Multi-Layer Neuromorphic Synapse for Reconfigurable Networks

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***Abstract*—In pulse-based neural networks, synaptic dynamics can have direct influence on learning of neural codes, and encoding of spatiotemporal spike patterns. In this paper, we propose an adaptive synapse circuit for increased flexibility and efficacy of signal processing units in neuromorphic structures. The synapse acts as a multi-layer computational network, and includes multi-compartment dendrites and different types of post-synaptic back propagating signals. With built-in temporal control mechanisms, the resulting reconfigurable network allows the implementation of synaptic homeostatics.**

Keywords—synapse, neuromorphic circuits, cognitive systems

I. Introduction

Advances in electrophysiology, neuroanatomical methods and molecular biology constantly exceed the technological limits, and offer access to understanding of neuronal connectivity and the brain's cognitive, computational and adaptive properties. At the microcircuit level, the non-random features of cortical connectivity, such as activity-dependent short-term (STP) and long-term plasticity (LTP), are experimentally demonstrated [1]. The brain adopts a hybrid analog-digital signal representation, i.e. the trains of pulses/spikes transmit analog information in the timing of the events, which are converted back into analog signals in the dendrites (inputs) of the neuron. Information is encoded by patterns of activity occurring over populations of neurons, and the synapses (connection to the subsequent neurons) can adapt their function depending on the pulses they receive, providing signal transmission energy-efficiency, and flexibility to store and recall of information in the brain [2]. Synaptic interactions can be efficiently realized in silicon using analog VLSI circuits [3], allowing designs that offer energy-efficient solutions to problems ranging from on-line classification of complex patterns to the real-time sensory processing. The circuits in [3] offer a wide range of trade-offs between complexity, size and functionality of temporal dynamics; however, a number of the biological plausible features of our solution are absent.

In this paper, we define a synapse learning circuit for activity adaptation, and increased flexibility and efficacy in signal processing of a given time-varying task. The synapse circuit acts as a multi-layer computational network, and includes multi-compartment dendrites and postsynaptic back propagating signals to model local and global post-synaptic influences. With built-in temporal control mechanisms, the resulting network allows the implementation of synaptic homeostatics [4], e.g. global activity dependent synaptic scaling [5], Hebbian learning [6].

II. Neuromorphic Synapse for Reconfigurable Networks

A. Dynamics of the Neuromorphic Structures

The dynamics of the integrate-and-fire neuron model (either excitatory or inhibitory) can be described by [6]

$$\frac{dv_i}{dt} = -\frac{1}{\tau_m^i}(v_i - V_L) - \sum_j g_{ij}(v_i - e_{rev}^i) \qquad (1)$$

where v_i is the membrane potential of neuron i, $\tau_m{}^i$ its time constant, V_L is the leak potential, g_{ij} is the maximal synaptic conductance for synaptic connection between neuron j to neuron i, and e_{rev} is the synaptic reversal potential (30 mV). The second term on the right hand side of (1) represents the current across the membrane due to the synaptic connections between neurons, and is triggered by the arrival of external spikes. The postsynaptic input consist of a current source ($g_{ij}e_{rev}$) and a conductance (g_{ij}), which defines the current flow through ionotropic receptors (ionic ligand-gated membrane channels), e.g. AMPA channels, and the current through ligand-gated synaptic channels, similar to excitatory and inhibitory synapses.

When excitatory-postsynaptic potentials (EPSPs) generated by neuron j arrive at the input of pre-synaptic neuron i, each of the conductances g_{ij} with i=1, …N, i≠j is modified by w_{ij}, i.e. weight, synaptic conductance [7], as the trigger for changes in synaptic plasticity. The weight is directly linked to the computational role it performs, e.g. to classify sensory stimuli, to optimize the encoding of sensory information [8]. The synaptic conductance (both excitatory and inhibitory) normalized by the membrane capacitance follow differential equation model

$$\frac{dg_{ij}}{dt} = -\frac{g_{ij}}{\tau_s} + \sum_j w_{ij} \sum_{t_{ij}<t} \delta(t - t_{ij}) \qquad (2)$$

for a single exponential decay ($e^{-[t-tij)/\tau s]}$), where τ_s is synaptic time constant (kinetics is estimated from electrophysiological data, τ_s~150 ms for NMDA and τ_s~2-3 ms for AMPA receptors, respectively [9]), $\delta(t)$ is the delta function, and t_{ij} represents the time at which spikes arrive at the synapse, i.e. the delay of presynaptic input from the j-th neuron. The number of exponentials could be further increased to obtain even more accurate synaptic conductance model, however, the computational costs in the case of a single exponential decay is only in the order of the number of neurons, i.e. comparable to the cost of merely updating the neuron's membrane potentials.

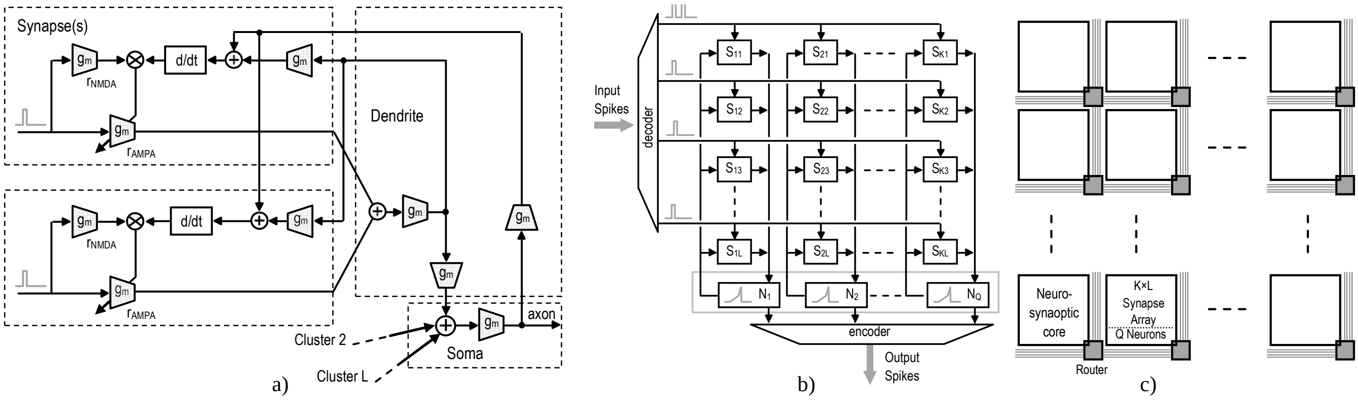

Figure 1: a) Conceptual diagram of the neuromorphic synapse, and a dendrite (input) and an axon soma (output) of a biological neuron, b) Internal blocks of the neuromorphic core with dedicated synapse, c) High-level architecture for learning systems with an array of neuromorphic cores.

Sensory events imprint data traces at the synaptic level, i.e. through changes in the synaptic weight with Hebbian co-activation of the presynaptic and postsynaptic neuron (triggering long-term potentiation or long-term depression). Synaptic weight induced by Hebbian co-activation deteriorate unless it is consolidated [10]. In [11], the initial trace of synaptic plasticity sets a tag at the synapse, functioning as a marker for potential consolidation of the changes in synaptic efficacy. Conceptually, the synaptic tag represents, both, the suitability of particular synapses for consolidation, and the functional unit that captures plasticity-related products. Consolidation entails the transmission of information through a write process. The three variables, which implement the write protection mechanism; weight w_{ij} and of two hidden variables, the tag η_{ij} and the scaffold z_{ij}, are coupled to its nearest neighbour(s) via time-dependent gating variables

$$\begin{aligned}
\frac{dw_{ij}}{dt} &= \frac{1}{\tau_w} f(w_{ij}) + \frac{\alpha_{\eta w}}{4\tau_w} \overline{g_{ij}}(t)(\eta_{ij} - w_{ij}) + \sigma\xi_{ij}^{w}(t) + I_{ij}^{w} \\
\frac{d\eta_{ij}}{dt} &= \frac{1}{\tau_\eta} f(\eta_{ij}) + \frac{\alpha_{w\eta}}{4\tau_\eta} g_{ij}(t)(w_{ij} - \eta_{ij}) + \frac{\alpha_{z\eta}}{4\tau_\eta} \overline{p_i}(t)(z_{ij} - \eta_{ij}) + \sigma\xi_{ij}^{\eta}(t) \quad (3) \\
\frac{dz_{ij}}{dt} &= \frac{1}{\tau_z} f(z_{ij}) + \frac{\alpha_{\eta z}}{4\tau_z} p_i(t)(\eta_{ij} - z_{ij}) + \sigma\xi_{ij}^{z}(t)
\end{aligned}$$

where I_w is the external input, $\xi_i(t)$ are independent Gaussian white noise processes with the properties $\langle\xi(t)\rangle=0$ and $\langle\xi(t)\xi(t')\rangle=\delta(t-t')$, $\alpha_{\eta w}$, $\alpha_{w\eta}$, $\alpha_{z\eta}$, $\alpha_{\eta z}$, are the coupling parameter terms, which determine the strength of the interactions between the variables, and $f(.)$ is the function, which models bistable dynamics. The different variables are coupled to each other through two functions g and p acting as gating variables [12]. The write protection of tagging-related variable and the scaffold is set if g=0, and p=0, respectively.

B. *Neuromorphic Networks in Neural Spike Classification*

We use spike based learning to optimize the classifier, i.e. the neurons that perform classification are equivalent to hyperplanes tuned by local spike timing dependent plasticity. For each time t, we consider the decision function

$$f_i(t) = \sum_i w_i \sum_i K_x(t - t_{ij}) = \langle w, \Phi_x(t) \rangle \qquad (4)$$

Classification of new instances for one-versus-all case is completed with a winner-takes all scheme, which suggests that the neurons inhibit each other having only one winner, i.e. the classifier with the highest output function assigns the class.

The kernel function $K_{x\in\{1,2,3\}}(t-t_{ij})$ includes both pre- and postsynaptic factors (with single, an alpha-function or double *exp* precision, respectively)

$$\begin{aligned}
K_1(t-t_{ij}) &= \kappa_0[\exp(-(t-t_{ij})/\tau_s)] \\
K_2(t-t_{ij}) &= \kappa_0[(t-t_{ij})/\tau_s)\exp(1-(t-t_{ij})/\tau_s)] \qquad (5) \\
K_3(t-t_{ij}) &= \kappa_0[\exp(-(t-t_{ij})/\tau_f) - \exp(-(t-t_{ij})/\tau_r)]
\end{aligned}$$

where κ_0 is the normalization constant, and τ_f and τ_r are the fall and rise time constants, respectively. To extend the classifier to cases in which the data are not linearly separable, we minimize

$$\min_w \varepsilon = \min_w \{\lambda \| w \|^2 + \frac{1}{n}\sum_{j=1}^{n} \max[0, 1 - y_j \langle w, \Phi_x(t) \rangle]\} \qquad (6)$$

where parameter λ regulates margin size, y_i=sgn($f_i(t)$), and the constraints of the weight-vectors $w_j^{H} w_i=0$ if $i\neq j$, $w_i^{H} w_i=1$. Since learning is online, the weight adaptation is performed every time when an input is offered to the system [13]

$$-\left.\frac{\partial\varepsilon}{\partial w}\right|_{t_j} = \begin{cases} -w + \eta y_j \Phi_x(t)/n & \text{if } y_j(f_1(t) - f_2(t)) \leq 1 \\ -w & \text{otherwise} \end{cases} \qquad (7)$$

where η is a learning rate, i.e. the extent of synaptic change, and $\Phi_x(t)$ generally accounts for activity dependent plasticity. The connectivity structure and connection weights of neural networks are highly nonrandom; the amplitudes of EPSPs between neurons are distributed as lognormal [8], suggesting that some synapses are more effective in propagating spikes (note that delays follow Gaussian distribution). In the Hebbian theory, if a neuron j connects to neuron i with w_{ij}, and both neurons are active simultaneously, the synaptic conductance between neurons j and i is reinforced. Consequently, a vector proportional to $\Phi_x(t_i)$ is added (potentiating, excitatory) to or subtracted (depressing, inhibitory) from w of the active output neuron if the output is correct or incorrect, respectively [13].

C. *Implementation Details*

Reconfigurable neuromorphic networks, typically, consist of the circuits that contain only partially dendritic properties. However, increased experimental evidence indicates presence of a wide range of dendritic channels [14]-[15] that modify synaptic response in multiple ways, e.g. through amplification, regulation, detection of coincident inputs, the dendritic structure scaling.

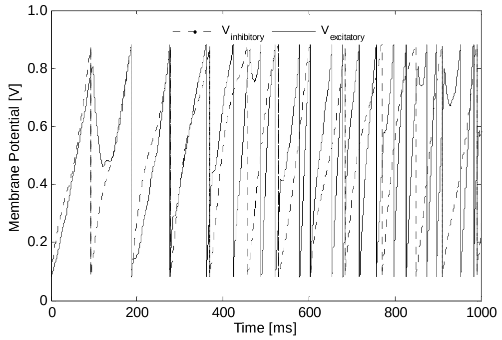

Figure 2: Membrane potential dynamics for inhibitory and excitatory synapse.

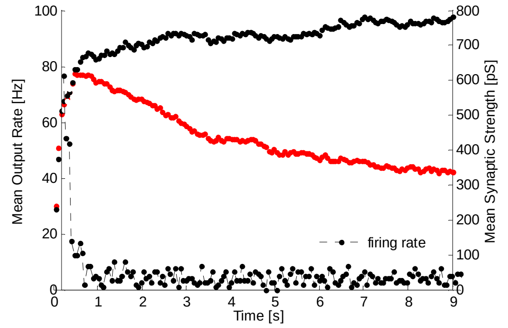

Figure 3: Average synaptic weights of the inhibitory synapses and temporal evaluation of firing rate.

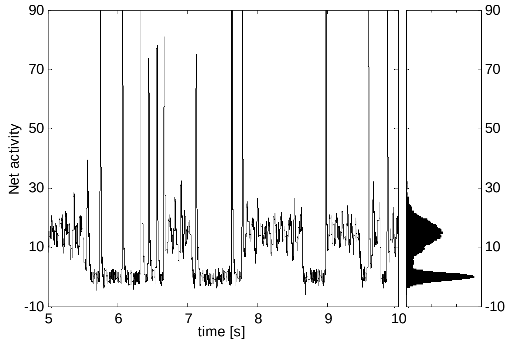

Figure 4: Net activity of the network.

Consequently, a synaptic circuit can be much more computationally effective than just as a simple point processing unit [15]. Implemented synapse circuit [16] (Fig. 1a) acts as a multi-layer computational system and offer infrastructure for (unsupervised) spike-based learning [15]-[18]. The circuit includes multi-compartment dendrites and different types of postsynaptic back-propagating signals. The changes in synaptic morphology lead to modifications of receptor content, affecting synaptic dynamics and efficacy, and consequently, lead to alterations in network signal processing capabilities. The effective synaptic conductance efficacy is determined by both presynaptic (depression and facilitation) and postsynaptic factors. At the circuit input, two receptors are available. NMDA receptor, which acts as the pre-synaptic part, generates stable persistent spikes, and offers activity-dependent modifications of synaptic conductance. AMPA receptor mediates a fast glutamatergic synaptic current to drive the soma.

In the post-synaptic part, the temporal summation of a back propagating spikes, i.e. dendrite [19] and soma [20] spikes, respectively, is completed. The transconductance amplifiers have an enable/disable capability for power-efficient operation. The presynaptic spike is connected to the enable control terminal of the amplifier and leads to an EPSP. Temporal summation of EPSPs initiates a dendritic spike. If groups (bursts) of dendritic spikes are sufficiently strong to drive the soma, the neuron will generate action potentials. Resulting spike is back propagated into the dendrite. The back propagated dendrite and soma signals are multiplied and added to NMDA receptor signals to form the weight control signal. Repeating units form a neuromorphic core (Fig. 1b) for a learning network (Fig. 1c). Each core is composed of an input decoder that connects $K \times L$ programmable synapses to Q integrate-and-fire neurons, and the I/O network communication layer. Each core has a local router, which communicates to the routers of other cores through a dedicated real-time reconfigurable network-on-chip .

The real-time synaptic dynamics is reproduced by utilizing arrays of pulse/spike integrators. The log domain integrator [15] circuit models slow NMDA receptor-mediated currents. The circuit operates in subthreshold region and offers low area and linear filtering properties. The spike lengths of fast AMPA mediated current, are, however, too short to inject sufficient charge in the postsynaptic neuron membrane capacitor. The differential pair integrator circuit [4], amplify the signal, and subsequently, it generates adequate charge to be sourced into the neuron's integrating capacitor. The integrator translates fast presynaptic pulses into long-lasting postsynaptic currents while preserving temporal dynamics. Additionally, the integrator offers the means to multiplex time spikes, and it provides tunable gain independent from the (tunable) time constant. The transconductance amplifier implemented in the synapse is a typical differential pair amplifier with three current mirrors and enable/disable capability. To save the power, the circuits are during normal operation mainly in the disabled mode. A utilized hysteretic differentiator circuit with an exponential resistive element offers large range of the time-constants of the feedback loop (over several orders of magnitude).

III. Experimental Results

In network simulations, we initialize the excitatory synaptic weight matrices to uniform values. The values used are typical for neuromorphic and biomedical applications [4]. External input is then applied to the network with learning rule mediating synaptic plasticity. Both excitatory and inhibitory synapse response properties, when stimulated by a constant injection current, are illustrated in Fig. 2. The small bumps exemplify the postsynaptic potentials generated by the synapse as a reaction to the presynaptic input spikes. Fig. 3 illustrate temporal evolution of the postsynaptic firing rate and the average synaptic weights of the inhibitory synapses, i.e. a weight decrease, (or depression), when a spike at presynaptic input follows a spike at post-synaptic input, and a weight increase, (or potentiation), when a spike at post-synaptic input follows a spike at presynaptic input. Fig. 4 illustrates both, a several activity ranges due to the synchronous firing, and consequently, a mean network activity histogram.

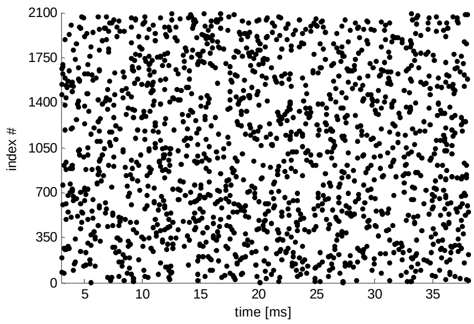

Figure 5: Asynchronous irregular regime in the network (with fast synaptic rise time.

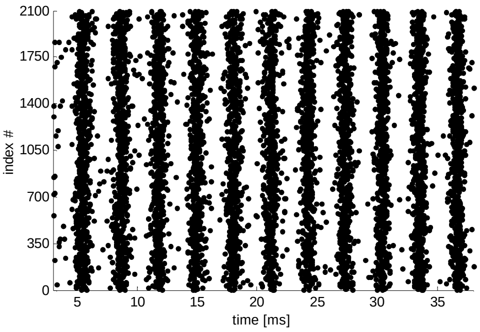

Figure 6: Synchrony in the network (with slow synaptic rise time).

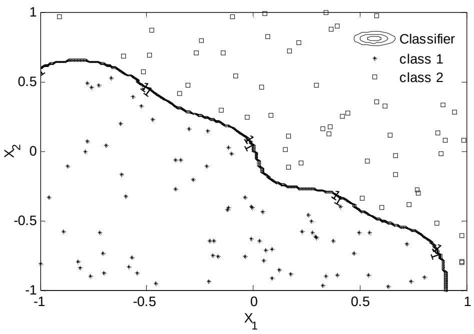

Figure 7: The separation hypersurface - two classes graphical representation example; bold line represent decision boundaries.

Synchrony of a reconfigurable network consisting of 64 neurons and 2048 synapses (32 per neuron) is illustrated in Fig. 5 and Fig. 6. When synchronized at 300 Hz, the network receive approximately 600k events per second, and transmit 18.75k events/s. The stimulation leads to an increase in synchrony and more correlated dynamics, i.e. the phase locking between stimulated neurons drives them in-phase with each other by the back propagating signals. The neuron is more sensitive to the neurotransmitter release variability in a weak synapse than in a strong synapse; increasing the frequency of the test stimulus during constant background activity generates a stronger depression. The information encoded in the spike trains is classified with a reconfigurable learning network as illustrated in Fig. 7, where the bold line represents the decision boundary. The classifier test dataset is based on recordings from the human neocortex and basal ganglia. An asymptotic classification success rate of ~ 97 % is obtained over the entire dataset.

IV. CONCLUSIONS

In this paper, we propose a self-learning neuromorphic synapse for reconfigurable networks. The synapse includes multi-compartment dendrite and postsynaptic back propagating signals to model local and global post-synaptic influences. With built-in temporal control mechanisms, the resulting network allows the implementation of synaptic homeostatics. Reconfigurable network based on the proposed synapse obtains an asymptotic classification success rate of ~ 97 % over the entire dataset.

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