Configuring of Spiking Central Pattern Generator Networks for Bipedal Walking Using Genetic Algorthms

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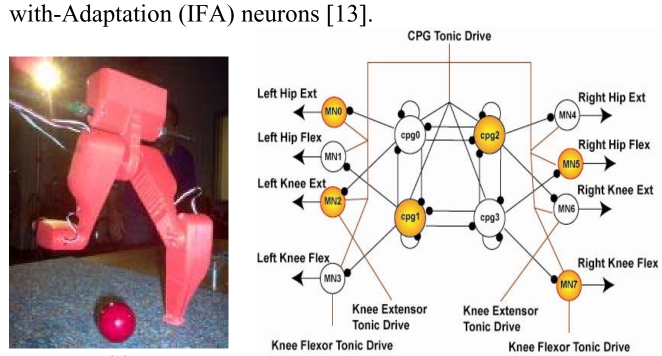
***Abstract*—In limbed animals, spinal neural circuits responsible for controlling muscular activities during walking are called Central Pattern Generators (CPG). CPG networks display oscillatory activities that actuates individual or groups of muscles in a coordinated fashion so that the limbs of the animal are flexed and extended at the appropriate time and with the required velocity for the animal to efficiently traverse various types of terrain, and to recover from environmental perturbation. Typically, the CPG networks are constructed with many neurons, each of which has a number of control parameters. As the number of muscles increases, it is often impossible to manually, albeit intelligently, select the network parameters for a particular movement. Furthermore, it is virtually impossible to reconfigure the parameters on-line. This paper describes how Genetic Algorithms (GA) can be used for on-line (re)configuring of CPG networks for a bipedal robot. We show that the neuron parameters and connection weights/network topology of a canonical walking network can be reconfigured within a few of generations of the GA. The networks, constructed with Integrate-and-Fire-with-Adaptation (IFA) neurons, are implemented with a microcontroller and can be reconfigured to vary walking speed from 0.5Hz to 3.5Hz. The phase relationship between the hips and knees can be arbitrarily set (to within 1 degree) and prescribed complex joint angle profiles are realized. This is a powerful approach to generating complex muscle synergies for robots with multiple joints and distributed actuators.**

I. INTRODUCTION

Over the past few years there has been a flurry of activity in developing locomotion controllers for legged robots that mimic the neural circuits found in limbed and un-limped organism [1-3]. In particular, we have witness a number of implementations of snake-like robots [1,4], quadrupedal and hexapedal robots [2,5-7,15] and bipedal robots [8-10] that use models of lamprey, leech, cat, stick insect and other mammalian Central Pattern Generator (CPG) networks. CPG networks are collections of neurons that are able to endogenously produce sustained rhythmic or oscillatory, patterned outputs [11]. The outputs of central pattern generators are responsible for most rhythmic motor patterns such as walking, flying, swimming and breathing. The motivation for all this work is the drive to develop mobile robotic systems that are equally adept at handling the terrain complexities and clutter of natural environments, while using the same minimal amount of energy as exhibited by living organisms.

Recently, there has also been movement towards interfacing robots to humans, e.g. prosthetic devices for amputees and spinal injury patients, which has elevated the need for devices that "seamlessly" interface with the human body. For locomotion and other muscular actuation, as encountered in reach, grasp and dexterous manipulations, biological CPG networks are the neural systems with which the robots have to interact [12]. Hence artificial CPG networks that bridge the gap between the biological organism and the robot should "speak" the same language as their biological counterpart, i.e. they should be constructed with spiking neurons and process spike data. The CPG networks described in this paper follows this philosophy and are constructed with spiking Integrate-and-Fire-with-Adaptation (IFA) neurons [13].



(a) (b)

Figure 1: (a) The RedBot biped. The hips and knees are independently actuated with servo motors. (b) Lewis et al's canonical walking network for Iguana Robotics' RedBot [5]. The central oscillators are used to generate the hip and knee control waveforms.

Typically, the CPG network for controlling the RedBot biped in figure 1(a) with hip and knee actuators are constructed with the canonical walking network shown in figure 1(b) [5]. The canonical network is composed of 12 neurons, each of which has 6 parameters. The network itself has 34 connection weights. Hence, the parameter space (assuming complete independence of each parameter) has 106 dimensions. Practically, the dimension of the problem is reduced by allowing similar neuron types (i.e. central oscillator neurons, left/right hip motor neurons and left/right knee motor neurons) to have similar properties. This reduces the dimensionality to 64. This number can be reduced further if other symmetries are imposed on network (e.g. connections forming the main oscillator are symmetric and left and right hips are 180 degrees out of phase and knees are 90 degrees out of phase with hips). Nonetheless, it is clear that the curse of dimensionality is significant in this network, and it will only get worse as ankle joints are added, or more distributed actuators are used per joint [14]. The latter is fundamental in the prosthetic limb application. Hence, it is necessary to

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simplify the network, and to find an automated means of determining these parameters. Furthermore, an approach that allows on-line modifications as a function of environmental condition is even more desirable.

This paper describes four main advances in the design of artificial CPG networks and attempts to address the problems outlined above: 1) Spiking IFA neurons are used to implement biologically compatible networks to control a biped with hip and knee actuators (uses the neural model in [13]); 2) The canonical walking network in [5] is modified to allow more general control waveforms for the joints; 3) A hierarchical Genetic Algorithm (GA) is used to find the parameters of the network to achieve walking with prescribed frequency and joint-ankle profiles (this extends the work of Lewis [15] and Inada and Ishii [10]; 4) Demonstrates GA mitigated on-line modification of gait patterns and walking speed in the RedBot biped.

II. The Neuron, CPG Network and Genetic Algorithm

A. The Neuron Model

We chose spiking neurons to construct our networks to stay somewhat bio-realistic and compatible with biological nervous systems. Izhekevich in [13] lays out the trade-offs between implementation complexity and computational power of various neuron model. For our purpose, the Integrate-and-Fire-with-Adaptation (IFA) model is computationally efficient whilst having enough functionality to form our CPG networks. The IFA model we used includes a slight modification to reset the adaptation term if the neuron does not fire after prescribe period. The model for the ith neuron in a network of size n is then given by:

$$v_i' = \sum_{all\, n, n \neq i} I_{n \to i} + a - bv_i + g_i(d - v_i)$$

$$if\ v_i > v_{thresh}\ then\ \ v_i = c$$

$$g_i' = \frac{e\delta(t) - g_i}{\tau}$$

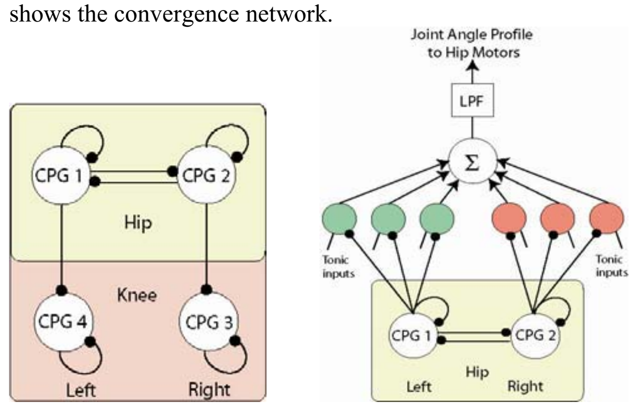
$$if\ t_{fire} > t_{reset}\ \ then\ g = 0$$

Where v is the membrane potential, a the tonic input, $I_{j\text{-}I}$ the coupling from the jth to ith neuron, c is the reset voltage, b is the membrane impedance, g, e, d, τ are variables for adaptation and t_{fire} is the time since the neuron last fired, t_{reset} is the maximum time the neuron can remain inactive for before the adaptation term is reset. The value of t_{reset} was set to ~50% of the walking period.

B. The CPG Network

Lewis et al [5] showed that the network of neurons in Figure 1(b), constructed with IFA neurons, can be used to generate gaits for walking. In that implementation, only specific gaits (i.e. specific hip to knee relationships), which were particularly sensitive to the chosen parameters were shown.

We have modified this network to allow arbitrary walking frequency, gait and joint angle profiles to be realizable and reconfigurable on-line. To facilitate these three levels of control, we decompose the canonical network into three parts: 1) the central oscillator to set the walking frequency; 2) the hip neuron to knee neuron coupling to realize specific gaits; 3) convergence of the hip and knee neurons onto a network of motor neurons, each having its own firing characteristics, to produce a prescribed joint angle profile. Figure 2(a) shows the network for defining the walking frequency and gait, while 2(b) shows the convergence network.



(a) (b)

Figure 2: (a) The simplified caconical CPG network in fig1 1(b) for training the walking frequency (hip oscillations) and gait (hip to knee relationship). (b) The convergence network to generate a particular joint angle profile for the hips. Similar networks are realized for the knees. The circles labelled "CPG #" are IFA neurons. Arrows represent excitatory connection and closed circles are inihibitory connections.

C. The Genetic Algorithm (GA)

Genetic Algorithms allows various combination of the network topology to be constructed, and their performance evaluated against desired behavior to determine fitness. The qualities of the fitter networks are then passed to subsequent generations of the network. Typically, the convergence rate of the GA is the stumbling block for this approach. De Garis (1990) [16] showed that the evolution of a controller can be sped up by choosing the right starting point and by using two fitness functions, where the first fitness function is more easily satisfied and is used to pre-evolve the solution to an appropriate level. Next the second fitness function is used to further improve the solution. De Garis named the above concept Behavioral Memory. This concept was also use by Lewis et al (1992) used genetic algorithms to optimize the weights in a network of neurons to control a 12 degree of freedom hexapod robot [15]. To improve the convergence rate of the GA, Lewis used the concept of staged evolution (which is similar to Behavioral Memory) which involves breaking the problem into a set of manageable challenges, which are solved hierarchically. More recently, Inada and Ishii (2004) also used a genetic algorithm and a staged evolution approach to optimize parameters for CPG control of ankle, knee, hip and pitching of the waste movements in a simulated biped [10]. Non-spiking CPG networks were evolved to match the desired joint angles in this simulated system.

We also follow a staged or hierarchical GA process where we first evolve the desired walking frequency, then the gait and lastly the joint angle profile. Our network is constructed entirely with spiking IFA neurons. The genetic algorithm (GA) used was based on FBGAMIN, a single goal optimizer, which falls into the class of an Adaptive Mutation Breeder Algorithm (AMBA) [17]. Breeder algorithms are well suited for the optimization of real-valued functions and the adaptive mutation characteristic of the algorithm utilizes a simple feedback loop within the algorithm to ensure that the mutation rate is always at its optimum. FBGAMIN uses elitism to ensure that the best solution always propagates, unchanged, to the next generation and hence the fitness over generations can only improve or remain the same.

The population size of the GA was set to 200, where 1 chromosome was the suggested trial solution and the remaining 199 chromosomes were generated by multiplying each gene of the trial solution by a random number between 0 and 5. This ensured that the initial population searched a very wide parameter space.

Our fitness function for frequency of walking is:

$$T = \frac{1}{desired\ frequency}$$

$$error1 = \left(\frac{T}{2} - delay(CPG1, CPG2)\right)^2$$

$$error2 = \left(\frac{T}{2} - pulse\_width(CPG1)\right)^2$$

$$if\ CPG1_{end} = 0 \rightarrow error3 = 10000\ \ else\ error3 = 0$$

$$fitness(frequency) = (error1 + error2 + error3)$$

Our fitness function for gait is:

$$f = \frac{1}{pulse\_width(CPG1) + pulse\_width(CPG2)}$$

$$actualphase = delay(CPG3, CPG1) \times f \times 360$$

$$error1 = (desired\_phase - actualphase)^2$$

$$if\ on\_set(CPG3) < on\_set(CPG1) \rightarrow error2 = 100000\ else\ error2 = 0$$

$$fitness(gait) = (error1 + error2)$$

In both cases, the maximum number of generations the algorithm was allowed to evolve for was set to 10, however if convergence was terminated if the fitness went below $9\times10^{-6}.s^2$ and $1deg^2$, respectively.

Our fitness function for joint angle profile is the Mean Squared Error (MSE) for one period of the network joint angle profile and one period of the desired (human) walking data:

$$fitness = \frac{\sum_{\forall n}(desired\_angle - CPG\_angle)^2}{n}$$

where n =67. For both knee and hip angles, the maximum number of generations allowed was 20, however if the fitness went below $7.5deg^2$ then the search ended.

The initial conditions for the IFA neurons are listed below, which causes CPG1 to fire at a rate of 125 spikes per second with no oscillations by CPG2 and CPG3.

Initial Conditions for the Neuron Parameters						
Vthresh (v)	*a*	*b*	*e/tau*	*d*	*τ*	I_{1-2}
0.5	100	50	0.02	-60	1.0	-1500

III. Results

Evolving the Walking Frequency: The GA easily and quickly found the parameters to realize walking frequencies from 0.5Hz to 3.5Hz (figure 3). The system converged within 3 generations (not shown). Figure 4 shows the parameters for the IFA neurons used to construct the master oscillator (CPG1 and CPG2). Despite the wide range of parameter values, all play important roles in the network because of the non-linear and off-on nature of spiking networks. Notice that *both* IFA neurons have the same parameters, which reduces the dimension of the problem.

Evolving the Walking Gait: Given the frequency of walking, we now evolve the hip to knee relationship for effective

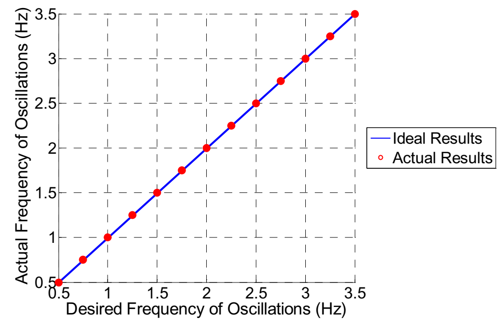


Figure 3: The walking frequency produced by the CPG network after a maximum of 3 generations.

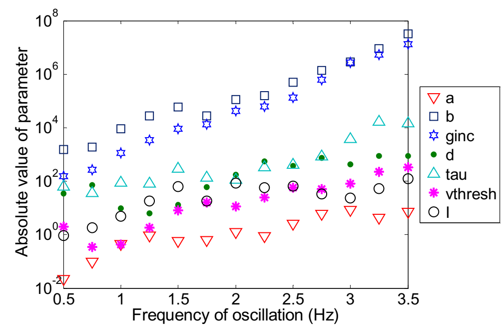


Figure 4: Shows the parameter value distribution for each frequency of walking. The actual values are scaled based on physical constraints.

stepping. In this network, there is only a feed-forward relationship from the hip to the knee, hence the parameter search is simple and converges very quickly, usually after a maximum of 2 generations to < 1 degree accuracy. Figure 5 shows a plot of the desired versus actual phase difference between the hip and knee for a walking frequency of 1Hz. Similar accuracy is obtained at all the walking frequencies we test (i.e. 0.5Hz to 3.5Hz in steps of 0.25Hz). Figure 6 shows the CPG network's hip to knee phase distribution when evolved to reach 45 degrees at various walking frequencies. Again, similar plots are obtained for different desired gaits with similar accuracy.

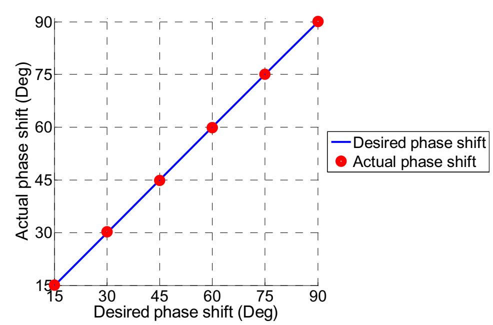


Figure 5: Shows the evolved CPG network's hip to knee phase for a walking frequency of 1Hz.

Evolving Joint Angle Profiles: Once the frequency and gait networks have been evolved, the control signals are applied to the robot. Since the robot are actuated with servo-motors, a lowpass filtered version of the spikes is generated by the micro-controller, and PWM signals are sent to the servo-motors. With no further training, the network displays the walking gait whose joint angle profiles are shown in figure 7(a). This profile is sufficient to make the robot walk effectively.

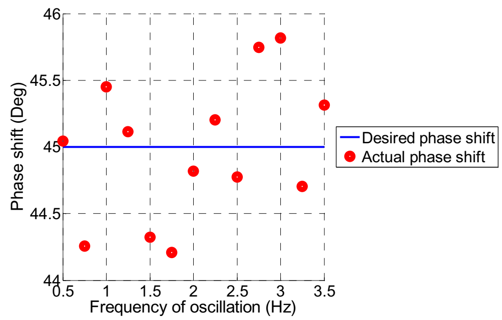
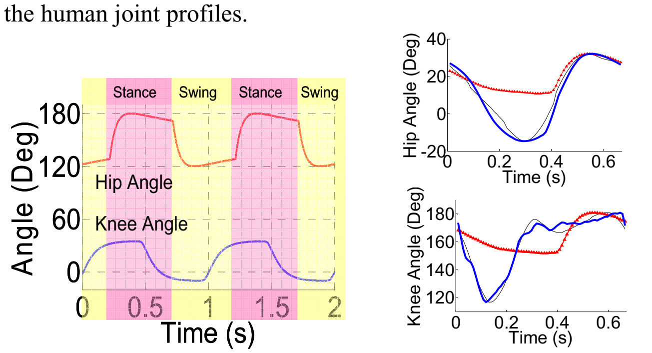


Figure 6: Shows the evolved hip to knee phase (desired phase is 45 degrees) at different walking frequencies.

As a further demonstration of the power of this approach, we wanted to impose a more physiological joint angle profile on the robot. Hence, we evolved a network whose outputs mimic the shape of the human joint angles [18]. Figure 7(b) shows the pre- and post-evolution joint angle profiles for one hip and knee, showing that network has evolved a fairly close replication of the human joint profiles.



(a) (b)

Figure 7: (a) Shows the joint angle profile for hip and knee after frequency and gait evolution only. (b) Shows the joint angle profile after the CPG network have been evolved to mimic human hip (left) and knee (right) angle profiles. Black: human, red: pre-evolution and blue: post-evolution.

Making RedBot Walk: In this final step, we hosted the evolved CPG networks onto our biped and recorded the joint angles as our robot walked across a ground at 1.5Hz. Figure 8 shows the joint angle profiles for the 2 hips and 2 knees of RedBot. The robot replicating the human joint angle profile. With the ability to reconfigure the network within a handful of generations, the decoupling of the walking frequency, gait and joint angle profiles (joint angle profile evolution is the most complex and least likely to be changed on-line) and using hardware CPG networks as in [5,8,9], we envision that the system can be easily modified in real-time and on-line.

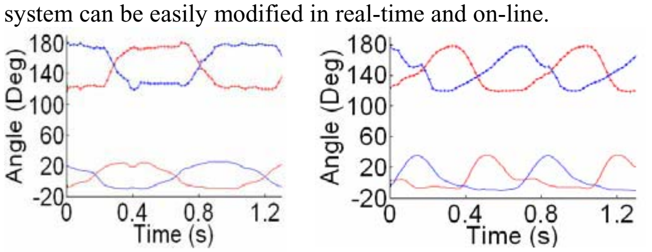


Figure 8: (a) Shows the recorded joint angle profile for hips (top) and knees (bottom) after frequency and gait evolution only for 1Hz walking. (b) Shows the recorded joint angle profile after the CPG network have been evolved to mimic human hip and knee angle profiles for 1.5Hz walking.

IV. CONCLUSION

We have developed biologically inspired locomotion control networks to generate the "muscle synergies" for walking in a bipedal robot. The network is constructed with spiking IFA neurons, and a hierarchical GA is used to determine the neuron and network parameters for walking. We show that the frequency of walking evolves quickly and independently of the gait and the desired joint angle profiles. By first evolving the frequency, then the gait (hip to knee phase) and then the joint angle profiles, we are able to obtain stable, low error walking solutions within a few generations, provided reasonable initial conditions are used. Furthermore, using our hardware CPG networks in [5,8,9], to replace the microcontroller neurons, we expect real-time end-to-end performance (currently the network update during GA computation prevents real-time evolution). We finally demonstrated the walking efficacy of our evolved networks by hosting them in our Redbot bipedal robot.

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