SCHOOL ON NONLINEAR DYNAMICS, COMPLEX NETWORKS, INFORMATION THEORY, AND MACHINE LEARNING IN NEUROSCIENCE

INTRODUCTION TO SYNCHRONIZATION PHENOMENA AND THE KURAMOTO MODEL

LECTURE 2: SYNCHRONIZATION IN COMPLEX NETWORKS





Universidad Zaragoza



Institute for Biocomputation & Physics of Complex Systems (BIFI)

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GROUP OF THEORETICAL & APPLIED MODELING

The Kuramoto model

MOTIVATION

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The Kuramoto model

From Kuramoto to Crawford: exploring the onset of synchronization in populations of coupled oscillators **MOTIVATION**

Steven H. Strogatz Center for Applied Mathematics and Department of Theoretical and Applied Mechanics, Kimball Hall, Cornell University, Ithaca, NY 14853, USA

$$\dot{\theta}_i(t) = \omega_i + Kr(t)\sin(\Psi(t) - \theta_i(t))$$

In this form, the mean-field character of the model becomes obvious. Each oscillator appears to be uncoupled from all the others, although of course they are interacting, but only through the mean-field quantities r and ψ .

Steady State $\begin{cases} |\omega_i| \le Kr^* & \text{Locked} \\ |\omega_i| > Kr^* & \text{Drifting} \end{cases}$ $\omega_i = Kr^* \sin(\theta_i^*)$ Yoshiki Kuramoto (蔵本 由紀)



@ Kyoto University

The Kuramoto model

MOTIVATION



MOTIVATION



MOTIVATION



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KURAMOTO MODEL IN COMPLEX NETWORKS

• SYNC. TRANSITION: THE CRITICAL COUPLING

• PLAYING WITH THE TRANSITION: EXPLOSIVE SYNC.

Index

KURAMOTO MODEL IN COMPLEX NETWORKS

• SYNC. TRANSITION: THE CRITICAL COUPLING

• PLAYING WITH THE TRANSITION: EXPLOSIVE SYNC.



 $N \, {\rm nodes} \, {\rm connected} \, {\rm by} \, L \, {\rm links}$

Adjacency Matrix

$$\mathbf{A} = \begin{pmatrix} 0 & A_{12} & A_{13} & \dots & A_{1N} \\ A_{21} & 0 & A_{23} & \dots & A_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ A_{N1} & A_{N2} & \dots & A_{N(N-1)} & 0 \end{pmatrix}$$

Undirected networks $A_{ij} = A_{ji}$ Non-weighted networks $A_{ij} \in \{1,0\}$

Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda \sum_{j=1}^N A_{ij} \sin(\theta_j(t) - \theta_i(t))$$

N

j=1

KM in Complex Networks

 $P(k) \sim k^{-\gamma}$

Scale-free







SF topologies anticipate (favor) the onset of Sync



The more heterogeneous the degree distribution $P(k) \sim k^{-\gamma}$ of the SF graph, the lower the synchronization threshold

Can we connect in a precise way the critical coupling with the topology of the network?



Can we connect in a precise way the critical coupling with the topology of the network?

$$K_c = rac{2}{\pi g(0)}$$
 Critical Coupling

Index

KURAMOTO MODEL IN COMPLEX NETWORKS

• SYNC. TRANSITION: THE CRITICAL COUPLING

• PLAYING WITH THE TRANSITION: EXPLOSIVE SYNC.



Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda \sum_{j=1}^N A_{ij} \sin\left(\theta_j(t) - \theta_i(t)\right)$$

Kuramoto Order Parameter

$$r(t)e^{i\Psi(t)} = \frac{1}{N}\sum_{j=1}^{N}e^{i\theta_j(t)}$$

Main Question:

What is the influence of network structure (A) in the synchronization transition? A $\rightarrow \lambda_c \& r(\lambda)$

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CRITICAL COUPLING

Main Question:
$$\dot{\theta}_i(t) = \omega_i + \lambda \sum_{ij} A_{ij} \sin\left(\theta_j(t) - \theta_i(t)\right)$$

What is the influence of network structure (A) in the synchronization transition? $A \rightarrow \lambda_c \& r(\lambda)$

Main difficulty: we lose the MF behavior of the model equations

Approaches: $\left\{ egin{array}{c} & \textit{Continuum limit approach} \\ & \rho_{\omega,k}(\theta,t) \\ & & & \\ & & \\ & & & \\ & & \\ & & & \\ & & \\ & & & & \\ & & & \\ & & &$





Restrepo, Hunt & Ott (2005)



@gomezgardenes

CRITICAL COUPLING

Oscillator density functional $\rho_{\omega,k}(\theta,t)$:

Density of oscillators with degree k and natural frequency ω located at angle θ at time t

 $g(\omega) \& P(k)$



Ichininomiya

(2004)

Restrepo, Hunt & Ott (2005)



Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda \sum_{j=1}^N A_{ij} \sin\left(\theta_j(t) - \theta_i(t)\right)$$

Kuramoto Order Parameter

$$r(t)e^{i\Psi(t)} = \frac{1}{N}\sum_{j=1}^{N} e^{i\theta_j(t)}$$

Local Order Parameter

Global Order Parameter

$$r_i e^{i\Psi_i} = \sum_{j=1}^N A_{ij} \langle e^{i\theta_j(t)} \rangle_T \longrightarrow \tilde{r} e^{i\tilde{\Psi}} = \frac{\sum_{j=1}^N r_j}{\sum_{j=1}^N k_j} = \frac{\sum_{j=1}^N r_j}{2L}$$



Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Steady State: (Q(t) - V(t))

Locking condition

$$\omega_i = \lambda r_i \sin\left(\theta_i(t) - \psi_i\right) \longrightarrow |\omega_i| \le \lambda r_i$$

Local Order Parameter

$$r_i e^{i\Psi_i} = \sum_{j=1}^N A_{ij} \langle e^{i\theta_j(t)} \rangle_T \longrightarrow r_i = \sum_{j=1}^N A_{ij} e^{-i\Psi_i} \langle e^{i\theta_j(t)} \rangle_T$$

Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Steady State: Locking condition $\omega_i = \lambda r_i \sin \left(\theta_i(t) - \psi_i \right) \longrightarrow |\omega_i| \le \lambda r_i$

Local Order Parameter

$$\longrightarrow r_{i} = \sum_{j=1}^{N} A_{ij} e^{-i\Psi_{i}} \langle e^{i\theta_{j}(t)} \rangle_{T} = \sum_{j=1}^{N} A_{ij} \langle e^{i(\theta_{j}(t) - \Psi_{i})} \rangle_{T}$$
$$= \sum_{|\omega_{j}| \le \lambda r_{j}}^{N} A_{ij} \langle e^{i(\theta_{j}(t) - \Psi_{i})} \rangle_{T} + \sum_{|\omega_{j}| > \lambda r_{j}}^{N} A_{ij} \langle e^{i(\theta_{j}(t) - \Psi_{i})} \rangle_{T}$$

Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Steady State: Locking condition $\omega_i = \lambda r_i \sin \left(\theta_i(t) - \psi_i \right) \longrightarrow |\omega_i| \le \lambda r_i$

Local Order Parameter

$$\longrightarrow r_{i} = \sum_{j=1}^{N} A_{ij} e^{-i\Psi_{i}} \langle e^{i\theta_{j}(t)} \rangle_{T} = \sum_{j=1}^{N} A_{ij} \langle e^{i(\theta_{j}(t) - \Psi_{i})} \rangle_{T}$$
$$= \sum_{|\omega_{j}| \le \lambda r_{j}}^{N} A_{ij} e^{i(\theta_{j} - \Psi_{i})} + \sum_{|\omega_{j}| > \lambda r_{j}}^{N} A_{ij} \langle e^{i(\theta_{j}(t) - \Psi_{i})} \rangle_{T}$$

Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Steady State:

Locking condition

$$\omega_i = \lambda r_i \sin\left(\theta_i(t) - \psi_i\right) \longrightarrow |\omega_i| \le \lambda r_i$$

Local Order Parameter

$$\longrightarrow r_i = \sum_{j=1}^N A_{ij} e^{-i\Psi_i} \langle e^{i\theta_j(t)} \rangle_T = \mathbf{R} \underbrace{\mathbf{R}}_{|\omega_j| \le \lambda} r_j |\omega_j| \le \lambda r_j$$

Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Steady State:

Locking condition

$$\omega_i = \lambda r_i \sin\left(\theta_i(t) - \psi_i\right) \longrightarrow |\omega_i| \le \lambda r_i$$

Local Order Parameter

$$\rightarrow r_{i} = \sum_{j=1}^{N} A_{ij} e^{-i\Psi_{i}} \langle e^{i\theta_{j}(t)} \rangle_{T} = \mathbf{Re} \left[\sum_{|\omega_{j}| \leq \lambda r_{j}}^{N} A_{ij} e^{i(\theta_{j} - \Psi_{j})} e^{i(\Psi_{j} - \Psi_{i})} \right]$$
$$= \sum_{|\omega_{j}| \leq \lambda r_{j}}^{N} A_{ij} \left[\cos(\theta_{j} - \Psi_{j}) \cos(\Psi_{j} - \Psi_{i}) - \sin(\theta_{j} - \Psi_{j}) \sin(\Psi_{j} - \Psi_{i}) \right]$$

Ste

Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Steady State: Locking condition $\omega_i = \lambda r_i \sin \left(\theta_i(t) - \psi_i \right) \longrightarrow |\omega_i| \le \lambda r_i$

Local Order Parameter

$$r_{i} = \sum_{|\omega_{j}| \le \lambda r_{j}}^{N} A_{ij} \left[\sqrt{1 - \left(\frac{\omega_{j}}{\lambda r_{j}}\right)^{2}} \cos(\Psi_{j} - \Psi_{i}) - \frac{\omega_{j}}{\lambda r_{j}} \sin(\Psi_{j} - \Psi_{i}) \right]$$
Symmetry of $g(\omega)$

the second secon

Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Steady State: Locking condition $\omega_i = \lambda r_i \sin \left(\theta_i(t) - \psi_i \right) \longrightarrow |\omega_i| \le \lambda r_i$

Local Order Parameter

$$r_{i} = \sum_{|\omega_{j}| \le \lambda r_{j}}^{N} A_{ij} \sqrt{1 - \left(\frac{\omega_{j}}{\lambda r_{j}}\right)^{2} \cos(\Psi_{j} - \Psi_{i})} = \sum_{|\omega_{j}| \le \lambda r_{j}}^{N} A_{ij} \sqrt{1 - \left(\frac{\omega_{j}}{\lambda r_{j}}\right)^{2}}$$

Smallest possible λ

S

Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Steady State: Locking condition $\omega_i = \lambda r_i \sin \left(\theta_i(t) - \psi_i \right) \longrightarrow |\omega_i| \le \lambda r_i$

Local Order Parameter

Global Order Parameter



TAT Auto-consistent equation for r_i

S

Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Steady State:

Locking condition

$$\omega_i = \lambda r_i \sin\left(\theta_i(t) - \psi_i\right) \longrightarrow |\omega_i| \le \lambda r_i$$

Local Order Parameter

$$r_{i} = \sum_{\substack{N \\ |\omega_{j}| \le \lambda r_{j}}}^{N} A_{ij} \sqrt{1 - \left(\frac{\omega_{j}}{\lambda r_{j}}\right)^{2}}$$

Requires:

- Adjacency Matrix
- Set of nodes' frequencies

TAT Auto-consistent equation for r_i

St

Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Steady State: Locking condition $\omega_i = \lambda r_i \sin \left(\theta_i(t) - \psi_i \right) \longrightarrow |\omega_i| \le \lambda r_i$

Local Order Parameter

$$r_{i} = \sum_{|\omega_{j}| \le \lambda r_{j}}^{N} A_{ij} \sqrt{1 - \left(\frac{\omega_{j}}{\lambda r_{j}}\right)^{2}} \simeq \sum_{j}^{N} A_{ij} \int_{-\lambda r_{j}}^{\lambda r_{j}} g(\omega) \sqrt{1 - \left(\frac{\omega}{\lambda r_{j}}\right)^{2}} d\omega$$

Frequency distribution approximation (FDA)

Stea

Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Steady State: Locking condition $\omega_i = \lambda r_i \sin \left(\theta_i(t) - \psi_i \right) \longrightarrow |\omega_i| \le \lambda r_i$

Local Order Parameter

$$r_i \simeq \sum_j A_{ij} \int_{-\lambda r_j}^{\lambda r_j} g(\omega) \sqrt{1 - \left(\frac{\omega}{\lambda r_j}\right)^2} d\omega \qquad x = \frac{\omega}{\lambda r_j}$$

Frequency distribution approximation (FDA)

S

Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Steady State: Locking condition $\omega_i = \lambda r_i \sin \left(\theta_i(t) - \psi_i \right) \longrightarrow |\omega_i| \le \lambda r_i$

Local Order Parameter

At
$$\lambda_c$$
 we have $r_i \to 0^+$:
 $r_i \simeq \lambda \sum_j A_{ij} r_j \int_{-1}^1 g(x \lambda r_j) \sqrt{1 - x^2} dx$

Requires:

Adjacency Matrix
 Frequency Distribution

Frequency distribution approximation (FDA)

St

Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Steady State: Locking condition $\omega_i = \lambda r_i \sin \left(\theta_i(t) - \psi_i \right) \longrightarrow |\omega_i| \le \lambda r_i$

Local Order Parameter

At λ_c we have $r_i \to 0^+$: $r_i \simeq \lambda_c \sum_j A_{ij} r_j g(0) \int_{-1}^1 \sqrt{1 - x^2} dx$

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Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Steady State: Locking condition $\omega_i = \lambda r_i \sin \left(\theta_i(t) - \psi_i \right) \longrightarrow |\omega_i| \le \lambda r_i$

Local Order Parameter

At λ_c we have $r_i \rightarrow 0^+$:

$$r_i \simeq \lambda_c \sum_j A_{ij} r_j g(0) \frac{\pi}{2}$$

Requires:

Adjacency Matrix
 Frequency Distribution

Frequency distribution approximation (FDA)

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Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Steady State: Locking condition $\omega_i = \lambda r_i \sin \left(\theta_i(t) - \psi_i \right) \longrightarrow |\omega_i| \le \lambda r_i$

Local Order Parameter

At λ_c we have $r_i \to 0^+$: $r_i \simeq \frac{\lambda_c g(0)\pi}{2} \sum_j A_{ij} r_j$

Requires:

Adjacency Matrix
 Frequency Distribution

Frequency distribution approximation (FDA)

S

Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Steady State: Locking condition $\omega_i = \lambda r_i \sin \left(\theta_i(t) - \psi_i \right) \longrightarrow |\omega_i| \le \lambda r_i$

Local Order Parameter

At
$$\lambda_c$$
 we have $r_i \to 0^+$:
 2
 $\vec{r}_i \simeq A A_{ij} r_j$
 j is an eigenvector of A!!!

Requires:

Adjacency Matrix
 Frequency Distribution

Frequency distribution approximation (FDA)

Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Steady State: Locking condition $\omega_i = \lambda r_i \sin \left(\theta_i(t) - \psi_i \right) \longrightarrow$ $|\omega_i| \leq \lambda r_i$

Local Order Parameter

At
$$\lambda_c$$
 we have $r_i \to 0^+$:

$$\frac{2}{\lambda_c g(0)\pi} = \Lambda_{max}(A)$$
is an eigenvector of A!!!

Requires:

Adjacency Matrix Frequency Distribution

Frequency distribution approximation (FDA)

S

Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Steady State:

Locking condition

$$\omega_i = \lambda r_i \sin \left(\theta_i(t) - \psi_i \right) \longrightarrow |\omega_i| \le \lambda r_i$$

Critical Coupling

$$\lambda_c = \frac{2}{g(0)\pi} \frac{1}{\Lambda_{max}(A)}$$

Requires:

Adjacency Matrix
 Frequency Distribution

Frequency distribution approximation (FDA)

Steady State: **Critical Coupling** KKM

Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Locking condition

$$\omega_i = \lambda r_i \sin \left(\theta_i(t) - \psi_i \right) \longrightarrow |\omega_i| \le \lambda r_i$$

Requires:
▶ Adjacency Matrix
▶ Frequency Distribution

Critical Coupling

Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Steady State:

Locking condition

$$\omega_i = \lambda r_i \sin \left(\theta_i(t) - \psi_i \right) \longrightarrow |\omega_i| \le \lambda r_i$$

HMF: $r_i = \tilde{r}k_i \longrightarrow \lambda_c =$

Requires: Adjacency Matrix Frequency Distribution

Requires:

Degree Distribution Frequency Distribution

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CRITICAL COUPLING

Kuramoto model in a Network

$$\dot{\theta}_i(t) = \omega_i + \lambda r_i \sin(\psi_i - \theta_i(t))$$

Steady State:

Locking condition

$$\omega_i = \lambda r_i \sin \left(\theta_i(t) - \psi_i \right) \longrightarrow |\omega_i| \le \lambda r_i$$

Critical Coupling

$$\lambda_{c} = \frac{2}{g(0)\pi} \frac{1}{\Lambda_{max}(A)} = K_{c}^{KM} \frac{1}{\Lambda_{max}(A)}$$
HMF: $r_{i} = \tilde{r}k_{i} \longrightarrow \lambda_{c} = \frac{2}{\sqrt{k}} \frac{\langle k \rangle}{\langle 1 \rangle \rangle}$

Requires:

Adjacency Matrix
 Frequency Distribution

Requires:

Degree Distribution
 Frequency Distribution

Scale-free Networks $P(k) \sim k^{-\gamma}$

$$\langle k^2 \rangle \simeq \int_0^\infty k^2 P(k) dk \sim \int_0^\infty k^{2-\gamma} dk$$

As γ decreases the network becomes more heterogeneous and the second moment increases

$$\lambda_c = \frac{2}{\pi g(0)} \frac{\langle k \rangle}{\langle k^2 \rangle}$$

The critical coupling λ_c decreases as γ decreases



Microscopic view

LOCAL SYNCHRONIZATION

New Measure:

the degree of synchronization between pairs of connected nodes:

$$D_{ij} = \lim_{T \to \infty} A_{ij} \left| \frac{1}{T} \int_{T}^{\tau+T} e^{i \left[\theta_i(t) - \theta_j(t) \right]} dt \right|.$$

 $D_{ij} \simeq 0 \rightarrow \text{local incoherence}$ $D_{ij} = 1 \rightarrow \text{local synchronization}.$



CRITICAL COUPLING

LOCAL SYNCHRONIZATION

New Measure:

the degree of synchronization between pairs of connected nodes:

$$D_{ij} = \lim_{T \to \infty} A_{ij} \left| \frac{1}{T} \int_{T}^{\tau+T} e^{i \left[\theta_i(t) - \theta_j(t) \right]} dt \right|.$$

 $D_{ij} \simeq 0 \rightarrow \text{local incoherence}$ $D_{ij} = 1 \rightarrow \text{local synchronization}.$



CRITICAL COUPLING

LOCAL SYNCHRONIZATION

$$D_{ij} = \lim_{T \to \infty} A_{ij} \left| \frac{1}{T} \int_{\tau}^{\tau+T} e^{i \left[\theta_i(t) - \theta_j(t)\right]} dt \right| .$$

 $D_{ij} \simeq 0 \rightarrow \text{local incoherence}$ $D_{ij} = 1 \rightarrow \text{local synchronization}.$

Studying *D_{ij}*: We can monitor how synchronized links are created as a function of the coupling. Different paths towards synchronization:



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Gómez-Gardeñes et al. Phys. Rev. Lett. (2007)

CRITICAL COUPLING

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www.sciencemag.org SCIENCE VOL 323 13 MARCH 2009 Explosive Percolation in Random Networks

Dimitris Achlioptas,¹ Raissa M. D'Souza,^{2,3*} Joel Spencer⁴



Networks in which the formation of connections is governed by a random process often undergo a percolation transition, wherein around a critical point, the addition of a small number of connections causes a sizable fraction of the network to suddenly become linked together. Typically such transitions are continuous, so that the percentage of the network linked together tends to zero right above the transition point. Whether percolation transitions could be discontinuous has been an open question. Here, we show that incorporating a limited amount of choice in the classic Erdös-Rényi network formation model causes its percolation transition to become discontinuous.





Gómez-Gardeñes et al. Phys. Rev. Lett. (2011)

EXPLOSIVE SYNCHRONIZATION?



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Gómez-Gardeñes et al. Phys. Rev. Lett. (2011)

EXPLOSIVE SYNCHRONIZATION?

• We compute for each value of λ the effective frequency of each node:

$$\omega_i^{\text{eff}} = \frac{1}{T} \int_t^{t+T} \dot{\theta}_i(\tau) \, \mathrm{d}\tau \,, \text{ with } T \gg 1 \,.$$



Gómez-Gardeñes et al. Phys. Rev. Lett. (2011)

Other possible Explosive set-ups

Other possible Explosive set-ups



Suppressing the emergence of a Sync macroscopic component

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Explosive Sync in Experiments

NEXT STEP

We now explore the possibility of obtaining an explosive synchronization transition in an experimental setup.

- Possibility of using simple network configurations as the star graph.
- Robustness of results under perturbations.

Bad News

However, we have to move from the Kuramoto model to a more realistic and complicated dynamical systems.

Rossler System: $\dot{x} = -(y+z)$ $\dot{y} = \sigma y + x$ $\dot{z} = \beta + z(x-c)$



ROSSLER SYSTEM

Let us consider an ensemble of N piecewise Rössler units, interacting in a network via a bidirectional diffusive-like coupling:

$$\begin{aligned} \dot{x}_i &= -\alpha_i \left[0.05 \left(x_i - d \sum_{j=1}^N A_{ij}(x_j - x_i) \right) + 0.5 y_i + z_i \right] , \\ \dot{y}_i &= -\alpha_i (-x_i + \nu y_i) , \\ \dot{z}_i &= -\alpha_i (-g(x_i) + z_i) , \end{aligned}$$

where the piecewise part is:

$$g(x_i) = \begin{cases} 0 & \text{if } x_i \leq 3\\ \mu(x_i - 3) & \text{if } x_i > 3 \end{cases}$$

The parameter $\nu = 0.02 - 10/R$ controls the dynamical state of the system. For $R \in [55, 110]$ the above system is in the chaotic phase.

ROSSLER SYSTEM

Each of the natural frequencies depends linearly on each value α_i . Thus we include the correlation between structure and dynamics by setting:

$$lpha_{i} = lpha \left(1 + \Delta lpha rac{k_{i} - 1}{N}
ight) \,, ext{ with } lpha = 10^{4}$$



controlled by digital potenciometers and the output signals are recorded and analyzed.

ROSSLER SYSTEM



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Gómez-Gardeñes et al. Phys. Rev. Lett. (2011)

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EXPLOSIVE SYNC.

OTHER EXPERIMENTS



SCIENCE ADVANCES | RESEARCH ARTICLE

PHYSICS

First-order synchronization transition in a large population of strongly coupled relaxation oscillators

Dumitru Călugăru^{1,2}, Jan Frederik Totz^{1,4,4}, Erik A. Martens⁶, Harald Engel⁸

Onset and loss of synchronization in coupled oscillators are of fundamental importance in understanding energent behavior in natural and man-made systems, which range from neural networks to power grids. We report on experiments with hundreds of strengly coupled photochemical relaxation oscillators that exhibit a discontinuous synchronization transition with hysteresis, as opposed to the periodigmatic continuous transition expected from the widely used weak coupling theory. The resulting first-order transition is robust with respect to changes in network connectivity and natural frequency distribution. This allows us to identify the relaxation character of the usoillators as the essential parameter that determines the nature of the synchronization transition. We further support this hypothesis by revealing the mechanism of the transition, which cannot be accounted for by standard phase reduction techniques.

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Explosive Sync in Real World?

Explosive Sync. Evidences

Ongoing consensus about the role of bistability as a natural framework for biological switches

Abrupt transitions and hypersensitive responses have been analyzed from the perspective of ES

Conscious-Unconscious Transitions (Anesthesia) [Kim et al. 2016, Kim et al. 2017]

Choroid Plexus & Circadian clocks [Myung et al. 2018]

Epileptic Seizures [Wang et al. 2017]

Frequency detection of the cochlea [Wang et al. 2016]

Hypersensitivity of Fibromyalgia patients [Lee et al. 2018]

EXPLOSIVE SYNC. EXPLOSIVE SYNC.

Hypersensitivity of Fibromyalgia patients [Lee et al. 2018]

Experiment & Analysis



EXPLOSIVE SYNC. EXPLOSIVE SYNC. EVIDENCES

Hypersensitivity of Fibromyalgia patients [Lee et al. 2018]

SCIENTIFIC **Reports**

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OPEN Functional Brain Network Mechanism of Hypersensitivity in Chronic Pain

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