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Propagation of Synfire Activity in Cortical Networks-
a Dynamical Systems Approach

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1 Introduction

During the last years, several models and related theories discussed the possible functional role of synchronized neuronal activity in cortical function. Here, we focus on recent findings by Abeles and colleagues on the abundance of accurate spatio-temporal spike patterns in the activity of neurons in the prefrontal cortex of awake behaving monkey, and their dependence on stimulus and behavioral context [1,2]. These findings support the hypothesis, that synchronous spike volleys propagate through the cortex in 'reverberating synfire chains' (RSC): feedforward networks with additional feedback connections. Using simulations of simplified, purely feedforward 'synfire chains', Diesmann and Gewaltig could demonstrate [3] that the stability of propagation of 'synfire volleys' in such chains strongly depends on the density of inter-node connectivity. Thus, the stability properties of these systems are described by iterative maps, which exhibit stable and instable fixpoints for the mean activity and the temporal width of the propagating 'pulse packet'. Motivated by these results we set out to develop a theoretical analysis of the stability properties of synfire propagations based on dynamical systems theory.

2 The 'Synfire chain' Model

The theory we present here is designed to describe the propagation of synchronous spike activity in a simple feedforward 'synfire chain' [4] without reverberating connections (Fig. 1). The network consists of a number of layers with *w* neurons per layer. Each neuron receives *m* inputs from the neurons of the preceding node. For a fully connected ('complete') chain the multiplicity of interlayer connectivity is equal to the number of neurons per node, i. e. $m=w$.

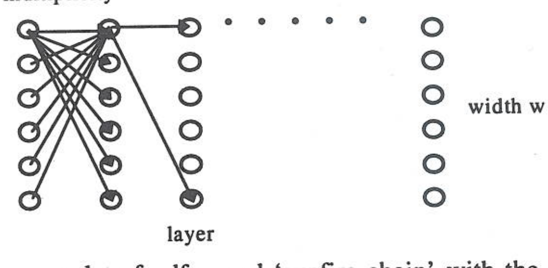

Fig. 1: Graph of a complete feedforward 'synfire chain' with the main structural parameters

For the individual model neuron we chose an 'integrate-and-fire' neuron for which the postsynaptic potential *u* is modeled by a leaky integrator. The firing probability is described by a sigmoid function (threshold Θ), the refractory dynamics *v* by a second leaky integrator. This leads to the following set of equations for the single neuron dynamics:

$$\tau_e \cdot \dot{u}_k = -u_k + v_e \cdot \sum_l [f(u_l - \Theta)] - v_{ie} \cdot v_k$$

$$\tau_i \cdot \dot{v}_k = -v_k + v_{ei} \cdot f(u_k - \Theta)$$

3 Stability of Synfire Propagation

3.1 Results from Simulation

We studied the activity dynamics in such simplified synfire chains by stimulating the first layer of the network with a brief volley of 1 ms . As a result, synchronous spike activity propagates along the network. The parameter varied during the simulation was the threshold level of the single neuron. The dynamics of synfire activity are described by the velocity (Fig. 2) and the temporal width of the propagating volley (Fig. 3) are shown below.

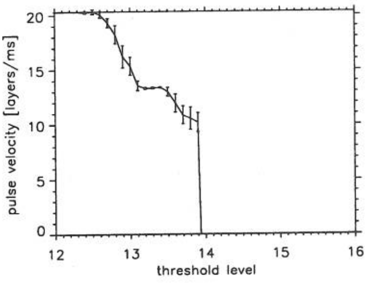

Fig. 2: Volley velocity vs. threshold

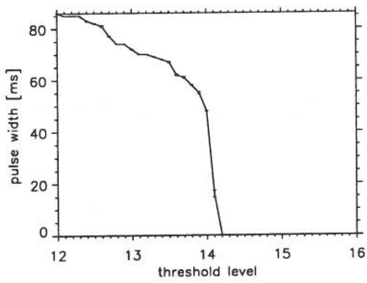

Fig. 3: Volley width vs. threshold

We found that for increasing threshold the velocity of the volley steadily decreases to zero up to the critical threshold value. Similarly, the width of the volley decreases to zero. Below the critical threshold stable propagations exist. If the threshold value is further increased the propagation becomes instable, i. e. the volley amplitude decreases to zero. Motivated by these separate ranges of stable and instable synfire propagations we developed a theoretical analysis using dynamical systems theory to predict velocity and width of the volley.

3.2 Results from Theory

For the case of a 'complete synfire chain', i. e. with fully connected nodes, the network can be simplified to a chain of single neurons, since every neuron in the complete chain receives the same input. This simplification allows a transition from the description of neuronal activity by discrete firings of single neurons to a continuous mean field description in terms of the interacting dynamics of membrane potential *u* and threshold *v*.

Fig. 4: Graph of a complete feedforward 'synfire chain' reduced to a chain of node neurons

The interaction of the neurons is described by a convolution (*) between the neuronal output and a gaussian kernel that describes the local neighborhood connectivity This leads to a neural field description as given by Amari [5]:

$$\tau_e \cdot \dot{u} = -u + w(x)*f(u(x) - \Theta) - v_{ie} \cdot v; \qquad w(x) = v_e \cdot \left[e^{-\frac{1}{\sigma}\cdot(x-1)^2} + e^{-\frac{1}{\sigma}\cdot(x+1)^2} \right]$$

$$\tau_i \cdot \dot{v} = -v + v_{ei} \cdot u$$

Transformation to a reaction-diffusion-system yields a system that is similar to Fitzhugh-Nagumo equations [6,7], developed to describe the propagation of action potentials along the axon:

$$\tau_e \cdot \dot{u} = w_2 u'' - u + f(w_0 u) - v_{ie} \cdot v; \quad w_0 = 2\sqrt{\pi} \cdot v_e \sigma, \quad w_2 = \frac{\sqrt{\pi}}{2} \cdot v_e \sigma^3,$$

$$\tau_i \cdot \dot{v} = -v + v_{ei} \cdot u$$

Further analysis of the corresponding characteristic equation following the work of Rinzel and Terman [8] yields velocity (Fig. 5) and width (Fig. 6) of the volley solution as a function of the threshold level Θ.

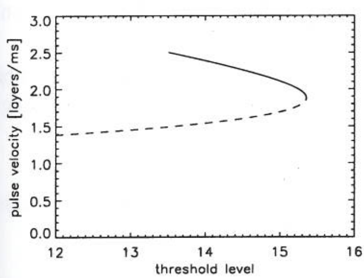

Fig. 5: Volley velocity vs. threshold

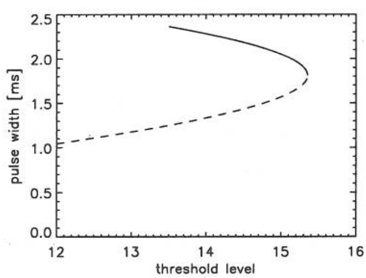

Fig. 6: Volley width vs. threshold

Together with the stable solutions (solid curves in Figs. 5 and 6) there exist also instable solutions (dashed curves in Figs. 5 and 6) with lower propagation velocities and smaller widths of the volley. The knee of the curves marks the critical threshold above which a stable propagation is no longer possible.

4 Discussion

We developed a theoretical description of the dynamics of activity propagation in simplified 'synfire chains'. The results of the analysis allow the prediction of propagation stability depending on single neuron parameters, i. e. threshold level.

In a related simulation study [3] it was shown that stable propagation requires a minimum amount of coincident activation at the input. In a related paper at this conference [9] they give an alternative analytical approach by using a statistical description for the shape of their puls packets.

The discrete spike dynamics in a discrete network of 'complete synfire chains' was analytically transformed to continuous field dynamics. After further transformation to a reaction-diffusion-system, the propagation of 'synfire' activity could be described by Fitzhugh-Nagumo like dynamics. The range of stable propagation can therefore be predicted. The analysis of the propagation velocities for stable and instable solutions provides a basis for the understanding of synchronization and binding phenomena. We are currently investigating whether this theory can also describe the shape of the stable solution and synchronization effects in incompletely connected chains.

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