# An Analog Artificial Nervous System for Locomotion

Iván R. Zapata and A. Antonio Arroyo
Machine Intelligence Lab
Department of Electrical and Computer Engineering
University of Florida
ivan@mil.ufl.edu, arroyo@mil.ufl.edu

## Abstract

We propose a biologically inspired nervous system for an autonomous mobile agent. Individual neural cell dynamics exhibit a high degree of fidelity to their biological counterparts, omitting the simplifying assumptions usually taken by computational neural networks. In order to further duplicate a biological system that operates in continuous time, our implementation is strictly through analog electronics. This is a progress report on the early stages of the research, facilitated by National Science Foundation funding.

# 1 Introduction

Only in recent years has the scientific community turned to biology to answer the problems posed by Artificial Intelligence. The trend toward simple, distributed, decentralized control schemes is, we firmly believe, headed in the right direction. For this reason, our research develops from discoveries in the field of neurobiology, specifically, from the study of simple organisms and their interaction with their environment.

# 2 Biological Bases

## 2.1 Neurobiology

We wish to solve a grossly unconstrained problem: to negotiate an unknown environment, one about which we have only sparse general information, and one which our **(robot, agent?)** must continually evaluate. Biological organisms, through evolution, have solved this open-ended problem quite successfully. Thus we base our solution on careful study of one of nature's mechanisms: the nervous system. We wish to emulate a biological nervous system, to some degree of accuracy, so that we can take advantage of its robustness and flexibility, at the cellular and macro levels. No brief introduction to the immense complexities of nervous systems is possible, so we shall only touch on the major elements that form the foundations of this research.

## 2.2 Neurons

Neurons are specialized cells whose function is to integrate information (electrical impulses) from different sources (other cells), and transmit this information to some destination (more cells). Two types of neurons that will become relevant to this work are motor neurons and sensory neurons. There are several specialized types of neurons, all of which share common morphological traits: a *cell body*, one or more *dendrites* (which receive signals from other cells) and an *axon* (which transmits signals to other neurons). Signals from one neuron to another can either be inhibitory or excitatory, thus one cell can either elicit or repress the response of another cell. Like all living cells in an organism, neurons are extremely complex, exhibiting a collection of electrochemical and biochemical properties beyond their input/output characteristics. Even while passive (no active inputs), a neuron can be electrochemically active, depending on its recent activity (Pearson, 1976; Rall, 1977). A neuron's more subtle electrical characteristics are a fundamental part of its overall behavior, and consequently, of a nervous system's overall behavior.

## 2.3 Neural Circuits

Although possible, single neurons generally do not undertake processing tasks on their own. This is usually done by distributed networks of interconnected neurons called n*eural circuits*, whose interactions underlie both simple and complex behaviors (Selverston, 1985).

### 2.3.1 Central Pattern Generators

All moderately complex behaviors (i.e., walking, swimming) require the presence of temporally extended patterns of activity (Beer, 1990). The neural basis for such fixed-action patterns lies in the concept of central pattern generators (CPGs). We can distinguish two general types of CPGs: those made up of *pacemaker cells* and those made up of *oscillator networks.* A pacemaker cell is a neuron that, due to its intrinsic biochemistry, produces some type of rhythmic output. An oscillator network produces a rhythmic pattern from the interactions between some number of interconnected neurons. CPGs are believed to drive essentially any behavior, conscious or unconscious, which exhibits a rhythmic pattern: swimming, scratching, swallowing, breathing, or the beating of a heart.

### 2.3.2 Central Nervous System

Nature has managed to decentralize a great number of primitive control mechanisms within an organism; however, they must all be coordinated in such a way that there exist no conflicting actions by two or more systems. The central nervous system (CNS) is the combination of several individual neural circuits, making provisions for some sort of behavior mediation. One hypothesis for behavior selection is the idea of a command neuron, i.e., a single neuron which decides which of several conflicting actions should occur. Some newer and more generally accepted hypotheses suggest that mutual inhibition between CPGs gives rise to behavior selection, rather than some control neuron. Thus, the CPG for one behavior may suppress the CPG for a conflicting behavior; or two or more CPGs may share neural connections in such a way that only one action can occur at a time.

## 2.4 Biological Organisms as Models

We know we want to take our cues from biological nervous systems. Which animals should we look to? After all, we wish to take advantage of existing research, all of which exists in the form of detailed case studies. To understand and incorporate the fundamental mechanisms of control and behavior, we believe that the organisms that most suitably answer our questions are invertebrates. Much research in neurobiology has centered on invertebrates (locusts, cockroaches, snails) mostly because an invertebrate's CNS is orders of magnitude more simple than larger animals, yet it provides a model that can be generalized to more complex organisms (Selverston, 1985).

# 3 Previous Work

We have defined our research to be a problem in situated robotics. We assume no *a priori* knowledge of the environment, therefore we cannot assume any sort of model for it. A purely reactive, Brooksian approach is indispensable to this research. We briefly discuss two such studies on whose shoulders we will hopefully stand, and a third as an example of a simplified implementation of our proposed approach.

## 3.1 Finite State Machine Networks

Rodney Brooks at the MIT Artificial Intelligence Lab designed a control network for a six-legged walking robot (Brooks, 1989). The network consisted of several augmented finite state machines (AFSM), each of which, on its own, performed some rudimentary control task. This control scheme provides a largely decentralized signal flow, which makes for a particularly robust structure. The approach was largely reactive, i.e., the robot acted almost exclusively on reflexes, and was based on the subsumption architecture (Brooks, 1986). We also share Dr. Brooks' conviction that real agents are ultimately the only way a hypothesis can truly be tested.

## 3.2 Computational Neuroethology

Randall Beer at Case Western University simulated an artificial neural network for a six-legged, virtual insect, *Periplaneta computatrix* (Beer, 1990). His approach used a neural model more faithful to a neuron's real dynamics than is generally used in connectionist networks (perceptrons, etc.). Each neuron's passive cell membrane properties, as well as synaptic and intrinsic currents, were accounted for in his model. In simulation, *P. computatrix* was able to generate, on its own, walking gaits observed in real cockroaches.

## 3.3 CPG Implementations

Mark Tilden at Los Alamos National Lab, has centered his research on the concept of the CPG in walking. His designs are based around a simple ring oscillator (CPG) driving some leg actuators; the CPG's pulse train is controlled by the amount of load present at each leg, making this approach a truly reactive scheme.

# 4 Platform

All implementation will take place on a six-legged, 12 DOF platform, shown in Figure 1. Two orthogonal DC motors control each leg; one motor lifts the leg vertically, the other motor swings the leg forward or backward. Each leg has a ground touch sensor, which is active when the leg is in contact with the ground. A dual-axis, ±45 degree/axis analog inclinometer provides tilt orientation feedback. Power comes from a 6V commercial camcorder battery.

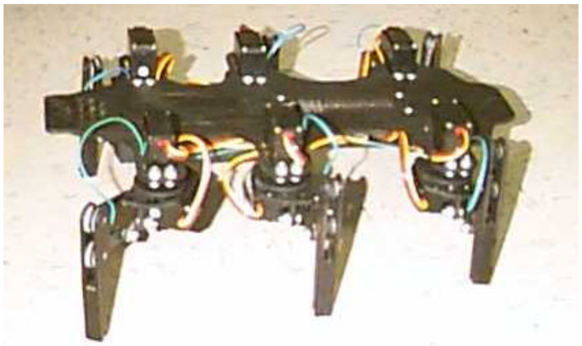

**Figure 1. 12 DOF Walking Robot**

# 5 Proposed Network Topology

## 5.1 Leg Controllers

Each articulated joint will have two motor neurons: a flexor and an extensor. Thus, 4 units control each leg, two for lift and two for swing. Figure 2 shows the basic leg controller with interconnections. The solid circles indicate inhibitory connections. Each neuron can inhibit its counterpart's response, in order to avoid contradicting actions from happening

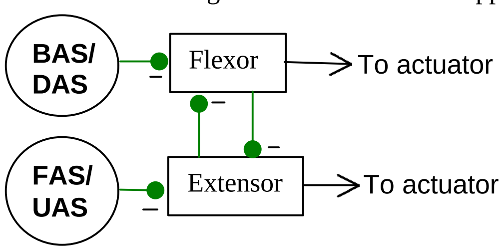


**Figure 2. Generalized Leg Controller**

simultaneously. The two lift control neurons (one flexor and one extensor) receive feedback from an upwards angle sensor (UAS) and a downwards angle sensor (DAS). As Figure 2 shows, UAS inhibits the lift extensor's response, and DAS inhibits the lift flexor. Similarly, a backward angle sensor (BAS) and a forward angle sensor (FAS) inhibit the swing flexor and swing extensor. These sensors' purpose is to act as limiting devices, as well as to dampen each leg's response to fast-changing stimuli.

## 5.2 Leveling Control

Our robot's first simple behavior will be to balance itself. The inclinometer produces two zero-centered balance signals (one per axis) which each leg uses to determine some action (i.e. "flex", "extend"). A sensory neuron transfers the output from one of the inclinometer's channels to each leg controller. Note that the sensory neuron's output only affects a leg's lift neuron, as there should be no swing response to a change in tilt angle. Figure 3 shows the excitatory and inhibitory connections from one tilt sensor neuron to the lift control neurons. Connections from the other tilt channel are arranged similarly. It should be noted that a "flexed" leg lowers the robot, and an "extended" leg pushes the robot up. Again, solid circles indicate inhibitory connections, and solid squares indicate excitatory connections.

## 5.3 Walking

The next behavior we wish to develop is walking. The key element in the walking controller is the

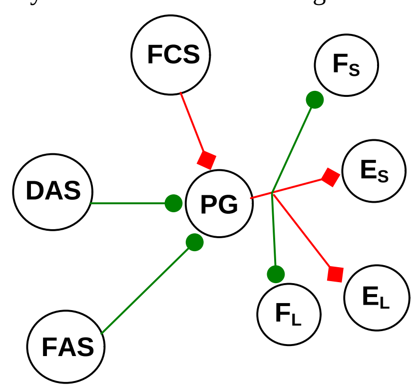


**Figure 4. Leg Walking Controller**

introduction of a pattern generator (PG) for each leg. The controller of Figure 4 is repeated once for every

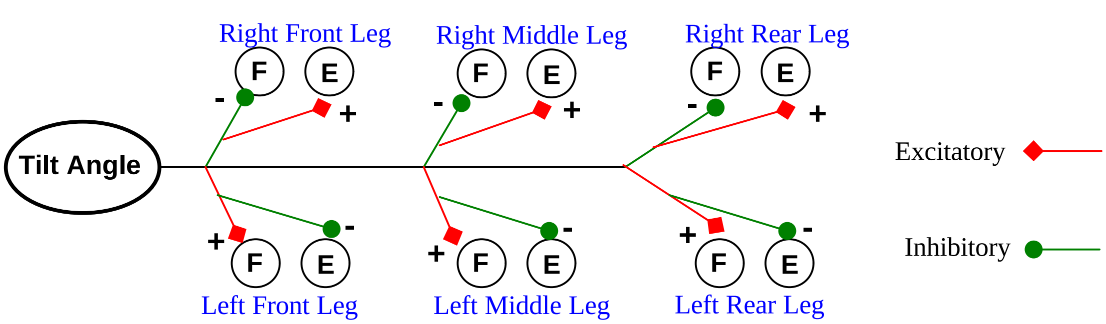


**Figure 3. Sensor Neuron Connections for Leveling Controller (one axis).**

leg. The PG is an oscillatory network, as defined previously, and produces periodic impulses at some arbitrary rate. As the Figure shows, the PG for each leg yields some control to DAS, FAS, and floor contact sensors (FCS). The PG directly stimulates both the swing and lift extensors ($E_S$, $E_L$) as well as the flexors ($F_S$, $F_L$). To ensure that the robot is always in equilibrium, we must guarantee that no two

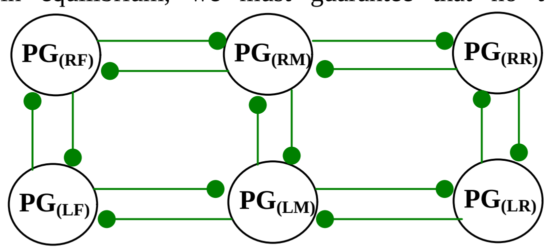


**Figure 5. Mutual Inhibition of Pattern Generators**

adjacent legs swing simultaneously (Beer, 1990). Therefore, the PG for each leg should inhibit its adjacent legs' PGs, as shown in Figure 5.

# 6 Future Work

## 6.1 Multiple Gait Generation

In biological organisms, the same neural circuitry is capable of producing different modes of locomotion, or gaits (Robertson and Pearson, 1985). Different walking gaits allow an organism to walk efficiently at different speeds. Generating multiple gaits, perhaps by adding extra neural circuitry to the walking controller, is a feature we are certainly working towards.

## 6.2 Taxes

All our current research is towards a synthetic animal that can walk about aimlessly, in the most literal sense. We've made no effort so far to steer our robot one way or another; fortunately the nature of our control scheme allows us to add extra control structures on top of the existing controllers with relative ease. It would then be a logical step to provide our robot with taxes to certain stimuli, such as light (phototaxis), sound (phonotaxis), heat (thermotaxis) and so on.

## 6.3 Network Plasticity

The great majority of neural circuitry in lower animals is acquired through evolution, not learning. That is to say, a cockroach, for example, is able to walk from time zero, it does not learn to do so through trial and error. However, all animal nervous systems exhibit some sort of plasticity, otherwise no animal would be able to learn from its environment. It is highly desirable for our network to exhibit the same kind of plasticity

# 7 Conclusions

We've proposed a model for an artificial nervous system with robotics applications. This nervous system will be implemented through analog electronics on a six-legged mechanical platform. Our approach lies somewhere between a biological nervous system and computer science's connectionist networks, as we believe the latter to be inadequate for analog realization, and the former too complex. This project is still in its infancy, but we find our early work to be encouraging and full of promise.

# 8 References


Beer, R (1990) *Intelligence as Adaptive Behavior: An Experiment in Computational Neuroethology.* Academic Press, Inc.

Brooks, R (1986) A Robust Layered Control System for a Mobile Robot. *IEEE Journal of Robotics and Automation*, RA-2.

Brooks, R (1989) *A Robot That Walks; Emergent Behaviors from a Carefully Evolved Network.* A.I. Memo 1091. MIT Artificial Intelligence Laboratory.

Pearson, K (1976) Nerve Cells Without Action Potentials. In J.C. Fentress (Ed.): *Simpler Networks and Behavior.* Sinauer and Associates.

Rall,W. (1977) Core Conductor Theory and Cable Properties of Neurons. On Brookhart, Monstcastle and Kandel (Eds.): *Handbook of Physiology, Vol 1, Pt 1, The Nervous System, Cellular Biology of Neurons.* Bethesda, MD: American Physiological Society.

Robertson, R M and Pearson, K G (1985) *Neural Networks Controlling Locomotion in Locusts.* Plenum Press.

Selverston, A (1985) *Model Neural Networks and Behavior.* Plenum Press.