33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

# Towards Neuro-Silicon Interface Using Reconfigurable Dynamic Clamping

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*Abstract*— **Dynamic clamp emerges as an important apparatus to study the intrinsic neuronal properties through close-loop interactions between models and biological neurons. Modelling large-scale neuronal networks in software will result in significant computational delay that becomes a bottleneck to apply dynamic clamp for more complicated systems. In this paper, we present a real-time dynamic clamping system based on field programmable gate arrays (FPGAs) to accelerate the necessary computations. It also provides a flexible platform to reconfigure various model parameters and topologies. Real-time neuronal and synaptic models were implemented in FPGA, and interconnected with the stomatograstric ganglion (STG) nervous system to exemplify the real-time dynamics. Results show that our method can be effectively configured to mimic various biological neural networks and is two orders of magnitude faster than software approach using desktop computer.**

## I. Introduction

Dynamic clamping is a novel technique that bridges the communication gap between neurological and artificial systems. Using this technique, biological neurons and computational models can form a close-loop network, and leads to a wide range of applications and neuroscience research methods [1]. By realizing different neuronal models, the biological systems that to be studied can be modulated or reconfigured in such closed-loop, such as synaptic strengths, intrinsic properties of single neurons and wirings. This technique can also lead to future cyborg systems that consist of components of both biological and silicon elements.

Realization of dynamic clamping is challenging. It requires both fine experimental physiology skills and artificial models with sufficiently high accuracy and ample computational speed. In term of physiological techniques, both intra- and extra-cellular recording are essential to identify neuron in nervous systems and required special physiological techniques include micro-dissection and ultra-fine and precise manipulation of micro-electrodes. On the other hand, it is important to have high-speed artificial neuronal model to catch up with biological neural dynamics. For example, computational model updating frequency must be faster than the smallest time constant of biological neurons. Also, a wide range of fidelity and high accuracy are required to support different experimental requirements

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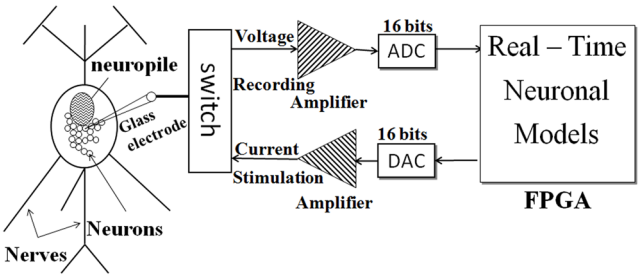


Fig. 1. FPGA based dynamic clamp system.

Field-programmable gate arrays (FPGAs) provides a real-time computational platform to implement complex neuronal models [2]. Abundance logics and interconnect fabrics are available to construct various neuronal models and, more importantly, the capability of reconfigurable enables variation of models to capture and interact with the biological neurons dynamically.

In this paper, we present a framework that leads to build dynamic clamping systems using FPGAs. The stomatograstric ganglion (STG) nervous system of crabs [6] is employed to exemplify the physiological techniques and implementation of computational model in FPGAs. This approach leads to future neuron-silicon closed-loop systems for brain-machine interface and neuron-rehabilitation.

## II. The dynamic clamp system

Dynamic clamp system [1] consists of two main parts. One is the biological nervous systems and the other one is a computational neuronal model. Fig. 1 shows an example of a basic configuration of a dynamic clamp system for stomastograstric ganglion (STG) nervous system of crabs. This close-loop system runs under recording mode and stimulation mode separately. The cell membrane potentials are recorded by glass electrodes and are regarded as inputs into the computational model. The computational model is able to compute the feedback current and injects to the recording cells. Since the current updating time is very short, usually in milliseconds, high-speed computational systems are required for the necessary modelling. FPGAs provide high computing speed and updating frequency, thus, the device is suitable as computational model to exhibit real-time and scalable solutions.

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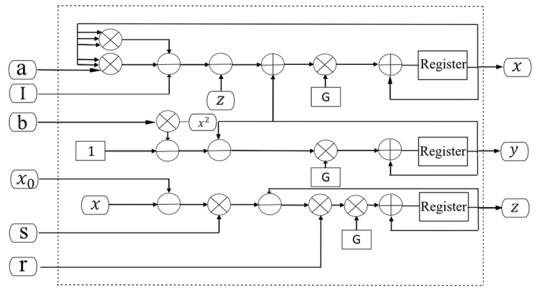


Fig. 2. Datapath diagram of HR model.

## III. Hardware architecture of neruonal models

### A. Neuronal model

Hindmarsh - Rose (HR) model is adopted in our system due to its simplicity[3]. Alternative models could be employed to improve the model complexity and accuracy. In this model, three coupled first order differential equations are used to represent neuronal action potential. These three equations were originally developed for isolated triggered bursts, and later improved to explain more general phenomenon of burst pattern discharge [3]. Several main characteristics, such as adaption, burst generation, random burst structure and post inhibitory rebound can be represent in this model.

$$\frac{d}{dx}x = (-x^3 + a * x^2 + y + I - z)G \tag{1}$$

$$\frac{d}{dy}y = (1 - b * x^2 - y)G \tag{2}$$

$$\frac{d}{dz}z = (r(s(x - x_0) - z))G \tag{3}$$

Data path diagram of HR model is shown in Fig. 2.Sampling rate, G, is introduced to meet the requirements of sampling frequency in hardware. Reconfigure ability of this model is achieved by varying phase plane according to different combinations of input values. As a result, we could generate three typical neuron states and specific burst patterns.

### B. Synaptic model

Synaptic model exerts an indispensable effect on overall system results in dynamic clamp system. Both electrical and chemical synapses exist in STG and many other nervous systems. For electrical synapse, it can be modelled by resistances to capture gap junction behaviours that are both bidirectional signal transfer and synchronization. In most of nerves systems, chemical synapses are key communication unit for neurons. In line with [4], we employed a synaptic model:

$$I_c = G_c S(t)(X_{rev} - X_{post}) \tag{4}$$

$$(1 - S_\infty)\tau_s \frac{d}{dt}S(t) = (S_\infty - S(t)) \tag{5}$$

$$S_\infty(X_{pre}) = \tanh \frac{X_{pre} - X_{th}}{X_{slope}} \tag{6}$$

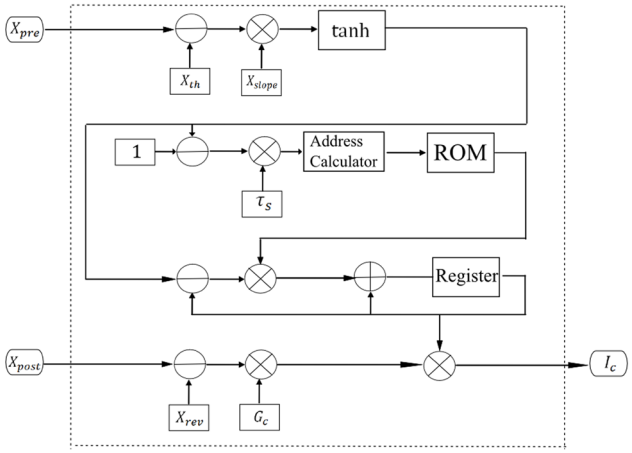


Fig. 3. Datapath diagram of chemical synapse.

Data path diagram is shown in Fig. 3. Different behaviours are mathematically embedded in equations. Eq. (4): synaptic output $I_c$ are decided by reversal potential $X_{rev}$, postsynaptic potential $X_{post}$, synaptic conductance $G_c$ and instantaneous synaptic activation $S(t)$; Eq. (5): the relationship between instantaneous synaptic activation $S(t)$ and steady-state synaptic activation $S_\infty$; Eq.(6): steady-state synaptic activation $S_\infty$ is depended on presynaptic potential $X_{pre}$, synaptic threshold voltage $X_{th}$ and synaptic slope voltage $X_{slope}$.

The divider circuit is realized using look up table with a proper addressing scheme.It could decrease computation delay apparently compare to divider algorithm.Integration circuit is achieved by adder and register. Every synaptic parameter could as an input in this circuit to satisfied diverse experiment targets.

### C. Neuronal Network

Neuronal networks with different topologies can be implemented on FPGA. The STG is taken as an example, as shown in Fig. 4. 12 different neurons are configured through using different parameters of the HR model. Electrical and chemical synapses are involved. Various chemical synapses can be achieved by varying parameters. According to the interconnections of STG, neuronal models and synapse models are connected to form a FPGA based STG.

## IV. Experiment and results

### A. Experimental Preparation

Adult Cancer pagurus L. were stuffing in ice for half an hour for anesthetizing. Then we detached the stomatogastric nervous system (STNS) and pined down in a silicone elastomer - lined petri dish with chilled saline (10 -13°C). For extracellular recordings, a petroleum jelly-based cylindrical compartment was built around a part of the nerve to electrically isolate STNS nerves from the bath. One steel electrode was placed in this compartment while the other one placed in the bath as a reference point. An AC differential amplifier (Univ. Kaiserslautern, Germany) was used

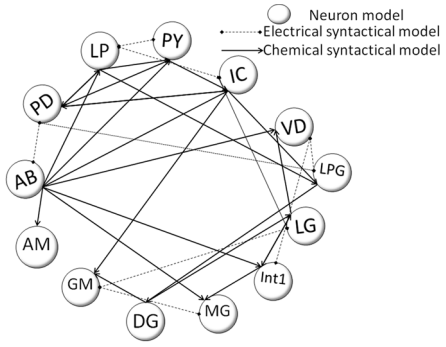


Fig. 4. An example of reconfigurable neural network based on the real crab STG network. The STG consists of 13 different kinds of neurons, which are labeled on the cells. Four different synaptic states (active, inactive, strengthen and weaken) could be switched in real time.

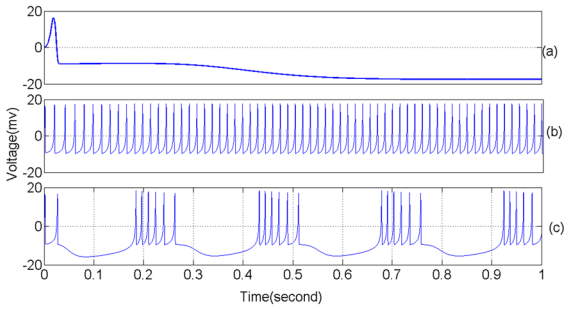


Fig. 5. Three states of HR model: (a) silence; (b) slow wave; (c) burst patterns

for amplifying and recording. For intracellular recordings, first we desheathed the STG to inject the glass electrodes (GB 100TF-8P, Science Products, Hofheim, Germany; 25-40Mohm). A BA 01X Amplifier (NPI, Tamm, Germany) was used for signal amplifying. Files were then converted and analysed using Spike 2 v6.10 (Cambridge Electronic Design, Cambridge, UK).

For hardware design, we use Xilinx System Generator [5] to design neuronal models. The targeting device is Xinlinx Virtex4 xc4vsx35-10ff668.

### B. Cell Behaviours

By changing the parameter $x_0$, three different model states can be achieved, as shown in Fig. 5, which are silence state, slow wave states and burst pattern state.The results indicate that our method can efficiently mimic main neuronal states in the Fig. 5. Even more, in burst pattern state, various burst patterns can be generated by changing three balance points's location in nullclines of equations(1-3). Fig. 6 shows two different burst patterns. According to these results, the HR computational model shows a strong reconfigurable ability.Also, patterns produced by FPGAs are almost the same as real neuron patterns.

### C. Synaptic model

We use intracellular recording lateral pyloric neuron(PD) cell membrane potential as inputs for both electrical synapse

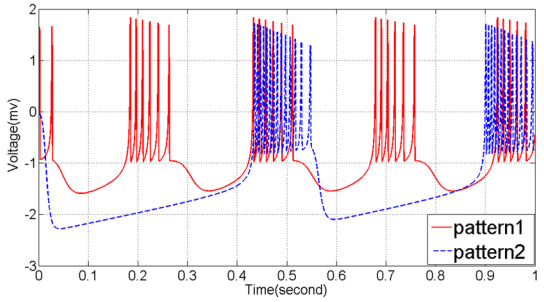


Fig. 6. Two different patterns in burst states of HR model.

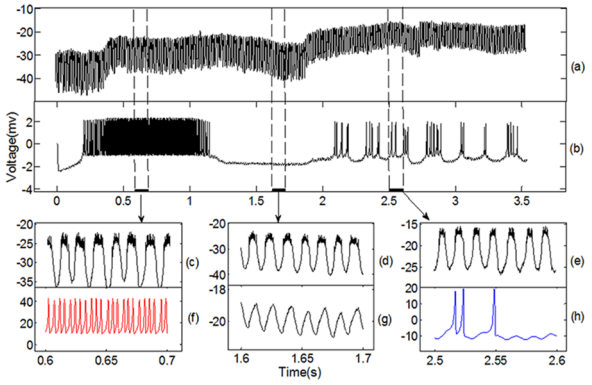


Fig. 7. Artificial electrical synapse between a biological and a FPGA neuron model. (a) Membrane potential of biological PD cell. (b)Membrane potential of FPGA neuron model . Biological PD cell membrane potential (c) from 0.6s to 0.7s, (d) from 1.6s to1.7s, (e) from 2.5s to 2.6s. (f) The membrane potential of FPGA cell model in slow wave state (0.6s - 0.7s). (g) The membrane potential of FPGA cell model in silence state (1.6s -1.7s). (h) The membrane potential of FPGA cell model in burst patterns state (2.5s - 2.6s).

and chemical synapse to confirm and inspect synapse functions. The results of electrical synapse are shown in Fig. 7. We changed neuronal model states in sequence. During 0s-1s, 1s-2s and 2s-3s, the neuron is at slow wave, silence and burst pattern states separately. The FPGA model outputs show strong synchronizing with biological neuron outputs due to resistant behaviour of electrical synapse.

Chemical synapse results are shown in Fig. 8. In the slow wave state (0s-1s in Fig. 8(b)), spike frequency is much higher than the neuron with electrical synapse (0s-1s in Fig. 7(b)). In the silence state, tiny spikes can be seen in Fig. 8(b) (1s-2s), which may results from chemical synapse accumulation function. In the burst state, the burst patterns in Fig. 8(b) (2s-3s) are stronger and more regular than that in Fig. 7(b) (2s-3s). In a summary, both synapse models express physiological behaviours (silence,slow and burst) correctly.

### D. Neuronal Network

We design a simple pyloric network which consists of four types of cell and both electrical and chemical synapse. This network is implemented on FPGA. A constant current (3nA) was injected to the network to observe the burst patterns while changing neuron topologies in real time.

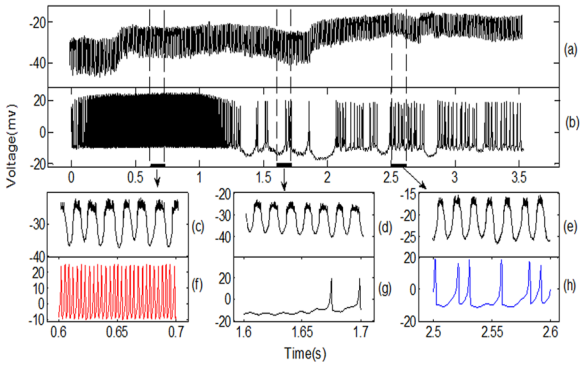


Fig. 8. Artificial chemicial synapse between a biological and a FPGA neuron model. (a) Membrane potential of biological PD cell. (b)Membrane potential of FPGA neuron model . Biological PD cell membrane potential (c) from 0.6s to 0.7s, (d) from 1.6s to1.7s, (e) from 2.5s to 2.6s. (f) The membrane potential of FPGA cell model in slow wave state (0.6s - 0.7s). (g) The membrane potential of FPGA cell model in silence state (1.6s -1.7s). (h) The membrane potential of FPGA cell model in burst patterns state (2.5s - 2.6s).

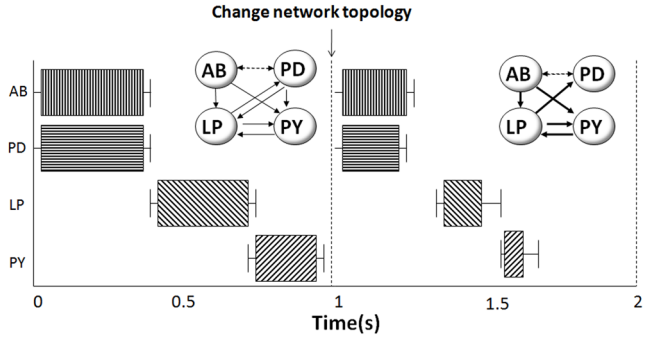


Fig. 9. Different output patterns under two topologies. Arrow of dash line represents electrical synapse and arrow of solid line represents chemical synapse. In the second topology, some synapses are strengthened in bold line while some synapses are inactive.

As it can be seen in the Fig. 9, we change the pyloric network structure at time 1s by changing input control signals, which make synapses (PD to PY, PD to LP) inactive and synapses (other synapses except electrical synapse) strengthened. The LP and PY burst patterns changed dramatically while AB and PD neurons changed a little bit. Based on the capability of changing topologies in real-time, we can mimic neuronal modulators such as dopamine that usually exerts a vital influence on synapse [6].

### *E. FPGA Performance*

Comparing to the software, FPGA demonstrates good scalability and high-speed computational performance. We compared the computational delay for generating three bursts using software and FPGAs. Fig. 10 shows that FPGA is very scalable and deliver same computational performance with increasing number of cells. The software computational delay increases exponentially with the cell number due to the sequential computation. For accuracy aspect, hardware shows a good capability to represent burst patterns as software because of high number bits in circuits.

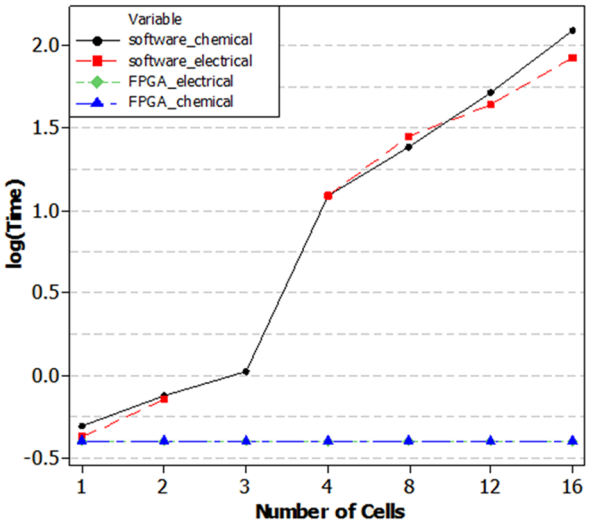


Fig. 10. Comparsion the delay for generating three bursts between software and FPGA.

## V. Conclusion

This paper described a dynamic clamping system based on the FPGA, especially focus on the computational models: three kinds of states neuron model and two types of synapse create a good reconfigurable small network. By injecting intrcellular recording PD data, it displays various output motor patterns by changing its neuron states in real time. This model is vital to investigate deep centre pattern generator mechanism in neurons through dynamic clamping. Also, two orders of magnitude improvement in computational speed can be achieve by utilizing FPGA effectively. This scalable dynamic clamping system enables new experiments to uncover new biological mechanisms in nerves systems.

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