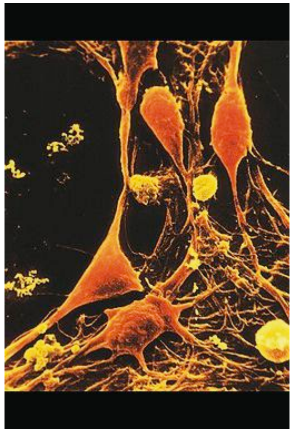
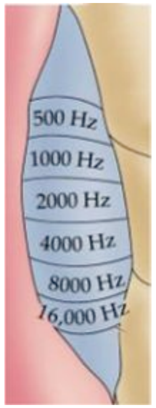
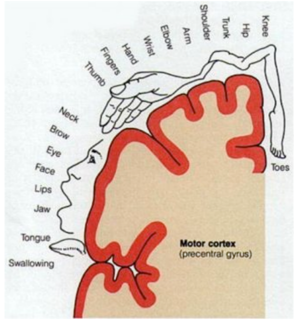
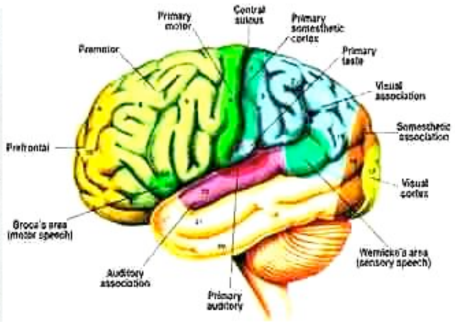








A few problems on functional self-organization in brain

Swan Kim

M. W. Cho, U. C. Lee, C. W. Shin

Asia Pacific Center for Theoretical Physics (APCTP)
Nonlinear & Complex Systems Laboratory,
Dept. Physics, POSTECH

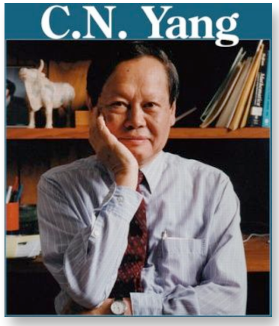
swan@postech.ac.kr

YITP What's Life 2007.10

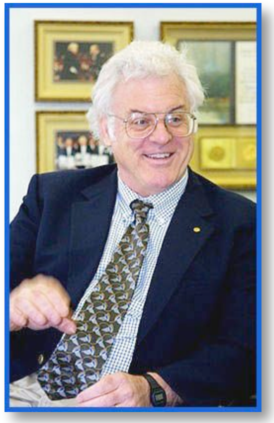
APCTP

http://www.apctp.org

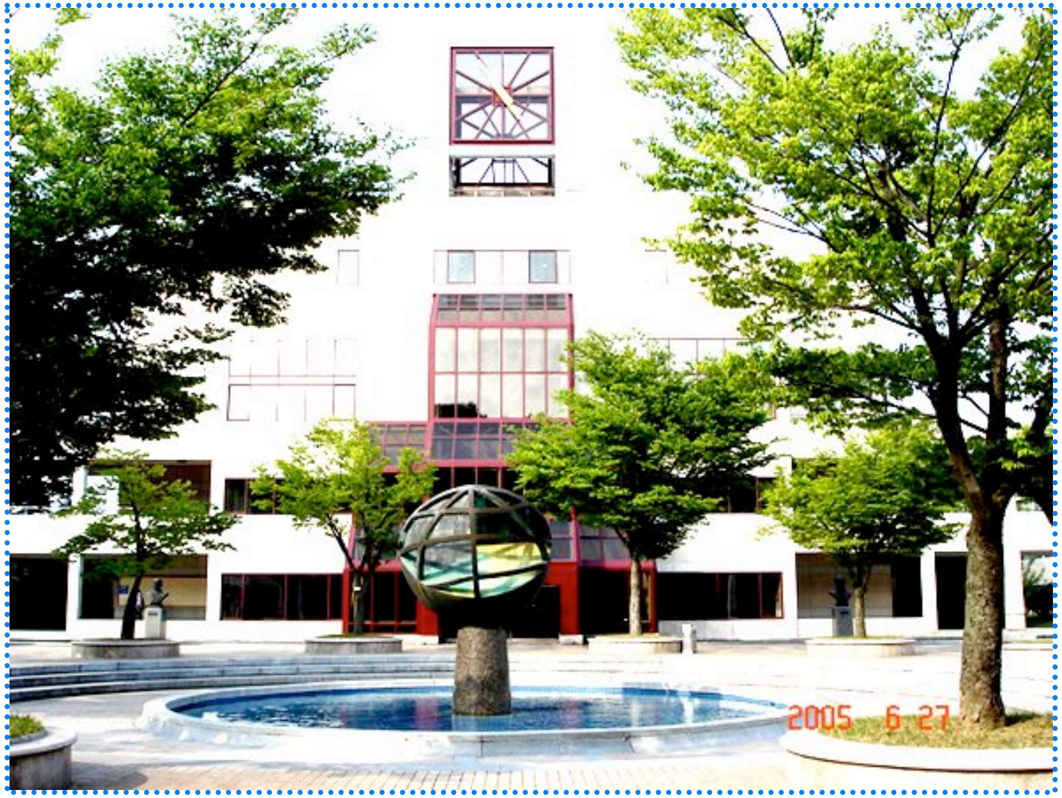
Asia Pacific Center for Theoretical Physics



Founding President



Second President



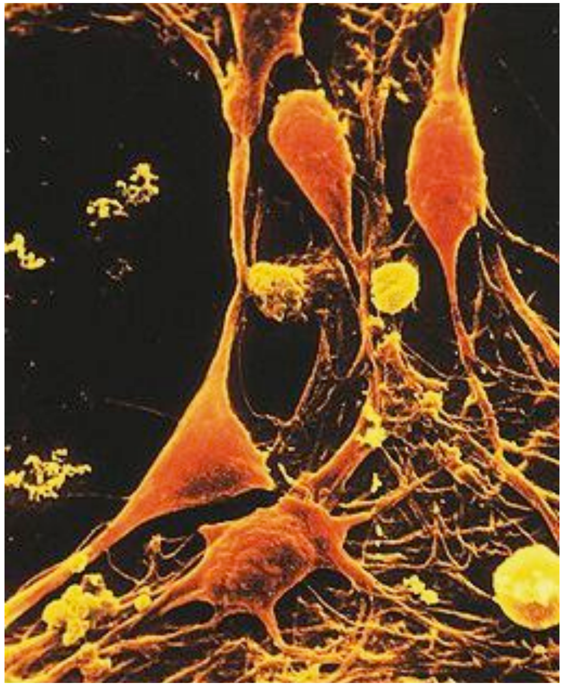
Peter Fulde

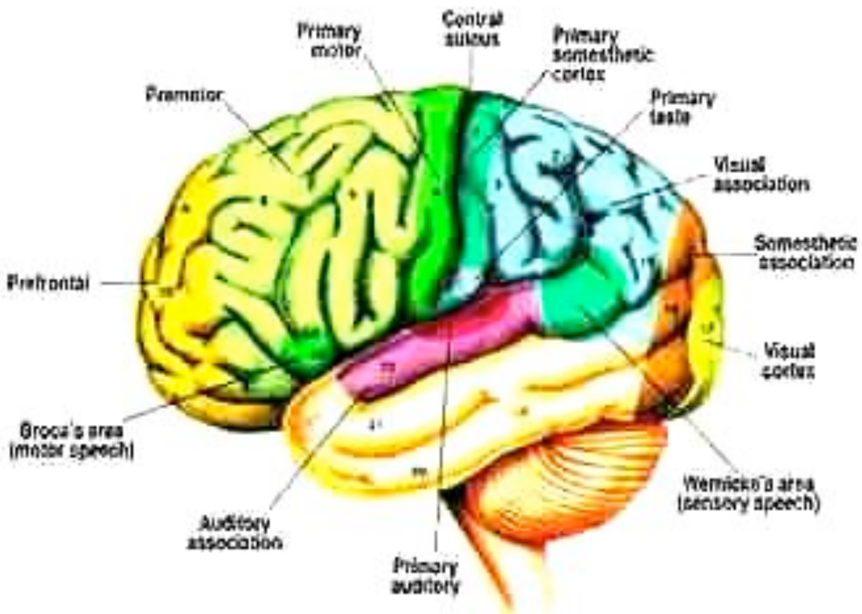
Third President

- Founded in 1996, located in Pohang, Korea
- 12 member countries, coop. with YITP, KEK, RIKEN, ISSP,…
- International cooperation, academic activities, young sci. training
- 3 M $/year, 40 activities, ~2,000 visitors

Outline

1. Introduction
2. Functional Self-organization in Cortical Dev elopment
3. Functional network formation in a STDP Neu ral Network Model
4. Functional Pathways in EEGs
5. Conclusion





Brain

- Neuron : Fundamental building blocks
  – slow (~60Hz), nonlinear, complex response

- Massively interconnected
  1,000,000,000,000 neurons
  1,000,000,000,000,000 synapse

  Circuits: layers, feedback loops, ...
  "networks of networks"

- Highly complex & correlated responses

⇒ Sensory information processing, movement coordination, learning, memory, cognition...

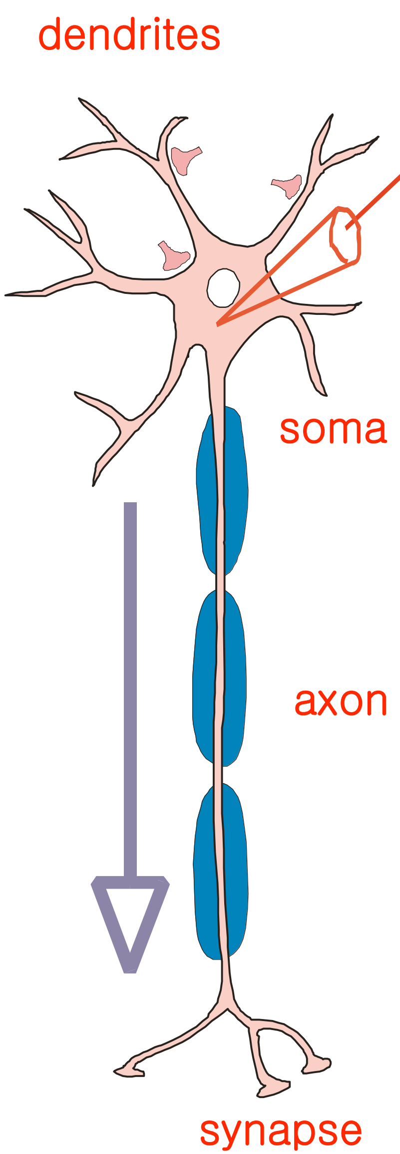
- Activity dependent neural plasticity

  e.g. Learning and memory

Q: Structure <-> Function?

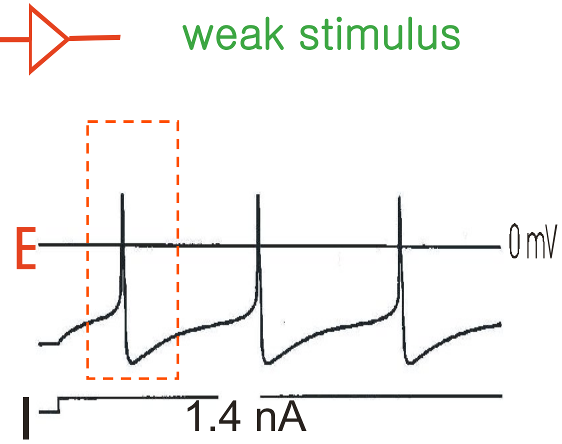
Functional self-organization

Neural signal generation –Electrochemical



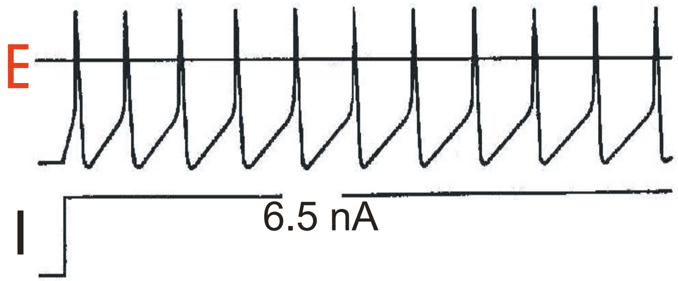
Neuron computes by dynamics of membrane potentials

weak stimulus

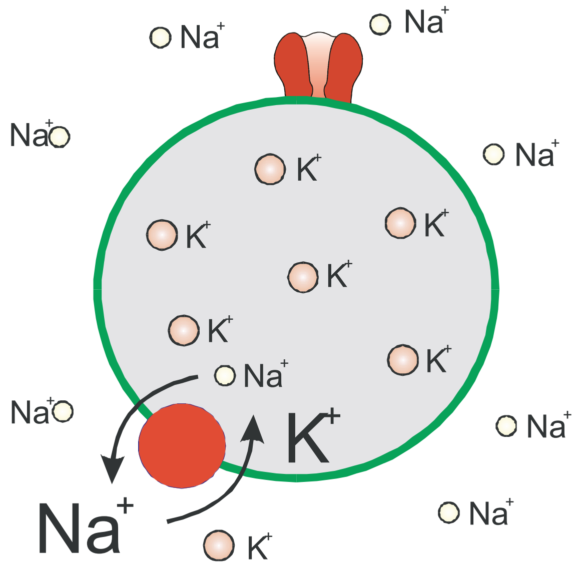


Action potential :
1 msec, 0.1 V
0 & 1 signals of brain

strong stimulus



Complex electro–biochemical processes underlie neural signal generation

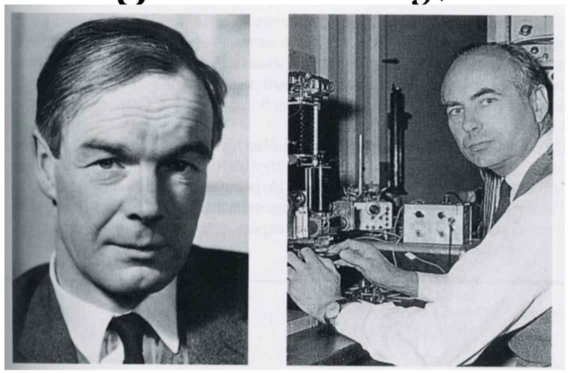


Na-K pump

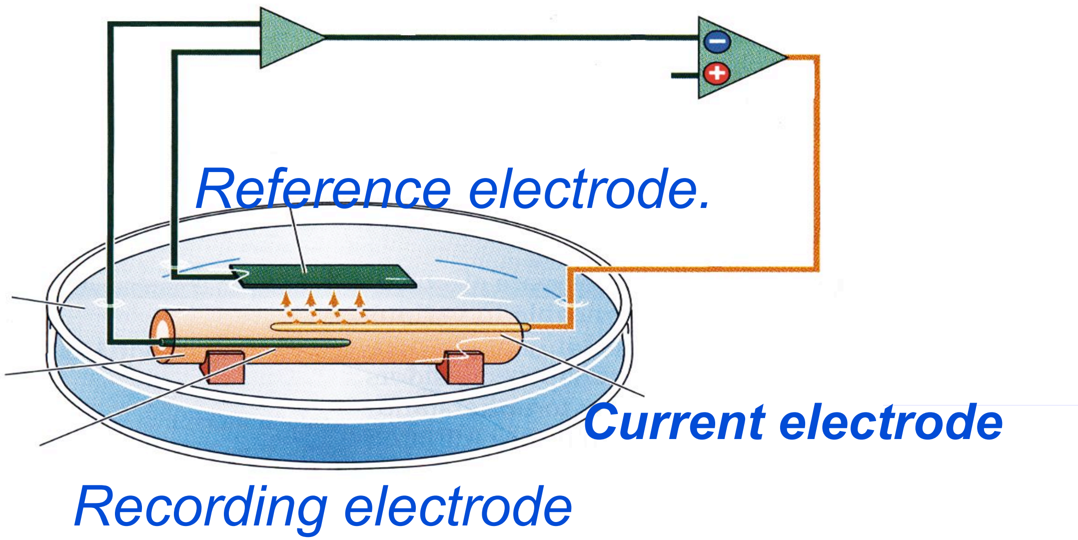
- Ion conductances => currents
- Nonlinear voltage gating

Modeling a neuron – Hodgkin-Huxley

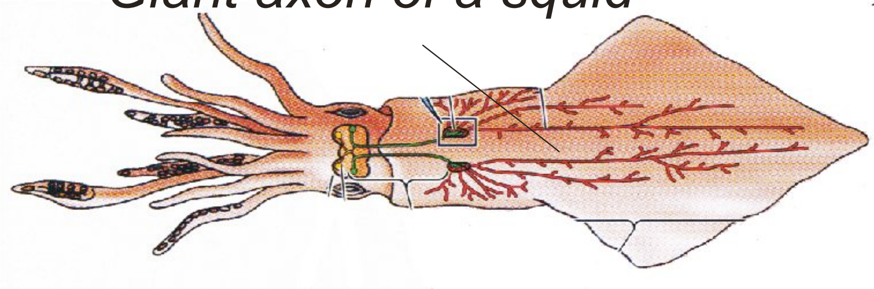
Hodgkin-Huxley, 1963

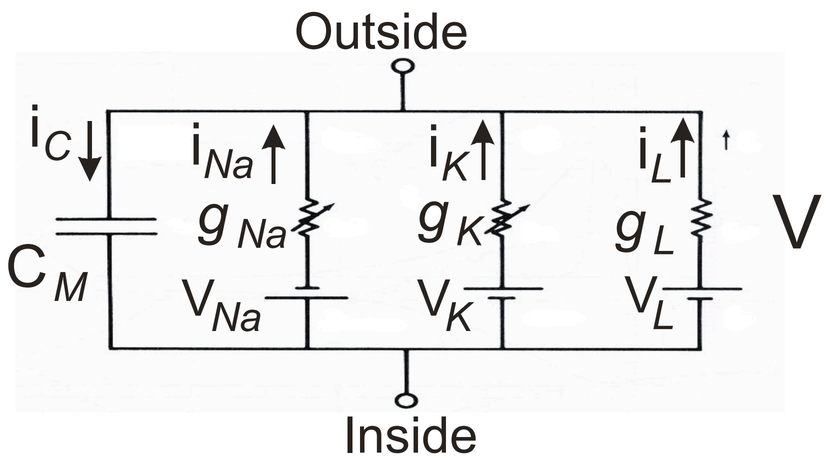


Voltage clamp experiment, 1952



Giant axon of a squid





Single-compartmental circuit model

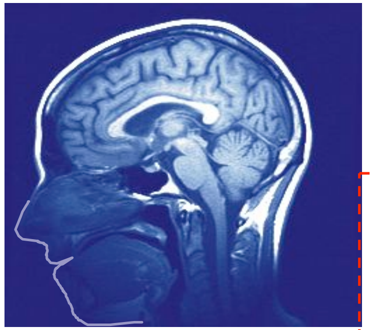
⇒ H-H neuron "Circuits" – 4-d ODE
& variations of conduction-based models

Connection geometry : Global, local, sparse
Synaptic interactions : STDP, α, ...
External stimulus : dc, ac, noise

⇒Dynamical System Models
for Nervous Dynamics

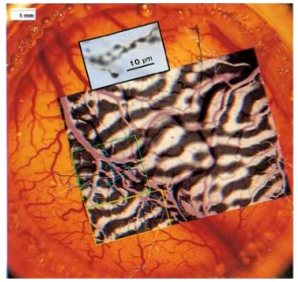
Studying self-organization in a brain hierarchy

m



Nonlinear Time Series

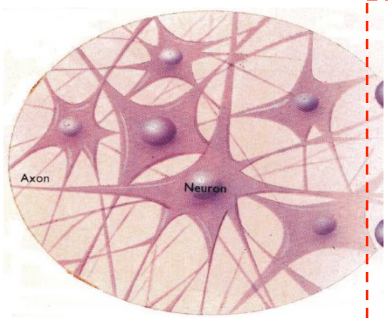
EEG/MEG pathways



Areas

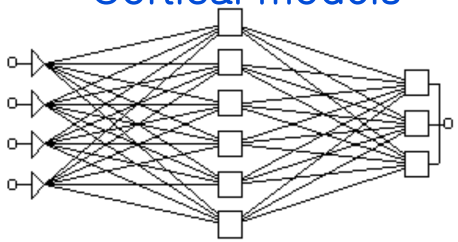
Complex systems
Statisitical physics

Cortical models

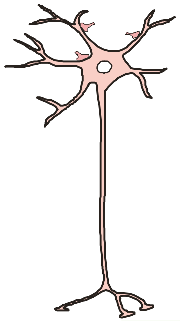


Functional columns

Neural networks

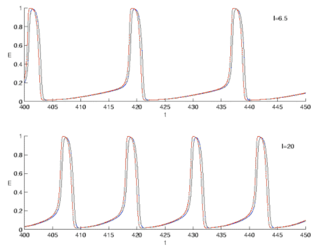


Neural network models



Nonlinear dynamics

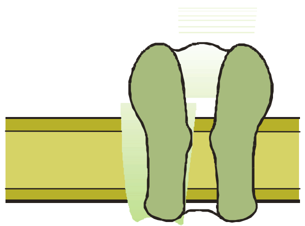
Neuron



Nonlinear dynamic models

Biophysics

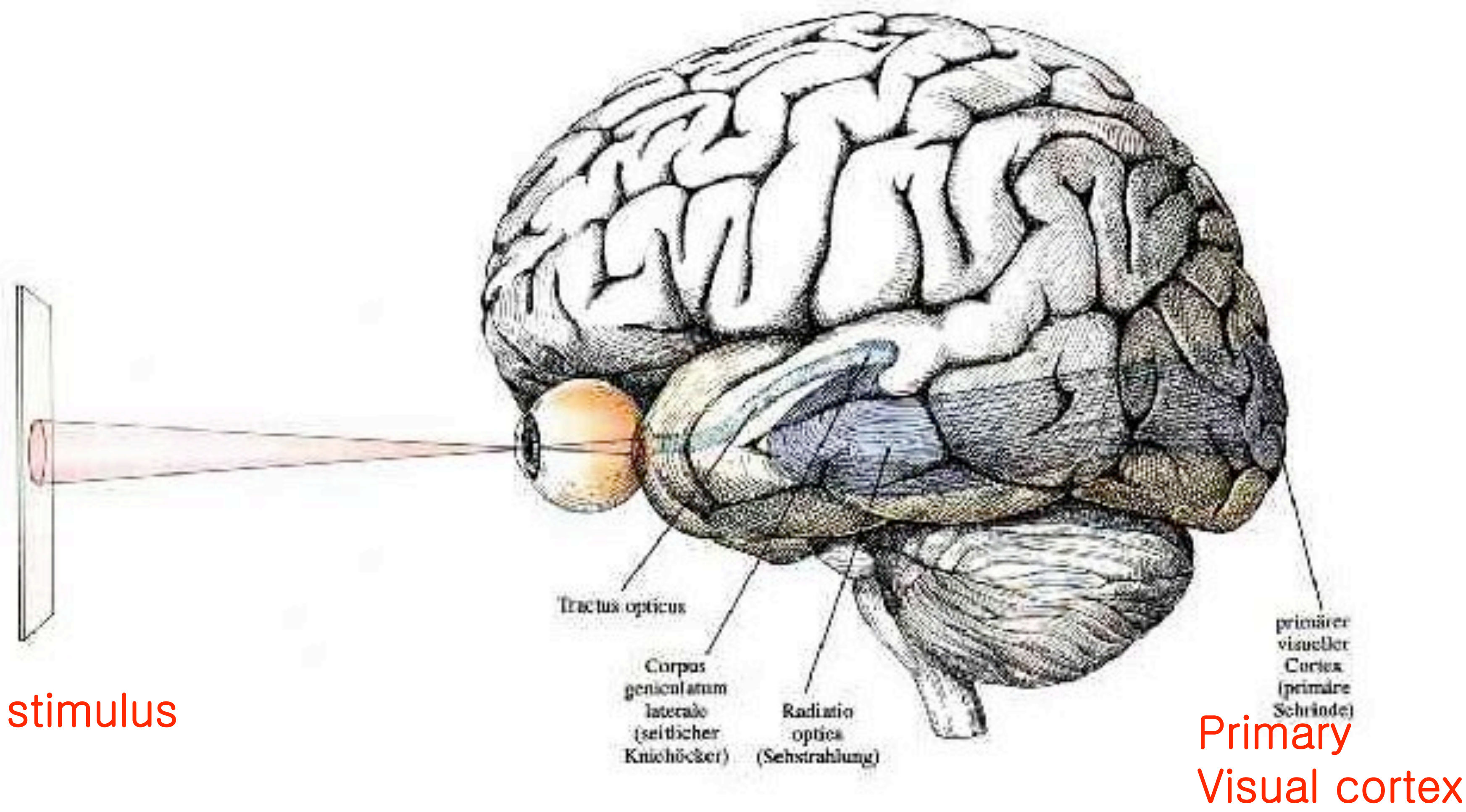
Ion channel
Proteins



nm (10^{-9})

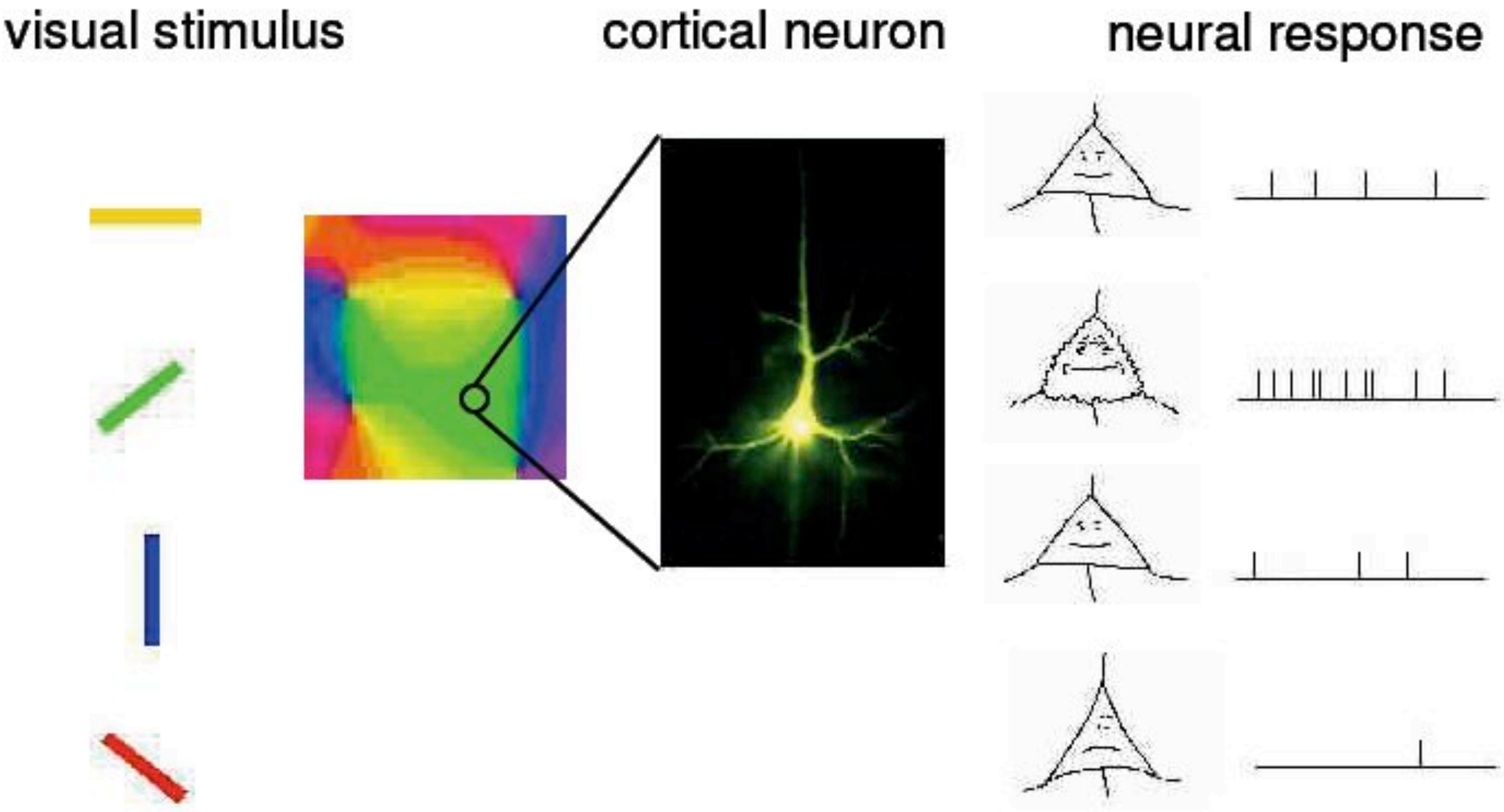
Biophysical models
LTP, LDP,STDP

Functional Self-organization in visual maps



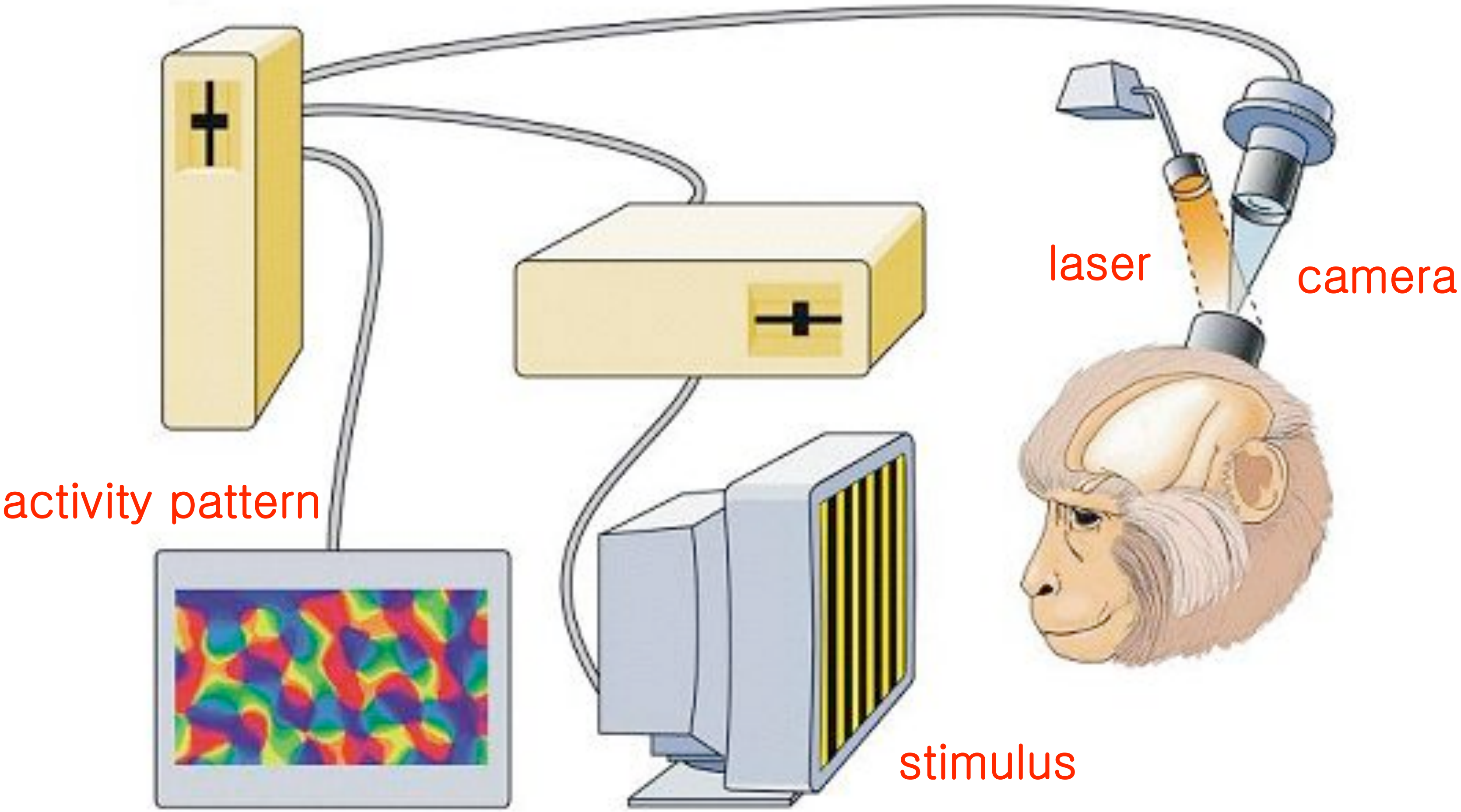
Hubel (1989)

Orientation preference



Hubel, Wiesel, J. Physiol. (1962)

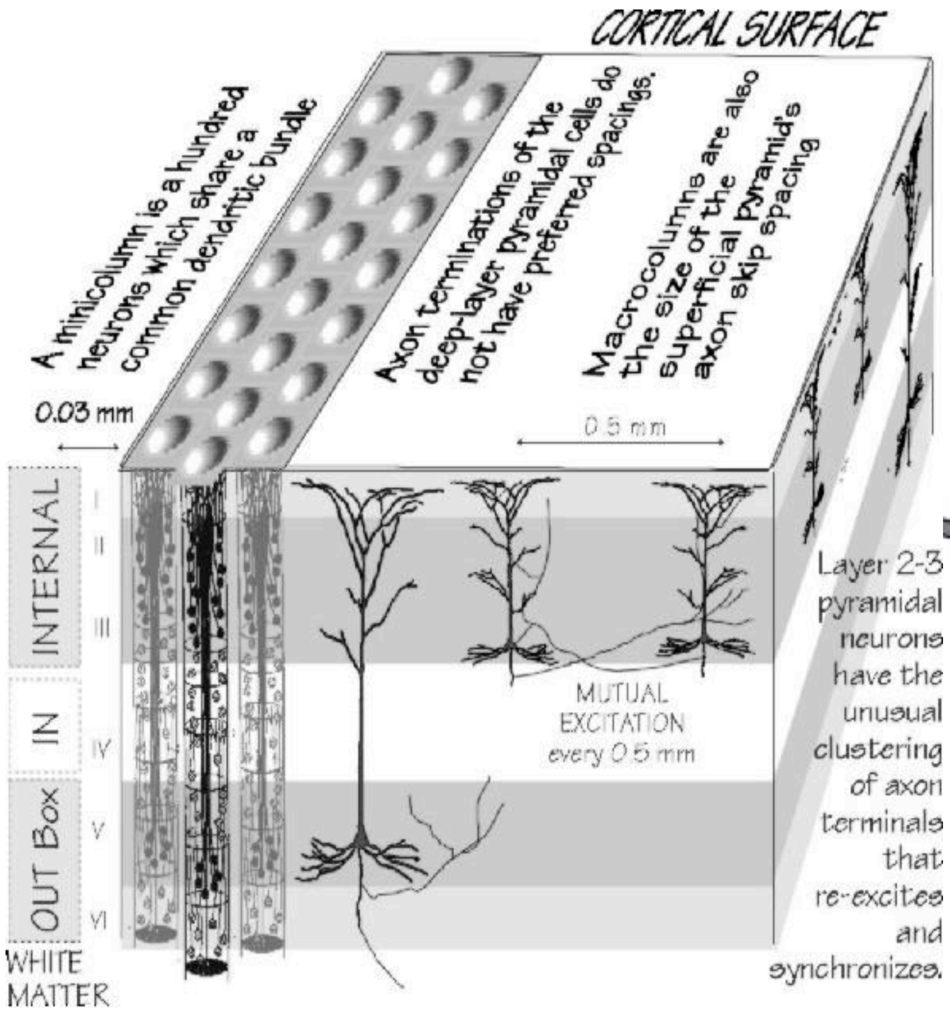
Optical imaging technique

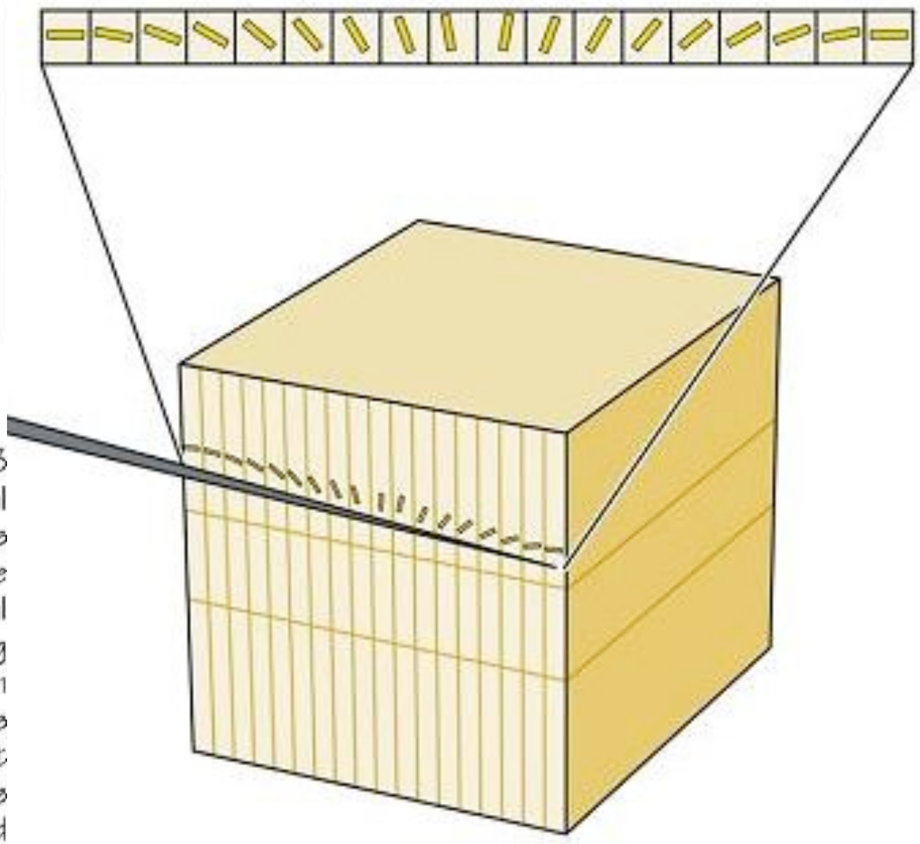


Basis: neural activity ⟺ haemodynamics

Bonhoeffer & Grinvald, J Neurosci (1993)

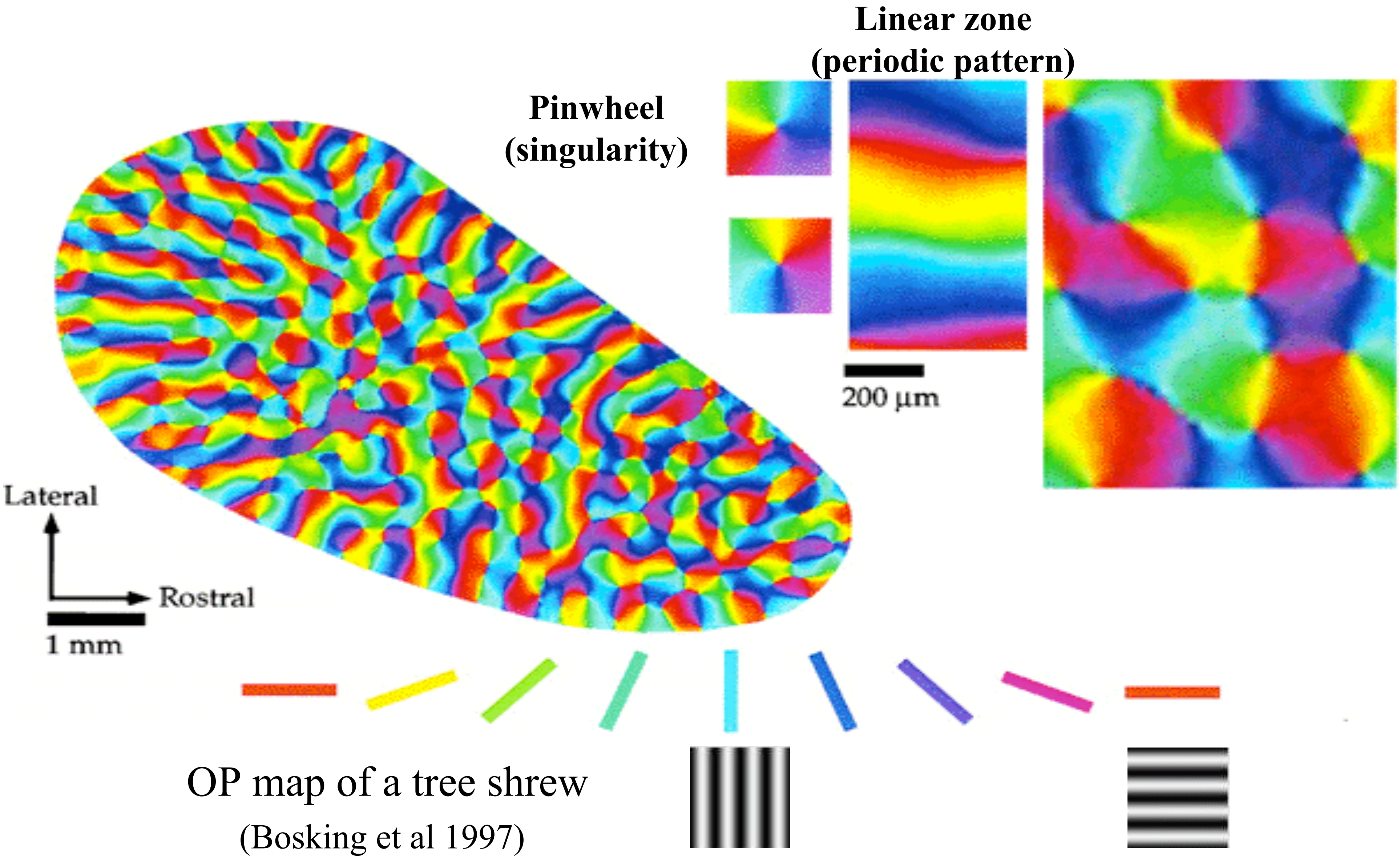
Orientation preference columns





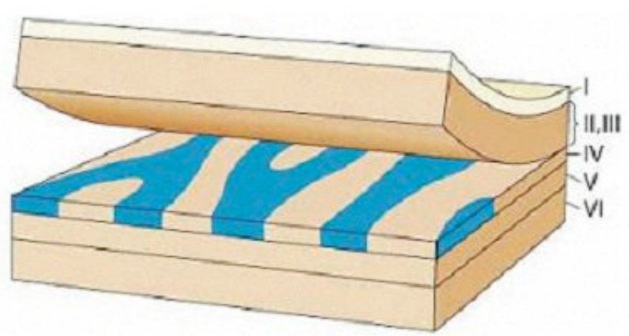
Array of orientation preference (OP)

Orientation preference (OP) map

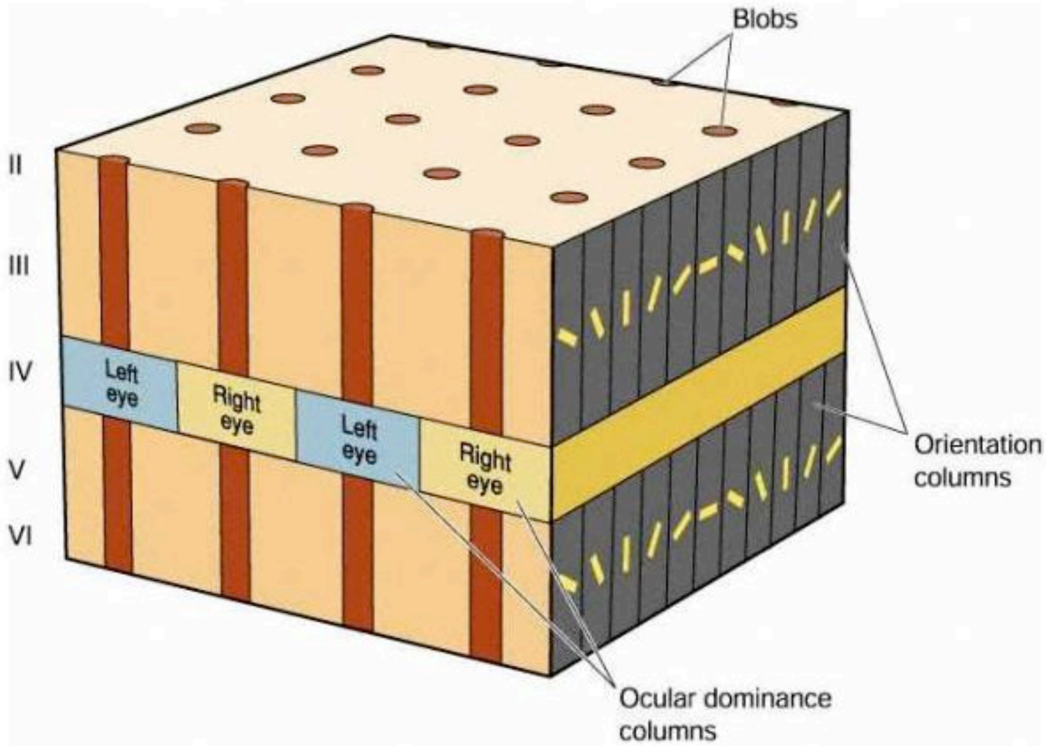


OP map of a tree shrew
(Bosking et al 1997)

Ocular dominance (OD) map in V 1

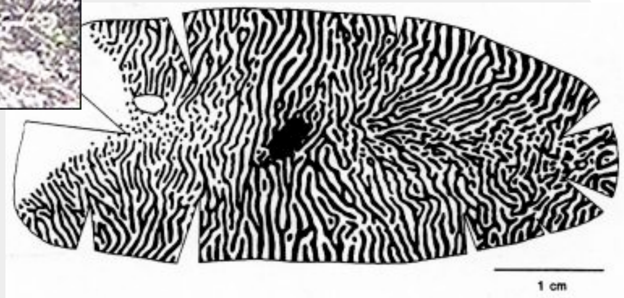


Ocular (left or right eye) dominance column

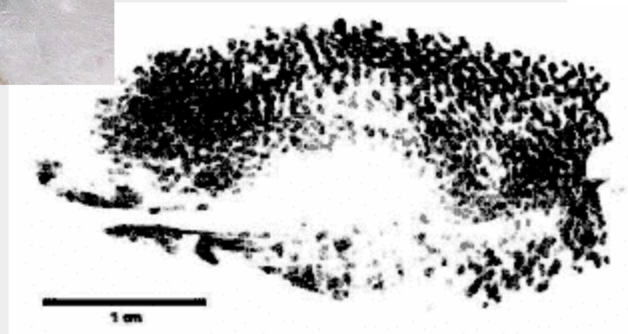


The structure of the primary visual cortex

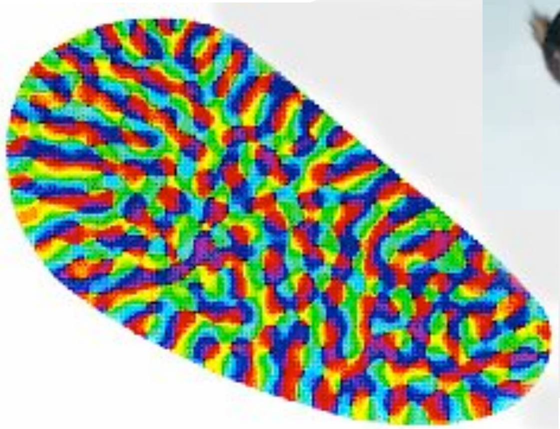
Different visual map types in mammals



Macaque Monkey
- Stripe patterns in OD maps
- Strong OD segregation



Cat
- island patterns in OD maps
- intermediate OD segregation



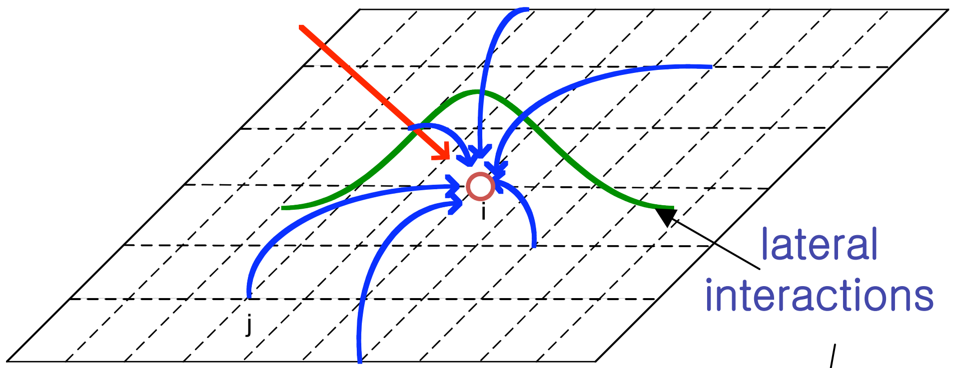
Tree Shrew
- Weak OD segregation (no OD map)
- Strong orientation selectivity

A Biophysical model for visual map formation

2-dim layer of visual columns → Orientation preference

ϕ

LGN input



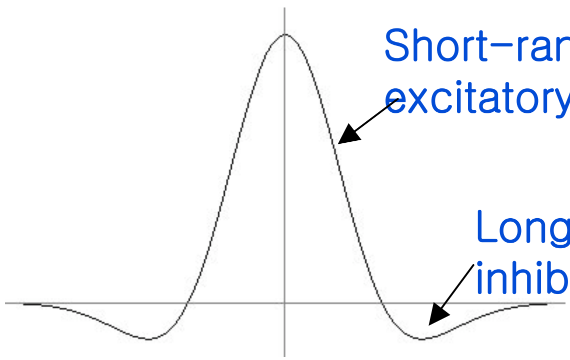
$$\frac{\partial \phi_i}{\partial t} = -\frac{\partial H}{\partial \phi_i} = -2\varepsilon \sum_j I(\vec{r}_i, \vec{r}_j)\sin(2\phi_i - 2\phi_j)$$
$$- 2\mu B_i \sin(2\phi_i - 2\phi'_i)$$

LGN input

Coarse-grained picture at the functional column level

Neuron -> functional column -> area maps

Distance dependent interaction



***I(r)* : Mexican hat type**

$$I(r) = \frac{1}{2}\left(1 - k\frac{r^2}{\sigma^2}\right)\exp(-r^2/2\sigma^2)$$

M.W. Cho & S. Kim, PRL, 2004

Analogy with a Spin Hamiltonian

Orientation Preference **Ocular Dominance**

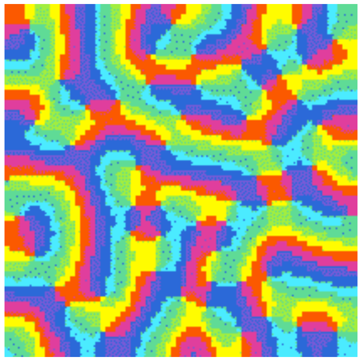
S_i=(cos2ϕ, sin2ϕ) **S_i=+1 or -1**

Maxican hat
Distance dependent

$$H = -\sum_{i,j} J(\vec{r}_i, \vec{r}_j) S_i \cdot S_j - \sum h_i \cdot S_i$$

X-Y model like

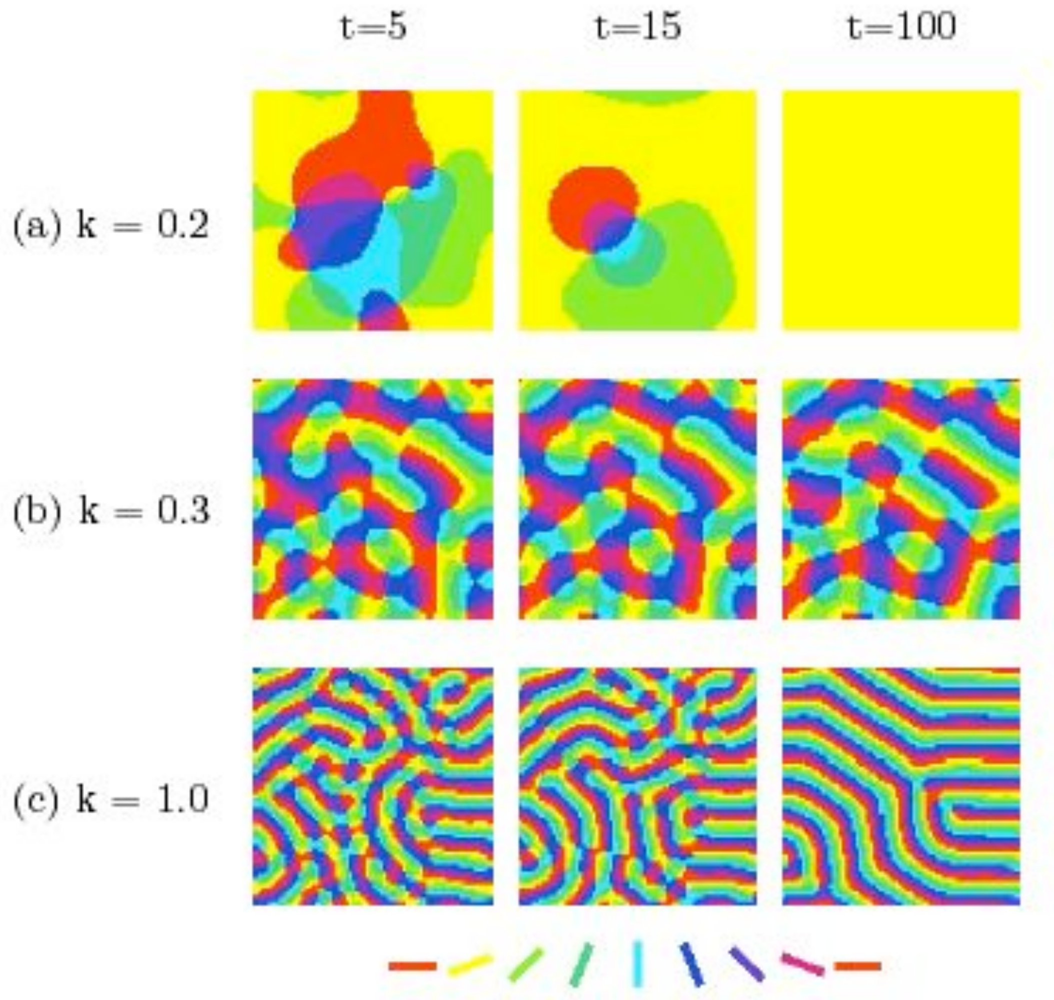
Ising model like



OP

OD

Time evolution of visual map over time



Homogeneous State (No map)

Spin wave state (OP map)

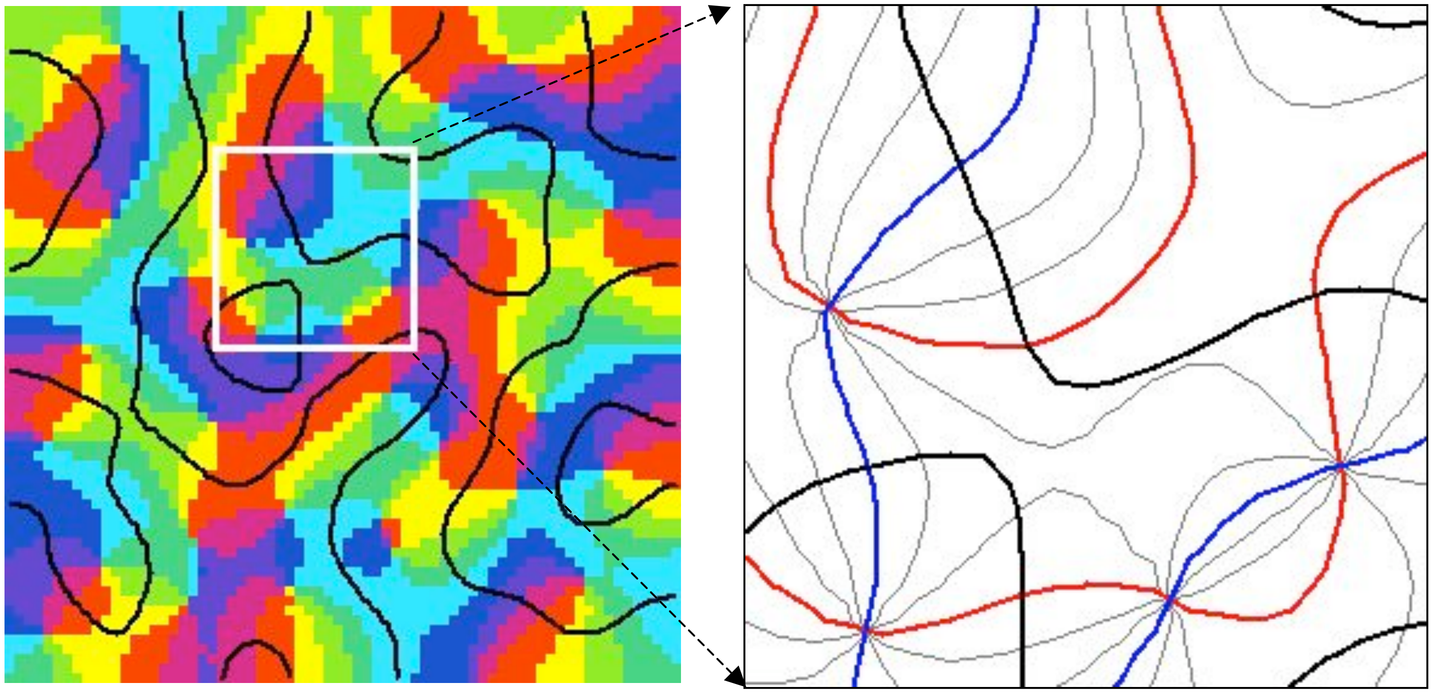
FIG. 2: Simulation results of the OP map using Eq. (1). Maps are generated with $\sigma^2 = 6$, $\varepsilon = 10^{-3}$, $\mu = 0$ (zero temperature), periodic boundary condition and an initially random state in 70×70 lattice.

OP & OD correlations in a spin model

$$H = -\sum_{i,j} \left\{ J_{OP}(r_{ij})(S_i^x S_j^x + S_i^y S_j^y) + J_{OD}(r_{ij}) S_i^z S_j^z \right\}$$

Red : $S_x=0$ (OP, ϕ=0 or $\pi/2$)
Blue : $S_y=0$ (OP, ϕ= $\pi/4$ or $3\pi/4$)

Black : $S_z=0$ (OD, +/- boundary)



OP/OD correlation <= synaptic input normalization & competition

Theoretical predictions are consistent with experiments.

Analogy with vortices in magnetism

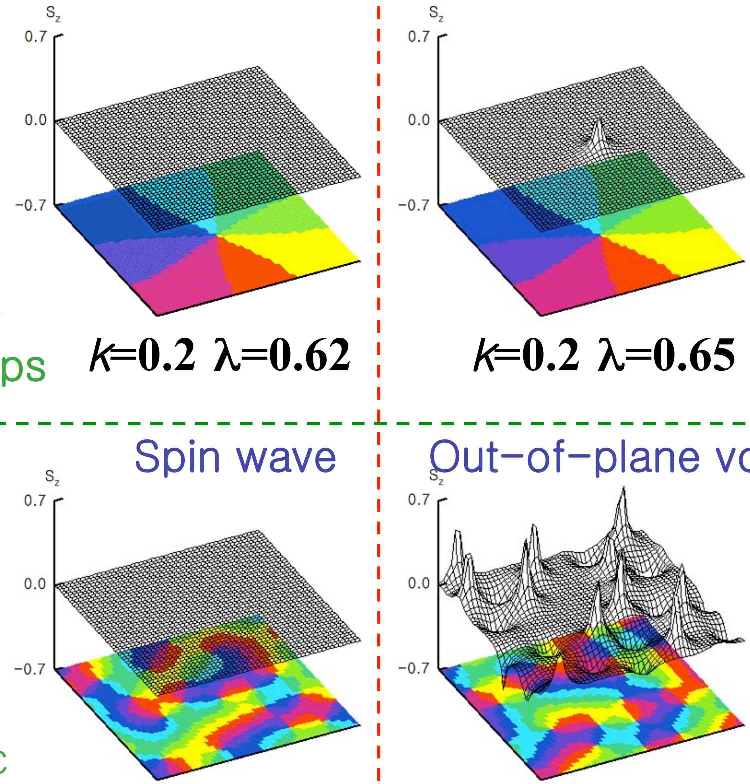
Generalized Model of OP+OD

$$H = -\sum_{i,j}\left\{J_{OP}(r_{ij})(S_i^x S_j^x + S_i^y S_j^y) + J_{OD}(r_{ij})S_i^z S_j^z\right\}$$

Exist bifurcations

– Bifurcation over k (inhibitory strength) :
  homogeneous ⇔ spin waves (OP map)

– Bifurcation over $\lambda \propto J_{OD}/J_{OP}$ (anisotropy)
  in-plane ⇔ out-of-plane vortices (OD map)



k < k c
No OP maps

k=0.2 λ=0.62 | **k=0.2 λ=0.65**

Spin wave | Out-of-plane votex

k > k c
OP maps

k=0.3 λ=0.62 | **k=0.3 λ=0.65**

λ < λ c | λ > λ c

No OD maps | OD maps

OP pinwheels ⇔ in-plane vortices

OD beaded bands ⇔ out-of-plane vortices

* Anisotropic Heisenberg model $H = -K\sum_{\langle i,j\rangle}\left\{S_i^x S_j^x + S_i^y S_j^y + \lambda S_i^z S_j^z\right\}$

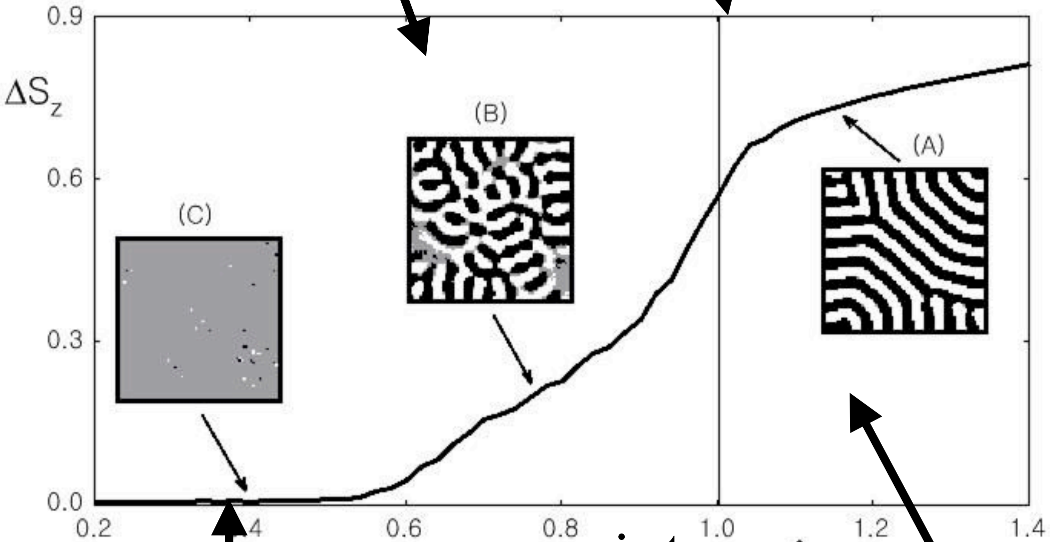
M.W. Cho & S. Kim, PRB, 2004

Different OD map formation in a spin model

OD segregation strength

XY-like

Pure Heisenberg model

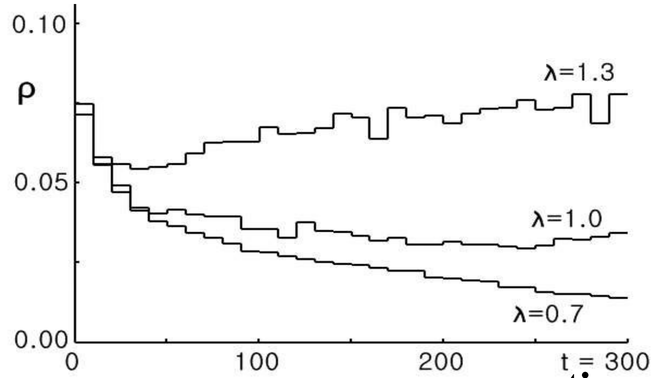


anisotropy λ

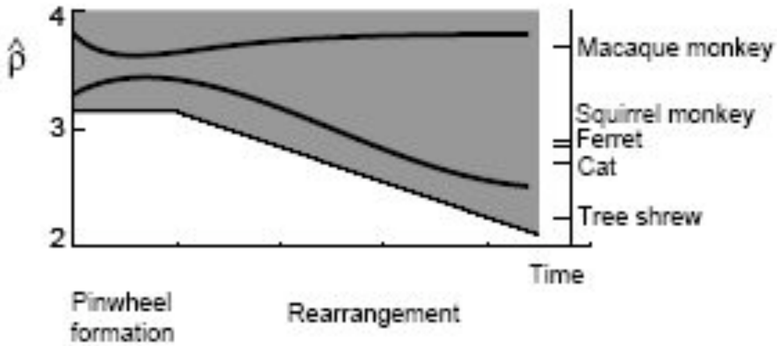
Instability of out-of-plane vortices

Ising-like

Pinwheel density



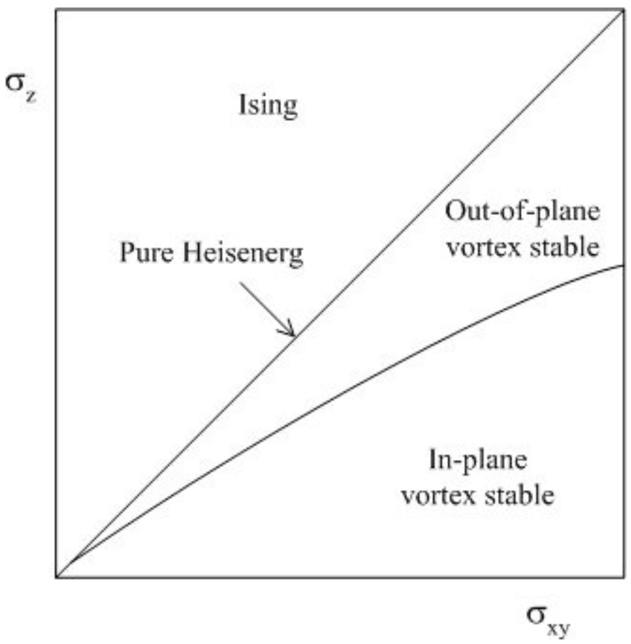
time



Wolf & Geisel, Nature 1998

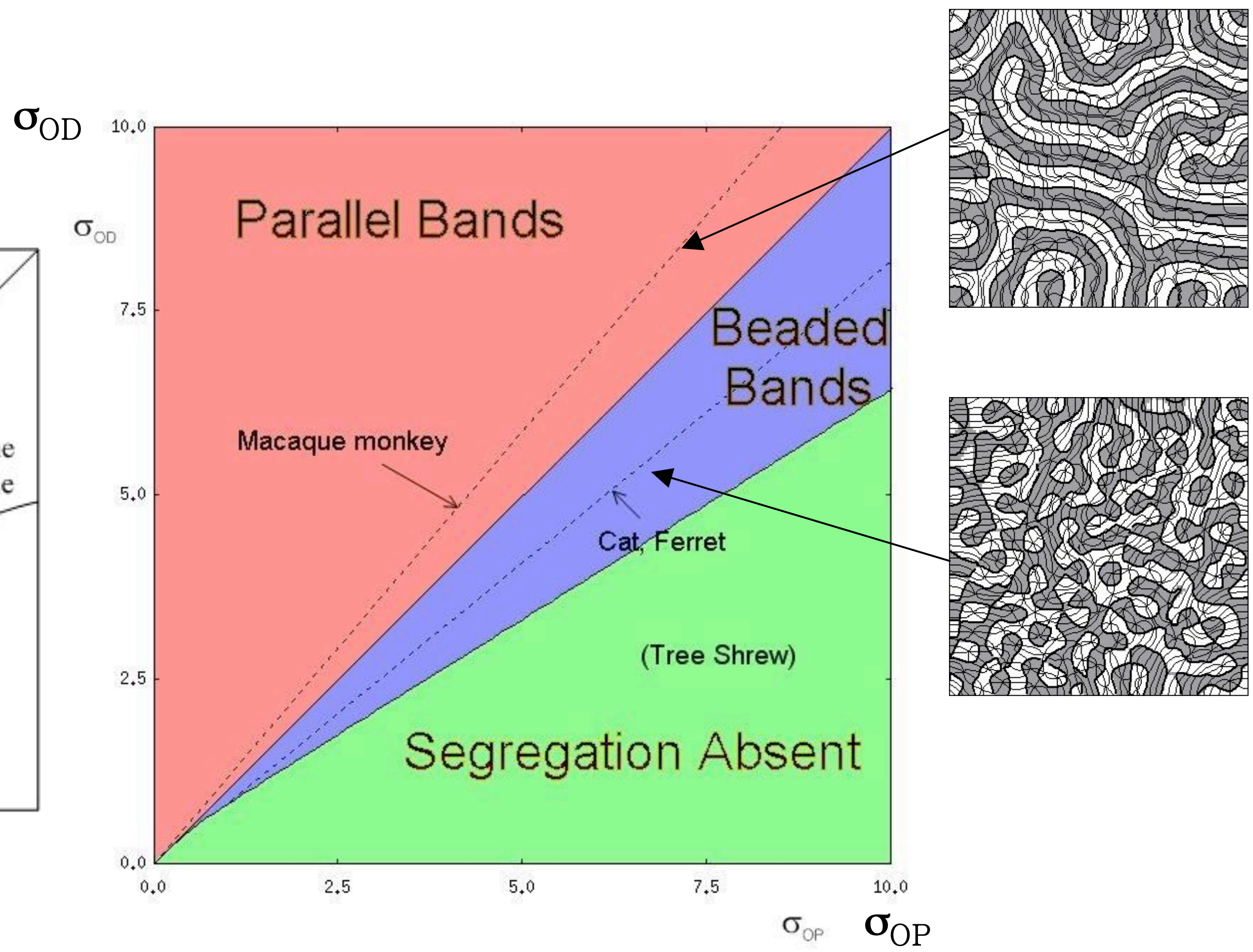
λ : anisotropy between OP and OD columns $\lambda \sim J_{OD} / J_{OP}$

Phase diagram of visual maps



M.W. Cho & S. Kim, Phys.Rev.B , 2004

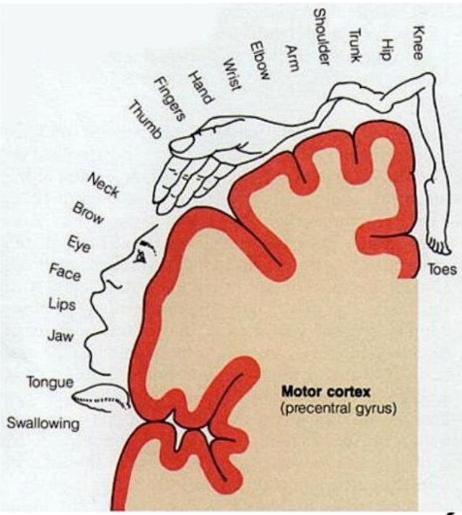
OD maps



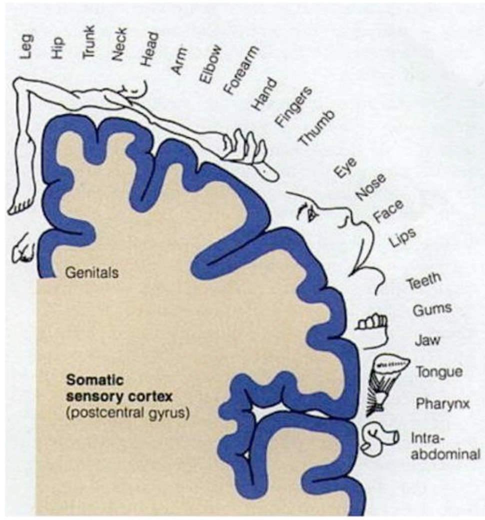
σ_{OP}, σ_{OD}: cooperation range in OP and OD columns

M.W. Cho & S. Kim, PRL, 2005

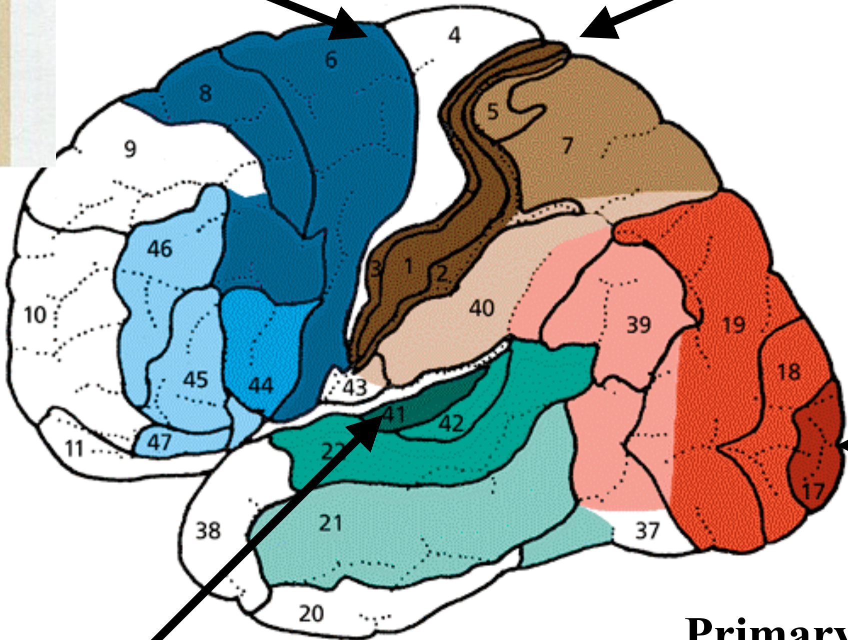
Functional maps in a brain

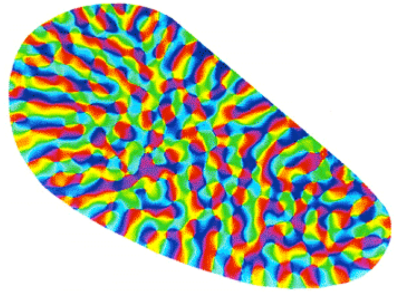


Motor cortex

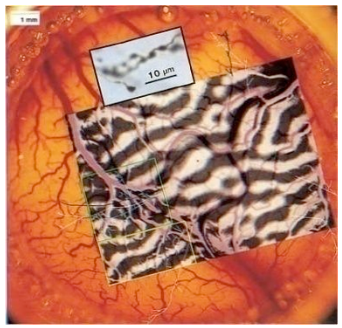


Somatosensory cortex





Orientation preference map



Ocular dominance map

Symmetry breaking

-in order parameter
-in space

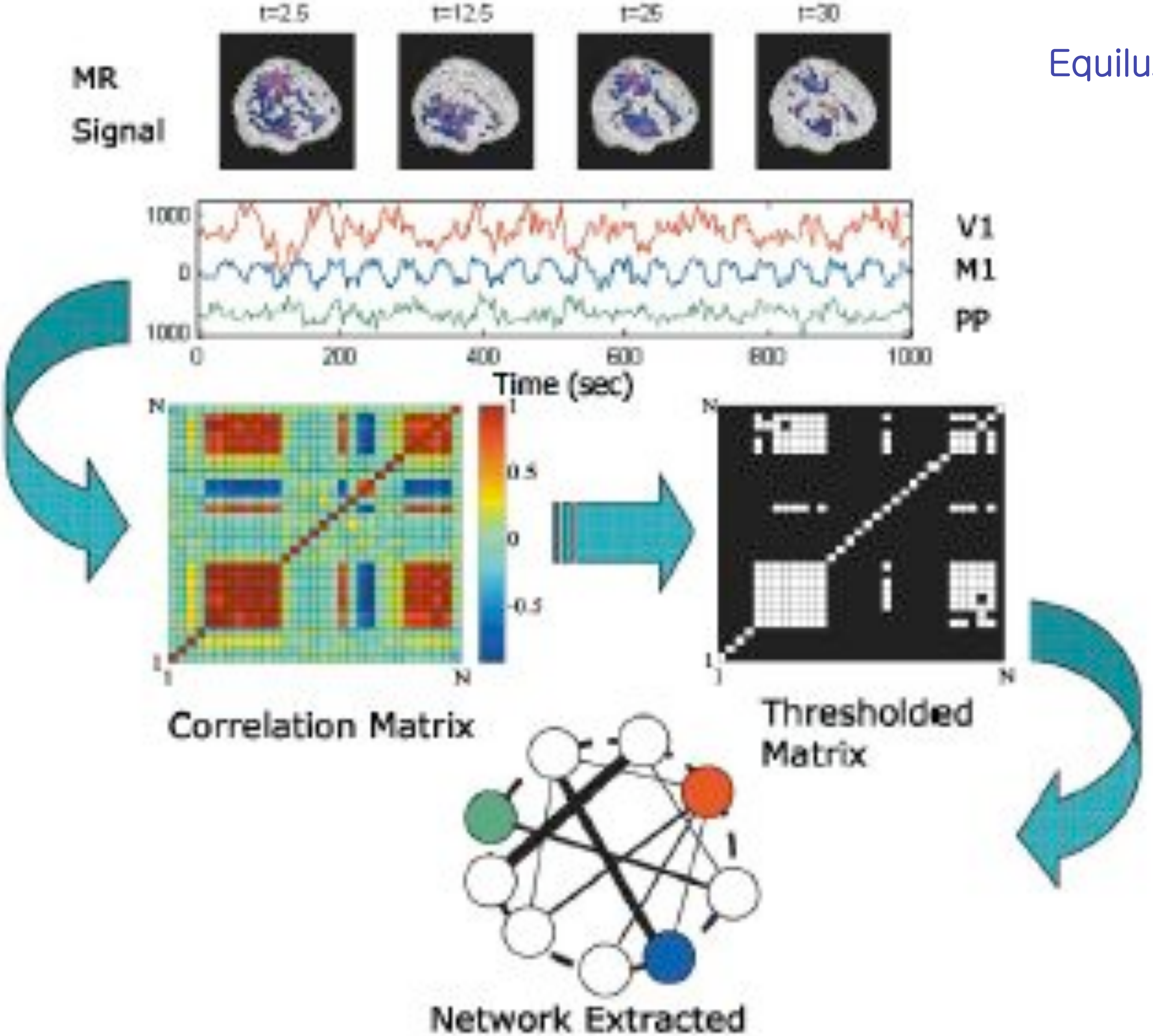
Primary auditory cortex (A1)

Primary visual cortex (V1)

Functional network formation in brain

f-MRIs

Equiluz et al, PRL64 2005

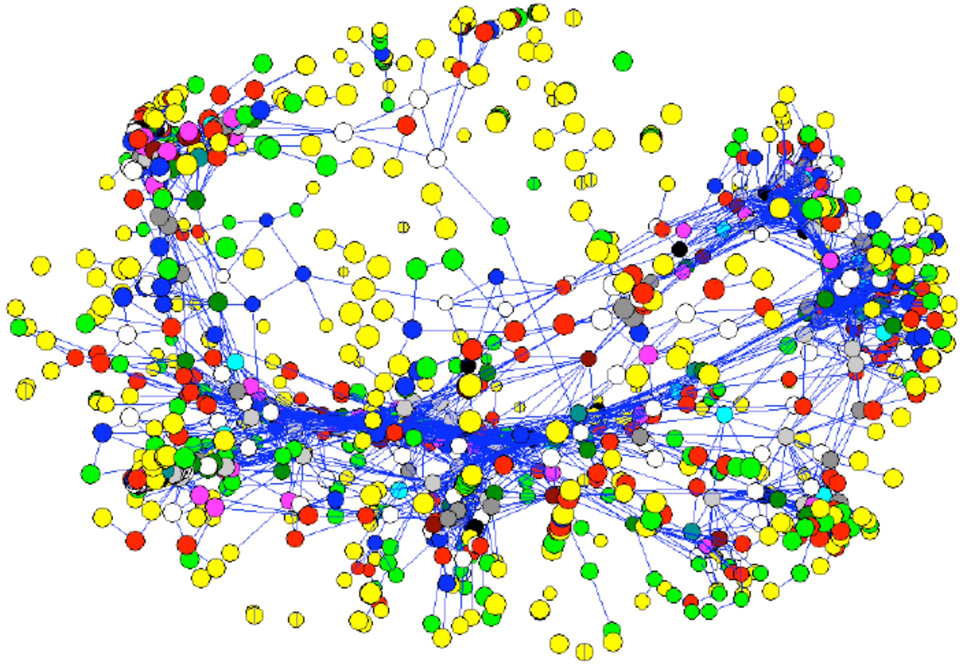


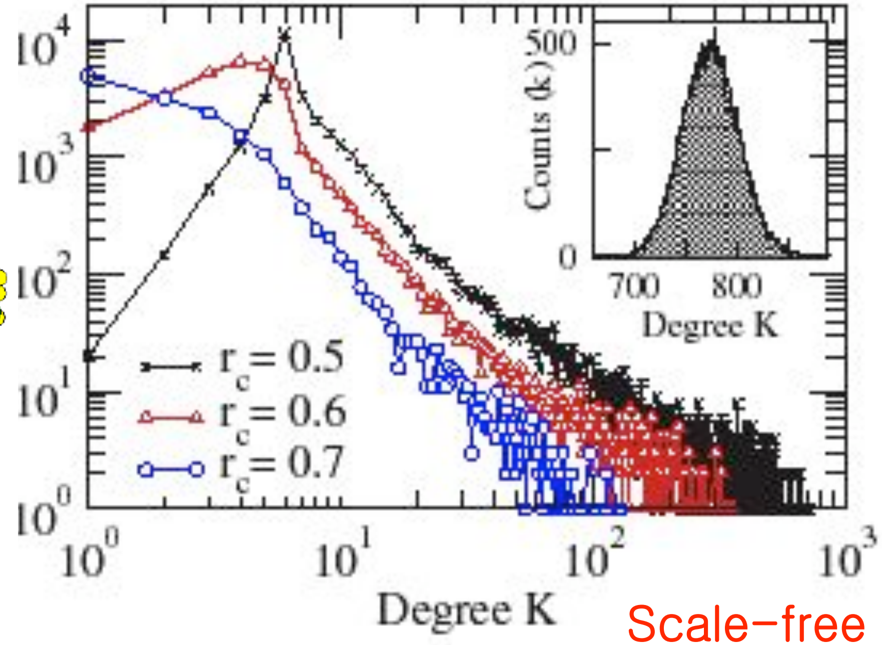
36x64x64 voxels
400 x 2.5s

- •Measure V(x,t)
- •Compute linear correl ations
- •Thresholded matrix
- •Functional networks

Functional networks in a brain

Equiluz et al, PRL64 2005
f-MRI in humans





Scale-free

Robust for seven subjects at different tasks

FIG. 2 (color online). Degree distribution for three values of the correlation threshold. The inset depicts the degree distribution for an equivalent randomly connected network.

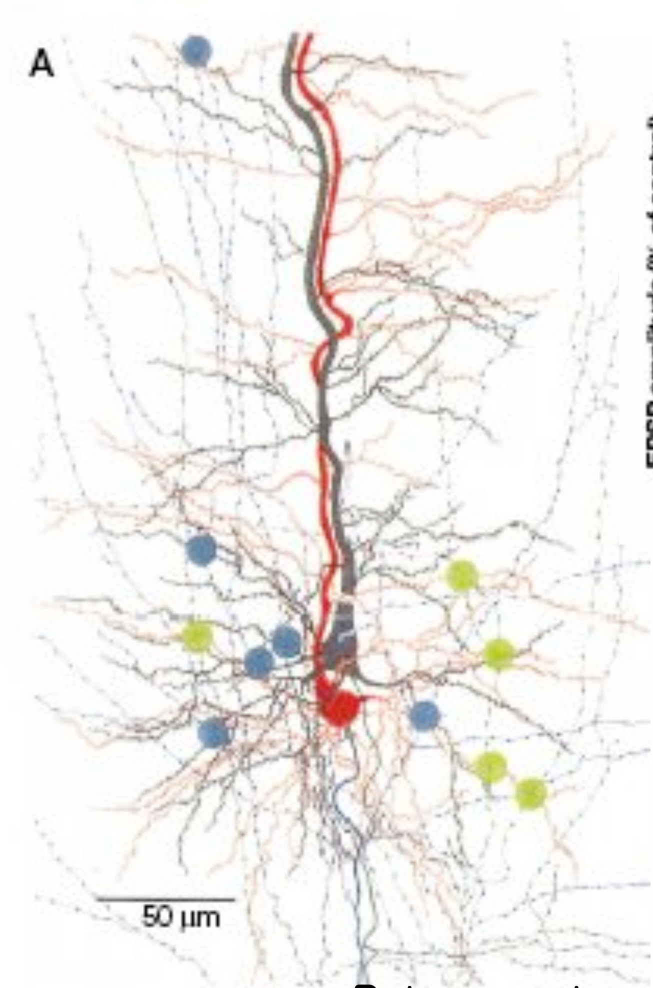
Small-world

r_c	N	C	L	$\langle k \rangle$	γ	$C_{\rm rand}$	$L_{\rm rand}$
0.6	31 503	0.14	11.4	13.41	2.0	4.3×10^{-4}	3.9
0.7	17 174	0.13	12.9	6.29	2.1	3.7×10^{-4}	5.3
0.8	4891	0.15	6.0	4.12	2.2	8.9×10^{-4}	6.0

Previous studies

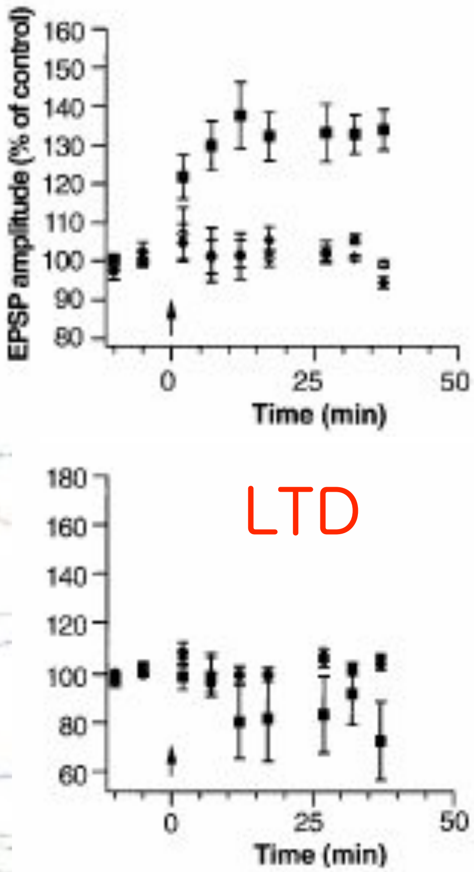
Network	N	C	L	$\langle k \rangle$	γ	$C_{\rm rand}$	$L_{\rm rand}$
C. Elegans	282	0.28	2.65	7.68	not applicable	0.025	2.1
Macaque VC	32	0.55	1.77	9.85	not applicable	0.318	1.5
Cat Cortex	65	0.54	1.87	17.48	not applicable	0.273	1.4

Spike timing dependent plasticity (STDP)



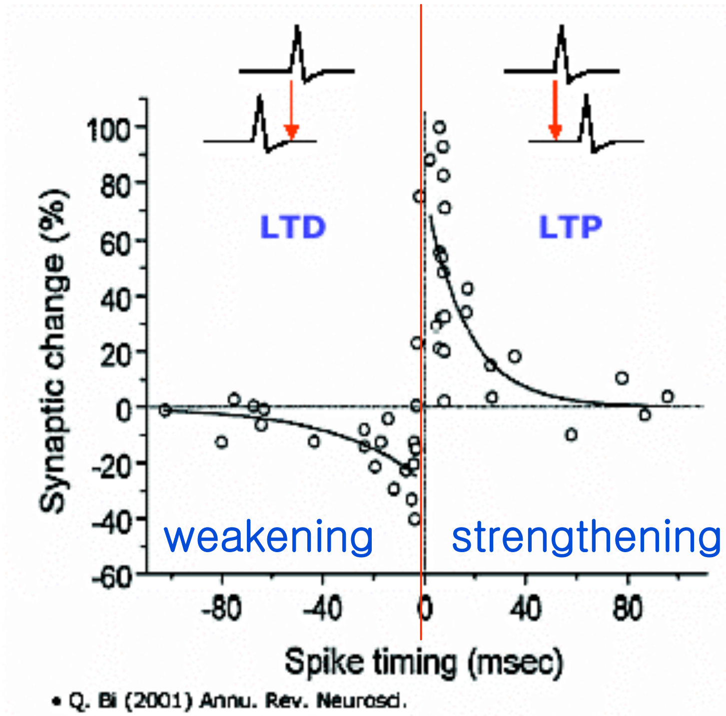
Rat neocortex
Pyramidal cells

LTP



Synaptic
Plasticity

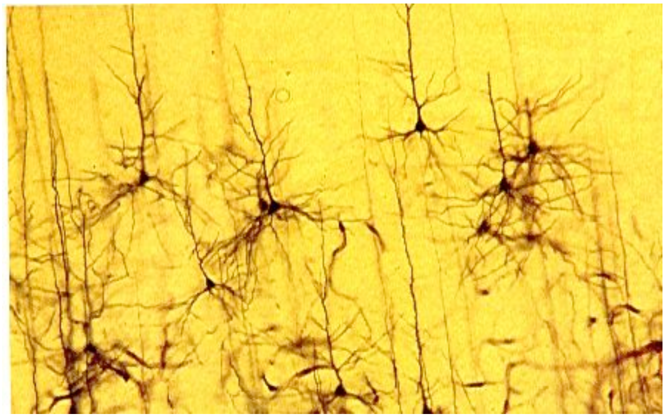
STDP



Temporal order ⇔ synaptic plasticity

Model of a STDP neural network

Dynamic Model of Neural Networks
+ Synaptic plasticity by STDP



Neuron : FitzHugh-Nagumo model

$$\epsilon \dot{v} = I_{ion} + I_{syn} + I_{ext}$$

$$\dot{w} = v - w - b$$

$$\tau_{syn} \frac{dg_{ij}}{dt} = -g_{ij}$$

$$I_{ion} = v(v-a)(1-v) - w$$

$$I_{syn}(t) = \sum_{j \neq i} [g_{ij}(t)(V - v_i(t)) + \bar{g}_{ij}(t)(\bar{V} - v_i(t))]$$

excitatory inhibitory

Initial all-to-all coupling

Synapse : STDP

$$W(\Delta t) = \begin{cases} A_+ \exp(-\Delta t/\tau_+) & \text{if } \Delta t > 0 \\ -A_- \exp(\Delta t/\tau_-) & \text{if } \Delta t < 0 \end{cases}$$

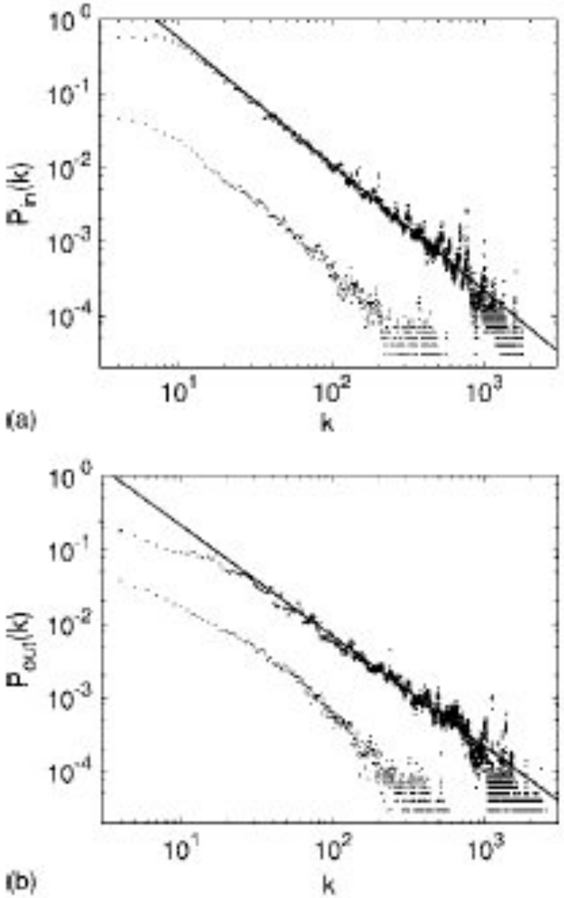
$$\Delta G_{ij} = G_{ij} \cdot W(\Delta t) \qquad 0 < G_{ij} \leq G_{max}$$

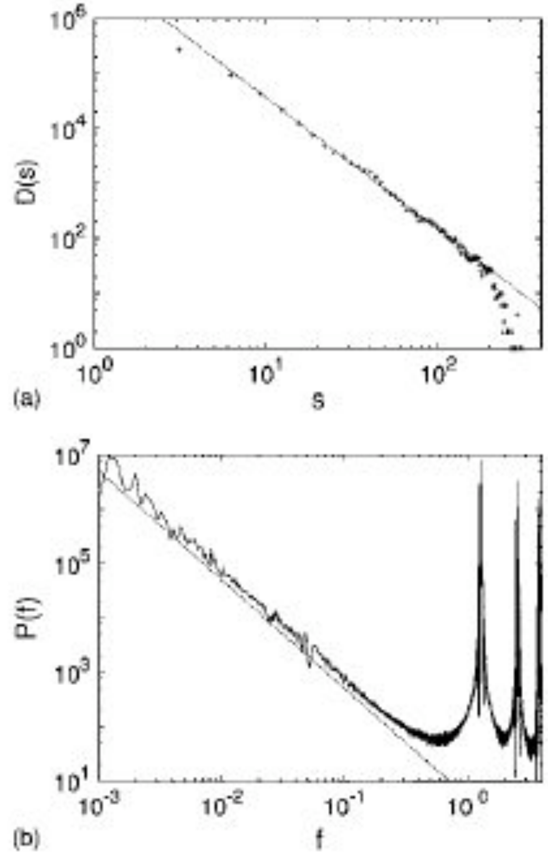
$$\bar{G}_{ij}(t) = G_{inh}$$

Q: How does the functional ne
work emerge through self-org
anization?

Dynamics ⇔ Structure
- Activity dependent development

Complex network formation through self-organization





- Sparse, small world
- Scale-free properties

- Self-organized criticality

Fast, high coherhence & fast, strong synchronization
=> Dynamically more effective and structurally more robust

C. W. Shin & S. Kim, PRE, 2006

Functional pathways in EEGs

Cooperating with Dep. Anesthesiology, Hyundae Asan Hospital, Seoul, Korea

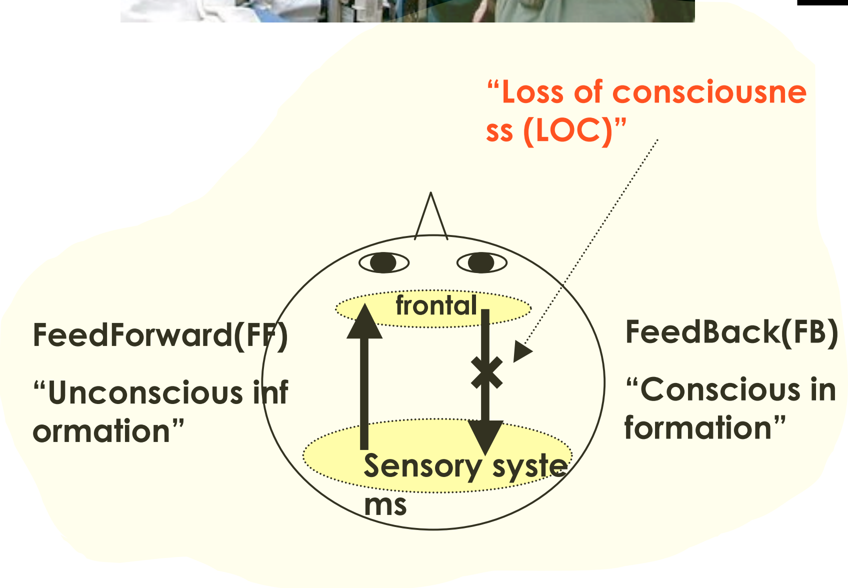
Want to understand the correlation between the feed back integration in the frontal-posterior network with conscious information processing in brain.

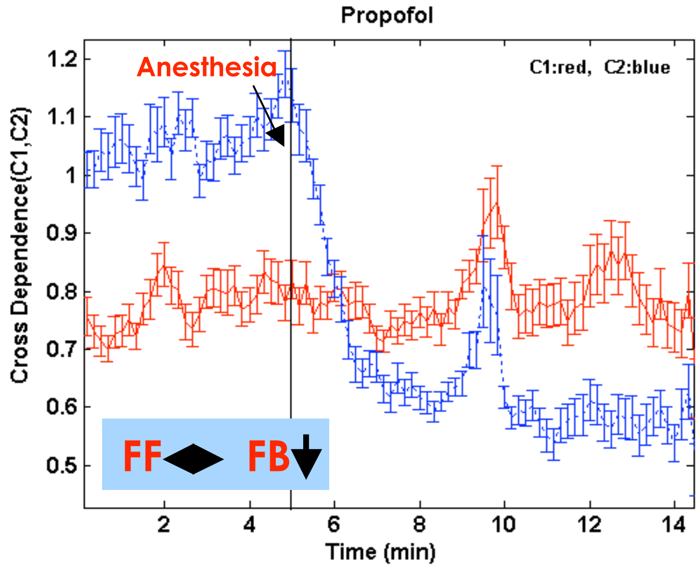
↓

Anesthesia experiments with human subjects

↓

Analysis based on the Information Flow of EEG.



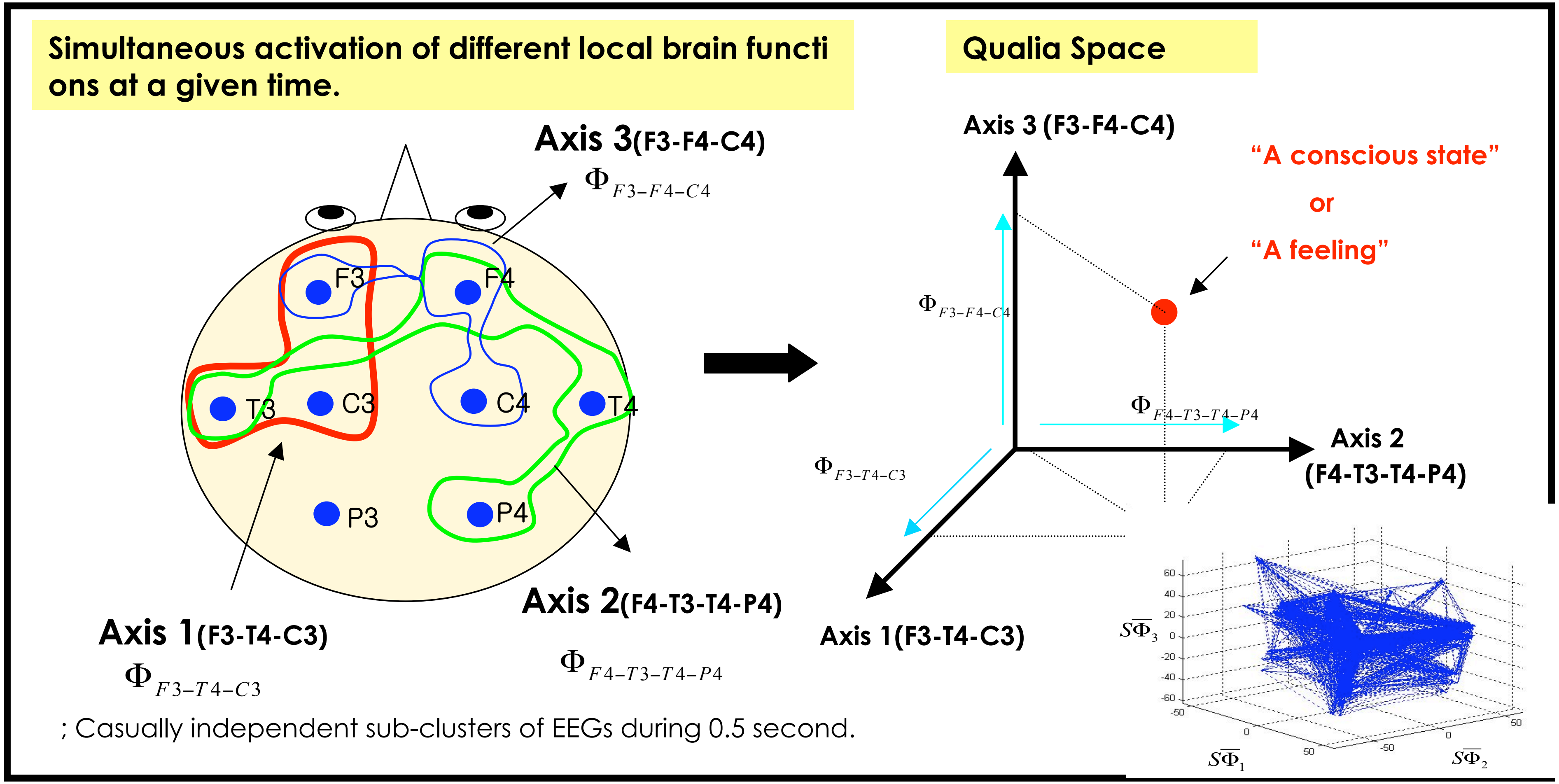


U.C.Lee, S. Kim, G.J. Nho, B. M. Choi, 2007

Dynamics of consciousness in qualia space of EEG

Research Goals:

1. Development of a way to reconstruct the qualia space with EEG
2. Investigation of time evolution of conscious state.



U.C.Lee, G.J. Nho, B. M. Choi, S. Kim, preprint, 2007

Brain : Frontier of complex systems

- Studies of functional self-organization in brain (NCSL)
  - Map formation in visual cortex : M.W. Cho & S. Kim, PRL '04, PRL '05, PRB '05
    Functional development of asymmetry and area differentiation, preprint, '07
  - Functional complex network formation by STDP : C.W. Shin & S. Kim, PRE '06
  - Orientation tuning through synchronization : S.-G. Lee & S. Kim, PRE, '05
  - Functional networks in EEG : U.C. Lee & S. Kim, PRE, '06, preprint, '07

- Brain : Paradigm for complex biological systems
  - Highly nonlinear neuron, and complex network structure
  - Self-organization and activity dependent neural plasticity

- Fertile interdisciplinary grounds for new quantitative methods

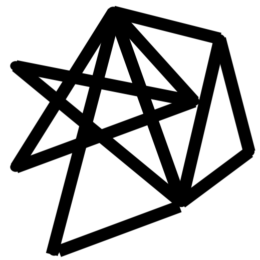
  Nonlinear Dynamics + Statistical Mechanics + Computations

  ⇒ Understanding biocomplexity of the nervous system & its role in brain function

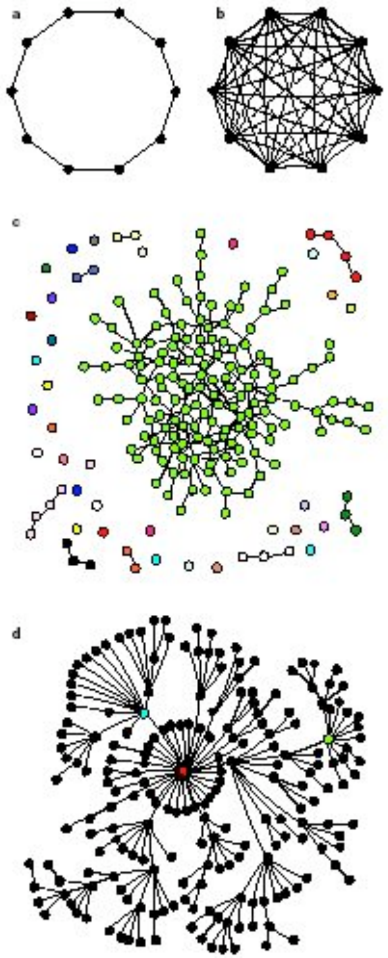
Work in progress and challenges ahead!

* One of the 10 unsolved problems in physics! *IOP,1999

Complex networks



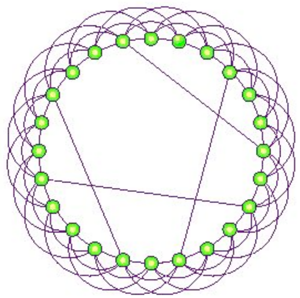
- Networks
  - node → network
  - regular, random, complex networks
  - Bionetworks, www, internet, airport, social relations



Strogatz, Nature 410, 268 (2001)

Q. Network structure vs functions?

Eg. Robustness, efficiency



- Complex networks
  - Small World networks
    - Short path length : "six deg. of seperation"
    - High clustering : A->B, B->C => A->C
  - Scale-Free networks
    - Degree distribution : Power-law $p(k) \sim k^{-\gamma}$

    <cf> random networks : Poisson distribution

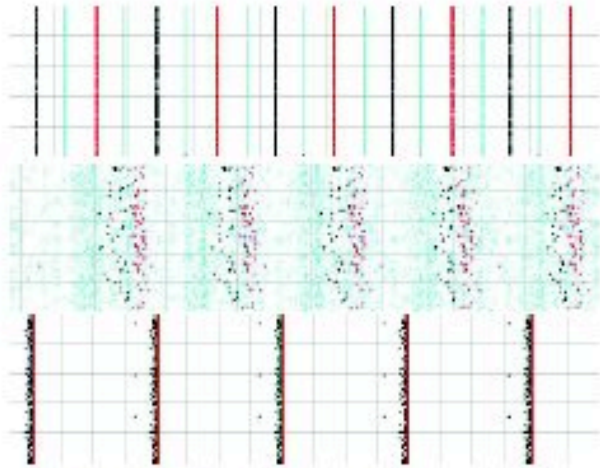
Functional Structure by STDP

Globally coupled network

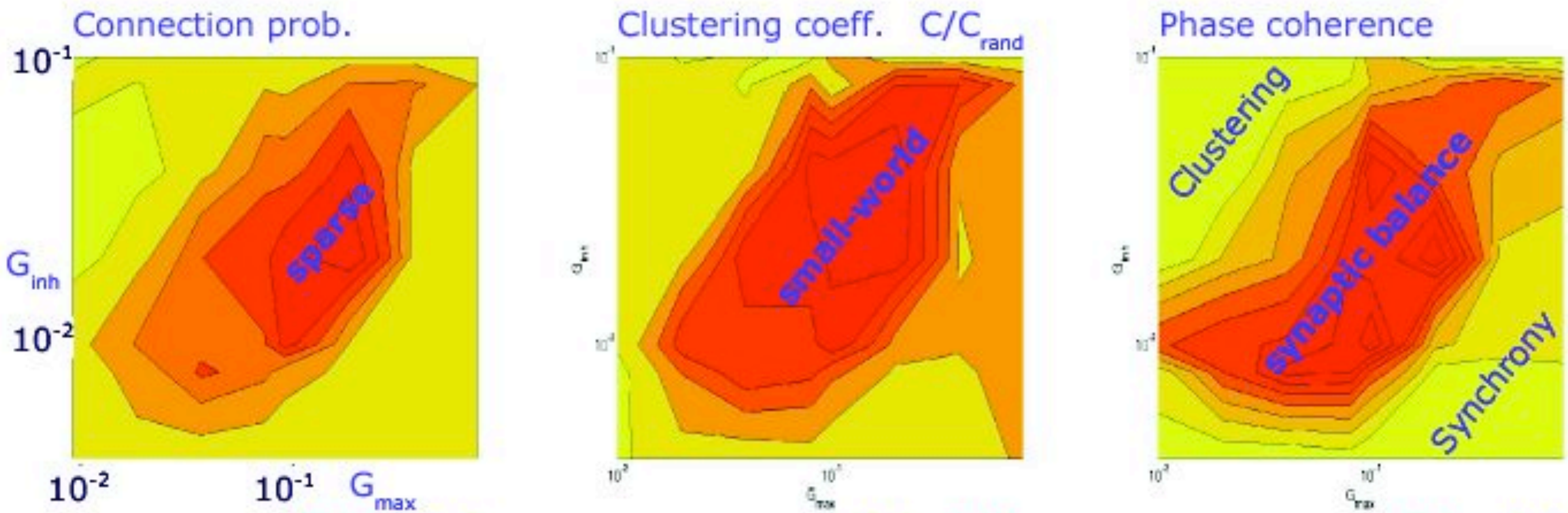
STDP

Functional Structure

cluster



synchrony



0.03 ~ 0.6

0.5 ~ 8.0

Fraction of connections between maximal connected neighbours

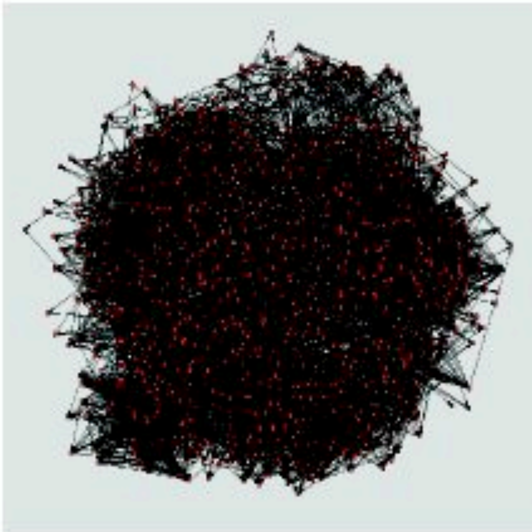
0.4 ~ 1.0

Degree of phase coherence among clusters

Small-world and Scale-free Network

Small-world properties

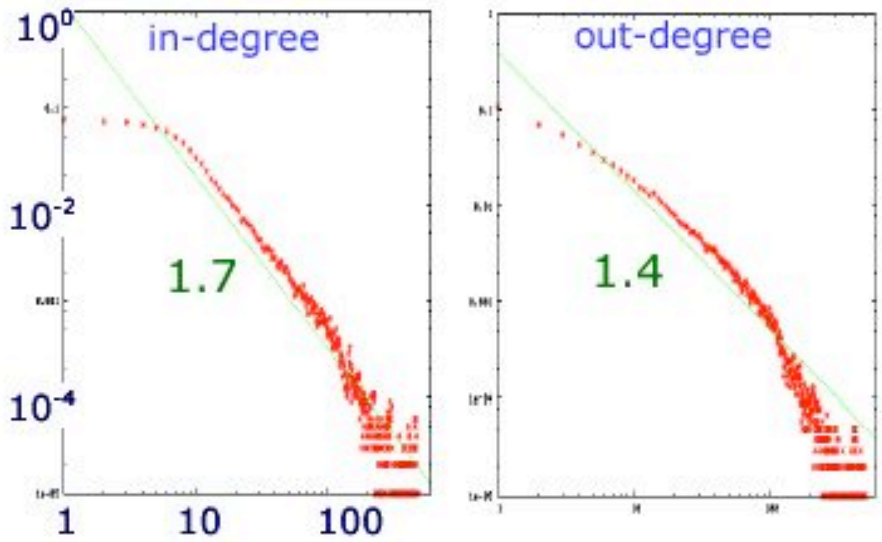
- clustering coefficient
  - C = 0.23 >> Crand = 0.03
- Average path length
  - L = 3.19 ~ Lrand = 2.03



Scale-free properties

- Degree distributions

$$P_{in}(k) \sim k^{-\gamma_{in}}$$
$$P_{out}(k) \sim k^{-\gamma_{out}}$$

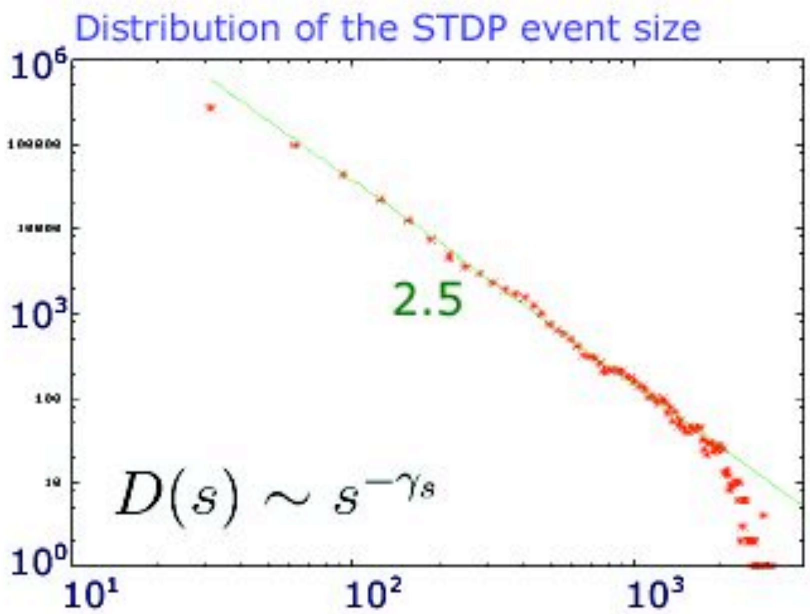


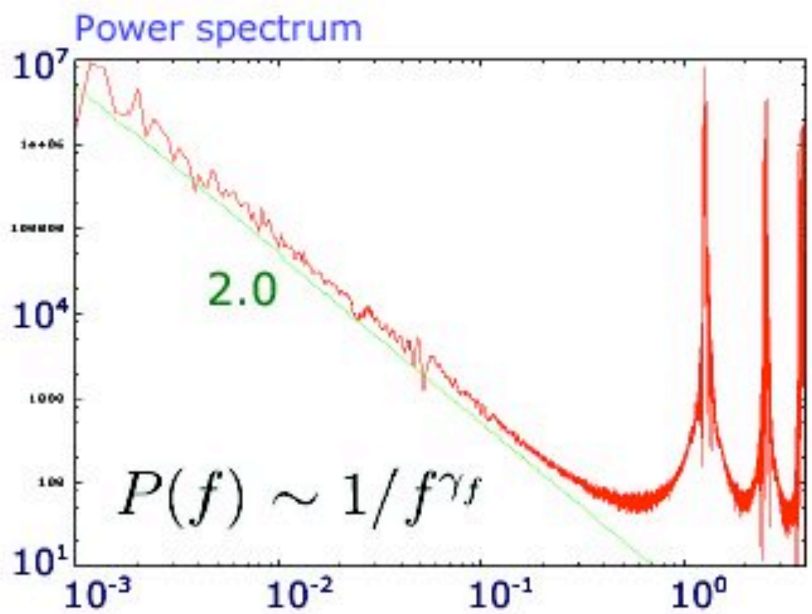
G_{max} =0.2, G_{inh}=0.02

Self-organized Criticality

Quasi−steady state in ne
twork properties

Fluctuation of synaptic coupling strength





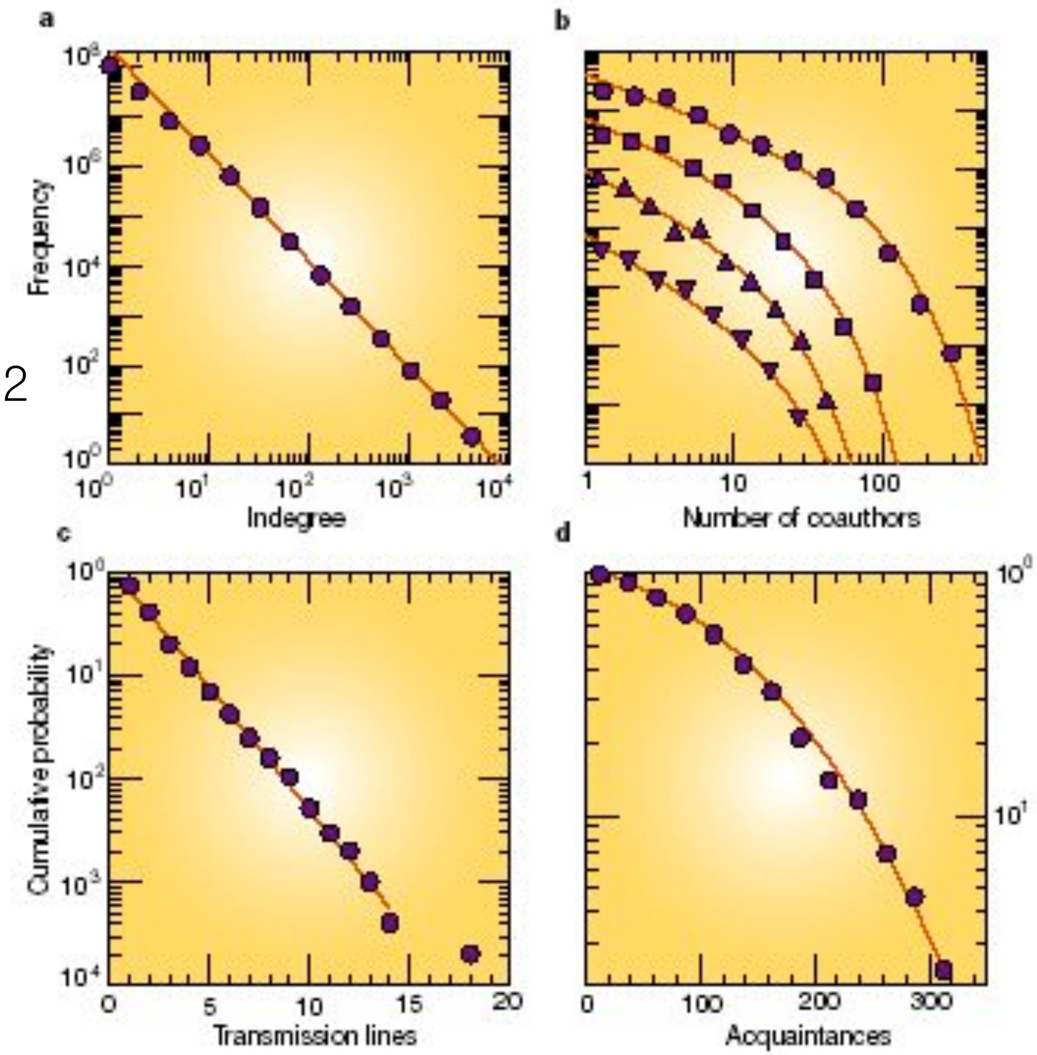
- Functional strucure lies in a self-organized critical state
- STDP events have no long-time correlation

Phase flips propagate in an avalanche manner

<cf> sandpile

Diverse networks

WWW
Scale-free γ=2.2

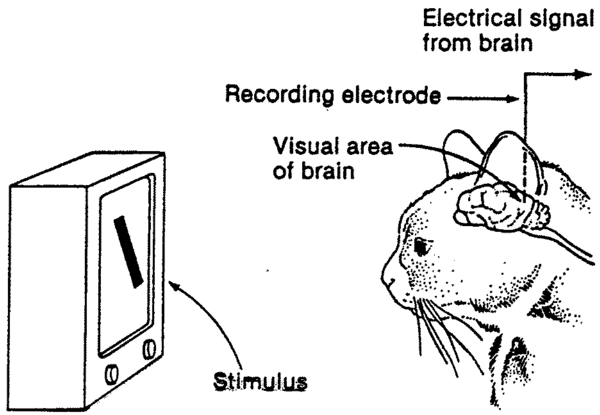


Coauthorship
(arxiv.org,.SPIRES,NCSTRL)
Exponential cutoff

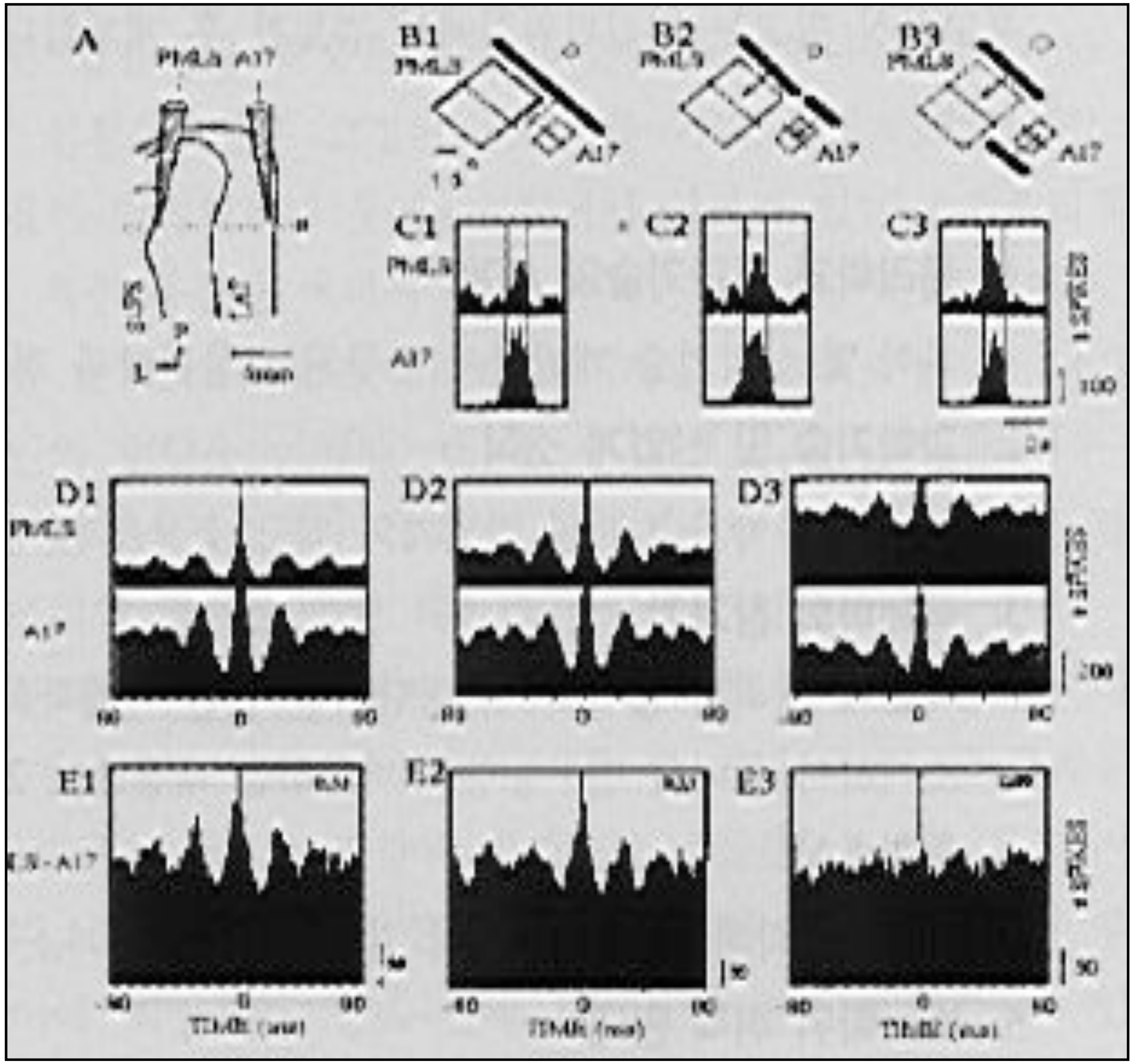
Power grid
exponential

Social (Mormon)
Gaussian

Synchrony in cat visual cortex



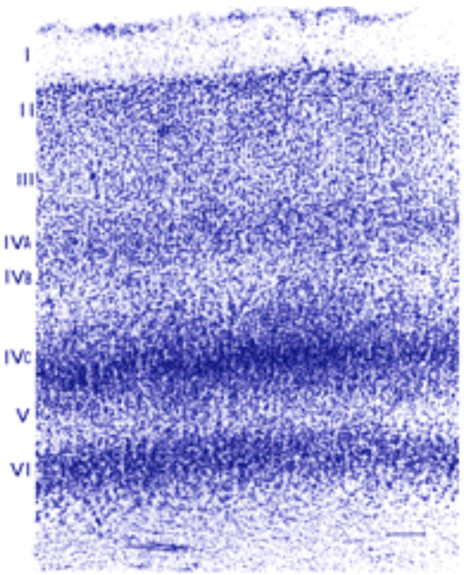
- Neurophysiological experiments on neuron pairs far apart
- Observation: Stimulus dependent, long-range synchronization
- Synchronization – same orientation columns
- Non-synchronization – different orientation columns



Engel et al, 1990

Orientation columns in visual cortex

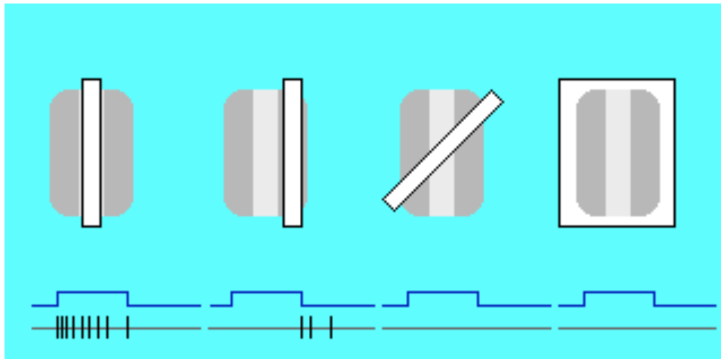
Q: How do neurons become selective to a stimulus?



Visual cortex

Orientation selectiviey

Hubel & Wiesel, 1959



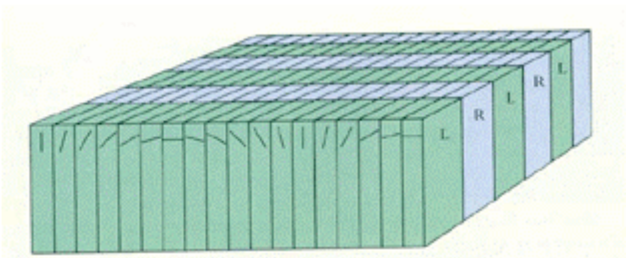
Elongated patterns of convergence fro m thalamic inputs

Observations:

LGN input weakly tuned. Fester et al, 1990

Orientation selectivity is sharp ~ 18^{o}

Q: How is the weakly tuned input from LGN sharpened?



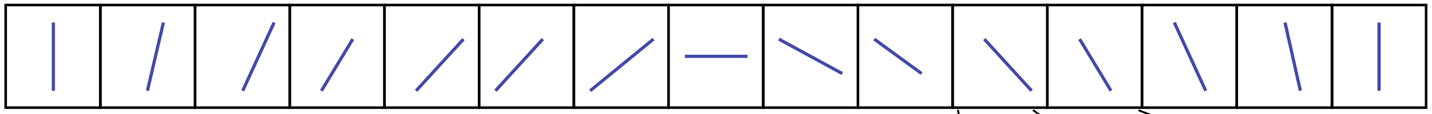
Orientation columns

Orientation tuning <= Intracortical connections?
relevance to synchronization?

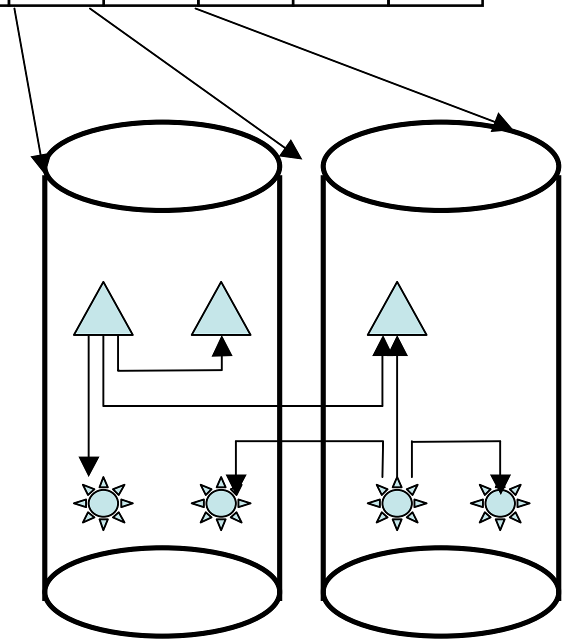
Q: Why is the orientation tuning not dependent on contrast?

Contrast invariance

Orientation Column Model



Spiking neuron model at subcolumnar level



Orientation columns

Synaptic connection model

- **All-to-all excitatory within a column**
- **All-to-all excitatory between neighboring columns:**
  Connection strength 15 % smaller
- **Inhibitory cells in the same column receive same inputs**
- **Global inhibitory to all excitatory cells**
- **Global inhibitory to all inhibitory cells**

Neuron & synapse models

- **Hodgkin-Huxley neurons:**
- **α synaptic coupling (Jack, 1975)**
- **Correlated noisy current :**
  Ornstein-Uhlenbeck

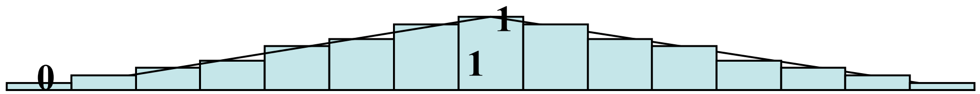
Lee, Tanaka, Kim, 2004

- **A column → 12 excitatory cells + 3 inhibitory cells**
- **Angular difference : 12.85**

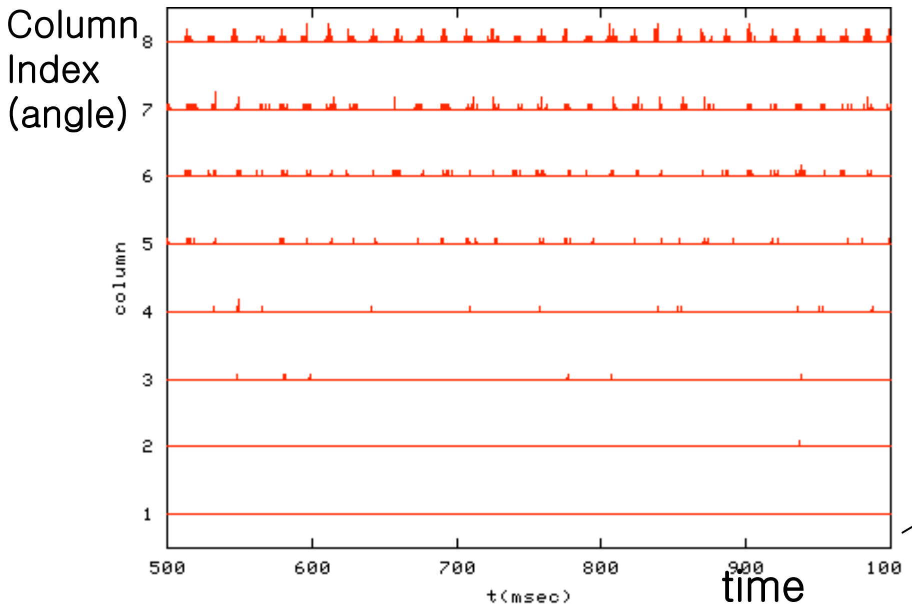
225 neurons

Orientation tuning

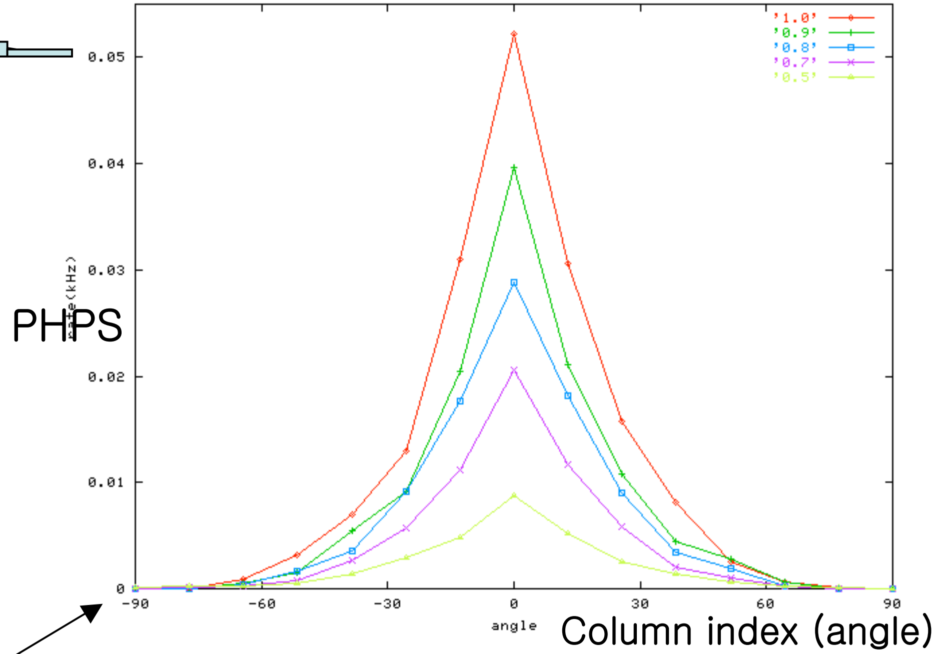
S.G. Lee & S. Kim, 2004.



Weakly tuned LGN input



Orientation tuning curve



- Orientation selectivity through synchronization ~17°
- Contrast invariance

- **Quantifiers**
  - **Averaged firing rate of all columnar cells**
  - **PHPS (peak height of power spectrum) for synchrony**

=> Robust

- **Noise**
- **Type I and Type II neurons (IF neurons)**
- **Different synapses (e.g. Kinetic synapse model)**
- **Size independence (# of neurons/# of columns)**