Proceedings of the 26th Annual International Conference of the IEEE EMBS
San Francisco, CA, USA • September 1-5, 2004

# Model of the effect of extracellular fields on spike time coherence

Lucas C. Parra, Marom Bikson
Department of Biomedical Engineering
City College of New York
New York, NY 10031
Email: parra@ccny.cuny.edu, bikson@ccny.cuny.edu

*Abstract*— **Accurate spike timing is emerging as an important comcept in the encoding of sensory stimuli. Accurately timed spiking has been recorded in-vivo in the visual and auditory cortex, many layers removed from the primary sensory neurons. This temporal accuracy may be maintained despite noisy synaptic transmission by the simultaneous firing of multiple neurons [1]. Here we show in simulations that a coherent polarization of a population of neurons through extracellular fields can further increase the coherence of the population's firing times. We discuss the potential relevance of such a common input as an external "clock" signal in a spatio-temporal code.**

## I. Introduction

Temporal coding is emerging as an important concept of information processing in the central nervous system. While neurons often encode information in their firing rate, the timing of individual action potentials ('spikes') has also been shown to carry significant information [2]. Cortical neurons have been identified that fire in response to a sensory stimulus with an temporal accuracy of a few milliseconds. In sensory areas such as the LGN, visual cortex, and auditory cortex spike timing with as little as 1 ms 'jitter' (temporal variability) relative to an external stimulus have been demonstrated [3]–[6]. The timing of place cells in the hippocampus show remarkable accuracy in their timing relative to ongoing theta (7 Hz) oscillations in the extracellular field potentials [7]. Similarly accurate spike timing relative to theta oscillations are observed in the olfactory bulb [8]. This high temporal precision seems paradoxical given the stochastic nature of signal propagation, i.e. variable conduction delays, stochastic transmitter release, and stochastic background activity impinging on each neuron.

Recently, it has been demonstrated that temporal accuracy may be mantained by a high degree of synaptic input convergence [1], [9]. A volley of action potentials reaches a set of neurons and generates there a new volley of firing with reduced temporal spread. This is consistent with the finding that in the LGN temporal precision is conserved across neurons of the same class [10]. The model proposed by Diesmann et al. [1] requires almost 100% connectivity in assemblies of approximately 100 neurons. A related concept is that of a dynamic cell assembly whereby neurons participate in the encoding a stimulus, not by being permanently connected to a specific population of neurons, but by dynamically joining a group of simultaneously firing cells. In this paper we propose an additional mechanisms that may contribute to the synchronization of such dynamic cell assemblies while reducing the requirement of highly convergent inputs.

## II. Stable propagation of spike volleys

The analysis in [1], [9] focuses on the response of an ensemble of $N$ model neuron to an incoming spike volley. The identical incoming volley to each neuron is characterized by the number, $N_{in}$, of incoming excitatory post synaptic potentials (PSP) and their temporal variability through the standard deviation $\sigma_{in}$. The neurons are subject to a stochastic background synaptic input. The output of multiple neurons subject to the same excitatory input volley is thus variable due to this noisy background. Therefore, each neuron may or may not fire, and its firing time will vary relative to the time of the incoming volley. This variability can be quantified by the likelihood of firing, $p_{out}$, and the temporal jitter of the output spikes, $\sigma_{out}$. The simulations in [1] estimate this likelihood as the fraction of neurons that fire over the total number on neurons, $p_{out} = N_{out}/N$. In this paradigm *stable* propagation of the spike volley in successive layers of neurons is preserved if $\sigma_{out} \leq \sigma_{in}$ and $N_{out} \geq N_{in}$, i.e. if the spike volley does not dissipate.

Diesmann et al. [1] estimate this mapping $(\sigma_{in}, N_{in}) \rightarrow (\sigma_{out}, N_{out})$ through simulations of a population of leaky integrate-and-fire neurons with parameters typical for cortical pyramidal neurons. Their main finding is that if a sufficient number of synaptic input (incoming spikes) fall within a given time window the output jitter will be reduced as compared to the input. They also determine that an network of approximately $N = 89$ neurons with *full* connectivity is required to guarantee stable propagation (see Figure 3).

## III. Effect of synchronous extracellular potentials

We note that *in vivo* simultaneous neuronal activity always generates extracellular field potentials, which, in turn, will coherently polarize a neuronal population ('field effect'). Experimental evidence from the hippocampus suggests that during epileptiform activity extracellular potentials contribute significantly to the synchronization of neuronal activity [11]. Endogenous local field potentials observed during normal

0-7803-8439-3/04/$20.00©2004 IEEE

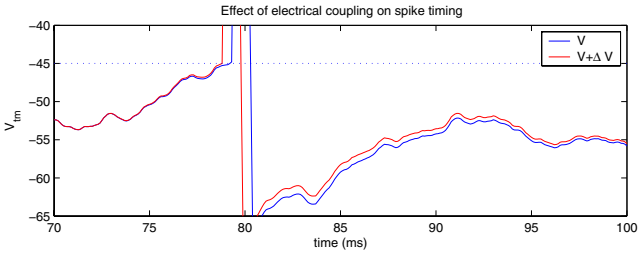


Fig. 1. Effect of extracellular contibution on spike timing in a simple integrate-and-fi re neuron. Input to the neuron is detailed in Figure 2. The two curves show the membrane potential with and without additive contribution of 1 mV. Note the change in the time of threshold crossing. The action potential is cut off for better visualization. Dotted line represents membrane fi ring threshold. Membrane resting potential is at -60 mV.

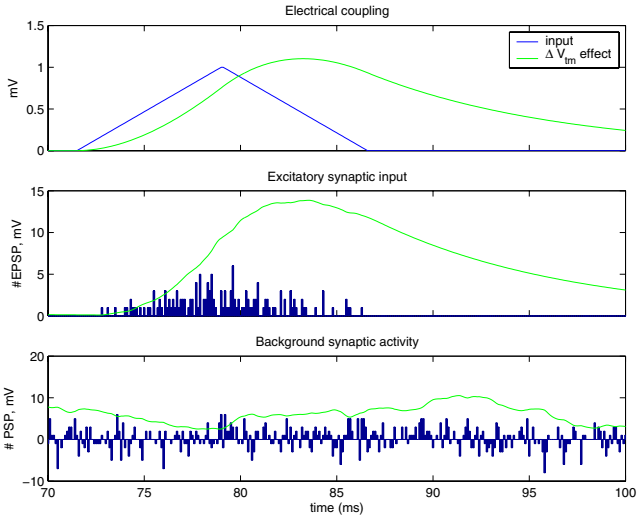


Fig. 2. Inputs considered in the simulations: Top panel shows extracellular contribution. The corresponding input current is plotted in arbitrary units, its effect on the membrane potential in given in millivolts. Middle panel shows synchronous volley of EPSPs. The total number of EPSPs and their temporal spread is determined according to $N_{in}$, and $\sigma_{in}$ respectively. Bottom panel represents background synaptic input. Here we show the number of EPSP minus the number of IPSP over time. The PSPs counts are measured in time bins of 0.1 ms.

brain function are much smaller than epileptic activity. However, there is not lower bound on the effect of extracellular field on the transmembrane potential [12]. Detailed single neuron simulations (not shown) indicate that at the soma, the site of spike generation, the effect can be up to 1-2 mV. These values are conciderably smaller than the ≈15 mV polarization needed to reach action potential threshold; however, a key observation of the present report is that because this small contribution is *synchronously* experienced by a large number of neurons, it can have a significant effect on spike timing.

Figure 1 demonstrates how a small change in the transmembrane potential can have a significant effect on the time at which the membrane reaches firing threshold. To quantify the effect of this small contribution to a population of neurons we reproduced the simulations by Diesmann et al. [1]. However here we include an additional field effect term modeled as a 1 mV simultaneous depolarization of the transmembrane potential of all neurons within an assembly. Figure 2 shows the three distinct contributions to our model neurons:

1) Electric coupling: 1 mV transmembrane depolarization aligned to the excitatory spike volley and with a fixed duration of 5 ms.
2) Spike volley: $N_{in}$ excitatory post synaptic potentials arriving with a spread of $\sigma_{in}$.
3) Background synaptic input: Poison distributed excitatory (EPSP) and inhibitory (IPSP) post-synaptic potentials such that cell fires by chance at a rate of 2 Hz.

The details of the simulation are described in section V.

In this simulation the output spikes of the $N$ cells are used as input to the next set of of $N$ cell, each receiving an identical exitatory spike volley. This arrangement simulates a fully connected network. The process is repeated until the spike volley has either dissipated or stabilized. These iterations are analogous to the propagation of a spike volley across successive layers of excitatory neurons, or equivalently, as iterations of a recursive excitatory network.

Figure 3 contrasts the results with and without electrical coupling. Note that in both cases the neurons are subject to the same balanced inhibitory and excitatory stochastic background activity, which is the source of variability. Clearly electrical coupling contributes to the stability of the spike volley, which otherwise dissipates due to the background noise.

The stability of the spike volley is dependent on the initial conditions $N_{in}$, and $\sigma_{in}$. This is demonstrated in Figure 4, which shows an area in the space of $(\sigma_{in}, N_{in})$ with stable propagation across successive layers. The important observation is that the area of stability is significantly increased when an additional electrical contribution to the membrane potential is considered.

In successive layers of $N$ fully connected neurons the number of spikes converging on the neuron in the next layer will be $N_{in} = p_{out}N$. Given the dependence on $N_{in}$ (shown for an initial $N_{in}$ in Figure 4), stable spike propagation is facilitated as the size of the ensemble increases. Figure 5 shows the dependence of stable propagation on $N$, and the initial $N_{in}$. We find that the minimum assembly size that still shows stable propagation is included is $N = 89$ vs. $N = 78$ when a 1 mV effect is included (not shown). Again, the range of parameters that guarantee stable propagation is increased when a coherent field effect is included.

Finally, Figure 6 shows the effect of a common extracellular field on disjoint groups of neurons. The three group of cells have no synaptic connectivity across groups and, therefore, fire independently. Without a common field effect the initial random average offset persist and the spike volley converges to packets that are similarly offset by a few milliseconds. The addition of a common field effect drive to all three groups reduces that offset such that the three groups now fire synchronously.

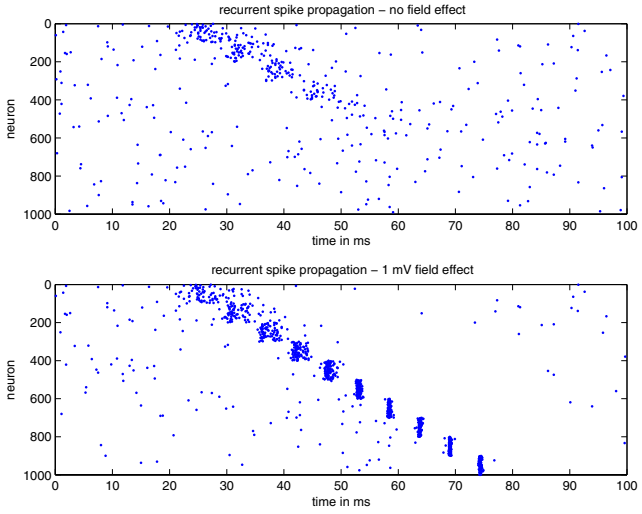


Fig. 3. Effect of coherent electrical input on synchrony of cell assembly. The two panels show the propagation of a spike volley in a network of 100 neurons per layer (1000 neurons total). The spike times generated by one layer of neurons is used as direct input to the next layer. An arbitrary delay of 5 ms in each step has been introduced for the purpose of visualization. Top panel: The coherence and/or size of the starting volley is not strong enough for stable propagation. Bottom panel: Additional synchronous membrane polarization is included. The propagating spike volley is now preserved, indeed the spike jitter $\sigma_{out}$ decreases. Starting spike volley and background activity for the length of the simulation are identical. Note random fi ring prior to initial spike voley at 25 ms and lack of fi ring after each volley due to refractoriness.

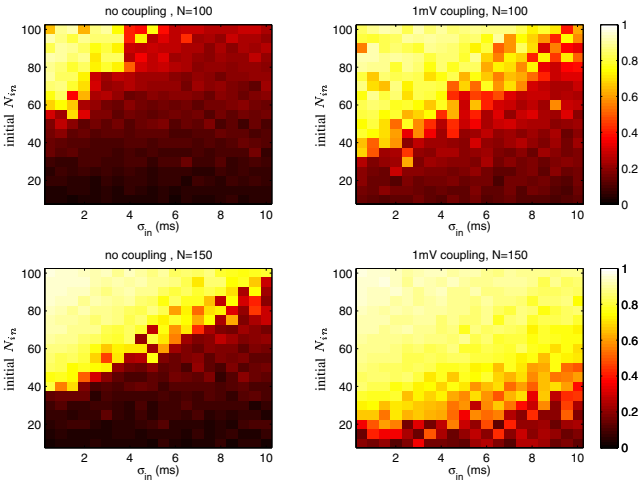


Fig. 4. Stability of spike volley as a function of starting conditions. Stability is assessed here simply by the intensity of the spike volley ($N_{out}/N$) averaged over the 10 iterations/layers. Top two panels correspond to assembly of $N = 100$ neurons and bottom panel to $N = 150$ neurons.

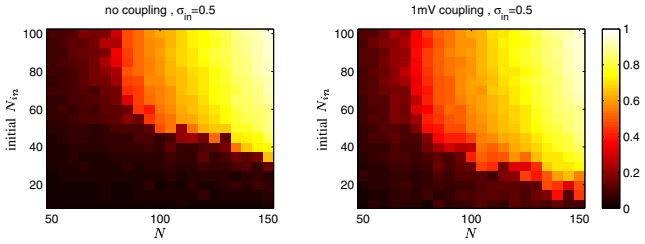


Fig. 5. Stability of spike volley as a function of population size, $N$, and size of initial input volley, $N_{in}$. Stability is assessed as in Figure 4.

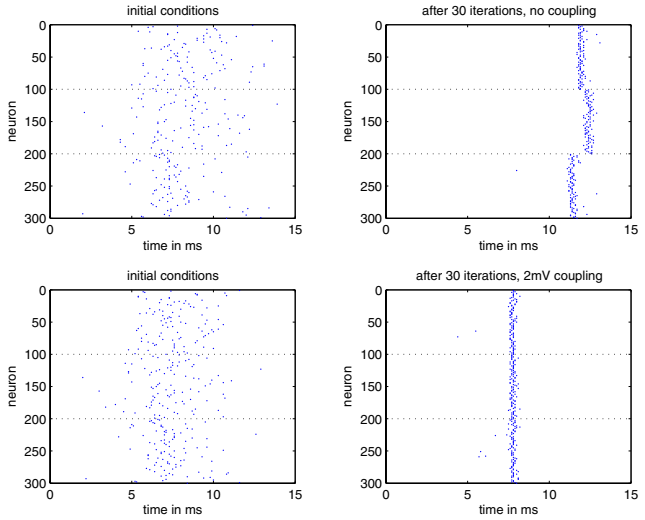


Fig. 6. Synchronization of disjoint groups of neurons by common extracellular potentials. Three disjoint groups of 100 neurons each are shown. The initial conditions (left) have a jitter of $\sigma_{in}$=3 ms. The jitter is reduced after 20 iterations (right). Random fluctuations make the three populations converge to spike volleys that are offset by approximately 2 ms (top, right). Common extracellular fi eld contributing here 2 mV depolarization reduce that drift (bottom, right). They also reduce the delay here by approximately 0.15 ms per iteration. The background activity is identical for both conditions.

## IV. Discussion

Stability and convergence of a spike volley in this simulation is critically determined by the number of incoming spikes. The slope at which the membrane crosses the action potential threshold increases as the number of incoming spikes increases and their temporal jitter decreases. A sharper transition through the membrane potential makes the spike times less susceptible to random fluctuations. Hence the jitter in the new spike times is reduced and stable spike propagation is obtained. A coherent drive to the membrane potential further synchronizes the output times by simultaneously pushing the cells that are close to firing across the threshold.

In the simulations of Diesmann et al. [1] a network requires that neurons in the assembly receive synchronous input from at least 89 presynaptic neurons for stability. With a 1 mV field effect that number is reduced to 75 (not shown). That means that the requirements on input convergence are somewhat reduced. Accordingly we find that the size of the assembly

can be reduced while still preserving accurate spike timing.

Finally, we find that disjoint cell assemblies can be made to fire synchronously. Therefore, different stimulus properties encoded and processed by separate groups of neurons, can remain grouped in time due to the effect of common extracellular fields. This is in line with the notion that "what fires together, belongs together" and suggest a novel mechanism for the classic feature binding problem.

## V. METHODS

Integrate-and-fire neurons, with transmembrane dynamic governed by, $\tau_{tm} dV_{tm}(t)/dt = -V_{tm}(t) + RI(t)$, were implemented according to the spike response model of Gerstner et al. [13]. The membrane time constant was $\tau_{tm} = 10\ ms$. The input current, $I(t)$, is the sum of synaptic currents and extracellular contirbution when applicable. Each incoming spikes elicits a synaptic current, $\alpha(t) = qt/\tau^2 exp(-t/\tau)$ with $\tau = 0.2\ ms$. The strength $q$ is set such that each spike contributes 0.14 mV peak amplitude to the transmembrane potential $V_{tm}$. Inhibitory and excitatory PSPs have the same strength but opposite sign. The number of incoming spikes in the background activity is Poison distributed with a mean rate of 35.2 $ms^{-1}$ and 30 $ms^{-1}$ for EPSPs and IPSPs respectively. The current profile due to the extracellular contribution - as shown in Figure 2 - is added to $I(t)$. It is scaled to contribute 1 mV peak amplitude to the transmembrane potential. The maximum current is aligned with the mean of the spike volley. To find this mean the spike counts are fit to a Gaussian (spikes due to background activity are subtracted prior to fitting). Our assumption is that the extracellular field is generated by the incoming dentritic input, and is therefore simultaneous with the incoming excitatory spike volley. Spike threshold is 15 ms above resting potential. Absolute refractory period of 1 ms is implicit in the 1 ms duration of action potential depolarization (neuron can not fire while it is still depolarized above threshold). Relative refractory period is implemented by a hyperpolarizing additive contribution that decays exponentially with a 15 ms decay constant. The simulation is performed with 0.1 ms time steps.

## REFERENCES


[1] M. Diesmann, M. Gewaltig, and A. Aertsen, "Stable propagation of synchronous spiking in cortical neural networks," *Nature*, vol. 402, no. 6761, pp. 529–533, December 1999.

[2] R. de Ruyter van Steveninck, G. Lewen, S. Strong, R. Koberle, and W. Bialek, "Reproducibility and variability in neural spike trains," *Science*, vol. 275, no. 5307, pp. 1805–8, March 1997.

[3] Z. Mainen and T. Sejnowski, "Reliability of spike timing in neocortical neurons," *Science*, vol. 268, no. 5216, pp. 1503–6, June 1995.

[4] P. Reinagel and R. Reid, "Temporal coding of visual information in the thalamus," *Journal of Neuroscience*, vol. 20, no. 14, pp. 5392–400, July 2000.

[5] P. Kara, P. Reinagel, and R. Reid, "Low response variability in simultaneously recorded retinal, thalamic, and cortical neurons," *Neuron*, vol. 27, no. 3, pp. 635–646, September 2000.

[6] M. DeWeese, M. Wehr, and A. M. Zador, "Binary spiking in auditory cortex," *Journal of Neuroscience*, vol. 23, no. 21, pp. 7940–7949, August 2003.

[7] K. Harris, J. Csicsvari, H. Hirase, G. Dragoi, and G. Buzsaki, "Organization of cell assemblies in the hippocampus," *Nature*, vol. 424, no. 6948, pp. 552–556, July 2003.

[8] H. Kashiwadani, Y. Sasaki, N. Uchida, and K. Mori, "Synchronized oscillatory discharges of mitral/tufted cells with different molecular receptive ranges in the rabbit olfactory bulb," *Journal of Neurophysiology*, vol. 82, no. 4, pp. 1786–92, October 1999.

[9] P. Marsalek, C. Koch, and J. Maunsell, "On the relationship between synaptic input and spike output jitter in individual neurons," *PNAS*, vol. 94, pp. 735–740, 1997.

[10] P. Reinagel and C. Reid, "Precise fi ring events are conserved across neurons," *Journal of Neuroscience*, vol. 22, no. 16, pp. 6837–6841, August 2002.

[11] F. Dudek, T. Yasumura, and J. Rash, "'non-synaptic' mechanisms in seizures and epileptogenesis," *Dell Biology International*, vol. 22, no. 11-12, pp. 793–805, November 1998.

[12] M. Bikson, M. Inoue, H. Akiyama, J. Deans, J. Fox, H. Miyakawa, and J. Jeffery, "Effects of uniform extracellular dc electric fi elds on excitability in rat hippocampal slices in vitro," *Journal of Physiology*, vol. in press, 2004.

[13] W. Gerstner and W. Kistler, *Spiking Neuron Models*. Cambridge Univ. Press, 2002.