BIO-BASED CONTROL FOR INTELLIGENT AUTONOMOUS SYSTEMS

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ABSTRACT

Our goal is to build robust, efficient, inexpensive autonomous robots that perform sensorimotor actions. Current computational approaches based on Turing Machines (TM) are fundamentally not robust, nor is there any evidence that the algorithmic solution to intelligent autonomous systems is solvable.

We propose to apply Prigogine's theory of irreversible processes in far from equilibrium systems to design robots which when immersed in a flow of sensory data create dissipative information structures to handle the data coherently. We are investigating Hoppensteadt's VCON model of the neuron as a specific framework for cell assemblies. Some advantages of this approach include the use of the same model across multiple scales, motor control is directly incorporated, the explanatory power of the theory applies to both biological and non-biological systems, and finally, hardware implementation is straightforward. We are applying this to the development of low-level vision and mobile vehicle subsystems; e.g., saccades, focus, object tracking, etc.

1. Introduction

Our goal is to achieve the design and development of intelligent autonomous robots that can perform useful tasks, such as exploration, guarding, cleaning, inspecting, etc.; moreover, they must be inexpensive, efficient, and robust. While many robotic systems have been proposed and built, none exhibit all the desired qualities. We believe that certain approaches are more likely to fail, namely those based on the standard theory of computation and its derivatives, and that biologically motivated methods have a more reasonable chance of success.

Intelligent autonomous systems which are physically instantiated require subsystems for:

- locomotion,
- power,
- sensing, and
- control.

The control subsystem is of major interest to us here, although these remarks may also hold for the other subsystems where they exploit digital techniques. In particular, we discuss control systems built from algorithms. (For the remainder of this discussion, we consider the Turing machine representation of algorithms.)

2. The Case against Turing Machines

The basic issue is that **Turing machines are fundamentally not robust.** Given a Turing machine (TM) encoded as 0's and 1's, then the change of any bit produces a new machine; moreover, the new machine can, and generally will, be quite different from the original intended machine. In addition, the implementation of a TM is even less robust. TM's are usually implemented as compiled programs that are executed on serial hardware. The possibility of error in non-trivial code, and certainly in any complex set of codes as found in autonomous robots, is very nearly certain; the possibility of error in the hardware which executes the code, while low, is not zero (e.g., the known Pentium chip bug!). The problem resulting from these two facts is that any error completely changes the behavior of the system; moreover, **systems with errors in implementation do not exhibit graceful degradation of behavior.** What's worse, if error handling code is added, this only compounds the problem.

One possible approach to overcome these problems is to use multiple processors. Suppose we run multiple versions and use the majority result? This addresses the issue of hardware error, but not algorithm error. It also adds the necessity of communication and protocols. Protocols based on regular automata may have provable properties, and that helps ensure robustness, but this area has not been explored much in robotics (for some work see [2,3]).

Another major problem with the digital approach is the loss of continuous functions. The digital representation of R is not R. This may be an insurmountable problem if biological systems can in fact exploit continuity of signals. The relation of this to chaos theory[1,14] is also of interest since if biological systems are chaotic controllers, then initial conditions are extremely important for the system trajectory, and the limited representation of numbers has a large impact.

Of course, the search for algorithms to implement Intelligent Autonomous Systems implies a belief that this class of problem (call it the IAS problem) is solvable (decidable). However, it may be that no solution exists. As an example of a seemingly much simpler problem is Hilbert's Tenth Problem (find an integer solution for integer coefficient polynomial), which has been proved unsolvable, as has showing the equivalence of two context-free grammars. Not only do these look easier, but they may even be part of the ultimate solution. Does it seem likely that the vision problem is computable? Other problems abound, and no TM solution is in sight: learning, motivation, self-reference, adaptation, general knowledge, judgment, evolution, etc.

Are these problems real? After all, the fact that men have walked on the moon indicates that engineering can overcome difficult problems. However, that trip was not cheap, and probably not efficient either, although it was robust (enough!). Perhaps a comparison to the automobile gives a better comparison in that there were similar difficulties early on, but mass production lowers cost and may raise efficiency and robustness.

Our thesis, however, is that these problems with TM's cannot be overcome. One alternative is to consider more closely the following existence proof: biological systems.

3. The Case for Analog Bio-Based Systems

First, let's consider the issue of whether or not biological systems can compute. (For a good discussion on the biological constraints imposed on early vision, see Koenderinck[10].) Claude Shannon showed the equivalence between electronic circuits and logic, after which McCollough and Pitts demonstrated that logic could be implemented on top of idealized neurons.

If, in fact, intelligent systems have their basis in logic, then this establishes the chain linking biological systems to logic, and one is free to pursue the implementation of intelligent systems independently of the embodiment (neurons or circuits). This is a crucial commitment to abstraction, however, and one we believe is not sound.

We contend that intelligence is an emergent property of the physical system, and cannot be abstracted away, but must be understood in terms of the dynamics of the organism: **The physical embodiment is the basis of intelligence.** Thus, we are led to the study of organic and neural systems.

A vital question is: **Can neurons be built on top of logic?** Neurons and systems built from them are very complicated chemically and functionally. The perfect simulation of physical systems is impossible; thus, properties of interest are usually abstracted and the hope is that the simulation can be made as arbitrarily close to the real process as necessary. (Although we take neurons as the basis for solving the IAS problem, we have not addressed, and will not address here, whether or not neurons can represent or process continuous functions.)

Can we use TM's to simulate neurons? This is a question that is somewhat easier to answer than the original question of whether the IAS problem is solvable, and depends on the model of the neuron used. For example, if we take the simplified McCollough-Pitts model, then it is possible to simulate that on a TM.

Of course, it may eventually be feasible to grow actual organic cells (genetically designed) and connect them up to form the required system. This may be the desired approach, for example, in building prosthetics.

Alternatively, it is possible to look to artificial neurons (AN) as the basis for a solution to the IAS problem; these can be physical devices or mathematical models which are solved analytically or numerically. Some of the desirable properties of AN's are that they:

- capture the essence of the cell and cell assemblies (model)
- permit simulation (numerically)
- straightforward realization (hardware)
- provide basis for loose coupling to higher level (emergent properties).

In general, the AN solution to the IAS problem is derived directly from the biological versions which makes them more likely correct; however, the choice of a particular AN model and its parameters, as well as the determination of the principles of organization of a system of AN's are the difficult problems to be solved in this approach[4,8]. In this paper, we describe a useful AN model and a theory we hope will provide some organizational principles.

4. The VCO AN Model

After reviewing the literature and trying various models, we represent AN's using the Hoppensteadt Voltage Controlled Oscillator Neuron (VCON) model [7]. The VCON model views the neuron as a clock in which:

- the cell membrane serves as an oscillatory system (ion flow)
- metabolism of the cell provides the source of energy to drive the clock,
- controlled ionic channels provide the trigger mechanism, and
- the phase of the membrane voltage provides the output and can be viewed as the hands of a clock.

The global action of the body to complete system can be organized as:

- responding to and providing natural rhythm: day/night, heart beat, breathing, locomotion.
- muscles and glands serve as actuators and filters
- groups of cells interact with and modulate each other through chemical reactions, and

- information is transmitted by means of firing frequency modulation.

Hoppensteadt shows that a simple clock can be modeled as $d\theta/dt = \alpha$ where α is the frequency and θ is the phase variable, and a modulated clock is $d\theta/dt = \alpha + f(2\pi t/a)$ where the signal f (we'll use cosine as the carrier function) modulates the clock.

Such a model can behave much like a biological cell, exhibiting spike potentials and frequency locking. We let $N_1 \rightarrow^{+} N_2$ to designate N_1 excites N_2 and $N_1 \rightarrow^{-} N_2$ for N_1 inhibits N_2. These are modeled mathematically as:

$$d\theta_1/dt = \omega_1 + cos(\theta_1)$$

$$d\theta_2/dt = \omega_2 + cos(\theta_2) + Acos_{+}(\theta_1)$$

where ω_1 and ω_2 are the center frequencies of the particular VCONs, A is positive (negative) constant for excitation (inhibition) and cos_{+} is $max(0, cos)$.

Hoppensteadt gives various examples of biological systems modeled as VCON networks, including von Euler respiration control. We have implemented several low level mobile robot control functions as VCON networks.

4.1. VCON Systems in Mobile Robotics

As a step towards creating a VCON-based autonomous robot we have designed several simple VCON structures implementing low-level sensory and control functions for a mobile robot.

One example of such a structure is an obstacle avoidance system. This system takes as its inputs three sonar sensors mounted on the front of the robot. The sensors tell the system if there is an object ahead. The system's outputs go directly to the motors controlling the two wheels.

The system is composed of just six interconnected VCONs as seen on Figure 1. The constants on the arrows indicate the strength of the connections and whether they are excitory or inhibitory. The Control VCON is the pacemaker which sets the speed of the entire system. The left and right wheel VCONs directly control the motors on the wheels. In the absence of any sensory input these VCONs simply drive the robot forward at the speed set by the Control VCON. The three sensor VCONs are connected to the sonars. In the presence of an obstacle, they inhibit the corresponding wheel VCON slowing it down so that the other wheel can turn the robot away. The Central Sensor VCON inhibits both wheels so as to slow the robot down when an object is straight ahead. However, the Central VCON is itself inhibited by the other sensors so that it will not slow the robot to a halt.

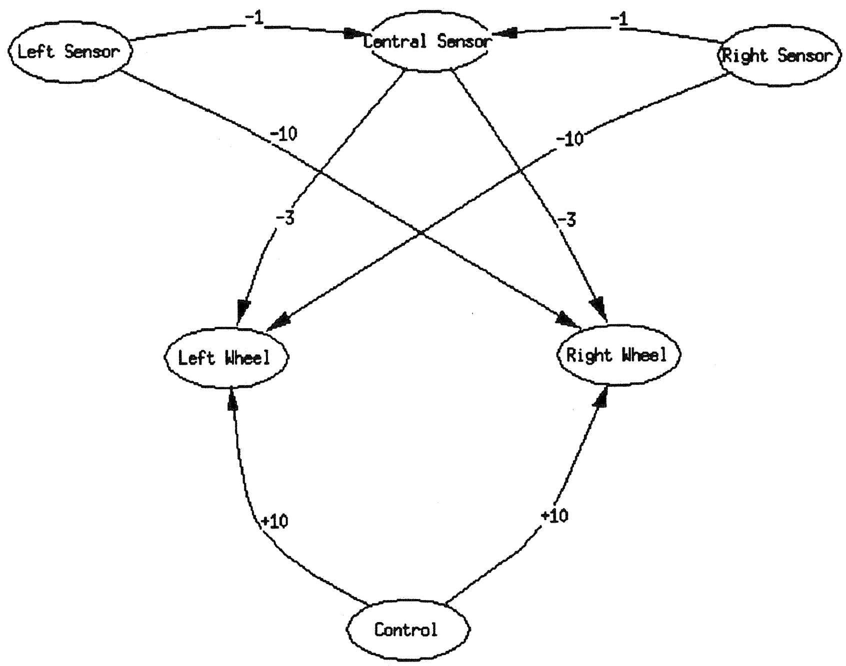

Fig. 1. VCON network for Obstacle Avoidance

A mathematical representation of the system on Figure 1 is given by the following system of six differential equations:

$$d\theta_{crl}/dt = 30 + cos(\theta_{crl})$$

$$d\theta_l/dt = 1 + cos(\theta_l) + 10cos_+(\theta_{crl}) - 10cos_+(\theta_{rs}) - 3cos_+(\theta_{cs})$$

$$d\theta_r/dt = 1 + cos(\theta_r) + 10cos_+(\theta_{crl}) - 10cos_+(\theta_{ls}) - 3cos_+(\theta_{cs})$$

$$d\theta_{cs}/dt = 1 + cos(\theta_{cs}) + sensor_{center}(t) - cos_+(\theta_{rs}) - cos_+(\theta_{ls})$$

$$d\theta_{ls}/dt = 1 + cos(\theta_{ls}) + sensor_{left}(t)$$

$$d\theta_{rs}/dt = 1 + cos(\theta_{rs}) + sensor_{right}(t)$$

where $sensor_{center}(t)$, $sensor_{left}(t)$, and $sensor_{right}(t)$ are the inputs from the sonar sensors. Finding analytical solution to such a system is very difficult, but a numerical answer is easily obtainable using the standard RK4 algorithm.

We have tested the above VCON system using our Multipurpose Robot Simulation program and obtained some good results (see Figure 2). The system functioned virtually without calibration and performed reasonably well under many different parameters. Figure 3 shows the graph of frequencies generated by the wheel VCONs versus time of the simulation. The peaks on the graph correspond to the turns made by the robot.

One of the most important properties of the given VCON system is the fact that the motors can be controlled directly by the VCONs eliminating the need for

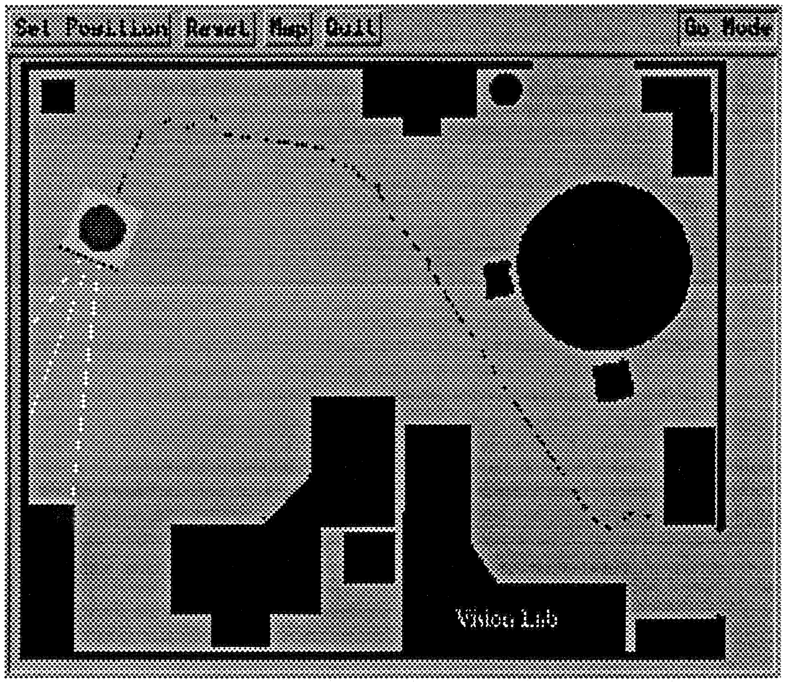

Fig. 2. Mobile Robot Simulation

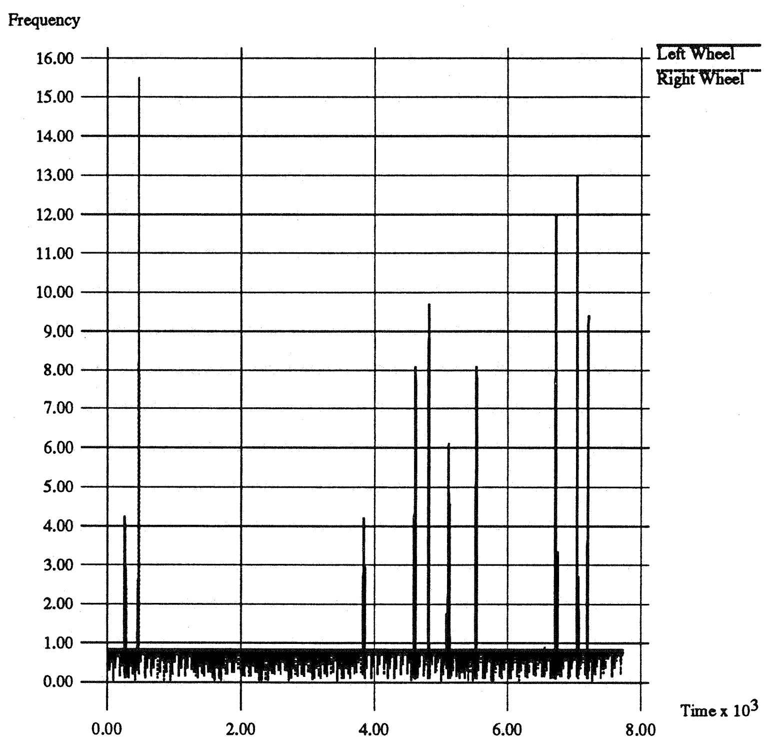

Fig. 3. Frequency outputs of the two wheel VCONs

complicated control circuits. Another interesting property of the system is that an arbitrary number of additional redundant VCONs can be added quite easily. Then, if any are damaged or function improperly, the system as a whole will continue to operate. In this simple example we have used only the three front sensors, however this system can be generalized to six, twelve, or all 24 sensors without changing the structure. Moreover, if one of the sensors fails (which happens quite often) the system will exhibit graceful degradation.

Obviously, the simulation is useful only insofar as it provides insight into the structure and parameters of the VCONs network – the real test of the system will be in the physical version operating with the VCONs connected to the sensors and actuators. We are in the process of constructing such systems.

5. A Theory for Emergent Properties

To adequately model IAS requires a set of behaviors which is context-free, but which operates in any context. That is, the theory must account for the dynamic interaction of the IAS and the environment. Recent developments in the theory of far from equilibrium systems provide the basis for the organizational principles of IAS [13]. The thesis of this theory is that:

- irreversible processes are real
- they play a fundamental constructive role
- irreversibility is deeply rooted in dynamics.

In such systems, *dissipative structures* arise to dissipate the energy entering the system; e.g., when water starts to boil, convection cells form which help transport heat. For an IAS, information is the energy source, and we believe that information dissipation requires the emergence of dissipative structures. These form the basis of the necessary emergent properties of a collection of AN's.

Prigogine has made a couple of relevant observations:

- "Living organisms are far from equilibrium objects separated by instabilities from the world of equilibrium and are necessarily 'large,' macroscopic objects requiring a coherent state of matter in order to produce the complex biomolecules that make the perpetuation of life possible."
- "The origin of life is related to successive instabilities somewhat analogous to the successive bifurcations that have led to a state of matter of increasing coherence."

The possibility of a new solution resulting from a bifurcation of some critical parameter value is intrinsic to emergent behavior (and learning, too). Note that one of the earliest studies of bifurcation in chemical kinetics was done by Alan Turing[15] and heavily influenced Prigogine's work.

6. Related Work

A number of similar proposals for modeling various aspects of biological systems have been proposed. Gregson[6] studies the generation of sensory intensity as a response to a physically varying environment. He is interested in the sequential dynamics of a system when it is:

- not in static equilibrium
- locally entropy producing
- dissipative: uses energy and is irreversible
- quasi-closed,
- not continuous (small input change does not necessarily mean small output change), and
- strongly dependent on initial conditions.

Thus, the goal is to determine the simplest dynamic structure which might support a diversity of observable input-output relationships whose parameters are potentially interpretable.

A strong discussion of coupled oscillator and the organization of behavior is given by Gallistel[5]. Elementary units of behavior include:

- reflexes,
- oscillators, and
- servomechanisms.

Several examples of animal behavior are given and it is shown that:

- Coupled oscillators can:
  - Interact through phase adjusting signals
  - Display wide variety of behavior
  - Be controlled by a few signals, and
  - Be at the heart of complex behavior units.
- Higher levels can control by:
  - Selective potentiation (lowers threshold)
  - Selective depotentiation (raises threshold)
  - Corresponds to concept of *drive* (ethology)

Finally, Kugler, Kelso and Turvey[9,11,12] have been making the argument for quite some time that locomotory patterns can be explained by non-equilibrium dynamics (stability theory, bifurcation theory, and fluctuation theory) rather than by an appeal to formal programs of instruction. They conceptualize living systems and their component subsystems, as well as their characteristic processes, as ensembles of coupled and mutually entrained nonlinear oscillators. For them, the problem is **not**:

- How the mind operates on sensory data,
- How past experience can interpret and give meaning to sensory data, or
- How the brain processes or organizes the input of nerves.

but rather:

- How perceptual systems resonate to new macroscopic qualities.

7. Conclusion

We believe that there is no TM solution to the IAS problem, and that some form of AN system is required. Moreover, the theory of far from equilibrium systems can provide crucial insight into the organization of any AN system which exhibits intelligent, autonomous behavior. The Hoppensteadt VCON model seems to be a reasonable and useful AN model. We are currently trying to understand how to structure networks of VCON's so as to exhibit emergent behavior.

If we consider information as energy:

- Biosystems may create dissipative information structures to handle information rich environments.
- The same theory of irreversible systems works across multiple scales and may allow loose coupling between them.
- Motor control is directly incorporated in the model.
- The explanatory power of the theory covers both biological and non-biological systems.
- Hardware implementation is straightforward.

We are currently applying these ideas to develop a mobile robot with vision and sonars and a binocular robot head. Our research program will proceed as follows:

1. VCON theory and practice provides a convenient, reasonable, bio-based theory of the neuron. We are actively exploring ways to get a better intuitive grasp of the differential equations governing systems designed this way.

2. The link between VCON models and dissipative structures needs to be worked out both theoretically and for examples. This is crucial to the success of the approach. There are some sample systems in chemical kinetics that we are looking at as to their relation and applicability to robotics.

3. We currently have tailor VCON models for various autonomous robot behaviors. This gives us particular systems to study parameters and connections. These are important to make progress, but the ultimate goal is to develop a basic VCON structure which through interaction with the environment adjusts itself and its parameters.

4. Given a VCON model for a behavior, it is useful to simulate the activity by solving the differential equations. This has led us to write some of our own numerical codes, and areas of further interest are large parallel simulations.

5. Another research area is designing and building hardware to implement the VCON models directly. We are exploring ways to do this efficiently, and also trying to determine if there is some basic general configuration that can be modified for each particular behavior subsystem.

6. The best system is one which evolves over time, and therefore, we are trying to determine how that can take place with respect to the VCON systems. This is also related to the dissipative structures and how they come into being and change over time.

7. Finally, dissipative structure construction is still the missing link between any AN model and theories of far from equilibrium dynamics. We are actively looking for a relevant example in vision or locomotion control.

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