Analysis and Control of Functional Brain Networks

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October 16, 2023

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Who really did the work







Giacomo Baggio

en Qin

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Why should we reverse-engineer the brain?

• personalized therapies & reversal of cognitive decline





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Why should we reverse-engineer the brain?

- personalized therapies & reversal of cognitive decline
- efficient computing systems & brain-computer interfaces

Why should we reverse-engineer the brain?

- personalized therapies & reversal of cognitive decline
- efficient computing systems & brain-computer interfaces
- next generation machine intelligence







[Deepmind]

neural scale







Models and scales of interest



Models and scales of interest



Models and scales of interest





Functional patterns of brain activity



Functional patterns of brain activity



- synchrony between brain regions long known (EEG, fMRI, [Berger & Gray, 1929])
- rich repertoire of synchrony patters (transient, long-range, clustered)
- different patterns are biomarkers of health and disease (epilepsy, Parkinson's)



- nodes = brain regions; edges = bundles of white matter fibers
- static brain networks carry structural and statistical information
- dynamic brain networks are useful for the prediction & control of neural dynamics

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Resting-state activity modeled by phase oscillators



each node of the brain network captures the dynamics of a population of neurons

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Excitatory Inhibitory

Resting-state activity modeled by phase oscillators

excitatory and inhibitory communities are in a regime of self-sustained oscillations (weakly coupled Wilson-Cowan) [Hoppensteadt and Izhikevich, 1997]

> neurons' firing rates describe a limit cycle

dynamics approximated by a single phase variable [Cabral et al., 2011]

Resting-state activity modeled by phase oscillators



Resting-state activity modeled by phase oscillators



Dynamical brain network to simulate neural activity



dynamical brain network with:

nodes = brain regions

edges = white matter fibers

node dynamics = Kuramoto

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Sanity check



Oscillator properties and functional patterns





Oscillator properties and functional patterns



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Invariance of cluster synchronization



oscillators 4 and 5 remain phase synchronized if:

- $\bullet\,$ diff. of natural frequencies =- diff. external coupling at all times
- equal natural frequencies $(\omega_4=\omega_5)$ and equal coupling $(a_{43}=a_{56})$





• the network weights are balanced

[Menara et al., 2020 TCNS]

balanced weights for partition $\mathcal{P} = \{\mathcal{C}_1, \mathcal{C}_2, \dots\}$:

$$\sum_{z \in \mathcal{C}_\ell} a_{iz} - a_{jz} = 0 \text{ for all } i, j \in \mathcal{C}_k \text{ and all partitions } \mathcal{C}_\ell \neq \mathcal{C}_k$$

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Invariance of cluster synchronization



Invariance of cluster synchronization



Cluster invariance in empirical brain networks



Cluster invariance in empirical brain networks



Cluster invariance in empirical brain networks





Local stability of cluster synchronization







Stability of multiple clusters



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[Menara et al., 2020 TCNS]

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An example



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• network weights provide conservative estimates of stability. frequencies?



- network weights provide conservative estimates of stability. frequencies?
- large frequency differences promote stability. why?



Approximate stability of cluster synchronization



• linearized dynamics:

$$\dot{x}_{intra}^{(1)} = J_1 x_{intra}^{(1)} + \eta_{12} \cos(x_{inter}) x_{intra}^{(2)}$$

• $x_{\text{inter}} \rightarrow (\omega_2 - \omega_1)t$ as $|\omega_2 - \omega_1|$ grows

Approximate stability of cluster synchronization



$$\dot{x}_{\mathsf{intra}}^{(1)} pprox J_1 x_{\mathsf{intra}}^{(1)} + \eta_{12} \cos((\omega_2 - \omega_1) t) x_{\mathsf{intra}}^{(2)}$$

• inter-cluster perturbation is modulated by $\omega_2 - \omega_1$

Approximate stability of cluster synchronization



Approximate stability of cluster synchronization



[Menara et al., 2020 TCNS]





Control of cluster synchronization

Control of functional patterns



so far...

- modeling of neural activity through oscillator network
- modeling of functional patterns via cluster synchronization
- conditions for invariance/stability of cluster synchronization





Control of functional patterns



Control of functional patterns	Control of functional patterns
frequency controlstructural control $u u$ ω	frequency controlstructural controlcoupling control $u \rightarrowu$ $\omega \rightarrowu$ $u \rightarrowu$
 external control of oscillator frequency [Menara et al., 2020 LCSS] design of structural weights and oscillator frequencies [Menara et al., 2019 CDC & 2022 NatComm] 	 external control of oscillator frequency [Menara et al., 2020 LCSS] design of structural weights and oscillator frequencies [Menara et al., 2019 CDC & 2022 NatComm] external control of oscillators coupling [Qin et al., 2022 CDC]
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Structural control of functional patterns



- control knobs = network weights + oscillator frequencies
- biological constraints: positive weights, sparsity of interventions
- reference signal is $n \times n$ matrix of the phase correlation values (time-varying)

Structural control of functional patterns



- control knobs = network weights + oscillator frequencies
- biological constraints: positive weights, sparsity of interventions
- reference signal is $n \times n$ matrix of the phase correlation values (time-varying) focus on time-invariant patterns, equilibrium assignment^{23/35}

Frequency-synchronization and functional patterns

network dynamics in matrix form (B = incidence matrix):

$$\begin{bmatrix} \dot{\theta}_1 \\ \vdots \\ \dot{\theta}_n \end{bmatrix} = \begin{bmatrix} \omega_1 \\ \vdots \\ \omega_n \end{bmatrix} - B \begin{bmatrix} \ddots & & \\ & \sin(\theta_j - \theta_i) \\ & & \ddots \end{bmatrix} \begin{bmatrix} \vdots \\ a_{ij} \\ \vdots \end{bmatrix}$$

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Frequency-synchronization and functional patterns

network dynamics in matrix form (B = incidence matrix):

$$\begin{bmatrix} \dot{\theta}_1 \\ \vdots \\ \dot{\theta}_n \end{bmatrix} = \begin{bmatrix} \omega_1 \\ \vdots \\ \omega_n \end{bmatrix} - B \begin{bmatrix} \ddots & & \\ & \sin(\theta_j - \theta_i) \\ & & \ddots \end{bmatrix} \begin{bmatrix} \vdots \\ a_{ij} \\ \vdots \end{bmatrix}$$

when oscillators are frequency-synchronized:

- oscillator frequencies are all equal to $\omega_{\text{mean}} = \frac{1}{n} \sum \omega_i$
- functional correlations are defined by phase differences
- feasible functional patterns have only n-1 degrees of freedom

Frequency-synchronization and functional patterns

frequency-synchronized configuration:

$$B\begin{bmatrix} \ddots \\ & \sin(\theta_j - \theta_i) \\ & & \ddots \end{bmatrix} \begin{bmatrix} \vdots \\ a_{ij} \\ \vdots \end{bmatrix} = \begin{bmatrix} \omega_1 - \omega_{\text{mean}} \\ \vdots \\ \omega_n - \omega_{\text{mean}} \end{bmatrix}$$

to generate a desired functional pattern:

- compute n-1 phase differences corresponding to desired functional values
- determine feasibility of the desired equilibrium (sign/sparsity constraints)
- find network weights and frequencies to satisfy the above equation

Feasibility of a functional pattern



Feasibility of a functional pattern



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Feasibility of a functional pattern





Feasibility of a functional pattern with positive weights

$\left[-1\right]$	0	0	1]	$\sin(\theta_2 - \theta_1)$			1	a	2	$\omega_1 - \omega_{\text{mean}}$
1	$^{-1}$	0	0		$\sin(heta_3 - heta_2)$			a	23 _	$\omega_2 - \omega_{\rm mean}$
0	1	$^{-1}$	0			$\sin(heta_4 - heta_3)$		a	34	$\omega_3 - \omega_{\rm mean}$
0	0	1	-1	L			$\sin(heta_1 - heta_4)$	a	11	$\omega_4 - \omega_{\text{mean}}$

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easibility of a	functional pattern with	1 positive weights	
	scaled inciden	ce matrix <i>Ē</i>	
$\begin{bmatrix} -1 & 0 & 0 \\ 1 & -1 & 0 \\ 0 & 1 & -1 \\ 0 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} 1\\0\\0\\-1 \end{bmatrix} \begin{bmatrix} \sin(\theta_2 - \theta_1) & \\ & \sin(\theta_3 - \theta_3) \end{bmatrix}$	$\left(\theta_{2} \right) = \left(\sin(\theta_{4} - \theta_{3}) + \sin(\theta_{1} - \theta_{4}) \right)$	$\begin{bmatrix} a_{12} \\ a_{23} \\ a_{34} \\ a_{41} \end{bmatrix} = \begin{bmatrix} \omega_1 - \omega_{\text{mean}} \\ \omega_2 - \omega_{\text{mean}} \\ \omega_3 - \omega_{\text{mean}} \\ \omega_4 - \omega_{\text{mean}} \end{bmatrix}$

Feasibility of a functional pattern with positive weights

scaled incidence matrix $ar{B}$				
$\begin{bmatrix} -1 & 0 & 0 \\ 1 & -1 & 0 \\ 0 & 1 & -1 \\ 0 & 0 & 1 \end{bmatrix}$	$\begin{bmatrix} 1\\0\\0\\-1 \end{bmatrix} \begin{bmatrix} \sin(\theta_2 - \theta_1) & \\ & \sin(\theta_3 - \theta_2) \end{bmatrix}$	$\sin(heta_4 - heta_3) \ \sin(heta_1 - heta_4) ight]$	$\begin{bmatrix} a_{12} \\ a_{23} \\ a_{34} \\ a_{41} \end{bmatrix} = \begin{bmatrix} a \\ a \\ a \\ a \\ a \end{bmatrix}$	$\omega_1 - \omega_{mean}$ $\omega_2 - \omega_{mean}$ $\omega_3 - \omega_{mean}$ $\omega_4 - \omega_{mean}$

The functional pattern is feasible with pos. weights if:

- the network $ar{B}$ contains a Hamiltonian path ${\cal H}$
- $\omega^{\mathsf{T}}\bar{B}_{\mathcal{H}} > 0$

[Menara et al., 2022 NatComm



Restoring functional connectivity in the damaged brain

brain regions

BOLD

Correlation

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brain

Hemodynamic Model

orain

desired pattern

brain regions

Control

 μ, Δ

 ω, A

Kuramoto Model

noise



- structural data from Human Connectome Project
- (synthetic) functional data inspired by brain injury
- Balloon-Windkessel hemodynamic model for BOLD signals



Restoring functional connectivity in the damaged brain



Beyond brain networks: power redistribution and fault recovery



Summary

Modeling, analysis, control of functional connectivity via cluster synchronization:

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Invariance: balanced weights + homogeneous intra-cluster frequencies

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Invariance: balanced weights + homogeneous intra-cluster frequencies

 $\label{eq:stability:stability:} intra-cluster \ coupling \gg inter-cluster \ coupling$

large inter-cluster frequency differences

weights + frequencies \Rightarrow tight small-gain conditions

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Summary

Modeling, analysis, control of functional connectivity via cluster synchronization:

Invariance: balanced weights + homogeneous intra-cluster frequencies

 $\label{eq:stability:stability:stability:} intra-cluster coupling \gg inter-cluster coupling \\ large inter-cluster frequency differences \\$

weights + frequencies \Rightarrow tight small-gain conditions

Control: graph-theoretic cond. for feasibility of functional patterns structural control of functional patterns in brain/power

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External control of oscillators coupling





Phase-amplitude synchronization



Brain-inspired, context-aware reinforcement learning



References and acknowledgements





Full vs cluster synchronization

Phase differences: $x_{ij} = \theta_j - \theta_i$			
full synchronization: $x \to 0$	cluster synchronization: $egin{array}{c} x_{intra} ightarrow 0 \ x_{inter} = ? \end{array}$		
 Difference dynamics x = F(x) 	◊ Difference dynamics $\dot{x}_{intra} = F(x_{intra}) + G(x_{intra}, x_{inter})$		
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Full vs cluster synchronization

