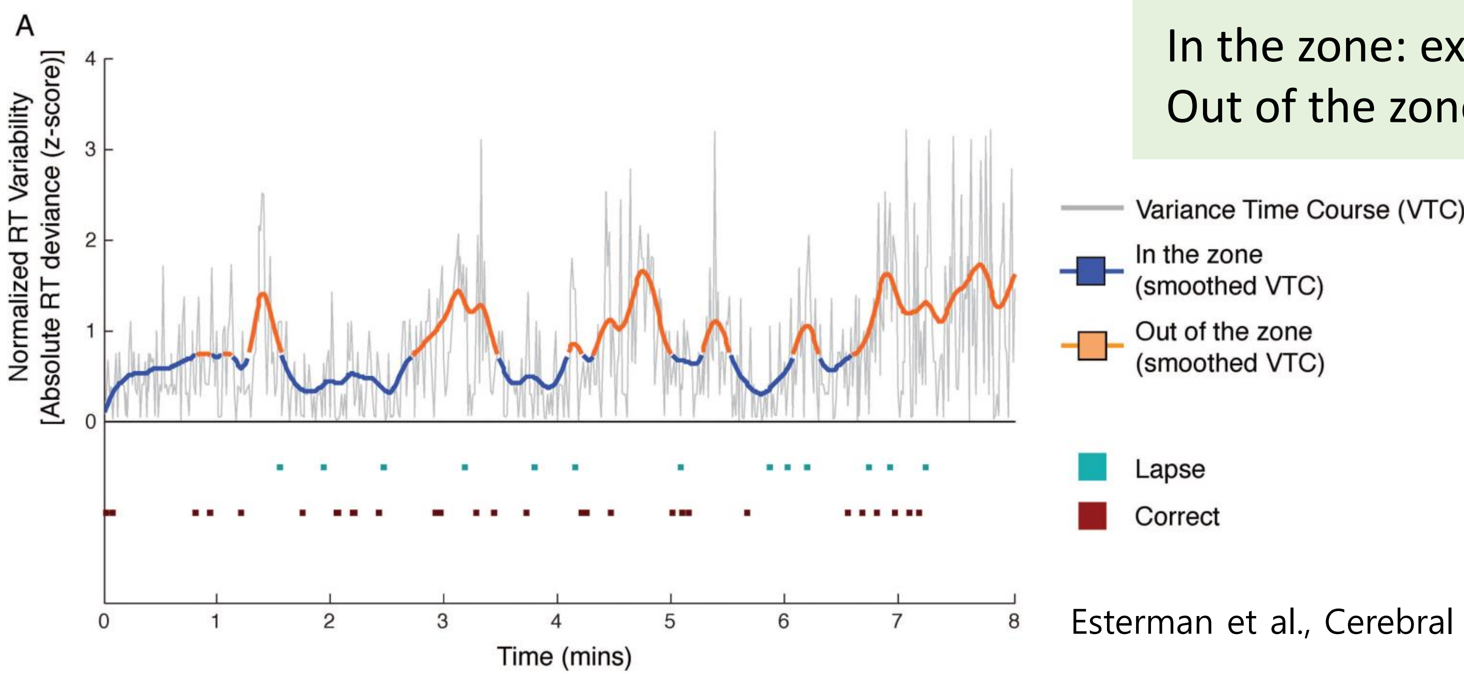
Esterman et al., Cerebral Cortex 2013

Experiments Utilizing Simultaneous EEG/fMRI: gradCPT





In the zone: external mode
Out of the zone: internal mode



Esterman et al., Cerebral Cortex 2013

BRAIN STATES & TRANSITIONS LAB

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Thank you

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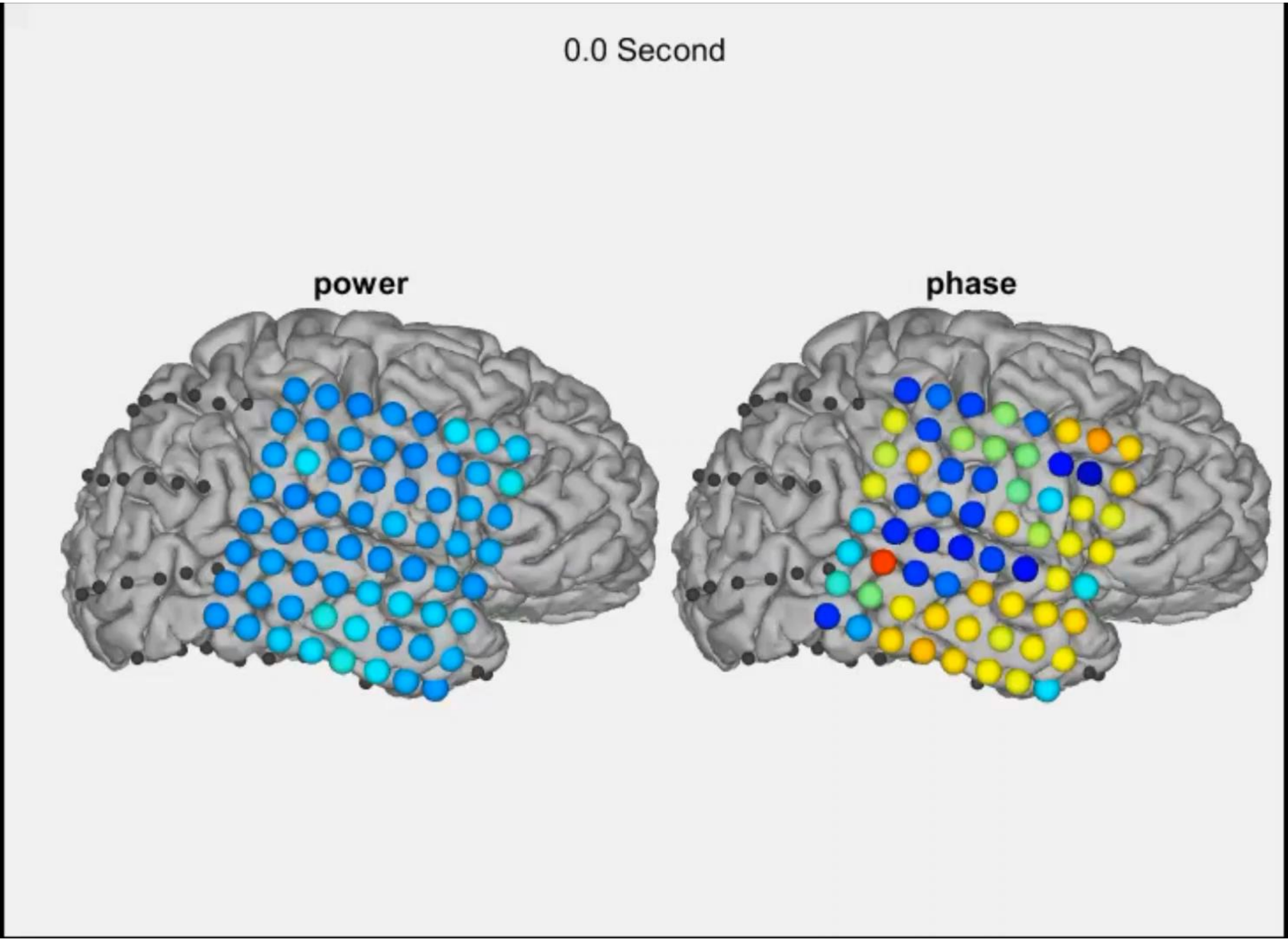


0.0 Second
power
phase

Directionality Change as a Common Metric for General Anesthesia

Table 2. Select Characteristics of Three Major Classes of General Anesthetics

Explanatory Level		Group 1 (*e.g.*, Propofol)	Group 2 (*e.g.*, Ketamine)	Group 3 (*e.g.*, Sevoflurane)
Molecular	Major GABA receptor agonist?	Yes	No	Yes
Neuroanatomic target	Depression of the thalamus?	Yes	No	Yes
Systems neuroscience	VLPO activation?	Yes	No	Yes
Neurophysiology	Increased alpha power?	Yes	No	Yes
Information theory	Inhibition of cortical feedback connectivity?	Yes	Yes	Yes

Group 1 anesthetics include primarily $GABA_A$ agonists such as propofol, etomidate, and thiopental. These drugs tend to be strong hypnotics, but weak immobilizers and analgesics. Group 2 anesthetics include non-GABAergic drugs (such as ketamine, nitrous oxide) that may antagonize the *N*-methyl-D-aspartate glutamatergic receptor. These drugs tend to be strong analgesics, but weak hypnotics and immobilizers. Groups 3 anesthetics have a mixed profile of $GABA_A$ agonism, two-pore potassium channel agonism, and excitatory neurotransmitter antagonism. These drugs—such as sevoflurane, isoflurane, and desflurane—are strong hypnotics and immobilizers. Inhibition of cortical feedback connectivity is potentially a common mechanism of anesthetic-induced unconsciousness across all three groups. VLPO contains neurons that are active during sleep.

GABA = γ-aminobutyric acid; VLPO = ventrolateral preoptic nucleus.

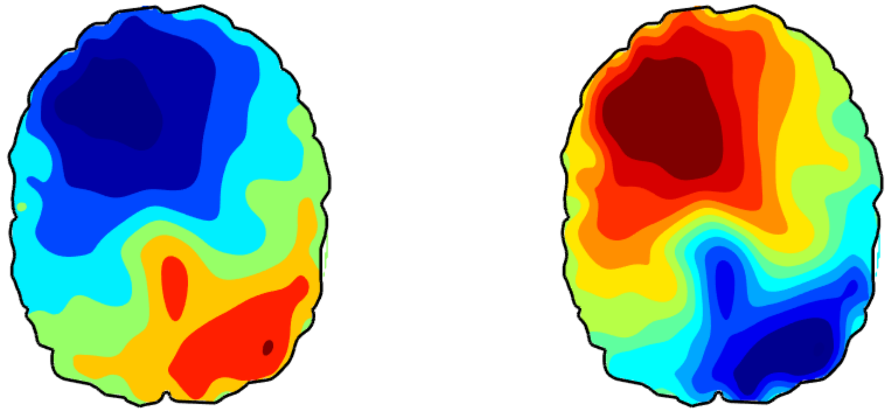
UC Lee et al., Anesthesiology 2013

Directionality Analysis across Different Species

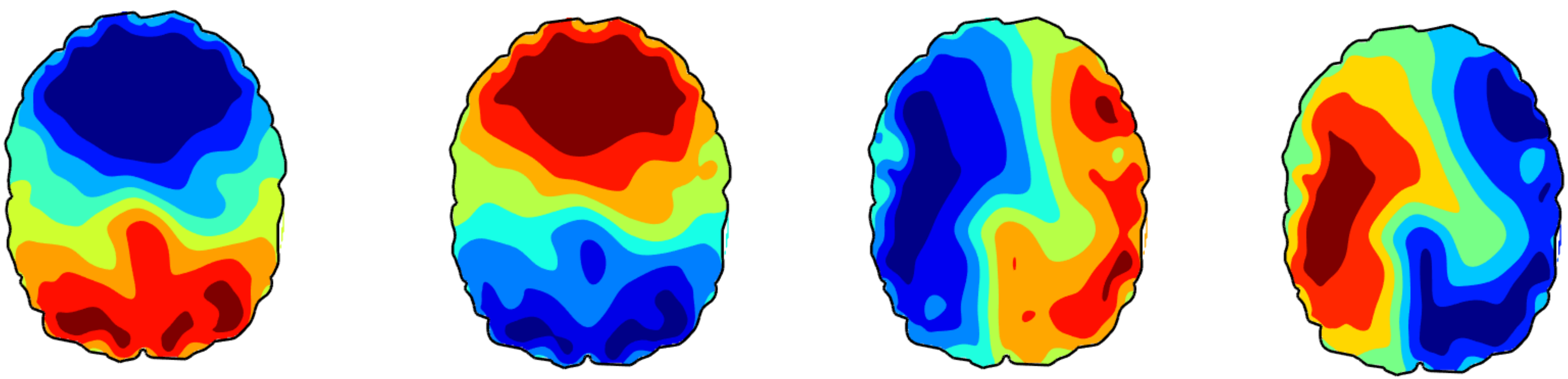
Human	Macaque	Mouse
Structural network:	**Structural network:**	**Structural network:**
80 subjects/78 parcels (Gong et al. 2009)	11 studies/71 parcels (Young 1993)	8 subjects/74 parcels (constructed from Wu et al. 2013)
Experimental data:	**Experimental data:**	**Experimental data:**
6 subjects/128 ch. EEG (U of Michigan)	4 subjects/128 ch. ECoG (http://neurotycho.org/)	9 subjects/38 ch. ECoG (Choi et al. from KIST)

J-Y Moon et al., Sci. Rep. 2017

2-Mean Clustering of Human Resting State Example



4-Mean Clustering of Human Resting State Example



Directional phase-lag index: *dPLI*

dPLI of two signals *i* and *j*:

1. Instantaneous Phase Difference (*IPD*): phase difference at *t*.

$$\Delta\varphi_{ij}(t) = \varphi_i(t) - \varphi_j(t)$$

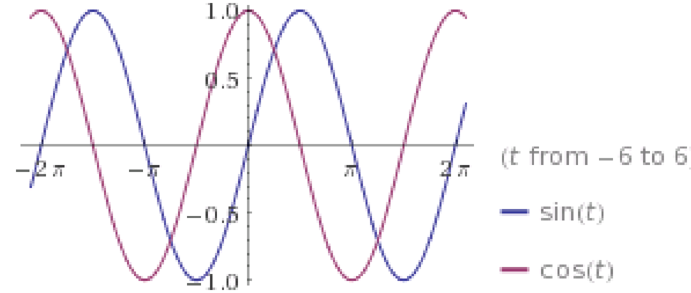
2. Directional Phase Lag Index ($dPLI_{ij}$): time average of sign of *IPD* captures the phase lead/lag relationship between *i* and *j*.

$$dPLI_{ij} = < sign\left(\Delta\varphi_{ij}(t)\right) >_t$$

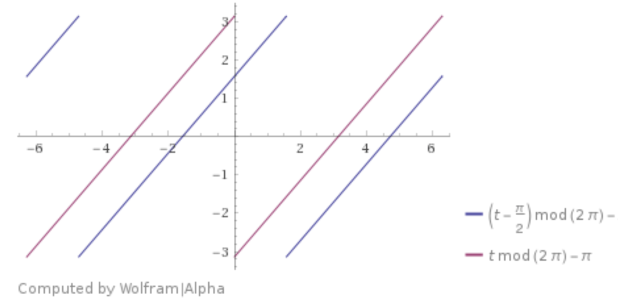
If 0<*dPLI*≤1, *i* lead *j*.
If -1≤*dPLI*<0, *i* lag *j*.
In *dPLI*=0, neither *i* or *j* lead/lag.

CJ Stam et al. NeuroImage 2012

Oscillations

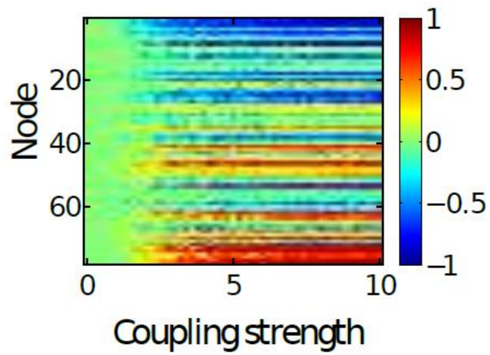


Phases

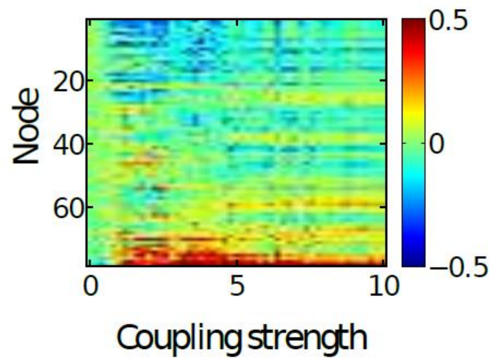


Phase Relationship Is Equivalent to Other Measures

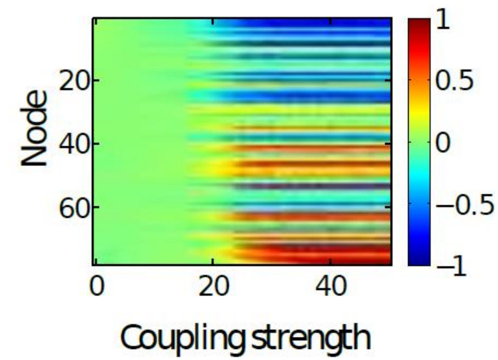
dPLI



Granger Causality

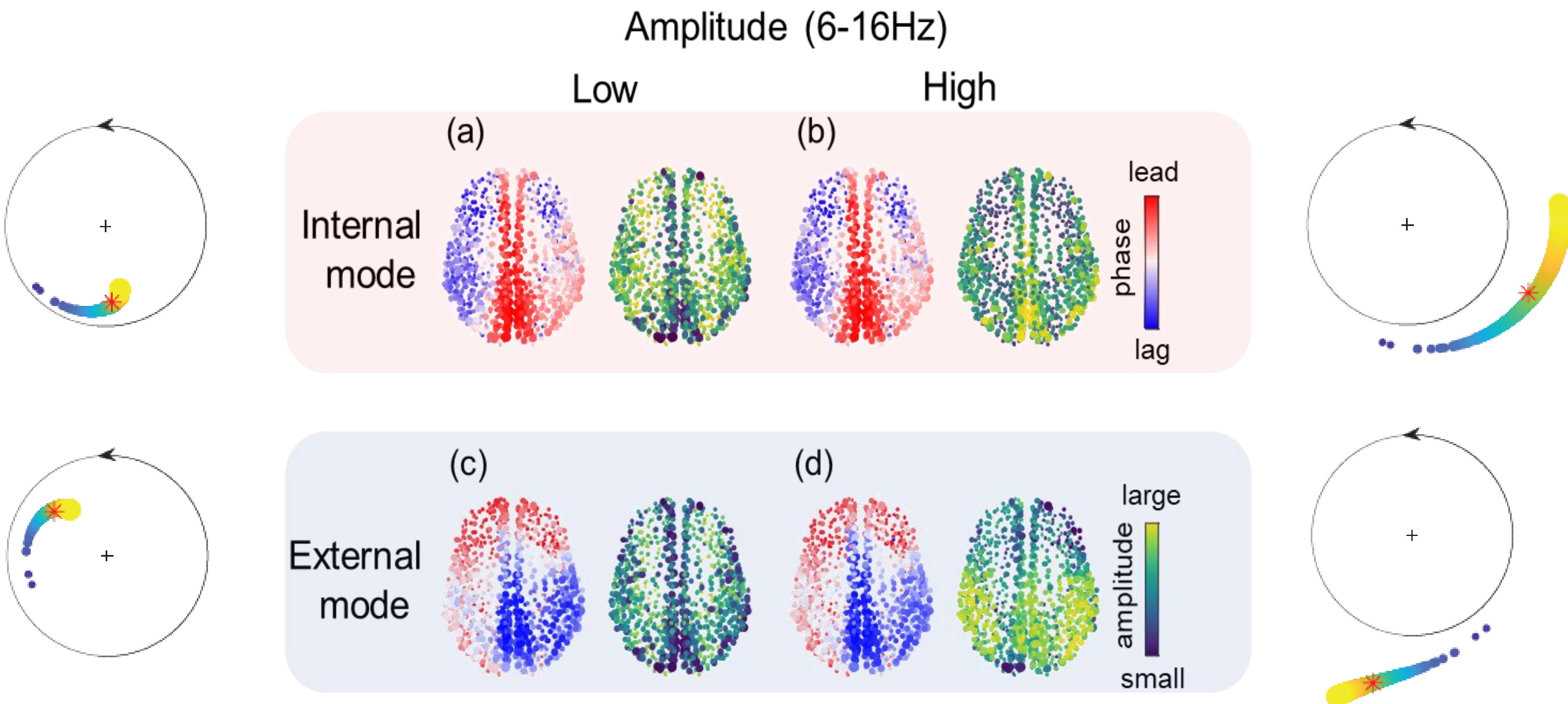


Transfer Entropy



Characterize Internal/External Modes in Our Oscillator Model

Hypothesis: Both internal and external states will allow for both high & low-amplitude oscillations.



Woo et al., Chaos 2020

Characterize Internal/External Modes in Our Oscillator Model

Idea: we can map how amplitude/phase dynamics are affected by diffusive coupling term in our model.

Lee, HaeSung

Stuart-Landau model with diffusive term

$$\dot{Z}_j(t) = \left\{\lambda_j + i\omega_j - |Z_j(t)|^2\right\} Z_j(t) + S \sum_{k=1}^{N} A_{jk}\left[Z_k(t)e^{-i\beta} - \boxed{Z_j(t) g e^{-i\alpha}}\right],$$

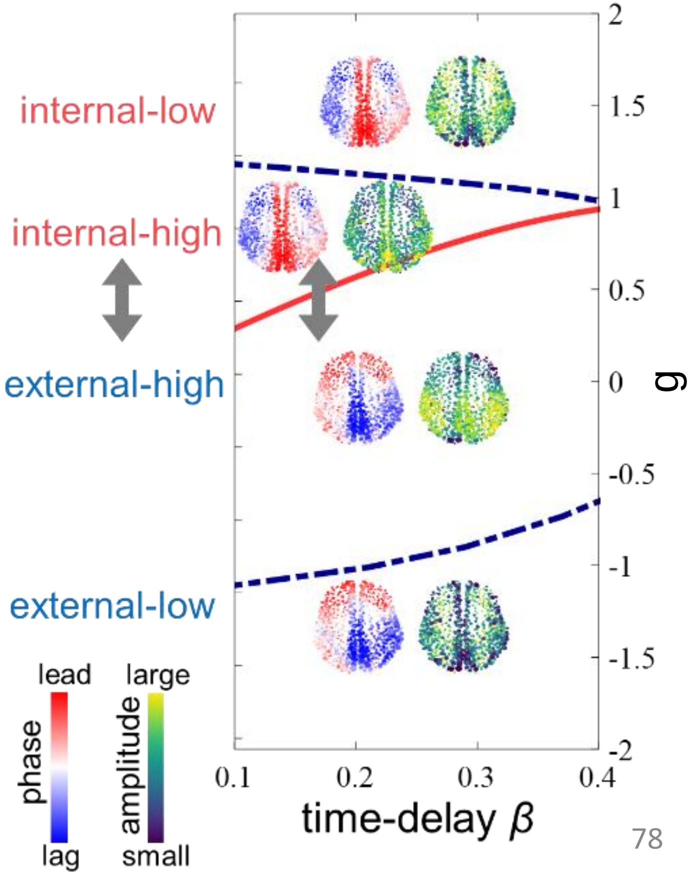
$$j = 1,2,\dots,N$$

equivalent to

$$\dot{r}_j(t) = \left\{\lambda_j - |r_j(t)|^2\right\} r_j(t) + S \sum_{k=1}^{N} A_{jk} r_k \left[\cos(\theta_k - \beta - \theta_j) - \boxed{r_j g \cos\alpha}\right],$$

$$\dot{\theta}_j(t) = \omega_j + S \sum_{k=1}^{N} A_{jk} \frac{r_k}{r_j}\left[\sin(\theta_k - \beta - \theta_j) + \boxed{g \sin\alpha}\right],$$

$$j = 1,2,\dots,N$$



Woo et al., Chaos 2020

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