

Biomorphic Circuits and Systems: Control of Robotic and Prosthetic Limbs

Francesco Tenore and Ralph Etienne-Cummings
Department of Electrical and Computer Engineering
Johns Hopkins University
Baltimore, Maryland 21218
Email: {ftenore, retienne}@jhu.edu

Abstract—Rhythmic motions of lower and upper limb prostheses for patients suffering from spinal cord injury (SCI) and amputees can be controlled and modulated using silicon neurons, designed in Very Large Scale Integration (VLSI) technology, that mimic pattern generation circuits found in the human spinal cord. Furthermore, synchronized patterns with arbitrarily phase delays, can easily be implemented using this technology. This allows locomotory gaits of any kind to be programmed *in silico* to control bipedal robotic locomotion. We argue that it is possible to use these circuits to control hand movements in prosthetic upper limbs using the same approach: the neurons’ oscillatory behavior can trigger rhythmic movements that can be started or stopped at any phase, thus enabling the production of discrete movements in upper limb prosthesis.

The bold endeavor of discovering an all-encompassing solution for control of upper and lower limbs will open up new perspectives in the fields of both robotics and prosthetics. In the process of doing so, we have shown how to successfully *decode myoelectric signals* from able bodied subjects and a *transradial amputee*, and how the technology developed is suitable for real-time applications, particularly multi-DoF upper limb prostheses.

The systems developed in this work have been validated on different platforms dependent on the type of prosthesis required. For lower limb prostheses, a bipedal robot with servomotors actuating its hips and knees was used to prototype walking motions generated by silicon neurons. Upper limb (finger) control was achieved on a Virtual Integration Environment (VIE), developed by JHU’s Applied Physics Laboratory (JHUAPL), characterized by real-time processing and visualization of any upper limb motion.

I. INTRODUCTION

Think of a vertebrate. Think of the way it moves, eats, breathes, digests. All of these everyday actions performed by the animal you’re thinking of have two things in common: they are all *repetitive in nature* and they are all *indispensable for survival*. In the hundreds of millions of years it has had to perfect itself, evolution has seen to it that the most fundamental actions performed everyday by your vertebrate be controlled in the simplest and most robust way it found, through the process of natural selection. Exploiting the periodicity of these actions, this process resulted in a “neural oscillator” that gives these tasks an underlying rhythm and that can work independently of everything else in the vertebrate’s Central Nervous System (CNS), from supraspinal commands dictated by the brain to sensory information coming from the limbs. What the higher levels of the CNS and the sensory information *can do*, however, is modulate these rhythmic signals in order to

achieve the desired output behavior, whether it’s a fast run to avoid a predator, or a deep breath, prelude to a long immersion.

In vertebrates, the biological rhythmic signals are produced by a set of specialized neural circuits, typically found in the lumbar region of the spinal cord, known collectively as the Central Pattern Generator, or CPG [1]. CPGs have been found in all vertebrates tested, from lampreys [1], eel-like creatures that live in coastal waters, to cats [2]. Evidence of its presence has also been found in humans in different scenarios: in the spontaneous rhythmic movements made by some patients after spinal cord injury (SCI) [3], and from the evolution of EMG activity in the legs of patients with paraplegia who are manually stepped on a treadmill or undergo unpatterned epidural stimulation in the lumbar region [4].

From an evolutionary perspective, human locomotion evolved through a series of transitions starting from a relatively compliant form of ape-like quadrupedalism, shown to be consistent with the anatomy of early hominids who had not yet renounced arboreal locomotion [5]. While this makes a strong case for CPGs having been involved in upper limb movements, it is unclear whether the evolutionary steps from *Australopithecus afarensis* to *Homo sapiens* have erased or reduced the influence of the CPG on the upper limbs, in favor of a more cortical-based control.

This leads us then to the following question: “Does the CPG also effect upper limb movements, which appear to be less periodic in nature and are almost exclusively a characteristic of primates?” A recent work by Schaal *et al.* [6] tried to answer this question by examining whether the rhythm generator, RG, was a subset of the discrete movement, DM, or if the opposite was true, i.e. is $DM \subseteq RG$. They concluded that because it was evident that rhythmic movement is not based on the use of the discrete movements system, in order to fully understand the neurobiological mechanisms of discrete movement, *it is first necessary to better understand those of rhythmic movement*.

To this end, Kurita *et al.* [7] have proposed the use of CPG-based networks for object manipulation tasks, specifically for rotation of cylindrical objects, which requires periodic abduction and adduction of the wrist. Their experimental results (albeit based on computer simulations) suggest that this approach is valid.

Successful emulation of spinal neural circuits will allow i) improvement of the chances of recovery from spinal cord in-

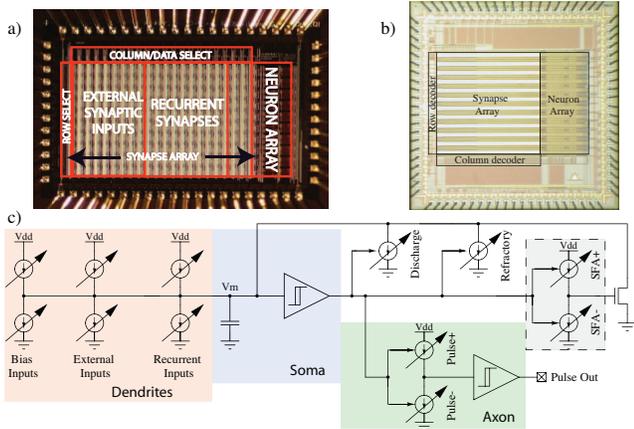


Fig. 1. Micrographs of two pattern generating chips. a) Digital approach: DAC-based synapses; b) analog approach: Floating gate-based synapses. c) Schematic representation of a single neuron and its three compartments. The dashed grey box represents circuitry that was implemented *externally* on the DAC-based chip and *internally* on the Floating gate-based chip.

jury; ii) human-like control of robotic locomotion; iii) control of exoskeletons for enhancement of human capabilities.

This premise was necessary to illustrate the foundation upon which this work is laid. Rhythmic movements, underlying both locomotory systems and fundamental, repetitive, upper limb movements, have been captured in *versatile, reprogrammable*, neuromorphic chips [8], [9] that have been used to control robotic locomotion in feedforward and feedback paradigms [10]–[12], as well as in animal locomotion [13] for more on this last application).

Control of repetitive upper limb movements using this approach also proved feasible, using networks similar to the ones used to control lower limb movements, as demonstrated in simulation by Kurita *et al.* [7], and has been shown in [14]. Here, however, we focus more on the ability to decode the intention of movement using non-invasive Electromyography (EMG) recordings. This crucial step is motivated by the fact that in order to appropriately control a prosthesis, it is first necessary to know the user’s intent.

II. SILICON CPGs FOR LOWER LIMB CONTROL

Our neuromorphic engineering approach to solve real-world problems stems from three important constataions:

- a biological entity (such as a cell, a tissue, an organ, or an organ system) exists that solves the problem efficiently and elegantly;
- the biological entity is the fruit of billions of years of evolution, that have allowed it to arrive to its present form;
- understanding how the problem is solved and why it is solved in that particular way allows the possibility of speeding up the evolutionary process by implementing new ways to improve on the current state.

Table 1 summarizes the features of the two chips, highlighting their differences.

TABLE I
COMPARISON SLIDE BETWEEN SILICON CPG IMPLEMENTATIONS

	FG-CPG	DAC-CPG
Neurons	24	10
Synapses	888 , analog	220, digital
Area (mm^2)	3×3	3.3×2.2
Power (mW)	< 1	8.3
External Inputs	12 ¹	4 analog + 4 digital
Spike Frequency Adaptation	On-chip	External + Analog inputs
Value post-SHDN	Retained	Not retained
Synaptic weight storage	Analog	Digital

¹All purpose synapses

This approach led to the designs of two variations of integrate-and-fire silicon neurons one with digitally programmable synapses, the other with an analog design. Fig. 1 a and b shows micrographs of these two chips. Broadly speaking, the two architectures from a neuronal standpoint are very similar. Specifically, with reference to Fig. 1c, each neuron can be divided into three biologically-inspired compartments, one each for the dendrites, soma, and axon. In this formulation, the dendrites contain the synaptic inputs, the soma consists of a membrane capacitance C_m and a hysteretic comparator, and the axon is composed of a digitally-controlled spike generator that converts brief outputs from the comparator into arbitrarily long digital pulses (allowing for mimicry of the plateau potentials commonly found in neurons within biological CPGs [15]). Calcium-dependent potassium current, important for pulse synchronization [16]), was also emulated through the use of adaptation circuitry that discharges the membrane potential as more spikes are output.

The integrate-and-fire neurons with digitally-programmable synapses, consisting of 8-bit (plus one for polarity) digital to analog converters, allow rapid prototyping of multi-neuron networks at the price of a relatively low number of neurons and synapses per neuron (10 and 19, respectively). The analog architecture, on the other hand, exploits floating gates as input voltages of an operational transconductance amplifier to charge and discharge the membrane capacitor. Prototyping multi-neuron networks in this domain requires a complete and extensive characterization of the behavior of each individual neuron/synapse pair, but is still a slower process than its digital counterpart. Its advantages, on the other hand, lie in the fact that the synapses are significantly smaller, allowing 24 neurons and 37 synapses per neuron in the same area. Also, the implementation with floating gates creates a non-volatile memory that leaves the synaptic weights unchanged during power cycling.

The chips were used to design CPG networks, in which centers of activity alternate periodically, as dictated by the network parameters (i.e. the excitatory and inhibitory weights). Appropriate configuration of the parameters of a CPG network generates the necessary signals (Fig. 2a) for controlling locomotion of a biped robot (Redbot, Alegrobot, Urbana, IL), through direct actuation of the robot’s hip and knee

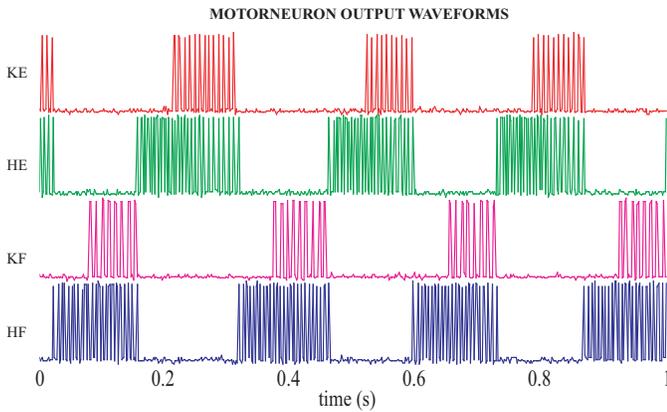


Fig. 2. a) Alternating CPG activity, used to drive hip and knee signals that control locomotion of a biped robot. The knee signals (extensor and flexor) are about 90° out-of-phase with the ipsilateral hip, and the hip signals are 180° out-of-phase with each other. These signals were used to drive a biped robot. b)

servomotors. Furthermore, we developed networks capable of emulating cat locomotion. Walking is controlled under closed-loop conditions with the aide of sensory feedback that is recorded from the animals legs and fed into the silicon CPG [17].

While the network parameters described here were implemented empirically to achieve the desired waveforms, we have also shown that it is possible to use learning algorithms such as Genetic Algorithms to automatically adjust the parameters for a specified gait and gait velocity [18].

III. UPPER LIMB CONTROL

When dealing with control of prosthetic or robotic upper limbs, the types of movements we seek to emulate and replicate can be seen as part of oscillatory cycles that are *triggered and stopped* at any phase within the cycle. This allows the neuromorphic circuits described in the previous section to actuate the upper limbs as well as the lower limbs, with the *caveat* that much more cortical control will be required to achieve the fine motions that the upper limb is capable of. One important difference that exists between the upper and lower limbs, therefore, is the significantly higher number of degrees of freedom (DoF) that characterize the former as opposed to the latter. It is therefore crucial that we first be able to decode the intended movements prior to trying to replicate them in a prosthesis. We will therefore focus this section on the decoding of repetitive individual finger and hand movements, that can then be used to control a multi-DoF prosthetic hand.

The breadth of motor-sensory information in the human upper limb cannot be achieved in today's state-of-the-art prostheses. What is more, this difference between the intact limb and the prosthesis seems so great that a study by Dudkiewicz *et al.* [19] showed that amputees consider current prostheses so limited in their functionality, that they either decide not to use it after having tried it for a brief time period, or to not even try it.

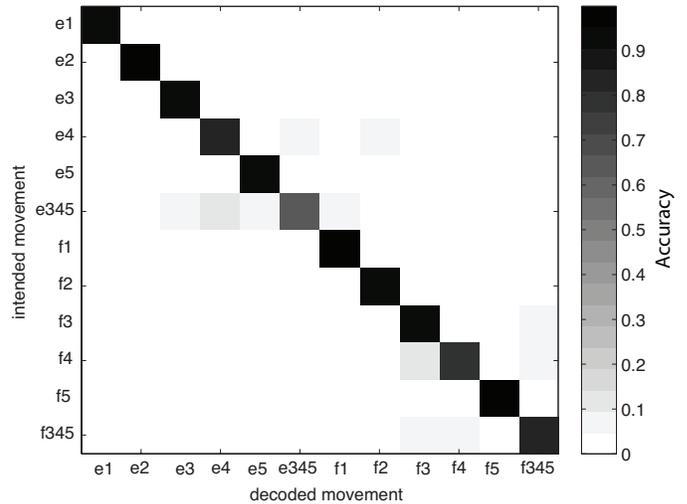


Fig. 3. Confusion matrix for the transradial amputee performing individual and combined finger movements. The average accuracy is $\sim 90\%$.



Fig. 4. Screenshot of the VIE's virtual prostheses as individual finger movements are being decoded (middle finger extension depicted). The data was collected from EMG from a transradial amputee, then streamed and decoded in real-time.

Using traditional biosignal processing methods, we have found that it is possible to reduce the motor information gap, through successful decoding of non-invasive surface EMG signals from the proximal part of human forearms to control fingers and wrist. A combination of time-domain features extracted every 25 ms on 200 ms windows of data and fed to an artificial neural network classifier, allowed real-time data processing and actuation (i.e. through a negligible delay between performed and decoded movements). This allows most upper limb amputees to be able to fully recover control over many DoF available to the hand, through non-invasive signal acquisition. Specifically, we have shown that it is possible to decode individual and combined finger flexion and extension movements with 90% accuracy from a transradial amputee.

Fig. 3 shows the confusion matrix for a transradial amputee performing 12 finger movements (extension and flexion of each finger and combined middle-ring-pinky movements). As can be seen, the classifier has difficulty in distinguishing the combined movements from the individual components. Our experiments suggest, however, that through several training sessions the classifier accuracy increases to the point of becoming faultless (assuming the subject performed the correct movement, in response to a specific cue). Further, we have also shown that the difference between this subject's accuracy and that obtained from similar recordings from 28 electrodes on the intact forearm of 4 able bodied subjects, is not statistically significant.

To test our ability to decode the movements in real-time, we implemented the system in a Virtual Integration Environment (VIE), developed by the JHUAPL. The data acquired from the transradial amputee were streamed, decoded and visualized on the VIE's virtual prosthesis, as shown in Fig. 4. We further tested and successfully validated this virtual real-time decoding paradigm on an able-bodied subject performing hand and combined finger movements.

IV. CONCLUSIONS

Central pattern generators, at the foundation of periodic systems in vertebrates, have been emulated in silicon chips that capture the essence of the CPG behavior in low-power, elegant and versatile solutions.

These chips have allowed a novel and successful approach to controlling bipedal robotic locomotion as well as repetitive motions of the upper limbs. Different network architectures have been implemented to exploit the periodicity of typical upper and lower limb movement cycles. Two iterations of chips have been developed to increase the number of DoF that can be controlled whilst diminishing power consumption. The networks prototyped on the chips have been used for a variety of purposes, a testimony to the extreme versatility embedded in our approach.

Our silicon neural networks have also been used to control periodic motions of a virtual hand. This approach, while not as biologically plausible due to the heavy involvement of cortical neurons, is based on repetitive movements of the fingers. In the process of achieving this, we have also successfully been able to non-invasively decode individual finger and wrist movements in able-bodied subjects as well as a transradial amputee. We therefore believe that the contributions brought forth by this work significantly advance the fields of both robotics and neuroprosthetics. This work ultimately advances the fields of *robotic locomotion* and *lower and upper limb prosthetics* through the design and implementation of spinal cord emulating VLSI circuits and real-time decoding of non-invasive biosignals for controlling prosthetic or robotic limbs.

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REFERENCES

- [1] S. Grillner, "Control of locomotion in bipeds, tetrapods, and fish," in *Handbook of Physiology. The Nervous System. Motor Control*. Bethesda, MD: American Physiological Society, 1981, pp. 1179–1236.
- [2] S. Grillner and P. Wallèn, "Central pattern generators for locomotion, with special reference to vertebrates," *Annual Review of Neuroscience*, vol. 8, pp. 233–261, 1985.
- [3] B. Jilge, K. Minassian, F. Rattay, M. M. Pinter, F. Gerstenbrand, H. Binder, and M. R. Dimitrijevic, "Initiating extension of the lower limbs in subjects with complete spinal cord injury by epidural lumbar cord stimulation," *Experimental Brain Research*, vol. 154, no. 3, pp. 308–326, 2004.
- [4] M. R. Dimitrijevic, Y. Gerasimenko, and M. M. Pinter, "Evidence for a spinal central pattern generator in humans," *Annals of the New York Academy of Sciences*, vol. 860, pp. 360–376, 1998.
- [5] D. Schmitt, "Insights into the evolution of human bipedalism from experimental studies of humans and other primates," *Journal of Experimental Biology*, vol. 200, pp. 1437–1448, 2003.
- [6] S. Schaal, D. Sternad, R. Osu, and M. Kawato, "Rhythmic arm movement is not discrete," *Nature Neuroscience*, vol. 7, no. 10, pp. 1137–1144, 2004.
- [7] Y. Kurita, J. Ueda, Y. Matsumoto, and T. Ogasawara, "CPG-based manipulation: Generation of rhythmic finger gaits from human observation," in *Proceedings of the IEEE International Conference on Robotics and Automation*, 2004, pp. 1209–1214.
- [8] F. Tenore, R. Etienne-Cummings, and M. A. Lewis, "A programmable array of silicon neurons for the control of legged locomotion," in *Proceedings of the IEEE International Symposium on Circuits and Systems*, vol. 5, 2004, pp. V349–V352.
- [9] F. Tenore, R. Vogelstein, R. Etienne-Cummings, G. Cauwenberghs, M. A. Lewis, and P. Hasler, "A spiking silicon central pattern generator with floating gate synapses," in *Proceedings of the IEEE International Symposium on Circuits and Systems*, 2005, pp. 4106–4109.
- [10] M. A. Lewis, F. Tenore, and R. Etienne-Cummings, "CPG design using inhibitory networks," in *Proceedings of the IEEE International Conference on Robotics and Automation*, 2005.
- [11] R. J. Vogelstein, F. Tenore, R. Etienne-Cummings, M. A. Lewis, and A. H. Cohen, "Dynamic control of the central pattern generator for locomotion," *Biological Cybernetics*, vol. 95, no. 6, pp. 555–566, 2006.
- [12] F. Tenore, R. J. Vogelstein, and R. Etienne-Cummings, "Sensor-based dynamic control of the central pattern generator for locomotion," in *Proceedings of the IEEE International Symposium on Circuits and Systems*, 2007.
- [13] R. J. Vogelstein, F. Tenore, L. Guevremont, R. Etienne-Cummings, and V. K. Mushahwar, "A silicon central pattern generator controls locomotion *in vivo*," submitted to *IEEE Transactions on Biomedical Circuits and Systems*.
- [14] A. Russell, F. Tenore, G. Singhal, N. V. Thakor, and R. Etienne-Cummings, "Towards control of dexterous hand manipulations using a silicon pattern generator," in *Proceedings of the IEEE Conference of the Engineering in Medicine and Biology Society*, 2008.
- [15] E. Marder and D. Bucher, "Central pattern generators and the control of rhythmic movements," *Current Biology*, vol. 11, no. 23, pp. R986–R996, 2001.
- [16] A. E. Manira, J. Tegner, and S. Grillner, "Calcium-dependent potassium channels play a critical role for burst termination in the locomotor network in lamprey," *Journal of Neurophysiology*, vol. 72, pp. 1852–1861, 1994.
- [17] R. J. Vogelstein, F. Tenore, L. Guevremont, R. Etienne-Cummings, and V. K. Mushahwar, "A silicon central pattern generator controls locomotion *in vivo*," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 2, no. 2, 2008.
- [18] G. Orchard, A. Russell, K. Mazurek, F. Tenore, and R. Etienne-Cummings, "Configuring silicon neural networks using genetic algorithms," in submitted to *Proceedings of the IEEE International Symposium on Circuits and Systems*, 2008.
- [19] I. Dudkiewicz, R. Gabrielov, I. Seiv-Ner, G. Zelig, and M. Heim, "Evaluation of prosthetic usage in upper limb amputees," *Disability and Rehabilitation*, vol. 26, no. 1, pp. 60–63, 2004.