

Single cell and population activities in cortical-like systems

Fülöp Bazsó^a, Ádám Kepecs^{a,b}, Máté Lengyel^a, Szabolcs Payrits^a,
Krisztina Szalischnyó^a, László Zalányi^a, Péter Érdi^{a*}

^aDepartment of Biophysics, KFKI Research Institute for Particle and Nuclear Physics
of the Hungarian Academy of Sciences; H-1525 Budapest P.O. Box 49, Hungary

^bDepartment of Biology, Brandeis University, U.S.A.

Keywords: single cell dynamics, population dynamics, location-dependent inhibition,
stochastic resonance, hippocampus, olfactory bulb

*The corresponding author. Tel: 36 1 3959220 ext. 2505, Fax: 36 1 3959151, E-mail: erdi@rmki.kfki.hu

Synopsis

Dynamics of single cells and large cell populations are the subject of investigation by using differently detailed models. Multicompartmental modeling techniques are used to systematically investigate the location-dependent effects of GABA-ergic inhibition on the firing patterns of hippocampal pyramidal cells. Appearance of stochastic resonance in a model of mitral and granule cells of the olfactory bulb is demonstrated by using single-compartmental model approach. Spatial propagation of synchronized activities in hippocampus slices are studied by a model of large neural populations.

1 Introduction

1.1 Neural modeling: multiple strategies

Structure-based bottom-up modeling has two extreme alternatives, namely multi-compartmental simulations, and simulation of networks composed of simple elements. There is an obvious trade-off between these two modeling strategies. The former method is appropriate to describe activity patterns of single cells, small and moderately large networks based on data on detailed morphology and kinetics of voltage- and ligand-dependent ion channels. The latter offers a computationally efficient method for simulating large network of neurons where details of single cell properties are neglected. As a compromise between the two extreme approaches, behavior of large networks of neurons may be studied by population theories [39,23,6].

In our studies specifically, the investigated neural centers are olfactory bulb (OB) and hippocampus. Olfactory bulb and hippocampus are both neural structures closely connected to the neocortex. Though the delimitation of the neocortex from its neighbours has been suggested to be quantitative rather than qualitative [11], both OB and hippocampus are considered in some extent as cortical-like structures. Hippocampus itself participates

in processing olfactory information and OB projects (albeit sparsely) to the entorhinal cortex as well. Both the hippocampus and the olfactory system exhibit complex dynamic behavior: they generate rhythmic temporal patterns with different frequencies and with variable spatial coherence. Both systems were suggested to be candidates for chaos generators, too. Global electric patterns measured by EEG have behavioral correlates, and have crucial roles in learning and memory formation. For some comparison of the olfactory system with the hippocampus, see Arbib et al [5].

In the present paper we briefly show two applications of compartmental modeling and one of the theory of neural populations. Our main aim is to illustrate that understanding neural phenomena occurring at different hierarchical levels and spatiotemporal scales requires different type of modeling strategies and tools. First, a distinction between somatic and dendritic inhibition for hippocampal pyramidal cells is studied. Here we use very detailed *multicompartmental* models, and effects due to relatively small differences in location are demonstrated. Second, we study the question whether or not stochastic resonance may be a candidate for being a mechanism of amplifying weak signals during odour information processing. Since we were interested in the interplay of a nonlinear system with an external periodic signal subject also to noise, we used again the Hodgkin-Huxley scenario. We concentrated to the mechanism of the amplification of weak external signals, and therefore nonlinear models of neurons had to be defined. We still used biophysically detailed but *single-compartmental* models reduced from multicompartmental models. Single compartmental models proved to be an efficient compromise between less realistic integrate-and-fire models and computationally more time-demanding multicompartmental models. Third, emergence and propagation of synchronized *population* activity in hippocampal CA3 region is examined. We developed a new theoretical method and a computational model to simulate neural population phenomena [6,23]. Having been motivated by Ventriglia's [37-39] assumptions we treat interactions between neural and spike populations statistically. To be able to make large-scale simulations many structural

details have to be sacrificed. This loss is partially compensated by incorporating a relatively detailed single cell model into the population mode. This model is capable to reflect basic firing patterns of a hippocampal pyramidal cell including its capability to exhibit bursting behaviour.

2 Effects of location of inhibition on hippocampal pyramidal cells

2.1 Location-dependent inhibition of pyramidal cells

Inhibitory synapses are known to be distributed throughout the dendrites and the soma of pyramidal cells in several cortical regions. Recent experimental evidence [24,29] suggests that inhibitory synapses of different locations are associated with specific actions based on their position. It has been observed that IPSP responses to GABA have different time-courses corresponding to different locations of receptors. This can be explained either by electrotonic filtering of the dendritic tree or by different subspecies of GABA_A receptors giving rise to distinct responses. Pearce [30] has found that these differences are explained by different ratios of two pharmacologically distinct species of GABA_A receptors in the dendrites versus the soma. Paired recordings conducted by Miles and coworkers [29], where response properties could be directly related to specific synapses, may support the hypothesis that differences are due to dendritic filtering, which is a possible mechanism to account for how different actions attributed to synaptical receptors with identical kinetics arise.

2.2 Methods

Given the inherent morphology-centric nature of the project, we have used standard multi-compartmental biophysical modeling techniques with GENESIS neurosimulator package [<http://www.bbb.caltech.edu/GENESIS>]. Following usual methods applied to similar problems [33], a passive pyramidal cell with simplified "ball & stick" and with detailed morphology was simulated, both based on the model described by Traub et al. [35]. Thus,

one compartment obeyed the

$$C_m \frac{dV_m}{dt} = \sum_i \frac{V_m^{(i)}(t) - V_m(t)}{R_a^{(i)}} + g_L (E_L - V_m(t)) + I_{syn}(t) \quad (1)$$

equation, C_m being the membrane conductance, V_m being the membrane potential of the compartment, $V_m^{(i)}$ the membrane potential of the i th compartment attached to it through an axial resistance $R_a^{(i)}$, g_L being the constant conductance of the leak current with equilibrium potential E_L , and I_{syn} being the synaptic current.

Synapses were modeled with double exponential kinetics:

$$I_{syn}(t) = g_{syn}(t) (E_{rev} - V_m) \quad (2)$$

$$g_{syn}(t) = \frac{A g_{max}}{\tau_2 - \tau_1} \left(e^{-\frac{t_0-t}{\tau_2}} - e^{-\frac{t_0-t}{\tau_1}} \right) \quad for \ (\tau_2 > \tau_1) \quad (3)$$

where E_{rev} is the reversal potential of the synaptic potential, g_{syn} is the synaptic conductance with a maximum of g_{max} (achieved by scaling normalizing factor A appropriately) and time constants τ_1 and τ_2 , and t_0 is the time when the most recent transmission event occurred.

Exploration of the parameter space (defined by E_{rev} , g_{max} , τ_1 and τ_2) was necessary to obtain a good fit for the somatic IPSP as measured experimentally by Miles et al. [29]. Traditionally, PSPs are characterized by three parameters: time to peak (ttp), amplitude (amp) and duration at half amplitude (daha). For each run we found the values of ttp, amp and daha for the simulated IPSPs and, by matching them to the respective values of their measured counterparts, calculated error of fit as the Euclidean distance in the ttp-amp-daha space.

2.3 Results

First, we tried to reproduce the somatic IPSP measured in [29] by finding optimal values for the parameters of our synaptic conductance kinetics. In this case we modeled applying inhibition to the soma and, as throughout our whole work, 'recorded' changes of

membrane potential in the somatic compartment. We made a rather detailed exploration of the parameter space and in the following simulations we used the parameters and parameter intervals found here to be best for reproducing measured averages and standard deviations resp. of the three characteristic properties (ttp, amp and daha) of somatic IPSPs.

Then location of inhibition, but *not* parameters of synaptic kinetics, was gradually changed by applying it to different dendritic compartments each time further from the soma. Membrane potential was recorded at the soma and change in IPSP parameters and the total error of the fit was calculated with respect to the dendritic IPSP measured in [29]. There was an optimal electrotonic distance needed for reproducing the average dendritic IPSP that translated into an anatomical distance of 250-500 micron. Deviation of dendritic IPSPs was also successfully reproduced by changing the parameters only in the intervals found previously.

Our simulations showed that it is possible to reproduce the differences seen between somatic and dendritic IPSPs as measured at the soma (Fig. 6), thus raising the possibility that although there are a number of known GABA_A receptors, interneuron to pyramidal cell synapses use the same one regardless of location. This is supported by that we simulated the electrotonic attenuation with morphological distances comparable to that seen in reconstructed cells.

Further simulations on active models (data not shown) gave preliminary results on the functional consequences of location dependent differences of inhibition on the bursting behavior of pyramidal cells. Somatic inhibition had a more pronounced effect in delaying or completely suppressing a burst, while dendritic inhibition tended to switch between firing modes (repetitive firing vs bursting) of hippocampal principal cells.

While trying to make variations in IPSPs by changing kinetic parameters of the synapse we were faced with the (not contraintuitive) fact that two properties of PSPs (ttp and daha) did not vary independently, indeed there was a pronounced linear relationship between them. Provided that these properties of experimentaly measured PSPs vary in the same manner (that cannot be clearly stated based on pooled published data as in [29]) our findings give a hint that the properties most commonly used to characterize PSPs by electrophysiologists are at least redundant and probably not appropriately chosen. Further investigations could enlighten the possible consequences of this linearity and also the parameters it is dependent of.

3 Stochastic resonance in cells of the olfactory bulb

3.1 Stochastic resonance and its role in neural systems

Eversince its discovery [8,9], stochastic resonance (SR) became a widely studied phenomenon. Stochastic resonance is a mechanism where noise plays a beneficial role in amplifying weak periodic signals arriving to some nonlinear system. Several different generic theoretical models for the occurrence of SR exist [40]. Though the phenomenon was first found in bistable systems, later it was also demonstarted in monostable, excitable systems. Neurons are prototypes of this latter class.

SR was found both experimentally and by model studies in various neurons and neural ensembles. Douglass et al. [19] showed that mechanoreceptor hair cells of the crayfish show SR, while Levin and Miller [26] demonstrated SR on the cercal system of crickets. Collins et al. [17] demonstrated SR in experiments on mammalian cutaneous mechanoreceptors. Both experimental [12] and modeling [27] studies of temperature receptors have concluded that the interplay of subthreshold oscillation and noise imply the generation of firing patterns. Presence of noise can enhance transmission of spike trains, [20] and transmission capacity [14]. The possible role of SR in neural coding is further discussed

in [16,13].

Noise can also enhance a neuron's sensitivity. Consider a deterministic receptor neuron in the olfactory system devoid of random spontaneous activity; it fires an action potential when the odorant concentration and consequently the receptor potential exceeds a certain threshold. This means that any odorant concentration smaller than this threshold cannot be signaled to the brain. Consider now a "stochastic neuron" where the receptor potential presents a random (thermal) component added to the deterministic component resulting from odorant stimulation. Presence of noise produces a finite probability for the signal+noise to be greater than the threshold value, and cell activity may result in firing. Consequently, a neuron sensitivity with noisy input becomes, at low concentrations, greater than without noise [36,42,25].

In future modeling, the origin of noise will probably be related to a statistical description of a more detailed model of synaptic junctions and ion channels, and to the collective behavior of large neural assemblies.

3.2 Modeling mitral and granule cells

Olfactory bulb is the first relay center of the olfactory system. Generation and propagation of action potentials in the two major cell types of the olfactory bulb, mitral and granule cells, had earlier been simulated by applying multi-compartmental modeling techniques. By using the traditional deterministic framework, four types of problems had been studied related to the signal generation and propagation in OB [3,4].

(i) Effects of individual currents and their role in generation and suppression of action potentials, and in the control of firing frequencies had been conferred (intracompartmental studies).

(ii) Signal propagation through compartments of both mitral and granule cells had been simulated. Effects of both orthodromic and antidromic stimulation had been demonstrated (intercompartment studies).

(iii) Excitatory-inhibitory coupling between mitral and granule cells through dendrodendritic synapses and effects of the (partial) blockade of GABAergic inhibition had been shown (interneuronal studies).

(iv) Dynamic behavior of a skeleton network of bulbar circuitry taking into account even the periglomerular cells had been studied.

In the present study, using single-compartment models based on previous studies, [3,4,10] possible realization of SR as a likely mechanism to boost odorant-related events in mitral and granule cells was investigated.

3.3 Methods

Response of mitral and granular cells were studied to some noise term superimposed on periodic input by using single compartmental model. Periodic input was a sinusoidal ($20Hz$) current injection ($20pA$ and $90pA$ for mitral and granular cells respectively) and, superimposed on it, an additive Gaussian white-noise term with short correlation time ($0.1ms$) was applied.

Output power spectrum was determined by using Fast Fourier Transformation (FFT) from the simulated membrane potential as a function of time, for different input noise intensities. Then signal-to-noise ratio (S/N) as a function of noise was calculated. Signal was measured by the peak of spectrum at $20Hz$ and noise intensity was calculated by averaging in tight frequency bands around $20Hz$ ($16.5 - 19.5Hz$; $20.5 - 22.5Hz$).

As reliable numerical simulations in case of additive noise (i.e to generate realization of stochastic processes) need careful consideration. Without going into technical details, usually an integration step shorter than the characteristic time interval of

the fastest events in the model has to be chosen with reasonable running time. In our simulations time step was $0.01ms$ compared to the $0.1ms$ long characteristic time interval of the fastest event (i.e. noise). As noise was deterministically generated, given independently on cells states, the implicit integration methods remain rather stable and reliable. All simulations were performed with the NEURON program package [<http://www.neuron.yale.edu/neuron/nrnnsim.html>] using second order Crank-Nicholson integration scheme throughout a 20957.0 ms long time interval.

3.4 Results

Fig. 1 and 2 show the output power spectra (1*a*, 2*a*) and the S/N curves derived from Fourier spectra of the membrane potential (1*b*, 2*b*) of mitral and granule cells, respectively.

There was no optimum noise level which is possibly due to the fact that phase shift of spikes is bad comparing to the sinusoidal membrane potential changes. However, when output signals are treated as series of binary 0 – 1 elements, and FFT is used to calculate the S/N as a function of noise, results are qualitatively different. Fig. 3*a* and 4*a* shows the Fourier spectra of the binary series for mitral and granule cells, while Fig. 3*b* and 4*b* show the calculated S/N – noise intensity curves.

Repeating the question put forward in [40], we may ask: 'What is the most appropriate measure of of "output performance?" Our results support that the binary character of neurons is the main feature of the performance of neurons.

Calculations showed optimum noise level for both cell types, hence the possibility of the existence of SR phenomenon has been demonstrated. Error limitation drawn on simulation S/N data was determined from the uncertainty of noise intensity, which itself was figured out by slight changes on the averaging band limits ($16.5 - 19.5Hz \rightarrow 16 - 19Hz$; $20.5 - 22.5Hz \rightarrow 21 - 23Hz$). However, significant fluctuation of resonance peak

curves cannot be explained by this estimation method. More precise error estimations by making simulations use a different random variable generator is needed. Neurons are often analysed by interspike interval histograms (ISIH). These histograms show a peak at the reciprocal value of the mean firing rate (MFR) corresponding to the characteristic frequency (spectrum). On Fig. 5*a* and 5*b*, ISIHs are presented pertaining to mitral and granular cells. These figures are obviously only illustrations; the simulations performed [43] were too short in run time to obtain definite conclusions. However, peaks arising at the driving frequency due to the noise can still be recognised even on these figures.

4 A Statistical Approach to Neural Population Dynamics

4.1 Statistical approach to the generation and propagation of hippocampal synchronized activity

There is a long tradition to try to connect ‘microscopic’ single cell behavior to global ‘macrostates’ of the nervous system, analogously to the procedures applied in statistical physics. Global brain dynamics is handled by using continuous (neural field) description instead of networks composed of discrete neurons. Both deterministic [22,32,41,2] and field-theoretic statistical approaches [1,31] have been developed. Here we briefly present the framework of a statistical model for describing synchronized population activities and wave propagation in large neural systems, such as cortical structures.

4.2 Basic model properties

Description of population activity of neurons requires different mathematical apparatus from that of individual neurons. In addition, the statistical approach presented here uses the notion of two separate populations, one for neurons and another for action potentials. The model describes neural population activity in terms of probability density functions (pdf’s) of (i) neurons and (ii) spikes travelling between the neurons, the basic concept

originating from earlier work by Ventriglia [37-39]. Populations of different cell types (pyramidal and inhibitory) are thought of as neural continua, each described by a pdf (g) which gives the distributions of neurons in *state* space at a given point (\mathbf{r}) of the neural tissue ('real space') at a given time (t). State space is two dimensional (one for inhibitory cells) consisting of a membrane potential coordinate u (both cell types) and intracellular calcium concentration χ (only for pyramidal cells). Intra- and interpopulation communication is based on spikes emitted (corresponding to action potential generation) and absorbed (corresponding to postsynaptic effects of presynaptic action potentials) at given points by the populations. While these processes are determined by the state dynamics of neurons, a third process with independent dynamics is introduced to define the propagation of spikes (corresponding to action potential spread in axonal arbors), thus there is a pdf (f) describing the distribution of spikes travelling in a given direction (α) at a given point of *real* space (\mathbf{r}) at a given time (t).

Both the dynamics of neural state space and that of spikes in real space involve diffusion processes described by terms with diffusion speed coefficient D_u , D_χ and D_r respectively. For the sake of simplicity, only basic equations are presented below, for a detailed description of the model see [6, 23].

$$\begin{aligned} \frac{\partial g(\mathbf{r}, u, \chi, t)}{\partial t} + \frac{\partial}{\partial u} (\varepsilon(\mathbf{r}, u, \chi, t)g(\mathbf{r}, u, \chi, t)) + \frac{\partial}{\partial \chi} (\eta(u, \chi)g(\mathbf{r}, u, \chi, t)) \\ - \frac{D_u}{2} \frac{\partial^2 g(\mathbf{r}, u, \chi, t)}{\partial u^2} - \frac{D_\chi}{2} \frac{\partial^2 g(\mathbf{r}, u, \chi, t)}{\partial \chi^2} = b(\mathbf{r}, u, \chi, t) - n(\mathbf{r}, u, \chi, t) \end{aligned} \quad (4)$$

where ε and η describe the electric current and the calcium influx to the cell, respectively, to be specified by the actual single cell model. The function n is the pdf expressing the rate at which neurons are starting to fire, and b is the same for neurons returning from firing.

$$\frac{\partial f^{(\alpha)}(\mathbf{r}, t)}{\partial t} + (\mathbf{v}^{(\alpha)} \nabla) f^{(\alpha)}(\mathbf{r}, t) - \frac{D_r}{2} \nabla^2 f^{(\alpha)}(\mathbf{r}, t) = -\sigma f^{(\alpha)}(\mathbf{r}, t) + \lambda^{(\alpha)} \int_{-\infty}^{\infty} du' \int_0^{\infty} d\chi' n(\mathbf{r}, u', \chi', t) \quad (5)$$

where $\mathbf{v}^{(\alpha)}$ is the velocity of spikes in direction α , σ and $\lambda^{(\alpha)}$ are the absorption and emission coefficients, respectively.

4.3 Results

In previous studies population activities as well as underlying single cell voltages were simulated during normal and epileptiform activities in the hippocampal CA3 slice.

The role of inhibitory and excitatory interactions is studied in the simulations presented here. A range of epileptiform and non-epileptic rhythms has been obtained. For a classification of these behaviors, the measure of synchronization is defined as the percentage of simultaneously (practically within 3ms) firing pyramidal cells. Underlying single cell activities can be studied by running the single cell model with synaptic inputs generated by the population model, thus providing an option to follow the activity of a 'randomly chosen' cell at any point of the neural continuum.

The composite figure shows a set of phenomena, such as fully synchronized population burst, synchronized synaptic potentials and low amplitude population oscillation (*Fig x*).

4.4 Wave propagation

Dynamics of activity propagation in cortical, thalamic and hippocampal system has been recently studied both experimentally and by simulation methods [28,34,18,21,15]. In totally disinhibited slices the velocity of propagation in longitudinal slices was found about 15cm/s in the hippocampus.

The spatial pattern of propagation is shown in Fig. 7. The model slice is shown with increasing time from top to bottom. High activity levels first appear in the stimulated subregion, then activity builds up in the neighboring regions, and finally propagates through the full length of the slice. The velocity of the simulated wave propagation exhibits a linear increase on the maximal synaptic conductance, and it is in the interval $5 - 10\text{cm/s}$. The velocity of activity propagation was investigated as a function of the maximal conductance of excitatory synapses (Fig. 8).

Dependence of velocity of the wavefronts on the synaptic parameters is a hot issue. Chen et al. [15] derived a power-law relationship between the velocity and the maximal synaptic conductance. Golomb and Amitai [21] found that in a large parameter region the velocity is a linearly increasing function of the maximal synaptic conductance, at least above some thresholds. Similar effect was found in model studies of the thalamic reticular nucleus [7].

5 Discussion

Computational neuroscience and neurodynamic system theory is pluralistic [5]. Neither the reductionistic research strategy which adopts biophysically detailed cell models nor the statistical treatment of large population of simplified elements can be qualified as the 'only' useful technique of neural modelling. We illustrated the power of compartmental modelling in taking into account (i) fine geometrical details, (ii) signal generation and amplification in single cells; while the kinetic model has been proven a proper tool for studying (iii) synchronization and propagation effects in large neuron populations.

Acknowledgments

We thank Péter Adorján, György Barna, and Tamás Gröbber their cooperation. This work was supported by the Fogarty International Research Collaboration Award, HHS Grant No. 1 R03

- TW00485-01., National Scientific Research Foundation (OTKA) No. T 017784, T 025500, T 025472.

References

1. Amari S. A method of statistical neurodynamics. *Kybernetik* 1974; 14: 201-25.
2. Amari S. Field theory of self-organizing neural nets. *IEEE Trans* 1983; SMC-13: 741-748.
3. Aradi I, Érdi P. Multicompartmental modelling of neural circuits in the olfactory bulb. *Int J Neural Syst* 1996; 7: 519-527.
4. Aradi I, Érdi P. Signal generation and propagation in the olfactory bulb: multicompartmental modeling. *Computers and Mathematics with Applications* 1996; 32: 1-27.
5. Arbib M, Érdi P, Szentágotai J. *Neural Organization: Structure, Function and Dynamics*. MIT Press, 1997.
6. Barna G, Gröbller T, Érdi P. Statistical model of the hippocampal CA3 region, II. The population framework: model of rhythmic activity in the CA3 slice. *Biol Cyb* 1998; 79: 309-321.
7. Bazhenov M, Timofeev I, Steriade M, Sejnowsky TJ. Self-sustained rhythmic activity in thalamic reticular nucleus mediated by depolarizing GABA-A receptor potentials *Nat Neurosci* 1999; 2: 168-174.
8. Benzi R, Sutera A, Vulpiani A. The mechanism of stochastic resonance. *J Phys* 1981; A: L453-L457.
9. Benzi R, Parisi G, Sutera A, Vulpiani A. A theory of stochastic resonance in climatic change. *SIAM J Appl Math* 1983; 43: 565-578.
10. Bhalla US, Bower JM. Exploring parameter space in detailed single neuron models: Simulations of the mitral and granule cells of the olfactory bulb. *J Neurophys* 1993; 69: 1948-1963.
11. Braitenberg V, Schuz A. *Anatomy of the Cortex. Statistics and Geometry*. Heidel-

berg, Springer-Verlag, 1991.

12. Braun H, Wising H, Schäfer K, Hirsh MC. ** Nature 1994; 367: 270-**.
13. Braun HA, Huber MT, Dewald M, Voigt K. The neuromodulatory properties of "Noisy neuronal oscillators". In: Kadtke JB, Bulsara A, eds. Applied Nonlinear Dynamics and Stochastic Systems Near the Millenium, AIP, 1997; 281-286.
14. Chapau-Blondeau F. Noise-enhanced capacity via stochastic resonance in an asymmetric binary channel. Physical Review 1997; 55E: 2016-2019.
15. Chen Z, Ermentrout B, Wang X. Wave propagation mediated by GABA-B synapse and rebound excitation in an inhibitory network: a reduced model approach. J Comp Neurosci 1998; 5: 53-69.
16. Chialvo DR, Longtin A, Muller-Gerking J. Stochastic resonance in models of neuronal ensembles. Physical Review 1997; 55E: 1798-1808.
17. Collins JJ, Imhoff TT, Grigg P. ** J Neurophysiol 1996; 76: 642-645.
18. Destexhe A, Bal T, McCormick DA, Sejnowski TJ. Ionic mechanism underlying synchronized oscillation and propagating waves in a model of ferret thalamic slices. J Neurophysiol 1996; 76: 2049-2070.
19. Douglass JK, Wilkens L, Pantazelou E, Moss F. ** Nature 1993; 365: 337-340.
20. Godivier X, Chapeau-Blondeau F. Noise enhanced transmission of spike trains in the neurons. Europhysics Let 1996; 35: 473-477.
21. Golomb D, Amitai Y. Propagating neuronal discharges in neocortical slices: computational and experimental study. J Neurophysiol 1997; 78: 1199-1211.
22. Griffith JA. A field theory of neural nets. I. Derivation of field equations. Bull Math Biophys 1963; 25: 111-120.
23. Gröbler T, Barna G, Érdi P. Statistical model of the hippocampal CA3 region, I. The single cell module: Bursting model of the pyramidal cell. Biol Cyb 1998; 79: 301-308.
24. Katona I, Acsády L, Freund TF. Postsynaptic targets of somatostatin-immunoreactive interneurons in the rat hippocampus. Neurosci 1999; 88: 37-55.
25. Lansky P, Rospars JP. Ornstein-Uhlenbeck neuron revisited. Biol Cyb 1995; 72:

397-406.

26. Levin JE, Miller JP. Broadband neural encoding in the cricket cercal sensory system enhanced by stochastic resonance. *Nature* 1996; 380: 165-168.

27. Longtin A, Hinzer K. *** Neural Comp* 1996; 8: 217-****.

28. Miles R, Traub RD, Wong KS. Spread of synchronous firing in longitudinal slices from the CA3 region of the hippocampus. *J Neurophysiol* 1988; 60: 1481-1496.

29. Miles R, Tóth K, Gulyás A, Hájos N, Freund T. Differences between somatic and dendritic inhibition in the hippocampus. *Neuron* 1996; 16: 815-823.

30. Pearce RA. Physiological evidence for two distinct GABA-A responses in rat hippocampus. *Neuron* 1993; 10: 189-201.

31. Peretto P. *An Introduction to the Modelling of Neural Networks*. Cambridge, Cambridge University Press, 1992.

32. Seelen W. Informationsverarbeitung in homogenen Netzen von Neuronen-modellen. *Kybernetik* 1968; 5: 181-194.

33. Spruston N, Jaffe DB, Williams SH, Johnston D. Voltage and space clamp errors associated with the measurement of electrotonically remote synaptic events. *J Neurophysiol* 1993; 70: 781-802.

34. Traub RD, Jefferys JGR, Miles R. Analysis of the propagation of disinhibition-induced after-discharges along the guinea-pig hippocampal slice in vitro. *J Physiol (Lond)* 1993; 473: 267-287.

35. Traub RD, Jefferys JGR. Mechanisms responsible for epilepsy in hippocampal slices predispose the brain to collective oscillations. In: Ventriglia F. ed. *Neural Modeling and Neural Networks*. Oxford, Pergamon Press, 1994; 111-127.

36. Treutlein H, Schulten K. Noise induced limit cycles of the Bonhoeffer-Van der Pol model of neural pulses. *Ber Bunsenges Phys Chem* 1985; 89: 710-718.

37. Ventriglia F. Kinetic approach to neural systems I. *Bull Math Biol* 1974; 36: 534-544.

38. Ventriglia F. Computational simulation of activity of cortical-like neural systems. *Bull Math Biol* 1988; 50: 143-185.

39. Ventriglia F. Towards a kinetic theory of cortical-like neural fields. In: F. Ventriglia, ed. *Neural Modeling and Neural Networks*. Oxford, Pergamon Press, 1994; 217-249.
40. Wiesenfeld K, Jaramillo F. Minireview of stochastic resonance. *Chaos* 1998; 8: 539-548.
41. Wilson HR, Cowan J. A mathematical theory of the functional dynamics of cortical and thalamic neurons tissue. *Kybernetik* 1973; 13: 55-80.
42. Yu X, Lewis ER. Studies with spike initiators: Linearization by noise allows continuous signal modulation in neural networks. *IEEE Trans Biomed Eng* 1989; 36: 36-43.
43. Zalányi L. Stochastic resonance in certain cells of the olfactory system. MSc thesis, Eötvös University, Budapest (in Hungarian) 1998.

















