An Artificial Brain

ATR's CAM-Brain Project Aims to Build/Evolve an Artificial Brain with a Million Neural Net Modules Inside a Trillion Cell Cellular Automata Machine

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ATR's Evolutionary Systems Department aims to build (i.e., grow/evolve) an artificial brain by the year 2000. This artificial brain should initially contain thousands of interconnected artificial neural network modules, and be capable of controlling approximately 1000 "behaviors" in a "robot kitten". The name given to this research project is "CAM-Brain", because the neural networks (based on cellular automata) will be grown inside special hardware called Cellular Automata Machines (CAMs). Using a family of CAMs, each with its own processor to measure the performance quality or fitness of the evolved neural circuits, will allow the neural modules and their interconnections to be grown/evolved at electronic speeds. State of the art in CAM design is about 10 to the power 9 or 10 cells. Since a neural module of about 15 connected neurons can fit inside a cube of 100 cells on a side (1 million cells), a CAM which is specially adapted for CAM-Brain could contain thousands of interconnected modules, i.e., an artificial brain.

Keywords: CAM-Brain, Cellular Automata (CAs), Cellular Automata Machines (CAMs), Artificial Brains, Neurite Networks, Genetic Programming (GP), Genetic Algorithms (GAs), GenNet (Genetically Programmed Neural Network Modules), CA Networks, Artificial Nervous Systems, Incremental GP, Biots (Biological Robots), Darwinian Robotics, 1000-GenNet Biotics, GenNet Accelerators, GenNet Shaping, CA Neurons, Darwin Machines, Nanotechnology, NanoCAM-Brain.

§1 Introduction

ATR's CAM-Brain Project introduces a new subfield into neural network research, called "Neurite Networks", where the distinction between the two is that with "Neurite Networks", the neural network gets GROWN, i.e., it has an embryological component. A "neurite" is a neurobiological term meaning a "baby neuron which grows connections with other neurites". ATR's artificial neurite networks are based on cellular automata (CA) networks whose branchings are "Genetically Programmed".
(i.e. they are grown under the control of a Genetic Algorithm). A sequence of a CA signals is sent down the middle of a CA “trail” (see Fig. 2). When a signal hits the end of a trail, it makes the trail extend, turn left, turn right, branch left, branch right, split, etc., depending upon the state of the CA signal. These signal sequences are treated as the chromosomes of a Genetic Algorithm. Once the CA network is formed, other CA state transition rules make it behave like a neural network. The fitness of this CA based neural network is measured in terms of how well it performs some task, e.g. controlling some behavior of a biological robot (biot). ATR’s “Brain Builder Group” (a part of the Evolutionary Systems Department) hopes to use such ideas to build Darwin Machines (i.e. machines which evolve), based on Cellular Automata Machines, as a tool to build an artificial brain.

As stated above, one of the research aims of ATR’s new Evolutionary Systems Department is to build an artificial brain by 2001. The very title of the department reflects one of its fundamental assumptions, i.e. that hyper complex systems (such as biological brains or embryos) will probably have to be built using an evolutionary approach rather than using human design. Complexity levels will be so high (especially when nanotechnology (i.e. molecular scale technology) becomes a reality) that no human being will be able to predict or even analyze how these systems function. The concept of “evolutionary building of complex systems” is called “Genetic Programming (GP)”.

This report shows how ATR’s artificial neural networks, based on cellular automata can be grown, using GP techniques. The ideas and results of this project will serve as the conceptual basis for the construction of what are called “Darwin Machines”². A Darwin Machine is a special hardware device used to perform GP in parallel. For example, Cellular Automata Machines could function in parallel to evolve the neurite networks described below. Each CAM would have a conventional programmable processor to measure the fitness of the evolved neurite network. A central processor could then perform the Genetic Algorithm (GA) aspects of the evolution (e.g. calculate the next generation of chromosomes etc.). Alternatively, a more distributed GA could be performed, where each CAM and its processor communicates only with its neighbors. ATR hopes that using these Darwin Machines, it will be possible to build/evo/evolve/GP a large number of neurite network modules and their connections to build an artificial brain capable of giving a biological robot (biot) some 1000 “behaviors”.

This report consists of the following sections. Section 2 gives a brief introduction to cellular automata and how cellular automata trails can be evolved into cellular automata networks. Section 3 expands on the initial ideas of section 2, especially in explaining how CA trails can be made to behave like neural networks. Section 4 presents ATR’s ideas for future research.

§2 The Genetic Programming of Cellular Automata Trails

Cellular automata are “cells” (e.g. squares in a 2D grid, or cubes in a 3D grid) each of which has one of a finite number of states. State transition rules (applying to all cells in the grid) determine how a cell updates (synchronously) its state depending upon its present state and the states of its neighbors. Fig. 1 shows an example of a CA state transition rule.

A 3 cell wide CA “trail” as shown in Fig. 2 can be fed a sequence of CA signals which propagate down the middle of the trail until they hit the end. When they do, CA
state transition rules are defined so that the trail is extended by one square, or made to turn left, turn right, split, branch left, branch right etc. (e.g. Ref. 5)). The sequence of these CA signals is then evolved using a conventional Genetic Algorithm®. When one trail collides with another, a “synapse” is formed, as shown in Fig. 3. The two cells of the synapse then absorb oncoming signals, thus keeping the configuration of the intersecting trails intact. Fig. 4 at the end of this report shows the results of a CA network evolution. In Fig. 4 there are 16 “CA neurons”. The chromosome was split...
§3 Cellular Automata Based Neurite Networks

One can then evolve CA networks. There is too little space in this short report to go into the many details, but CA rules can be defined to repair and clean up “destroyed” trails, i.e. those for which collision circumstances make synapse formation impossible, in which case no CA rules are defined, so by default the background state (black, zero) becomes the next state, which can destroy the trail. Usually the network stabilizes after several hundred clock cycles, i.e. all signal sequences get absorbed at synapses. Once this happens, other CA rules make the CA network behave like a neural network. For example, there are three kinds of sheath cells, two for “axons” (excitatory and inhibitory) and one for “dendrites”. Signal strengths in axons keep the same value they had at emission (at CA neurons), but once the axon signal passes through an axon-to-dendrite (A→D) synapse (created in the CA net growth phase), it becomes a dendrite signal, which drops off in strength as it advances. Thus the dendrite signal strength depends on its distance from its (A→D) synapse. Since these distances are evolvable, they are equivalent to the weights of conventional neural networks. Signal values can be positive or negative. At an excitatory synapse, the sign of the axon signal value is transmitted unchanged to the dendrite. At an inhibitory synapse, the sign of the axon signal value transmitted to the dendrite is reversed. Excitatory and inhibitory axons generate excitatory (+ve A→D) and inhibitory (−ve A→D) synapses when dendrite CA trails collide with them. Axon-axon (A→A), and dendrite-dendrite (D→D) synapses are simply not formed. Two merging dendrite signals add their incoming signal strengths at the junction. CA rules can be defined which allow this. When a dendrite CA trail splits, special “gating” cells are formed at the split junction.
which are later used (when the CA trails behave like neural nets) to direct the dendrite signals to turn towards the neuron which grew them. Finally, the axon output signal strength at a CA neuron can be a non-linear function of the sum of its incoming dendritic signal strengths. The strength of this axon signal remains unchanged as it travels through the axon.

§4 Future Research

A lot of work remains to be done. At the time of writing, the 2D version of a software simulation of CAM-Brain is nearing completion (having added nearly 7000 handcrafted CA state transition rules). Initial results are shown in Fig. 4. Unfortunately, on a Sun Sparcstation 10, the time necessary to grow a 16 neuron module is too long to be practical. Therefore it will be necessary to transfer the program to ATR’s CM5 supercomputer. Initial evolutionary experiments will be carried out on a 4 neuron module on the Sparc 10 to see how well it evolves. ATR already has experience with evolving simulated fully connected artificial neural modules (e.g. with 16 neurons) and has found them to be highly evolvable. Even if one cuts 70% of their evolved weights (i.e. one reduces their value to zero), the evolved function of the module remains more or less intact. Therefore it is expected that CAM-Brain’s neural circuits should still be evolvable despite less than full connectivity. If the 2D version shows good evolvability (i.e. if the CA based neural net modules evolve successfully to perform desired functions) then the next step will be to try a 3D version. Since collisions occur more easily in 2D, a 3D version will be qualitatively different. To help visualize the cubes of the 3D cellular automata space in order to conceive the 3D CA state transition rules (using a 6 neighborhood transition rule, i.e. “up, down, N, E, S, W”), a Silicon Graphics machine will be used. If the 3D version also proves to be evolvable, work will begin in earnest on the design of Cellular Automata Machine hardware adapted to CAM-Brain. Contact has already been made with the CAM building group at MIT to buy one of their recent CAM8 machines.

The beauty of using CAs as the basis for the CAM-Brain Project, is that they allow an initial growth of a structure which can later be used. Thus, in effect, one has a type of “evolvable hardware” (EHW). There are two broad categories of evolvable hardware approaches, called “intrinsic” and “extrinsic”. In “intrinsic EHW”, the evolution occurs inside (intrinsic) the “hardware” itself, e.g. FPGAs (field programmable gate arrays, or other kinds of programmable logic devices (PLDs)) can have their circuit configuring bitstrings be conceived as chromosomes in a Genetic Algorithm, so that one obtains a new hardware circuit for each chromosome, for each generation of the GA algorithm. In a CAM, the underlying hardware does not change, so strictly speaking, one is not doing EHW, but since a circuit gets evolved for each chromosome (where a chromosome is the sequence of signal cells which move down the middle of the CA trails), the process is equivalent to EHW. With “extrinsic EHW”, one uses software to simulate the evolution of a hardware circuit, e.g. by evolving a high level symbolic circuit description (e.g. using an HDL, (hardware description language)), and then writing (down loading) the elite chromosome’s solution into the configurable hardware. Hence the configurable circuit is written to just once. The real evolution occurs outside (extrinsic) the hardware. The CAM-Brain Project can thus be looked upon as a type of intrinsic EHW.

Another feature of CAM-Brain, is that it will be possible to grow connections incrementally between one neurite module (i.e. a GenNet = Genetically Programmed
Neural Network\(^1\)) and another, and thus build/evolve/GP an artificial brain with thousands of GenNets. This would be a kind of incremental evolution. Since most papers on neural networks are concerned with only a single neural module, to be dealing with thousands of modules, as may be the case with the CAM-Brain Project, will be a breakthrough in neural network research. If successful, it will create a tool within which to build artificial brains. Initially, these artificial brains will contain only a “small” number of modules, e.g. 100s, later 1000s etc. Gradually, as the number of modules increases, and insight is obtained as to how to evolve them incrementally, building artificial brains of increasing “intelligence” will become possible, thus creating a bridge between the two fields of Artificial Life (ALife) (whose long term goal is to create artificial life forms) and the more distant goal of Artificial Intelligence (AI) (whose long term goal is to create artificial intelligences). A sufficiently intelligent artificial life form becomes an artificial intelligence.

Commercially speaking, if electronic circuits can be successfully grown/evolved, rather than be humanly designed, it may be possible to create circuits of enormous complexity, and hopefully, superior functionality. If so, the notion of “evolvable hardware” may revolutionize the electronics industry.

By the year 2001, the last year of the CAM-Brain Project, ATR’s Brain Builder Group hopes to have the capacity to put a million neural net modules (GenNets) into a trillion cell Cellular Automata Machine. During the 1990s, the Brain Builder Group also intends to design/simulate molecular scale CAMs and similar machines, so that the number of neural modules which can be evolved can jump from millions to Avogadro’s number (i.e. a trillion trillion), once nanotechnology becomes a reality in the early 2000s\(^9\).

References

**Dr. Hugo de Garis:** He is an invited researcher of the Evolutionary Systems Department at ATR Human Information Processing Research Laboratories in Kyoto. He obtained his Ph. D. in the field of Genetic Programming (i.e. using evolutionary algorithms to build complex systems) from Brussels University, Belgium in January 1992, and was an STA postdoctoral fellow at the Electrotechnical Lab (ETL) in Tsukuba in 1992. He is now trying to grow/evolve an artificial brain inside a cellular automata machine.