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Influence of stochastic processes in the brain neural network on cognitive functions:

Modeling and experiments

- *Alexander N. Pisarchik*

Center for Biomedical Technology
Technical University of Madrid, Spain

CTB center for biomedical technology

POLITÉCNICA "Ingeniamos el futuro"

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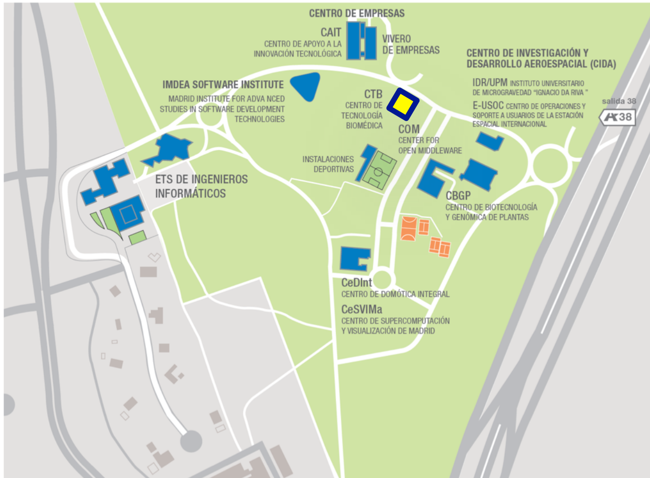
CENTRO DE TECNOLOGÍA BIOMÉDICA

UNIVERSIDAD POLITÉCNICA DE MADRID

Sep. 2011 Permanent seat at CTB Building, Montegancedo Campus



CTB Laboratories

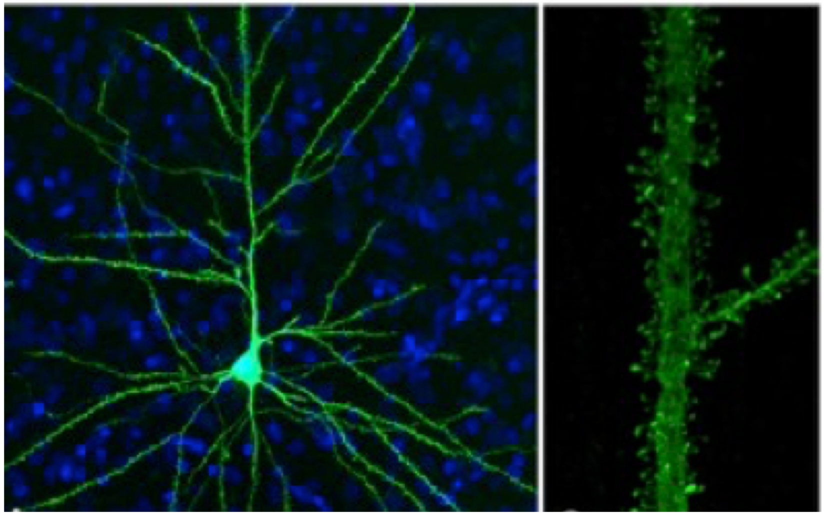
#	Laboratory	Partner	Area
1	Adv. Appl. Mathematics to Complex Systems	UPM-URJC	Basic
2	Biological Networks	UPM-URJC	
3	Medical Data Analytics		
4	Bioinstrumentation and Nanomedicine		Devices/ Biomaterials
5	Biomaterials and Regenerative Engineering		
6	Optics, Photonics and Biophotonics		
7	Surgical training and image guided surgery		
8	Cajal Cortical Circuits Laboratory	UPM-CSIC	Neuro/ Brain Science
9	Clinical Neuroscience		
10	Cognitive Neuroscience	UPM-UCM	
11	Experimental Neurology		
12	Neuromorphic Speech Processing		
13	Neurorehabilitation Engineering		
14	Ageing Lab	UPM-FIBHUG	Health
15	ICT for personalized medicine		
16	Personal Health Systems		

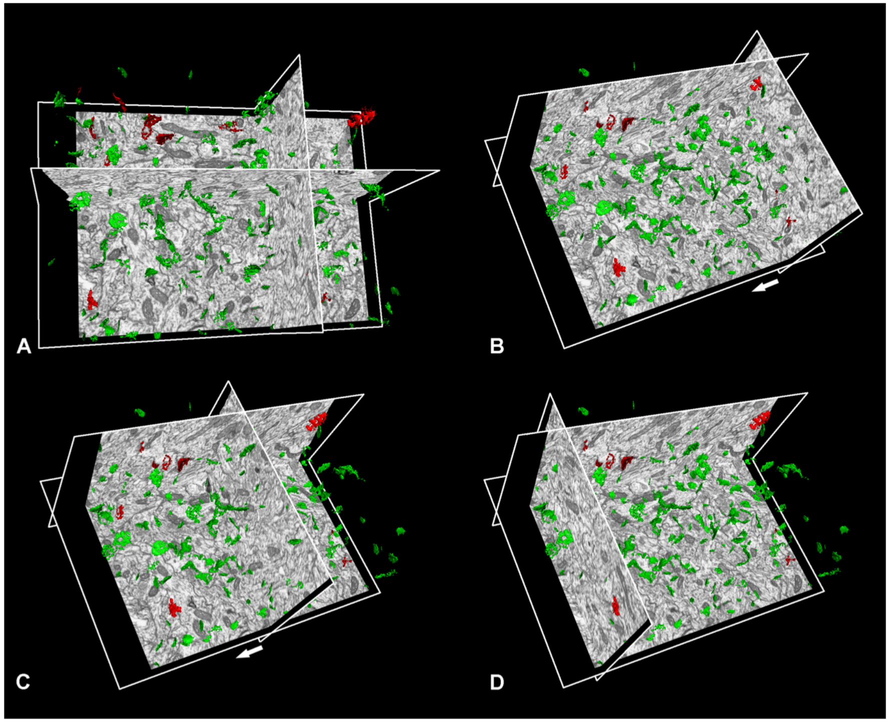
center for biomedical technology

Human Brain Project

POLITÉCNICA

2013-2023 1.2B€

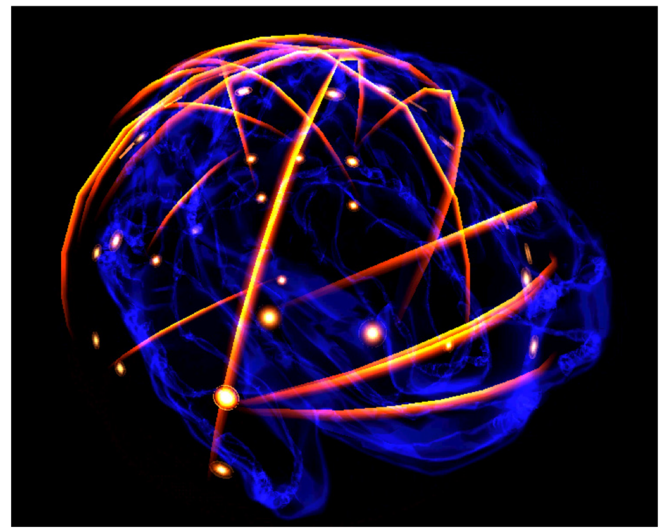




Subproject 1 - Mouse Brain Organisation

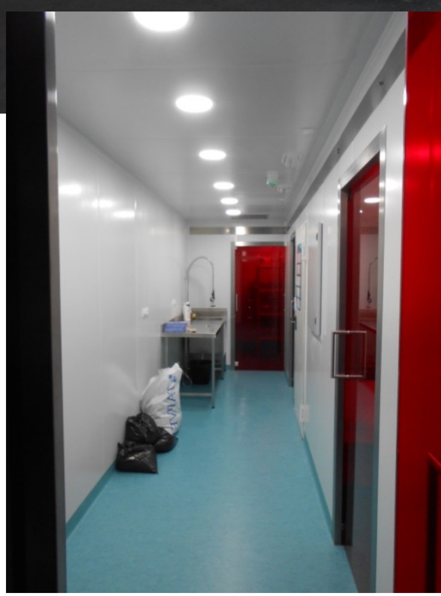
MEG facility

Elekta-Neuromag Magnetoencephalometer (306 sensors)



- *funcional analysis*
- *hight time & space resolution*

Animal facility



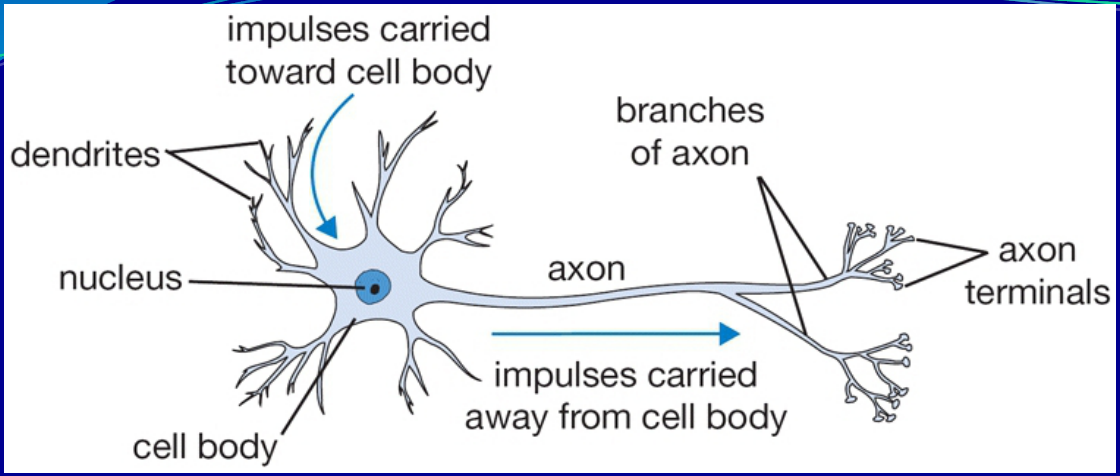
- *housing*
- *husbandry*
- *surgery*

- *small rodents*
- *GMO's*

Contents

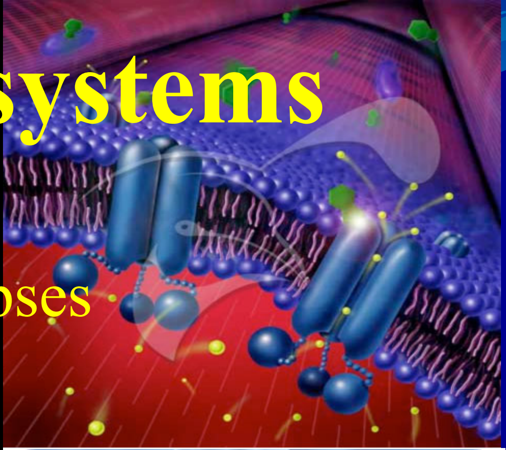
- Sources of stochastic brain activity
- Basic actions of brain noise
- Noise-induced coherence resonance
- Measuring brain noise
- Brain noise and attention
- Decision-making uncertainty

Brain neural network: network of networks



Human brain contains approx **86 billions of neural cells** (nodes). The neurons receive electrochemical signals from dendrites and transmit them through axons. Each neuron has approx. **10000 synapses** (links).

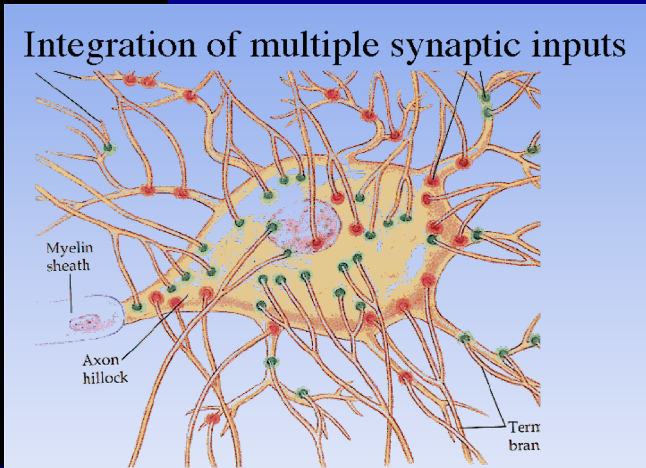
Sources of noise in neural systems



Endogenous noise:

- Quasi-random release of neurotransmitters by synapses
- Random synaptic input from other neurons
- Random switching of ion channels
- Stochasticity in N-methyl-D-aspartate activated receptors which affect the stability of short-term memory and attention
- Random alteration of gamma-amino-butyric acid receptor which activates synaptic ion channel conductances and determine how likely the system jumps into a pathological state

G. Deco, E. T. Rolls, R. Romo, Stochastic dynamics as a principle of brain function," Progress in Neurobiology 88, 1 (2009)



Exogenous noise:

- Environmental noise (temperature, pressure)
- Random stimulation (auditory, visual, taktil)

Why brain noise is important

Stochastic brain activity underlies important mechanisms of brain functionality and self-organization. It plays important advantageous role in signal detection and decision-making by preventing deadlocks.

◆ Human Brain Mapping 29:810–817 (2008) ◆

fMRI study reflects hemodynamic alterations related to brain functions.

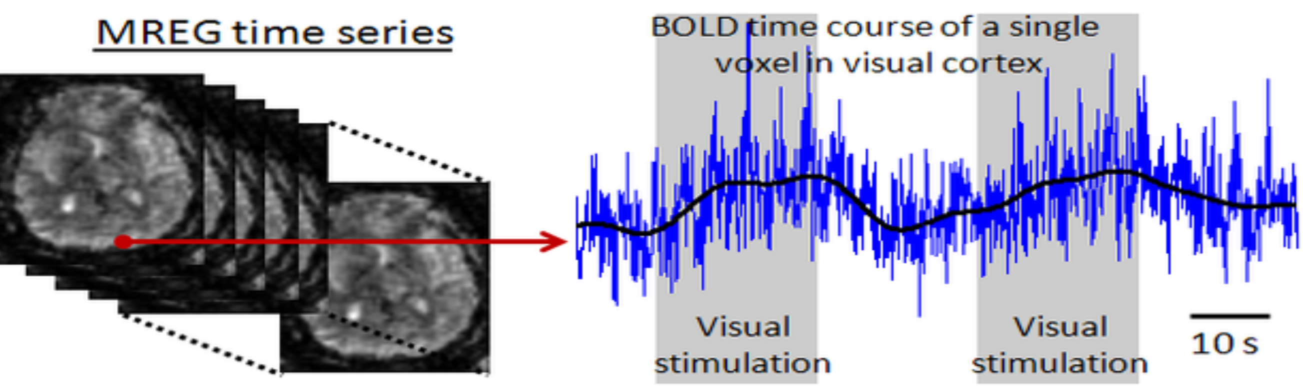
REVIEW ARTICLE

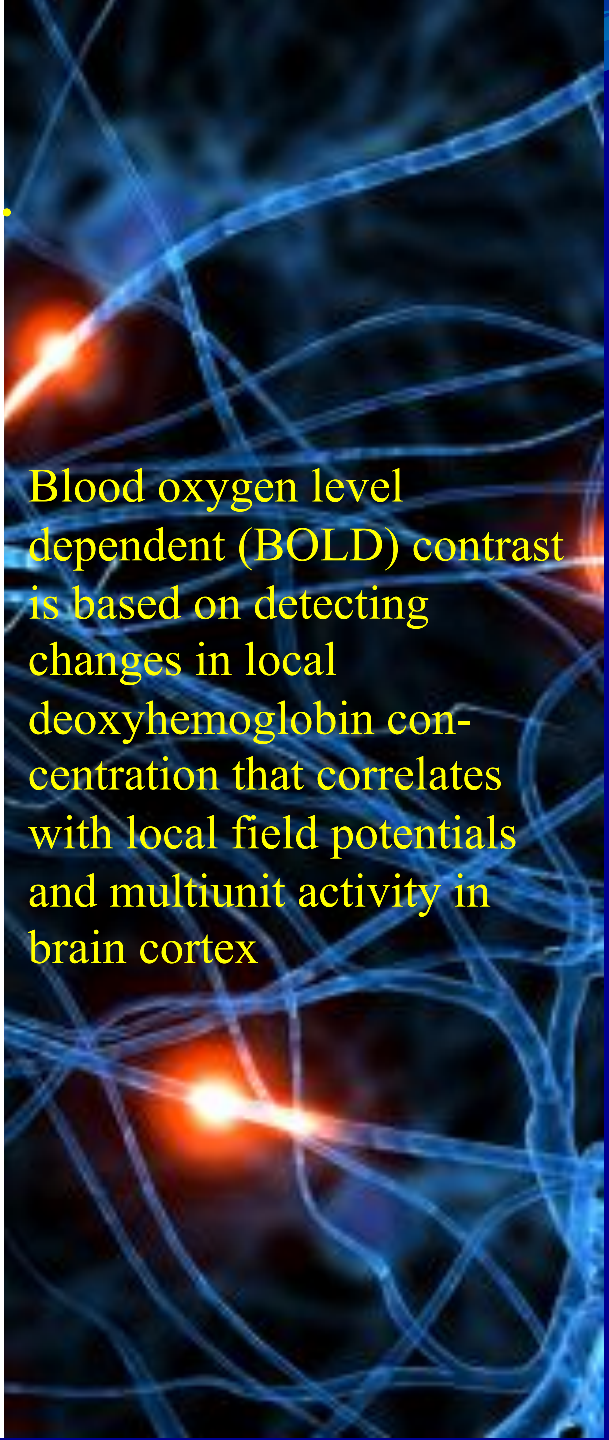
Endogenous Brain Fluctuations and Diagnostic Imaging

Vesa Kiviniemi*

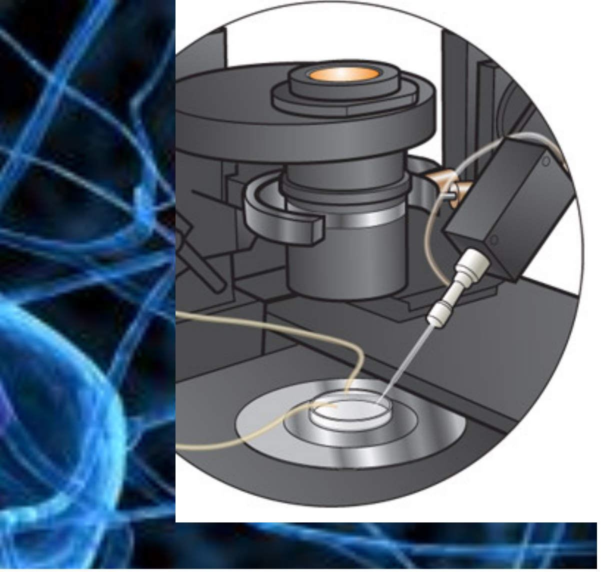
Department of Diagnostic Radiology, University of Oulu, Oulu, Finland

Abstract: Much of the rising health care costs in aging populations can be attributed to congenital disease and psychiatric and neurologic disorders. Early detection of changes related to these diseases can promote the development of new therapeutic strategies and effective treatments. Changes in tissue, such as damage resulting from continued functional abnormality, often exhibit a time-delay before detection is possible. Methods for detecting functional alterations in endogenous brain fluctuations allow for an early diagnosis before tissue damage occurs, enabling early treatment and a more likely positive outcome. A literature review and comprehensive overview of the current state of knowledge about endogenous brain fluctuations is presented here. Recent findings of the association between various pathological conditions and endogenous fluctuations are discussed. A particular emphasis is placed on research showing the relationship between clinical measures and pathological findings to the dynamics of endogenous fluctuations of the brain. Recent discoveries of methods for detecting abnormal functional connectivity are discussed and future research directions explored. *Hum Brain Mapp 29:810–817, 2008.*





Blood oxygen level dependent (BOLD) contrast is based on detecting changes in local deoxyhemoglobin concentration that correlates with local field potentials and multiunit activity in brain cortex



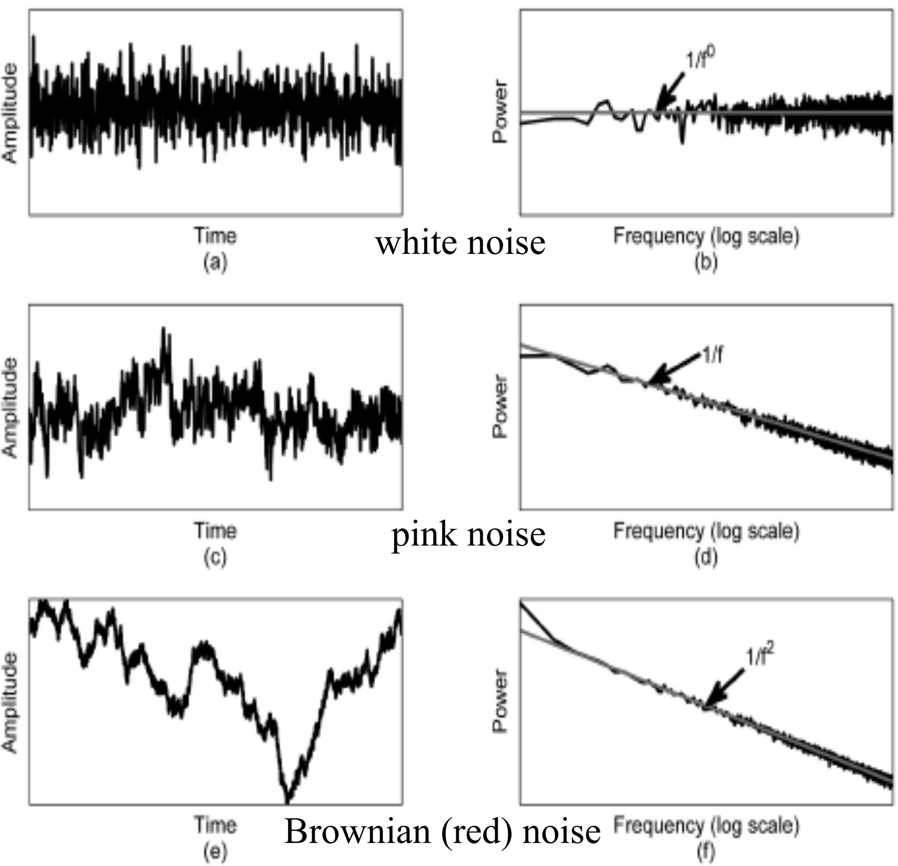
J Physiol 564.1 (2005) pp 145–160

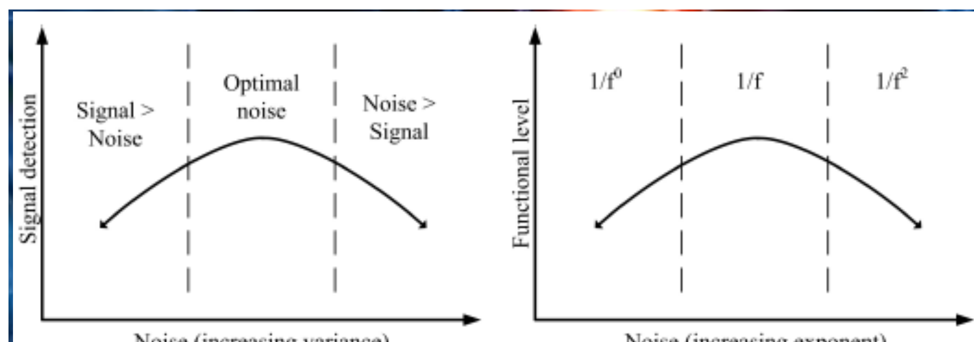
Subthreshold voltage noise of rat neocortical pyramidal neurones

Gilad A. Jacobson[1,2], Kamran Diba[3], Anat Yaron-Jakoubovitch[1,2], Yasmin Oz[1], Christof Koch[3], Idan Segev[1,2] and Yosef Yarom[1,2]

[1]Department of Neurobiology and [2]The Interdisciplinary Center for Neural Computation, The Hebrew University, Jerusalem 91904, Israel
[3]Computation and Neural Systems Program, California Institute of Technology, Pasadena, CA 91125, USA

Neurones are noisy elements. Noise arises from both intrinsic and extrinsic sources, and manifests itself as fluctuations in the membrane potential. These fluctuations limit the accuracy of a neurone's output but have also been suggested to play a computational role. We present a
y of the amplitude and spectrum of voltage noise recorded at the soma of layer
idal neurones in slices taken from rat neocortex. The dependence of the noise
otential, synaptic activity and Na^+ conductance is systematically analysed. We
that voltage noise increases non-linearly as the cell depolarizes (from a standard
D.) of 0.19 mV at −75 mV to an S.D. of 0.54 mV at −55 mV). The increase in
is accompanied by an increase in the cell impedance, due to voltage dependence
uctance. The impedance increase accounts for the majority (70%) of the voltage
e. The increase in voltage noise and impedance is restricted to the low-frequency
Hz). At the high frequency range (5–100 Hz) the voltage noise is dominated by
ity. In our slice preparation, synaptic noise has little effect on the cell impedance.
odel reproduces qualitatively these data. Our results imply that ion channel noise
ignificantly to membrane voltage fluctuations at the subthreshold voltage range,
conductance plays a key role in determining the amplitude of this noise by acting
lependent amplifier of low-frequency transients.





OPEN ACCESS Freely available online
PLOS ONE

Human Decision Making Based on Variations in Internal Noise: An EEG Study

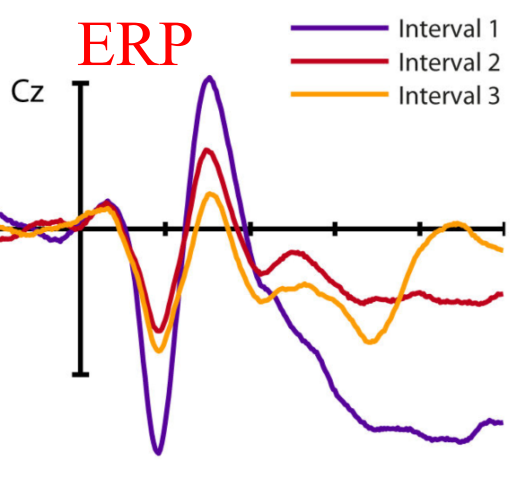
Sygal Amitay*, Jeanne Guiraud[¤a], Ediz Sohoglu[¤b], Oliver Zobay, Barrie A. Edmonds, Yu-Xuan Zhang[¤c], David R. Moore[¤d]

Medical Research Council Institute of Hearing Research, Nottingham, United Kingdom

2013

Abstract

Perceptual decision making is prone to errors, especially near threshold. Physiological, behavioural and modeling studies suggest this is due to the intrinsic or 'internal' noise in neural systems, which derives from a mixture of bottom-up and top-down sources. We show here that internal noise can form the basis of perceptual decision making when the external signal lacks the required information for the decision. We recorded electroencephalographic (EEG) activity in listeners attempting to discriminate between identical tones. Since the acoustic signal was constant, bottom-up and top-down influences were under experimental control. We found that early cortical responses to the identical stimuli varied in global field power and topography according to the perceptual decision made, and activity preceding stimulus presentation could predict both later activity and behavioural decision. Our results suggest that activity variations induced by internal noise of both sensory and cognitive origin are sufficient to drive discrimination judgments.



Listeners performed an auditory discrimination task. They were instructed to choose the odd-one-out of three consecutive tones, which, unbeknownst to them, were physically identical.
The subjects felt difference between three identical tones.

Noise-induced differences in internal representation of physically identical stimuli are treated by the brain in the same way as differences in physical stimuli.

autism

Original Article

Low endogenous neural noise in autism

Autism
2015, Vol. 19(3) 351–362

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DOI: 10.1177/1362361314552198
aut.sagepub.com
SAGE

Greg Davis and Kate Plaisted-Grant

Abstract

'Heuristic' theories of autism postulate that a single mechanism or process underpins the diverse psychological features of autism spectrum disorder. Although no such theory can offer a comprehensive account, the parsimonious descriptions they provide are powerful catalysts to autism research. One recent proposal holds that 'noisy' neuronal signalling explains not only some deficits in autism spectrum disorder, but also some superior abilities, due to 'stochastic resonance'. Here, we discuss three distinct actions of noise in neural networks, arguing in each case that autism spectrum disorder symptoms reflect *too little*, rather than too much, neural noise. Such reduced noise, perhaps a function of atypical brainstem activation, would enhance detection and discrimination in autism spectrum disorder but at significant cost, foregoing the widespread benefits of noise in neural networks.

Psychiatry and Clinical Neurosciences 2014; **68**: 206–215 doi:10.1111/pcn.12120

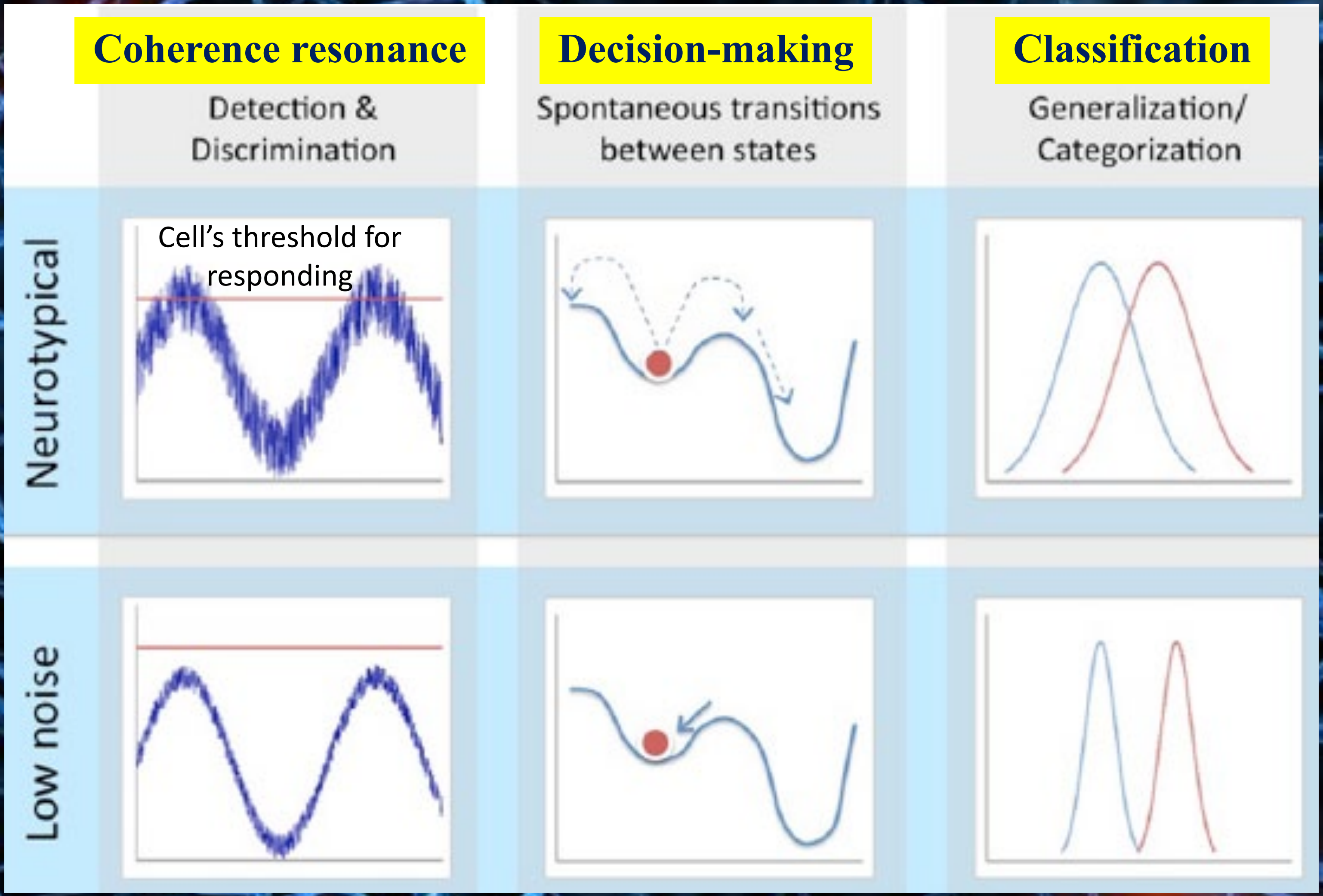
Regular Article

Structural correlates of cognitive deficit and elevated gamma noise power in schizophrenia

Vanessa Suazo, MSc,[1,3] Álvaro Díez, PhD,[2,3,6] Carlos Montes, MSc[3,4] and Vicente Molina, MD, PhD[1,3,5]*

[1]*Neuroscience Institute of Castilla y León,* [2]*Basic Psychology, Psychobiology and Methodology Department, School of Psychology, University of Salamanca,* [3]*Biomedical Research Institute of Salamanca,* [4]*Radiophysics Service, University Hospital of Salamanca, Salamanca,* [5]*Psychiatry Service, University Hospital of Valladolid, University of Valladolid, Valladolid, Spain, and* [6]*Mental Health Sciences Unit, Faculty of Brain Sciences, University College London, London, UK*

Three basic actions of noise in neural network



Noise-induced coherence resonance

Single neuron

VOLUME 78, NUMBER 5 PHYSICAL REVIEW LETTERS 3 FEBRUARY 1997

Coherence Resonance in a Noise-Driven Excitable System

Arkady S. Pikovsky* and Jürgen Kurths*

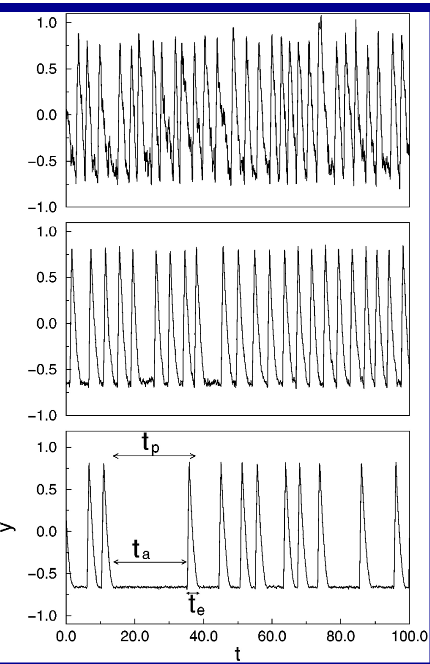
Max–Planck–Arbeitsgruppe "Nichtlineare Dynamik" an der Universität Potsdam Am Neuen Palais 19, PF 601553, D-14415, Potsdam, Germany

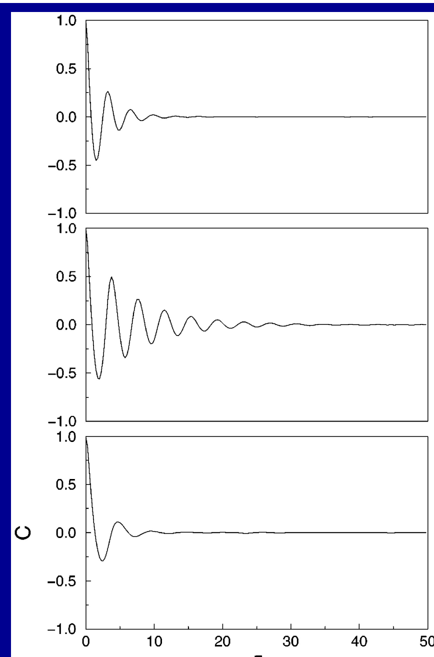
(Received 9 August 1996)

We study the dynamics of the excitable Fitz Hugh–Nagumo system under external noisy driving. Noise activates the system producing a sequence of pulses. The coherence of these noise-induced oscillations is shown to be maximal for a certain noise amplitude. This new effect of coherence resonance is explained by different noise dependencies of the activation and the excursion times. A simple one-dimensional model based on the Langevin dynamics is proposed for the quantitative description of this phenomenon. [S0031-9007(97)02349-1]

PACS numbers: 05.40.+j, 05.20.–y

Fitz Hugh-Nagumo model





Autocorrelation function

$$C(\tau) = \frac{\langle \tilde{y}(t)\tilde{y}(t + \tau)\rangle}{\langle \tilde{y}^2\rangle}, \qquad \tilde{y} = y - \langle y \rangle .$$

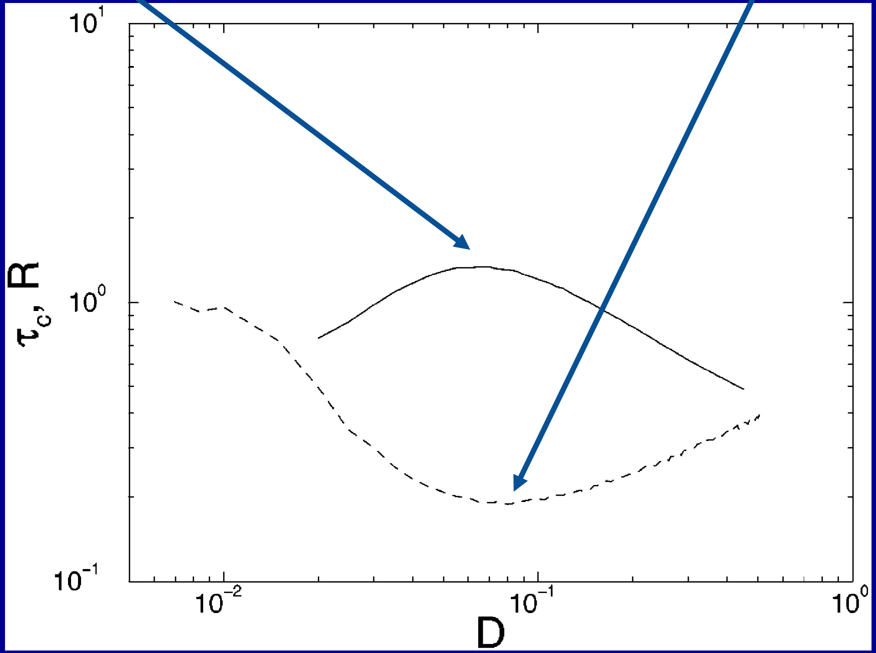
Coherence measures

Characteristic correlation time

$$\tau_c = \int_0^\infty C^2(t)\, dt\,.$$

Normalized fluctuation of phase duration (jitter)

$$R_p = \frac{\sqrt{\mathrm{Var}\,(t_p)}}{\langle t_p \rangle}\,.$$



EUROPHYSICS LETTERS 15 January 2003

Europhys. Lett., **61** (2), pp. 162–167 (2003)

Neural network

System size coherence resonance in coupled FitzHugh-Nagumo models

R. TORAL[1,2], C. R. MIRASSO[1] and J. D. GUNTON[2,3]

[1] *Departament de Física, Universitat de les Illes Balears E-07071 Palma de Mallorca, Spain*

[2] *Instituto Mediterráneo de Estudios Avanzados (IMEDEA), CSIC-UIB E-07071 Palma de Mallorca, Spain*

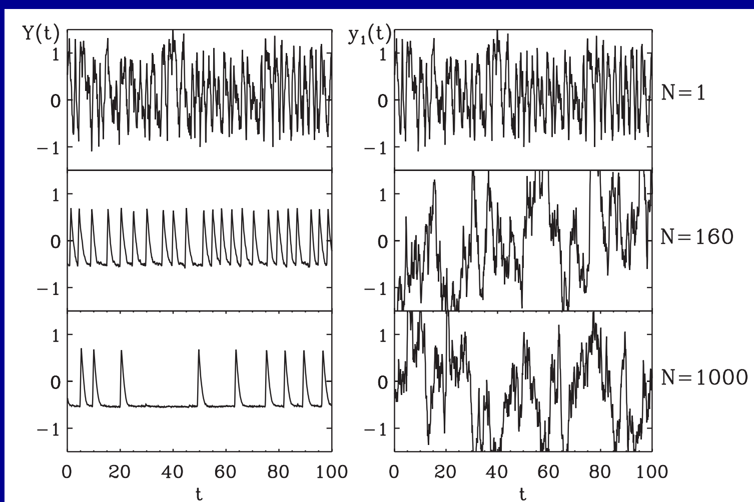
[3] *Department of Physics, Lehigh University - Bethlehem, PA 18015, USA*(*)

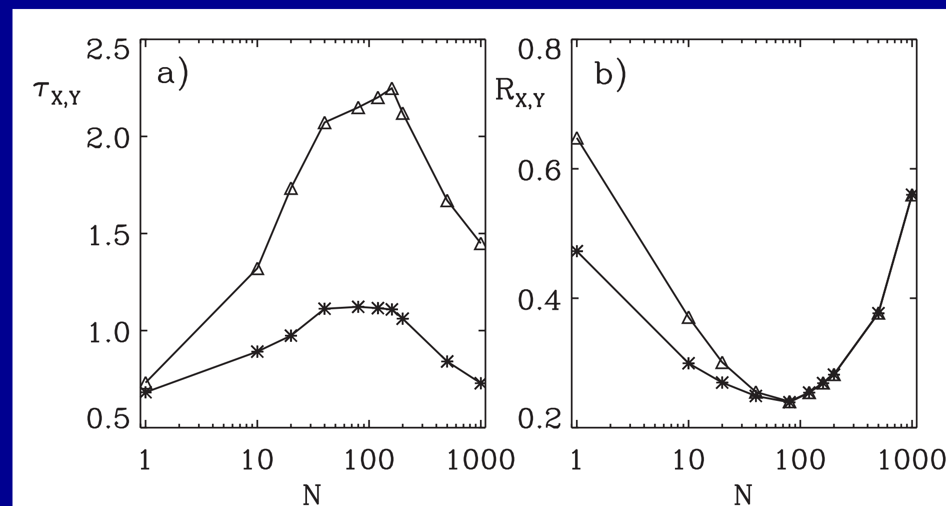
Globally coupled with the same electrical coupling

Collective variables:

$$X(t) = \frac{1}{N}\sum_{i=1}^{N} x_i(t),$$

$$Y(t) = \frac{1}{N}\sum_{i=1}^{N} y_i(t).$$





The coherence resonance has also been detected in other neuron models:

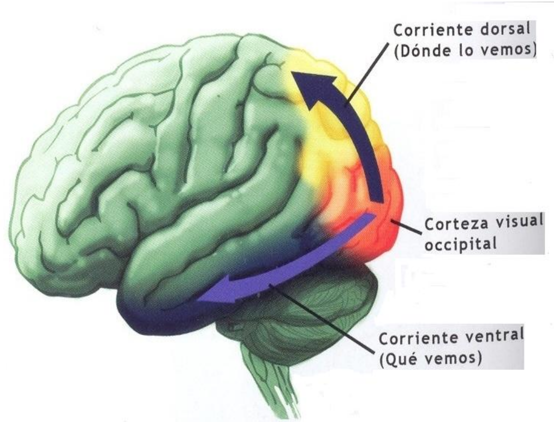
Morris–Lecar [Wang M S, Hou Z H, Xin H W 2006 Chin. Phys. 15 2553]

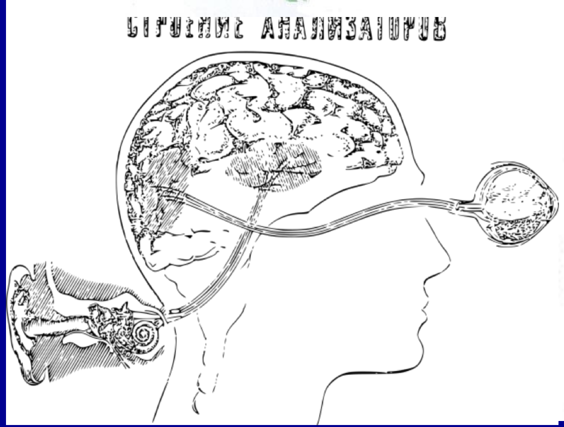
Hodgkin–Huxley [Lee S G, Neiman A, Kim S 1998 Phys. Rev. E 57 3292]

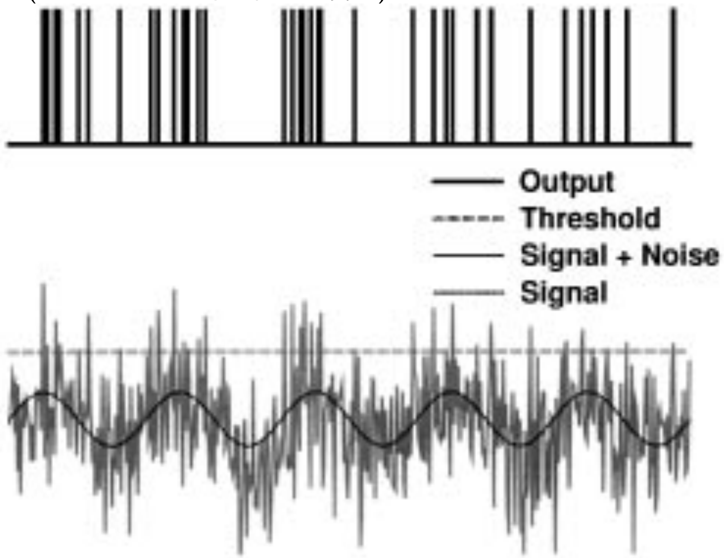
VOLUME 78, NUMBER 6 PHYSICAL REVIEW LETTERS 10 FEBRUARY 1997

Visual Perception of Stochastic Resonance

Enrico Simonotto,[1,3] Massimo Riani,[1] Charles Seife,[2,*] Mark Roberts,[2] Jennifer Twitty,[3] and Frank Moss[3]
[1]*INFM-Unitá di Genova and Dipartimento di Fisica, Universitá di Genova, 16146 Genova, Italy*
[2]The Economist, *25 St. James's Street, London, SW1A 1HG, England*
[3]*Center for Neurodynamics, University of Missouri at St. Louis, St. Louis, Missouri 63121*
(Received 31 October 1996)







Threshold changes

Chaos, Solitons and Fractals 106 (2018) 80–85

Contents lists available at ScienceDirect

Chaos, Solitons and Fractals

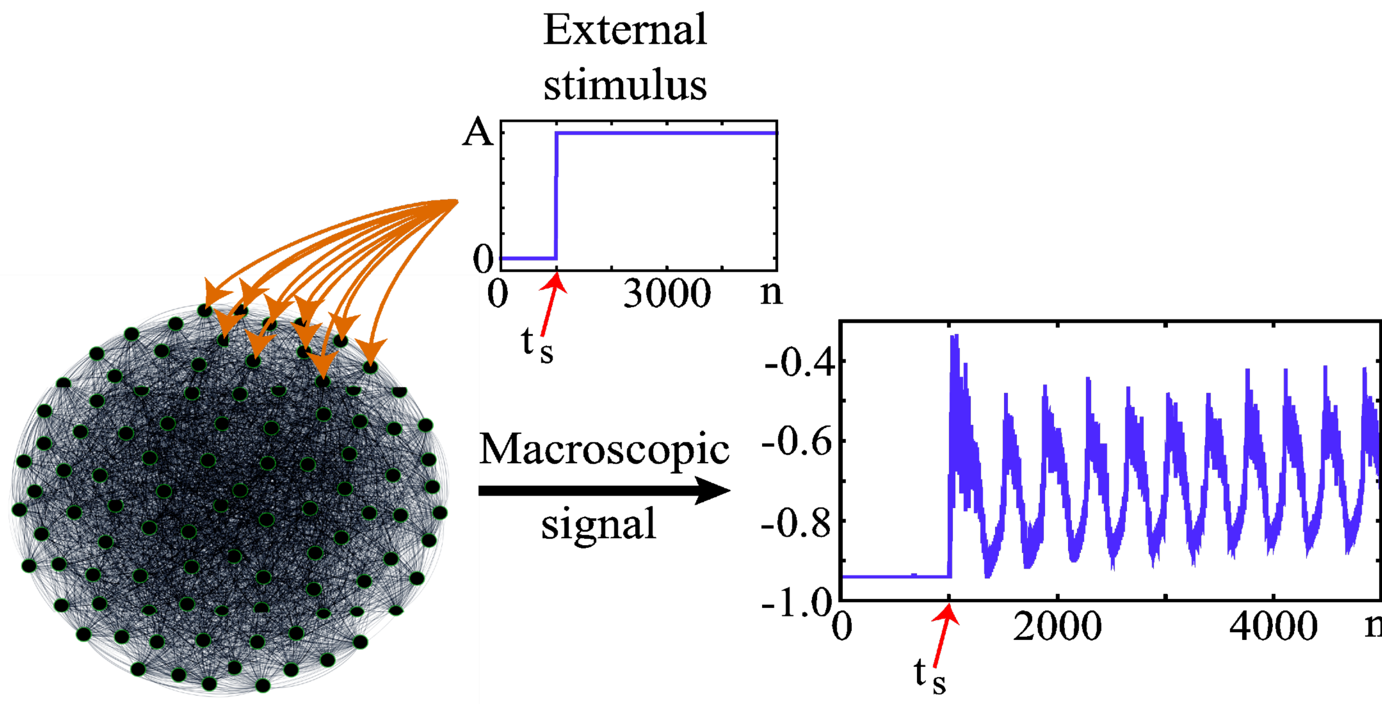
Nonlinear Science, and Nonequilibrium and Complex Phenomena

journal homepage: www.elsevier.com/locate/chaos

Coherence resonance in stimulated neuronal network

Andrey V. Andreev[a], Vladimir V. Makarov[a], Anastasija E. Runnova[a], Alexander N. Pisarchik[a,b], Alexander E. Hramov[a,c,*]

[a] Yuri Gagarin State Technical University of Saratov, Politechnicheskaya, 77, Saratov 410054, Russia
[b] Center for Biomedical Technology, Technical University of Madrid, Campus Montegancedo, Pozuelo de Alarcon, Madrid 28223, Spain
[c] Saratov State University, Astrakhanskaya, 83, Saratov 410012, Russia



Globally coupled non-active neurons with random coupling strengths.
Some neurons are activated by the external stimulus A at time t_s.

Model of a neural network based on coupled Rulkov maps

$$x_{n+1} = f(x_n, x_{n-1}, y_n + \beta_n), \tag{1}$$

$$y_{n+1} = y_n - \mu(x_n + 1) + \mu\sigma + \mu\sigma_n + \mu A^{\xi}\xi_n, \tag{2}$$

where x is a fast variable associated with membrane potential, y is a slow variable which has some analogy with gating variables, the parameters α, σ and $0 < \mu \leq 1$ control individual dynamics of the system, ξ is a Gaussian noise with a zero mean and standard deviation that equals 1, A^{ξ} is noise amplitude. β_n and σ_n are related to external stimuli, f is a piecewise function defined as

$$f(x_n, x_{n-1}, y_n) = \begin{cases} \alpha/(1 - x_n) + y_n, & \text{if } x_n \leq 0 \\ \alpha + y_n, & \text{if } 0 < x_n < \alpha + y_n \text{ and } x_{n-1} \leq 0 \\ -1, & \text{if } x_n \geq \alpha + y_n \text{ or } x_{n-1} > 0 \end{cases} \tag{3}$$

$$\beta_n = \beta^e I_n^{ext} + \beta^{syn} I_n^{syn}, \tag{4}$$

$$\sigma_n = \sigma^e I_n^{ext} + \sigma^{syn} I_n^{syn}. \tag{5}$$

Coefficients β^e and σ^e are used to balance the effect of external current I_n^{ext}. β^{syn} and σ^{syn} are coefficients of chemical synaptic coupling. I_n^{syn} is a synaptic current:

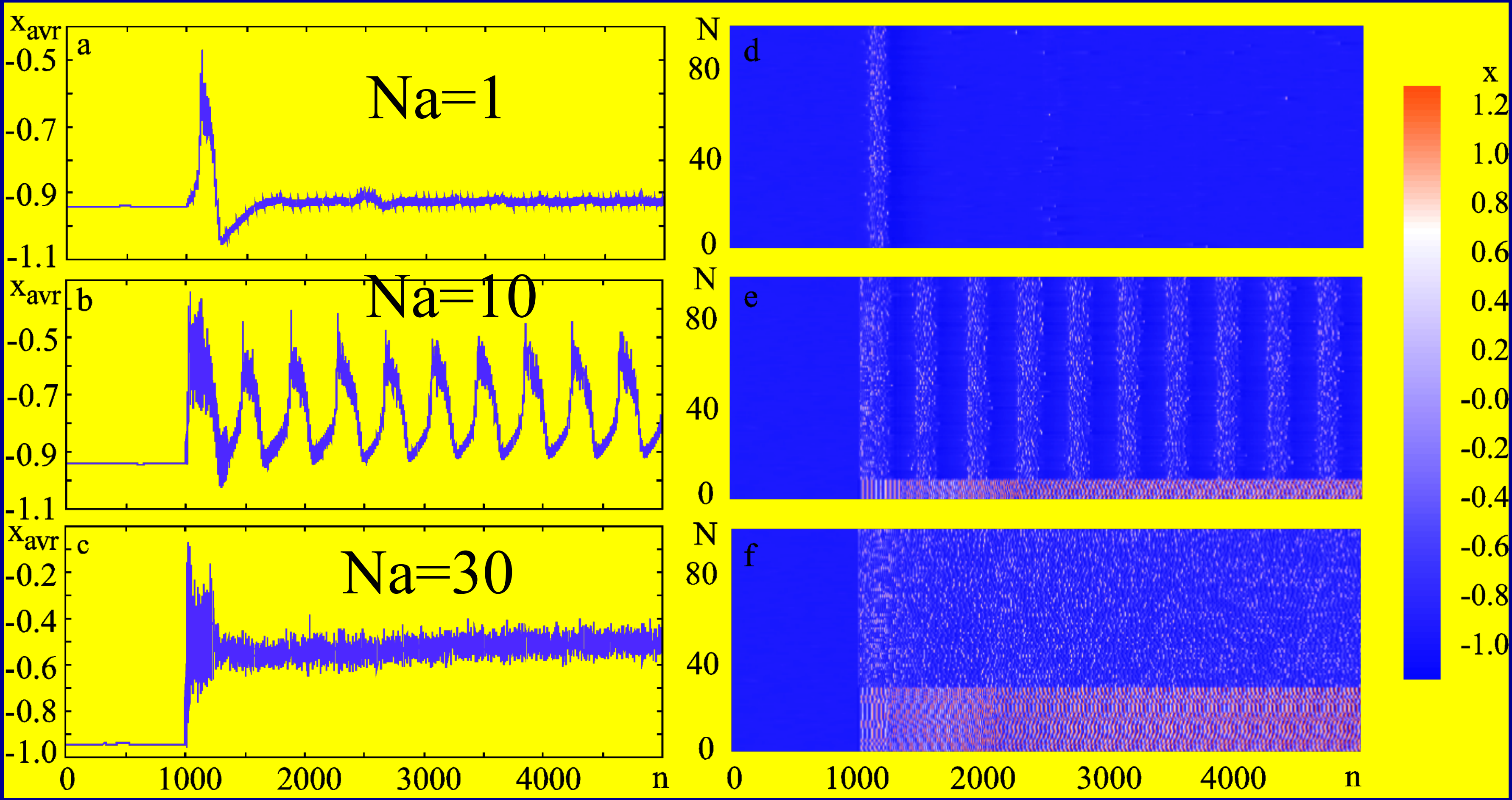
$$I_{n+1}^{syn} = \gamma I_n^{syn} - g_{syn} * \begin{cases} (x_n^{post} - x_{rp})/(1 + exp(-k(x_n^{post} - \theta))), & \text{spike}^{pre}, \\ 0, & \text{otherwise}, \end{cases} \tag{6}$$

Coherence resonance with respect to the number of excited neurons

$A^{\xi} = 0.1$, $A = 1$, $N = 100$

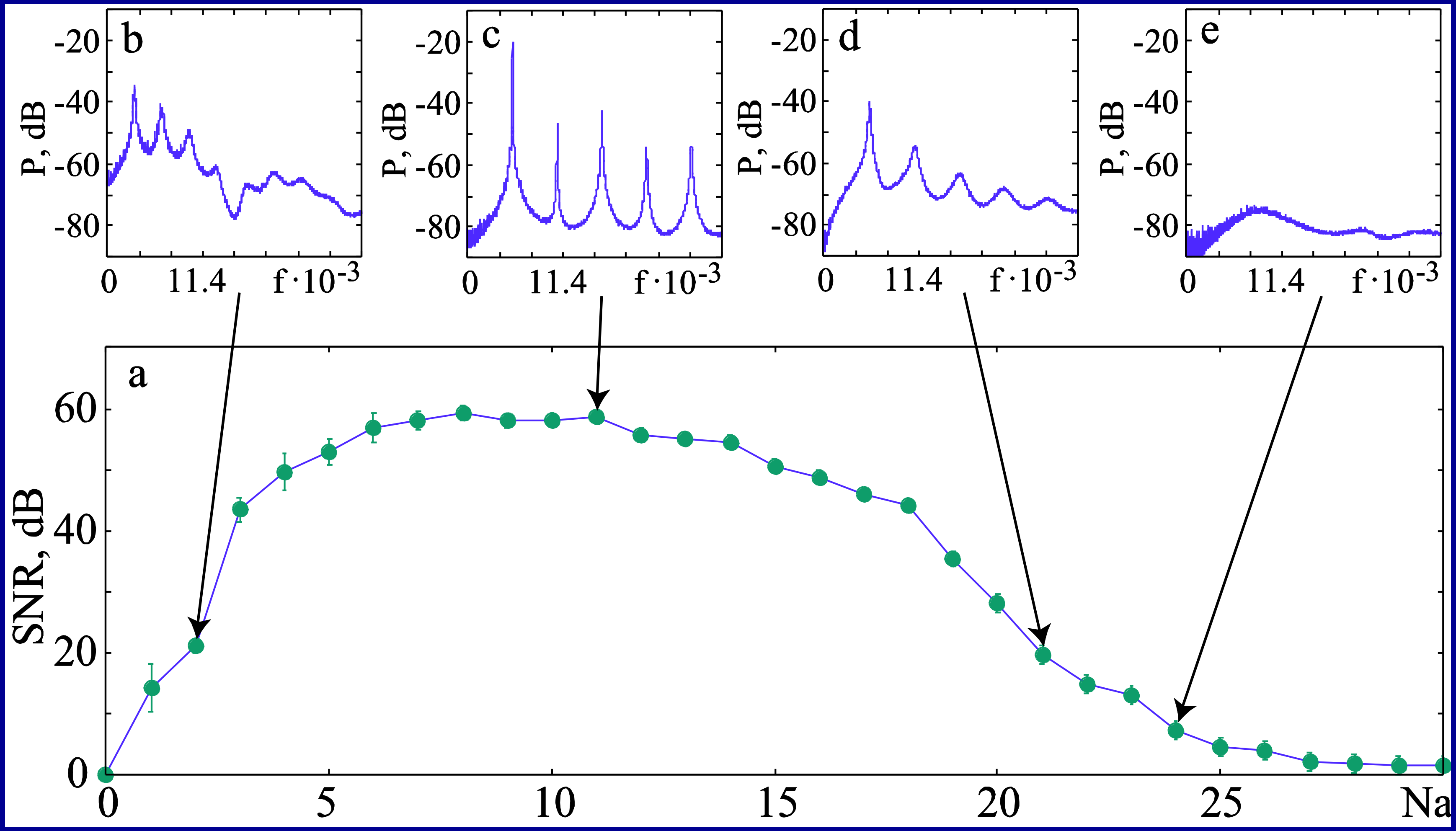
Average time series

Time diagrams of all neurons



Signal-to-noise ratio versus the number of stimulated neurons

$A = 1, A^{\xi} = 0.1, N = 100$



Autocorrelation function

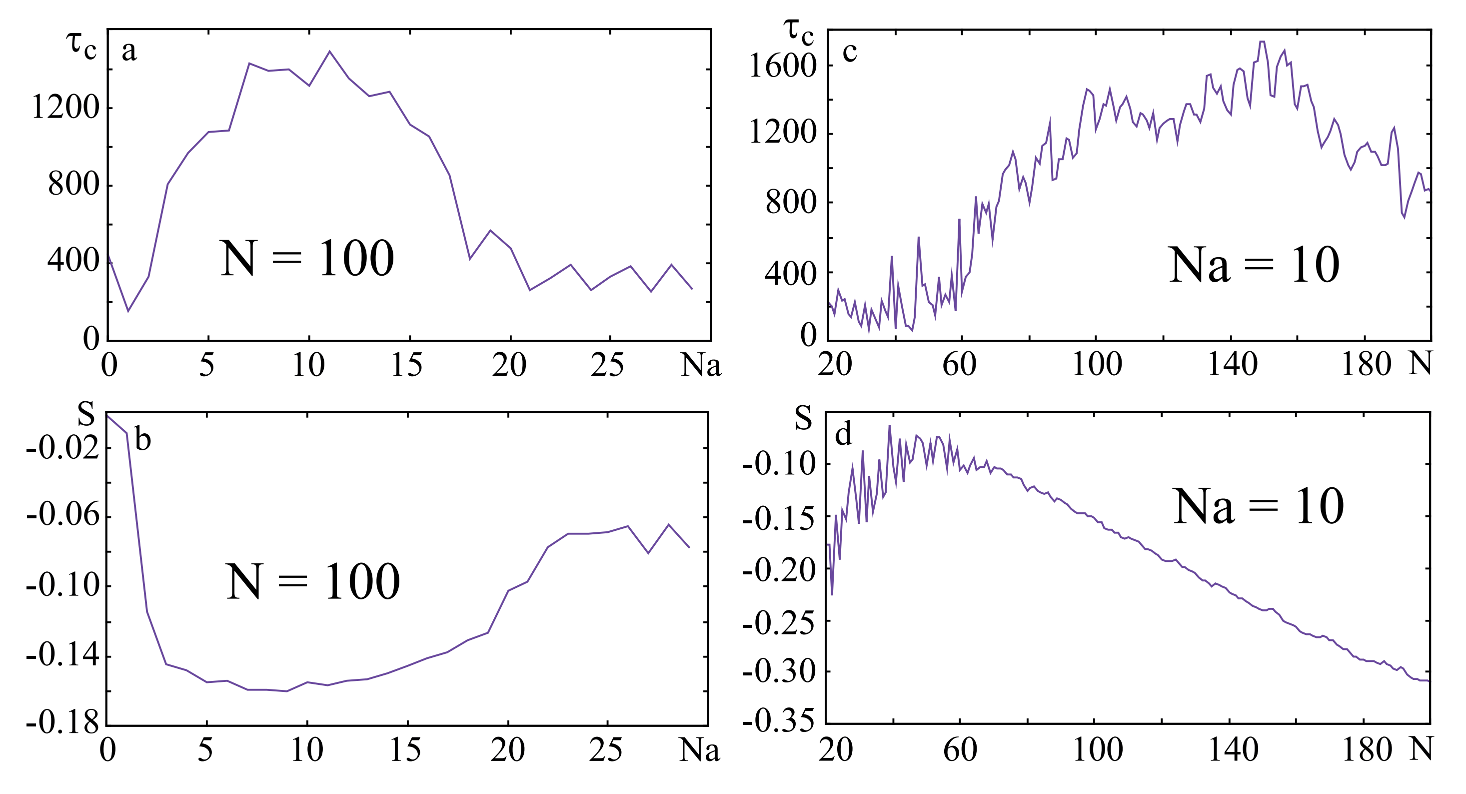
$$C(\tau) = \frac{\langle (x(n) - \langle x \rangle)(x(n+\tau) - \langle x \rangle) \rangle}{\langle (x(n) - \langle x \rangle)^2 \rangle},$$

Correlation time

$$\tau_c = \sum_{n_0}^{N} C(\tau)^2,$$

Jitter

$$S = \sqrt{\frac{\sum_{n_0}^{N} (x_n - \langle x \rangle)^2}{N - n_0}} / \langle x \rangle.$$



A = 1

$A^{\xi} = 0.1$

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SCIENTIFIC REPORTS

natureresearch

Hodgkin-Huxley neural network
Stochastic model

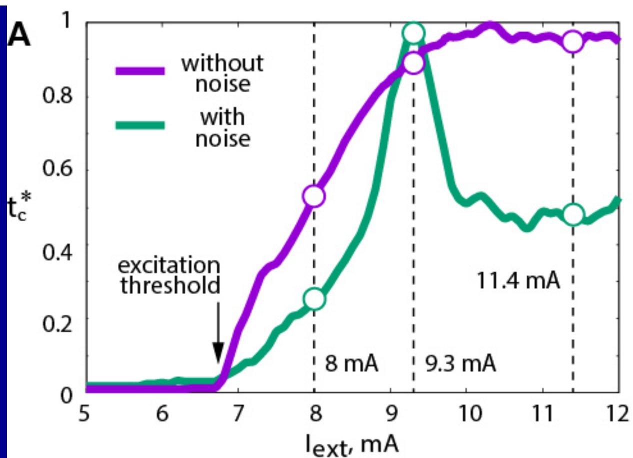
$$C_m \frac{dV_j}{dt} = -g_{Na}^{\max} m_j^3 h_j (V_j - V_{Na}) - g_K^{\max} n_j^4 (V_j - V_K) - g_L^{\max} (V_j - V_L) + I_j^{ex} + I_j^{syn}$$

$$\frac{dx_j}{dt} = \alpha_{x_j}(V_j)(1 - x_j) - \beta_{x_j}(V_j) x_j + \xi_{x_j}(t),$$

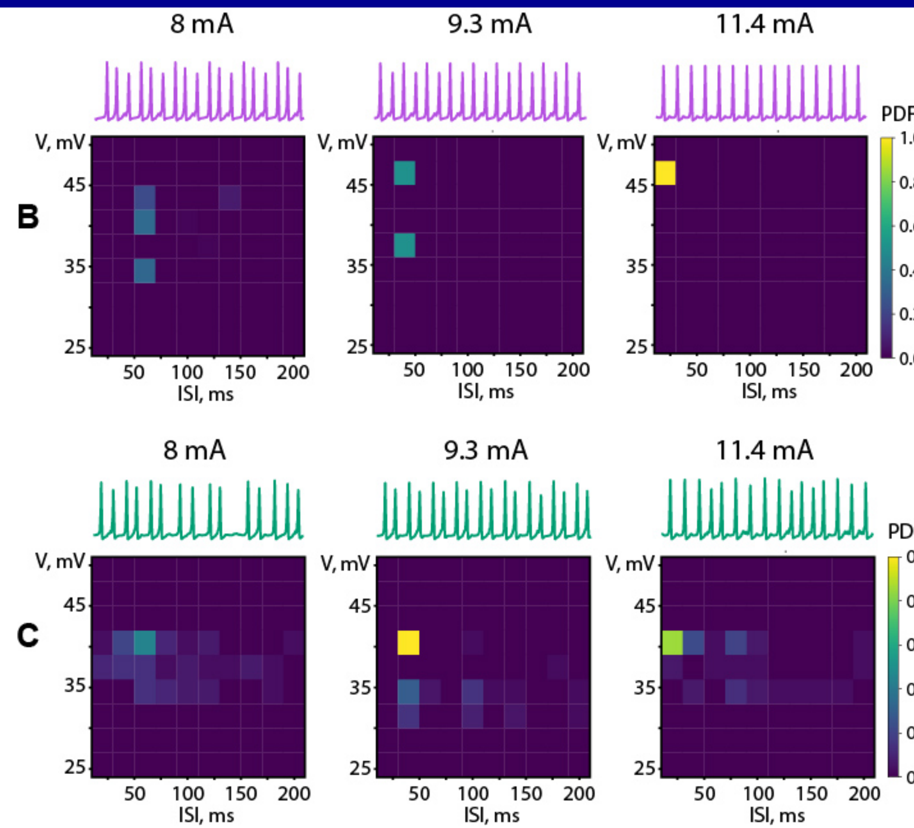
Coherent resonance in the distributed cortical network during sensory information processing

Alexander N. Pisarchik[1,2], Vladimir A. Maksimenko[2], Andrey V. Andreev[2], Nikita S. Frolov[2], Vladimir V. Makarov[2], Maxim O. Zhuravlev[2], Anastasija E. Runnova[2] & Alexander E. Hramov[2*]

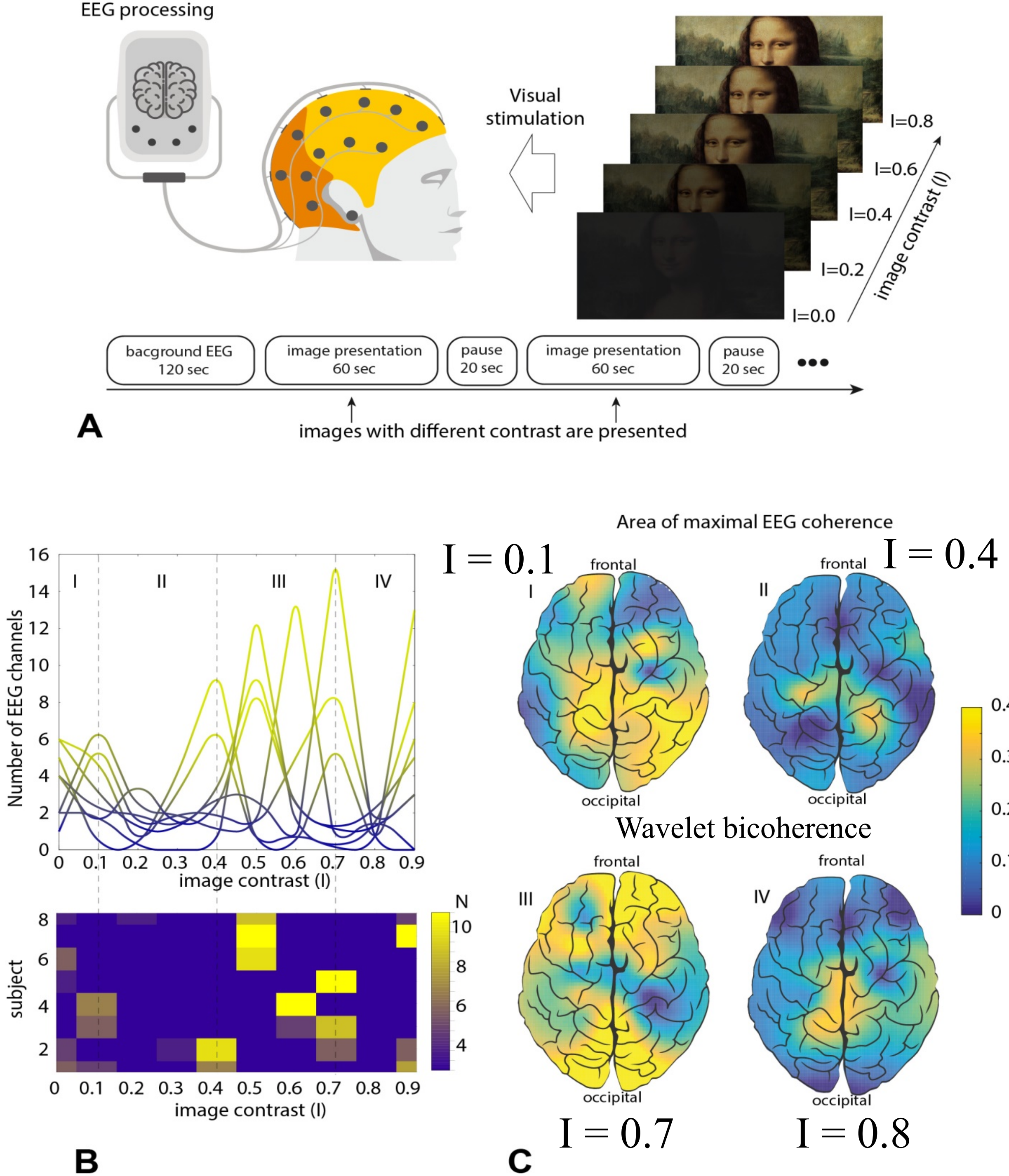
Neuronal brain network is a distributed computing system, whose architecture is dynamically adjusted to provide optimal performance of sensory processing. A small amount of visual information needed effortlessly be processed, activates neural activity in occipital and parietal areas. Conversely, a visual task which requires sustained attention to process a large amount of sensory information, involves a set of long-distance connections between parietal and frontal areas coordinating the activity of these distant brain regions. We demonstrate that while neural interactions result in coherence, the strongest connection is achieved through coherence resonance induced by adjusting intrinsic brain noise.

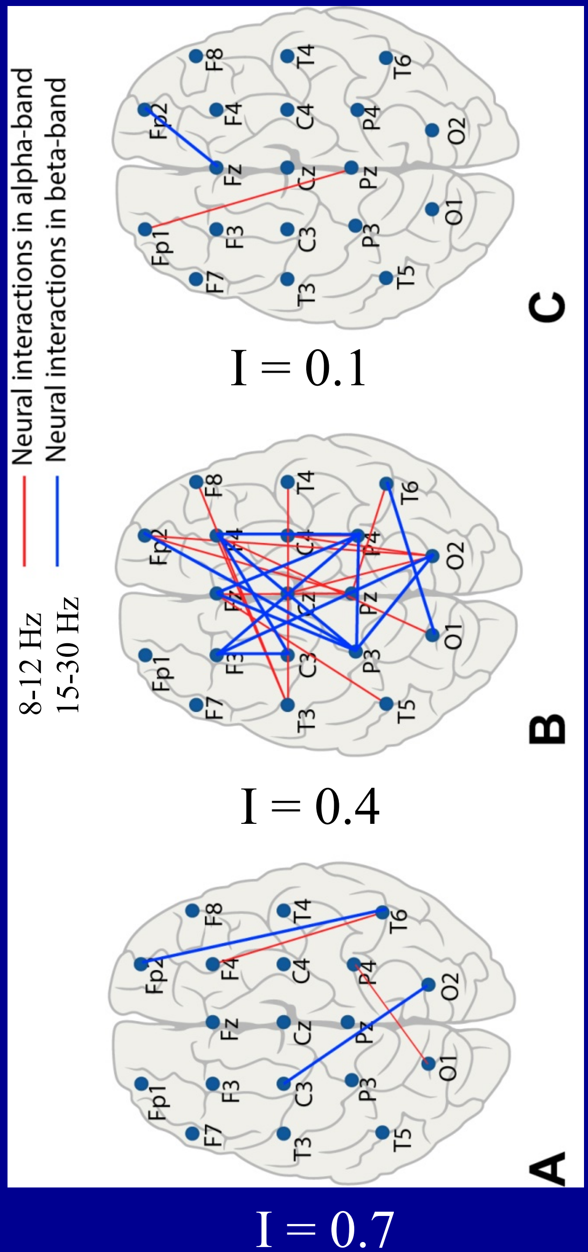


Correlation time vs external stimulus



Experimental evidence





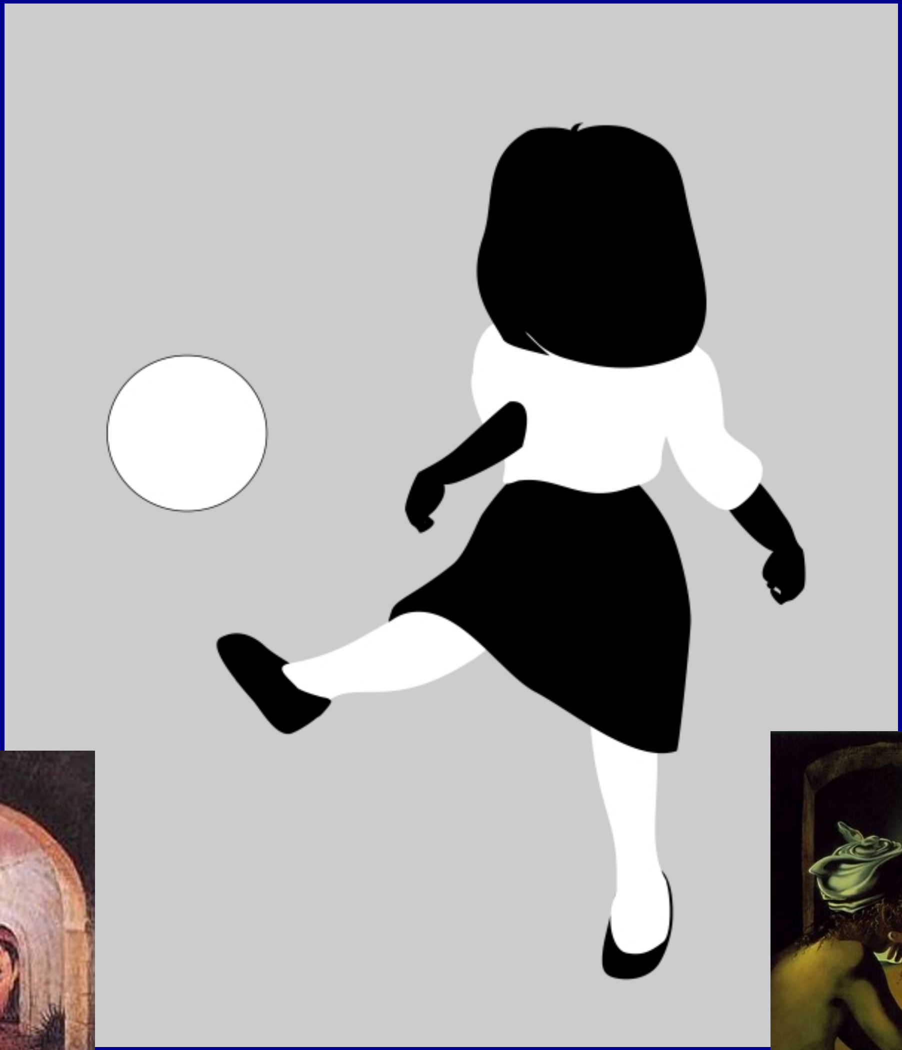
How to measure brain noise

Experimental methods based on multistable perception:

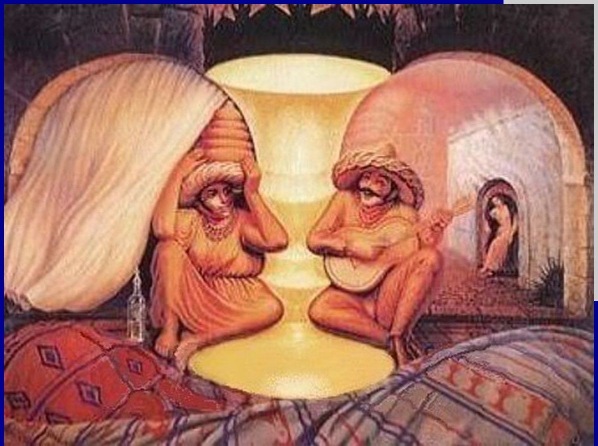
- Delayed bifurcation
- Probabilitity distribution
- Phase synchronization

Multistable visual perception

Psychology, cognitive science, art

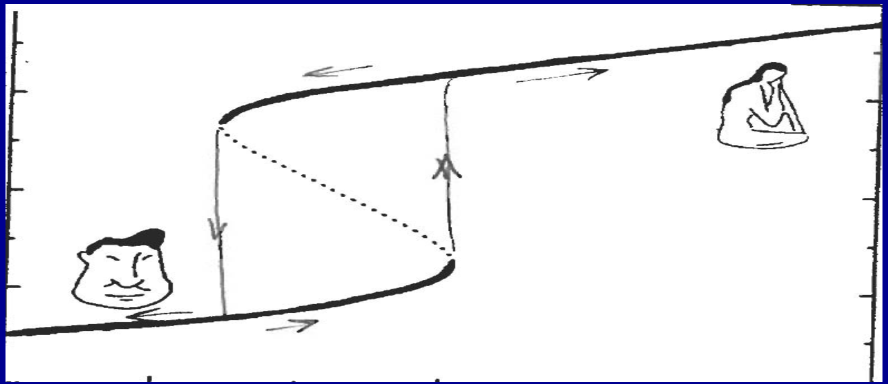


Ocampo

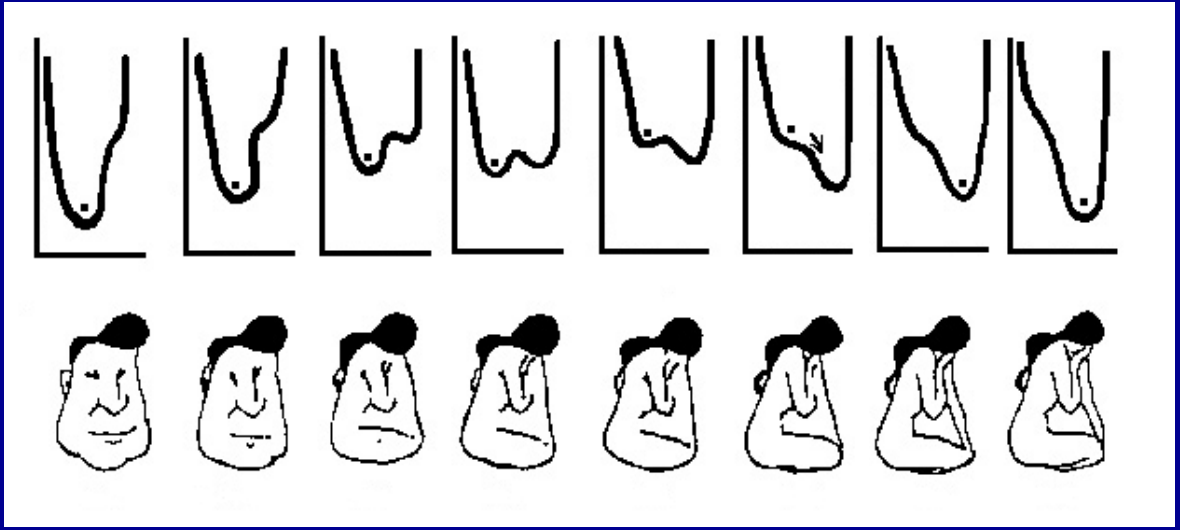


Salvatore Dali

Hysteresis in visual perception

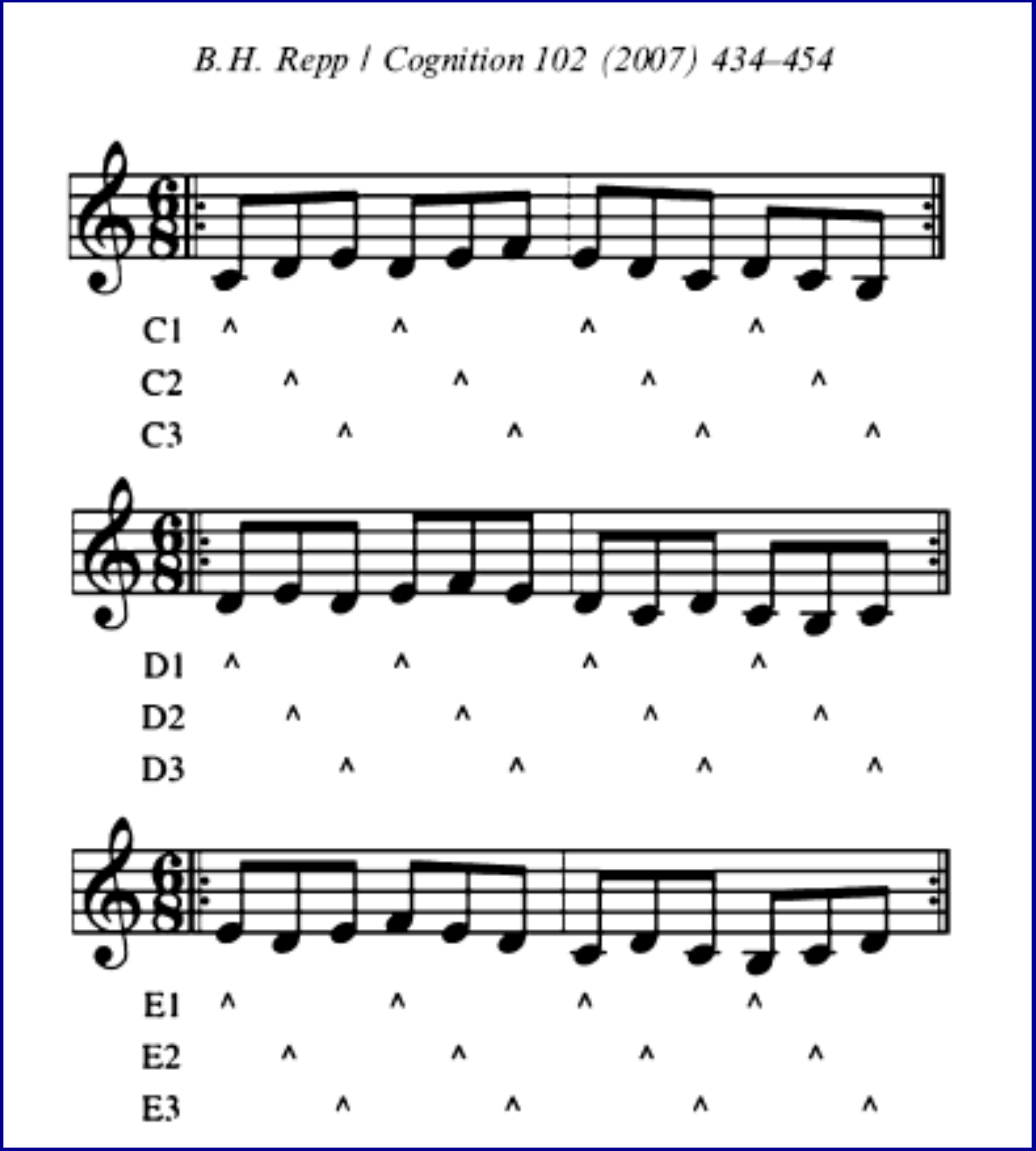


Hypothetic bifurcation diagram



Double-well potential

Multistability in audio perception



Delayed-bifurcation method

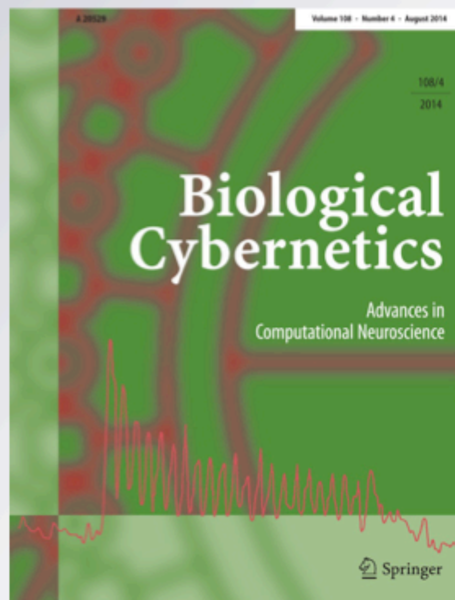
Critical slowing down and noise-induced intermittency in bistable perception: bifurcation analysis

Alexander N. Pisarchik, Rider Jaimes-Reátegui, C. D. Alejandro Magallón-García & C. Obed Castillo-Morales

Biological Cybernetics
Advances in Computational Neuroscience

ISSN 0340-1200
Volume 108
Number 4

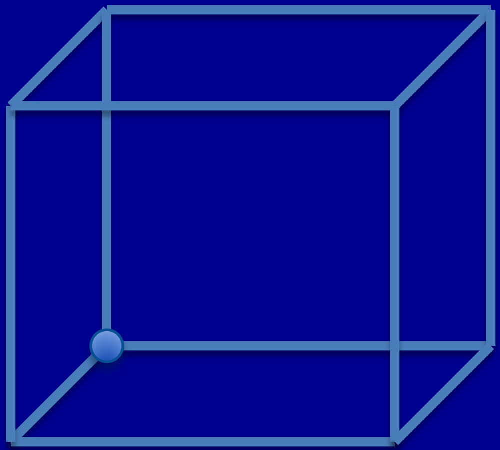
Biol Cybern (2014) 108:397-404
DOI 10.1007/s00422-014-0607-5

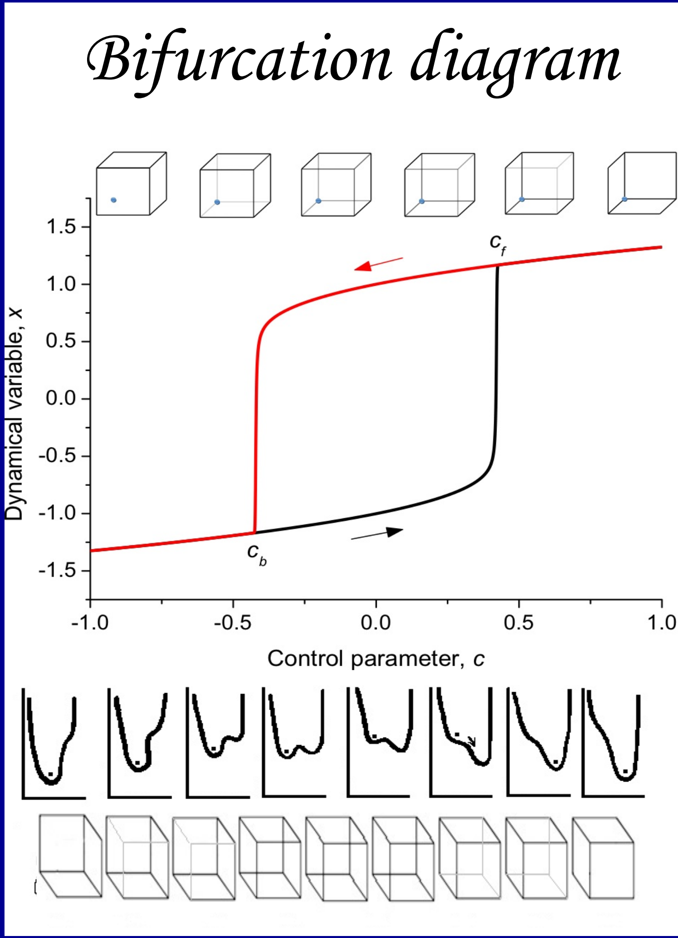


Springer

Psychological experiment

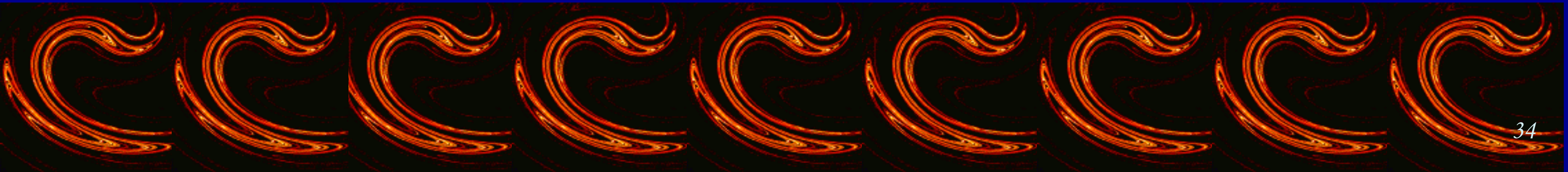
Necker cube





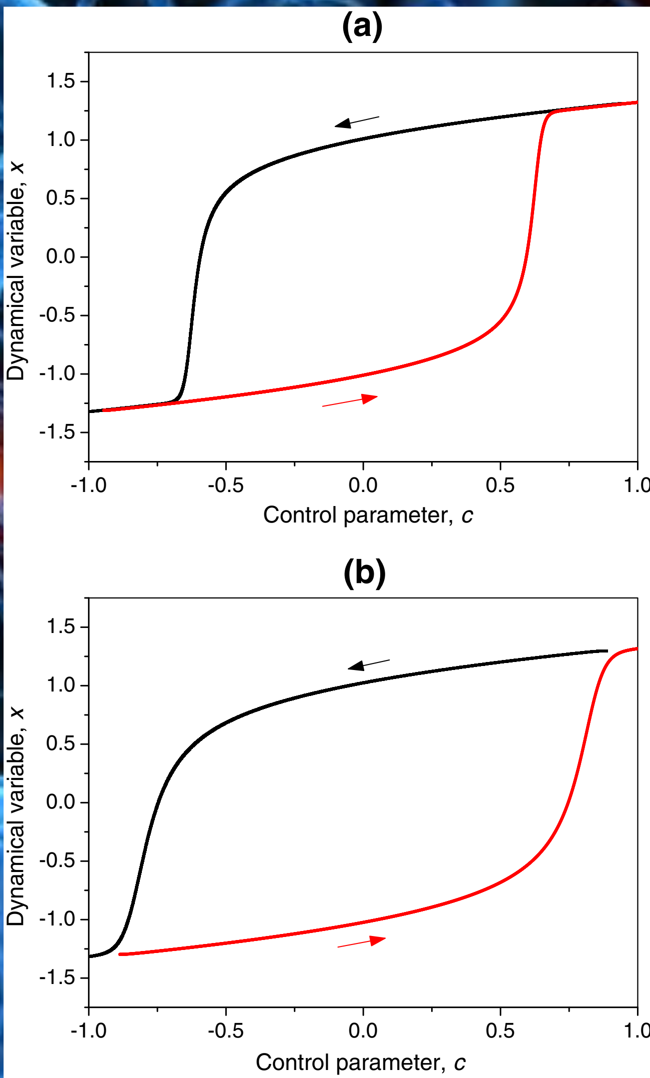
Perception energy model

$$\dot{x} = -4x(x^2 - 1) + 4c + \alpha\xi(t),$$



Critical slowing down

Without noise



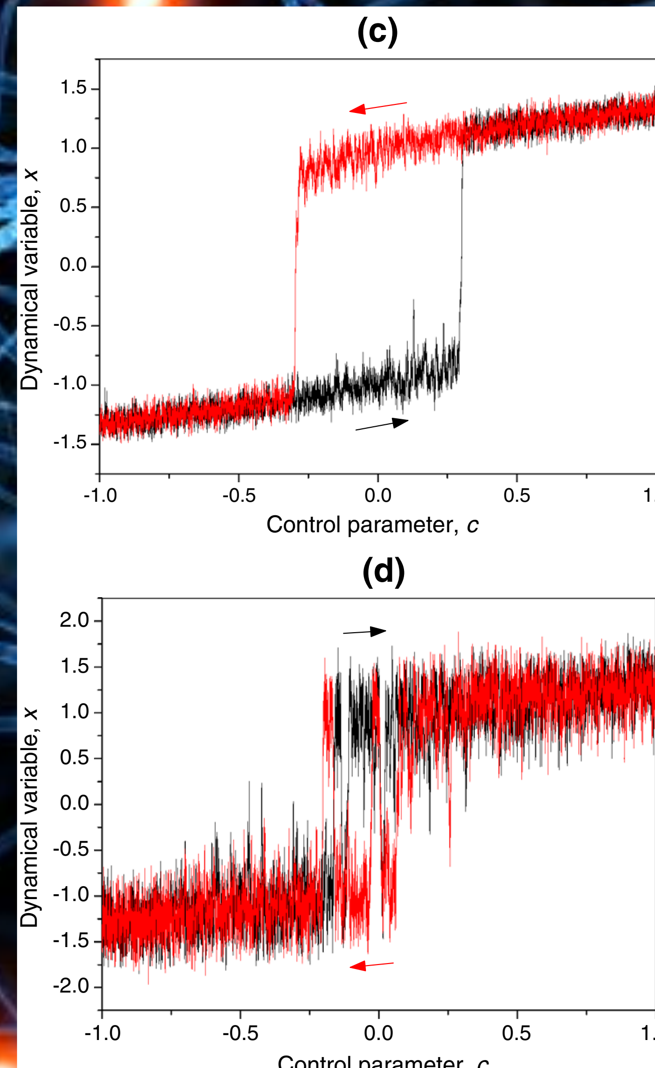
Time-dependent parameter:

$$c = c_0 \pm vt$$

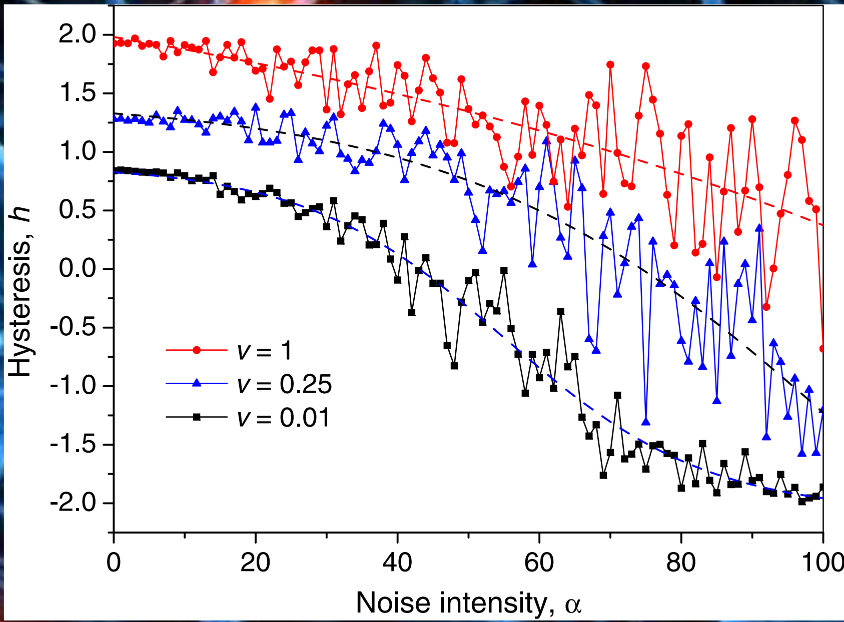
Hysteresis

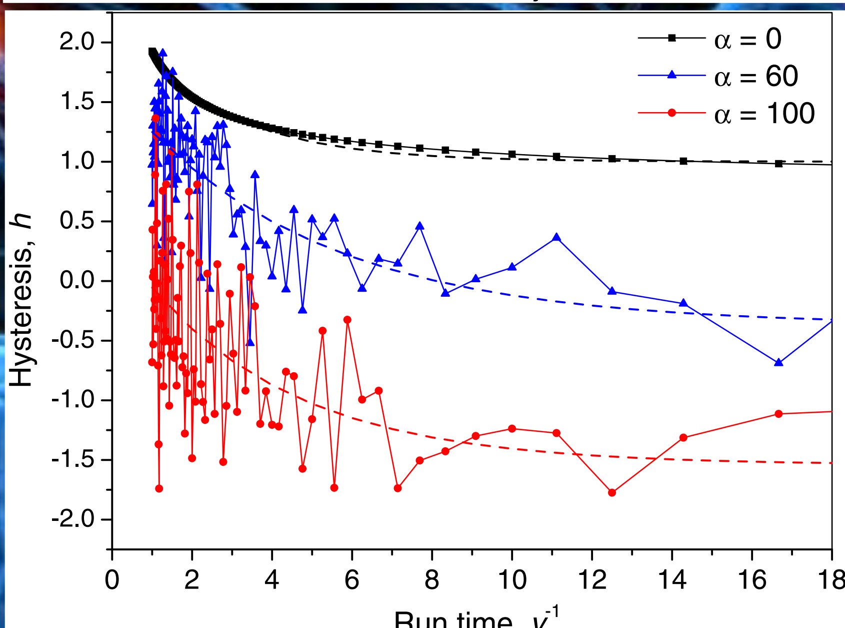
$$h = c_f - c_b$$

With noise

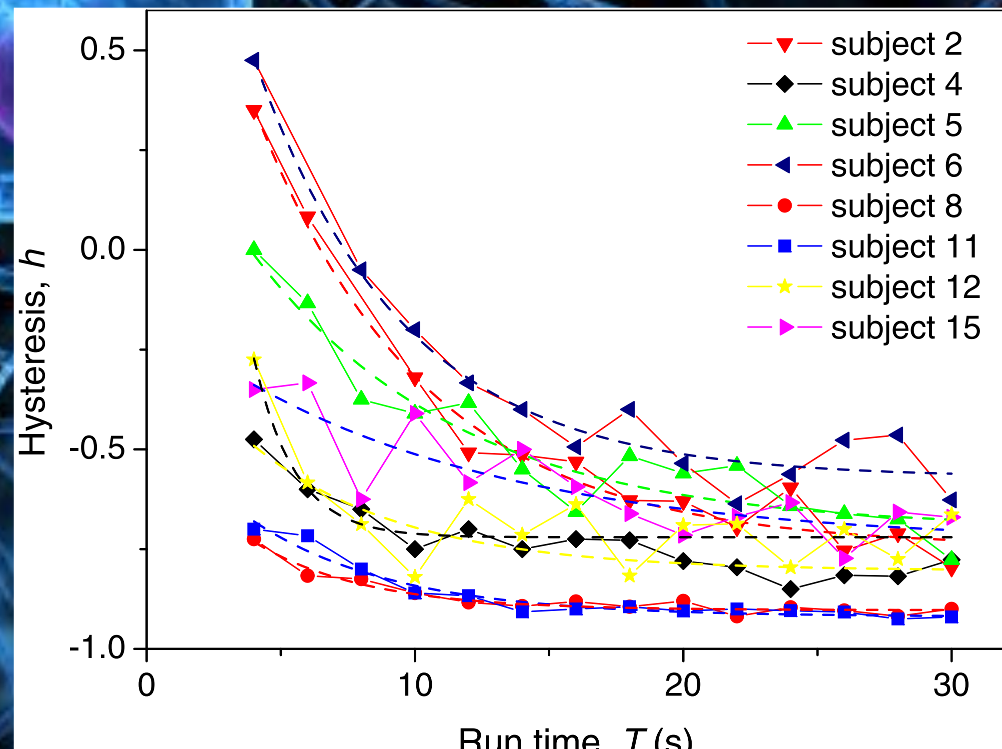


THEORY





EXPERIMENT



Probabilistic method

Chaos, Solitons and Fractals 93 (2016) 201–206

Contents lists available at ScienceDirect

Chaos, Solitons and Fractals

Nonlinear Science, and Nonequilibrium and Complex Phenomena

journal homepage: www.elsevier.com/locate/chaos

ELSEVIER

Theoretical background and experimental measurements of human brain noise intensity in perception of ambiguous images

Anastasiya E. Runnova[a,b], Alexander E. Hramov[a,b,*], Vadim V. Grubov[a], Alexey A. Koronovskii[b,a], Maria K. Kurovskaya[b,a], Alexander N. Pisarchik[a,c,d]

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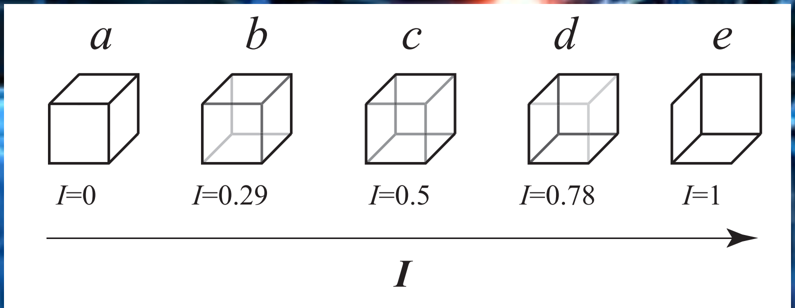
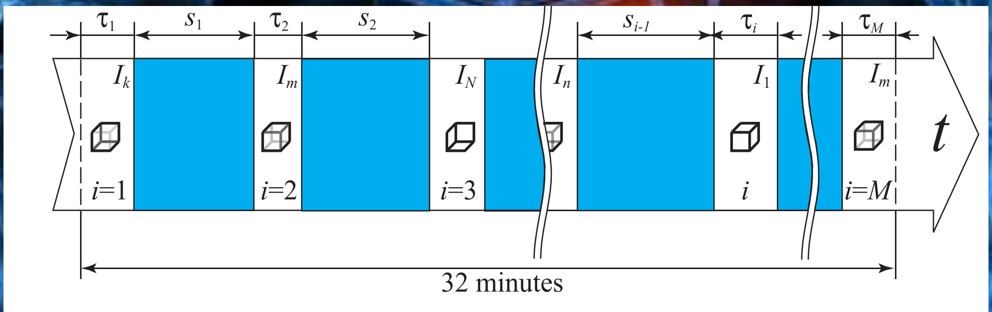
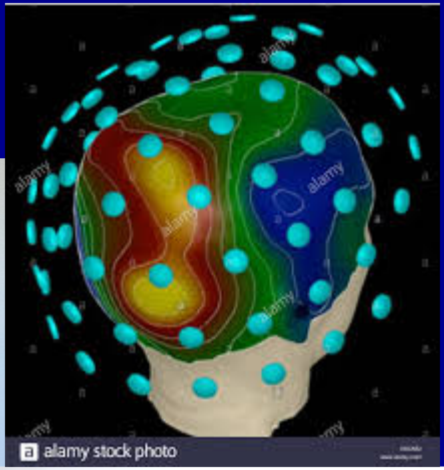
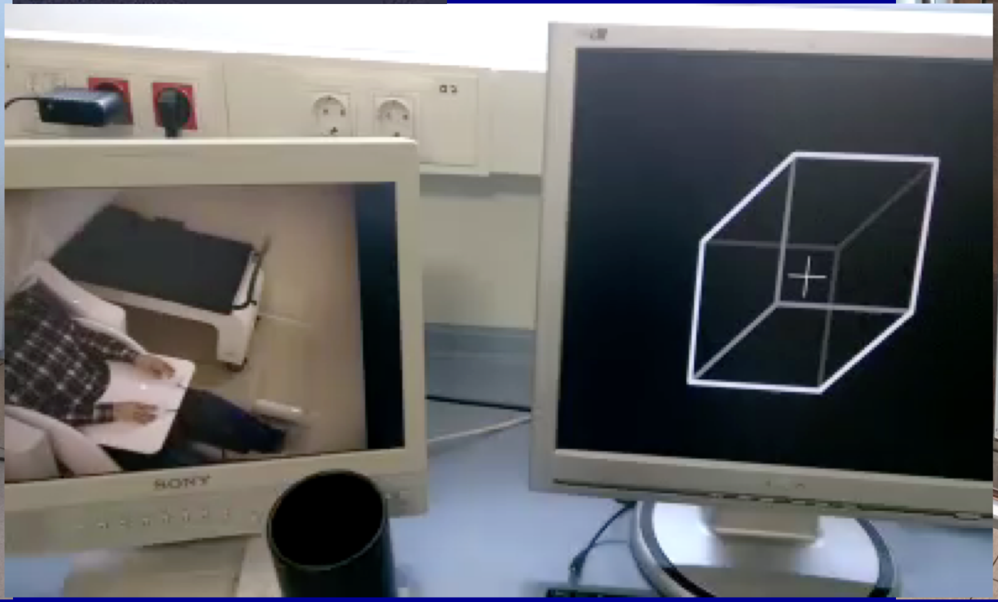
[d] Centro de Investigaciones en Optica, Loma del Bosque 115, Lomas del Campestre, 37150 Leon, Guanajuato, Mexico



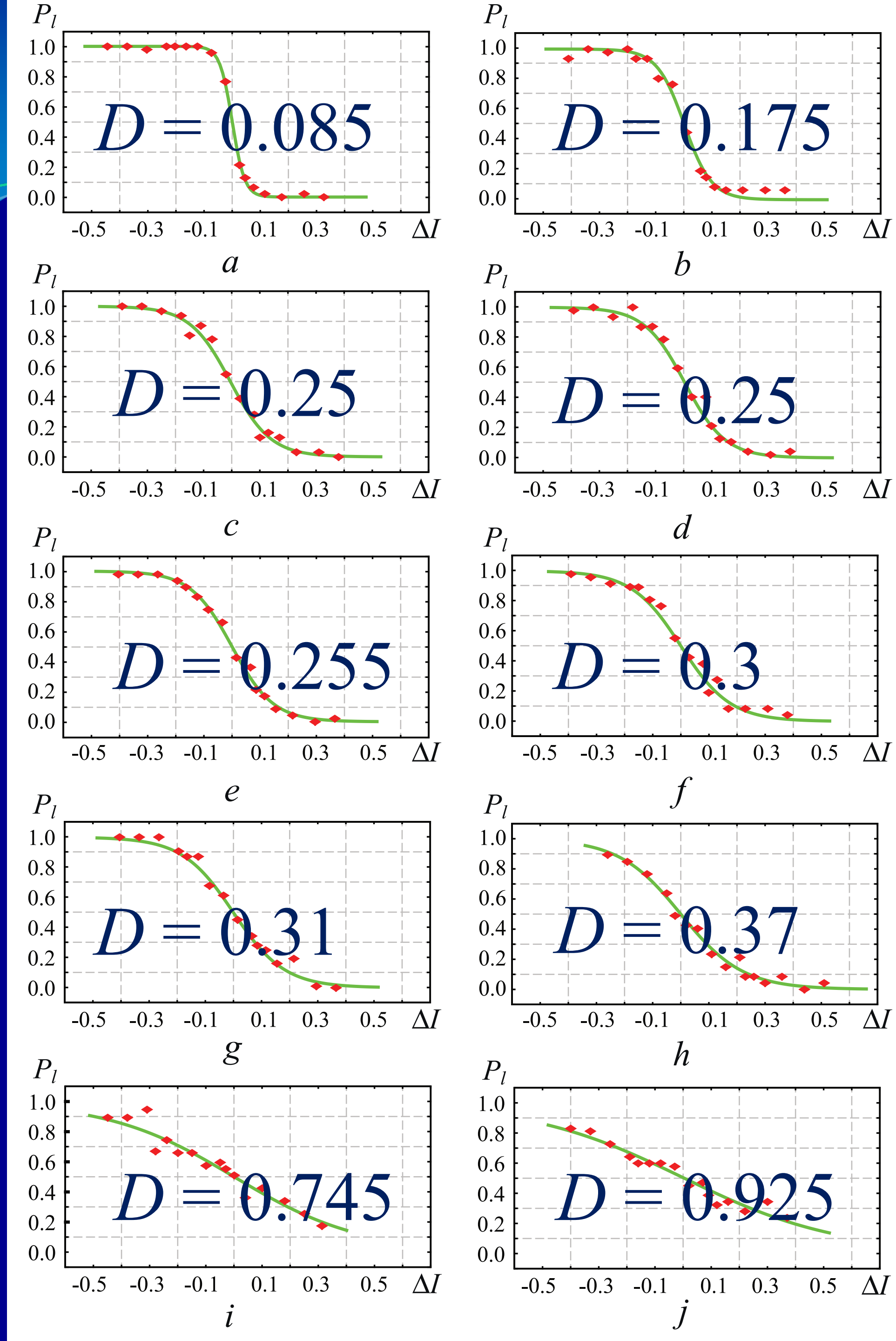


MagnetoEncefaloGraphy





306-channel (102 magnetometers and 204 planar gradiometers) Vectorview MEG system (Elekta AB, Stockholm, Sweden) in the magnetically shielded room.



Probability to perceive the left-oriented cube

$$P_l(I_j) = \frac{l(I_j)}{l(I_j) + r(I_j)}$$

where $l(I_j)$ and $r(I_j)$ are the numbers of clicks of left and right keys for the j-th Necker cube with control parameter I_j

Phase method

Chaos, Solitons & Fractals: X 1 (2019) 100005

Contents lists available at ScienceDirect

Chaos, Solitons & Fractals: X

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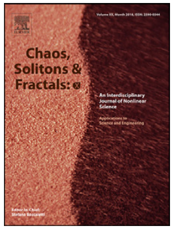

Brain noise estimation from MEG response to flickering visual stimulation

Alexander N. Pisarchik[a,b,*], Parth Chholak[a], Alexander E. Hramov[b]

[a] *Center for Biomedical Technology, Technical University of Madrid, Campus Montegancedo, Pozuelo de Alarcón, Madrid 28223, Spain*
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A R T I C L E I N F O

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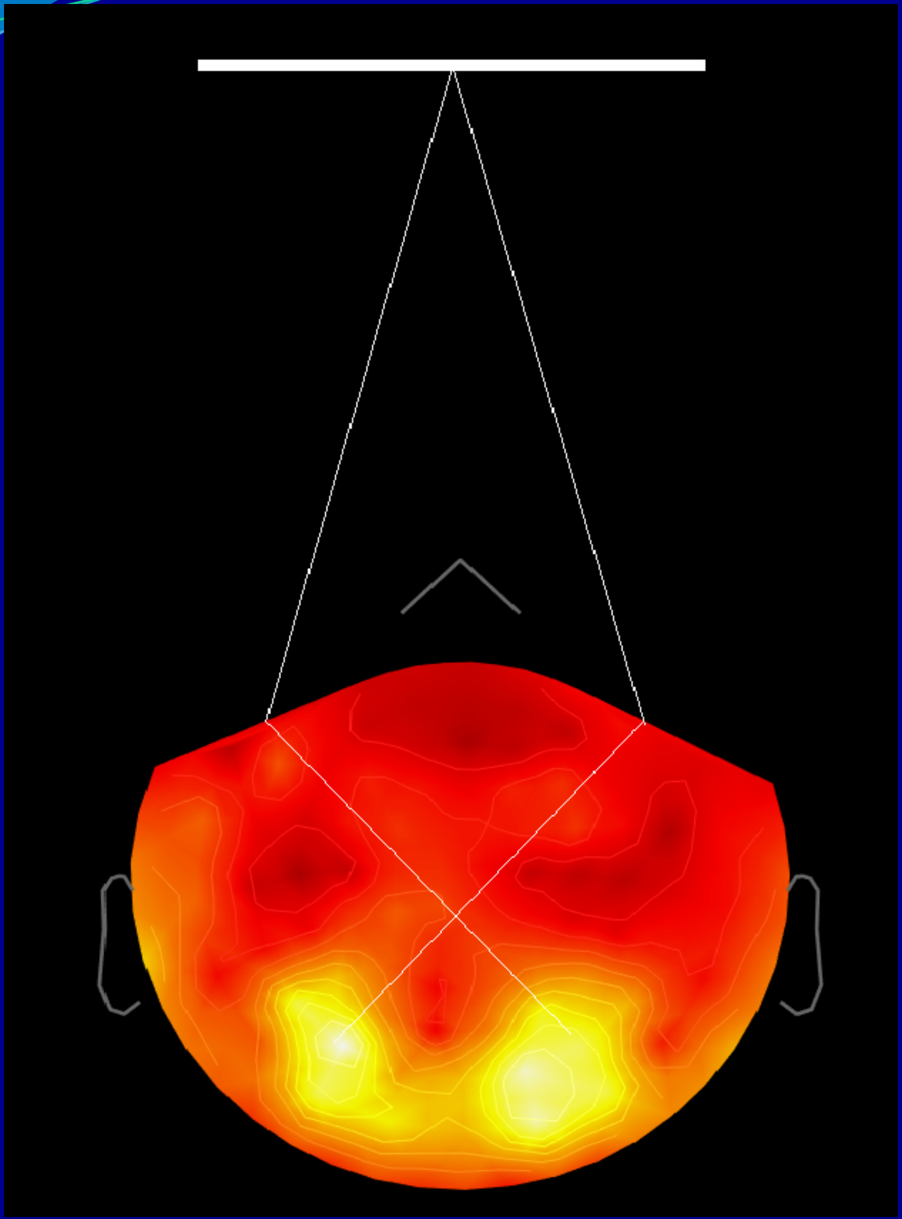
Modulation
Noise
Phase locking
Frequency tags

A B S T R A C T

We consider the brain as an autonomous stochastic system, whose fundamental frequencies are locked to an external periodic stimulation. Taking into account that phase synchronization between brain response and stimulating signal is affected by noise, we propose a novel method for experimental estimation of brain noise by analyzing neurophysiological activity during perception of flickering visual stimuli. Using magnetoencephalography (MEG) we evaluate steady-state visual evoked fields (SSVEF) in the occipital cortex when subjects observe a square image with modulated brightness. Then, we calculate the probability distribution of the SSVEF phase fluctuations and compute its kurtosis. The higher kurtosis, the better the phase synchronization. Since kurtosis characterizes the distribution's sharpness, we associate inverse kurtosis with brain noise which broadens this distribution. We found that the majority of subjects exhibited leptokurtic kurtosis ($K > 3$) with tails approaching zero more slowly than Gaussian. The results of this work may be useful for the development of efficient and accurate brain-computer interfaces to be adapted to individual features of every subject in accordance with his/her brain noise.

Coherence



Frequencies: 60/7 = 6.67 Hz
60/9 = 8.57 Hz

Shapes: sinusoidal, rectangular

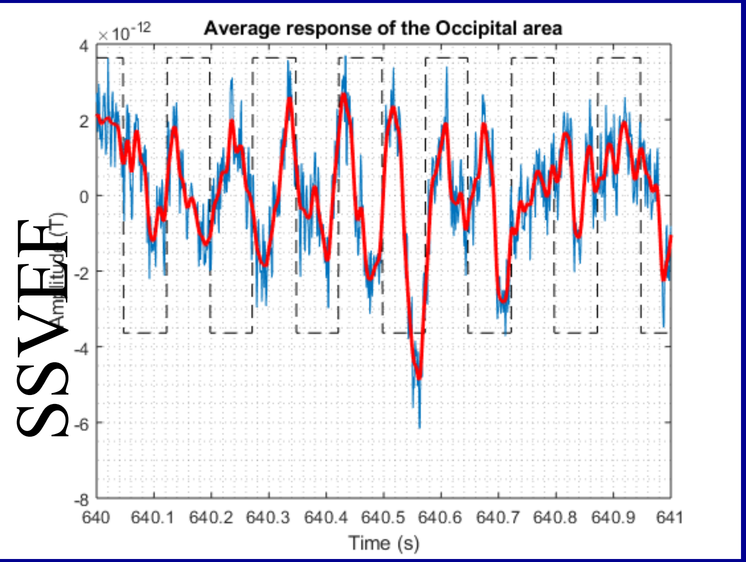
Modulation depth: 100%

Stimulus duration: 120 s

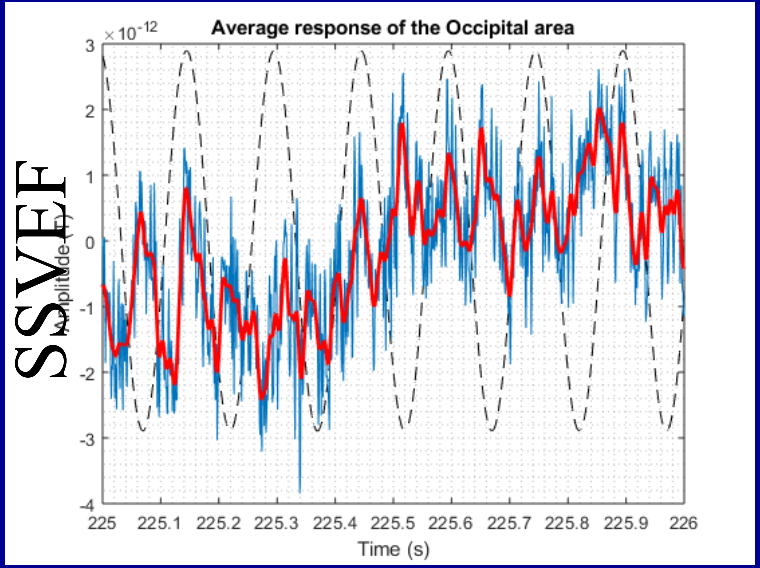
Time between: 30 s

Subjects: 13 subjects
20–64 years old

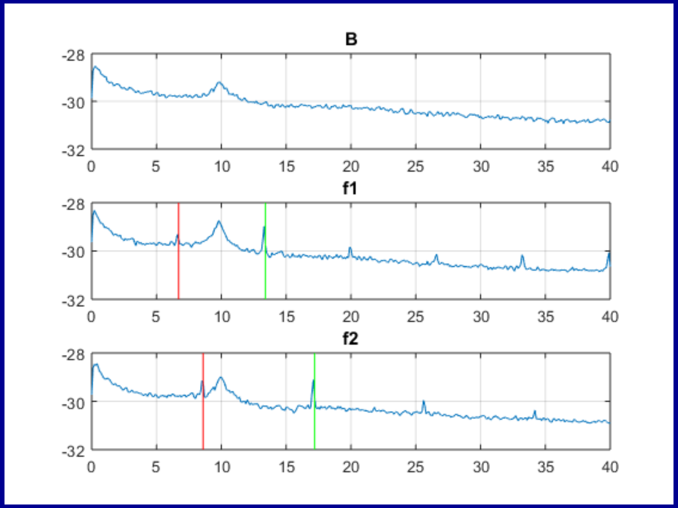
Visual evoked field (VEF)

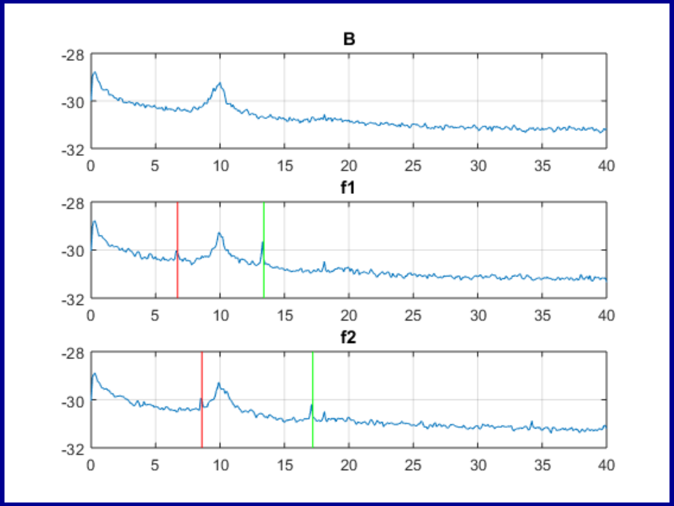


Second harmonic dominates



Power spectra of SSVEF

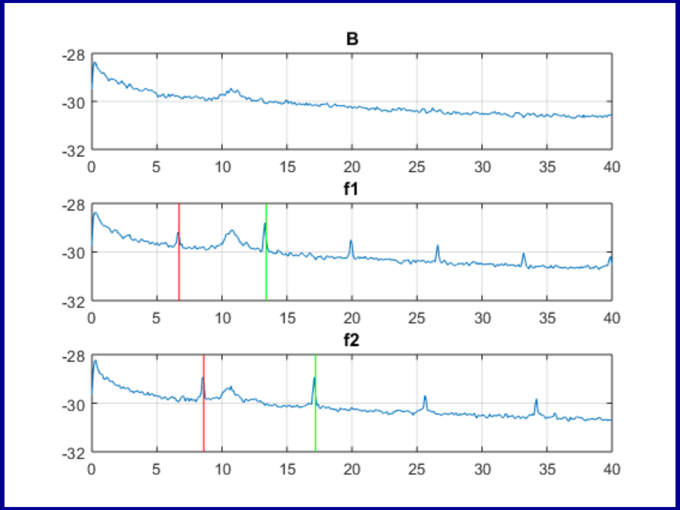


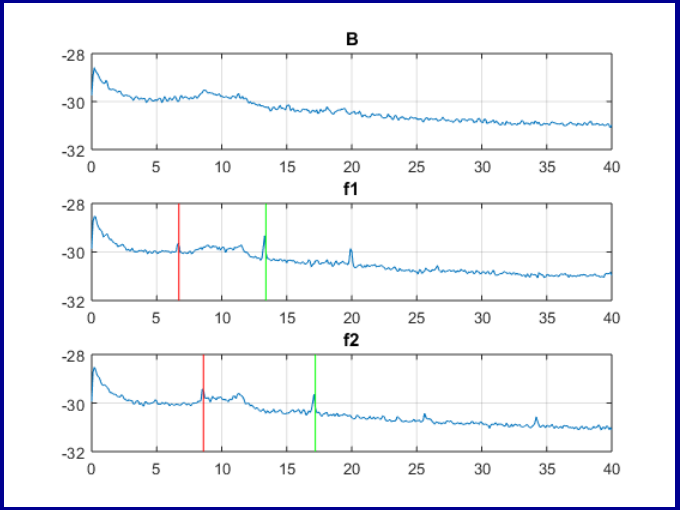


BG

6.67 Hz

8.57 Hz





BG

6.67 Hz

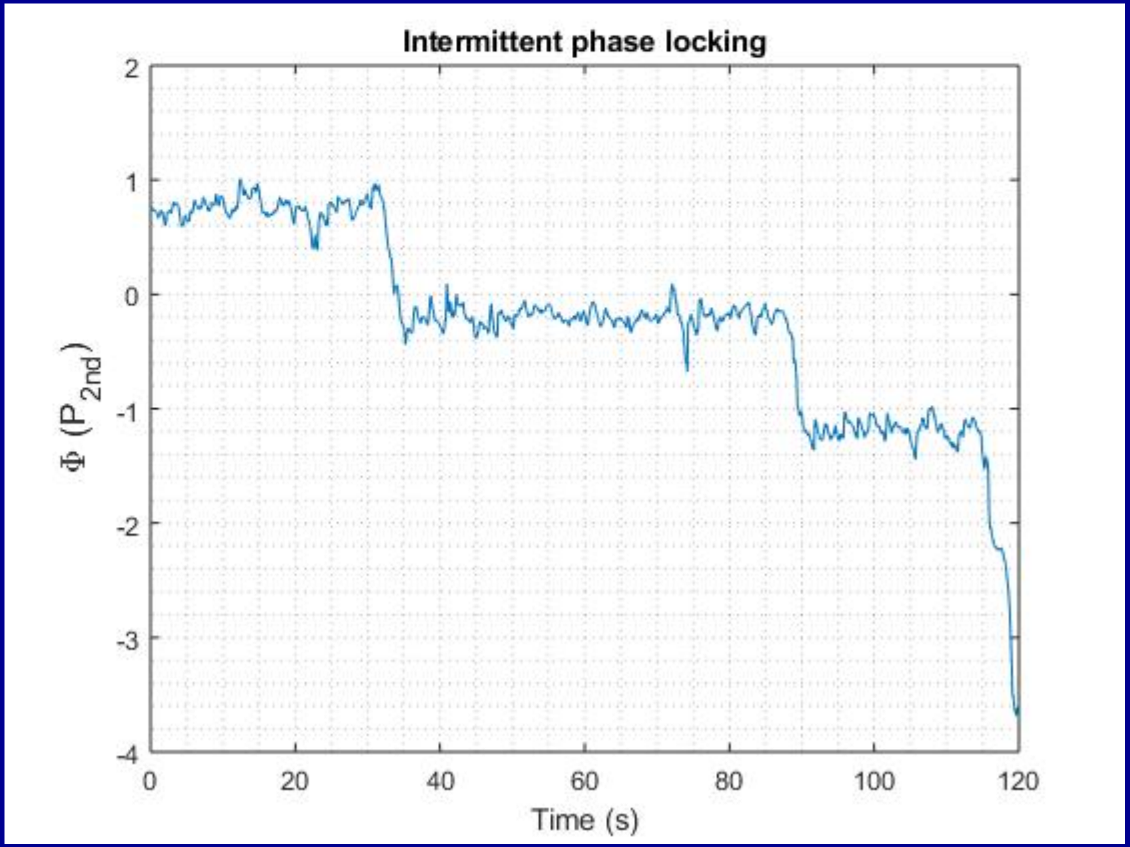
8.57 Hz

Second harmonic dominates

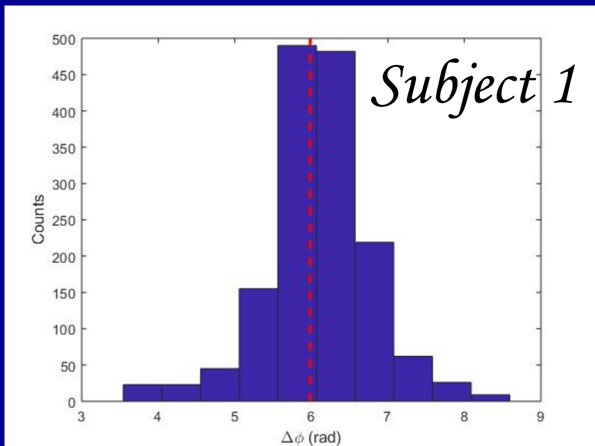
SSVEF phase

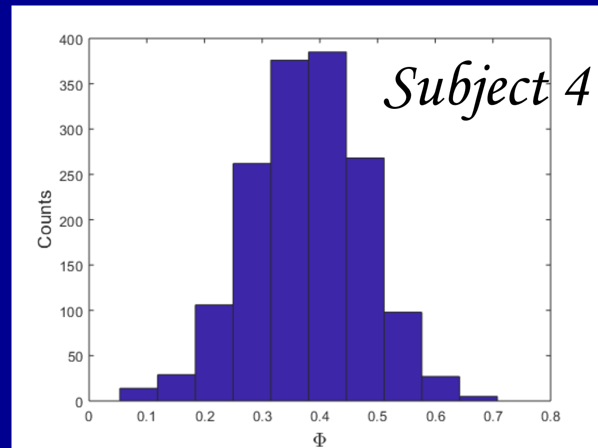
Phase difference between SSVEF and second harmonic of the flicker signal

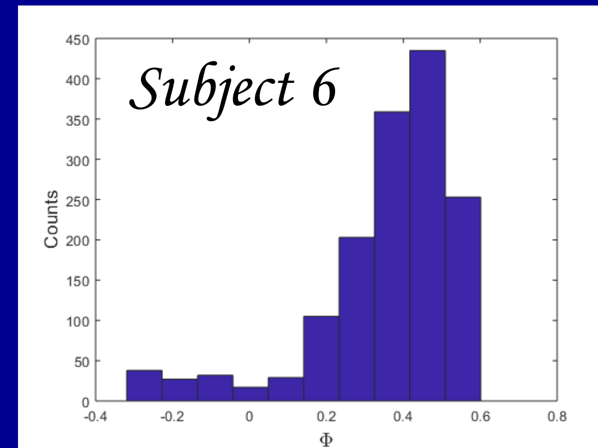
$$\Phi = (t^{b}_{n} - t^{s}_{n})\, 2fs$$

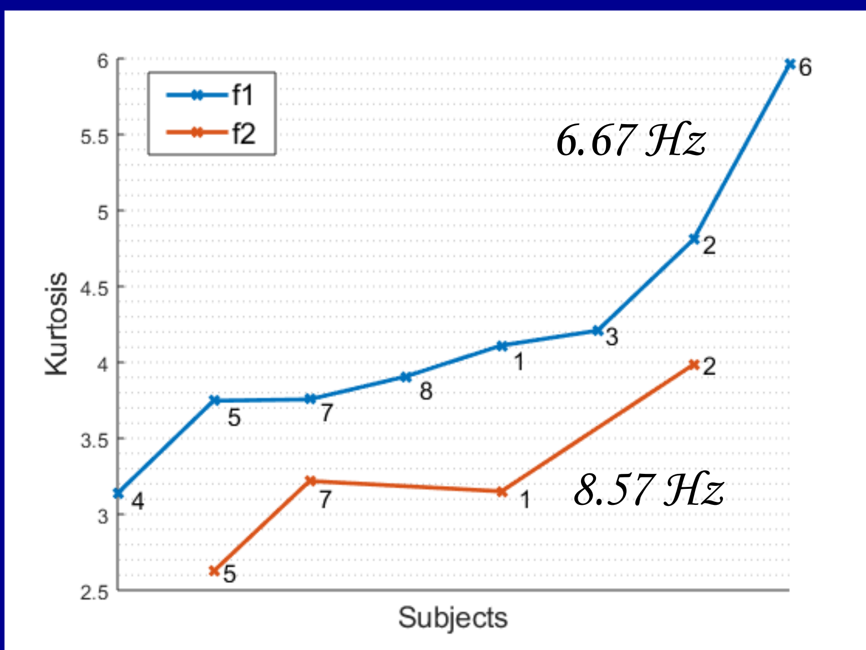


SSVEF probability distribution







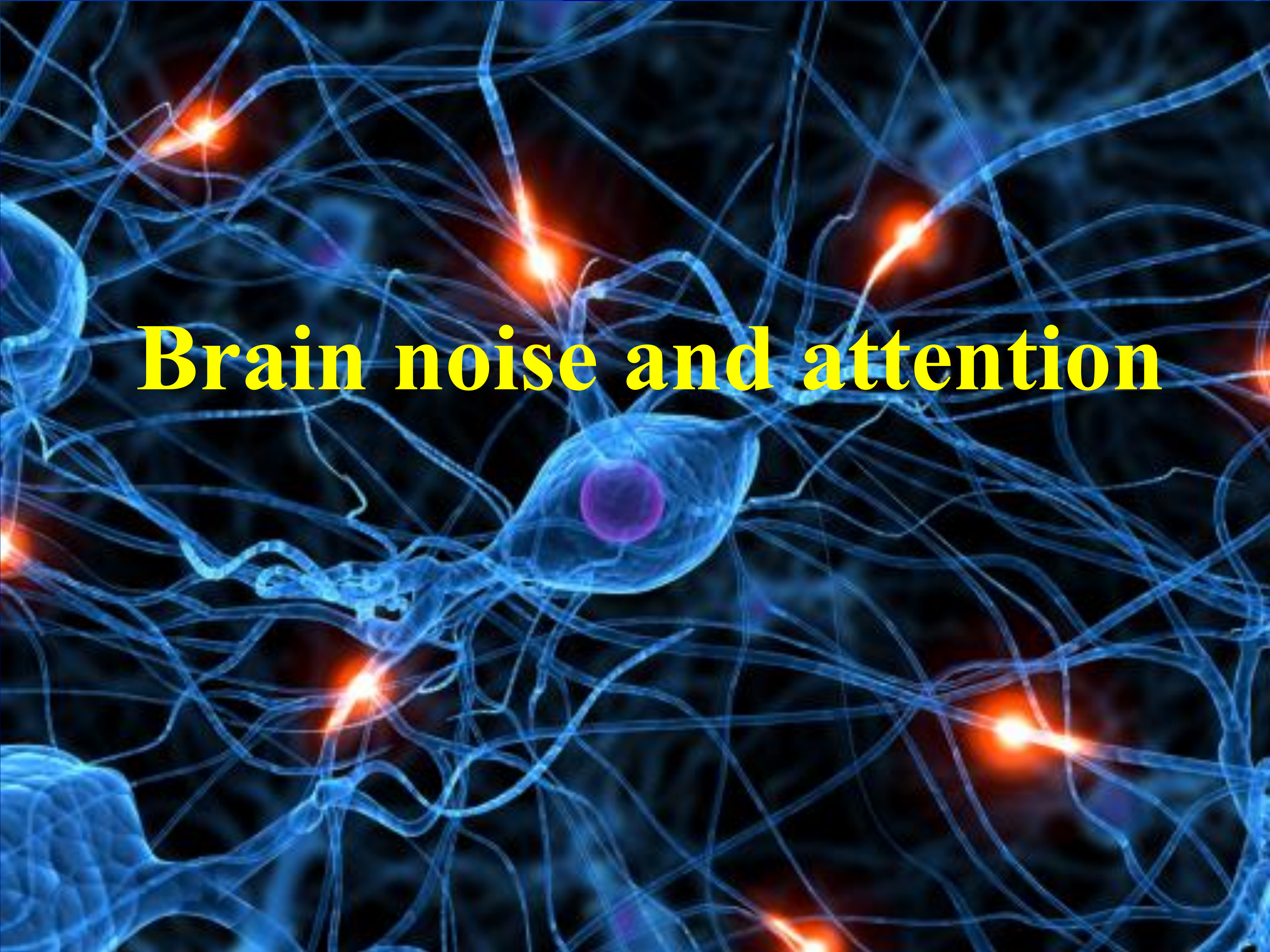


Kurtosis:

$$K = \frac{E(\Phi - <\Phi>)^2}{\sigma^4}$$

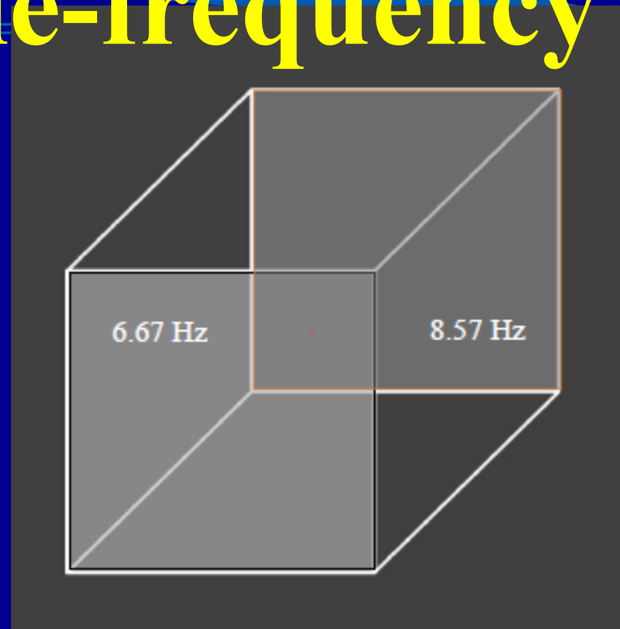
$<\Phi>$	average phase difference
σ	standard deviation
E	function of the expected value

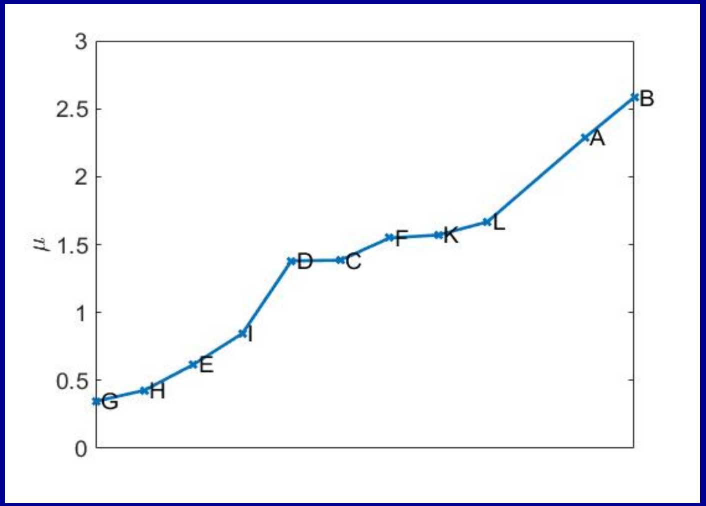
Brain noise and attention



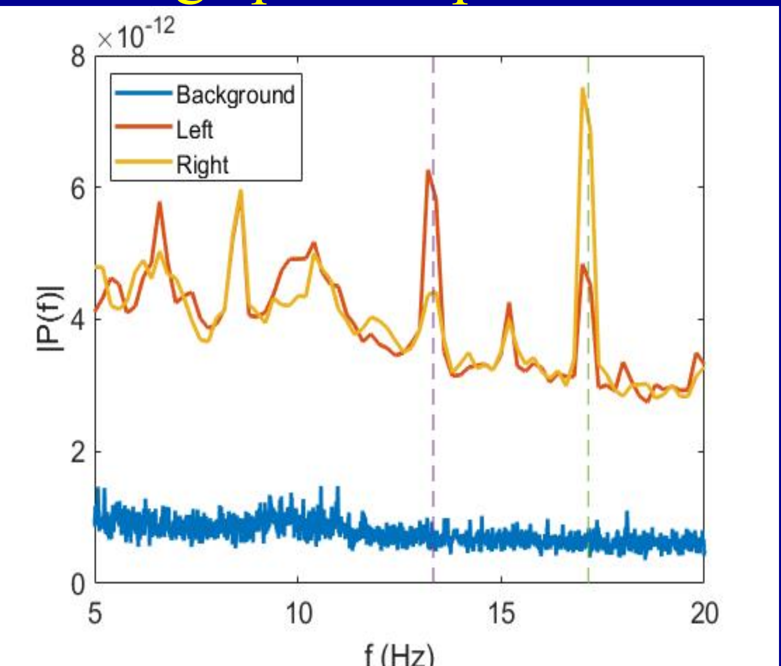
Double-frequency flickering

Voluntary attention





Average power spectra of VIF



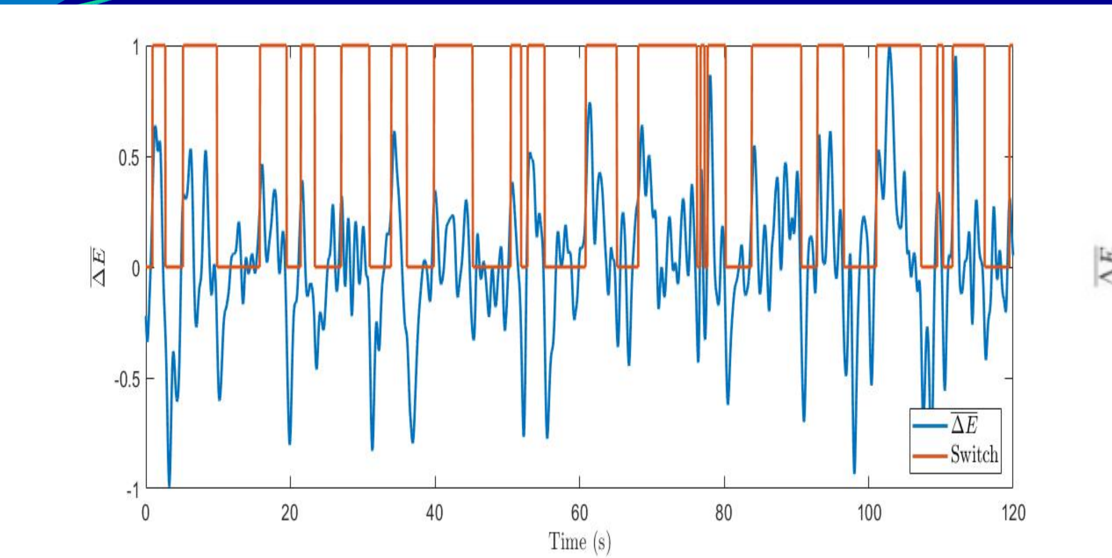
Attention performance

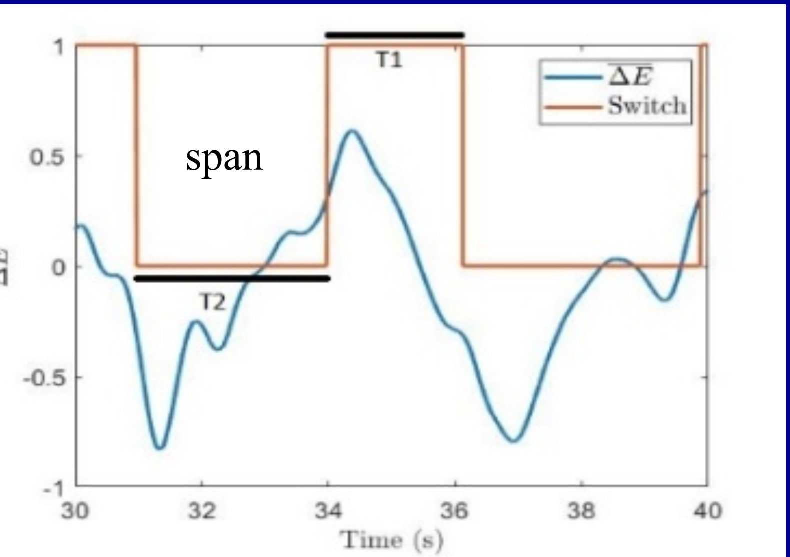
$$\boxed{\mu = D_1 - D_2}$$

$$D_{1,2} = P_{1,2}{}^{L} - P_{1,2}{}^{R}$$

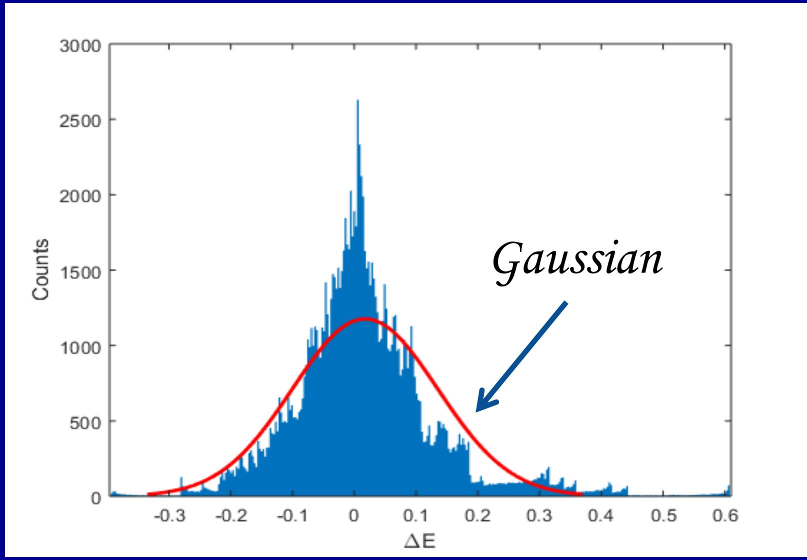
$P_{1,2}{}^{L}$ and $P_{1,2}{}^{R}$ wavelet powers averaged over all trials for left- and right-oriented cube interpretations

Involuntary attention

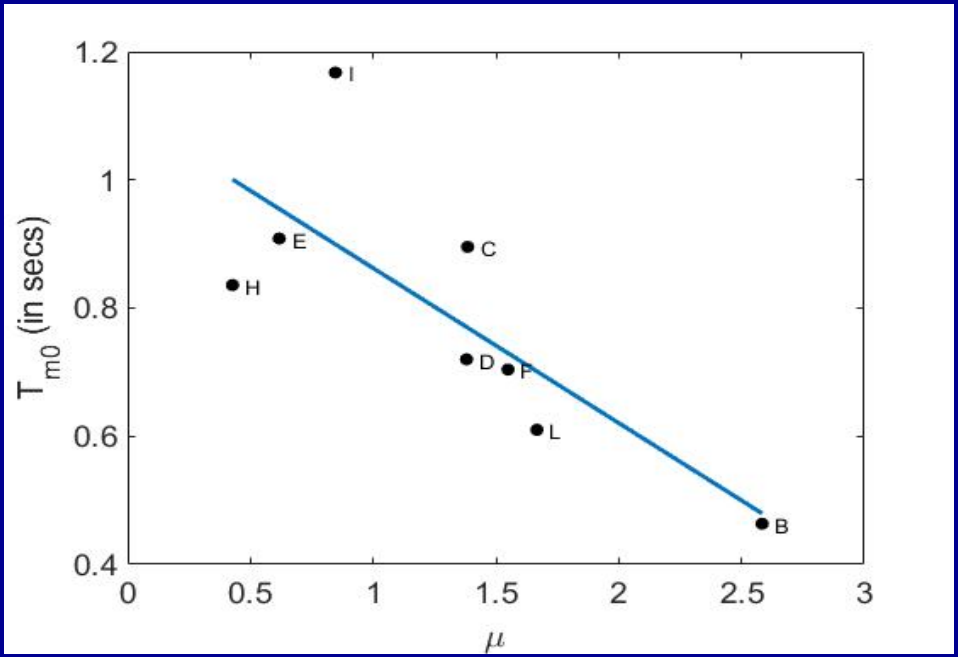


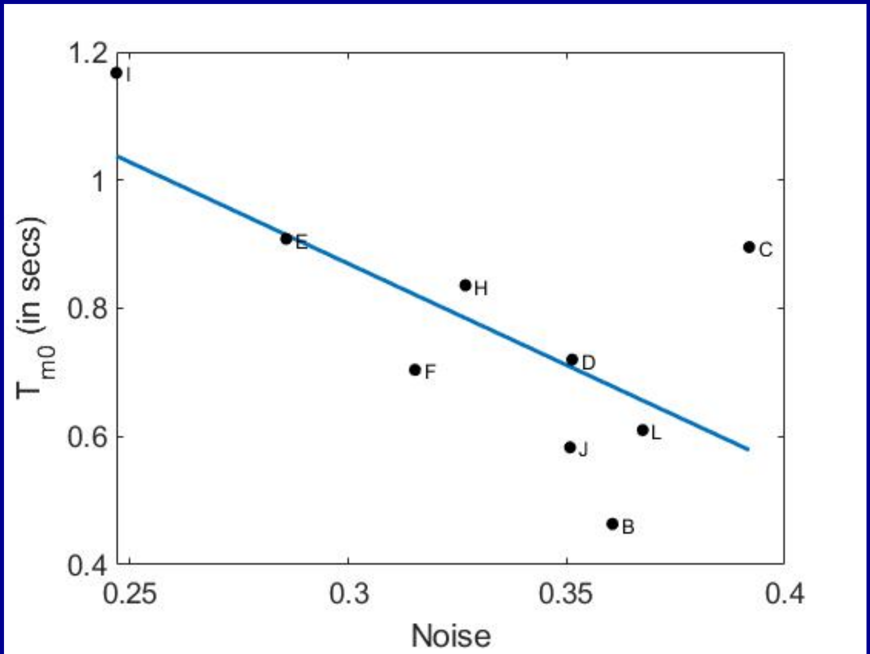


Wavelet power



Dominance time

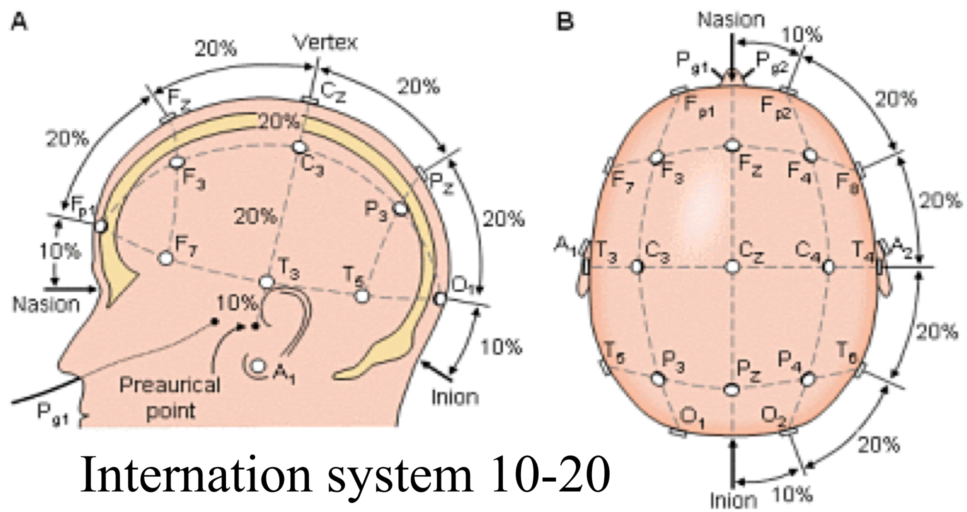




Higher attention requires a larger neuronal network to process information and make a decision, and hence brain noise is stronger

Decision-making uncertainty

NEUROPHYSIOLOGICAL EXPERIMENT



Internation system 10-20

frontiers in Neuroscience

ORIGINAL RESEARCH
published: 04 December 2017
doi: 10.3389/fnins.2017.00674

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Classifying the Perceptual Interpretations of a Bistable Image Using EEG and Artificial Neural Networks

Alexander E. Hramov[1,2], Vladimir A. Maksimenko[1], Svetlana V. Pchelintseva[1], Anastasiya E. Runnova[1], Vadim V. Grubov[1], Vyacheslav Yu. Musatov[1], Maksim O. Zhuravlev[1,2], Alexey A. Koronovskii[1,2] and Alexander N. Pisarchik[1,3]**

Chaos ARTICLE scitation.org/journal/cha

Percept-related EEG classification using machine learning approach and features of functional brain connectivity

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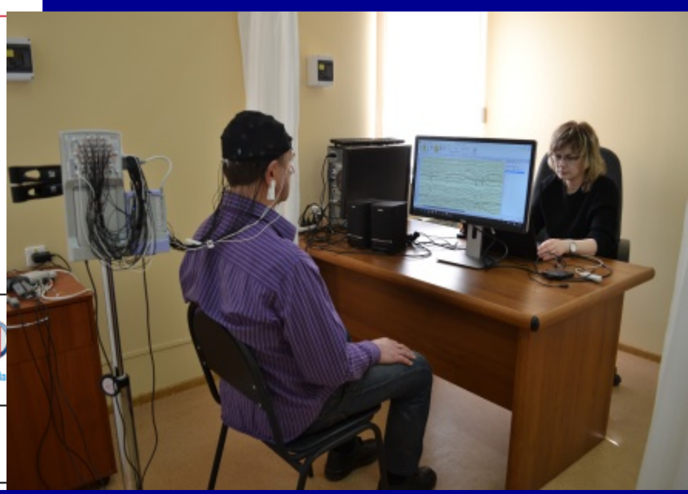
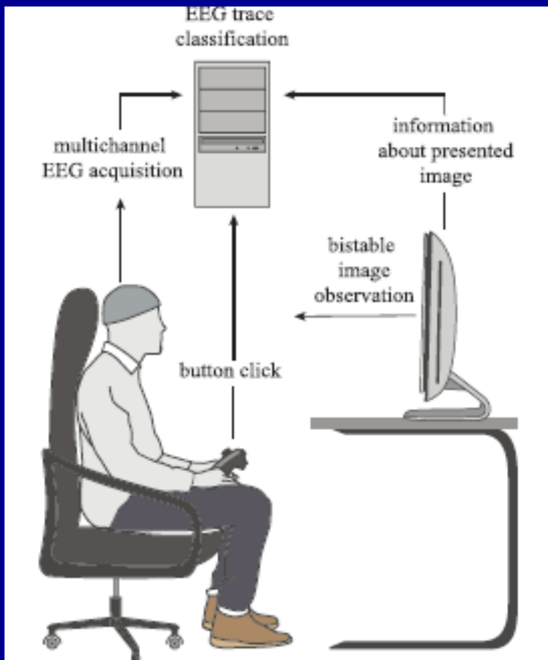
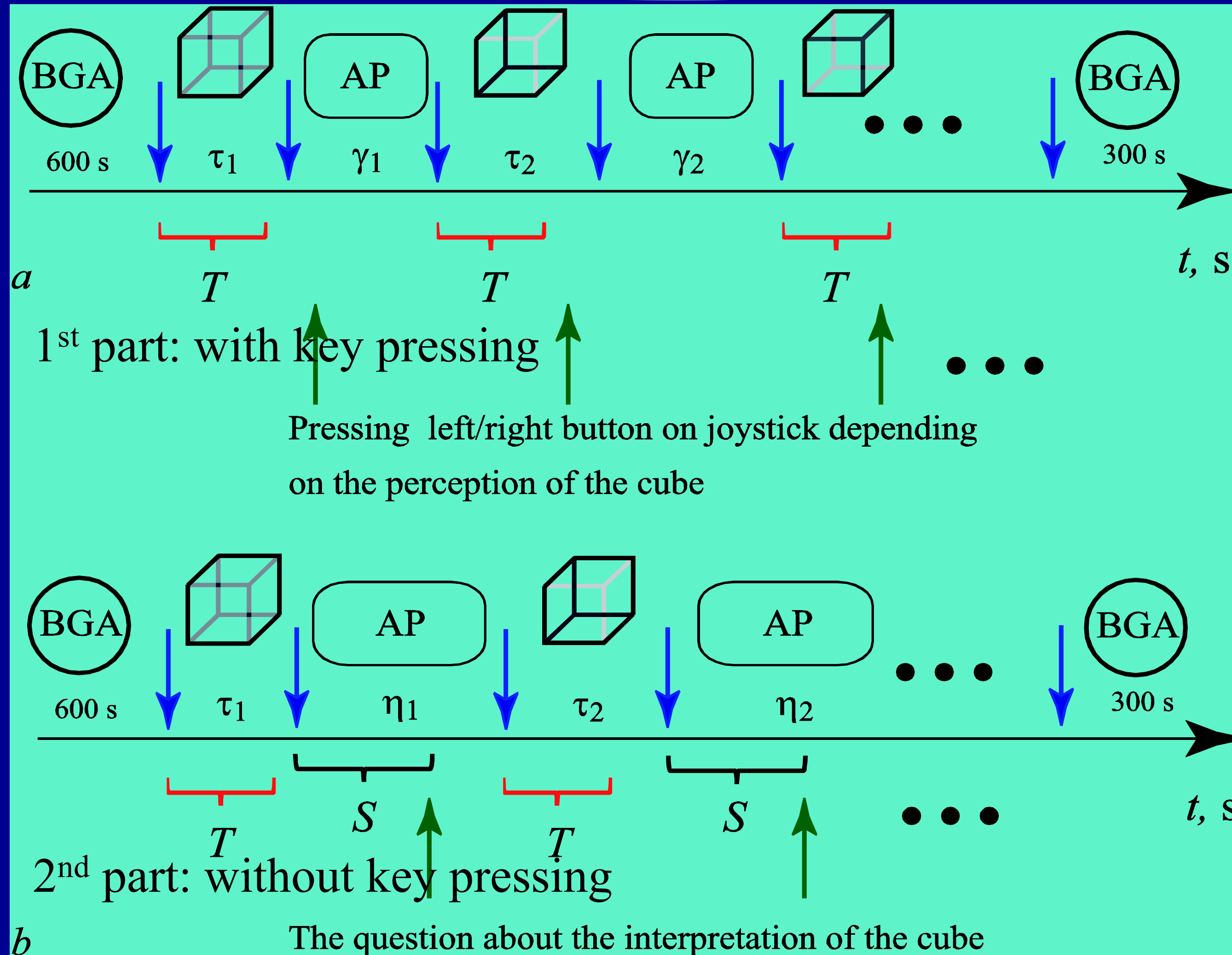
Alexander E. Hramov,[1,a)] Vladimir Maksimenko,[1] Alexey Koronovskii,[2] Anastasiya E. Runnova,[1] Maxim Zhuravlev,[1] Alexander N. Pisarchik,[1,3] and Jürgen Kurths[4,5,6]



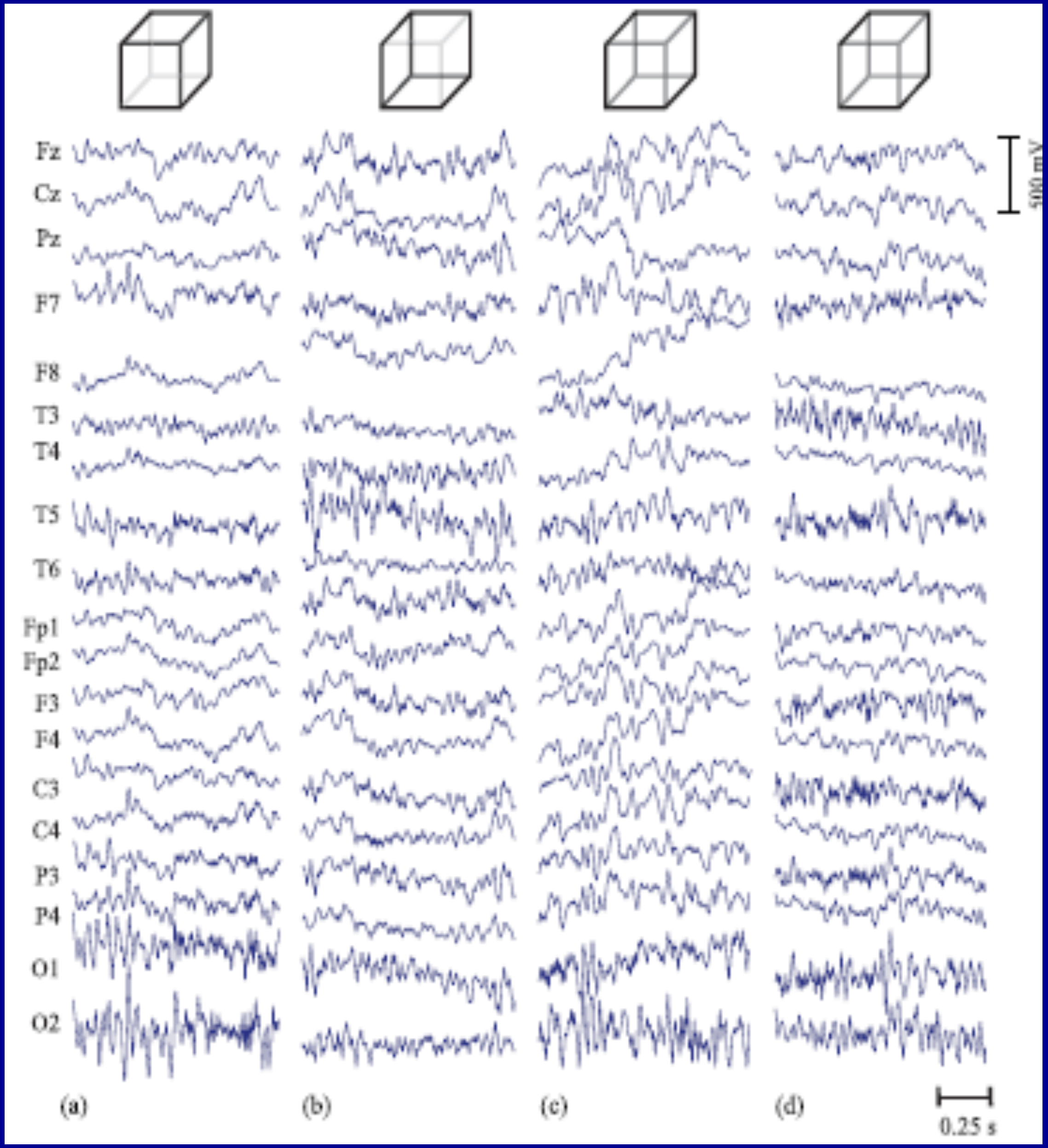
EXPERIMENTAL PROTOCOL



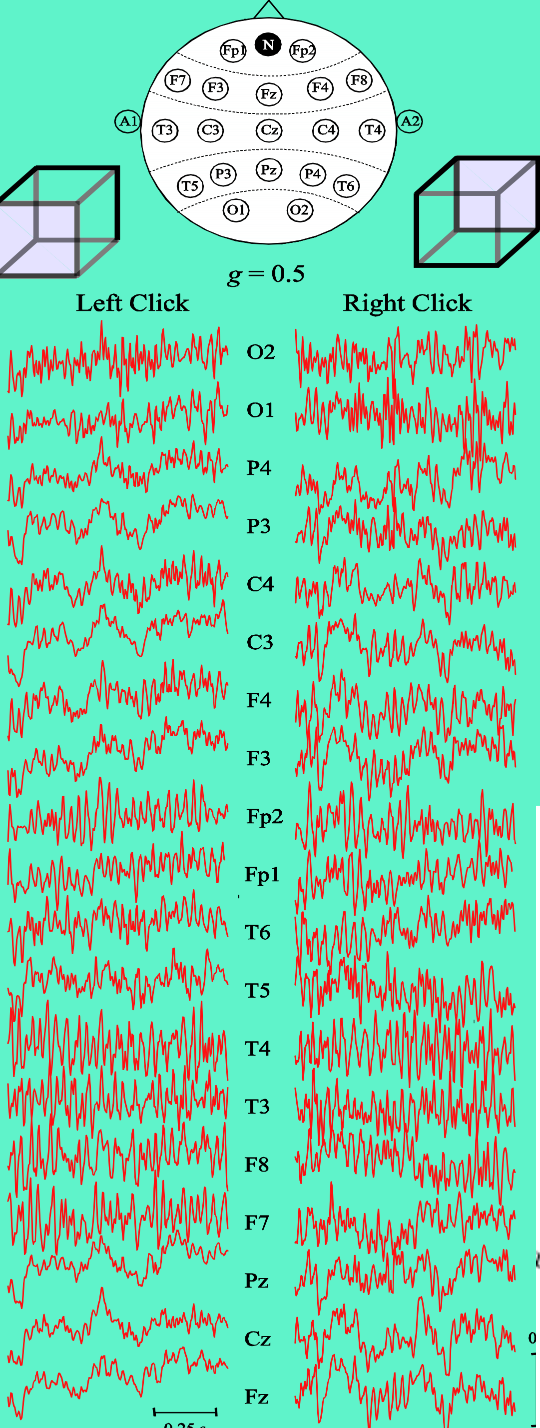


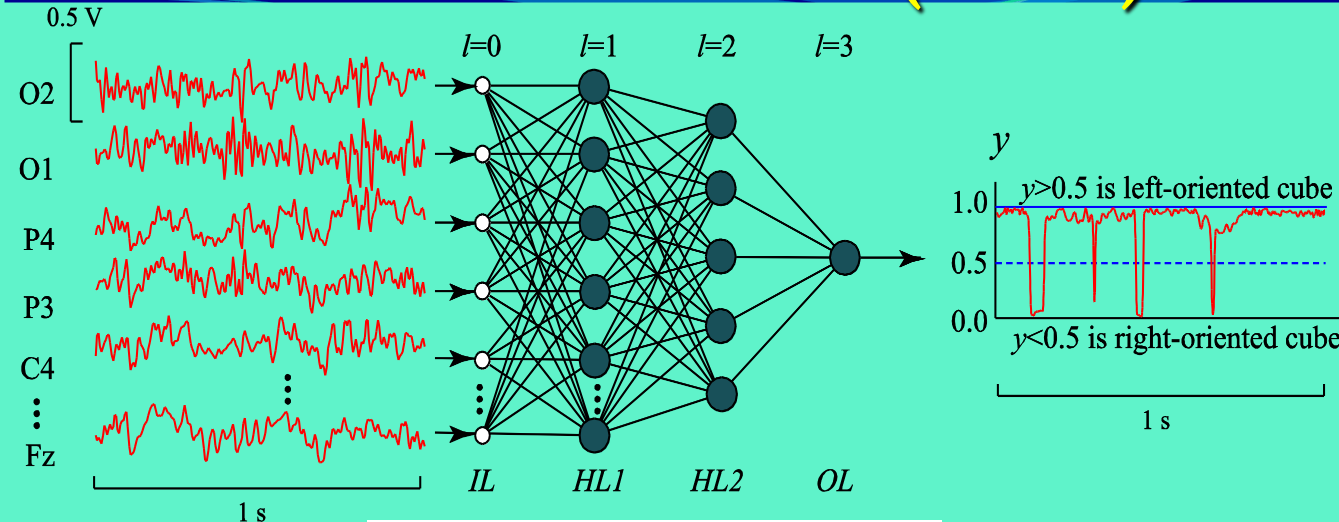
400 cubes randomly presented for $T = 0.8 - 1.3$ s
and abstract pictures in between for $S = 2 - 3$ s

Typical EEG trials



MLP architecture (EEG)





$$u_i^l(t) = F^l\left(\sum_{p=1}^{H^{l-1}} w_{pi}^l u_p^{l-1}(t) - \theta_i^l\right)$$

where H^l is the number of neurons in the l-th layer (a layer with $l = 0$ is supposed to be the input layer), $u_i^l(t)$ is the output signal of the i-th neuron belonging to the l-th layer ($u_i^0(t)$ being the signals from analyzed EEG channels), $\mathbf{W}^l = \{w_{pi}^l\}$ is the weight matrix of the l-th layer of dimension ($H^{l-1} \times H^l$), and w_{pi}^l ($p = 1, \ldots, H^{l-1}$, $i = 1, \ldots, H^l$) are the synaptic weights of input signals for the i-th neuron in the l-th layer, $\mathbf{\Theta}^l = \{\theta_i^l\}$ is the threshold vector for neurons in the l-th layer, and

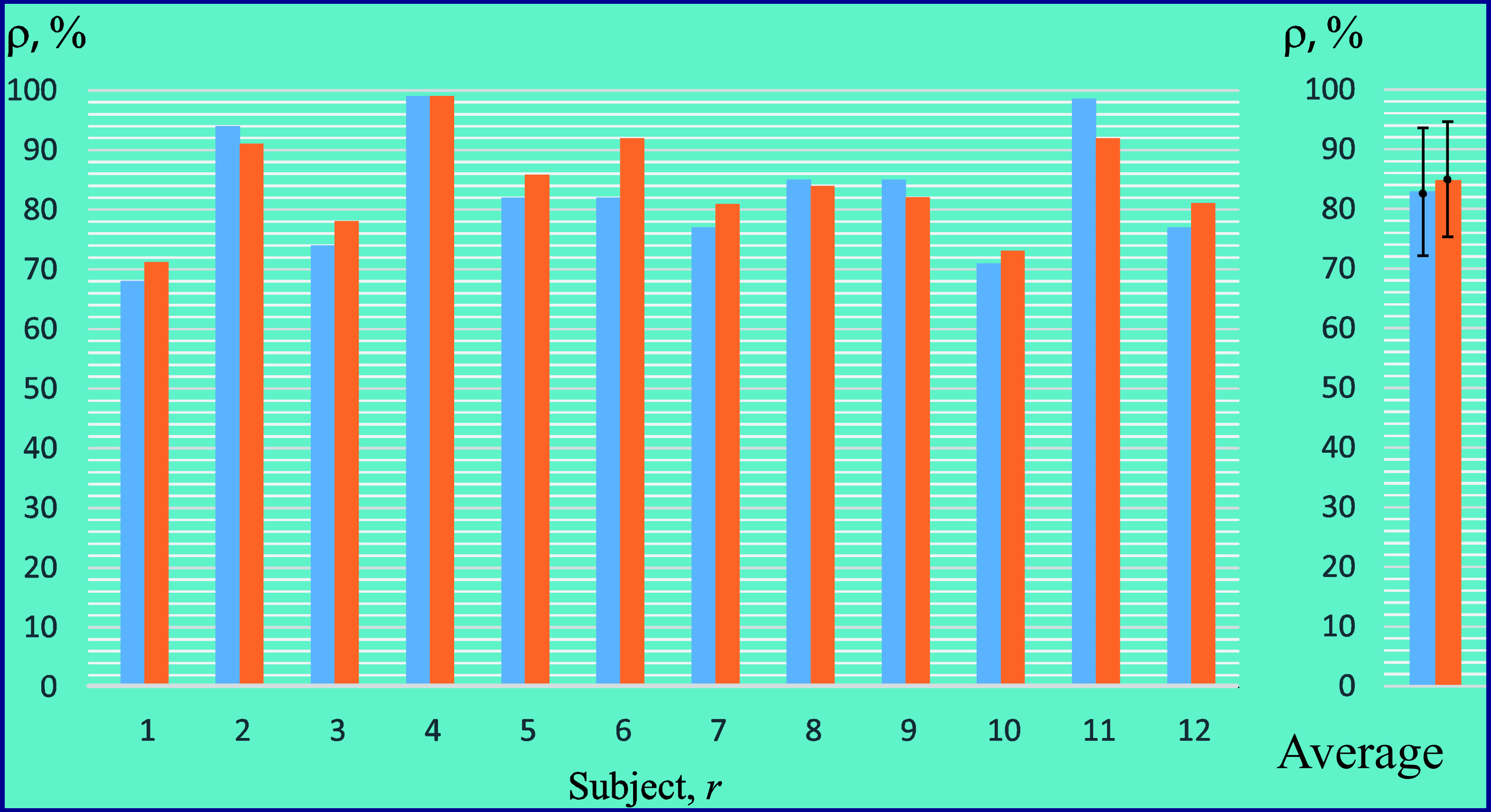
$$F^l(\eta) = f(\eta) = \frac{1}{1 + \exp(-\eta)} \tag{6}$$

is the nonlinear logistic activation function for neurons in the hidden and output layers $l = 1, 2, 3$.

A class of recognized objects can be characterized by the mean squared value of output signal $u(t) = u_1^3(t)$, as follows

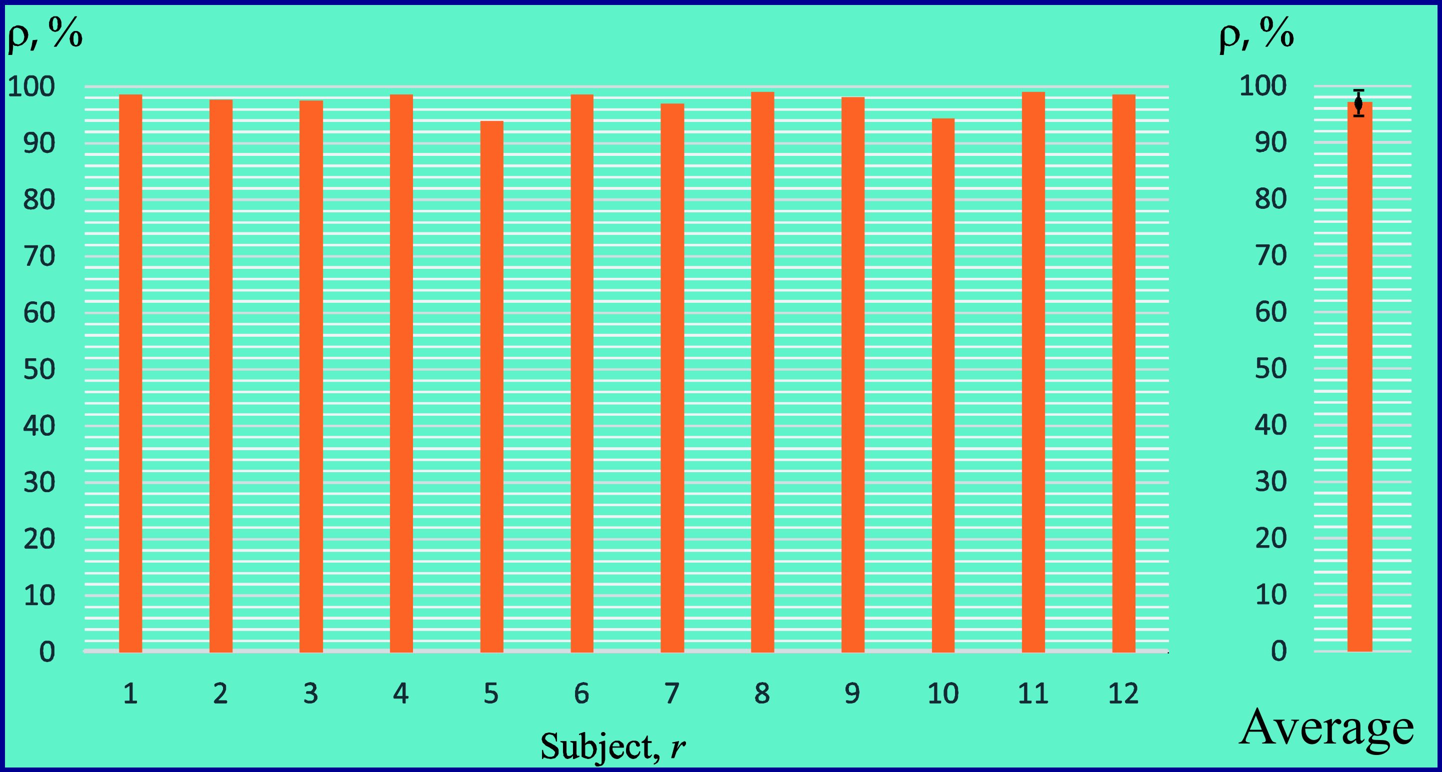
$$y = \sqrt{\frac{1}{T}\int_0^T (u(t))^2 \, dt}. \tag{7}$$

Recognition accuracy of ANN trained with own EEG

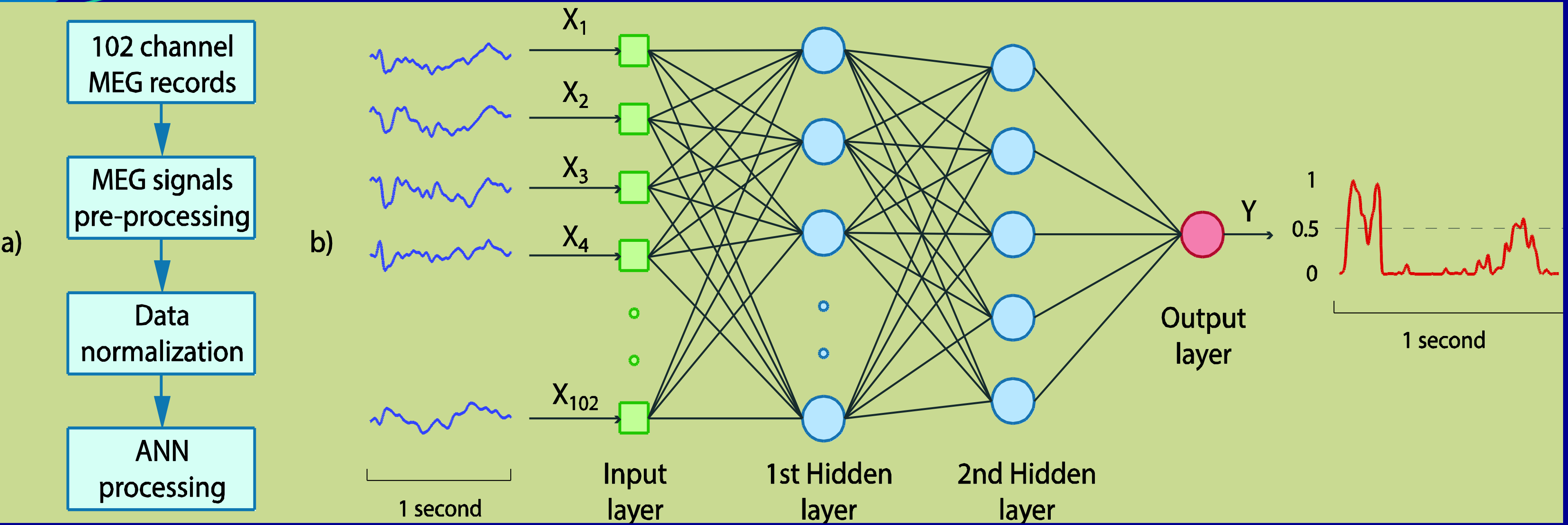


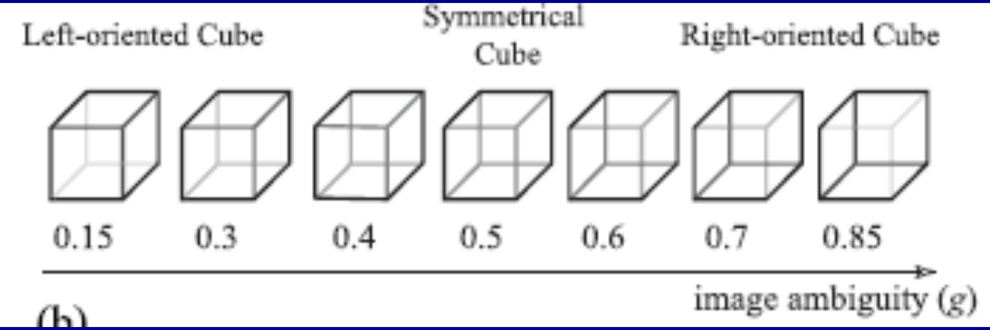
Left: with key pressing
Right: wthout key pressing

Recognition accuracy of ANN trained with EEG of subject 4



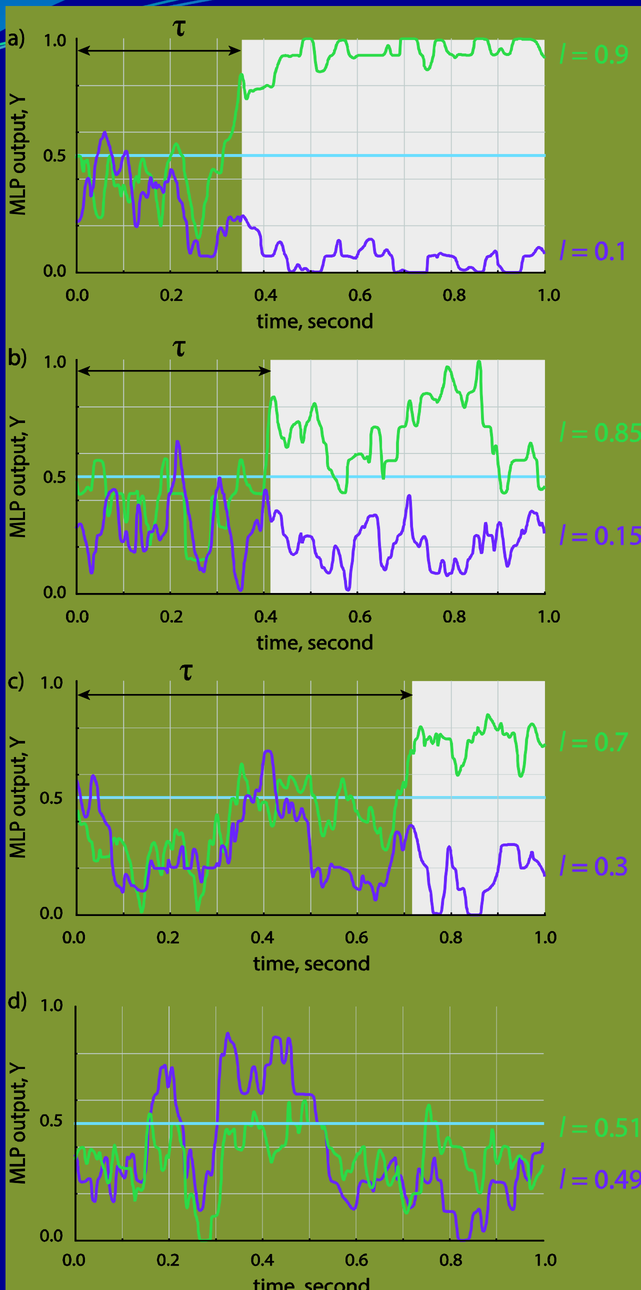
MLP architecture (MEG)



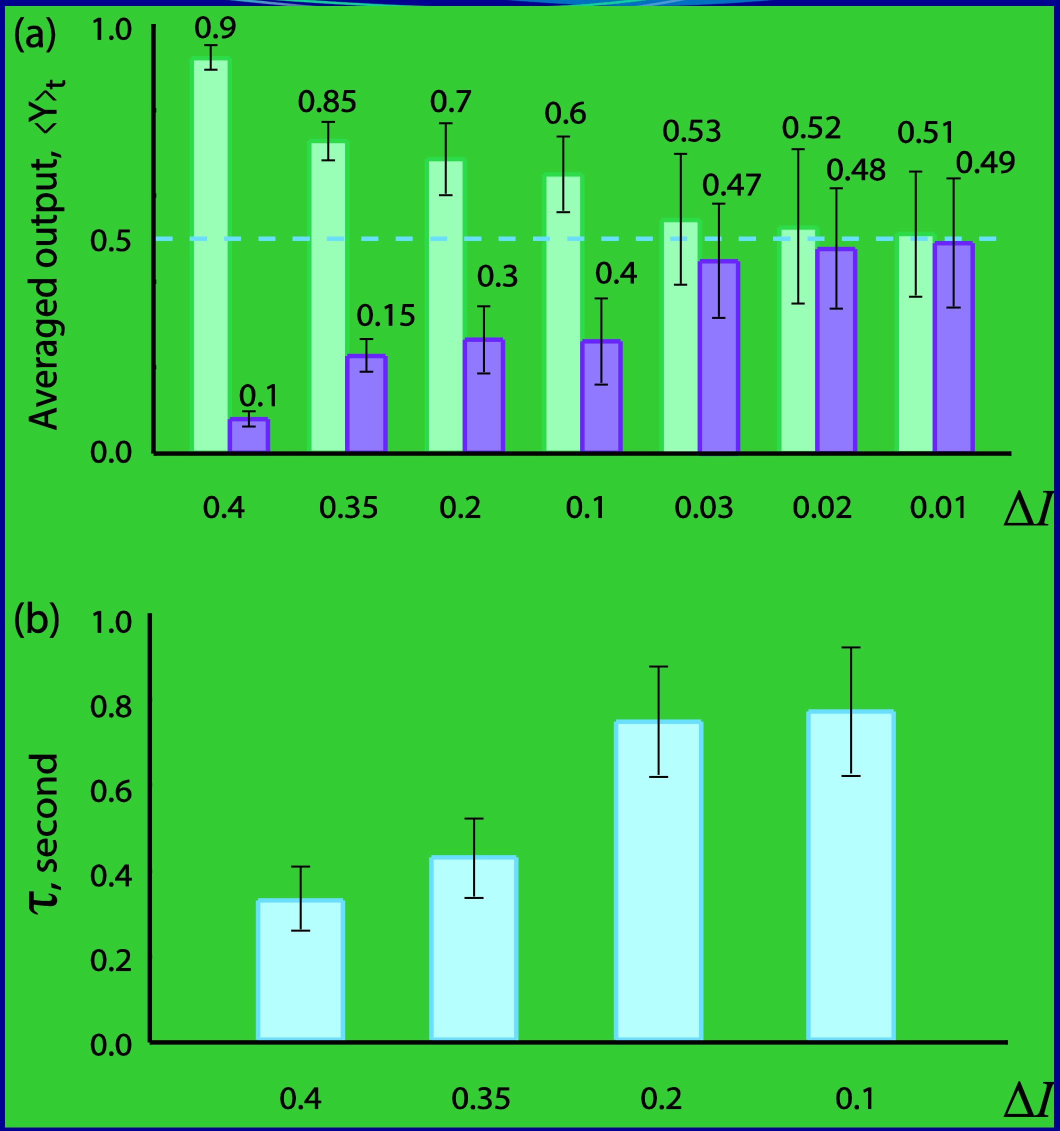


We used 15 unique stimuli, for which the value of the contrast parameter of the internal edges was randomly chosen from the set I = (0.1, 0.15, 0.3, 0.4, 0.47, 0.48, 0.49, 0.5, 0.51, 0.52, 0.53, 0.6, 0.7, 0.85, 0.9). Each contrast was presented 15 times for a short period.

MLP response to MEG trials



Statistical characteristics



Applications

The results can help in understanding pathological brain stability states, such as schizophrenia and obsessive-compulsive disorder. These states with a weak stability may result from very weak brain noise.

Instead, a very stable state may contribute to the attention deficit hyperactivity disorder (ADHD) due to very strong brain noise.

Large deviations of the cognition reaction time from its mean value can indicate on serious brain diseases, such as delayed response syndrome or reactive attachment disorder.

The results provide new promising applications of artificial neural networks that aim to quantitatively describe the decision-making process in different intelligent systems.

The results can also be demanded for the development of new generation of brain-computer interfaces enable to control and enhance human ability to make difficult decisions in stressful conditions.


Thank you