

Neural Networks with Dynamic Synapses

Misha Tsodyks

Department of Neurobiology, Weizmann Institute of Science, Rehovot 76100, Israel

Klaus Pawelzik

Max-Planck-Institut für Strömungsforschung, D-37073 Goettingen, Germany

Henry Markram

Department of Neurobiology, Weizmann Institute of Science, Rehovot 76100, Israel

Transmission across neocortical synapses depends on the frequency of presynaptic activity (Thomson & Deuchars, 1994). Interpyramidal synapses in layer V exhibit fast depression of synaptic transmission, while other types of synapses exhibit facilitation of transmission. To study the role of dynamic synapses in network computation, we propose a unified phenomenological model that allows computation of the postsynaptic current generated by both types of synapses when driven by an arbitrary pattern of action potential (AP) activity in a presynaptic population. Using this formalism, we analyze different regimes of synaptic transmission and demonstrate that dynamic synapses transmit different aspects of the presynaptic activity depending on the average presynaptic frequency. The model also allows for derivation of mean-field equations, which govern the activity of large, interconnected networks. We show that the dynamics of synaptic transmission results in complex sets of regular and irregular regimes of network activity.

1 Introduction ---

A marked feature of synaptic transmission between neocortical neurons is a pronounced frequency dependence of synaptic responses to trains of presynaptic spikes (Thomson & Deuchars, 1994). The nature of this dynamic transmission varies among different classes of neurons. In our recent article (Tsodyks & Markram, 1996; see also Abbott, Varela, Sen, & Nelson, 1997; Tsodyks & Markram, 1997) we studied synaptic depression between neocortical pyramidal neurons with the aid of a phenomenological model. We found that the rate of depression is a primary factor in determining which features of the action potential (AP) activity in the presynaptic population are most effective in driving the postsynaptic neuron.

The phenomenological formulation of Tsodyks and Markram (1996) and Abbott et al. (1997) can be generalized to describe facilitating synapses be-

tween pyramidal cells and inhibitory interneurons (Thomson & Deuchars, 1994; Markram, Tsodyks, and Wang, in press). This formulation has two major goals. First, it allows the quantification of the features of the AP activity of the presynaptic neurons and populations transmitted by these different types of synapses. Second, it can be used in deriving a novel mean-field dynamics of neocortical networks aimed at understanding the dynamic behavior of large neuronal populations without having to solve an equally large number of equations. Mean-field descriptions were extensively used in order to understand the possible computations of cortical neural networks (see, e.g., Wilson & Cowan, 1972; Amit & Tsodyks, 1991; Ginsburg & Sompolinsky, 1994; Tsodyks, Skaggs, Sejnowski, & McNaughton, 1997). The novel formulation that uses the generalized phenomenological model of dynamic properties of synaptic connections between different types of neocortical neurons allows the study of the effects of synaptic dynamics and synaptic plasticity on information processing in large neural networks.

2 Phenomenological Model of Neocortical Synapses

In order to derive a coarse-grained description of neuronal dynamics, we have to compute the postsynaptic current generated by a population of neurons with a particular firing rate. This can be done with the phenomenological model of neocortical synapses used in Tsodyks and Markram (1997) and Abbott et al. (1997), which was shown to reproduce well the synaptic responses between pyramidal neurons. The model assumes that a synapse is characterized by a finite amount of resources. Each presynaptic spike (arriving at time t_{sp}) activates a fraction (U_{SE} , utilization of synaptic efficacy) of resources, which then quickly inactivate with a time constant of few milliseconds (τ_{in}) and recover with a time constant of about 1 second (τ_{rec}). The corresponding kinetic equations read:

$$\begin{aligned}\frac{dx}{dt} &= \frac{z}{\tau_{rec}} - U_{SE}x(t_{sp} - 0)\delta(t - t_{sp}) \\ \frac{dy}{dt} &= -\frac{y}{\tau_{in}} + U_{SE}x(t_{sp} - 0)\delta(t - t_{sp}) \\ \frac{dz}{dt} &= \frac{y}{\tau_{in}} - \frac{z}{\tau_{rec}},\end{aligned}\tag{2.1}$$

where x , y , and z are the fractions of resources in the recovered, active, and inactive states, respectively. The postsynaptic current is taken to be proportional to the fraction of resources in the active state, $I_s(t) = A_{SE}y(t)$. The two major parameters of the model are A_{SE} , the absolute synaptic strength, which can be exhibited only by activating all of the resources, and U_{SE} , which determines the dynamics of the synaptic response. For an individual synapse, the model reproduces the postsynaptic responses generated

by any presynaptic spike train t_{sp} for interpyramidal synapses in layer V (Tsodyks & Markram, 1997).

2.1 Modeling Facilitating Synapses. The formulation of equation 2.1 does not include a facilitating mechanism, which is not evident between pyramidal neurons. It is, however, prominent in synapses between pyramidal neurons and inhibitory interneurons (Thomson & Deuchars, 1994). A standard way of modeling short-term facilitation is by introducing a facilitation factor, which is elevated by each spike by a certain amount and decays between spikes, possibly at several rates (see, e.g., Mallart & Martin, 1967; Zengel & Magleby, 1982). To add facilitation into our synaptic model, we therefore assume that the value of U_{SE} is not fixed but is increased by a certain amount due to each presynaptic spike. The running value of U_{SE} is referred to as U_{SE}^1 . The resulting model includes both facilitating and depressing mechanisms.

Increase in U_{SE} could reflect, for example, the accumulation of calcium ions caused by spikes arriving in the presynaptic terminal, which is responsible for the release of neurotransmitter (Bertram, Sherman, & Stanelly, 1996). For a simple kinetic scheme, assume that an AP causes a fraction of U_{SE} calcium channels to open, which subsequently close with a time constant of τ_{facil} . The fraction of opened calcium channels determines the current value of U_{SE}^1 . The corresponding kinetic equation therefore reads:

$$\frac{dU_{SE}^1}{dt} = -\frac{U_{SE}^1}{\tau_{facil}} + U_{SE}(1 - U_{SE}^1)\delta(t - t_{sp}). \quad (2.2)$$

U_{SE} determines the increase in the value of U_{SE}^1 due to each spike and coincides with the value of U_{SE}^1 reached upon the arrival of the first spike (in other words, at a very low frequency of stimulation).

This equation can be transformed into an iterative expression for the value of U_{SE}^1 reached upon the arrival of n th spike in a train, which determines the postsynaptic response according to equation 2.1,

$$U_{SE}^{1(n+1)} = U_{SE}^{1(n)}(1 - U_{SE})\exp(-\delta t/\tau_{facil}) + U_{SE}, \quad (2.3)$$

where δt is the time interval between the n th and $(n + 1)$ th spikes. If the presynaptic neuron emits a regular spike train at the frequency r , U_{SE}^1 reaches a steady value of

$$\frac{U_{SE}}{1 - (1 - U_{SE})\exp(-1/r\tau_{facil})}.$$

Thus in this formulation, U_{SE}^1 becomes a frequency-dependent variable, and U_{SE} is a kinetic parameter characterizing an activity-dependent transmission in a given synapse.¹

¹ One could introduce two independent parameters describing initial value and degree

Facilitating and depressing mechanisms are intricately interconnected since stronger facilitation leads to higher U_{SE}^1 values, which in turn leads to stronger depression. The value of U_{SE} therefore determines the contribution of facilitation in generating subsequent synaptic responses. Facilitation is marked for small values of U_{SE} and is not observed for higher U_{SE} . We found that the main features of synaptic transmission between pyramidal neurons and inhibitory interneurons are well captured by this model with $U_{SE} \sim 0.01 \rightarrow 0.05$, and τ_{rec} is typically several times faster than τ_{facil} (Markram et al., in press; see also Figure 1D). Figures 1A and 1B show responses from facilitating and depressing synapses with the same absolute strength to a regular spike train of 20 Hz (but with input resistance of the facilitatory synapse's target 10 times higher). Figure 1C illustrates the buildup of depression in facilitating synapses when they are stimulated at high frequencies. As a result, the stationary level of response exhibits a tuning curve dependence on the frequency, in agreement with experimental results (see Figure 1D).

3 Population Signal

We now return to our original problem of signaling from a large population of presynaptic neurons. There is an infinite number of ways the neurons of a population can fire relative to each other. Analysis of neurophysiological data revealed that individual neurons *in vivo* fire irregularly at all rates (Softky & Koch, 1993), reminiscent of the so-called Poisson process. Mathematically, the Poisson assumption means that at each moment, the probability that a neuron will fire is given by the value of the instantaneous firing rate and is independent of the timing of previous spikes. This assumption allows averaging equations 2.1 and 2.2 over different realizations of Poisson trains with a given rate, to obtain a new dynamics for the corresponding mean quantities (Amit & Tsodyks, 1991):

$$\begin{aligned} \frac{d\langle x \rangle}{dt} &= \frac{1 - \langle x \rangle}{\tau_{rec}} - \langle U_{SE}^1 \rangle \langle x \rangle r(t) \\ \frac{d\langle U_{SE}^- \rangle}{dt} &= -\frac{\langle U_{SE}^- \rangle}{\tau_{facil}} + U_{SE}(1 - \langle U_{SE}^- \rangle)r(t) \\ \langle U_{SE}^1 \rangle &= \langle U_{SE}^- \rangle(1 - U_{SE}) + U_{SE}, \end{aligned} \quad (3.1)$$

where $r(t)$ denotes the rate of a Poisson train for the neuron at time t . $\langle U_{SE}^- \rangle$ denotes the average value of U_{SE}^1 immediately before the spike. Depressing synapses are described by the first of these equations with the fixed value of U_{SE}^1 (see also Grossberg, 1969, for the earlier analysis of these equations).

of facilitation of U_{SE}^1 . More data are required to determine whether this is needed to model facilitating synapses in neocortex accurately.

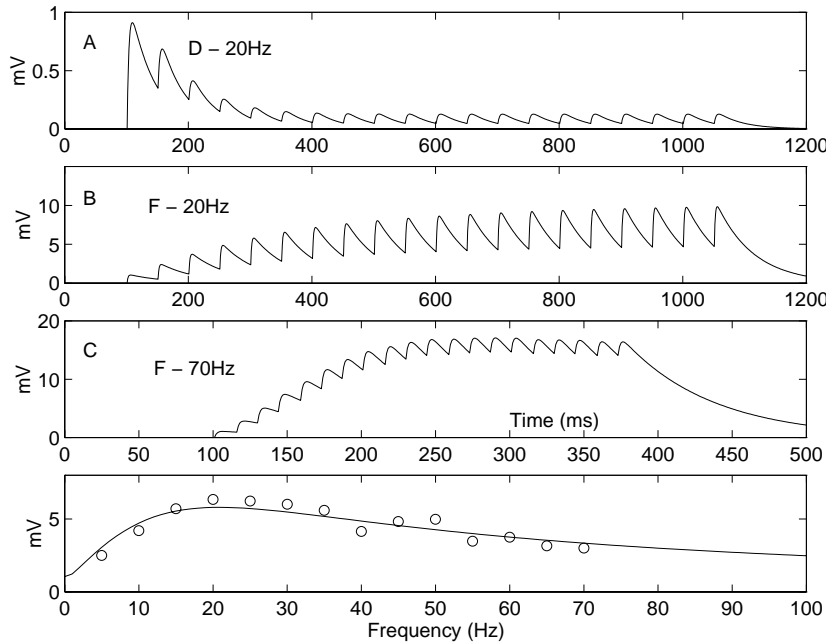


Figure 1: Phenomenological synaptic model. (A) Simulated postsynaptic potential generated by a regular spike train at a frequency of 20 Hz transmitted through a depressing synapse. (B) Same as A for facilitating synapse. (C) Same as B but for a presynaptic frequency of 70 Hz. (D) Stationary level of excitatory presynaptic potentials versus presynaptic frequency for facilitating synapses. Open circles: Experimental results for one of the recorded synaptic connections between pyramidal neuron and inhibitory interneuron (details of the experiments will be reported in Markram et al., in press). Solid line: Model results.

The postsynaptic potential is computed using a passive membrane mechanism ($\tau_{mem} \frac{dV}{dt} = -V + R_{in} I_{syn}(t)$) with an input resistance of $R_{in} = 100 \text{ M}\Omega$ for pyramidal target and $1 \text{ Giga}\Omega$ for interneuron. Parameters: (A): $\tau_{mem} = 40 \text{ msec}$; $\tau_{inact} = 3 \text{ msec}$; $A_{SE} = 250 \text{ pA}$; $\tau_{rec} = 800 \text{ msec}$; $U_{SE} = 0.5$; (BCD) $\tau_{mem} = 60 \text{ msec}$; $\tau_{inact} = 1.5 \text{ msec}$; $A_{SE} = 1540 \text{ pA}$; $\tau_{rec} = 130 \text{ msec}$; $\tau_{facil} = 530 \text{ msec}$; $U_{SE} = 0.03$;

In deriving equation 3.1, we made a further simplification by assuming that the inactivation time constant τ_{in} is much faster than the recovery one τ_{rec} . This assumption is valid for interpyramidal synapses studied in Markram and Tsodyks (1996) and for pyramidal interneuron synapses (Markram et al., in press). The evolution of postsynaptic current can be obtained from

the remaining equation for y and recalling that $I_s(t) = A_{SE}y(t)$:

$$\frac{d\langle y \rangle}{dt} = -\frac{\langle y \rangle}{\tau_{in}} + \langle U_{SE}^1(x) \rangle r(t), \quad (3.2)$$

which can be simplified to $y = r\tau_{in}U_{SE}^1(x)$ if one is interested only in the timescale slower than τ_{in} .

While averaging equation 2.1 over different realizations of Poisson spike trains, we assumed that there is no statistical dependence between the variables $x(t)$ and $U_{SE}^1(t)$ and the probability of spike emission at time t . This is strictly valid only if there is no facilitation since in this case U_{SE}^1 is a fixed parameter of the model, and $x(t)$, which is a function of the spike arrival times prior to the current time, is independent of the probability of a spike at time t due to the Poisson assumption. However, if facilitation is included, both $x(t)$ and $U_{SE}^1(t)$ are a function of previous spikes and are not statistically independent. We thus performed simulations of equations 2.1 and 2.2 for populations of presynaptic neurons firing Poisson spike trains with various modulations of their firing rate and compared the resulting postsynaptic current with the solution of the mean-field equation 3.1. We found that in all cases considered, mean-field solutions were good approximations (see, e.g., Figure 2). More detailed analysis, outlined in the appendix, showed that mean-field approximation works because for all frequencies, either U_{SE}^1 or x have small coefficients of variation (CV), and thus the effect of the statistical correlations between them is small.

Equations 3.1 and 3.2 can be solved analytically for an arbitrary modulation of the firing rates of the presynaptic population. In the case of depressing synapses, the solution takes a particular simple form:

$$\langle y(t) \rangle = U_{SE}r(t) \int_{-\infty}^t dt' \exp\left(-\frac{t-t'}{\tau_{rec}} - \int_{t'}^t dt'' U_{SE}r(t'')\right). \quad (3.3)$$

We use this equation to determine which features of the presynaptic AP train are transmitted by depressing synapses to their targets. Assuming that the presynaptic frequency changes gradually, one can write down the expansion over the derivatives of the frequency. The first two terms of this expansion are,

$$\frac{r}{1+rU_{SE}\tau_{rec}} + r' \frac{r}{(1+rU_{SE}\tau_{rec})^3} + \dots \quad (3.4)$$

This expression describes the relative contribution of rate and temporal signaling in generating the postsynaptic response. The first term depends on the current rate, which is dominant for frequencies that are small compared to the limiting frequency $\lambda \sim 1/(U_{SE}\tau_{rec})$. As the frequency increases, this term saturates, and thus progressively less rate signaling is possible.

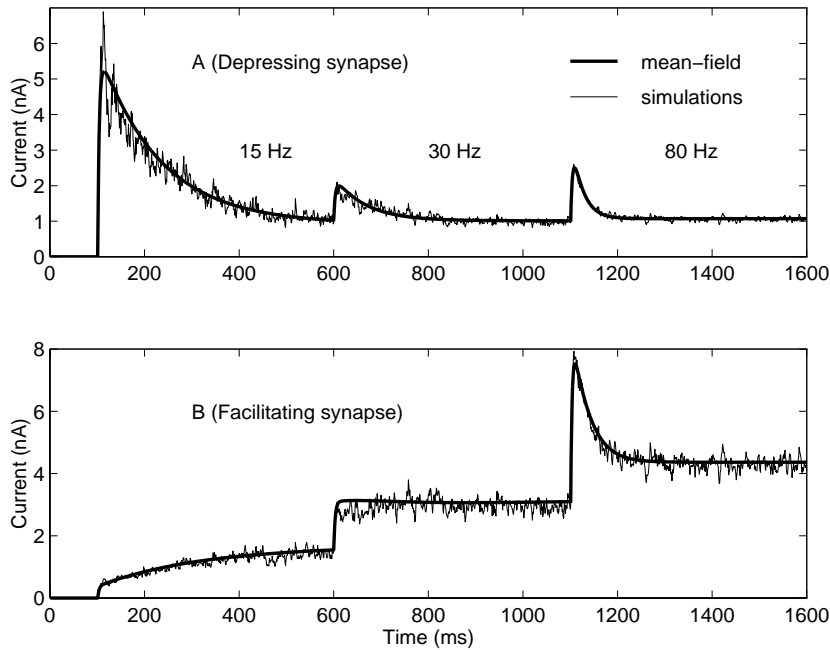


Figure 2: Postsynaptic current, generated by Poisson spike trains of a population of 1000 neurons with synchronous transitions from 0 Hz to 15 Hz to 30 Hz and then to 80 Hz, transmitted through facilitating (A) and depressing (B) synapses. Thick line: Solution of mean-field equation 3.1 and 3.2. Thin line: Simulations of 1000 spike trains with the use of the full model in equation 2.1. Parameters are the same as in Figure 1, with $A_{SE} = 250$ pA.

The main contribution at higher frequencies therefore comes from a transient term reflecting the changes in frequencies. In the context of population signaling, this means that only synchronous transitions in the population activity can be signaled to the postsynaptic neuron (Tsodyks & Markram, 1997).

The solution of the full set of equations 3.1 for facilitating synapse has the same form as equation 3.4, with the single complication due to the fact that U_{SE}^1 is now a functional of the frequency

$$U_{SE}^1 = U_{SE} \int_{-\infty}^t dt' r(t') \exp\left(-\frac{t-t'}{\tau_{facil}} - U_{SE} \int_{t'}^t dt'' r(t'')\right), \quad (3.5)$$

which has to be substituted in equation 3.3. One could still analyze the qualitative features of this solution by noting that at very high frequencies, $U_{SE}^1 \rightarrow 1$, and thus facilitating synapses behave in the same way as depressing ones, transmitting the information about the rate transitions. As the frequency decreases toward the peak frequency (see Figure 1D),

$$\theta = 1/\tau_{facil} + \sqrt{2/\tau_{facil}^2 + \frac{1 + U_{SE}}{U_{SE}\tau_{rec}\tau_{facil}}} \approx 1/\sqrt{U_{SE}\tau_{rec}\tau_{facil}}, \quad (3.6)$$

the presynaptic rate dominates in the postsynaptic response. The reason is that at this frequency, facilitating and depressing effects compensate each other, and the average amplitude of excitatory postsynaptic potential (EPSP), which is $\sim xU_{SE}^1$, is approximately constant. At even smaller frequencies, depressing effects become less relevant since x recovers almost to unity between the subsequent spikes. In this regime, the postsynaptic signal mainly reflects the current value of rate amplified by the value of U_{SE}^1 :

$$I_s \sim r(t) \int_{-\infty}^t dt' r(t') \exp(-(t-t')/\tau_{facil}). \quad (3.7)$$

The integral in this equation is roughly equal to the number of spikes emitted by the presynaptic neuron in the preceding time window of τ_{facil} . In this regime, postsynaptic response is a delayed and amplified transformation of the presynaptic frequency.

As an example, we show in Figure 2 the postsynaptic current resulting from a series of transitions in the firing rate for both depressing and facilitating synapses. All three regimes of transmission via facilitating synapses are illustrated in Figure 2B.

4 Mean-Field Network Dynamics

The analysis of the previous section allows the formulation of a closed system of equations for the dynamics of a large network consisting of subpopulations of neurons with uniform connections. Each population could describe a cortical column, which consists of neurons with similar receptive field properties. At this stage, we assume that at each cortical location, there are only two subpopulations of cortical neurons: pyramidal excitatory neurons and inhibitory interneurons. The coarse-grained equations, describing the firing rates of these populations, have the same form as in Wilson and Cowan (1972) and Amit and Tsodyks (1991),

$$\tau_e \frac{dE_r}{dt} = -E_r + g \left(\sum_{r'} J_{rr'}^{ee} y_{r'}^{ee} - J_{rr'}^{ei} y_{r'}^{ei} + I_r^e \right)$$

$$\tau_i \frac{dI_r}{dt} = -I_r + g \left(\sum_{r'} J_{rr'}^{ie} y_{r'}^{ie} - J_{rr'}^{ii} y_{r'}^{ii} + I_r^i \right), \quad (4.1)$$

where E_r (I_r) is the firing rate of excitatory (inhibitory) populations located at the site r ; $g(x)$ is a response function usually assumed to be monotonously increasing; and $J_{rr'}^{ec}$ denotes the absolute strength of the synaptic connection between excitatory neurons in the populations located at r and r' times the average number of such connections per one postsynaptic neuron, correspondingly for other interactions. Finally, I_r^e (I_r^i) is the external input to the excitatory (inhibitory) population. $y_{rr'}^{ec}$ (and corresponding values for all other synapses) has to be computed from equations 3.1 and 3.2 for each connection rr' with the corresponding set of kinetic parameters. Refractoriness of the neurons was ignored for simplicity.

These equations reduce to the ones of Wilson and Cowan (1972) if synaptic transmission is frequency independent, in which case $x_r \equiv 1$ and hence $y_r \sim E_r$. In the presence of frequency dependence, they include effects of ever-changing synaptic efficacy due to depression and facilitation. This formulation allows for an analysis of the behavior of the network with any pattern of connections and external inputs. Since the goal of this article is not to consider any particular computational model, we limit ourselves to two examples.

4.1 Network of One Population. As the simplest example, we consider a network that consists of only one population of excitatory neurons. Already in this case, synaptic depression makes the network dynamics nontrivial. Equations 4.1 reduce to,

$$\begin{aligned} \tau \frac{dE}{dt} &= -E(t) + g(JU_{SE}x(t)E(t)) \\ \frac{dx}{dt} &= -U_{SE}E(t)x(t) + \frac{1-x(t)}{\tau_{rec}}. \end{aligned} \quad (4.2)$$

For convenience, the factor of τ_{in} (see equation 3.2) was absorbed in the definition of J . We can solve these equations for the fixed point, where it simplifies to,

$$E = g \left(JU_{SE} \frac{E}{1 + EU_{SE}\tau_{rec}} \right) \quad (4.3)$$

and can be illustrated using the graphical method (see Figure 3A). The right-hand side of equation 4.3 always saturates for arbitrary response functions due to synaptic depression. The system will therefore have a nontrivial fixed point with $E > 0$, even in cases where without depression there is no stable solution.

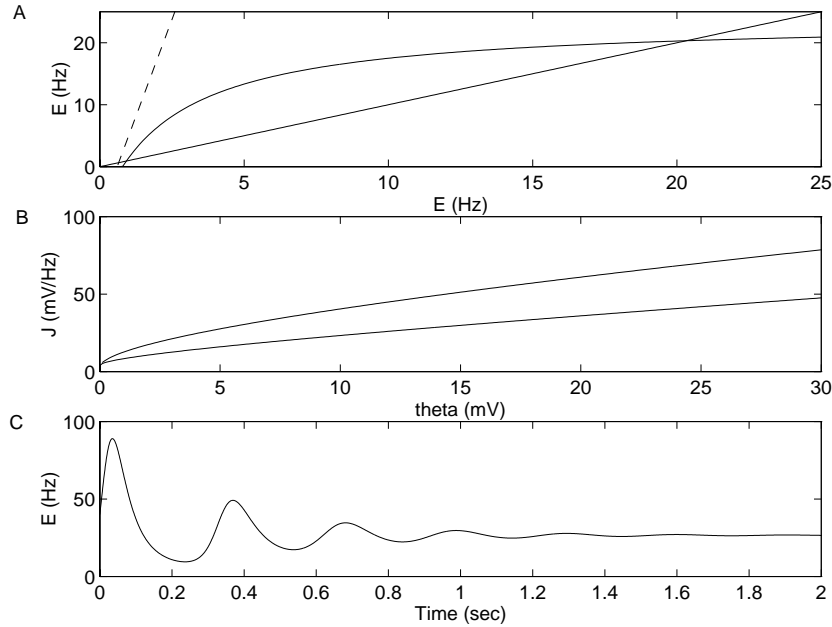


Figure 3: Solution of equations 4.2 for the network of one excitatory population with homogeneous connections. (A) Graphical solution of the fixed-point equation, 4.3. The response function had a linear-threshold shape (dashed line),

$$g(x) = \begin{cases} 0 & \text{if } x < \theta \\ \beta(x - \theta) & \text{if } x > \theta \end{cases} \quad (4.4)$$

The fixed-point solution is given by the intersection of the two solid lines. (B) Phase diagram of the system in the space of θ and J . (C) The solution of the dynamic equations, 4.2.

Parameters in (A) and (C): $\theta = 15$ mV; $\beta = 0.5$ mV⁻¹Hz; $J = 60$ mV*Hz⁻¹; $U_{SE} = 0.5$; $\tau_{rec} = 800$ msec; $\tau = 30$ msec.

The stability of the fixed-point solution can be analyzed from equations 4.2. The solution is stable if the following matrix has eigenvalues with negative real parts:

$$\begin{pmatrix} \frac{\beta J U_{SE} x^* - 1}{\tau} & \frac{\beta J U_{SE} E^*}{\tau} \\ -U_{SE} x^* & -U_{SE} E^* - \frac{1}{\tau_{rec}} \end{pmatrix}, \quad (4.5)$$

where E^* and x^* are the values of E and x at the fixed point, $\beta = g'(J U_{SE} x^* E^*)$. For a linear-threshold gain function ($\beta = const$) as in Figure 3A, the phase

diagram of the system is shown in Figure 3B. For a given threshold, a fixed-point solution appears when the synaptic strength exceeds the first critical value shown by the lower line on the diagram. Contrary to what one would expect from Figure 3A, this solution remains unstable until the synaptic strength grows above a second critical value (upper line).

Even if the fixed-point solution is stable, the system exhibits dampened oscillations before reaching the steady state due to synaptic dynamics (see Figure 3C).

4.2 Network of Two Interconnected Populations. This system was analyzed in Wilson and Cowan (1972) for the case of linear synapses. They showed that if the external inputs are fixed, mean-field equations have two basic types of stable solutions: fixed points and limit cycles with the period on the order of τ_e, τ_i . In our case, the mean-field equations have a much richer set of solutions, because in addition to the pair of equations for E and I (see equation 4.1), they also include dynamic equations for synaptic efficacies (see equation 3.1). As a result, in addition to fixed points and simple limit cycles, the system exhibits a variety of rhythmic and irregular solutions that dominate the network behavior but are difficult to analyze in a completely general manner. Two particular novel solutions, one periodic and another irregular, are shown in Figures 4A and 4B.

5 Conclusion

In this study, we introduce a phenomenological model that allows computation of the postsynaptic responses generated by either facilitating or depressing synapses for an arbitrary train of presynaptic spikes. The model was used to define the signals that can be transmitted by these synapses, and we show that signaling through these two types of synapses is fundamentally different at low firing rates but becomes more similar as the firing rate grows.

The model was also used to test the validity of the derivation of self-consistent mean-field equations for the dynamic behavior of large neural networks with arbitrary architecture of external inputs and internal interactions. The formalism was illustrated by considering two simple examples of networks consisting of one and two uniform populations of neurons. The purely excitatory network was shown always to possess a fixed-point solution, which can have arbitrary small firing rates. Adding an inhibitory population greatly increases the repertoire of behaviors, including the irregular sequence of population bursts of various amplitudes. Synaptic dynamics could therefore be an important factor in generating different states of cortical activity as reflected by electroencephalogram recordings.

An important challenge for the proposed formulation remains in analyzing the influence of the synaptic dynamics on the performance of other,

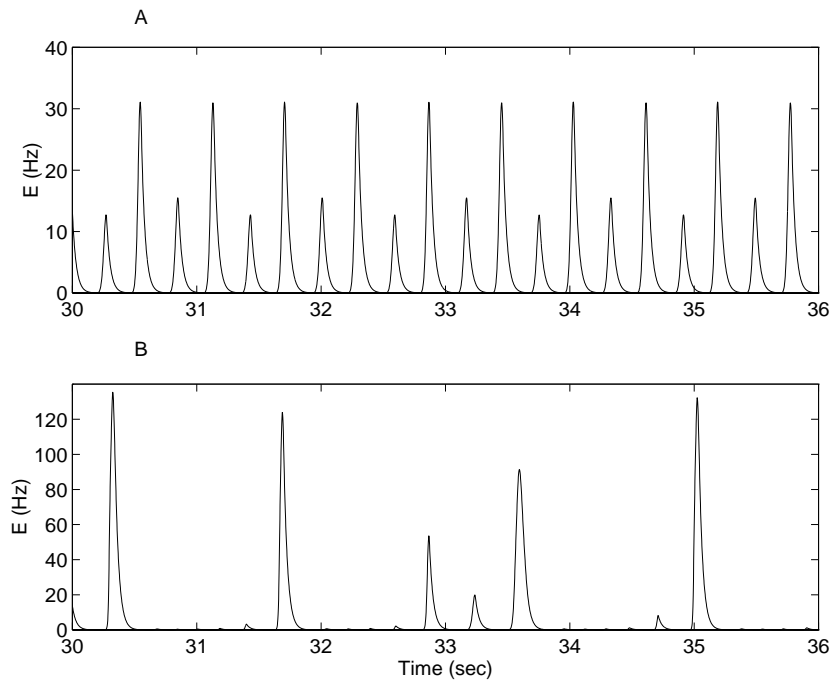


Figure 4: Solutions of equation 4.1 for the network of two populations with homogeneous connections. (A) Population activity $E(t)$ for the parameters $I^e = 17$ mV; $I^i = 15$ mV; $J_{ee} = 50$ mV*Hz $^{-1}$; $J_{ei} = 40$; $J_{ie} = 70$; $J_{ii} = 19.5$; $U_{SE} = 0.5$ (ee and ei); $U_{SE} = 0.05$ (ie); 0.03 (ii); $\tau_{rec} = 800$ msec (ee and ei); 600 msec (ie); 850 msec (ii); $\tau_{facil} = 1000$ msec (ie); 400 msec (ii); $\tau_e = 30$ msec; $\tau_i = 40$ msec. (B) The same as in A but with $J_{ii} = 0$. The gain functions for both populations have the same form as in Figure 3.

computationally more instructive neural network models. Work in this direction is in progress.

Note added in proof: After the work was completed, we learned that a network of excitatory population can have oscillating solutions under some conditions (J. Rinzel, private communication).

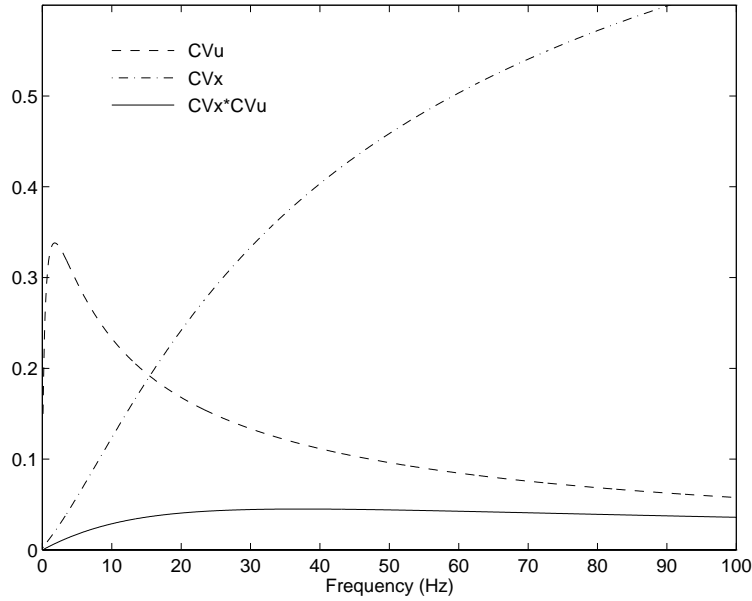


Figure 5: Coefficients of variation of U_{SE} , x , as well as their product, as a function of presynaptic frequency. Parameters are the same as in Figures 1B–D.

Appendix

The mean-field description in section 3 was derived by adopting an approximation,

$$\langle xU_{SE}^1 \rangle = \langle x \rangle \langle U_{SE}^1 \rangle. \quad (\text{A.1})$$

The relative error of this approximation can be estimated using the Cauchy-Schwarz inequality of the probability theory:

$$\frac{|\langle xU^1 \rangle - \langle x \rangle \langle U^1 \rangle|}{\langle x \rangle \langle U^1 \rangle} \leq CV_x CV_U, \quad (\text{A.2})$$

where CV_x (CV_U) stay for the coefficient of variation of the random variable x (U^1); we use U^1 instead of U_{SE}^1 for brevity. Intuitively, this inequality states that if one of the random variables has a small CV, its correlations with the other variables can be neglected. We can now use equation 2.2 to compute the CV of U_{SE}^1 for any presynaptic rate r . In the steady state, the result of

computation is,

$$CV_U^2 = \frac{r\tau_{facil}(1-U)^2}{2(1+r\tau_{facil})^2(1+Ur\tau_{facil}(1-U/2))}. \quad (\text{A.3})$$

CV_x can be computed from equation 2.1, again assuming the condition in equation A.1:

$$CV_x^2 = \frac{r\tau_{rec}\langle(U^1)2/2\rangle}{1+r\tau_{rec}\langle U^1(1-U1/2)\rangle}. \quad (\text{A.4})$$

The self-consistency of the mean-field theory can now be checked by plotting the product of CV_U and CV_x as a function of frequency (see Figure 5). The graph shows that for the set of parameters used in modeling facilitating synapses, derived from experimental traces, the relative error of equation A.1 does not exceed 5 percent for any frequency. More detailed analysis of equations A.3 and A.4 indicates that this error can exceed a 10 percent level only at the significantly shorter τ_{facil} and higher values of U at which the model does not exhibit facilitating behavior anymore.

Acknowledgments

This study was supported by grants from the Office of Naval Research and the Minerva Foundation. We thank Andreas Herz for discussions and two referees for useful comments on the article.

References

- Abbott, L. F., Varela, J. A., Sen, K., & Nelson, S. B. (1997). Synaptic depression and cortical gain control. *Science*, 275, 220–224.
- Amit, D. J. & Tsodyks, M. V. (1991). Quantitative study of attractor neural network retrieving at low spike rates I: Substrate-spikes, rates, and neuronal gain. *Science*, 2, 259–274.
- Bertram, R., Sherman, A., & Staley, E. F. (1996). Single-domain/bound calcium hypothesis of transmitter release and facilitation. *J. Neurophysiol.*, 75, 1919–1931.
- Ginsburg, I., & Sompolinsky, H. (1994). Theory of correlations in stochastic neural networks. *Phys. Rev. E*, 50, 3171–3191.
- Grossberg, S. (1969). On the production and release of chemical transmitters and related topics in cellular control. *J. Theor. Biol.*, 22, 325–364.
- Mallart, A., & Martin, A. R. (1966). Two components of facilitation at the neuromuscular junction of the frog. *J. Physiol.*, 193, 677–694.
- Markram, H., & Tsodyks, M. V. (1996). Redistribution of synaptic efficacy between pyramidal neurons. *Nature*, 382, 807–810.
- Markram, H., Tsodyks, M., & Wang, Y. (In press). Differential signaling via the same axon of neocortical pyramidal neurons. *Proc. Nat'l Acad. Sci. USA*.

- Softky, W. R., & Koch, C. (1993). The highly irregular firing of cortical cells is inconsistent with temporal integration of random EPSPs. *J. Neurosci.*, *13*, 334–350.
- Thomson, A. M., & Deuchars, J. (1994). Temporal and spatial properties of local circuits in neocortex. *Trends in Neurosci.*, *17*, 119–126.
- Tsodyks, M. V., & Markram, H. (1996). Plasticity of neocortical synapses enables transitions between rate and temporal coding. *Lect. Notes Comput. Sci.*, *1112*, 445–450.
- Tsodyks, M. V., & Markram, H. (1997). The neural code between neocortical pyramidal neurons depends on neurotransmitter release probability. *Proc. Nat'l Acad. Sci. USA*, *94*, 719–723.
- Tsodyks, M. V., Skaggs, W. E., Sejnowski, T., & McNaughton, B. L. (1997). Paradoxical effect of external modulation of inhibitory neurons. *J. Neurosci.*, *17*, 4382–4388.
- Wilson, H. R., & Cowan, J. D. (1972). Excitatory and inhibitory interneurons. *Biophys.*, *12*, 1–24.
- Zengel, J. E., & Magleby, K. L. (1982). Augmentation and facilitation of transmitter release: A quantitative description at the frog neuromuscular junction. *J. Gen. Physiol.*, *80*, 583–611.

Received February 26, 1997; accepted October 30, 1997.

This article has been cited by:

1. Stephen Grossberg. 2020. Developmental Designs and Adult Functions of Cortical Maps in Multiple Modalities: Perception, Attention, Navigation, Numbers, Streaming, Speech, and Cognition. *Frontiers in Neuroinformatics* 14. . [[Crossref](#)]
2. Kerstin Lenk, Eero Satu vuori, Jules Lallouette, Antonio Ladrón-de-Guevara, Hugues Berry, Jari A. K. Hyttinen. 2020. A Computational Model of Interactions Between Neuronal and Astrocytic Networks: The Role of Astrocytes in the Stability of the Neuronal Firing Rate. *Frontiers in Computational Neuroscience* 13. . [[Crossref](#)]
3. Yvonne Johansson, Gilad Silberberg. 2020. The Functional Organization of Cortical and Thalamic Inputs onto Five Types of Striatal Neurons Is Determined by Source and Target Cell Identities. *Cell Reports* 30:4, 1178-1194.e3. [[Crossref](#)]
4. A. Galves, E. Löcherbach, C. Pouzat, E. Presutti. 2019. A System of Interacting Neurons with Short Term Synaptic Facilitation. *Journal of Statistical Physics* 3. . [[Crossref](#)]
5. S.A. Lobov. 2019. Generalized Memory of STDP-Driven Spiking Neural Network. *Mathematical Biology and Bioinformatics* 14:2, 649-664. [[Crossref](#)]
6. Lucas A. Koelman, Madeleine M. Lowery. 2019. Beta-Band Resonance and Intrinsic Oscillations in a Biophysically Detailed Model of the Subthalamic Nucleus-Globus Pallidus Network. *Frontiers in Computational Neuroscience* 13. . [[Crossref](#)]
7. Mateo Lopez Espejo, Zachary P. Schwartz, Stephen V. David. 2019. Spectral tuning of adaptation supports coding of sensory context in auditory cortex. *PLOS Computational Biology* 15:10, e1007430. [[Crossref](#)]
8. Bastian Pietras, Federico Devalle, Alex Roxin, Andreas Daffertshofer, Ernest Montbrío. 2019. Exact firing rate model reveals the differential effects of chemical versus electrical synapses in spiking networks. *Physical Review E* 100:4. . [[Crossref](#)]
9. Hea-Lim Park, Yeongjun Lee, Naryung Kim, Dae-Gyo Seo, Gyeong-Tak Go, Tae-Woo Lee. 2019. Flexible Neuromorphic Electronics for Computing, Soft Robotics, and Neuroprosthetics. *Advanced Materials* 30, 1903558. [[Crossref](#)]
10. Seung-Ryeol Lee, Sujin Hyung, Seokyoung Bang, Younggyun Lee, Jihoon Ko, Somin Lee, Hyung Joon Kim, Noo Li Jeon. 2019. Modeling neural circuit, blood-brain barrier, and myelination on a microfluidic 96 well plate. *Biofabrication* 11:3, 035013. [[Crossref](#)]
11. Michael Jan Fauth, Mark CW van Rossum. 2019. Self-organized reactivation maintains and reinforces memories despite synaptic turnover. *eLife* 8. . [[Crossref](#)]
12. Alexander Seeholzer, Moritz Deger, Wulfram Gerstner. 2019. Stability of working memory in continuous attractor networks under the control of short-term plasticity. *PLOS Computational Biology* 15:4, e1006928. [[Crossref](#)]
13. Matteo di Volo, Alberto Romagnoni, Cristiano Capone, Alain Destexhe. 2019. Biologically Realistic Mean-Field Models of Conductance-Based Networks of Spiking Neurons with Adaptation. *Neural Computation* 31:4, 653-680. [[Abstract](#)] [[Full Text](#)] [[PDF](#)] [[PDF Plus](#)]
14. Anton V. Chizhov, Dmitry V. Amakhin, Aleksey V. Zaitsev. 2019. Mathematical model of Na-K-Cl homeostasis in ictal and interictal discharges. *PLOS ONE* 14:3, e0213904. [[Crossref](#)]
15. Tom Flossmann, Thomas Kaas, Vahid Rahmati, Stefan J. Kiebel, Otto W. Witte, Knut Holthoff, Knut Kirmse. 2019. Somatostatin Interneurons Promote Neuronal Synchrony in the Neonatal Hippocampus. *Cell Reports* 26:12, 3173-3182.e5. [[Crossref](#)]
16. Thomas McColgan, Paula T. Kuokkanen, Catherine E. Carr, Richard Kempter. 2019. Dynamics of synaptic extracellular field potentials in the nucleus laminaris of the barn owl. *Journal of Neurophysiology* 121:3, 1034-1047. [[Crossref](#)]
17. Selam W. Habtegiorgis, Christian Jarvers, Katharina Rifai, Heiko Neumann, Siegfried Wahl. 2019. The Role of Bottom-Up and Top-Down Cortical Interactions in Adaptation to Natural Scene Statistics. *Frontiers in Neural Circuits* 13. . [[Crossref](#)]
18. Éric Hamel, Richard Labib. 2019. Modeling biological refractory periods and synaptic depression in an artificial neuron. *Biomedical Physics & Engineering Express* 5:2, 025038. [[Crossref](#)]
19. Simon P. Perrier, Marie Gleizes, Caroline Fonta, Lionel G. Nowak. 2019. Effect of adenosine on short-term synaptic plasticity in mouse piriform cortex in vitro: adenosine acts as a high-pass filter. *Physiological Reports* 7:3, e13992. [[Crossref](#)]
20. Debmalya Chakrabarty, Mounya Elhilali. 2019. A Gestalt inference model for auditory scene segregation. *PLOS Computational Biology* 15:1, e1006711. [[Crossref](#)]
21. Maurizio De Pittà. Gliotransmitter Exocytosis and Its Consequences on Synaptic Transmission 245-287. [[Crossref](#)]
22. Marcel Stimberg, Dan F. M. Goodman, Romain Brette, Maurizio De Pittà. Modeling Neuron-Glia Interactions with the Brian 2 Simulator 471-505. [[Crossref](#)]
23. Nikola K. Kasabov. Methods of Spiking Neural Networks 127-167. [[Crossref](#)]

24. Christopher H. Bennett, Vivek Parmar, Laurie E. Calvet, Jacques-Olivier Klein, Manan Suri, Matthew J. Marinella, Damien Querlioz. 2019. Contrasting Advantages of Learning With Random Weights and Backpropagation in Non-Volatile Memory Neural Networks. *IEEE Access* 7, 73938-73953. [[Crossref](#)]
25. Christopher Thornton, Frances Hutchings, Marcus Kaiser. 2019. The Virtual Electrode Recording Tool for EXtracellular Potentials (VERTEX) Version 2.0: Modelling in vitro electrical stimulation of brain tissue. *Wellcome Open Research* 4, 20. [[Crossref](#)]
26. Radwa Khalil, Ahmed A. Karim, Eman Khedr, Marie Mofteh, Ahmed A. Moustafa. 2018. Dynamic Communications Between GABAA Switch, Local Connectivity, and Synapses During Cortical Development: A Computational Study. *Frontiers in Cellular Neuroscience* 12. . [[Crossref](#)]
27. Germán Mendoza, Juan Carlos Méndez, Oswaldo Pérez, Luis Prado, Hugo Merchant. 2018. Neural basis for categorical boundaries in the primate pre-SMA during relative categorization of time intervals. *Nature Communications* 9:1. . [[Crossref](#)]
28. Shi Gu, Matthew Cieslak, Benjamin Baird, Sarah F. Muldoon, Scott T. Grafton, Fabio Pasqualetti, Danielle S. Bassett. 2018. The Energy Landscape of Neurophysiological Activity Implicit in Brain Network Structure. *Scientific Reports* 8:1. . [[Crossref](#)]
29. Zachary P. Kilpatrick. 2018. Synaptic mechanisms of interference in working memory. *Scientific Reports* 8:1. . [[Crossref](#)]
30. Luziwei Leng, Roman Martel, Oliver Breitwieser, Ilja Bytschok, Walter Senn, Johannes Schemmel, Karlheinz Meier, Mihai A. Petrovici. 2018. Spiking neurons with short-term synaptic plasticity form superior generative networks. *Scientific Reports* 8:1. . [[Crossref](#)]
31. Elham Bayat Mokhtari, J. Josh Lawrence, Emily F. Stone. 2018. Effect of Neuromodulation of Short-term Plasticity on Information Processing in Hippocampal Interneuron Synapses. *The Journal of Mathematical Neuroscience* 8:1. . [[Crossref](#)]
32. Jochen Triesch, Anh Duong Vo, Anne-Sophie Hafner. 2018. Competition for synaptic building blocks shapes synaptic plasticity. *eLife* 7. . [[Crossref](#)]
33. Rajeev V. Rikhye, Ralf D. Wimmer, Michael M. Halassa. 2018. Toward an Integrative Theory of Thalamic Function. *Annual Review of Neuroscience* 41:1, 163-183. [[Crossref](#)]
34. Hesam Setareh, Moritz Deger, Wulfram Gerstner. 2018. Excitable neuronal assemblies with adaptation as a building block of brain circuits for velocity-controlled signal propagation. *PLoS Computational Biology* 14:7, e1006216. [[Crossref](#)]
35. Johannes Zierenberg, Jens Wilting, Viola Priesemann. 2018. Homeostatic Plasticity and External Input Shape Neural Network Dynamics. *Physical Review X* 8:3. . [[Crossref](#)]
36. Shriram Ramanathan. 2018. Quantum materials for brain sciences and artificial intelligence. *MRS Bulletin* 43:7, 534-540. [[Crossref](#)]
37. Alex D. Bird, Magnus J. E. Richardson. 2018. Transmission of temporally correlated spike trains through synapses with short-term depression. *PLoS Computational Biology* 14:6, e1006232. [[Crossref](#)]
38. Ziyu Lv, Ye Zhou, Su-Ting Han, V.A.L. Roy. 2018. From biomaterial-based data storage to bio-inspired artificial synapse. *Materials Today* 21:5, 537-552. [[Crossref](#)]
39. Anton V. Chizhov, Artyom V. Zefirov, Dmitry V. Amakhin, Elena Yu. Smirnova, Aleksey V. Zaitsev. 2018. Minimal model of interictal and ictal discharges “Epileptor-2”. *PLoS Computational Biology* 14:5, e1006186. [[Crossref](#)]
40. Jason S. Rothman, R. Angus Silver. 2018. NeuroMatic: An Integrated Open-Source Software Toolkit for Acquisition, Analysis and Simulation of Electrophysiological Data. *Frontiers in Neuroinformatics* 12. . [[Crossref](#)]
41. Keisuke Tanimoto, Yoshiteru Amemiya, Shin Yokoyama. 2018. Optical waveguides with memory effect using photochromic material for neural network. *Japanese Journal of Applied Physics* 57:4S, 04FH02. [[Crossref](#)]
42. Hazem Toutounji, Loreen Hertäg, Daniel Durstewitz. Neural Networks and Neurocomputational Modeling 1-40. [[Crossref](#)]
43. L. Michiels van Kessenich, M. Luković, L. de Arcangelis, H. J. Herrmann. 2018. Critical neural networks with short- and long-term plasticity. *Physical Review E* 97:3. . [[Crossref](#)]
44. Federico Devalle, Alex Roxin, Ernest Montbrío. 2017. Firing rate equations require a spike synchrony mechanism to correctly describe fast oscillations in inhibitory networks. *PLoS Computational Biology* 13:12, e1005881. [[Crossref](#)]
45. Grant Gillary, Rüdiger von der Heydt, Ernst Niebur. 2017. Short-term depression and transient memory in sensory cortex. *Journal of Computational Neuroscience* 43:3, 273-294. [[Crossref](#)]
46. Wilten Nicola, Claudia Clopath. 2017. Supervised learning in spiking neural networks with FORCE training. *Nature Communications* 8:1. . [[Crossref](#)]
47. Vahid Rahmati, Knut Kirmse, Knut Holthoff, Lars Schwabe, Stefan J. Kiebel. 2017. Developmental Emergence of Sparse Coding: A Dynamic Systems Approach. *Scientific Reports* 7:1. . [[Crossref](#)]

48. Abhyudai Singh. Noise mechanisms in synaptic transmission and their impact on spike-timing precision 5925-5930. [[Crossref](#)]
49. Vassilios Papaleonidopoulos, George Trompoukis, Andriana Koutsoumpa, Costas Papatheodoropoulos. 2017. A gradient of frequency-dependent synaptic properties along the longitudinal hippocampal axis. *BMC Neuroscience* **18**:1. . [[Crossref](#)]
50. Xiao Wang, Yan Wu, Mingsha Zhang, Si Wu. 2017. Learning Peri-saccadic Remapping of Receptive Field from Experience in Lateral Intraparietal Area. *Frontiers in Computational Neuroscience* **11**. . [[Crossref](#)]
51. N. Roy, P. Sanz-Leon, P. A. Robinson. 2017. Spectral signatures of activity-dependent neural feedback in the corticothalamic system. *Physical Review E* **96**:5. . [[Crossref](#)]
52. Radwa Khalil, Marie Z. Moftah, Ahmed A. Moustafa. 2017. The effects of dynamical synapses on firing rate activity: a spiking neural network model. *European Journal of Neuroscience* **46**:9, 2445-2470. [[Crossref](#)]
53. Tie-Jun Huang. 2017. Imitating the brain with neurocomputer a “new” way towards artificial general intelligence. *International Journal of Automation and Computing* **14**:5, 520-531. [[Crossref](#)]
54. Daniel Fine English, Sam McKenzie, Talfan Evans, Kanghwan Kim, Euisik Yoon, György Buzsáki. 2017. Pyramidal Cell-Interneuron Circuit Architecture and Dynamics in Hippocampal Networks. *Neuron* **96**:2, 505-520.e7. [[Crossref](#)]
55. Mark D. McDonnell, Bruce P. Graham. 2017. Phase changes in neuronal postsynaptic spiking due to short term plasticity. *PLOS Computational Biology* **13**:9, e1005634. [[Crossref](#)]
56. Stefano Masoli, Egidio D'Angelo. 2017. Synaptic Activation of a Detailed Purkinje Cell Model Predicts Voltage-Dependent Control of Burst-Pause Responses in Active Dendrites. *Frontiers in Cellular Neuroscience* **11**. . [[Crossref](#)]
57. Radwa Khalil, Marie Z. Moftah, Marc Landry, Ahmed A. Moustafa. Models of Dynamical Synapses and Cortical Development 321-331. [[Crossref](#)]
58. Abed Ghanbari, Aleksey Malyshev, Maxim Volgushev, Ian H. Stevenson. 2017. Estimating short-term synaptic plasticity from pre- and postsynaptic spiking. *PLOS Computational Biology* **13**:9, e1005738. [[Crossref](#)]
59. Axel Grzymisch, Cathleen Grimsen, Udo A. Ernst. 2017. Contour Integration in Dynamic Scenes: Impaired Detection Performance in Extended Presentations. *Frontiers in Psychology* **8**. . [[Crossref](#)]
60. Shirley Mark, Sandro Romani, Karel Jezek, Misha Tsodyks. 2017. Theta-paced flickering between place-cell maps in the hippocampus: A model based on short-term synaptic plasticity. *Hippocampus* **27**:9, 959-970. [[Crossref](#)]
61. Muyuan Xu, Yuichi Katori, Kazuyuki Aihara. 2017. Stability Analysis on Sparsely Encoded Associative Memory with Short-Term Synaptic Dynamics. *International Journal of Bifurcation and Chaos* **27**:10, 1730034. [[Crossref](#)]
62. Marie Gleizes, Simon P. Perrier, Caroline Fonta, Lionel G. Nowak. 2017. Prominent facilitation at beta and gamma frequency range revealed with physiological calcium concentration in adult mouse piriform cortex in vitro. *PLOS ONE* **12**:8, e0183246. [[Crossref](#)]
63. Lei Wan, Junxiu Liu, Jim Harkin, Liam McDaid, Yuling Luo. 2017. Layered tile architecture for efficient hardware spiking neural networks. *Microprocessors and Microsystems* **53**, 21-32. [[Crossref](#)]
64. Miao Hu, Yiran Chen, J. Joshua Yang, Yu Wang, Hai Helen Li. 2017. A Compact Memristor-Based Dynamic Synapse for Spiking Neural Networks. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems* **36**:8, 1353-1366. [[Crossref](#)]
65. Ariadne Costa, Ludmila Brochini, Osame Kinouchi. 2017. Self-Organized Supercriticality and Oscillations in Networks of Stochastic Spiking Neurons. *Entropy* **19**:8, 399. [[Crossref](#)]
66. Joanna Jędrzejewska-Szmek, Vincent Luczak, Ted Abel, Kim T Blackwell. 2017. β -adrenergic signaling broadly contributes to LTP induction. *PLOS Computational Biology* **13**:7, e1005657. [[Crossref](#)]
67. Khuong N. Nguyen, Yoonsuck Choe. Dynamic control using feedforward networks with adaptive delay and facilitating neural dynamics 2987-2994. [[Crossref](#)]
68. Pavel Esir, Alexander Simonov, Misha Tsodyks. 2017. Feature Detection in Visual Cortex during Different Functional States. *Frontiers in Computational Neuroscience* **11**. . [[Crossref](#)]
69. Tilo Schwalger, Moritz Deger, Wulfram Gerstner. 2017. Towards a theory of cortical columns: From spiking neurons to interacting neural populations of finite size. *PLOS Computational Biology* **13**:4, e1005507. [[Crossref](#)]
70. Kai Lu, Yanbo Xu, Pingbo Yin, Andrew J. Oxenham, Jonathan B. Fritz, Shihab A. Shamma. 2017. Temporal coherence structure rapidly shapes neuronal interactions. *Nature Communications* **8**:1. . [[Crossref](#)]
71. Takumi Sase, Yuichi Katori, Motomasa Komuro, Kazuyuki Aihara. 2017. Bifurcation Analysis on Phase-Amplitude Cross-Frequency Coupling in Neural Networks with Dynamic Synapses. *Frontiers in Computational Neuroscience* **11**. . [[Crossref](#)]
72. Friedemann Zenke, Wulfram Gerstner. 2017. Hebbian plasticity requires compensatory processes on multiple timescales. *Philosophical Transactions of the Royal Society B: Biological Sciences* **372**:1715, 20160259. [[Crossref](#)]

73. Fabrizio Pittorino, Miguel Ibáñez-Berganza, Matteo di Volo, Alessandro Vezzani, Raffaella Burioni. 2017. Chaos and Correlated Avalanches in Excitatory Neural Networks with Synaptic Plasticity. *Physical Review Letters* **118**:9. . [\[Crossref\]](#)
74. Dong-Ping Yang, Hai-Jun Zhou, Changsong Zhou. 2017. Co-emergence of multi-scale cortical activities of irregular firing, oscillations and avalanches achieves cost-efficient information capacity. *PLOS Computational Biology* **13**:2, e1005384. [\[Crossref\]](#)
75. Christoph Börgers. Short-Term Depression and Facilitation 341-348. [\[Crossref\]](#)
76. Yuling Luo, Lei Wan, Junxiu Liu, Jinlei Zhang, Yi Cao. An Efficient Hardware Architecture for Multilayer Spiking Neural Networks 786-795. [\[Crossref\]](#)
77. Arjen van Ooyen. Network Formation Through Activity-Dependent Neurite Outgrowth 95-121. [\[Crossref\]](#)
78. Yuanyuan Mi, Mikhail Katkov, Misha Tsodyks. 2017. Synaptic Correlates of Working Memory Capacity. *Neuron* **93**:2, 323-330. [\[Crossref\]](#)
79. S.A. Lobov, M.O. Zhuravlev, V.A. Makarov, V.B. Kazantsev. 2017. Noise Enhanced Signaling in STDP Driven Spiking-Neuron Network. *Mathematical Modelling of Natural Phenomena* **12**:4, 109-124. [\[Crossref\]](#)
80. Elena Bertolotti, Raffaella Burioni, Matteo di Volo, Alessandro Vezzani. 2017. Synchronization and long-time memory in neural networks with inhibitory hubs and synaptic plasticity. *Physical Review E* **95**:1. . [\[Crossref\]](#)
81. Muhammet Uzuntarla, Joaquin J. Torres, Paul So, Mahmut Ozer, Ernest Barreto. 2017. Double inverse stochastic resonance with dynamic synapses. *Physical Review E* **95**:1. . [\[Crossref\]](#)
82. Sayan Biswas. How diverse is the network information obtained from the nodes of a biological neural network? 145-149. [\[Crossref\]](#)
83. Carsen Stringer, Marius Pachitariu, Nicholas A Steinmetz, Michael Okun, Peter Bartho, Kenneth D Harris, Maneesh Sahani, Nicholas A Lesica. 2016. Inhibitory control of correlated intrinsic variability in cortical networks. *eLife* **5**. . [\[Crossref\]](#)
84. Chang-Hyun Kim, Sujin Sung, Myung-Han Yoon. 2016. Synaptic organic transistors with a vacuum-deposited charge-trapping nanosheet. *Scientific Reports* **6**:1. . [\[Crossref\]](#)
85. Ludmila Brochini, Ariadne de Andrade Costa, Miguel Abadi, Antônio C. Roque, Jorge Stolfi, Osame Kinouchi. 2016. Phase transitions and self-organized criticality in networks of stochastic spiking neurons. *Scientific Reports* **6**:1. . [\[Crossref\]](#)
86. Sarah Wahlstrom-Helgren, Vitaly A. Klyachko. 2016. Dynamic balance of excitation and inhibition rapidly modulates spike probability and precision in feed-forward hippocampal circuits. *Journal of Neurophysiology* **116**:6, 2564-2575. [\[Crossref\]](#)
87. Alex D. Bird, Mark J. Wall, Magnus J. E. Richardson. 2016. Bayesian Inference of Synaptic Quantal Parameters from Correlated Vesicle Release. *Frontiers in Computational Neuroscience* **10**. . [\[Crossref\]](#)
88. Anvesh Polepalli, Nicholas Soures, Dhireesha Kudithipudi. Digital neuromorphic design of a Liquid State Machine for real-time processing 1-8. [\[Crossref\]](#)
89. Grant Gillary, Ernst Niebur. 2016. The Edge of Stability: Response Times and Delta Oscillations in Balanced Networks. *PLOS Computational Biology* **12**:9, e1005121. [\[Crossref\]](#)
90. Joomin Lee, Eunsook Ahn, WYun Kon Park, Seyeon Park. 2016. Phosphoproteome Profiling of SH-SY5y Neuroblastoma Cells Treated with Anesthetics: Sevoflurane and Isoflurane Affect the Phosphorylation of Proteins Involved in Cytoskeletal Regulation. *PLOS ONE* **11**:9, e0162214. [\[Crossref\]](#)
91. Yansong Chua, Abigail Morrison. 2016. Effects of Calcium Spikes in the Layer 5 Pyramidal Neuron on Coincidence Detection and Activity Propagation. *Frontiers in Computational Neuroscience* **10**. . [\[Crossref\]](#)
92. Egidio D'Angelo, Alberto Antonietti, Stefano Casali, Claudia Casellato, Jesus A. Garrido, Niceto Rafael Luque, Lisa Mapelli, Stefano Masoli, Alessandra Pedrocchi, Francesca Prestori, Martina Francesca Rizza, Eduardo Ros. 2016. Modeling the Cerebellar Microcircuit: New Strategies for a Long-Standing Issue. *Frontiers in Cellular Neuroscience* **10**. . [\[Crossref\]](#)
93. Z. Kohus, S. Káli, L. Rovira-Esteban, D. Schlingloff, O. Papp, T. F. Freund, N. Hájos, A. I. Gulyás. 2016. Properties and dynamics of inhibitory synaptic communication within the CA3 microcircuits of pyramidal cells and interneurons expressing parvalbumin or cholecystokinin. *The Journal of Physiology* **594**:13, 3745-3774. [\[Crossref\]](#)
94. Brandon Reagen, Paul Whatmough, Robert Adolf, Saketh Rama, Hyunkwang Lee, Sae Kyu Lee, José Miguel Hernández-Lobato, Gu-Yeon Wei, David Brooks. 2016. Minerva. *ACM SIGARCH Computer Architecture News* **44**:3, 267-278. [\[Crossref\]](#)
95. Adeline Zbrzeski, Yannick Bornat, Brian Hillen, Ricardo Siu, James Abbas, Ranu Jung, Sylvie Renaud. 2016. Bio-Inspired Controller on an FPGA Applied to Closed-Loop Diaphragmatic Stimulation. *Frontiers in Neuroscience* **10**. . [\[Crossref\]](#)
96. Brandon Reagen, Paul Whatmough, Robert Adolf, Saketh Rama, Hyunkwang Lee, Sae Kyu Lee, Jose Miguel Hernandez-Lobato, Gu-Yeon Wei, David Brooks. Minerva: Enabling Low-Power, Highly-Accurate Deep Neural Network Accelerators 267-278. [\[Crossref\]](#)

97. Lei Wan, Yuling Luo, Shuxiang Song, Jim Harkin, Junxiu Liu. Efficient neuron architecture for FPGA-based spiking neural networks 1-6. [[Crossref](#)]
98. M. De Pittà, N. Brunel, A. Volterra. 2016. Astrocytes: Orchestrating synaptic plasticity?. *Neuroscience* **323**, 43-61. [[Crossref](#)]
99. Radu Berdan, Eleni Vasilaki, Ali Khiat, Giacomo Indiveri, Alexandru Serb, Themistoklis Prodromakis. 2016. Emulating short-term synaptic dynamics with memristive devices. *Scientific Reports* **6**:1. . [[Crossref](#)]
100. Wei Wei, Xiao-Jing Wang. 2016. Downstream Effect of Ramping Neuronal Activity through Synapses with Short-Term Plasticity. *Neural Computation* **28**:4, 652-666. [[Abstract](#)] [[Full Text](#)] [[PDF](#)] [[PDF Plus](#)]
101. Brent Doiron, Ashok Litwin-Kumar, Robert Rosenbaum, Gabriel K Ocker, Krešimir Josić. 2016. The mechanics of state-dependent neural correlations. *Nature Neuroscience* **19**:3, 383-393. [[Crossref](#)]
102. Wenhao Zhang, Hanyu Li, Minda Yang, Nima Mesgarani. Synaptic depression in deep neural networks for speech processing 5865-5869. [[Crossref](#)]
103. Roberto Latorre, Joaquín J. Torres, Pablo Varona. 2016. Interplay between Subthreshold Oscillations and Depressing Synapses in Single Neurons. *PLOS ONE* **11**:1, e0145830. [[Crossref](#)]
104. Frederic Lanore, R. Angus Silver. Extracting Quantal Properties of Transmission at Central Synapses 193-211. [[Crossref](#)]
105. Costas A. Anastassiou, Adam S. Shai. *Psyche, Signals and Systems* 107-156. [[Crossref](#)]
106. Yuichi Katori. Enhanced Memory Association on Neural Network with Dynamic Synapses 741-748. [[Crossref](#)]
107. Matteo di Volo, Raffaella Burioni, Mario Casartelli, Roberto Livi, Alessandro Vezzani. 2016. Neural networks with excitatory and inhibitory components: Direct and inverse problems by a mean-field approach. *Physical Review E* **93**:1. . [[Crossref](#)]
108. Anvesh Polepalli, Dhireesha Kudithipudi. Reconfigurable Digital Design of a Liquid State Machine for Spatio-Temporal Data 1-6. [[Crossref](#)]
109. Ivar L. Thorson, Jean Liénard, Stephen V. David. 2015. The Essential Complexity of Auditory Receptive Fields. *PLOS Computational Biology* **11**:12, e1004628. [[Crossref](#)]
110. Alan Veliz-Cuba, Harel Z. Shouval, Krešimir Josić, Zachary P. Kilpatrick. 2015. Networks that learn the precise timing of event sequences. *Journal of Computational Neuroscience* **39**:3, 235-254. [[Crossref](#)]
111. M. Uzuntarla, M. Ozer, U. Ileri, A. Calim, J. J. Torres. 2015. Effects of dynamic synapses on noise-delayed response latency of a single neuron. *Physical Review E* **92**:6. . [[Crossref](#)]
112. Alex D Bird, Magnus JE Richardson. 2015. Synaptic transmission of spike trains with arbitrary interspike intervals. *BMC Neuroscience* **16**:S1. . [[Crossref](#)]
113. Narayan Srinivasa, Nigel D. Stepp, Jose Cruz-Albrecht. 2015. Criticality as a Set-Point for Adaptive Behavior in Neuromorphic Hardware. *Frontiers in Neuroscience* **9**. . [[Crossref](#)]
114. Guido Gigante, Gustavo Deco, Shimon Marom, Paolo Del Giudice. 2015. Network Events on Multiple Space and Time Scales in Cultured Neural Networks and in a Stochastic Rate Model. *PLOS Computational Biology* **11**:11, e1004547. [[Crossref](#)]
115. Sergey Lobov, Vasilij Mironov, Innokentiy Kastalskiy, Victor Kazantsev. 2015. A Spiking Neural Network in sEMG Feature Extraction. *Sensors* **15**:11, 27894-27904. [[Crossref](#)]
116. Pradeep Krishnamurthy, Gilad Silberberg, Anders Lansner. 2015. Long-range recruitment of Martinotti cells causes surround suppression and promotes saliency in an attractor network model. *Frontiers in Neural Circuits* **9**. . [[Crossref](#)]
117. Clément Moutard, Stanislas Dehaene, Rafael Malach. 2015. Spontaneous Fluctuations and Non-linear Ignitions: Two Dynamic Faces of Cortical Recurrent Loops. *Neuron* **88**:1, 194-206. [[Crossref](#)]
118. Eric Y. Hu, Jean-Marie C. Bouteiller, Dong Song, Michel Baudry, Theodore W. Berger. 2015. Volterra representation enables modeling of complex synaptic nonlinear dynamics in large-scale simulations. *Frontiers in Computational Neuroscience* **9**. . [[Crossref](#)]
119. Ayal Lavi, Omri Perez, Uri Ashery. 2015. Shaping Neuronal Network Activity by Presynaptic Mechanisms. *PLOS Computational Biology* **11**:9, e1004438. [[Crossref](#)]
120. Stephen Grossberg. 2015. From brain synapses to systems for learning and memory: Object recognition, spatial navigation, timed conditioning, and movement control. *Brain Research* **1621**, 270-293. [[Crossref](#)]
121. Ying-Jen Yang, Chun-Chung Chen, Pik-Yin Lai, C. K. Chan. 2015. Adaptive synchronization and anticipatory dynamical systems. *Physical Review E* **92**:3. . [[Crossref](#)]
122. He Wang, Kin Lam, C. C. Alan Fung, K. Y. Michael Wong, Si Wu. 2015. Rich spectrum of neural field dynamics in the presence of short-term synaptic depression. *Physical Review E* **92**:3. . [[Crossref](#)]
123. Claire Guerrier, John A. Hayes, Gilles Fortin, David Holcman. 2015. Robust network oscillations during mammalian respiratory rhythm generation driven by synaptic dynamics. *Proceedings of the National Academy of Sciences* **112**:31, 9728-9733. [[Crossref](#)]

124. Khanh Dao Duc, Pierre Parutto, Xiaowei Chen, J me Epsztein, Arthur Konnerth, David Holcman. 2015. Synaptic dynamics and neuronal network connectivity are reflected in the distribution of times in Up states. *Frontiers in Computational Neuroscience* 9. . [\[Crossref\]](#)
125. Farzad Farkhooi, Carl van Vreeswijk. 2015. Renewal Approach to the Analysis of the Asynchronous State for Coupled Noisy Oscillators. *Physical Review Letters* 115:3. . [\[Crossref\]](#)
126. Michael Beyeler, Kristofor D. Carlson, Ting-Shuo Chou, Nikil Dutt, Jeffrey L. Krichmar. CARLsim 3: A user-friendly and highly optimized library for the creation of neurobiologically detailed spiking neural networks 1-8. [\[Crossref\]](#)
127. Byungik Ahn. Neuron-like digital hardware architecture for large-scale neuromorphic computing 1-8. [\[Crossref\]](#)
128. Henri Berestycki, Jean Pierre Nadal, Nancy Rodr guez. 2015. A model of riots dynamics: Shocks, diffusion and thresholds. *Networks and Heterogeneous Media* 10:3, 443-475. [\[Crossref\]](#)
129. Raffaella Burioni, Mario Casartelli, Matteo di Volo, Roberto Livi, Alessandro Vezzani. 2015. Average synaptic activity and neural networks topology: a global inverse problem. *Scientific Reports* 4:1. . [\[Crossref\]](#)
130. Christian Huyck, Carl Evans, Ian Mitchell. 2015. A comparison of simple agents implemented in simulated neurons. *Biologically Inspired Cognitive Architectures* 12, 9-19. [\[Crossref\]](#)
131. J r mie Sibille, Khanh Dao Duc, David Holcman, Nathalie Rouach. 2015. The Neuroglial Potassium Cycle during Neurotransmission: Role of Kir4.1 Channels. *PLOS Computational Biology* 11:3, e1004137. [\[Crossref\]](#)
132. Joaquin J. Torres, Irene Elices, J. Marro. 2015. Efficient Transmission of Subthreshold Signals in Complex Networks of Spiking Neurons. *PLOS ONE* 10:3, e0121156. [\[Crossref\]](#)
133. C. C. Alan Fung, S.-i. Amari. 2015. Spontaneous Motion on Two-Dimensional Continuous Attractors. *Neural Computation* 27:3, 507-547. [\[Abstract\]](#) [\[Full Text\]](#) [\[PDF\]](#) [\[PDF Plus\]](#)
134. Xuhui Huang, Zhigang Zheng, Gang Hu, Si Wu, Malte J Rasch. 2015. Different propagation speeds of recalled sequences in plastic spiking neural networks. *New Journal of Physics* 17:3, 035006. [\[Crossref\]](#)
135. Danke Zhang, Si Wu, Malte J. Rasch. 2015. Circuit Motifs for Contrast-Adaptive Differentiation in Early Sensory Systems: The Role of Presynaptic Inhibition and Short-Term Plasticity. *PLOS ONE* 10:2, e0118125. [\[Crossref\]](#)
136. Hirofumi Hayakawa, Toshikazu Samura, Tadanobu Chuyo Kamijo, Yutaka Sakai, Takeshi Aihara. 2015. Spatial information enhanced by non-spatial information in hippocampal granule cells. *Cognitive Neurodynamics* 9:1, 1-12. [\[Crossref\]](#)
137. F. D. Iudin, D. I. Iudin, V. B. Kazantsev. 2015. Percolation transition in active neural networks with adaptive geometry. *JETP Letters* 101:4, 271-275. [\[Crossref\]](#)
138. Nigel Stepp, Dietmar Plenz, Narayan Srinivasa. 2015. Synaptic Plasticity Enables Adaptive Self-Tuning Critical Networks. *PLOS Computational Biology* 11:1, e1004043. [\[Crossref\]](#)
139. Sandro Romani, Misha Tsodyks. 2015. Short-term plasticity based network model of place cells dynamics. *Hippocampus* 25:1, 94-105. [\[Crossref\]](#)
140. Yuichi Katori, Yosuke Otsubo, Masato Okada, Kazuyuki Aihara. Associative Memory Network with Dynamic Synapses 479-483. [\[Crossref\]](#)
141. J rgen Schmidhuber. 2015. Deep learning in neural networks: An overview. *Neural Networks* 61, 85-117. [\[Crossref\]](#)
142. Dayana Benny, Kumary R Soumya. Feed-forward neural network processing speed analysis and an experimental evaluation of Neural Network Frameworks 1-5. [\[Crossref\]](#)
143. . Silicon Synapses 185-217. [\[Crossref\]](#)
144. Narayan Srinivasa, Youngkwan Cho. 2014. Unsupervised discrimination of patterns in spiking neural networks with excitatory and inhibitory synaptic plasticity. *Frontiers in Computational Neuroscience* 8. . [\[Crossref\]](#)
145. Guilherme Testa-Silva, Matthijs B. Verhoog, Daniele Linaro, Christiaan P. J. de Kock, Johannes C. Baayen, Rhiannon M. Meredith, Chris I. De Zeeuw, Michele Giugliano, Huibert D. Mansvelder. 2014. High Bandwidth Synaptic Communication and Frequency Tracking in Human Neocortex. *PLoS Biology* 12:11, e1002007. [\[Crossref\]](#)
146. Arthur P. H. de Jong, Diasynou Fioravante. 2014. Translating neuronal activity at the synapse: presynaptic calcium sensors in short-term plasticity. *Frontiers in Cellular Neuroscience* 8. . [\[Crossref\]](#)
147. Susanne Kunkel, Maximilian Schmidt, Jochen M. Eppler, Hans E. Plesser, Gen Masumoto, Jun Igarashi, Shin Ishii, Tomoki Fukai, Abigail Morrison, Markus Diesmann, Moritz Helias. 2014. Spiking network simulation code for petascale computers. *Frontiers in Neuroinformatics* 8. . [\[Crossref\]](#)
148. Jonathan Laudanski, Benjamin Torben-Nielsen, Idan Segev, Shihab Shamma. 2014. Spatially Distributed Dendritic Resonance Selectively Filters Synaptic Input. *PLoS Computational Biology* 10:8, e1003775. [\[Crossref\]](#)

149. Fumitaka Kawasaki, Michael Stiber. 2014. A simple model of cortical culture growth: burst property dependence on network composition and activity. *Biological Cybernetics* **108**:4, 423-443. [[Crossref](#)]
150. Ali Yousefi, Alireza A. Dibazar, Theodore W. Berger. 2014. Synaptic dynamics: Linear model and adaptation algorithm. *Neural Networks* **56**, 49-68. [[Crossref](#)]
151. Guy Billings, Eugenio Piasini, Andrea Lőrincz, Zoltan Nusser, R. Angus Silver. 2014. Network Structure within the Cerebellar Input Layer Enables Lossless Sparse Encoding. *Neuron* **83**:4, 960-974. [[Crossref](#)]
152. Matteo di Volo, Raffaella Burioni, Mario Casartelli, Roberto Livi, Alessandro Vezzani. 2014. Heterogeneous mean field for neural networks with short-term plasticity. *Physical Review E* **90**:2. . [[Crossref](#)]
153. BEATA STRACK, KIMBERLE M. JACOBS, KRZYSZTOF J. CIOS. 2014. SIMULATING VERTICAL AND HORIZONTAL INHIBITION WITH SHORT-TERM DYNAMICS IN A MULTI-COLUMN MULTI-LAYER MODEL OF NEOCORTEX. *International Journal of Neural Systems* **24**:05, 1440002. [[Crossref](#)]
154. Andreas Bahmer, Uwe Baumann. 2014. Psychometric function of jittered rate pitch discrimination. *Hearing Research* **313**, 47-54. [[Crossref](#)]
155. Yuichi Katori. 2014. Memory association dynamics on neural network with dynamic synapses. *BMC Neuroscience* **15**:S1. . [[Crossref](#)]
156. Daniele Linaro, João Couto, Michele Giugliano. 2014. Command-line cellular electrophysiology for conventional and real-time closed-loop experiments. *Journal of Neuroscience Methods* **230**, 5-19. [[Crossref](#)]
157. Itamar Lerner, Oren Shriki. 2014. Internally- and externally-driven network transitions as a basis for automatic and strategic processes in semantic priming: theory and experimental validation. *Frontiers in Psychology* **5**. . [[Crossref](#)]
158. Anna Levina, J. Michael Herrmann, Theo Geisel. Theoretical Neuroscience of Self-Organized Criticality: From Formal Approaches to Realistic Models 417-436. [[Crossref](#)]
159. Eleni Vasilaki, Michele Giugliano. 2014. Emergence of Connectivity Motifs in Networks of Model Neurons with Short- and Long-Term Plastic Synapses. *PLoS ONE* **9**:1, e84626. [[Crossref](#)]
160. Daniele Linaro, Michele Giugliano. Markov Models of Ion Channels 1-14. [[Crossref](#)]
161. Robert Rosenbaum. Short Term Plasticity, Biophysical Models 1-5. [[Crossref](#)]
162. Marc-Oliver Gewaltig. Spiking Network Models and Theory: Overview 1-12. [[Crossref](#)]
163. Marc-Oliver Gewaltig. Spiking Network Models and Theory: Overview 1-13. [[Crossref](#)]
164. Marc-Oliver Gewaltig. Spiking Network Models and Theory: Overview 1-13. [[Crossref](#)]
165. Paul C. Bressloff. Single Neuron Modeling 3-62. [[Crossref](#)]
166. Paul C. Bressloff. Traveling Waves in One-Dimensional Excitable Media 63-99. [[Crossref](#)]
167. Paul C. Bressloff. Wave Propagation Along Spiny Dendrites 101-136. [[Crossref](#)]
168. Paul C. Bressloff. Calcium Waves and Sparks 137-181. [[Crossref](#)]
169. Paul C. Bressloff. Waves in Synaptically Coupled Spiking Networks 185-231. [[Crossref](#)]
170. Paul C. Bressloff. Population Models and Neural Fields 233-269. [[Crossref](#)]
171. Paul C. Bressloff. Waves in Excitable Neural Fields 271-318. [[Crossref](#)]
172. Paul C. Bressloff. Neural Field Model of Binocular Rivalry Waves 319-345. [[Crossref](#)]
173. Paul C. Bressloff. Waves in the Developing and the Diseased Brain 349-404. [[Crossref](#)]
174. Yuchao Yang, Ting Chang, Wei Lu. Memristive Devices: Switching Effects, Modeling, and Applications 195-221. [[Crossref](#)]
175. Jason S. Rothman, R. Angus Silver. Data-Driven Modeling of Synaptic Transmission and Integration 305-350. [[Crossref](#)]
176. Zachary P. Kilpatrick, Grégory Faye. 2014. Pulse Bifurcations in Stochastic Neural Fields. *SIAM Journal on Applied Dynamical Systems* **13**:2, 830-860. [[Crossref](#)]
177. Timothée Leleu, Kazuyuki Aihara. 2013. Spontaneous Slow Oscillations and Sequential Patterns Due to Short-Term Plasticity in a Model of the Cortex. *Neural Computation* **25**:12, 3131-3182. [[Abstract](#)] [[Full Text](#)] [[PDF](#)] [[PDF Plus](#)]
178. Matteo di Volo, Roberto Livi. 2013. The influence of noise on synchronous dynamics in a diluted neural network. *Chaos, Solitons & Fractals* **57**, 54-61. [[Crossref](#)]
179. Mikael Lundqvist, Pawel Herman, Matias Palva, Satu Palva, David Silverstein, Anders Lansner. 2013. Stimulus detection rate and latency, firing rates and 1-40Hz oscillatory power are modulated by infra-slow fluctuations in a bistable attractor network model. *NeuroImage* **83**, 458-471. [[Crossref](#)]

180. V. Delattre, D. La Mendola, J. Meystre, H. Markram, K. Markram. 2013. Nlgn4 knockout induces network hypo-excitability in juvenile mouse somatosensory cortex in vitro. *Scientific Reports* 3:1. . [[Crossref](#)]
181. Soheila Roohi Dehkordy, Fariba Bahrami. Impairment of Long-Term Potentiation in Alzheimer's Disease: A computational study based on tripartite synapse structure 37-41. [[Crossref](#)]
182. Pawel Andrzej Herman, Mikael Lundqvist, Anders Lansner. 2013. Nested theta to gamma oscillations and precise spatiotemporal firing during memory retrieval in a simulated attractor network. *Brain Research* 1536, 68-87. [[Crossref](#)]
183. Beata Strack, Kimberle M. Jacobs, Krzysztof J. Cios. Simulating lesions in multi-layer, multi-columnar model of neocortex 835-838. [[Crossref](#)]
184. Peng Wang, Thomas R. Knösche. 2013. A Realistic Neural Mass Model of the Cortex with Laminar-Specific Connections and Synaptic Plasticity – Evaluation with Auditory Habituation. *PLoS ONE* 8:10, e77876. [[Crossref](#)]
185. M. J. McGinley, G. L. Westbrook. 2013. Hierarchical excitatory synaptic connectivity in mouse olfactory cortex. *Proceedings of the National Academy of Sciences* 110:40, 16193-16198. [[Crossref](#)]
186. Thomas Rost, Harshwardhan Ramachandran, Martin Paul Nawrot, Elisabetta Chicca. A neuromorphic approach to auditory pattern recognition in cricket phonotaxis 1-4. [[Crossref](#)]
187. Steven Reich, Robert Rosenbaum. 2013. The impact of short term synaptic depression and stochastic vesicle dynamics on neuronal variability. *Journal of Computational Neuroscience* 35:1, 39-53. [[Crossref](#)]
188. Michael I. Kerr, Mark J. Wall, Magnus J. E. Richardson. 2013. Adenosine A1 receptor activation mediates the developmental shift at layer 5 pyramidal cell synapses and is a determinant of mature synaptic strength. *The Journal of Physiology* 591:13, 3371-3380. [[Crossref](#)]
189. Yuichi Katori, Kazuhiro Sakamoto, Hajime Mushiaki, Kazuyuki Aihara. 2013. Reorganization of effective network structure with dynamic synapses in cortical circuit and its possible functions. *BMC Neuroscience* 14:S1. . [[Crossref](#)]
190. Kyoung-Cheol Kwon, Jong-Sun Lee, Chul Geun Kim, Jea-Gun Park. 2013. Biological Synapse Behavior of Nanoparticle Organic Memory Field Effect Transistor Fabricated by Curing. *Applied Physics Express* 6:6, 067001. [[Crossref](#)]
191. Nicolas Brunel. Dynamics of Neural Networks 489-512. [[Crossref](#)]
192. Ammar Mohemmed, Stefan Schliebs, Satoshi Matsuda, Nikola Kasabov. 2013. Training spiking neural networks to associate spatio-temporal input-output spike patterns. *Neurocomputing* 107, 3-10. [[Crossref](#)]
193. Nikola Kasabov, Kshitij Dhoble, Nuttapod Nuntalid, Giacomo Indiveri. 2013. Dynamic evolving spiking neural networks for on-line spatio- and spectro-temporal pattern recognition. *Neural Networks* 41, 188-201. [[Crossref](#)]
194. David F. Ramirez-Moreno, Odelia Schwartz, Juan F. Ramirez-Villegas. 2013. A saliency-based bottom-up visual attention model for dynamic scenes analysis. *Biological Cybernetics* 107:2, 141-160. [[Crossref](#)]
195. Gleb Basalyga, Marcelo A. Montemurro, Thomas Wennekers. 2013. Information coding in a laminar computational model of cat primary visual cortex. *Journal of Computational Neuroscience* 34:2, 273-283. [[Crossref](#)]
196. Oliver Weihberger, Samora Okujeni, Jarno E. Mikkonen, Ulrich Egert. 2013. Quantitative examination of stimulus-response relations in cortical networks in vitro. *Journal of Neurophysiology* 109:7, 1764-1774. [[Crossref](#)]
197. Matthew A Webber, Paul C Bressloff. 2013. The effects of noise on binocular rivalry waves: a stochastic neural field model. *Journal of Statistical Mechanics: Theory and Experiment* 2013:03, P03001. [[Crossref](#)]
198. Matteo di Volo, Roberto Livi, Stefano Luccioli, Antonio Politi, Alessandro Torcini. 2013. Synchronous dynamics in the presence of short-term plasticity. *Physical Review E* 87:3. . [[Crossref](#)]
199. O. Bichler, W. Zhao, F. Alibart, S. Pleutin, S. Lenfant, D. Vuillaume, C. Gamrat. 2013. Pavlov's Dog Associative Learning Demonstrated on Synaptic-Like Organic Transistors. *Neural Computation* 25:2, 549-566. [[Abstract](#)] [[Full Text](#)] [[PDF](#)] [[PDF Plus](#)]
200. Eric Nichols, Liam J. McDaid, Nazmul Siddique. 2013. Biologically Inspired SNN for Robot Control. *IEEE Transactions on Cybernetics* 43:1, 115-128. [[Crossref](#)]
201. Robert Gütig, Tim Gollisch, Haim Sompolinsky, Markus Meister. 2013. Computing Complex Visual Features with Retinal Spike Times. *PLoS ONE* 8:1, e53063. [[Crossref](#)]
202. Daniel Martí, John Rinzel. 2013. Dynamics of Feature Categorization. *Neural Computation* 25:1, 1-45. [[Abstract](#)] [[Full Text](#)] [[PDF](#)] [[PDF Plus](#)]
203. Michael J. O'Brien, Narayan Srinivasa. 2013. A Spiking Neural Model for Stable Reinforcement of Synapses Based on Multiple Distal Rewards. *Neural Computation* 25:1, 123-156. [[Abstract](#)] [[Full Text](#)] [[PDF](#)] [[PDF Plus](#)]

204. Jung Hoon Lee, Joji Tsunada, Yale E. Cohen. 2013. A Model of the Differential Representation of Signal Novelty in the Local Field Potentials and Spiking Activity of the Ventrolateral Prefrontal Cortex. *Neural Computation* **25**:1, 157-185. [[Abstract](#)] [[Full Text](#)] [[PDF](#)] [[PDF Plus](#)]
205. C. C. Alan Fung, K. Y. Michael Wong, Si Wu. Dynamical Synapses Enhance Mobility, Memory and Decoding 131-137. [[Crossref](#)]
206. Ting Chang, Yuchao Yang, Wei Lu. 2013. Building Neuromorphic Circuits with Memristive Devices. *IEEE Circuits and Systems Magazine* **13**:2, 56-73. [[Crossref](#)]
207. Danke Zhang, Yuanqing Li, Si Wu. 2013. Concentration-Invariant Odor Representation in the Olfactory System by Presynaptic Inhibition. *Computational and Mathematical Methods in Medicine* **2013**, 1-6. [[Crossref](#)]
208. Tjeerd V. olde Scheper, Huibert D. Mansvelder, Arjen van Ooyen. 2012. Short Term Depression Unmasks the Ghost Frequency. *PLoS ONE* **7**:12, e50189. [[Crossref](#)]
209. Bret Fortenberry, Anatoli Gorchetchnikov, Stephen Grossberg. 2012. Learned integration of visual, vestibular, and motor cues in multiple brain regions computes head direction during visually guided navigation. *Hippocampus* **22**:12, 2219-2237. [[Crossref](#)]
210. Christian Tetzlaff, Christoph Kolodziejski, Irene Markelic, Florentin Wörgötter. 2012. Time scales of memory, learning, and plasticity. *Biological Cybernetics* **106**:11-12, 715-726. [[Crossref](#)]
211. Myongkeun Oh, Shunbing Zhao, Victor Matveev, Farzan Nadim. 2012. Neuromodulatory changes in short-term synaptic dynamics may be mediated by two distinct mechanisms of presynaptic calcium entry. *Journal of Computational Neuroscience* **33**:3, 573-585. [[Crossref](#)]
212. Yuichi Katori, Yasuhiko Igarashi, Masato Okada, Kazuyuki Aihara. 2012. Stability Analysis of Stochastic Neural Network with Depression and Facilitation Synapses. *Journal of the Physical Society of Japan* **81**:11, 114007. [[Crossref](#)]
213. Hiroki Asari, Markus Meister. 2012. Divergence of visual channels in the inner retina. *Nature Neuroscience* **15**:11, 1581-1589. [[Crossref](#)]
214. Itamar Lerner, Shlomo Bentin, Oren Shriki. 2012. Spreading Activation in an Attractor Network With Latching Dynamics: Automatic Semantic Priming Revisited. *Cognitive Science* **36**:8, 1339-1382. [[Crossref](#)]
215. T. Dowrick, S. Hall, L. J. McDaid. 2012. Silicon-Based Dynamic Synapse With Depressing Response. *IEEE Transactions on Neural Networks and Learning Systems* **23**:10, 1513-1525. [[Crossref](#)]
216. Daqing Guo, Chunguang Li. 2012. Stochastic resonance in Hodgkin-Huxley neuron induced by unreliable synaptic transmission. *Journal of Theoretical Biology* **308**, 105-114. [[Crossref](#)]
217. A. Yousefi, A. A. Dibazar, T. W. Berger. Synaptic dynamics: Linear model and adaptation algorithm 1362-1365. [[Crossref](#)]
218. M. Uzuntarla, M. Ozer, D. Q. Guo. 2012. Controlling the first-spike latency response of a single neuron via unreliable synaptic transmission. *The European Physical Journal B* **85**:8. . [[Crossref](#)]
219. AMMAR MOHEMMED, STEFAN SCHLIEBS, SATOSHI MATSUDA, NIKOLA KASABOV. 2012. SPAN: SPIKE PATTERN ASSOCIATION NEURON FOR LEARNING SPATIO-TEMPORAL SPIKE PATTERNS. *International Journal of Neural Systems* **22**:04, 1250012. [[Crossref](#)]
220. Itamar Lerner, Shlomo Bentin, Oren Shriki. 2012. Excessive Attractor Instability Accounts for Semantic Priming in Schizophrenia. *PLoS ONE* **7**:7, e40663. [[Crossref](#)]
221. Mark A. Bourjaily, Paul Miller. 2012. Dynamic afferent synapses to decision-making networks improve performance in tasks requiring stimulus associations and discriminations. *Journal of Neurophysiology* **108**:2, 513-527. [[Crossref](#)]
222. Robert Rosenbaum, Jonathan Rubin, Brent Doiron. 2012. Short Term Synaptic Depression Imposes a Frequency Dependent Filter on Synaptic Information Transfer. *PLoS Computational Biology* **8**:6, e1002557. [[Crossref](#)]
223. Daqing Guo, Qingyun Wang, Matjaž Perc. 2012. Complex synchronous behavior in interneuronal networks with delayed inhibitory and fast electrical synapses. *Physical Review E* **85**:6. . [[Crossref](#)]
224. C. C. Alan Fung, K. Y. Michael Wong, He Wang, Si Wu. 2012. Dynamical Synapses Enhance Neural Information Processing: Gracefulness, Accuracy, and Mobility. *Neural Computation* **24**:5, 1147-1185. [[Abstract](#)] [[Full Text](#)] [[PDF](#)] [[PDF Plus](#)]
225. Paul C. Bressloff, Matthew A. Webber. 2012. Neural field model of binocular rivalry waves. *Journal of Computational Neuroscience* **32**:2, 233-252. [[Crossref](#)]
226. Gianluigi Mongillo, David Hansel, Carl van Vreeswijk. 2012. Bistability and Spatiotemporal Irregularity in Neuronal Networks with Nonlinear Synaptic Transmission. *Physical Review Letters* **108**:15. . [[Crossref](#)]
227. J. A. Wall, L. J. McDaid, L. P. Maguire, T. M. McGinnity. 2012. Spiking Neural Network Model of Sound Localization Using the Interaural Intensity Difference. *IEEE Transactions on Neural Networks and Learning Systems* **23**:4, 574-586. [[Crossref](#)]

228. Max L. Schiff, Alex D. Reyes. 2012. Characterization of thalamocortical responses of regular-spiking and fast-spiking neurons of the mouse auditory cortex in vitro and in silico. *Journal of Neurophysiology* **107**:5, 1476-1488. [[Crossref](#)]
229. Julius Stroffek, Petr Marsalek. 2012. Short-term potentiation effect on pattern recall in sparsely coded neural network. *Neurocomputing* **77**:1, 108-113. [[Crossref](#)]
230. J. F. Mejias, B. Hernandez-Gomez, J. J. Torres. 2012. Short-term synaptic facilitation improves information retrieval in noisy neural networks. *EPL (Europhysics Letters)* **97**:4, 48008. [[Crossref](#)]
231. Paul C Bressloff. 2012. Spatiotemporal dynamics of continuum neural fields. *Journal of Physics A: Mathematical and Theoretical* **45**:3, 033001. [[Crossref](#)]
232. Joaquin J. Torres, Pablo Varona. Modeling Biological Neural Networks 533-564. [[Crossref](#)]
233. Mikael Lundqvist, Pawel Herman, Anders Lansner. 2012. Variability of spike firing during theta-coupled replay of memories in a simulated attractor network. *Brain Research* **1434**, 152-161. [[Crossref](#)]
234. Robert Mill, Martin Coath, Thomas Wennekers, Susan L. Denham. 2012. Characterising stimulus-specific adaptation using a multi-layer field model. *Brain Research* **1434**, 178-188. [[Crossref](#)]
235. Yasuhiko Igarashi, Masafumi Oizumi, Masato Okada. 2012. Theory of correlation in a network with synaptic depression. *Physical Review E* **85**:1. . [[Crossref](#)]
236. John J. Wade, Liam J. McDaid, Jim Harkin, Vincenzo Crunelli, J. A. Scott Kelso. 2011. Bidirectional Coupling between Astrocytes and Neurons Mediates Learning and Dynamic Coordination in the Brain: A Multiple Modeling Approach. *PLoS ONE* **6**:12, e29445. [[Crossref](#)]
237. Pradeep Krishnamurthy, Gilad Silberberg, Anders Lansner. 2011. A cortical attractor network with dynamic synapses. *BMC Neuroscience* **12**:S1. . [[Crossref](#)]
238. Maurizio De Pittà, Vladislav Volman, Hugues Berry, Eshel Ben-Jacob. 2011. A Tale of Two Stories: Astrocyte Regulation of Synaptic Depression and Facilitation. *PLoS Computational Biology* **7**:12, e1002293. [[Crossref](#)]
239. Yuichi Katori, Kazuhiro Sakamoto, Naohiro Saito, Jun Tanji, Hajime Mushiake, Kazuyuki Aihara. 2011. Representational Switching by Dynamical Reorganization of Attractor Structure in a Network Model of the Prefrontal Cortex. *PLoS Computational Biology* **7**:11, e1002266. [[Crossref](#)]
240. Yo Horikawa. 2011. Exponential transient propagating oscillations in a ring of spiking neurons with unidirectional slow inhibitory synaptic coupling. *Journal of Theoretical Biology* **289**, 151-159. [[Crossref](#)]
241. Itai Hayut, Erika E. Fanselow, Barry W. Connors, David Golomb. 2011. LTS and FS Inhibitory Interneurons, Short-Term Synaptic Plasticity, and Cortical Circuit Dynamics. *PLoS Computational Biology* **7**:10, e1002248. [[Crossref](#)]
242. Robert B. Levy, Alex D. Reyes. 2011. Coexistence of Lateral and Co-Tuned Inhibitory Configurations in Cortical Networks. *PLoS Computational Biology* **7**:10, e1002161. [[Crossref](#)]
243. Mikael Lundqvist, Pawel Herman, Anders Lansner. 2011. Theta and Gamma Power Increases and Alpha/Beta Power Decreases with Memory Load in an Attractor Network Model. *Journal of Cognitive Neuroscience* **23**:10, 3008-3020. [[Abstract](#)] [[Full Text](#)] [[PDF](#)] [[PDF Plus](#)]
244. T. Gritsun, J. le Feber, J. Stegenga, W. L. C. Rutten. 2011. Experimental analysis and computational modeling of interburst intervals in spontaneous activity of cortical neuronal culture. *Biological Cybernetics* **105**:3-4, 197-210. [[Crossref](#)]
245. Pan-Yue Deng, Vitaly A. Klyachko. 2011. The diverse functions of short-term plasticity components in synaptic computations. *Communicative & Integrative Biology* **4**:5, 543-548. [[Crossref](#)]
246. Robert Mill, Martin Coath, Thomas Wennekers, Susan L. Denham. 2011. A Neurocomputational Model of Stimulus-Specific Adaptation to Oddball and Markov Sequences. *PLoS Computational Biology* **7**:8, e1002117. [[Crossref](#)]
247. Nevo Taaseh, Amit Yaron, Israel Nelken. 2011. Stimulus-Specific Adaptation and Deviance Detection in the Rat Auditory Cortex. *PLoS ONE* **6**:8, e23369. [[Crossref](#)]
248. Ali Yousefi, Alireza A. Dibazar, Theodore W. Berger. Supervised learning in a single layer Dynamic Synapses Neural Network 2250-2257. [[Crossref](#)]
249. Ammar Mohemmed, Satoshi Matsuda, Stefan Schliebs, Kshitij Dhoble, Nikola Kasabov. Optimization of Spiking Neural Networks with dynamic synapses for spike sequence generation using PSO 2969-2974. [[Crossref](#)]
250. Romain Brette, Dan F. M. Goodman. 2011. Vectorized Algorithms for Spiking Neural Network Simulation. *Neural Computation* **23**:6, 1503-1535. [[Abstract](#)] [[Full Text](#)] [[PDF](#)] [[PDF Plus](#)] [[Supplemental Material](#)]
251. Cornelius Glackin, Liam Maguire, Liam McDaid, Heather Sayers. 2011. Receptive field optimisation and supervision of a fuzzy spiking neural network. *Neural Networks* **24**:3, 247-256. [[Crossref](#)]

252. B. Ibarz, J.M. Casado, M.A.F. Sanjuán. 2011. Map-based models in neuronal dynamics. *Physics Reports* **501**:1-2, 1-74. [[Crossref](#)]
253. Lucas Baggio Figueira, Antonio Carlos Roque. Pattern Recognition Using a Recurrent Neural Network Inspired on the Olfactory Bulb 275-285. [[Crossref](#)]
254. J.J. Torres, S. Johnson, J.F. Mejias, S. de Franciscis, J. Marro. Nonequilibrium Behavior in Neural Networks: Criticality and Optimal Performance 597-603. [[Crossref](#)]
255. Horacio Rostro-Gonzalez, Bruno Cessac, Bernard Girau, Cesar Torres-Huitzil. 2011. The role of the asymptotic dynamics in the design of FPGA-based hardware implementations of gIF-type neural networks. *Journal of Physiology-Paris* **105**:1-3, 91-97. [[Crossref](#)]
256. Paul C. Bressloff, Zachary P. Kilpatrick. 2011. Two-Dimensional Bumps in Piecewise Smooth Neural Fields with Synaptic Depression. *SIAM Journal on Applied Mathematics* **71**:2, 379-408. [[Crossref](#)]
257. Tiina Manninen, Katri Hituri, Eeva Toivari, Marja-Leena Linne. 2011. Modeling Signal Transduction Leading to Synaptic Plasticity: Evaluation and Comparison of Five Models. *EURASIP Journal on Bioinformatics and Systems Biology* **2011**:1, 797250. [[Crossref](#)]
258. Paul C Bressloff, Yi Lai. 2011. Stochastic synchronization of neuronal populations with intrinsic and extrinsic noise. *The Journal of Mathematical Neuroscience* **1**:1, 2. [[Crossref](#)]
259. ERIC NICHOLS, L. J. McDAID, N. H. SIDDIQUE. 2010. CASE STUDY ON A SELF-ORGANIZING SPIKING NEURAL NETWORK FOR ROBOT NAVIGATION. *International Journal of Neural Systems* **20**:06, 501-508. [[Crossref](#)]
260. J J Wade, L J McDaid, J A Santos, H M Sayers. 2010. SWAT: A Spiking Neural Network Training Algorithm for Classification Problems. *IEEE Transactions on Neural Networks* **21**:11, 1817-1830. [[Crossref](#)]
261. Jean-Pascal Pfister, Peter Dayan, Máté Lengyel. 2010. Synapses with short-term plasticity are optimal estimators of presynaptic membrane potentials. *Nature Neuroscience* **13**:10, 1271-1275. [[Crossref](#)]
262. Yasuhiko Igarashi, Masafumi Oizumi, Masato Okada. 2010. Mean Field Analysis of Stochastic Neural Network Models with Synaptic Depression. *Journal of the Physical Society of Japan* **79**:8, 084001. [[Crossref](#)]
263. Sandro Romani, Misha Tsodyks. 2010. Continuous Attractors with Morphed/Correlated Maps. *PLoS Computational Biology* **6**:8, e1000869. [[Crossref](#)]
264. Cornelius Glackin, Liam Maguire, Liam McDaid. Feature extraction from spectro-temporal signals using dynamic synapses, recurrency, and lateral inhibition 1-6. [[Crossref](#)]
265. Zachary P. Kilpatrick, Paul C. Bressloff. 2010. Stability of bumps in piecewise smooth neural fields with nonlinear adaptation. *Physica D: Nonlinear Phenomena* **239**:12, 1048-1060. [[Crossref](#)]
266. Max Welling, Yutian Chen. 2010. Statistical inference using weak chaos and infinite memory. *Journal of Physics: Conference Series* **233**, 012005. [[Crossref](#)]
267. Zachary P. Kilpatrick, Paul C. Bressloff. 2010. Effects of synaptic depression and adaptation on spatiotemporal dynamics of an excitatory neuronal network. *Physica D: Nonlinear Phenomena* **239**:9, 547-560. [[Crossref](#)]
268. T. A. Gritsun, J. Le Feber, J. Stegenga, W. L. C. Rutten. 2010. Network bursts in cortical cultures are best simulated using pacemaker neurons and adaptive synapses. *Biological Cybernetics* **102**:4, 293-310. [[Crossref](#)]
269. Zachary P. Kilpatrick, Paul C. Bressloff. 2010. Spatially structured oscillations in a two-dimensional excitatory neuronal network with synaptic depression. *Journal of Computational Neuroscience* **28**:2, 193-209. [[Crossref](#)]
270. Elad Ganmor, Yonatan Katz, Ilan Lampl. 2010. Intensity-Dependent Adaptation of Cortical and Thalamic Neurons Is Controlled by Brainstem Circuits of the Sensory Pathway. *Neuron* **66**:2, 273-286. [[Crossref](#)]
271. Fabien Alibart, Stéphane Pleutin, David Guérin, Christophe Novembre, Stéphane Lenfant, Kamal Lmimouni, Christian Gamrat, Dominique Vuillaume. 2010. An Organic Nanoparticle Transistor Behaving as a Biological Spiking Synapse. *Advanced Functional Materials* **20**:2, 330-337. [[Crossref](#)]
272. P. Hehrmann, J. K. Maier, N. S. Harper, D. McAlpine, Maneesh Sahani. Adaptive Coding for Auditory Spatial Cues 357-366. [[Crossref](#)]
273. Zachary P. Kilpatrick, Paul C. Bressloff. 2010. Binocular Rivalry in a Competitive Neural Network with Synaptic Depression. *SIAM Journal on Applied Dynamical Systems* **9**:4, 1303-1347. [[Crossref](#)]
274. Lawrence Christopher York, Mark C. W. van Rossum. 2009. Recurrent networks with short term synaptic depression. *Journal of Computational Neuroscience* **27**:3, 607-620. [[Crossref](#)]
275. Tjeerd olde Scheper. 2009. Emergent pitch perception using short term plasticity. *BMC Neuroscience* **10**:S1. . [[Crossref](#)]

276. Frank Michler, Reinhard Eckhorn, Thomas Wachtler. 2009. Using Spatiotemporal Correlations to Learn Topographic Maps for Invariant Object Recognition. *Journal of Neurophysiology* **102**:2, 953-964. [[Crossref](#)]
277. PakMing Lau, GuoQiang Bi. 2009. Reverberatory activity in neuronal networks in vitro. *Science Bulletin* **54**:11, 1828-1835. [[Crossref](#)]
278. Jorge F. Mejias, Joaquín J. Torres. 2009. Maximum Memory Capacity on Neural Networks with Short-Term Synaptic Depression and Facilitation. *Neural Computation* **21**:3, 851-871. [[Abstract](#)] [[Full Text](#)] [[PDF](#)] [[PDF Plus](#)]
279. Anna Levina, J. Michael Herrmann, Theo Geisel. 2009. Phase Transitions towards Criticality in a Neural System with Adaptive Interactions. *Physical Review Letters* **102**:11. . [[Crossref](#)]
280. Bjørn Gilbert Nielsen. 2009. Calcium and the role of motoneuronal doublets in skeletal muscle control. *European Biophysics Journal* **38**:2, 159-173. [[Crossref](#)]
281. Dong Song, Vasilis Z. Marmarelis, Theodore W. Berger. 2009. Parametric and non-parametric modeling of short-term synaptic plasticity. Part I: computational study. *Journal of Computational Neuroscience* **26**:1, 1-19. [[Crossref](#)]
282. Pak-Ming Lau, Guo-Qiang Bi. Reverberatory Activity in Neuronal Networks 61-75. [[Crossref](#)]
283. Joachim Hermann, Benedikt Grothe, Achim Klug. 2009. Modeling Short-Term Synaptic Plasticity at the Calyx of Held Using In Vivo-Like Stimulation Patterns. *Journal of Neurophysiology* **101**:1, 20-30. [[Crossref](#)]
284. Giancarlo La Camera, Michele Giugliano, Walter Senn, Stefano Fusi. 2008. The response of cortical neurons to in vivo-like input current: theory and experiment. *Biological Cybernetics* **99**:4-5, 279-301. [[Crossref](#)]
285. J.J. Torres, J. Marro, J.M. Cortes, B. Wemmenhove. 2008. Instabilities in attractor networks with fast synaptic fluctuations and partial updating of the neurons activity. *Neural Networks* **21**:9, 1272-1277. [[Crossref](#)]
286. Ivan Y. Tyukin, Danil Prokhorov, Cees van Leeuwen. 2008. Adaptive Classification of Temporal Signals in Fixed-Weight Recurrent Neural Networks: An Existence Proof. *Neural Computation* **20**:10, 2564-2596. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
287. Ofer Melamed, Omri Barak, Gilad Silberberg, Henry Markram, Misha Tsodyks. 2008. Slow oscillations in neural networks with facilitating synapses. *Journal of Computational Neuroscience* **25**:2, 308-316. [[Crossref](#)]
288. Marc de Kamps, Volker Baier, Johannes Drever, Melanie Dietz, Lorenz Mösenlechner, Frank van der Velde. 2008. The state of MIIND. *Neural Networks* **21**:8, 1164-1181. [[Crossref](#)]
289. Heejin Lim, Yoonsuck Choe. 2008. Extrapolative Delay Compensation Through Facilitating Synapses and Its Relation to the Flash-Lag Effect. *IEEE Transactions on Neural Networks* **19**:10, 1678-1688. [[Crossref](#)]
290. Magteld Zeitler, Pascal Fries, Stan Gielen. 2008. Biased competition through variations in amplitude of γ -oscillations. *Journal of Computational Neuroscience* **25**:1, 89-107. [[Crossref](#)]
291. S. Johnson, J. Marro, J. J. Torres. 2008. Functional optimization in complex excitable networks. *EPL (Europhysics Letters)* **83**:4, 46006. [[Crossref](#)]
292. Mark C. W. van Rossum, Matthijs A. A. van der Meer, Dengke Xiao, Mike W. Oram. 2008. Adaptive Integration in the Visual Cortex by Depressing Recurrent Cortical Circuits. *Neural Computation* **20**:7, 1847-1872. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
293. F. Saraga, T. Balena, T. Wolansky, C.T. Dickson, M.A. Woodin. 2008. Inhibitory synaptic plasticity regulates pyramidal neuron spiking in the rodent hippocampus. *Neuroscience* **155**:1, 64-75. [[Crossref](#)]
294. Abigail Morrison, Markus Diesmann, Wulfram Gerstner. 2008. Phenomenological models of synaptic plasticity based on spike timing. *Biological Cybernetics* **98**:6, 459-478. [[Crossref](#)]
295. John J. Wade, Liam J. McDaid, Jose A. Santos, Heather M. Sayers. SWAT: An unsupervised SNN training algorithm for classification problems 2648-2655. [[Crossref](#)]
296. Boris Gourvitch, Jos J. Eggermont. 2008. Spectro-temporal sound density-dependent long-term adaptation in cat primary auditory cortex. *European Journal of Neuroscience* **27**:12, 3310-3321. [[Crossref](#)]
297. Jorge F. Mejías, Joaquín J. Torres. 2008. The role of synaptic facilitation in spike coincidence detection. *Journal of Computational Neuroscience* **24**:2, 222-234. [[Crossref](#)]
298. Bastien Fernandez, Lev S. Tsimring. 2008. Athermal Dynamics of Strongly Coupled Stochastic Three-State Oscillators. *Physical Review Letters* **100**:16. . [[Crossref](#)]
299. G. Mongillo, O. Barak, M. Tsodyks. 2008. Synaptic Theory of Working Memory. *Science* **319**:5869, 1543-1546. [[Crossref](#)]
300. Aydin Farajidavar, Sohrab Saeb, Khosrow Behbehani. 2008. Incorporating synaptic time-dependent plasticity and dynamic synapse into a computational model of wind-up. *Neural Networks* **21**:2-3, 241-249. [[Crossref](#)]
301. Z Li, Z Wang, S Shao. 2008. Memory switching in a neural network with chaotic neurons and synaptic depression. *Journal of Physics: Conference Series* **96**, 012181. [[Crossref](#)]

302. N.T. Carnevale, Michael Hines. The Neuron Simulation Environment in Epilepsy Research 18-33. [[Crossref](#)]
303. Anne J. Catllá, David G. Schaeffer, Thomas P. Witelski, Eric E. Monson, Anna L. Lin. 2008. On Spiking Models for Synaptic Activity and Impulsive Differential Equations. *SIAM Review* **50**:3, 553-569. [[Crossref](#)]
304. Zhijie Wang, Hong Fan. 2007. Dynamics of a continuous-valued discrete-time Hopfield neural network with synaptic depression. *Neurocomputing* **71**:1-3, 181-190. [[Crossref](#)]
305. A. Levina, J. M. Herrmann, T. Geisel. 2007. Dynamical synapses causing self-organized criticality in neural networks. *Nature Physics* **3**:12, 857-860. [[Crossref](#)]
306. Romain Brette, Michelle Rudolph, Ted Carnevale, Michael Hines, David Beeman, James M. Bower, Markus Diesmann, Abigail Morrison, Philip H. Goodman, Frederick C. Harris, Milind Zirpe, Thomas Natschläger, Dejan Pecevski, Bard Ermentrout, Mikael Djurfeldt, Anders Lansner, Olivier Rochel, Thierry Vieville, Eilif Muller, Andrew P. Davison, Sami El Boustani, Alain Destexhe. 2007. Simulation of networks of spiking neurons: A review of tools and strategies. *Journal of Computational Neuroscience* **23**:3, 349-398. [[Crossref](#)]
307. Maryam Esmaeili, Mohamad H. Jabalameli, Zeinab Moghadam. A New Scheme of EEG Signals Processing in Brain-Computer Interface Systems 522-522. [[Crossref](#)]
308. Leslie S. Smith, Steve Collins. 2007. Determining ITDs Using Two Microphones on a Flat Panel During Onset Intervals With a Biologically Inspired Spike-Based Technique. *IEEE Transactions on Audio, Speech, and Language Processing* **15**:8, 2278-2286. [[Crossref](#)]
309. J. J. Torres, J. M. Cortes, J. Marro, H. J. Kappen. 2007. Competition Between Synaptic Depression and Facilitation in Attractor Neural Networks. *Neural Computation* **19**:10, 2739-2755. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
310. David H. Goldberg, Andreas G. Andreou. 2007. Distortion of Neural Signals by Spike Coding. *Neural Computation* **19**:10, 2797-2839. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
311. Akira Sakurai, Robert J. Calin-Jageman, Paul S. Katz. 2007. Potentiation Phase of Spike Timing-Dependent Neuromodulation by a Serotonergic Interneuron Involves an Increase in the Fraction of Transmitter Release. *Journal of Neurophysiology* **98**:4, 1975-1987. [[Crossref](#)]
312. Sohrab Saeb, Shahriar Gharibzadeh, Farzad Towhidkhalah, Aydin Farajidavar. 2007. Modeling the primary auditory cortex using dynamic synapses: Can synaptic plasticity explain the temporal tuning?. *Journal of Theoretical Biology* **248**:1, 1-9. [[Crossref](#)]
313. ZHIJIE WANG, HONG FAN, KAZUYUKI AIHARA. 2007. AN ASSOCIATIVE NETWORK WITH CHAOTIC NEURONS AND DYNAMIC SYNAPSES. *International Journal of Bifurcation and Chaos* **17**:09, 3085-3097. [[Crossref](#)]
314. Sohrab Saeb, Aydin Farajidavar, Shahriar Gharibzadeh. A Model of Wind-up based on Short-term and Long-term Synaptic Plasticity Mechanisms 1055-1060. [[Crossref](#)]
315. Daniele Marinazzo, Hilbert J. Kappen, Stan C. A. M. Gielen. 2007. Input-Driven Oscillations in Networks with Excitatory and Inhibitory Neurons with Dynamic Synapses. *Neural Computation* **19**:7, 1739-1765. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
316. J. Marro, Joaquín J. Torres, Jesús M. Cortés. 2007. Networks with heterogeneously weighted connections and partial synchronization of nodes. *Computer Physics Communications* **177**:1-2, 180-183. [[Crossref](#)]
317. J.J. Torres, J.M. Cortes, J. Marro, H.J. Kappen. 2007. Attractor neural networks with activity-dependent synapses: The role of synaptic facilitation. *Neurocomputing* **70**:10-12, 2022-2025. [[Crossref](#)]
318. David Sussillo, Taro Toyozumi, Wolfgang Maass. 2007. Self-Tuning of Neural Circuits Through Short-Term Synaptic Plasticity. *Journal of Neurophysiology* **97**:6, 4079-4095. [[Crossref](#)]
319. Dipayan Chaudhuri, John B. Issa, David T. Yue. 2007. Elementary Mechanisms Producing Facilitation of Cav2.1 (P/Q-type) Channels. *The Journal of General Physiology* **129**:5, 385-401. [[Crossref](#)]
320. K. M. MacLeod, T. K. Horiuchi, C. E. Carr. 2007. A Role for Short-Term Synaptic Facilitation and Depression in the Processing of Intensity Information in the Auditory Brain Stem. *Journal of Neurophysiology* **97**:4, 2863-2874. [[Crossref](#)]
321. Joaquín Marro, Joaquín J. Torres, Jesús M. Cortés. 2007. Chaotic hopping between attractors in neural networks. *Neural Networks* **20**:2, 230-235. [[Crossref](#)]
322. Gilad Silberberg, Henry Markram. 2007. Disynaptic Inhibition between Neocortical Pyramidal Cells Mediated by Martinotti Cells. *Neuron* **53**:5, 735-746. [[Crossref](#)]
323. Christian R. Huyck. 2007. Creating hierarchical categories using cell assemblies. *Connection Science* **19**:1, 1-24. [[Crossref](#)]
324. J.M. Cortes, J.J. Torres, J. Marro. 2007. Control of neural chaos by synaptic noise. *Biosystems* **87**:2-3, 186-190. [[Crossref](#)]
325. Yaochu Jin, Ruoqing Wen, Bernhard Sendhoff. Evolutionary Multi-objective Optimization of Spiking Neural Networks 370-379. [[Crossref](#)]

326. Matthew de Breecht, Jun Saiki. 2006. A neural network implementation of a saliency map model. *Neural Networks* **19**:10, 1467-1474. [[Crossref](#)]
327. Jean-Vincent Le Bé, Henry Markram. 2006. Un nouveau mécanisme de mémoire : connexions et déconnexions de neurones dans le néocortex de jeunes rats. *médecine/sciences* **22**:12, 1031-1033. [[Crossref](#)]
328. Ammar Belatreche, Liam P. Maguire, Martin McGinnity. 2006. Advances in Design and Application of Spiking Neural Networks. *Soft Computing* **11**:3, 239-248. [[Crossref](#)]
329. J.-V. Le Be, H. Markram. 2006. Spontaneous and evoked synaptic rewiring in the neonatal neocortex. *Proceedings of the National Academy of Sciences* **103**:35, 13214-13219. [[Crossref](#)]
330. M. Giugliano, M. Arsiero. Biological Neuronal Networks, Modeling of . [[Crossref](#)]
331. Sandro Romani, Daniel J. Amit, Gianluigi Mongillo. 2006. Mean-field analysis of selective persistent activity in presence of short-term synaptic depression. *Journal of Computational Neuroscience* **20**:2, 201-217. [[Crossref](#)]
332. J. M. Cortes, J. J. Torres, J. Marro, P. L. Garrido, H. J. Kappen. 2006. Effects of Fast Presynaptic Noise in Attractor Neural Networks. *Neural Computation* **18**:3, 614-633. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
333. Christo Panchev, Stefan Wermter. 2006. Temporal sequence detection with spiking neurons: towards recognizing robot language instructions. *Connection Science* **18**:1, 1-22. [[Crossref](#)]
334. Henry Markram. 2006. The Blue Brain Project. *Nature Reviews Neuroscience* **7**:2, 153-160. [[Crossref](#)]
335. Karina Odinaev, Igal Raichalgauz, Yehoshua Y. Zeevi. Mapping of Natural Patterns by Liquid Architectures Implementing Neural Cliques 123-131. [[Crossref](#)]
336. T. Berger, H.-R. Lüscher, M. Giugliano. 2006. Transient rhythmic network activity in the somatosensory cortex evoked by distributed input in vitro. *Neuroscience* **140**:4, 1401-1413. [[Crossref](#)]
337. Stephen Grossberg, Don Seidman. 2006. Neural dynamics of autistic behaviors: Cognitive, emotional, and timing substrates. *Psychological Review* **113**:3, 483-525. [[Crossref](#)]
338. I. Raichalgauz, K. Odinaev, Y.Y. Zeevi. Natural Signal Classification by Neural Cliques and Phase-Locked Attractors 6693-6697. [[Crossref](#)]
339. Heejin Lim, Yoonsuck Choe. Delay Compensation Through Facilitating Synapses and STDP: A Neural Basis for Orientation Flash-Lag Effect 4269-4276. [[Crossref](#)]
340. Hua Yu Sun, Susan A. Lyons, Lynn E. Dobrunz. 2005. Mechanisms of target-cell specific short-term plasticity at Schaffer collateral synapses onto interneurons versus pyramidal cells in juvenile rats. *The Journal of Physiology* **568**:3, 815-840. [[Crossref](#)]
341. S. Hardy, P.N. Robillard. 2005. Phenomenological and molecular-level Petri net modeling and simulation of long-term potentiation. *Biosystems* **82**:1, 26-38. [[Crossref](#)]
342. Yoav Banitt, Kevan A. C. Martin, Idan Segev. 2005. Depressed Responses of Facilitatory Synapses. *Journal of Neurophysiology* **94**:1, 865-870. [[Crossref](#)]
343. Oliver Beck, Marina Chistiakova, Klaus Obermayer, Maxim Volgushev. 2005. Adaptation at Synaptic Connections to Layer 2/3 Pyramidal Cells in Rat Visual Cortex. *Journal of Neurophysiology* **94**:1, 363-376. [[Crossref](#)]
344. Chris L. Baker, Aaron P. Shon, Rajesh P.N. Rao. 2005. Learning temporal clusters with synaptic facilitation and lateral inhibition. *Neurocomputing* **65-66**, 877-884. [[Crossref](#)]
345. Gianluigi Mongillo, Emanuele Curti, Sandro Romani, Daniel J. Amit. 2005. Learning in realistic networks of spiking neurons and spike-driven plastic synapses. *European Journal of Neuroscience* **21**:11, 3143-3160. [[Crossref](#)]
346. Lucinda A. Grande, William J. Spain. 2005. Synaptic Depression as a Timing Device. *Physiology* **20**:3, 201-210. [[Crossref](#)]
347. A. Rancillac, J.G. Barbara. 2005. Frequency-dependent recruitment of inhibition mediated by stellate cells in the rat cerebellar cortex. *Journal of Neuroscience Research* **80**:3, 414-423. [[Crossref](#)]
348. Joaquín J. Torres, Jesús M. Cortés, Joaquín Marro. Instability of Attractors in Auto-associative Networks with Bio-inspired Fast Synaptic Noise 161-167. [[Crossref](#)]
349. Igal Raichalgauz, Karina Odinaev, Yehoshua Y. Zeevi. Co-evolutionary Learning in Liquid Architectures 241-248. [[Crossref](#)]
350. Biswa Sengupta. Modeling of Short-Term Synaptic Plasticity Using Dynamic Synapses 429-438. [[Crossref](#)]
351. M. Tsodyks. Course 7 Activity-dependent transmission in neocortical synapses 245-265. [[Crossref](#)]
352. B. Sengupta, D. Halliday. Neuronal Dynamics of Dynamic Synapses 3636-3639. [[Crossref](#)]
353. Erez Persi, David Horn, Vladislav Volman, Ronen Segev, Eshel Ben-Jacob. 2004. Modeling of Synchronized Bursting Events: The Importance of Inhomogeneity. *Neural Computation* **16**:12, 2577-2595. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]

354. Manuel A. Castro-Alamancos. 2004. Dynamics of sensory thalamocortical synaptic networks during information processing states. *Progress in Neurobiology* 74:4, 213-247. [[Crossref](#)]
355. Ken-Ichi Amemori, Shin Ishii. 2004. Self-organization of delay lines by spike-time-dependent learning. *Neurocomputing* 61, 291-316. [[Crossref](#)]
356. MICHELE RUCCI, ANTONINO CASILE. 2004. Decorrelation of neural activity during fixational instability: Possible implications for the refinement of V1 receptive fields. *Visual Neuroscience* 21:5, 725-738. [[Crossref](#)]
357. S.-C. Liu, R. Douglas. 2004. Temporal Coding in a Silicon Network of Integrate-and-Fire Neurons. *IEEE Transactions on Neural Networks* 15:5, 1305-1314. [[Crossref](#)]
358. M. Giugliano, P. Darbon, M. Arsiero, H.-R. Lüscher, J. Streit. 2004. Single-Neuron Discharge Properties and Network Activity in Dissociated Cultures of Neocortex. *Journal of Neurophysiology* 92:2, 977-996. [[Crossref](#)]
359. Christo Panchev, Stefan Wermtner. 2004. Spike-timing-dependent synaptic plasticity: from single spikes to spike trains. *Neurocomputing* 58-60, 365-371. [[Crossref](#)]
360. Paulo Aguiar, David Willshaw. 2004. Hippocampal mossy fibre boutons as dynamical synapses. *Neurocomputing* 58-60, 699-703. [[Crossref](#)]
361. Stephen Grossberg, Gurumurthy Swaminathan. 2004. A laminar cortical model for 3D perception of slanted and curved surfaces and of 2D images: development, attention, and bistability. *Vision Research* 44:11, 1147-1187. [[Crossref](#)]
362. Xiaohui Xie, H. Sebastian Seung. 2004. Learning in neural networks by reinforcement of irregular spiking. *Physical Review E* 69:4. . [[Crossref](#)]
363. Y. Kanazawa, T. Asai, M. Ikebe, Y. Amemiya. 2004. A Novel CMOS Circuit for Depressing Synapse and its Application to Contrast-Invariant Pattern Classification and Synchrony Detection. *International Journal of Robotics and Automation* 19:4. . [[Crossref](#)]
364. H. Sebastian Seung. 2003. Learning in Spiking Neural Networks by Reinforcement of Stochastic Synaptic Transmission. *Neuron* 40:6, 1063-1073. [[Crossref](#)]
365. Urs Achim Wiedemann, Anita Lüthi. 2003. Timing of Network Synchronization By Refractory Mechanisms. *Journal of Neurophysiology* 90:6, 3902-3911. [[Crossref](#)]
366. Armen R Sargsyan, Albert A Melkonian, Costas Papatheodoropoulos, Hovhannes H Mkrtchian, George K Kostopoulos. 2003. A model synapse that incorporates the properties of short- and long-term synaptic plasticity. *Neural Networks* 16:8, 1161-1177. [[Crossref](#)]
367. Alexander Rauch, Giancarlo La Camera, Hans-Rudolf Lüscher, Walter Senn, Stefano Fusi. 2003. Neocortical Pyramidal Cells Respond as Integrate-and-Fire Neurons to In Vivo-Like Input Currents. *Journal of Neurophysiology* 90:3, 1598-1612. [[Crossref](#)]
368. Aaron P. Shon, Rajesh P.N. Rao. 2003. Learning temporal patterns by redistribution of synaptic efficacy. *Neurocomputing* 52-54, 13-18. [[Crossref](#)]
369. Andrew F. Teich, Ning Qian. 2003. Learning and Adaptation in a Recurrent Model of V1 Orientation Selectivity. *Journal of Neurophysiology* 89:4, 2086-2100. [[Crossref](#)]
370. Malte Boegerhausen, Pascal Suter, Shih-Chii Liu. 2003. Modeling Short-Term Synaptic Depression in Silicon. *Neural Computation* 15:2, 331-348. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
371. Richard H. R. Hahnloser. 2003. Stationary transmission distribution of random spike trains by dynamical synapses. *Physical Review E* 67:2. . [[Crossref](#)]
372. Henry Markram. Elementary Principles of Nonlinear Synaptic Transmission 125-169. [[Crossref](#)]
373. Thomas Natschläger, Henry Markram, Wolfgang Maass. Computer Models and Analysis Tools for Neural Microcircuits 123-138. [[Crossref](#)]
374. Daniel L. Cook, Peter C. Schwandt, Lucinda A. Grande, William J. Spain. 2003. Synaptic depression in the localization of sound. *Nature* 421:6918, 66-70. [[Crossref](#)]
375. Arnaud Delorme, Simon J Thorpe. 2003. SpikeNET: an event-driven simulation package for modelling large networks of spiking neurons. *Network: Computation in Neural Systems* 14:4, 613-627. [[Crossref](#)]
376. Lovorka Pantic, Joaquín J. Torres, Hilbert J. Kappen, Stan C.A.M. Gielen. 2002. Associative Memory with Dynamic Synapses. *Neural Computation* 14:12, 2903-2923. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
377. M.A. Sanchez-Montanes, P. Konig, P.F.M.J. Verschure. 2002. Learning sensory maps with real-world stimuli in real time using a biophysically realistic learning rule. *IEEE Transactions on Neural Networks* 13:3, 619-632. [[Crossref](#)]

378. Gail A. Carpenter, Boriana L. Milenova. 2002. Redistribution of Synaptic Efficacy Supports Stable Pattern Learning in Neural Networks. *Neural Computation* 14:4, 873-888. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
379. Misha I Rabinovich, R D Pinto, Henry D I Abarbanel, Evren Tumer, Gregg Stiesberg, R Huerta, Allen I Selverston. 2002. Recovery of hidden information through synaptic dynamics. *Network: Computation in Neural Systems* 13:4, 487-501. [[Crossref](#)]
380. Henk Haarmann, Marius Usher. 2001. Maintenance of semantic information in capacity-limited item short-term memory. *Psychonomic Bulletin & Review* 8:3, 568-578. [[Crossref](#)]
381. Ronen Segev, Yoash Shapira, Morris Benveniste, Eshel Ben-Jacob. 2001. Observations and modeling of synchronized bursting in two-dimensional neural networks. *Physical Review E* 64:1. . [[Crossref](#)]
382. T. Natschlgger, W. Maass, A. Zador. 2001. Efficient temporal processing with biologically realistic dynamic synapses. *Network: Computation in Neural Systems* 12:1, 75-87. [[Crossref](#)]
383. Hideo Hasegawa. 2000. Spike-Train Responses of a Pair of Hodgkin-Huxley Neurons with Time-Delayed Couplings. *Journal of the Physical Society of Japan* 69:11, 3726-3735. [[Crossref](#)]
384. Wolfgang Maass, Eduardo D. Sontag. 2000. Neural Systems as Nonlinear Filters. *Neural Computation* 12:8, 1743-1772. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
385. Stephen Grossberg. 2000. The imbalanced brain: from normal behavior to schizophrenia. *Biological Psychiatry* 48:2, 81-98. [[Crossref](#)]
386. Gideon Dror, Misha Tsodyks. 2000. Activity of coupled excitatory and inhibitory neural populations with dynamic synapses. *Neurocomputing* 32-33, 359-364. [[Crossref](#)]
387. Gideon Dror, Misha Tsodyks. 2000. Chaos in neural networks with dynamic synapses. *Neurocomputing* 32-33, 365-370. [[Crossref](#)]
388. Michele Giugliano. 2000. Synthesis of Generalized Algorithms for the Fast Computation of Synaptic Conductances with Markov Kinetic Models in Large Network Simulations. *Neural Computation* 12:4, 903-931. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
389. D. Bibitchkov, J.M. Herrmann, T. Geisel. Synaptic depression in associative memory networks 50-55 vol.5. [[Crossref](#)]
390. M. Migliore, P. Lansky. 1999. Long-Term Potentiation and Depression Induced by a Stochastic Conditioning of a Model Synapse. *Biophysical Journal* 77:3, 1234-1243. [[Crossref](#)]
391. Michele Giugliano, Marco Bove, Massimo Grattarola. 1999. Fast Calculation of Short-Term Depressing Synaptic Conductances. *Neural Computation* 11:6, 1413-1426. [[Abstract](#)] [[PDF](#)] [[PDF Plus](#)]
392. P. C. Bressloff. 1999. Mean-field theory of globally coupled integrate-and-fire neural oscillators with dynamic synapses. *Physical Review E* 60:2, 2160-2170. [[Crossref](#)]
393. Gideon Dror, Misha Tsodyks. 1999. Analysis and modeling of population dynamics in the visual cortex. *Neurocomputing* 26-27, 361-366. [[Crossref](#)]
394. Matthias Bethge, Klaus Pawelzik, Theo Geisel. 1999. Brief pauses as signals for degressing synapses. *Neurocomputing* 26-27, 1-7. [[Crossref](#)]
395. Peter Adorján, Christian Piepenbrock, Klaus Obermayer. 1999. Contrast Adaptation and Infomax in Visual Cortical Neurons. *Reviews in the Neurosciences* 10:3-4. . [[Crossref](#)]
396. Henry Markram, Anirudh Gupta, Asher Uziel, Yun Wang, Misha Tsodyks. 1998. Information Processing with Frequency-Dependent Synaptic Connections. *Neurobiology of Learning and Memory* 70:1-2, 101-112. [[Crossref](#)]
397. Cornelius Glackin, Liam McDaid, Liam Maguire, Heather Sayers. Implementing Fuzzy Reasoning on a Spiking Neural Network 258-267. [[Crossref](#)]
398. S.H. Srinivasan, A. Narayan. Information transfer in neurons with depressing synapses 1587-1591. [[Crossref](#)]
399. J.G. Taylor. A mathematical analysis of adaptive synapses 46-51. [[Crossref](#)]
400. T. Asai, Y. Kanazawa, T. Hirose, Y. Amemiya. A MOS circuit for depressing synapse and its application to contrast-invariant pattern classification and synchrony detection 2619-2624. [[Crossref](#)]
401. Shih-Chii Liu, R. Dougl. Spike synchronization in a network of silicon integrate-and-fire neurons V-397-V-400. [[Crossref](#)]