Building Large Networks of Biological Neurons

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***Abstract*— We envision the building of many realistic cortical neurons on a single Integrated Ciruit (IC). This goal requires efficiently utilizing the similarilities between silicon and biological physics. We present recent results building Silicon models of biological channel utilizing the physics connections to MOSFET devices and the gating effect modulating its channel. Using this approach, we present recent results on voltage-clamp measurements for Silicon Sodium and Potassium Channels, biologically realistic action potentials from these channels, models of programmable and learning synapses with biological responses, and active models of dendritic cables. These results, combined with recent advances in reconfigurable analog IC approaches, currently allows the detailed implementation of a pyramidal cell in a few mm^2 in 0.35μm CMOS. Using modern CMOS processes, one could envision 1000s of realistic neurons on an IC with millions of state variables (computing nodes) on a single IC, accelerating the day we can build synthetic systems to represent significant cortical regions.**

I. Building Biological Networks on ICs

The authors envision the building of many realistic cortical neurons on a single Integrated Ciruit (IC) (Fig. 1a). This goal requires efficiently utilizing the similarilities between silicon and biological physics. Figure 1b-d shows some of the similarities between biological channel populations (Fig. 1b), which we refer as channels throughout, and MOSFET channel populations (Fig. 1c). In both cases, we have a gate modulating the channel between two electrical points, that is inside to outside for the biological channels and source to drain for the MOSFET channel (Fig. 1d). The fundamental forces causing ion flow in biology are the same fundamental forces causing electron flow in a MOSFET operating with low currents [2], [3]. In the following sections, We will use this approach to efficiently build up the components needed for realistic cortical neurons on a single IC requiring similar area to biological cells.

II. Transistor Channels / Biological Channels

Biological Channel measurements and modeling originates from the pioneering work of Hodgkin and Huxley [4] that not only measured the electrical properties, but developed empirical equations that predicted current-voltage relationships of several channel population types. Our approach revisits channel modeling by starting with common physics between MOSFET channels and biological channels, and developing circuit modeling for the resulting gating function required in these devices [3]. Figure 2a,b shows the transitor channels and resulting gating function model for the Sodium (Na) and Potassium (K) channels. As seen by the measured data,

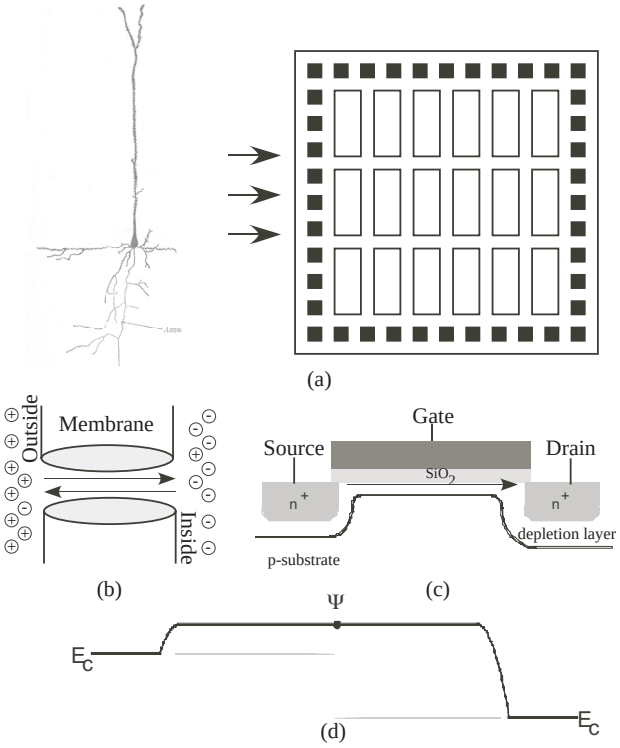

Fig. 1. Building networks of neurons in silicon. (a) Our goal is to make ICs with the key computational features of Si neurons (i.e. pryamidal cells). The key to building this bridge is utilizing all of the Si physics to model key biological physics, starting at the level of channels. Figure adapted from [1]. (b) Cross-Section of a Biological channel, with ions moving through the channel. (c) Cross-Section of a MOSFET with electrons moving through the channel. (d) Band Diagram looking through the channel of the MOSFET. A similar Band Diagram is seen looking through a Biological Channel.

a Na channel and gating function behaves like a bandpass filter (Fig.2c), and a K channel and gating function behaves like a lowpass filter (Fig.2d). Figure 2e shows a resulting action potential expected when making an input current step to membrane voltage for a neuron circuit comprising an Na channel and a K channel. The resulting circuit requires six transistors, roughly the area of a static digital memory cell, which is significantly smaller than systems emulating model equations [5], while also closely modeling biological physics. Because we utilize the similarilites betwee biological and silicon channels, the voltage difference between the Na and K resting potentials on the silicon implemention is roughly 150mV, similar to the biological power supplies. Because the W/L ratio of the transistor channels are 1500, the resulting

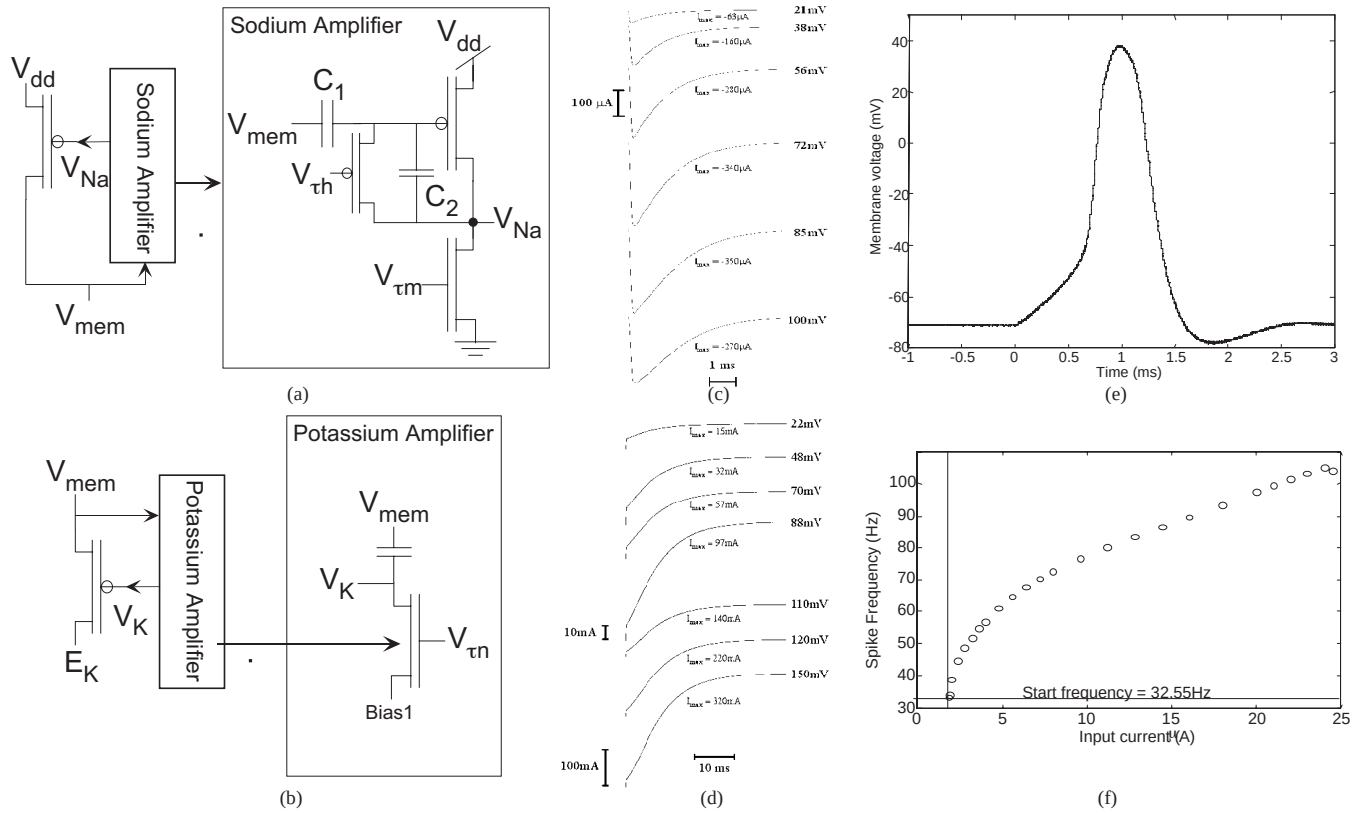

Fig. 2. Transistor Channels that model Biological channels. We show data from IC devices, which look very close to experimental biological data. (a) Circuit diagram for the Na Channel and resulting (bandpass) gating function. (b) Circuit diagram for the K Channel and resulting (lowpass) gating function. (c) Voltage step response for the transistor Na (or bandpass) channel. (d) Voltage step response for the transistor K (or lowpass) channel. (e) An action potential generated by these active channels. The action potential is a stereotyped waveform present in the neurons of all species of animals. The currents generated by these circuits interact with each other on the membrane capacitor (C_{mem}) to generate an action potential. (f) Spiking frequency for a range of constant current input steps to the neuron membrane.

measured currents are in the muA range. Smaller W/L ratios, similar in dimensions to biological channel populations, result in stimulation currents of nA to pA for similar effects.

III. Building Neurons from Transistor Channels

Figure 3 shows the necessary elements needed to build channel models into full neurons: synapses and active dendrite cables.

A. Channel Models of Synapses

We developed a family of analog VLSI synapses that includes three types of biological synapses: ACh-excitatory, NMDA-excitatory, and inhibitory synapses citekn: . Here, an electrical response in the first (pre-synaptic) cell causes chemicals to leave and be deposited into the second (post-synaptic) cell. These chemicals, called neurotransmitters, then cause an electrical response in the second cell [6], [7], [8]. These synapses reproduce EPSPs and IPSPs similar to what is found in biology [9], as well as can adapt based on Long-Term Potentiation (LTP) and Long-Term Depression (LTD) learning rules. The storage and adaptation results from using programmable and adaptive floating-gate circuits. We use floating-gate circuit approach for these synapses, as well as the other compoents of the neuron models. We originally developed floating-gate devices to efficiently build single-transistor learning synapses [10], but the floating-gate circuit technology has expanded to allow ICs with simultanious non-volitile analog storage [11], programmable transistors [12], programmable and adaptive signal processing (e.g. [13], [14]), and reconfigurable analog approaches [15].

Figure 3a shows the viewpoint for transistor channel implementation for biological synapses. Our silicon synapse has been highlighted in red to illustrate how it functionally relates to the biological synapse. Figure 3b shows experimental output for an excitatory synapse, including the gating function for the Ca synapse channels. Thousands of these synapses can be implemented per mm^2 For the NMDA-excitatory synapse, we add additional circuit feedback to the basic excitatory synapse to model the gating of the synapse by both the type of neurotransmitter present and the voltage across the cell membrane. in a 0.35μ CMOS process.

B. Channel Models of Active Dendrites

Dendrites are frequently thought of as the wiring between the input synapses and action-potential generating somai at the output. With thousands of state variables in each dendrite, the potential for large-scale computation in the dendrites is significant, as well as significantly more energy efficient per

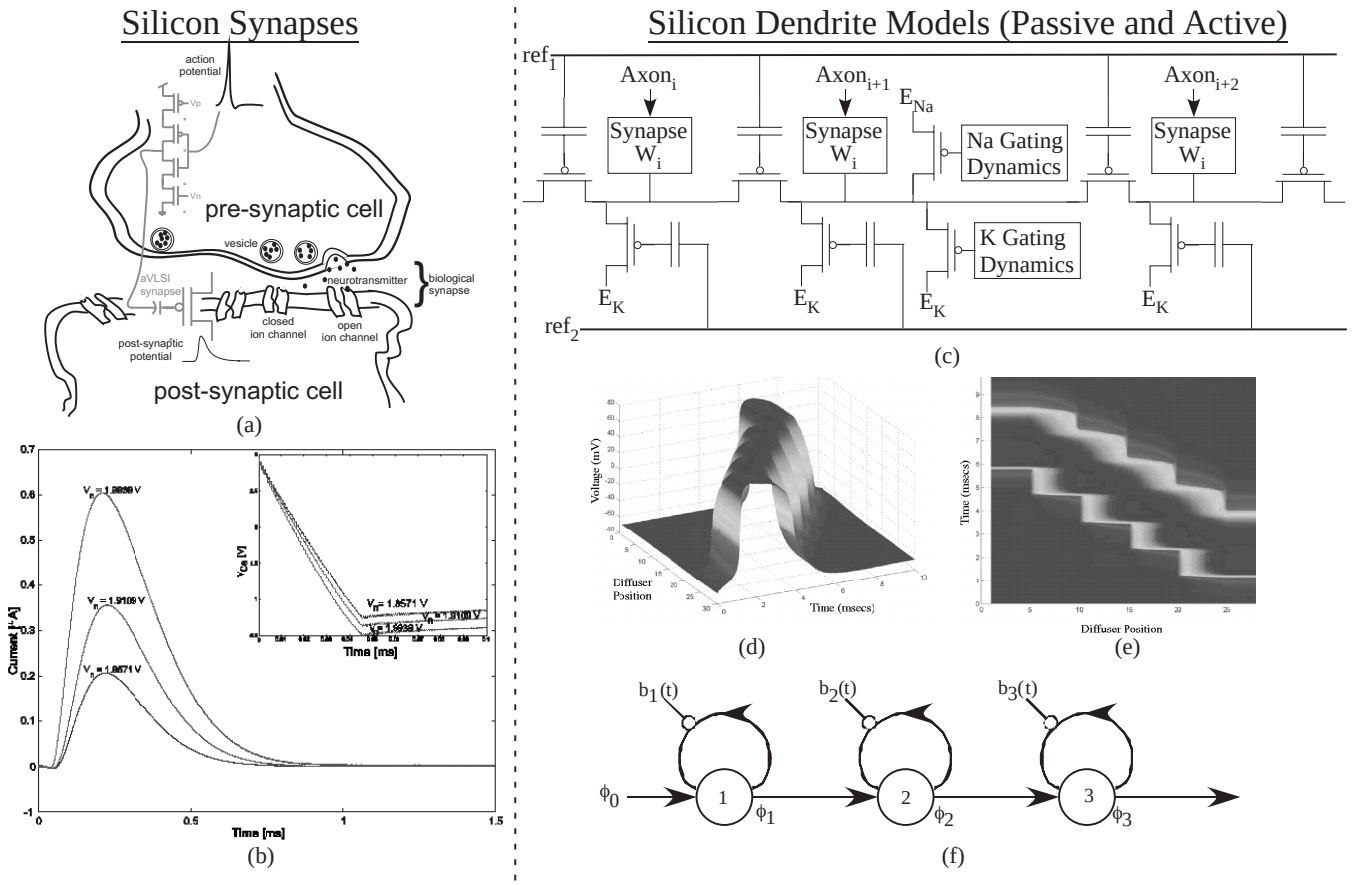

Fig. 3. Demonstration of the required IC modeling of dendrites and synapses, based on transistor channel modeling, required for building detailed neuron models. (a) The biological synapse is the main communication port for the nervous system. Our silicon synapse has been highlighted in red to illustrate how it functionally relates to the biological synapse. (b) Measurement results for an excitatory synapse. We show both the results of the current output of the synapse as well as the output going into the floating-gate capacitor that corresponds the the gating of the post-synaptic Ca channels. The charge stored on the floating-gate can be programmed to emulate the actual weight of the synapse, and can be adapted based along biological LTP and LTD learning rules. (c) Circuit schematic for an active dendrite. (d) Dendrite measurement for a 1 by 30 array of dendrite segments. Active nodes have been placed at every 5th node. A stimulus is applied at node 30. The axial conductances are programmed to be equal. (e) Top view of the same date measurement. The action potential propagates from one node to the next. Since it takes more time to charge an active node, there is a 'd2step like'd3 appearance to this figure. (f) The computation in a dendrite cable corresponds to Hidden Markov Model (HMM) classifier chain.

computation than the transmission of action potentials. Our recent results show a similarity between a dendritic cable and an HMM classifier branch, as well as between a network of neurons with significant dendrites and an HMM classifier [16]. Our current hypothesis that the computation in the dendrites is at least as critical as the computations by the soma and synapses.

Figure 3c shows the extension of the transistor channel approach to building active dendrite models. Ions in a dendrite are able to diffuse either across the membrane, or axially along the length of the dendrite. Since diffusion is the macro-transport method of ion flow here, sub-threshold MOSFET transistors are being used to model the conductances seen along and across the membranes. The resulting single dimensional circuit looks very similar to the diffuser circuit described in citekwabena. The *conductances* of each of the MOSFETs can be individually programmed to the desired neuron properties. Figure 3d,e show results from an active dendrite model showing action potential generation down a cable of uniform diameter with active channels every 5 segments. These active models can be rigorously connected to the wave propagation mechanism in passive and active dendrites (Fig. 3f).

IV. Field Programmable Neural Arrays (FPNA)

To move towards a single complex neuron, like a pryamidal cell from Cortex, and then to networks of these cells, we need a mechanism to configure (and eventually grow) each of these cells in silicon because each neuron is different with potentially complex dendritic configurations. We leverage recent work in Large-Scale Field Programmable Analog Arrays (FPAA), devices similar in complexity and function to FPGAs with nearly the power efficiency of custom analog functions, that utilizes programmable analog devices for switching and routing elements [15]. The resulting structure, which we call a Field-Programmable Neural Array (FPNA), which comprises of analog blocks that are geared towards building neuro-inspired and neuro-mimetic systems. This structure is can be used to for complex cell models (i.e. pryamidal cell)

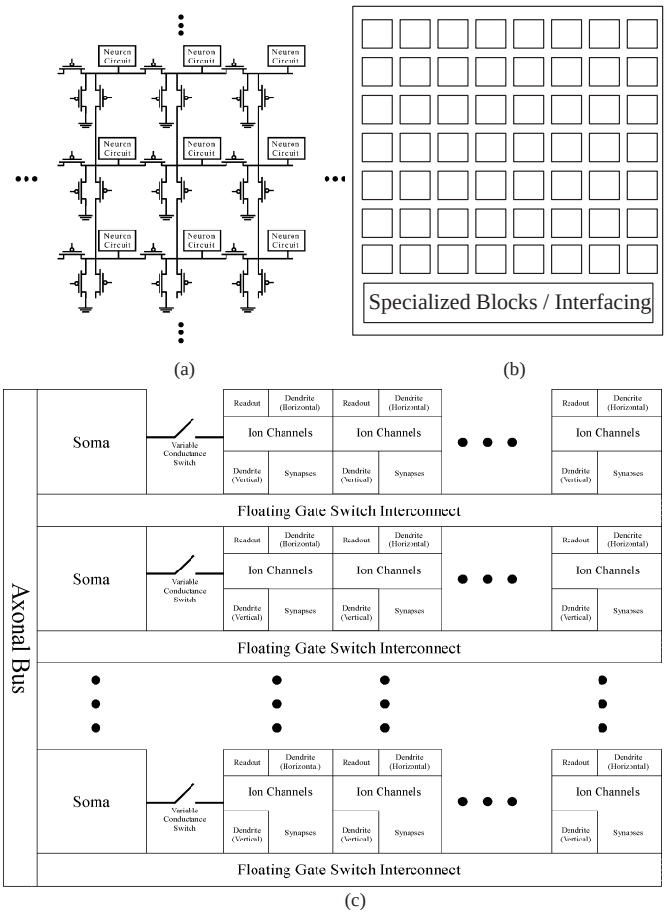

Fig. 4. Field Programmable Neural Array (FPNA): A reconfigurable network of transistor elements, and synapse elements connected through dendritic connections. Therefore, full utilization of this IC is possible. (a) The basic routing architecture, based upon two-dimensional programmable interconnect structures. In addition to active channels, we have a leak transistor channel at every node. (b) The routing architecuture can be generalized to a reconfigurable architecture, including specialized computing blocks, interfacing blocks, and other computational fabrics. (c) Architecture for our first FPNA ICs. The output of each row is sent to the soma block. The soma creates the triangle shaped waveform used in the synapse circuit and is similar to biological data [7]. This output, along with external inputs, are sent to other areas of the circuit depending on the arrangement of switches in the floating gate switch network. This switching scheme allows for full connectivity throughout the matrix. As the system size grows, more advanced axonal routing schemes will be required.

by configuring small sections of the cell in each subblock, small central pattern generator networks by connecting a few approximate models of neurons, or large neuronal networks by connecting hundreds of the individual blocks.

Figure 4 shows a basic reconfigurable fabric based on extending the dendritic model to a programmable two-dimensional matrix. Using this 2D interconnection, one can program a wide range of dendritic morphologies utilizing nearest neighbor interconnects. Active channels are also present at every node. By programming the gate voltage on the diffusive / leak transistors one can vary the conductance through that transistor. This architecture can be generalized into a reconfigurable device (Fig. 4), based upon other analog reconfigurable techniques [15].

Our current FPNA IC is composed of two primary operational section as well as some supporting structures (Fig. 4) [17]. The first operational part is the dendrite matrix. Each node of the dendrite is connected to its neighbors on the left, right, above, and below through programmable analog devices. By controlling the conductance through this transistor, the different dendritic topologies can be approximated. Each node in the dendrite contains the simple dendrite previously discussed, the two active channels, one inhibitory synapse, and one excitatory synapse element. Our recent FPNA generation can achieve over 12K connections. These results, combined with recent advances in reconfigurable analog IC approaches, currently allows the detailed implementation of a pyramidal cell in a few mm^2 in 0.35μm CMOS.

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