Phase Transitions in Multi-Stable Systems for Integrated Distributed Decision Support IDDS

Robert Kozma
FedEx Institute of Technology, University of Memphis, TN
& US Air Force Research Laboratory, Sensors Directorate, HAFB

With Leonid Perlovsky, Murali Rangaswamy, AFRL/Sensors Directorate
Walter Freeman, Division of Neuroscience, UC Berkeley
Bela Bollobas, Mathematics, U of Cambridge, UK & U of Memphis, TN
Oliver Riordan, Mathematics, U of Oxford, UK

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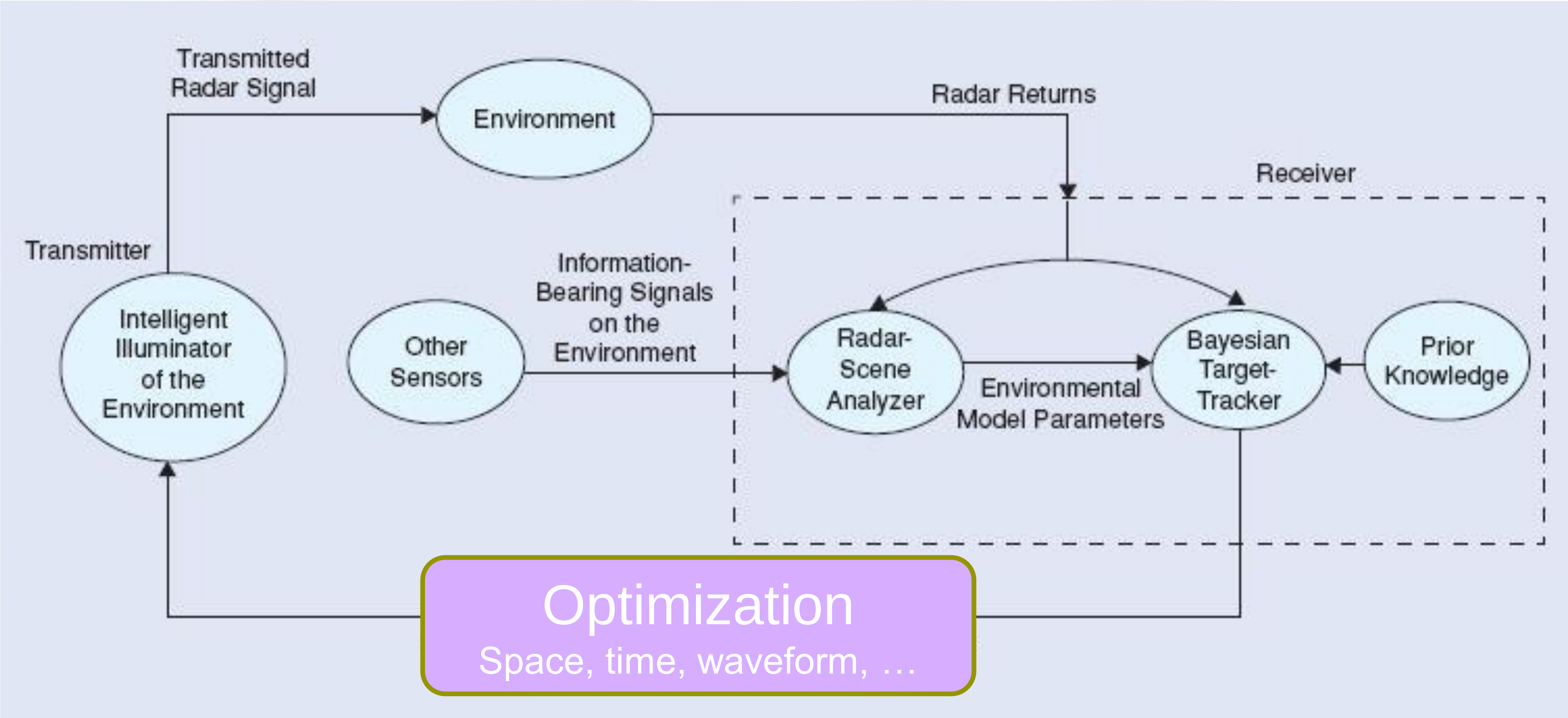
Overview – Layered Sensing

1. Problem statement
   - Distributed sensing is a complex probabilistic optimization task
   - Typical approach: point and detect
   - Layered sensing: on-line adaptation to dynamically changing scenarios using cognitive radar paradigm
2. Proposed solution
   - Adapt sensor to the environment to satisfy warfighter's need on the battlefield
3. Challenges in environment models
   - Computationally complex radar environment
   - Limited access to data
   - Rapidly changing environment
   - No universal approach exists
   - Presently mostly empirical, case-by-case approach

Cognitive Radar

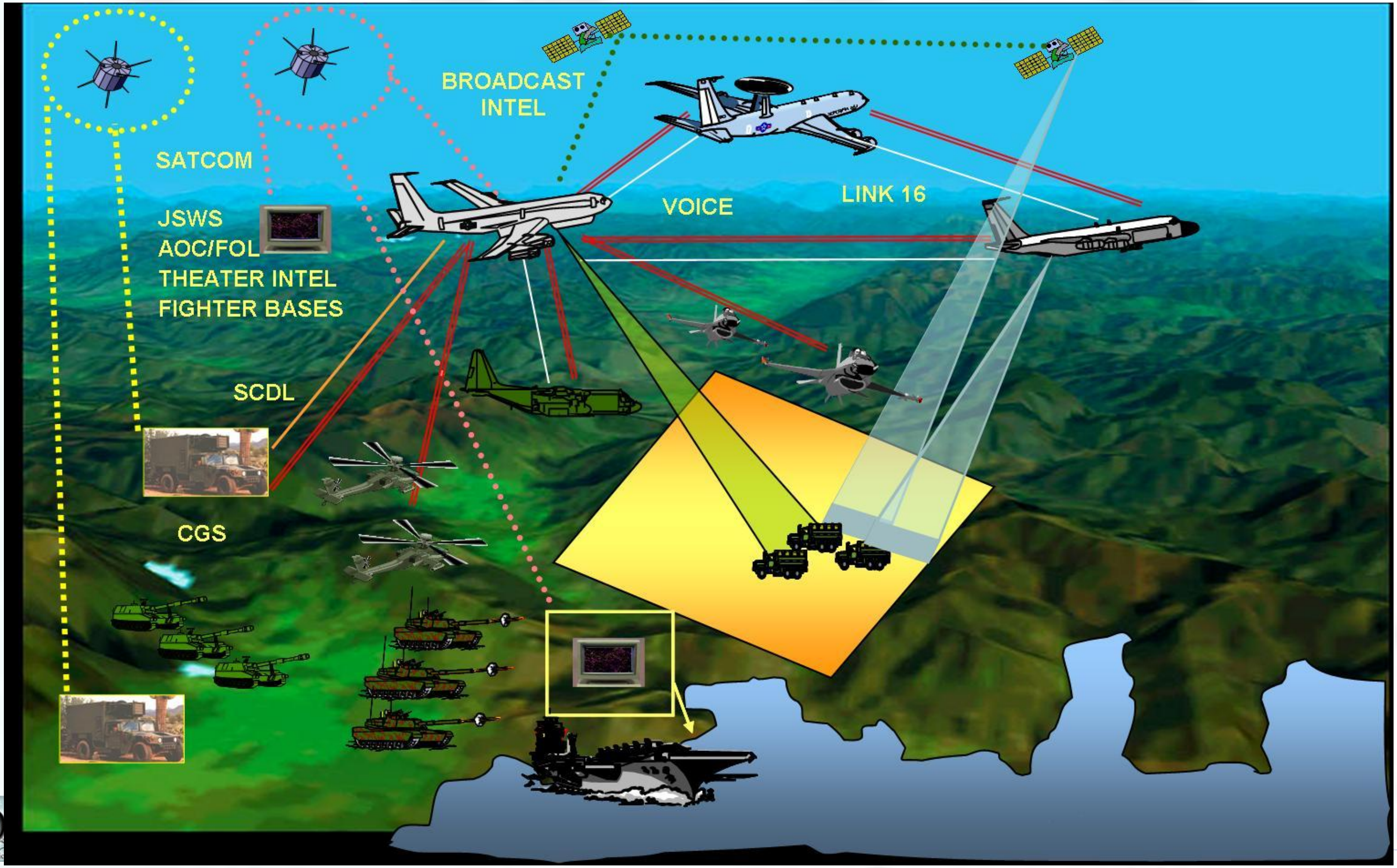
Closed loop dynamic system



(Haykin, 2008, in Gini/Rangaswamy, 2008)

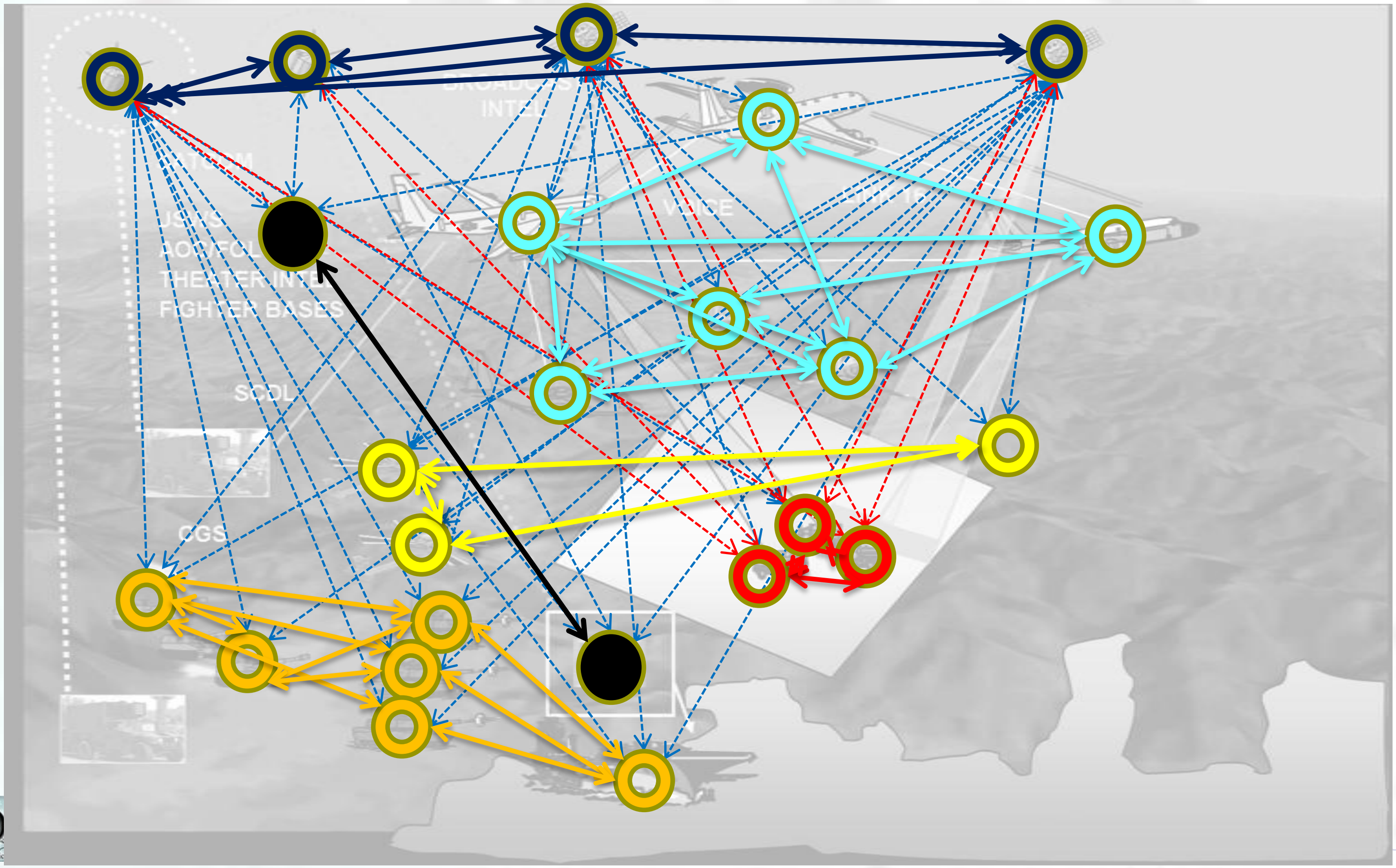
Distributed Sensing in Battlefield Scenario

JSTARS surveillance with multiple observation platforms and their communications



Network Centric Integration

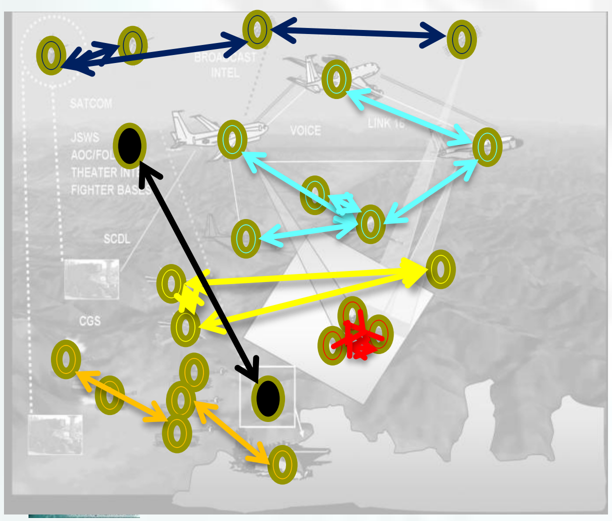
JSTARS surveillance with multiple observation platforms and their communications



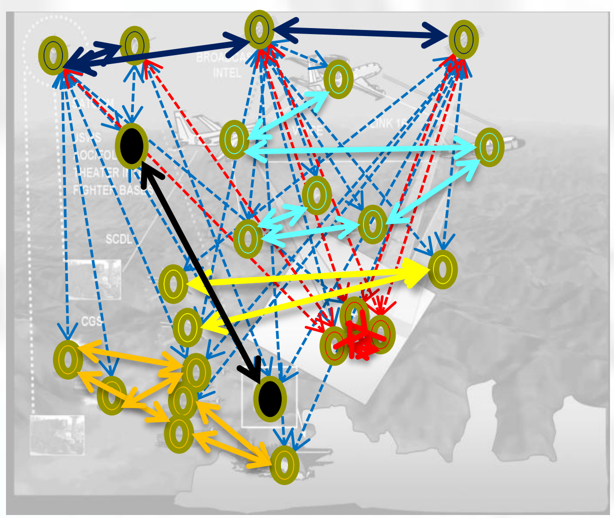
Major Challenge in Network Theory

- Stable and robust operation in complex networks
  - Achieved with reconfigurability at multiple spatial and temporal scales.
- Maintain the balance between
  - Flexibility of local fragmentation of individual components and
  - Rigidity due to dominant global effects in the distributed structure.

FRAGMENTED



OPTIMUM CRITICAL



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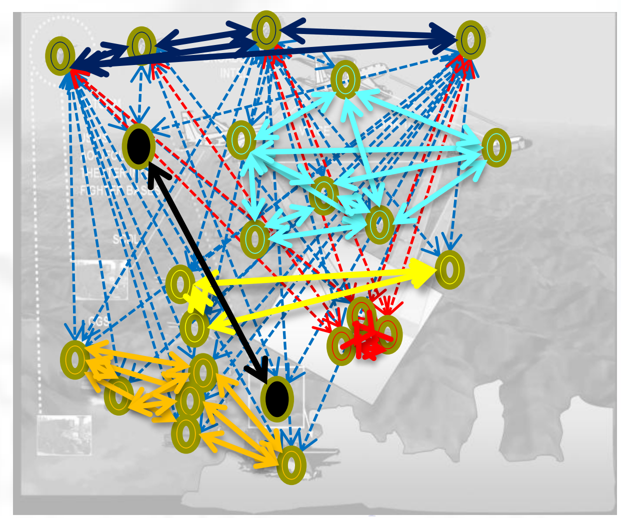


Aspects of Multi-level Systems

Aspects	A	B	~
System hierarchy	Low-level	High-level	Intermediate
Control	Feedback	Feed-Forward	Adaptive control (AC)
Math (Diff. Eqs.)	Diffusive 2nd order PDE	Drift 1st order PDE	Mixed PDE
Math (Graphs)	Cellular Automata Lattice topology	Random Graphs No topology	Mixed Planar/ Topologic Graphs
Physics	Energy	Information	Knowledge
Cognition	Bottom-up	Top down	Integral Dyn Logic

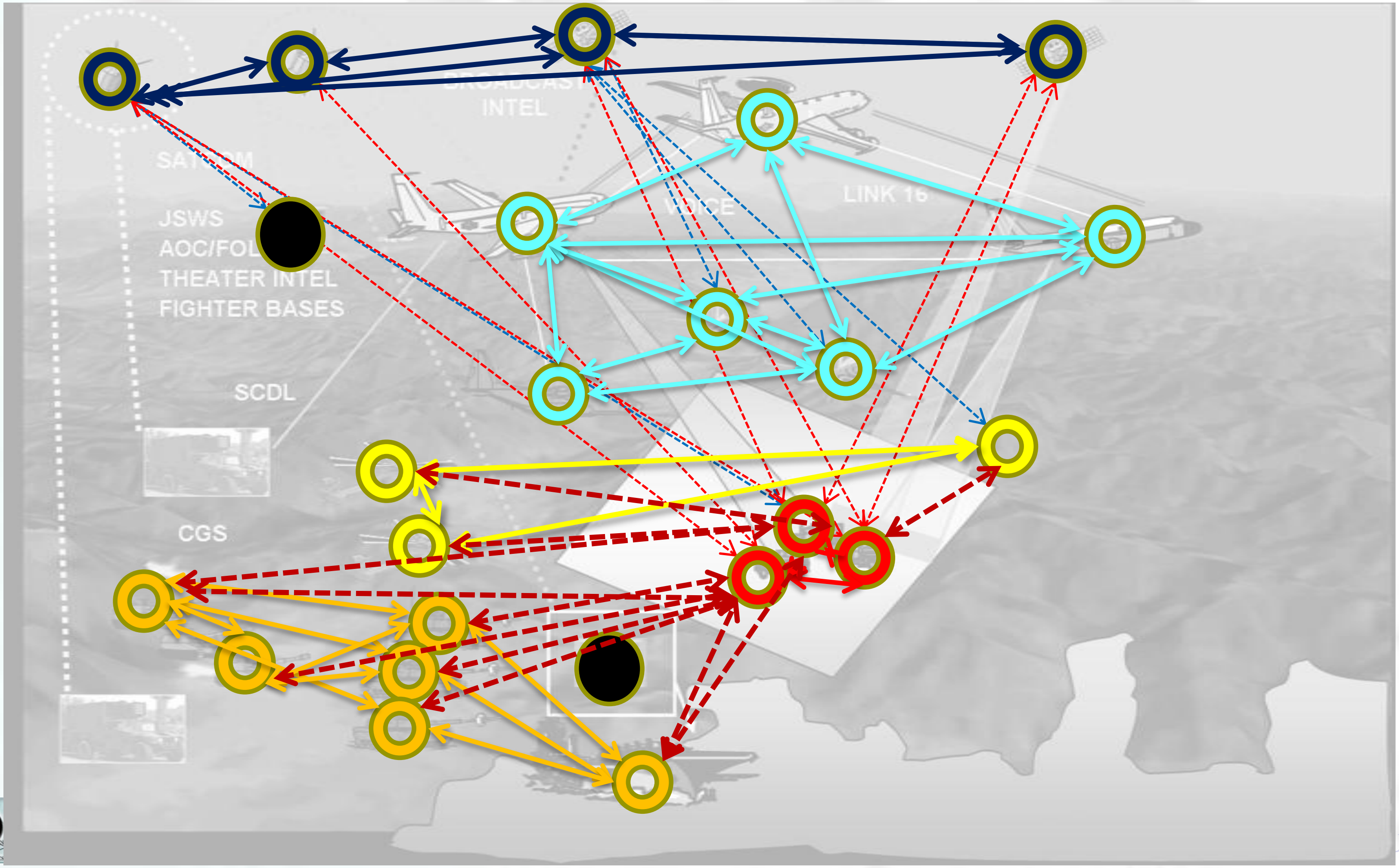
Decision Support Systems

- Task:
  - Information rich scenarios with heterogeneous data sources
  - Robust response to dynamic changes and often adversary environment
  - Multi-sensor integration of uncertain, noisy, contradictory data
  - Rapid decisions efficiently with limited resources, suboptimal conditions
  - Decision must be made between various potential scenarios

- Example scenarios
  - Joint operation of GMTI and SAR tracking of slowly moving targets
  - Tracking a commercial aircraft continuously in space and time while making maneuvers
  - Ubiquitous surveillance of the environment

Operation Modes of the Distributed System

- Independent operation of units solving specific monitoring tasks
- Integrate information across the system for global optimum decision



Warfighter Support via Efficient Human-Computer Interaction

- Huge amount of massive data which must be interpreted rapidly and make effective decisions
- Brains address such task routinely and efficiently
- Learn from brains and cognitive processing

→<u>New mathematical theory of cognition:</u>

Intentional decision making based on phase transitions between meta-stable cognitive states manifested in spatio-temporal neurodynamic correlates, and modeled by random graph theory.

Computer-Assisted Decision Support

- **Data acquisition**
  - Optimal sensing, data collection, processing
  - Knowledge extraction and inference, accumulation of evidence on scenarios
  - Reasoning system using information integration, action oriented
- **Control**
  - Anticipatory control based on past experience and comparing prediction and actual sensing
  - Planning future action in dynamically varying situations
  - Decision system with time and resource constraints
- **Human-computer interface**
  - Cognitive models of human decisions and memory
  - Efficient simulation of human cognition
  - Information exchange H-C for robust decisions

Integrated Distributed Decision Support

IDDS Highlights

- IDDS is based on the theory of random networks
- Constrained by limited bandwidth and by rapidly shifting spectra
- Open problems
  - Self-reconfigurability in rapidly varying scenarios
  - Continuous adaptation and learning new environment
  - Fast reaction and switch to new operational modes
  - Spatio-temporal integrity of the system in face of computational complexity
  - Robust operation with noisy and contradictory sensors data

Potential Benefits of IDDS

- Anticipation and prediction
- High-dimensional search
- Data selection and integration
- Validation with known models
- Convergence properties
- Prediction update

Project Tasks/1

1. Mathematics to interpret the behavior of distributed dynamic networks
   - Apply the theory of large-scale random networks to model the dynamic switching in the system behavior through phase transitions.
   - Develop a model of heterogeneous populations of nonlinear components, including modular structures in sensor networks.
   - Implement adaptation and learning under dynamically varying conditions.
   - A dynamic system is developed which exhibits the required switching properties.
   - Performance metrics include: mean time until failure, transition time, average waiting time.

Project Tasks/2

2. <u>Implement and validate IDDS using simulations</u>

- Implement the integrated distributed decision support system in the simulated sensor network
- Derive practical metrics for robustness, and reliability of the IDDS system.
- Demonstrate the concept with a variety of distributed sensor agents acting in real time.
- Perform IDDS experiments with large number of free parameters

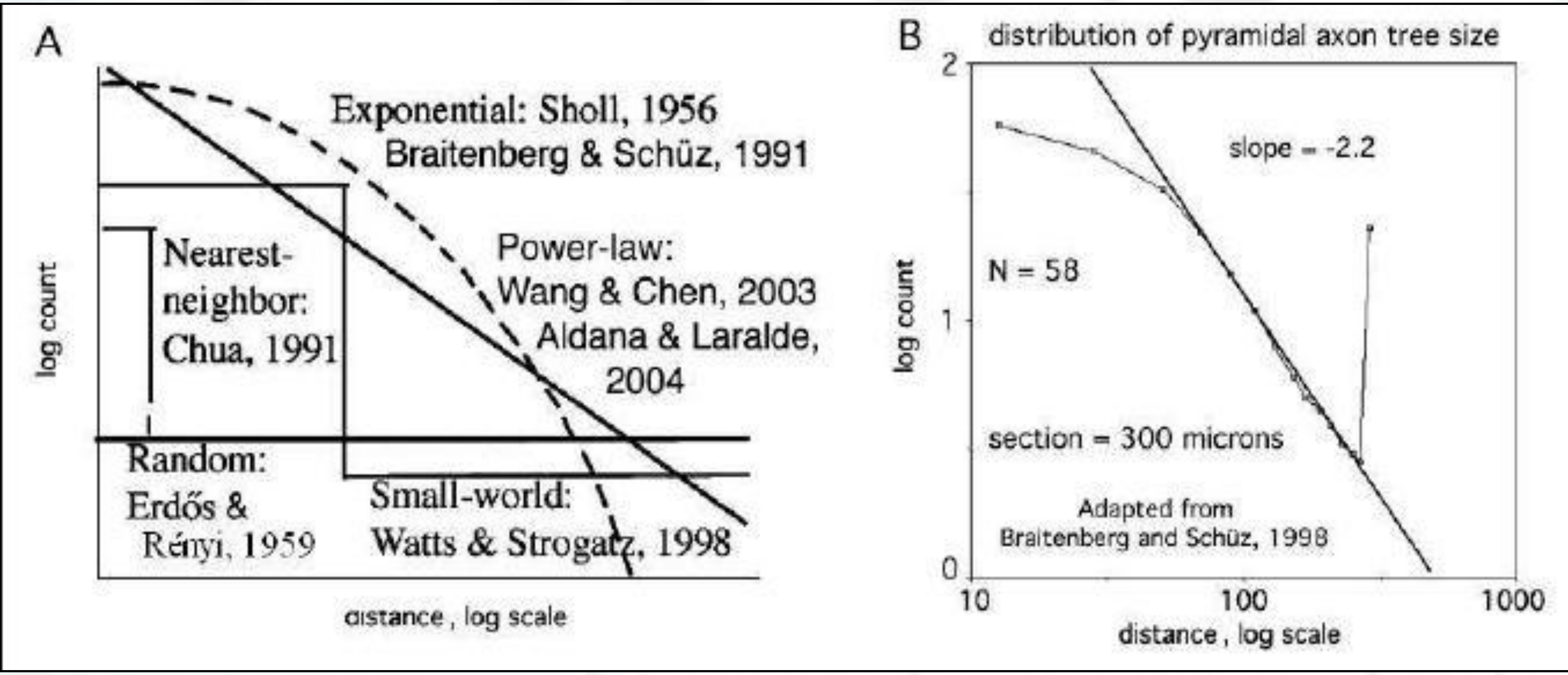
Random Graph Theory of Cortex
OVERVIEW

1. Connectivity structure
   - Scale-free length distribution
2. Evolution of cortical structures
   - Pioneer neurons/subplate, column, cortices, hemisphere
3. Random graph growth models
   - Preferentiality, Hebbian, exponential
4. Dynamics of functional connections
   - Scale free PSD in time and space near criticality
5. Correlates of intentional decision making
   - Intermitted frames of AM patterns in beta/gamma gated in theta

Random Graph Theory of Cortex

1. Connection Length - Scale Free

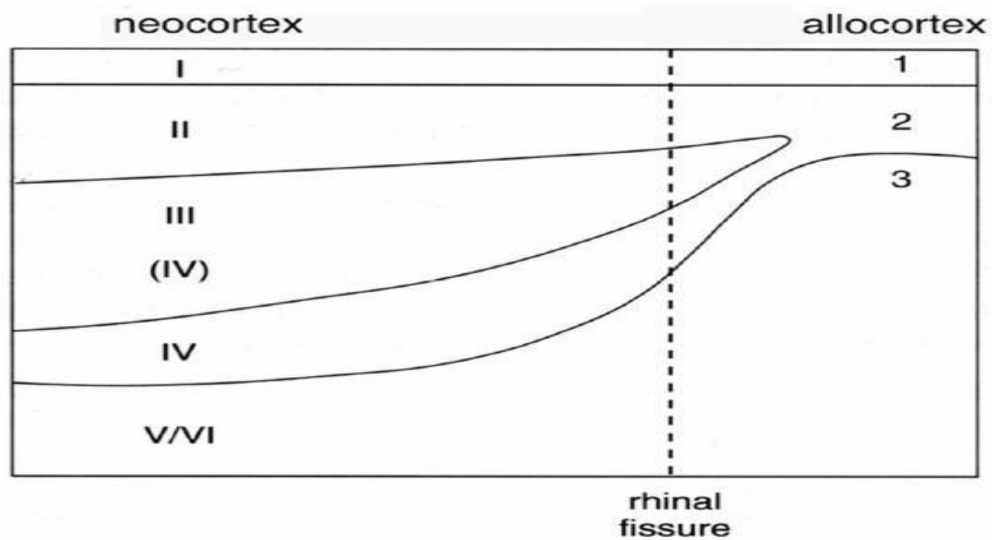
Models (A)   Experiment (B)



Random Graph Theory of Cortex

2. Evolution of Cortical Structures

Linear size	# of neurons	Structure
10 μ	10^3	Pioneer neurons
100 μ	10^5	Evolving population
1 mm	10^7	Cortical columns
10 mm	10^9	Cortices
100 mm	10^11	Hemispheres, brain



3. Random Graph Growth Models

Preferentiality

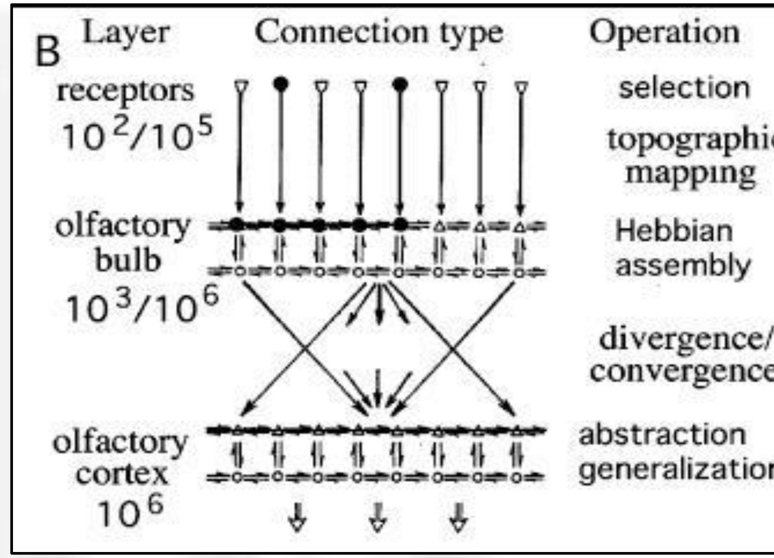
- Popular, gives scale-free
- Drawbacks: math & bio

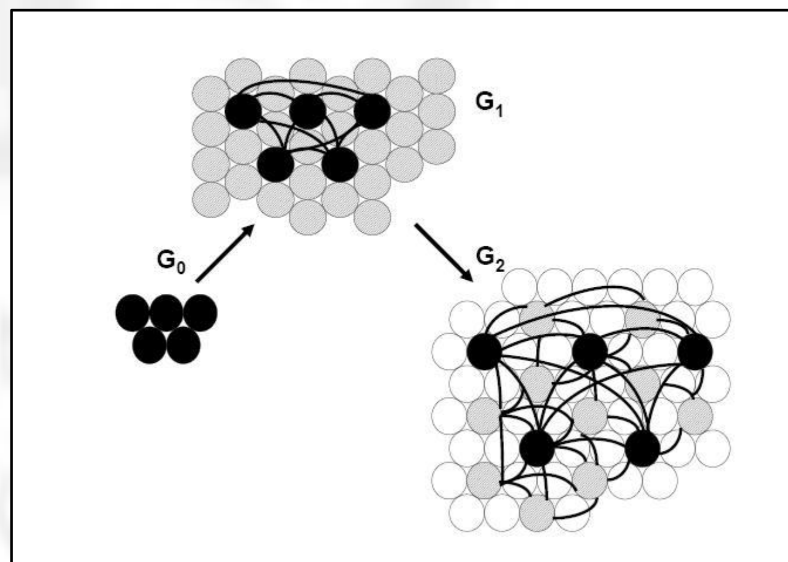
Hebbian Assembly

- Mesoscopic population
- Associative learning

Exponential expanding graph

- Novel, physiologically and mathematically firm
- Produces scale-free
  - (Bollobas,Kozma,Miklos, Handbook, 2008)



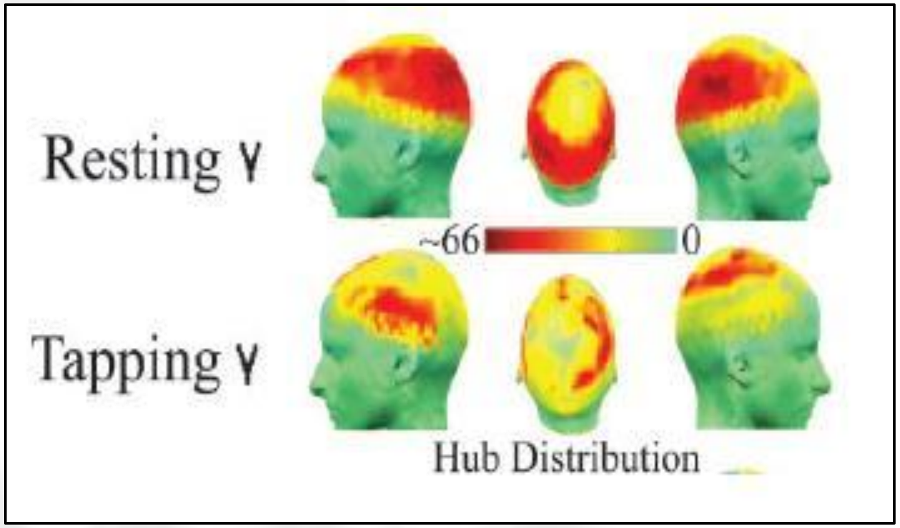


Random Graph Theory of Cortex

4. Dynamics & Functional Connectivity

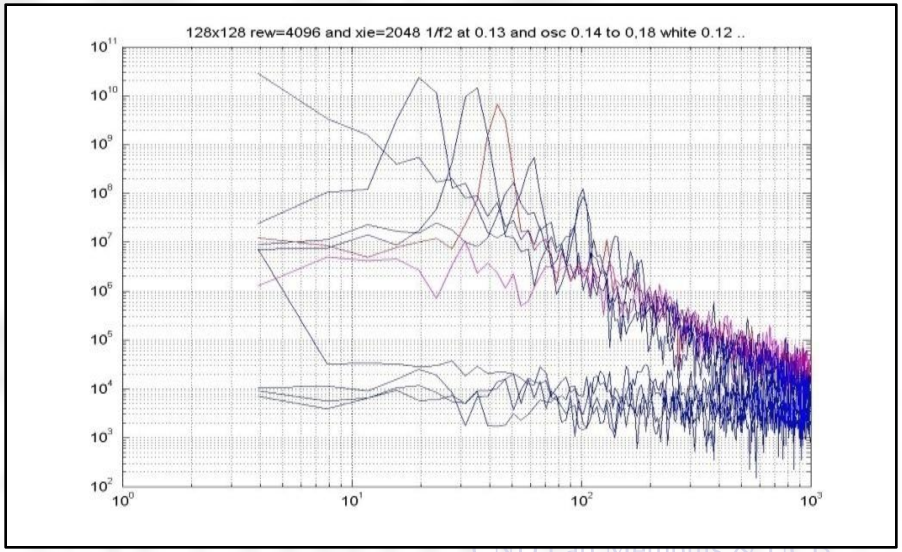
Scale-free degree distribution

- Functional hub structure
- Structural – not likely
  - (Bassett, et al, PNAS06)



Scale-free dynamics

- Temporal and spatial
- Power spectral densities 1/f^2
- Near criticality



Random Graph Theory of Cortex

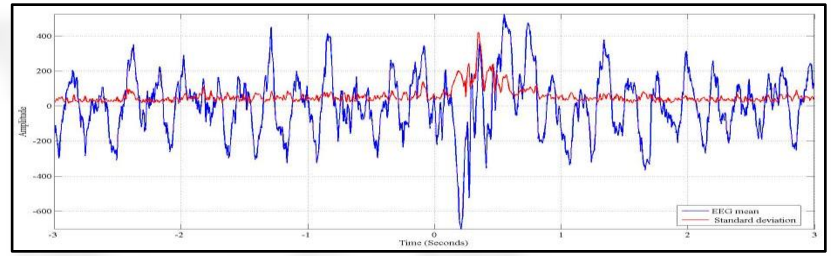
5. Correlates of Intentional Decisions

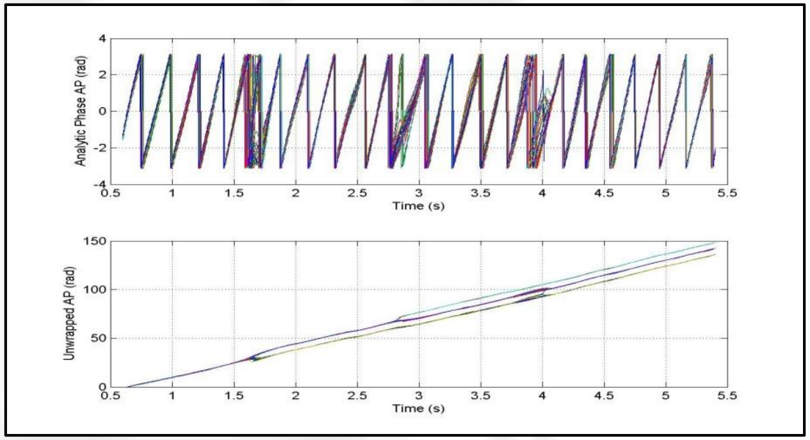
Cinematographic theory of cognition & decision

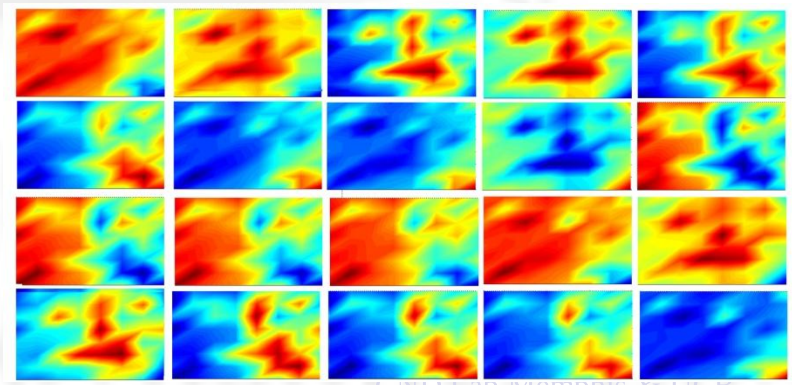
- AM patterns in gamma-beta carrier waves
- Frames rates at theta band

Transition dynamics

- Micro-scale: fractal
- Meso-scale: phase cone vertex
- Macro-scale: Intermittent synchrony-desynchrony
  - (Kozma,Freeman,Chaos,2008)







Summary

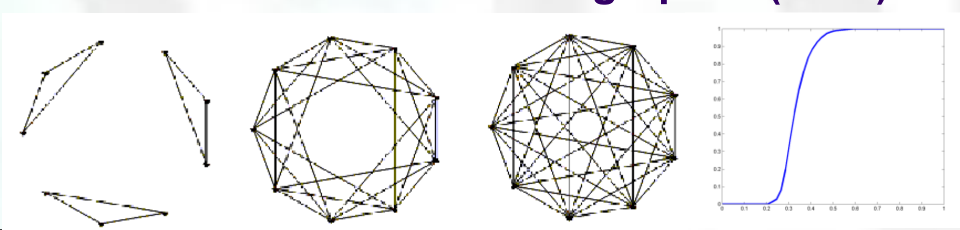
1. Multi-resolution approach is developed for integrated distributed decision support
   - Meets the requirements of layered sensing paradigm with dynamically reconfigurable structure
   - Online adaptation of radar sensors using cognitive radar framework
2. IDDS main features
   - Based on solid mathematical theory of random graphs and networks
   - Proof-of-concept in simulated sensor network with heterogeneous structure and rapidly varying environment

Phase Transitions in Random Graphs and Networks

Invent of digital computers
Self-Reproducing Automata
Computability, Intelligence
J. Von Neumann
“Theory of Self-Reproducing Automata”
“The Computer & the Brain” (1958)

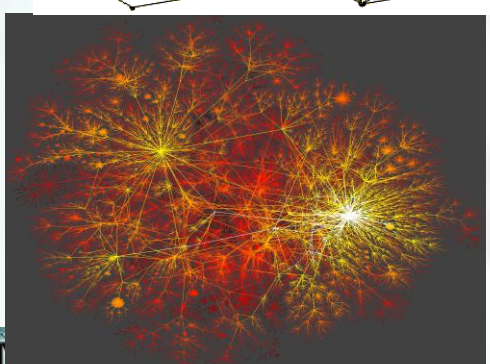
John Von Neumann (1903-1957)

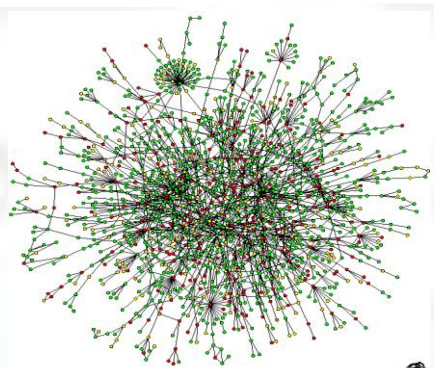
Random Graph Phase Transitions
A. Renyi, P. Erdos
“On the evolution of random graphs” (1960)



Alfred Renyi (1921-1970)

Paul Erdos (1913-1996)



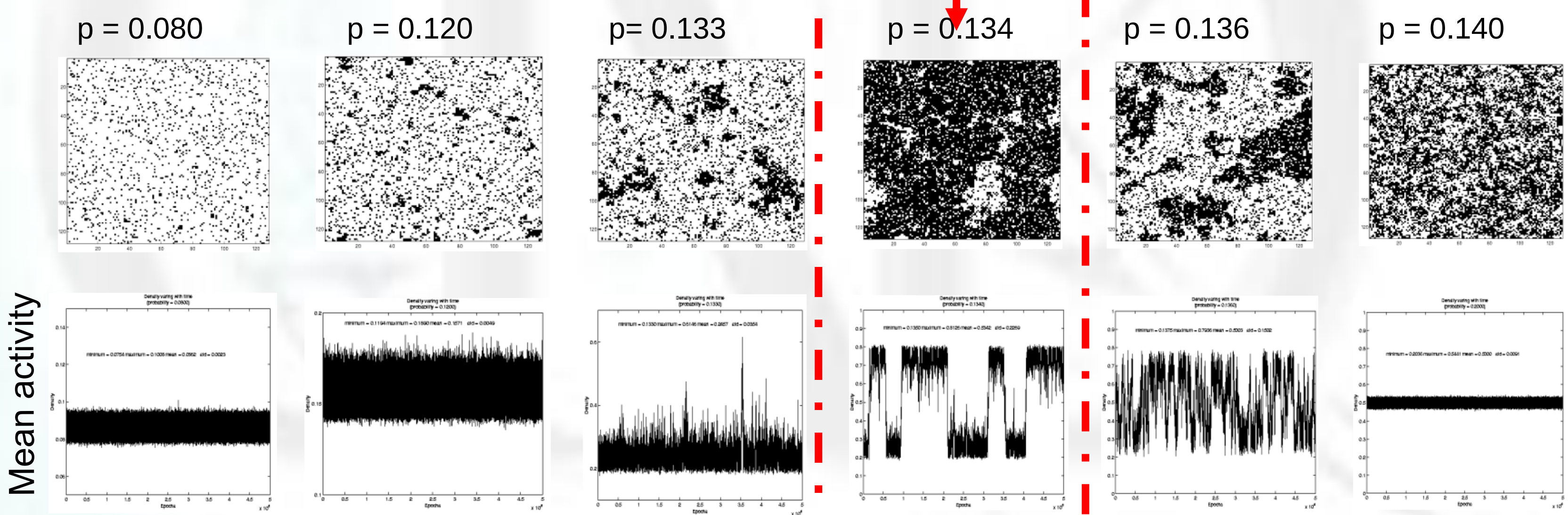


Hubs: in www yeast (Barabasi et al, Science, 1999)

Critical Behavior in Network Dynamics
Fragmentation versus unification

Illustration of model simulations:

Activity patterns in lattices in the sub- and supercritical regimes, as well as in the window of phase transition. Notice the emergent giant cluster near the critical probability (p_c) similarly as it has been described in the evolution of random graphs. Lattice size is N x N = 128 x 128.



Time / Iteration step (total number of iterations is $5x10^6$)

Subcritical regime
weak- /no clustering

Phase transition
prominent clustering

Supercritical regime
clustering / decreases

Graph Theoretical Models

LOCAL	MESOSCOPIC	GLOBAL
Diffusion	Neuropercolation	Mean-field
Physics	Biology	Physics
Ising class	Transitional	Analytical
$\beta = 1/8$	$1/8 < \beta < 1/2$	$\beta = 1/2$
Phase transition	~ (New class)	Phase transition

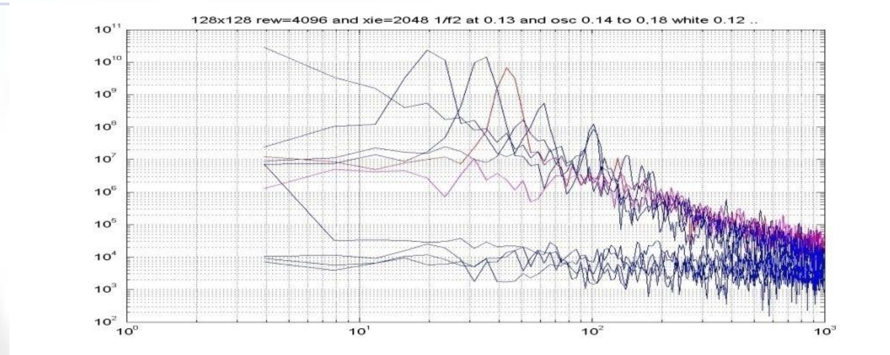
Scale Free Behavior with Inhibition: Approaching Criticality

Dynamic states:

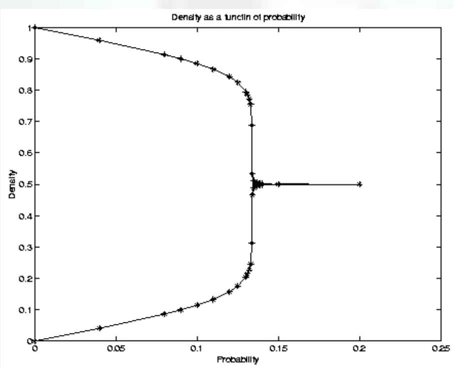
Criticality: 1/f2 power spectrum

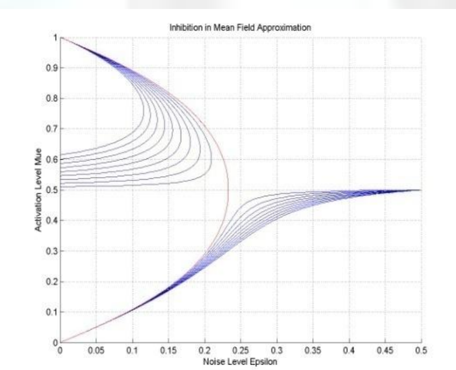
Approaching criticality: gamma oscillations increase

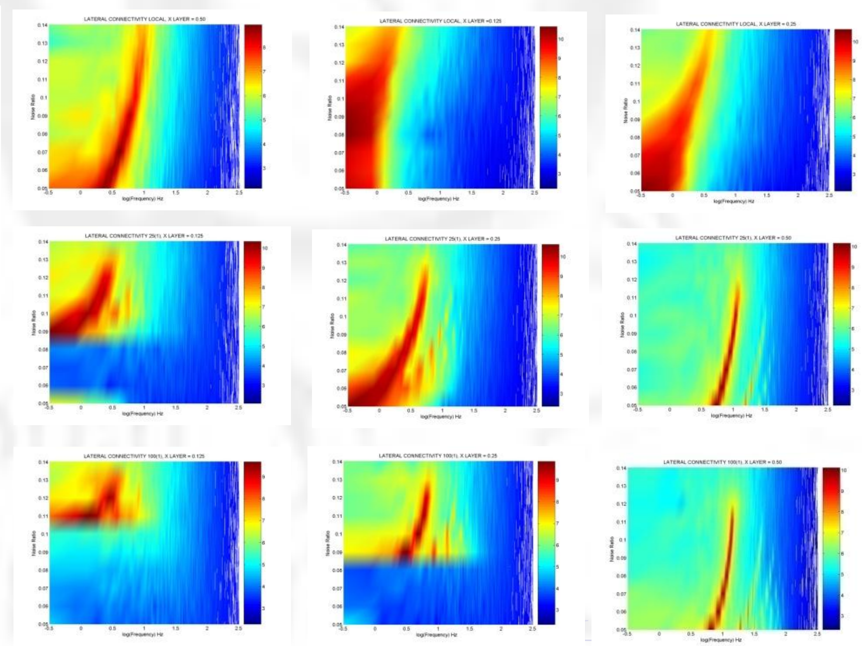
Far from criticality: broad spectrum



Parameters:
inhibition, noise, long axon fraction





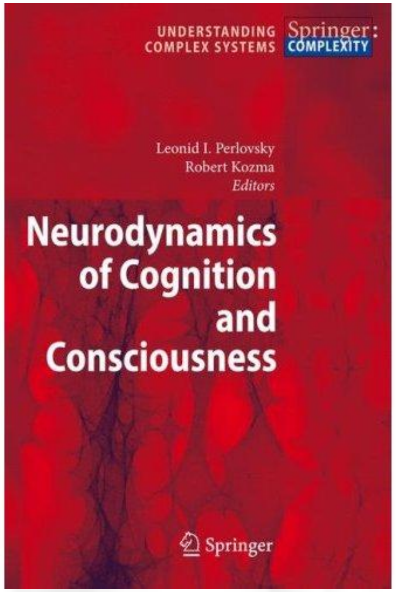


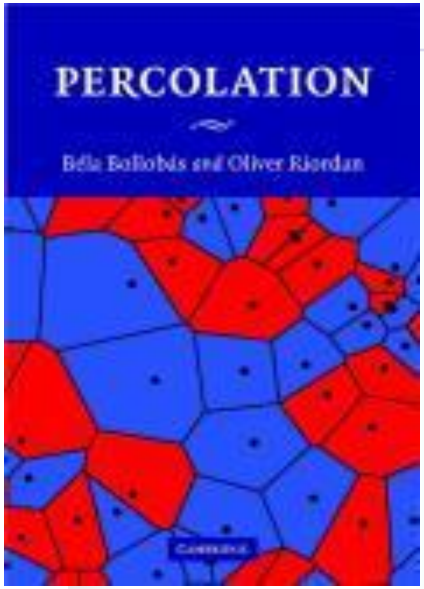
No inhibition model: Modeling inhibition on mean field gives critical noise/gain level

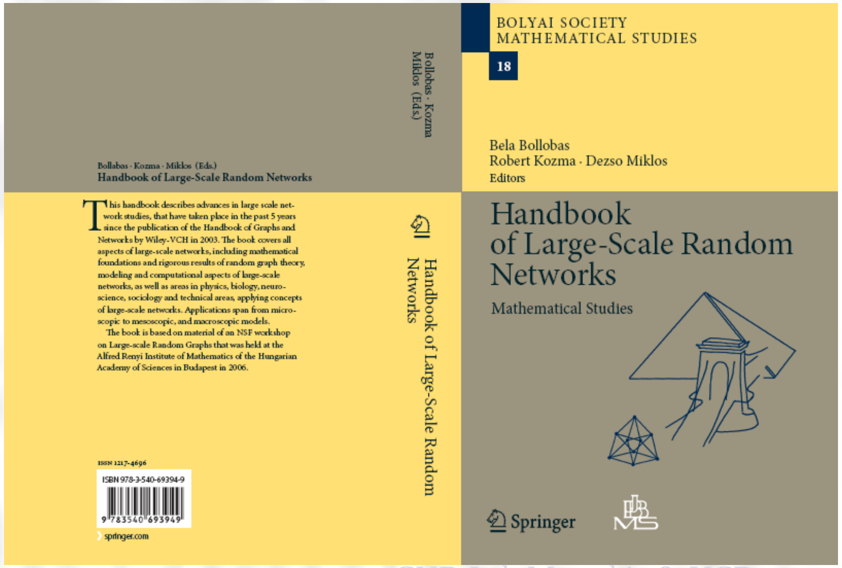
Modeling inhibition on mean field: given critical noise/gain level critical noise decreases vs. inhibition

Contributions

- Joint work with
  - Bela Bollobas, Mark Walters, U of Cambridge, UK
  - Oliver Riordan, Oxford Univ, UK
  - Paul Balister, U of Memphis, TN
  - Marko Puljic, Lemoyne College, TN
  - Walter Freeman, UC Berkeley, CA
- http://www.scholarpedia.org/article/Neuropercolation
  http://cnd.memphis.edu/neuropercolation/







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