An Adaptive Frequency Central Pattern Generator for Synthetic Nervous Systems

William Nourse(✉), Roger D. Quinn, and Nicholas S. Szczecinski

Case Western Reserve University, Cleveland, OH 44106, USA
wrn13@case.edu

1 Introduction

For robots using legged locomotion, mathematical models of Central Pattern Generators (CPGs) are being used for controlling the complicated gaits and timing required for stable walking. Traditionally, these models are precisely designed for oscillation at a set of specific frequencies and phase relationships, which while easier to design is not conducive to robust and stable walking.

In recent years, work has been done on designing adaptive models of CPGs. These CPGs are able to exhibit complex behaviors such as learning the resonant dynamics of a system [1] to improve walking stability, as well as using mathematical learning rules to learn arbitrary signals and embed their relationships within the system [2,3].

This work explores the possibility of implementing an adaptive frequency CPG with a similar behavior to these systems, using conductance-based models of dynamic non-spiking neurons connected as a synthetic nervous system (SNS) [4].

2 Methods and Results

When designing an adaptive system, it is important to first characterize the existing model. We used conductance-based non-spiking neurons where the membrane voltage varies with a differential equation

$$C_m \frac{dV}{dt} = I_{leak} + I_{syn} + I_{NaP} + I_{app} \tag{1}$$

where

$$I_{leak} = G_m \cdot (E_r - V) \tag{2}$$

$$I_{syn} = \sum_{i=1}^{n} G_{s,i} \cdot (E_{s,i} - V) \tag{3}$$

$$I_{NaP} = G_{Na} \cdot m_\infty(V) \cdot h \cdot (E_{Na} - V) \tag{4}$$

This work was funded by National Science Foundation (NSF) Award #1704366.

V. Vouloutsi et al. (Eds.): Living Machines 2018, LNAI 10928, pp. 361–364, 2018.
https://doi.org/10.1007/978-3-319-95972-6_38

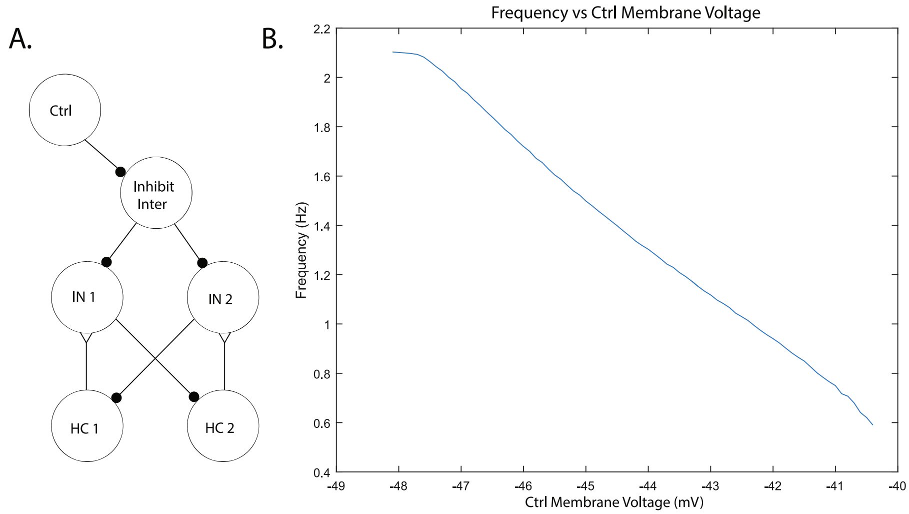

Fig. 1. (A) The CPG network consists of two neurons with nonlinear persistent sodium channels (HC 1 and HC 2), which mutually inhibit one another via two nonspiking interneurons (IN 1 and IN 2). A pair of additional neurons can exploit neural dynamics to control the oscillation frequency of the CPG by effectively weakening the strength of mutual inhibition. **(B)** The membrane voltage of the controlling neuron (Ctrl) has a linear relationship with the oscillation frequency of the associated CPG.

and there is an externally applied current I_{app}. As shown in Fig. 1, if a pair of inhibiting neurons is added to an SNS model of a CPG, the natural frequency can be linearly controlled by an applied voltage and behaves as a voltage-controlled oscillator. Through the use of previously designed functional subnetworks for arithmetic, integration, and differentiation [4], a larger network can be realized which acts as an arbitrary frequency-to-voltage converter and maps an input signal to the appropriate controlling voltage for the CPG (see Fig. 2). Since these subnetworks have already been successfully tuned for their respective operations, a complicated network can be constructed by combining desired mathematical operations as needed, with minor tuning of the individual neurons and synapses bridging between subnetworks. While the exact topology of this overall network has no direct biological source, the internal subnetworks are all based on results seen from biology [4]. This subnetwork approach may not lead to the most minimal network design for a desired functionality, however it allows the development of very large scale networks where time-intensive optimization need only be performed on a small subset of the network.

In this work, phase information is fed forward from the initial processing of an input signal. Future work could use information from separate sources to control phase, allowing such behavior as inter-leg communication providing frequency control and intra-leg sensory feedback controlling the phase in legged locomotion.

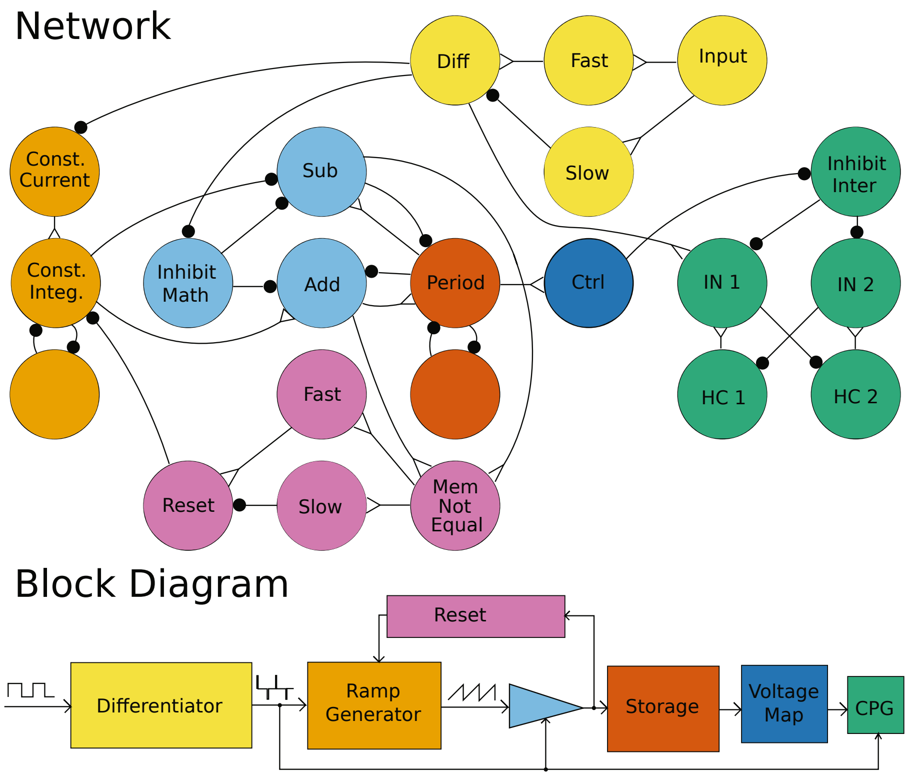

Fig. 2. A network which uses functional neural subnetworks [4] to alter a CPG's frequency and phase to match that of an incoming signal, as well as a corresponding block diagram. First, a differentiator network subtracts a delayed copy of an input signal to approximate a derivative. An integrator (Const. Integ.) is then supplied with constant current, inducing a ramp which is periodically reset. An addition and subtraction network then equalizes a storage integrator (Period) to the first every input cycle, and resets the original integrator when equalization has occurred. The stored voltage is then mapped to the voltage range demonstrated in Fig. 1 for controlling the frequency of a CPG. Differential spikes from the input are sent to a CPG interneuron, to correct the phase.

Preliminary testing (see Fig. 3) shows that for square wave inputs the system has some slight difficulty adapting to very low frequency signals, but as the frequency increases towards typical walking speeds and up, the system behaves as intended and locks in both frequency and phase with the input. Further work is required to fully characterize the frequency and phase response of this network, including the use of more biologically realistic input signals as well as those with asymmetric phase. Additionally the effects of using more complicated neural models, or the presence of any long-term plasticity could also be analyzed.

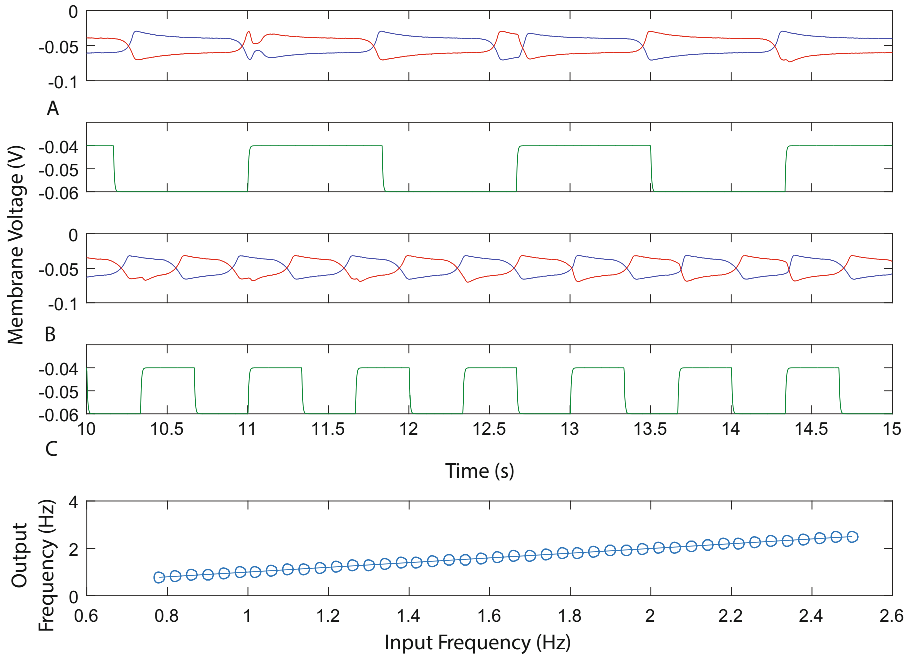

Fig. 3. The network shown in Fig. 2 is able to match frequency and phase with a periodic input signal. At lower frequencies (0.6 Hz shown in **(A)**) the CPG can exhibit some unintended phase shifting. At frequencies above 0.8 Hz, the network effectively locks to the input signal's frequency and phase (see 1.5 Hz in **(B)**). As can be seen in **(C)**, the frequency of the input square wave and output of the network match once CPG oscillation is stable.

References

1. Buchli, J., Iida, F., Ijspeert, A.J.: Finding resonance: adaptive frequency oscillators for dynamic legged locomotion. In: IEEE International Conference on Intelligent Robots and Systems, pp. 3903–3909 (2006). https://doi.org/10.1109/IROS.2006.281802
2. Righetti, L., Buchli, J., Ijspeert, A.J.: From dynamic Hebbian learning for oscillators to adaptive central pattern generators. In: Proceedings of 3rd International Symposium on Adaptive Motion in Animals and Machines, AMAM 2005, pp. 1–7 (2005). https://doi.org/record/58529, http://infoscience.epfl.ch/record/58528/files/righetti05b.pdf?version=1
3. Righetti, L., Buchli, J., Ijspeert, A.J.: Dynamic Hebbian learning in adaptive frequency oscillators. Phys. D Nonlinear Phenom. **216**(2), 269–281 (2006). https://doi.org/10.1016/j.physd.2006.02.009
4. Szczecinski, N.S., Hunt, A.J., Quinn, R.D.: A functional subnetwork approach to designing synthetic nervous systems that control legged robot locomotion. Front. Neurorobot. **11**, 1–19 (2017). https://doi.org/10.3389/fnbot.2017.00037. http://journal.frontiersin.org/article/10.3389/fnbot.2017.00037/full