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An Improved Method of Redundant Robotic Control Using Neural Network

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ABSTRACT

The goal for this paper is to construct a simulated robot to explore data encoding and processing in living neuronal network. Information was encoded by varying timings between neuronal input simulations. This response if interpreted as a computation can be used to emulate any logic gate and even a universal turning machine. This neural response was used to control a simulated robot in real time to approach an object if it was too far away or to avoid an object it was too close. Sometimes, Robot can hardly be controlled as a result of the distance not easily identified unlike redundant robot control using neural network where interpreted prove interval IPI are trained to calculate the distance at a glance through two different delay channels.

Keywords: Animat and Robot, Multielectrode Array.

I. INTRODUCTION

The main utilizes a highly distributed parallel architecture for encoding information and can manipulate this information efficiently to allow an animal to process sensory information in real time. Information in encoded through varying timings between inputs to a living neuronal network. Encoding information by varying the time delay between inputs to a living neural network produces a nonlinear IPI probing response in the neurons. Interception this response as a computation, it is shown that living neural networks are capable of emulating a universal turning machine and can execute any computer program with polynomial slow down. The nonlinear to information response encoding is to use to construct a simulated robot, which behaves as a simulated animal or animal, or animate. The ainmat is constructed in a way such that it approaches an object that is far away and to avoid an object that are very close. Neural controlled simulated robot is built to handle a type of approach and avoidance problems. The constructed animat can be a useful tool for studying properties or individual neurons in a population setting at a behavioral level of testing. The major interest to neuroscientist is the ability of synapses or connections between neurons to change strength based on activity within those neurons. Changes in neuronal properties can change the non linear dynamics of the IPI probing response, changes at the neuronal level which may be expressed at the behavioral level of the animate. The simulated robot body and virtual world is implemented in software and this software is also used to control hardware for neural simulation and recording. Linear mappings are used to convert sensory information to neural input. No sensory information is directly passed to the software modules coding for robotic movement.

II. METHODS AND MATERIAL

2.1 Multi Electrode Array

The use of multi electrode array is made possible by several recent technological advances and allows researchers to study cultured networks of neurons in vitro. Neurons are cultured over a grid of no invasive external electrodes, which allows the researchers to monitor activity in a large number of neuron simultaneously, and these can also provide a means of electrical stimulation. Multi electrode array have been used successful to study information coding in system such as the retina. Demonstrations of synaptic plasticity in culture are also of great interest.

2.2 Animats and Robots

These animats can be used to perform behavioural studies in the real (or simulated) world. Complex patterns of behavior can arise from a collection of very simple rules. Such behavior is called emergent, and results largely from the fact that even a simple system in a complex environment can behave unpredictable. Because of his unpredictability, the animat offers a nice emphirical alternative to test the dynamics of these systems in the real world. Several mechanisms have typically been used to control an animat including artificial neural networks and genetic algorithms. Over the past decade some prosthetic type robots or simulated embodiments have been developed using live animals or even humans. In one case, a "ratrobot" was developed, whereby the researchers could give a rat hints through electrical stimulation of particular brain regions which corresponded to a recommended direction for the animal to turn while it tried to complete a maze. In several other studies, robots are controlled by recording from multiple electrodes in the motor cortex. These studies generally attempt to mimic the animal behavior (i.e arm movement) in a robotic form. One may note that in these studies, information in the subject brain has already been processed substantially, and the motor cortex is typically a short step away from muscle control. Thus these breakthroughs represent developments in our understanding of how information is decoded from the brain to control muscle movement, but may not shed light on neural computation and information processing. In the prosthetic-type robots described above, we generally only have monitoring abilities near the output level of the information flow in the brain. The central question remains, how does the brain actually process information? What does this information look like as it is being processed? Recently living neurons in vitro culture have been used to control animats. However, the behavior of the animat under such control was arbitrary, and not related to any known computation of input stimuli.

2.3 Methodology

The method adopted in this paper is inter probe interval unlike behavioral test method which deals in placement of animate in specified distance which retards. The control of the robot unlike PID that is trained to choose its intervals pending on the robot.PID channel enhances the control of robot efficiently and fast unlike behavioral testing method that waste time. The PID effect which shows that cultured neural networks that is used to control robot when inter problem intervals are computed from two different delayed channels of one and two. These equally show how it can be used to control a robot to handle an artificial intelligent task in real time.

III. RESULTS AND DISCUSSION

Data Presentation and Analysis

The data collection which includes the two hidden training layers n^1 and n^2 of proportional integral Derivatives parts of the controllers.

Table 1:

x	n^1
0	0
0.1047	0.3090
0.2094	0.5878
0.3142	0.8090
0.4198	0.9511
0.5236	0.0000
0.6283	0.9511

Table 2: Data analysis for hidden training output of n^2 layer

x	n^1
0	1.0000
0.1047	0.9781
0.2094	0.9135
0.3142	0.8090
0.4189	0.6691
0.5236	0.5000
0.6283	0.3090

Table 3 : Data Analysis for ANN structure

p	**T**
-1.000	0.0538
-0.9500	0.4924
-0.8500	0.3619
-0.8000	0.8952

-0.7500	0.9829
-0.7000	0.8692
-0.6500	0.9077

Where p - Input of the trained data t – Output that depends input of the trained data

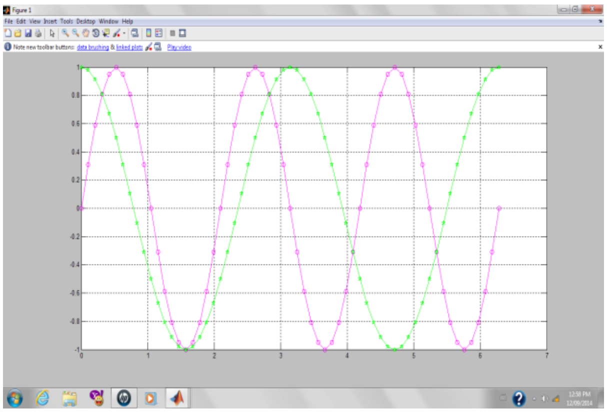

Figure 1. Digital Output Mapping Based on Responses to IPI

IV. CONCLUSION

Redundant Robot control using neural network can be achieved by calculating inter probe intervals IPI from different delay channels. The table for probe interval and digital output not gate was also presented.

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