

# SYNCHRONY STATE GENERATION: AN APPROACH USING STOCHASTIC SYNAPSES

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## Abstract

In this study, the generation of temporal synchrony within an artificial neural network is examined considering a stochastic synaptic model. A network is introduced and driven by Poisson distributed trains of spikes along with white-Gaussian noise that is added to the internal synaptic activity representing the background activity (neuronal noise). A Hebbian-based learning rule for the update of synaptic parameters is introduced. Only arbitrarily selected synapses are allowed to learn, i.e. update parameter values. Results show that a network using such a framework is able to achieve different states of synchrony via learning. Thus, the plausibility of using stochastic-based models in modeling the neural process is supported. It is also consistent with arguments claiming that synchrony is a part of the memory-recall process and copes with the accepted framework in biological neural systems.

## 1 Introduction

Temporal coherence in the firing activity of groups of neurons is widely observed as a common feature throughout the neocortex [40]. The analysis of the responses of stimulated neurons of cat's visual cortex [18] confirmed that activated neurons can reliably produce synchronous discharge with the precision of a few milliseconds. Investigating the key factors in exhibiting such synchronous activity [13] related these observations to both the pure excitatory and the intrinsic time course of synaptic interactions. This coherence is believed to play an important role in neural coding and computational principles [34]. Synaptic background activity (namely the noise) was reported through the theoretical and experimental studies of synchronous activities as a key feature and it was emphasized that such background activity can affect driving coherent spiking activity [10, 23, 19, 7].

Although the real mechanism underlying neuronal synchrony (or temporal correlation) is not completely investigated [40], the issue gained more importance in the research since it has been viewed as a plausible solution to the "binding problem" [35, 12, 32] discussed in [41]. These studies argued that such neuronal temporal synchrony could allow the information about stimuli to be conveyed as temporal relations between neural sites and provide the basis for integrating different features representing the same object. Thus, binding can be defined as the ability of the biological neural system, in terms of inherited flexibilities, to construct higher level symbols by combining more elementary symbols [37].

States of synchrony are involved when any group of neurons realize a degree of synchronous activity, consequently this group of neurons exhibits a state of mental activity [41]. By entertaining such conceptual assumption and in order to observe this state, this temporal synchrony (or temporal correla-

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<sup>1</sup>In the referred study, the mathematically known cross-correlation was not meant explicitly, instead the general sense of temporal correlation was meant

tion)<sup>1</sup> is defined over a time period  $T_{\text{sync}}$ . With this period of time (or Psychological Moment) a brain, mental or neurological state is defined. At times greater than  $T_{\text{sync}}$  one sees only a sequence of states (state history). Below this time window, a state cannot be defined. The need to maintain this state of temporal correlation for periods greater than a few milliseconds was supported by the argumentation in [37] in order to confine the behavioral conditions fitting the higher brain functions and difficult tasks that require sustained level of activity. In this sense, states of synchrony are believed to be involved in the processing of sensory inputs [11]. Moreover, it is argued in [38] that attention and awareness emerge from the interacting dynamics in terms of synchrony states among distributed neural ensembles. Von der Malsburg stated that plausible values for this time window to define such state could be in the range of 50 - 200 millisecond and may be also extended to involve minutes if other mental aspects are in concern [41]. Within this time window, the actual signal fluctuations are not relevant (for a complete review please refer to [32, 37, 1]).

The generation of synchrony in artificial neural networks (ANN) is addressed in many theoretical and numerical studies, e.g. [13, 4, 31, 2, 42, 26]. These studies confirmed the ability of an ANN to realize the temporal synchrony on the time scales of a few milliseconds even with sharp synchronization on the time scale of single spikes. In general, these studies simulated a population of integrate-and-fire (IAF) neurons with adequate interconnectivity. Their discussions highlighted the major role of excitatory interconnections to achieve a certain degree of synchronous activity. Tsodyks et al presented a notable study in [40]. They considered the non-linear (frequency dependent) synapses for the generation of synchronous firing. Their results showed that the incorporation of nonlinear synapses in recurrent networks provide the basis for the emergence of short-time synchronous activity.

However, it has been shown that deterministic representation of the neural actions does not *model the biological neural behavior realistically* [24, 28, 29]. In addition, Kröger showed in [20] that probabilistic option in regard to neuroscience offers advantages over the deterministic one. A stochas-

tic pulsed-coupled neural network was presented in [5] showing synchronous and asynchronous behavior. A reduced stochastic dynamic model of an interconnected population of excitatory neurons with activity-dependent synaptic depression was proposed in [15], the discussion was focused on the bistability of voltage activities as up and down states. This is believed to be also related to the states of temporal synchrony within the neural ensemble. However, these studies and other did not consider the potential effects of *stochastic dynamic synapses* on synchronization of neural activity in ANN.

In the general case of modeling a biologically-observed neural aspect, we proposed that the stochastic modeling of neuronal and synaptic activity are better than the deterministic one; Because the stochastic approaches are able to account for the essence of neural variability [8]. This was clearly elucidated in [16] trying to predict the exact spike timing of a thalamic neuron. This statement was further supported by our results in the international Quantitative Single-Neuron Modeling 2009<sup>2</sup> (succeeding one of the 2008-challenge [17]). In this challenge and using our stochastic synaptic model [8], we have defined the new benchmark in predicting the spike timing of a single post-synaptic neuron in the lateral geniculate nucleus knowing the spike train on the pre-synaptic side (i.e. in a retinal ganglion cell) [9, 30].

In [8] we have proposed a basic framework with a modified version of the basic stochastic synaptic model (presented in [24]) coupled to a leaky IAF neuron. Our preliminary results showed that an ANN with the introduced framework was able to realize special regimes of activity with synchronous discharge over biologically tenable periods of time. Here, we report the detailed description and analysis of this framework along with the involved results. Specifically, in this paper, we investigate the ability of a network comprising IAF neurons and stochastic synapses to realize the concept of synchrony (the temporal correlations) between the signals of grouped neurons as states of synchronous activity. The goals are: a) to construct an ANN so that when driven by trains of spikes should be able to transform input signals combined with background synaptic activity (here introduced as synap-

<sup>2</sup><http://incf.org/community/competitions/spike-time-prediction/2009/>

tic noise) into correlated outputs and b) to show the ability to sustain such level of synchrony over a considerable time course  $T_{\text{sync}}$ . For this task, a Hebbian-based Reinforcement-like learning algorithm is introduced as well.

## 2 The Model

### Neuron Model:

Neurons are modeled as leaky-IAF neurons usually used in such type of simulations [40]. Each neuron is described by its voltage membrane potential  $V$ , with the following dynamics:

$$\tau_V \frac{dV}{dt} = -V + E_{\text{psp}} + \varepsilon, \quad (1)$$

where  $\tau_V$  is the membrane time constant set at 20 msec, and  $E_{\text{psp}}$  is the total observed excitatory post-synaptic potential from all pre-synaptic terminals.  $\varepsilon$  is the added white-Gaussian noise<sup>3</sup> representing the background synaptic activity, with  $\langle \varepsilon \rangle = 0$ . When  $V$  exceeds a certain threshold  $V_{\text{th}}$ , a spike is generated and  $V$  is reset to a resting value,  $V_{\text{rest}} = -70\text{mV}$ .

### Synaptic Model:

We have first introduced the modified stochastic synaptic model (MSSM) in [8, 9]. According to this model, each synaptic connection is modeled as a stochastic activity-dependent connections. This model estimates the transmission probability of an arriving action potential, i.e. spike, from a presynaptic neuron via a synapse to a postsynaptic neuron. The probability-of-release involved is governed by two counteracting mechanisms: facilitation and depression. Facilitation reflects the  $\text{Ca}^{2+}$  concentration in the presynaptic neuron, while depression represents the effect of the concentration of ready-to-release vesicles in the pre-synaptic neuron. The probability that the  $i$ th spike in the spike train triggers the release of a vesicle at time  $t_i$  at a given synapse is given by:

$$P(t_i) = 1 - e^{-(C(t_i) \cdot V(t_i))}, \quad (2)$$

where  $C(t_i)$  and  $V(t_i)$  represent the facilitation and depression mechanisms respectively at  $t_i$ .  $C(t)$  and

$V(t)$  are expressed as [29]:

$$C(t) = C_o + \sum_{t_i} \alpha e^{-(t-t_i/\tau_C)} \quad (3)$$

$$V(t) = \max(0, V_o - \sum_{t_i} e^{-(t-t_i/\tau_V)}) \quad (4)$$

In eq. 3,  $\tau_C$  and  $\alpha$  represent the decay constant and the magnitude of the response respectively.  $C_o$  represents the initial concentration of  $\text{Ca}^{2+}$  in the pre-synaptic terminal. In eq. 4,  $V(t)$  is the expected number of vesicles of neurotransmitter molecules (Nt) in the ready-for-release pool at time  $t$ .  $V_o$  is the max. number of vesicles that can be stored in the pool.  $\tau_V$  is the time constant for refilling the vesicles. For the simulation, a discrete version of equations 3 and 4 adopted from [28] is used. Thus, these equations read:

$$C(n) = \alpha \cdot \theta(n-1) + k_C \cdot (C(n-1) - C_o) + C_o, \quad (5)$$

$$V(n) = -P(n-1) \cdot \theta(n-1) + k_V \cdot (V(n-1) - V_o) + V_o. \quad (6)$$

In eq. 5,  $k_C$  corresponds to the decay time constant,  $\tau_C$ , of the response to a single incoming spike.  $k_V$  corresponds to the time constant,  $\tau_V$ , for refilling the vesicles.  $\theta(n)$  represents the instantaneous input firing rate observed at the synapse at time instant  $n$ ; it equals then  $\Delta_{\text{isi}}^{-1}$ , where  $\Delta_{\text{isi}}$  is the last observed inter-spike-interval (ISI).

Recalling that the binding process of Nt on the postsynaptic membrane induce  $E_{\text{psp}}$ . Thus,  $E_{\text{psp}}$  is related to this process through the following dynamics [27]:

$$\tau_{\text{epsp}} \frac{dE_{\text{psp}}}{dt} = -E_{\text{psp}} + N_t, \quad (7)$$

where  $\tau_{\text{epsp}}$  is a decay time-constant.  $N_t$  is the concentration of the Nt in the synaptic cleft. We assume that the latter can be estimated by tracing the amount of vesicles of Nt that remains in the presynaptic neuron,  $V(t)$ , over time. We introduce the following equation to estimate  $N_t(n)$  and consequently couple the SSM with the IAF neuron model:

$$N_t(n) = \max(0, V(n) - V(n-1)) + N_t(n-1)e^{-\Delta_{\text{isi}}/\tau_{N_t}} \quad (8)$$

<sup>3</sup>The MATLAB function (wgn) is used with overall 0 db power over 1 ohm load impedance

In eq. 8,  $N_t$  at any time instant  $n$  is the summation of: a) the estimated amount of Nt added with each release at any time step  $n$  (or the decrease in  $V(n)$  over the time step); where the  $\max(\dots)$  avoids negatives and b) the amount of Nt that remains in the cleft from previous releases. The decay with  $\tau_{N_t}$  reflects the biological cleaning action, or the removal of the Nt from the cleft. Equations 1 and 7 are implemented as discrete forms introduced by [27] using Impulse Invariant Transform in order to facilitate the computations (Please refer to the articles [21, 27] for the derivation).

### 3 Network and Simulation

Up to our knowledge, the biologically accepted network size, in which temporal correlation can be observed and effectively utilized, is not precisely specified [40]. However, there are some hypothetical suggestions discussing the tenability of the network size. Singer, for example, analyzed the major factors affecting the ability of a group of neurons to exhibit synchronous activity [37]. He pointed out that the network size could be as small as two mutually coupled neurons and may be up to 100 neurons. Herzog and Gerstner argued that if synchrony is an essential feature for the brain activities, it should also be feasible in small networks [14]. They called this "the small network argument", or the new benchmark for consciousness. Thus, they reported, there is a minimal model or a small network that satisfies the criteria underlying consciousness, e.g. temporal synchrony, but is not conscious itself. They stated that groups of up to seven neurons are sufficient to realize memory, learning, or synchrony. Based on the analysis done in [6], a network of two neurons should be able to achieve spike-to-spike synchrony when enough mutual conductance is available.

Thus, two network structures are used in this study. A schematic of the first introduced network is in Fig. 1(a) with the input being fed only to the first neuron,  $N_1$ . The network consists of 3 mutually interconnected neurons with only excitatory synapses. Also a bigger network is used with 8 neurons as in Fig. 1(b). In the latter one, the input is also fed to  $N_1$ , and similar to the smaller network, the feed back to the input neuron is only possible from the neighboring neurons; in this case from  $N_2$ ,

$N_3$  and  $N_4$ . All synaptic connections are MSSM synapses as described in section 2 supported with white Gaussian noise generators.

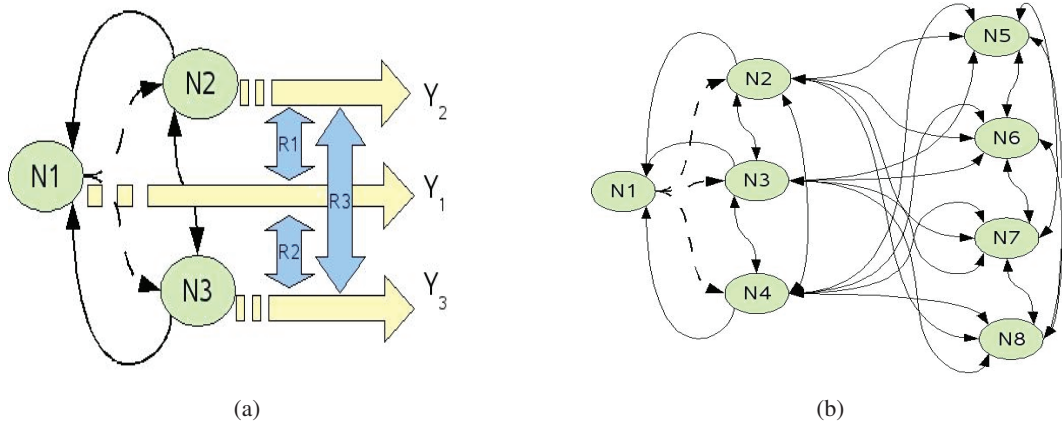
The input is a set of 200 trains of spikes, each with a Poisson distributed inter-spike intervals for an epoch of 150 and 100 msec at 1 msec discretization for the 3 neuron and the 8 neuron networks respectively. This time epoch is arbitrarily used as a median value for the proposed time scale of  $T_{\text{sync}}$  over which synchrony is plausible. The spike generator is adjusted to generate spikes with a maximum overall firing-rate of 300 Hz. Meanwhile, at each synapse a white Gaussian noise is added locally to the induced postsynaptic potential from this synapse. The level of the noise is modulated via simulated linear amplification.

For representing synchrony, the cross-correlation based measures are accepted in the detection of similarities in responses and for synchrony [40, 26]. Correlograms are not considered in this study based on reviews to the analytical reliability of its results [3]. A correlation-based measure is introduced in [33] that calculates the cross-correlation coefficient between neural responses after applying a Gaussian filtration on the responses. Here, the max. of cross-correlation coefficients between the filtered signals is used to indicate the degree of synchrony. The width of the Gaussian filter is chosen to be equal to the chosen neuronal refractory period of 2 msec.

### 4 Learning Rule

Generally, if no learning is implemented, the input signal and noise are fed to the network. At the end of each epoch, the mean  $R_m$  of the max. cross-correlation coefficients is calculated from all possible combinations between the responses from the three neurons. For example in the case of the network with 3 neuron  $R_m = \text{mean}(R_1, R_2, R_3)$ , where  $R_1$  is the max. cross correlation coefficient between the Gaussian filtered versions of  $Y_1$  and  $Y_2$ . Similarly  $R_2$  and  $R_3$ , as in Fig. 1(a). An analogous approach is used with the bigger network.

A Hebbian-based learning rule is introduced in [22, 27] showing how both the timing parameters and constants can be updated based on the spiking activity of pre- and postsynaptic neurons. Here,



**Figure 1.** Network schematic. a) 3 neuron network. The dashed lines are those synapses permitted to be trained. Double arrowed connections represent a mutual connection. Horizontal-right oriented arrows: output signals from each neuron:  $Y_1$ ,  $Y_2$  and  $Y_3$ . Vertical-two-headed arrows: the corresponding cross-correlation coeff.:  $R_1$ ,  $R_2$  and  $R_3$ . The trained synapses are from  $N_1$  to  $N_2$  and  $N_3$ . b) 8 neuron network. The dashed lines are those synapses permitted to be trained. Double arrowed connections represent a mutual connection. The details of the outputs and the calculation of cross correlation are omitted for clarity. The trained synapses are the synapses from  $N_1$  to  $N_2$ ,  $N_3$  and  $N_4$

this rule is extended to MSSM parameters. Specifically, the dynamics of synaptic or neural activities are governed through the contribution of electrochemical mechanisms. Each of them is represented via a value,  $m$ , i.e.  $\alpha$  in eq. 3 represents the max. allowed incurrent of  $\text{Ca}^{+2}$  ions to the presynaptic terminal [24]. A mechanism  $m$  could be either excitatory or inhibitory. According to the pre- and post-synaptic activity, the value of  $m$  is either increased or decreased following the Hebbian approach [22]. The update of the contribution values could be basically mathematically formed as:

$$m_{\text{new}} = (1 \pm r)m_{\text{current}}, \quad (9)$$

where  $r$  is the learning rate. In the proposed MSSM, such parameters are for example  $\tau_N, \tau_V, \tau_C, \alpha, C_o$  and  $V_o$ .

We introduce a feedback parameter,  $K$ , that represents the advance in the direction of getting both more and stable synchrony between the responses (i.e. a higher cross-correlation coefficient). Thus, it is the difference in the observed synchrony  $R_m$  from the current run and the previous one, let

$$K = R_{m_{\text{current}}} - R_{m_{\text{previous}}} \quad (10)$$

$K$  is used as a modulator to the learning rate. Thus, the learning rule can be rewritten:

$$m_{i_{\text{new}}} = (1 \pm r \cdot K) \cdot m_{i_{\text{current}}} \quad (11)$$

$K$  can reverse the direction of the updating process of the parameters since it is a signed value, and can either accelerate or decelerate the learning process. This learning rule has the implicit objective of correlating the outputs corresponding to the same input properties. It emphasizes the sensitivity of the network to temporal and statistical properties embedded in input signals [27]. In this study, only forward MSSM synapses are allowed to update their parameters via this rule as illustrated in Fig. 1(a) and 1(b).

## 5 Results

Figures 2(a) and 2(b) illustrate the performance of the networks during the simulation with and without learning. In each subfigure, the two different traces can be taken as an indicator for two neuronal states of synchrony: Ground-State (Learning Off) and New-State (Learning On). The network needs about 20 - 40 learning runs until it reaches the New-State. The introduced networks with MSSM are able to show two states of synchrony over a time window of 150 and 100 msec in 3 neuron and 8 neuron network respectively. In this case the noise intensity is held constant and this noise intensity is referred as the zero-level white Gaussian noise,  $wgn^{(0)}$ .

There may be no clear analytical evidence that

biological neural systems can turn learning on and off. However, the logical analysis of cognitive control tasks in [7] still accepts that the biological neural circuitry can perform something similar to the control of task sharing and non-physical rewiring of neural ensembles, e.g. the control over the flow of information. This makes the idea of using the on/off learning rule acceptable. In the following, however, the use of switching learning On/Off is avoided by using the intensity of the noise as a controlling factor. This is a direct consequence of the experimental and theoretical analysis mentioned before in the introduction.

In order to view the realization of the synchrony states in parallel with the involved synaptic dynamics, using only the 3 neuron network, a higher intensity of noise is fed to the network,  $wgn^{(1)}$ , where  $wgn^{(1)} > 2wgn^{(0)}$ . Furthermore, one more randomly chosen synapse is allowed to be tunned. This is meant to allow for non planned transition between the internal available states of the network, if exists, to take place. In other words, the objective of this setup is to observe how the network behaves in general and to test if it is able to accomplish any other available stable state of synchrony than the first reachable one. In Fig. 3(a), the observed synchrony level is shown. The network is able to sustain both of the states defined before keeping learning on along the entire simulation. The vertical dashed lines show when the network decided to change its state from the upper synchrony level to the lower one. Within the dashed lines, there is a finite overshoot in the synaptic strength value. We interpret this disturbance to be the search for the new stable state as the network is pushed out of the first stable state.

However, a network that achieves only synchrony is not so useful unless it can desynchronize its activity [4]. Hence, the ability of the network to desynchronize itself is also investigated. By setting the input to zero, the only remaining input is the noise which is equal for all synapses. Thus, the neurons start with typical firing patterns, this can be (obviously) seen in Fig. 3(b), since the two traces of the cross-correlation coefficient start almost with a value of 1. Since learning is on, and while the network is trying to reach a general stable level of synchrony, the networks desynchronized itself reaching a middle level near those upper ones achieved as in

Fig. 3(b).

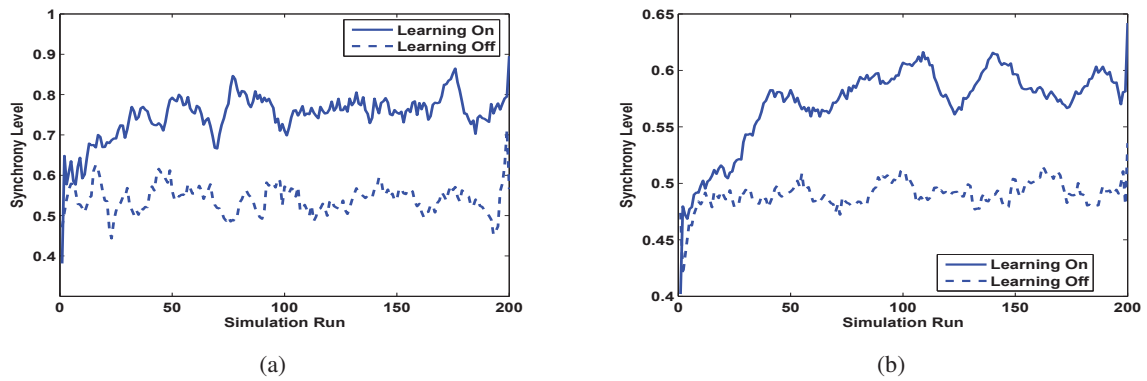
## 6 Discussion and Conclusion

The simulations presented here demonstrate that networks of neurons interconnected with stochastic synapses have a real tendency to realize special regimes of activity with synchronous discharge over biologically tenable periods of time. The simulation here is restricted to excitatory connections based on the mentioned discussion in the introduction section, however, the role of synaptic depression or specific inhibitory connections in case of using stochastic synapses needs further investigation.

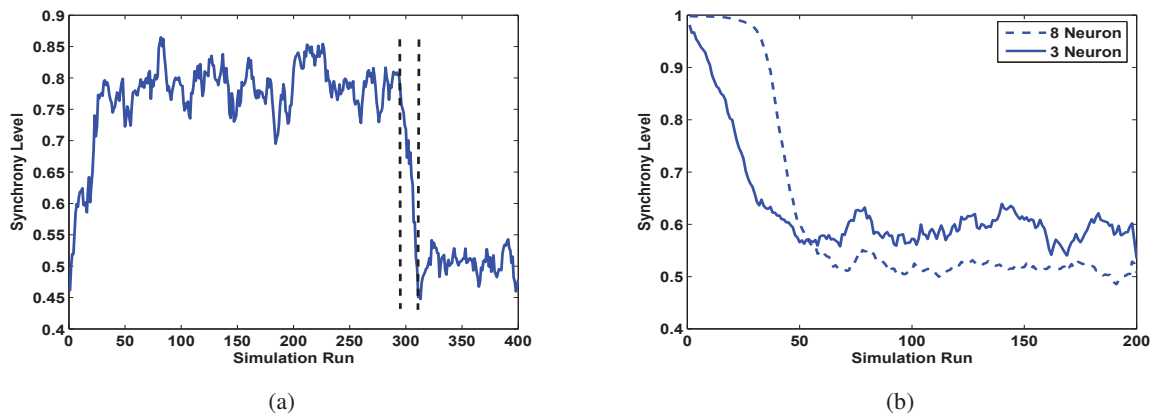
Considering the network size in this study, it cannot represent a cortical minicolumn [40] consisting of neurons, however, it could be viewed, in the context of synchronous activity, to have similar receptive field properties [1]. Other possibilities are issues of further study, e.g. it is expected that in larger simulated networks, such as a cortical mini- and hyper-column, where interconnections between neurons reflect their receptive field properties, other profiles of activity, may be with multiple internal states or with shorter time course, could exist.

As for the learning algorithm, and up to our knowledge, there may be no clear analytical evidence that biological neural systems can turn learning on and off. However, the logical analysis as in [7] still accepts that the biological neural circuitry can perform something similar to control, e.g. the control over the flow of information, the task sharing and non-physical rewiring of neural ensembles. This makes the idea of using the on/off learning rule acceptable.

In this paper, an ANN of IAF neurons coupled via MSSM synapses is introduced. In case of the evoked simulations, the network is driven by Poisson distributed trains of spikes and white-Gaussian noise. The latter is fed to synaptic activities. Considering that the Poisson distributed input represents a neural activity that carries certain information, the change in the level of synchrony could be seen as if the network, is likely to be, *memorizing* or *internally recalling* this input by pushing all its activities to *sync* with it. On the other hand, and in the case of spontaneous activity as the in-



**Figure 2.** Simulation result. a) The detected level of internal synchrony of the 3 neuron network in two cases: when learning is allowed, and when not allowed.  $T_{sync} = 150$  msec. b) The detected level of internal synchrony of the 8 neuron network in two cases: when learning is allowed, and when not allowed.  $T_{sync} = 100$  msec.



**Figure 3.** a) The observed behavior of the network with 3 neuron with MSSM in case of allowing more than the feedforward synapses to be tuned. The level of fed noise is higher than the standard one. b) Desynchronization. The networks reach a stable level of synchrony lower than the starting level. Results from both networks, 3 and 8 neuron, are illustrated.

put is set to zero, the networks are able to find a lower stable state of synchrony, since they desynchronize their firing pattern. Both synchrony and desynchrony cope with the conceptual postulations discussed in the context of synchrony [41] and the role of noise in neural information processing [10]. Hence, the proposed framework achieved successfully the general sense of sustaining a defined state of synchronous activity within a group of neurons over a considerable time course of 100 - 150 milliseconds.

It is worth mentioning that the dynamics of facilitation and depression in this MSSM model are conceptually similar to those presented in the famous synaptic model by Markram et al [25], since the facilitation and depression dynamics in our model replace the efficacy and utilization parameters respectively (Please review [39, 25] for more details). The main difference between the two models, however, are mainly seen in two perspectives: a) MSSM realizes the stochastic nature of the release process of Nt, and b) It accounts explicitly for the activity of two synaptic resources which are  $Ca^{2+}$  and Nt. However, in Markram's model, the input synaptic current is deterministically evaluated by tracing both the utilization and recovery of a single synaptic resource [25].

It remains, however, that the expressive power of the proposed dynamics in terms of the number of achievable states is to be tackled. On simulation basis, there are some obstacles standing against defining more stable states for the whole network. Basically, although there are some analytical methods, the exact definition of a stable state of synchronous activity in the network is still questionable [36]. The proposed means in this paper as a cross correlation coefficient may lack the fine resolution that is probably needed to differentiate between different states or even sub-states of neural activity. Secondly, advances in the way to define a stable state of activity should be directly combined with dramatic changes in the learning rules.

The stochastic based synaptic model MSSM demonstrated high sensitivity to the change in the noise level, or background activity level. This deeply agrees with the experimental results and the logical considerations reported in [10] that the background activity *controls* the input output characteristics. This envisages the stochastic-based

synaptic models as more plausible for modeling biological neural activities. Moreover, it reflects the importance of considering *both* the concentration of Nt and  $Ca^{2+}$  as key players in the synaptic dynamics. This allows MSSM to meet a rich repertoire of realistic dynamical behaviors and features.

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