Simulation of a recurrent neurointerface with sparse electrical connections

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Abstract. With the technical development of multi-electrode arrays, the monitoring of many individual neurons has become feasible. However, for practical use of those arrays as bidirectional neurointerfaces, feedback signals have to be generated in real-time to integrate the electrodes into the existing spatio-temporal context as a new information source. In this modeling study we will introduce a recurrent neurointerface, which uses a biologically plausible artificial neural network to pre-process electrode signals and generate adequate feedback signals to the biological network. The artificial network is more transparent for advanced methods to analyze synchronous firing patterns and reacts more stably to external input signals.

1   Introduction

The mature firing profile of biological neural networks shows complex high-order patterns of spikes and bursts. To integrate a neurointerface as a new information source, the actual state of the network has to be taken into account. The recorded data must be analyzed, and the feedback signals must be generated in real time. Multi-electrode arrays with bidirectional connections and real-time environment were successfully established to monitor ongoing activity and send feedback signals to the network [1]. However it is still unclear what is the actual network state and how to synchronize external inputs with this state. Already in single neurons the actual position in the phase response curve influences how an external stimulus affects the timing of spikes immediately after the stimulus [2]. The states of the whole network are even more complex and the transparency of the processes is limited by the scarcity of electrodes compared with the excess of connections inside the biological network and between cortical areas. Lin et al. [3, 4] show a detection of network-level coding units (neural assemblies) in real-time by analyzing two half seconds bins of up to 260 spiking neurons in a living animal. They can safely distinguish between three different startle events and visualize the actual network state with a one second delay, what seems too much for input synchronization. A faster response may be possible, if, instead of the spike frequencies during time bins, the precisely timed spatio-temporal

patterns of neural activity are analyzed [5]. A pattern is recurring occurrence of spikes from different or same neurons with a specific temporal delay. These recurring patterns of neural activity may represent a potential substrate of both information transfer and transformation in cortical networks. At least two major problems must be considered before using the patterns directly as a trigger signal for an external network stimulation. A number of preprocessing steps, like filtering, spike detection, spike sorting, are needed to get useful spike trains, what increase the time delay. Without the knowledge of the internal connection structure and the delays between neurons, detecting all patterns is hard because of the enormous number of possible combinations. The recorded data may not be enough to generate adequate feedback signals into the existing spatio-temporal context.

On other hand artificial biological realistic networks are fully transparent and can be controlled at anytime. Izhikevich shows that with given delays between the neurons all patterns (polychronizations) can be detected [6].

In this modeling study we have investigated some properties of a new recurrent neurointerface and show first biologically plausible simulations of two connected networks.

2 Recurrent neurointerface

The projected recurrent neurointerface connects the biological network via a multi-electrode array with an artificial network. The dynamics of both networks influence each other, and all analyzes and manipulations can be done on the transparent artificial network. The idea is the integration of an artificial network in the spatio-temporal patterns of a biological network like an additional brain section. Both networks can adapt to each other in a simulated and a biological learning process and the intrinsic calculation power of the artificial network can be used for signal processing.

Figure 1 gives an overview of the projected system. The biological network is coupled by a multi-electrode array. An electrode interface converts the electrode signals to channel signals of the artificial networks and back. The finished versions of the artificial network and the electrode interface have to run in a real time environment. In this preliminary modeling study both networks and the electrode interface are simulated.

2.1 Network simulations

To simulate the biological network and the artificial network 800 excitatory neurons and 200 inhibitory neurons were assembled on a planar area of 1 x 1 mm^2 and connected by local and distant connections. We use the neuron model by Izhikevich [7, 8] in the same configuration as in [9]

$$\dot{v} = 0.04v^2 + 5v + 140 - u - I_{syn} + I_{intr}, \tag{1}$$
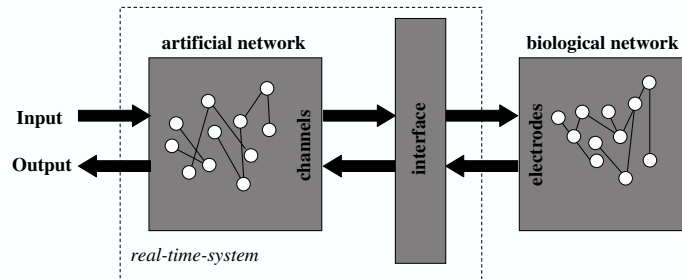$$\dot{u} = a\,(bv - u)\,. \tag{2}$$

Fig. 1: Overview of the projected neurointerface system.

Where v is the membrane potential, u is a recovery variable and a, b, c, d are the dimensionless model parameters, which allow to tune the model to different dynamics and build the two different types of neurons (see [7] for details). The intrinsic current I_{intr} is a stochastic component that drives the spontaneous activity of the neurons. If v reaches a threshold of 30 mV, a spike is generated and the variables are updated $v \leftarrow c$, $u \leftarrow u + d$.

To implement depression and facilitation, we use the dynamic synapse model by Markram et al. [10] with the parameters and modifications of [9].

The neurons were connected by statistical methods [11] with a local and a random displaced cluster of output connections from each neuron (connection parameters as in [12]). The standard integration time step is 0.1 ms and all parameters are chosen in a way that the network is balanced [13].

2.2 Multi-electrode array

To simulate the electrode array, a number of 64 electrodes (orthogonal grid 8x8) placed in an area of 500 x 500 μm in the center of the simulated biological network. Each electrode can be work as a receiver or a transmitter of signals. To approximate the complex relationship between the electrodes and the surrounding neurons, each electrode was virtually connected to a set of nearby neurons with a probability depending of the Euclidean distance (d_{en}) between electrode and neuron modulated by a Gaussian function $p_e = e^{-d_{en}/\sigma^2}$. The received signal by an electrode k was estimated by the weighted sum of the membrane potential v_i of connected neurons: $S_k = \sum w_{ik} v_i$. The weight w_{ik} is set randomly in a range of [0..1] to reflect the complex relationships of parts of the neuron to the electrode.

If the electrode works as a transmitter (send signals into the biological network), an new current source to the synaptic current I_{syn} is added to all connected neurons weighted by an individual factor (randomly set in a range of [0..1]). In our first experiments the input from a sending electrode to connected neurons is simplified as additional glutamatergic synapses with random weights.

2.3 Channels of the artificial network

The artificial network was generated and simulated with similar parameters as the biological network. However, approximating electrodes for the connections to the biological network is not necessary. We define a number of input and output channels. An input channel simulated a branched axon, which connect neurons in a displaced cluster [12].

Depending on the used method the signals from the electrodes of the simulated biological network are transmitted to one or more channels of the artificial network. The received signal of the electrode can be analyzed by a set of standard algorithms in the electrode interface. A bandpass filtering is used to reduce the noise, the spike detection tries to find the spikes of all connected neurons and a spike sorting algorithm separate the spike by the source neurons (see Fig 2). In the simulation we approximate these processing steps by a variable delay in signal transmission.

An input channel of the artificial network can be one of the following: a fast analog channel without any processing steps; a delayed multi-unit spike channel for the collected activity of several neurons by an electrode; or a number of delayed single spike channels isolated by a spike sorting algorithm (see Fig 2). Each of the preprocessing steps increases the transmission delay of the signals from the source neurons in the biological network to the destination neurons in the artificial network.

The output channels transmit the spikes from a set of neurons of the artificial network to the electrodes of the biological networks.
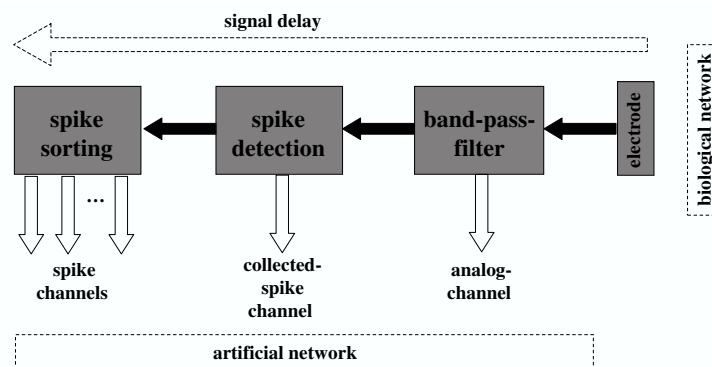
Fig. 2: Possible channels from electrode signals.

3 Results and Discussion

In a first step we establish a connection between two networks by 64 electrodes (32 in each direction) in the given configuration. Figure 3 shows the spike plot of the free running networks. The networks are weakly synchronized, mainly dur-

ing the bursting like events. The next step will be the complete implementation of the electrode interface and estimate the information transmission between the networks. That means with which probability can we distinguish different dynamics in one network after different stimulation protocols in the other network.
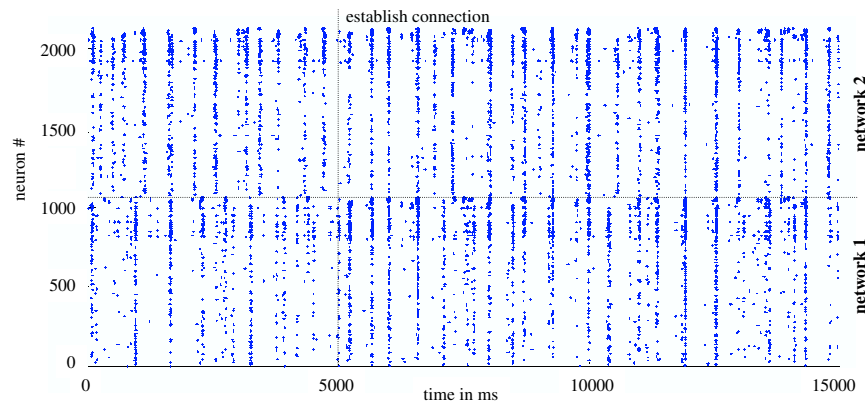

Fig. 3: Spike plot of two coupled networks (1000 neurons and 64 electrodes each). After establish the connection at 5000 ms the networks fire in weak synchronization.

One of the assumed advantages of using the artificial network in our interface is the intrinsic calculation power. The implemented balanced network is a complex dynamical system at the edge of chaos and can be considered as a reservoir in reservoir computing [14]. In this way the artificial network may work with single spike channels (after spike sorting) as well as with the undecoded analog channels. The use of the analog channels would reduce the delay and the artificial network may generate adequate feedback signals for the biological network to overcome the real-time barrier.

Both networks may adapt to each other to integrate their respective spatio-temporal contents. The biological network is expected to learn to interpret the signals from the new information source by its several self organizing mechanisms. In the artificial network, similar self-organizing mechanisms (STDP, synaptic scaling, pruning) can be implemented, and, due to the total accessibility, also supervised mechanisms can be used to adjust weights and other parameters. Moreover, due the total accessibility of the artificial network, also supervised mechanisms can be used adjust weights and other parameters.

But most importantly due the integrated feedback generation, the artificial network represents a transparent system, which be can implemented in real-time, by a fast computer or even by a neural network hardware. The signal analysis can be done by advanced algorithms (e.g. polychronizations [6]) on the transparent artificial network without requiring real-time. Additionally, external inputs can be imposed into the artificial network without destroying the spatio-temporal patterns of the biological network.

The aim of the further work is to test the assumed interaction of a small artificial network with established natural biological cultured networks growing on multi-electrode arrays [15]. The following step is to adjust the adaptation properties of the artificial network off-line with recorded data [16]. The needed hardware and software for the real time environment to connect the multi-electrode array by a break out box and an I/O card to a real time PC is in development in our lab.

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