I don’t know how to start this shit, yo.. now

Summary

Write your summary here...

Preface

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Abbreviations

ANN	=	*Artificial* Neural Network
RC	=	Reservoir Computing

Chapter 1

Introduction

> They're trying to understand what space is. That's tough for them. They break distances down into concentrations of chemicals. For them, space is a range of taste intensities.
>
> Greg Bear, Blood Music

Countless manhours have been spent improving the design and manufacturing process of the digital computer, creating more and more complex architectures capable of operating at ever greater speeds while maintaining stability, as even a single glitch can cause the program to crash. Neurons on the other hand have no architectural blueprint to follow, but still organize themselves into networks capable of solving complex tasks, with far greater energy efficiency, robustness and parallellism than any designed processor. Inspired by work done in the field of material computing systems such as the mecobo platform of nascence [citation needed], living neural networks grown from human stem cells *in vitro* on *Micro Electrode Arrays* (MEA) are interfaced with a digital computer, forming a hybrid neuro-digital system. This system utilizes the theoretical framework of *Reservoir Computing* to help translate between the digital and biological parts of the system, allowing it to solve simple tasks as a proof of concept.

In the 50's and 60's there was much optimism in the burgeoning field of artificial intelligence. In 1965 H. A. Simon claimed "machines will be capable, within twenty years, of doing any work a man can do."[7] , while Marvin Minsky boldly claimed in 1967 that "Within a generation ... the problem of creating 'artificial intelligence' will substantially be solved." [1]. These claims seem ridiculous now, but at the time the optimism made sense. After all great strides was made in symbolic programming, computers had finally become powerful enough to efficiently manipulate logic symbols such as predicates, negations and implications. With these programs the machine could inferr conclusions based on previously known information using symbolic logic, mimmicking the high level reason-

ing that humans are capable of. While the computers at the time were only capable of very simple logic inference, such as concluding the grass was wet based on prior knowledge it had recently rained, it was believed that the machines ability to infer would grow at the same pace as processor speeds. The driving force behind the great leaps made in symbolic computation was the exponential growth in transistors per area, dubbed moore's law. This growth allowed processors to maintain exponential performance increases without straying from the fundamental Von Neumann architecture, sequentially performing instructions to manipulate memory. With these performance gains yesteryears intractable problems were turned into routine operations, and AI it was thought, was no different. Why then did Minsky's predictions fail so badly? In short, processors are *designed* in a top down fashion to perform an instruction set of logical operations, which in turn allows us to design and run programs on them, for instance programs that operate on logical propositions superficially similarly to human reasoning. As complex as they are, each component in a processor has an obvious purpose (such as adding numbers) and like clockwork these parts work together to execute the program. The brain on the other hand is the result of a self-organizing process forming a network where each component works in parallel leading to a global behavior much greater than the sum of its parts. In order to understand the difference, it is quite revealing that humans are so bad at simple arithmetic compared to the processor. This is because unlike processors, there is no adder neuron, thus our ability to add numbers is a property that arises from the collective behavior of neurons, and cannot be traced back to any single neuron. The goal of the processor designer is to provide a component capable of addition, while the "goal" of the neurons is to create a network whose dynamics are capable of responding to any input, including arithmetic.

Unconvential computing, as implied by the name, comes in many forms such as buckets of water [3], or blobs of carbon nanotubes [cite nascence]. These approaches utilize the inherent computation that happens in all physical processes. Consider the effort spent modelling and simulating snow [Cite SIGGRAPH frozen paper] used in motion pictures such as Disney's frozen. Dozens of machines in large rendering farms spend weeks rendering the snow in final movie, however if you bring some dynamite and a helicopter nature will gladly provide you with an avalanche "for free".
Motion pictures aside, all natural processes, going from order to entropy are performing calculations, the only difference between avalanches and silicone processors from a computational standpoint is the fact that the silicone processor has been shaped in such a way that the process happens in an orderly, controlled fashion. Avalanches are unlikely to have a big impact on the computing world. Computation may occur, but it is far too unstructured to have any practical use. Still, the processes governing an avalanche are not that different from the processes happening in the primordial soup, save for one key difference, in the primordial soup life formed, and with life came evolution. What is the difference between an avalanche and slime mould? While it's certainly relevant to mention that an avalanche might crush you, from a computational standpoint the difference is that the process that unfolds in slime mould serves a purpose. The slime mould seeks food which allows it to spread and propagate its genes. In short, it responds to its environment, reacting to sources of food and avoiding danger. Indeed, the slime mould can be directly applied to solve computational problems, such as Adamatzky's application of mould for road plan-

ning [Cite Adamatzky Mould Paper]. The interconnected nature of life and computation is perhaps best shown in DNA, which can even be directly utilized in computations such as in Adlemans DNA computer [Cite Adleman].
Still, the most impressive example of computation is the human brain, vastly outperforming silicone computers in complex tasks such as the manufacturing of funny internet referential humor. The vast complexity of the human brain has made it a very difficult subject to study and copy. Rather than understanding the human brain as a whole a more feasible approach is to understand the underlying processes that allow neural networks to self-organize into computationally capable networks. In [Cite DeMarse flight controller] a neural network is grown in an MEA and interfaced with a flight simulator. [Cite AHDNN] follows a similar approach, using neurons to control a simple robot. The contribution presented in this paper builds on this work, but adding RC...

Chapter 2

Background

2.1 Complex Systems

In this body of work references are made to computations done by both artificial and real neurons. To make the distinction between these cases clear all computation done by computer simulated approximations of neurons will be prefixed as artificial.

Creating a bridge between machine and neural culture is not useful in itself without a way to interpret the electrical activity measured from the network, and a way to encode information as electrical pulses to be transmitted back to the network. To harness the computational power of neural networks it is necessary to employ a simplified model of neurons capable of describing how they self-organize into computationally capable networks, but leaving out the implementation details. In this endeavor it is very helpful that nature, through the process of evolution seems predisposed to creating systems that in many ways exhibit behavior similar to the brain. Eco-systems, ant-hills and social networks have much in common: They all exhibit complex non-linear behavior where the global behavior of the system cannot be traced back to a single part. Furthermore, their behavior is certainly not designed, but has arisen from millions of years of evolution. In these *Complex Systems* positive feedback can loops amplify small perturbations into cascading effects, changing the entire system, while negative feedback loops may cause other states to be relatively stable, resulting in multiple meta-stable states, so called *attractors*, that give the system some measure of order.

The first step in creating a theoretical framework for bridging the gap between neuron and machine is then to study simpler bio-inspired models exhibiting this complex behavior, such as *cellular automata*. A cellular automaton is a model of a single cell that will change its state based only on its immediate neighbors. They are capable of solving global problems such as contour-extraction [6], establishing that local interactions can produce interesting global behavior.

Cellular automata are even sufficiently powerful to express a turing machine, but as Sipper puts it: “This is perhaps the quintessential example of a slow bullet train: embedding a sequential universal Turing machine within the highly parallel cellular-automaton model.”

Embeddeding turing machines into cellular automatas is of little use, but it's useful to know that cellular automata are sufficiently powerful if we are to apply it as a model for the processes governing neural networks. The real power of cellular automatas as a model for neural networks is how they model the *phase transitions* in behavior (i.e dynamics). In Langton's pioneering paper *Computation on the Edge of Chaos* [4] the system dynamics of cellular automata are shown to follow phase transitions similar to physical matter. Langton explored the rule space of cellular automata and found that the ratio between transitions that led to cell death and life had similarities to temperature in physical systems. As expected, rules which tended to favor cell death led to static or periodic systems, while rules favoring life over death led to chaotic systems. More interstingly is what happened when the rules favored life and death equally. In these systems which exists at the border between orderly and chaotic systems Langton found a *critical* phase where the system was neither chaotic nor ordered. It is important to note that Langton did not seek to solve a specific problem with his automatons, but to explore which automatas capable of supporting universal computation, hypothesized by Wolfram [8]. Criticality applies to any dynamic system, not just cellular automata, and the study of adaptive networks [5] suggests that many systems exhibit a homeostatic regulation of system dynamics to ensure that it stays in the critical phase, including neurons [2].

2.2 Evolution In Materio

aaa

2.3 Reservoir Computing

bbb

2.4 Neurons As Computers

Even a single neuron is an extremely complex system when compared to the transistor. Together they form vast interconnected networks where information is exchanged using electrochemical signals. A fundamental difference between neurons and conventional computers is that these networks have not been designed, they do not come with a blueprint, and they constantly modify themselves in response to the environment. Due to the complexities of this process it is completely necessary to restrict ourselves to a simple model of the neuron, leaving genetic activations and chemical pathways to the neurologists and chemists. In order to understand how neurons can assemble into complex networks capable of thought one must of course understand the underlying chemical and biological principles, but from a computer scientists perspective these are mere implementation details necessitated by existing in a physical universe. Were the physical laws altered the chemical pathways would surely differ, but the resulting behavior would probably [According to who?] still be similar to our universe. In this viewpoint, the very essence of neurons is their ability to self-organize into structures in a bottom-up fashion in a complex interplay between behavior and form. Following this rationale the neuron will be seen

as a simple node in a network, communicating using electrical pulses, so-called spikes or action potentials. These spikes are short bursts of electricity which after firing causes a quick refactory period in which the firing cell will not respond to stimuli. When fired these spikes stimulates connected neurons, which may in turn release their charge causing a signal to cascade in a feedback loop. These electrical pulses can be seen as the “language” of neurons, and by measuring electrical activity and stimulating the network using electrodes, it is possible to set up two-way communication between a machine and a cluster of neurons.

2.5

Chapter 3

Making Of A Cyborg

This chapter describes the physical components, biological and mechanical, used to create a cyborg.

3.1 Concept

A biological neural network is grown in a *MEA*, short for *micro electrode array* which contains electrodes which interface with neurons using electrical signals. These MEAs are then *embodied* in a physical robot which is controlled by the electrical signals as shown in [ref cyborg concept] This system is a *closed loop*, it does not require any outside intervention, such as a human controller using a joystick to operate, it's simply driven by the neurons response to what the sensors of the machine senses.

3.2 Platform

Providing an interface between neurons and a computer allows using neural network for computation, however it is impractical to move the neural cultures outside of the laboratory. Rather than moving the cell cultures outside the safe confines of the incubator, the robot and cell cultures are linked over a network connection. Thanks to this decoupling the cell cultures do not have to be embedded in a physical robot, instead they can be interfaced with any robot connected to the internet, and even to virtual robots that only exist as a simulation.

Similar network architectures have been implemented, in [Cite Application] a neuron culture is used to control a simple wall-avoiding robot as a proof of concept. In contrast with previous work the robot used in the NTNU cyborg project is a sophisticated robot which is programmed to move by itself, follow a person, take a selfie with someone and upload it to facebook, and even perform a secret handshake. By utilizing an already functioning robot as a host the cyborg project can focus on extending the capabilities of the robot, making it a true hybrid between digital and cellular computing.

3.3 Growing Neurons In Vitro

The neuron cultures used in the cyborg are being grown in MEAs at the department of neuroscience. The MEAs are seeded with neural stem cells of either human or rat origin which then spontaneously form networks. At seeding there is no network at all, only a "soup" of dissociated neurons which over the course of several weeks start forming networks. As the networks starts "maturing" a common phenomenon is neurons firing monotonic spikes automatically. The activity from these so-called pacemaker neurons can be seen in **??**. In the figure each cell corresponds to one of the electrodes as seen in **??**, however at this stage the monotonic spiking activity tends to be transient, starting and stopping randomly.

3.4 Neuron Interfacing Hardware

The hardware used to interface with neuron cultures for the cyborg is an *MEA2100* system purchased from multichannel systems. The MEA2100 system is built to conduct in-vitro experiments electrically active cell cultures such as neurons. The principal components of the MEA2100 systems are:

3.5 Micro Electrode Array

Introduced in the previous chapter, the *MEA* is equipped with an array of microscopic electrodes capable of sensing and delivering voltages to and from nearby neurons. **??** shows an empty MEA, **??** shows an MEA used by the department of neuroscience with a live neuron culture.

3.6 Headstage

The electrodes of the MEAs are measured and stimulated by the headstage which contains the necessary high precision electronics needed for microvolt range readings. **??** shows the same type of headstage used in this paper along with an MEA.

3.7 Interface board

The interface board connects to up to two head-stages and is responsible for interfacing with the data acquisition computer, as well as auxiliary equipment such as temperature controls. The interface board has two modes of operation. In the first mode the interface board processes and filters data from up to two headstages as shown in **??** which can then be acquired on a normal computer connected via USB. In the second mode of operation a Texas instruments TMS320C6454 digital signal processor is activated which can then be interfaced with using the secondary USB port as shown in **??**

Chapter 4

An RC Cyborg Platform

This chapter provides an overview of the components comprising the final system. fig??? shows an early idealized version of the cyborg which remains the core focus of the system. In this ideal cyborg an interface connects the biological nerual network to an ANN readout layer, which in turn controls a robot whose input is processed and relayed back to the neural network. With this guiding principle the final system has been designed with the following components.

Core Reservoir Interface
: Responsible for providing a bdirectional bridge between the reservoir and the outside world.

Data Processing
: Processes the signals from the biological neural network, as well as the sensory input from the robot to a neuro-compatible format.

Agent Control
: Embodies the biological neural network in a robot, either artificial or real.

These components are enough to satisfy the ideal version of the cyborg, but for a cyborg to function in a practical setting additional components are necessary:

Communication
: While the Core Reservoir Interface provides a bidirectional bridge, it is the Communications module that extends that bridge to any machine connected to a network.

Recording
: Data from reservoirs is stored in a database, making experiment data accessible to any computer connected to the network.

Online Reconfiguration
: The Online Reconfiguration module is responsible for providing the cyborg with a filter that interprets the data from the biological neural network which is achieved by reconfiguring the filter when the system is running to adapt to the current reservoir.

Together these components form a system, whose architecture shown in fig. ??? looks quite different from the ideal cyborg.

4.1 A Closed Loop Example

The final architecture is quite extensive compared to the ideal version, but it still exists to provide a closed loop embodiment of the neural network. To give an idea of how the system is used it is necessary with an example run.

Setup The user accesses a web interface provided by the main server (SHODAN) and configures the experiment. This entails setting up a database recording, selecting filter and parameters and selecting what sort of agent should be running.

Launch Once the experiment is configured the main server contacts the lab computer (MEAME) and requests data acquisition to start. MEAME creates a TCP socket which holds the data read from the reservoir.

Execution After setup is done the

4.2 SHODAN

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Appendix

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