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ANALYSING RECURRENT DYNAMICAL NETWORKS EVOLVED FOR ROBOT CONTROL

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Abstract

This paper shows how a mixture of qualitative and quantitative analysis can be used to understand a particular brand of arbitrarily recurrent continuous dynamical neural network used to generate robust behaviours in autonomous mobile robots. These networks have been evolved in an open-ended way using an extended form of genetic algorithm. After briefly covering the background to our research, properties of special frequently occurring subnetworks are analysed mathematically. Networks evolved to control simple robots with low resolution sensing are then analysed using a combination of knowledge of these mathematical properties and careful interpretation of time plots of sensor, neuron and motor activities.

1 Introduction

We have argued elsewhere (Husbands and Harvey (1), Harvey et al (2)), that continuous real-valued artificial neural networks with time delays between units and with unrestricted topologies are a powerful material for building autonomous mobile robot control systems. But their usefulness carries a high price tag: extreme design complexity. In (1) and (2) we explain the reasons behind our belief that the design by hand of such control systems becomes prohibitively difficult as increasingly complex or sophisticated robot behaviours are required, especially in complex, uncertain and dynamic environments. When dealing with such environments, visual sensing is likely to be highly advantageous, but adding visual guidance mechanisms compounds the design problem.

We have attempted to address these issues by developing a new methodology whereby robot network controllers are *evolved* rather than designed. An extended form of genetic algorithm (GA), as described in Harvey (3), allows a genuine form of artificial evolution, where new capabilities are built on older ones and there is a gradual increase in complexity of the control networks as the robot tasks are made incrementally more difficult. This open ended

3 Neuron Model

The neuron model employed to date has been designed for its usefulness in control applications rather than for biological plausibility or ease of analysis. Figure 1 represents the operation of a neuron. There are separate channels for excitation and inhibition. Real values in the range [0,1] propagate along excitatory links subject to delays

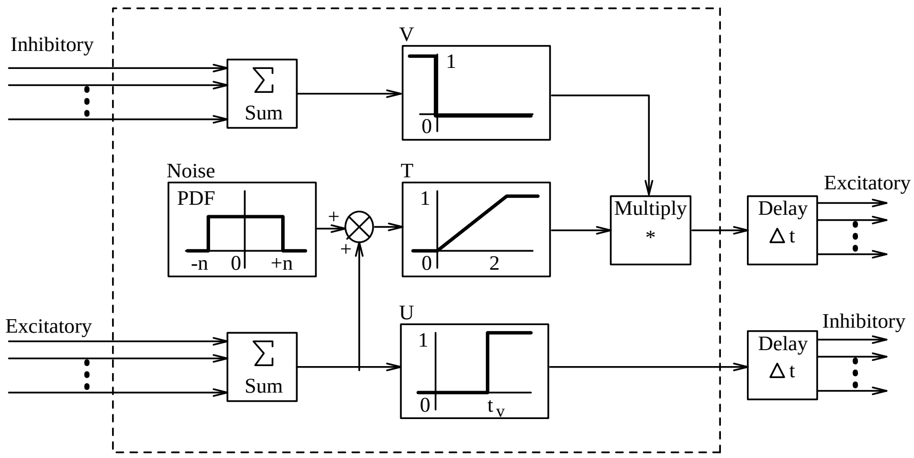


Figure 1: Block diagram of neuron operation.

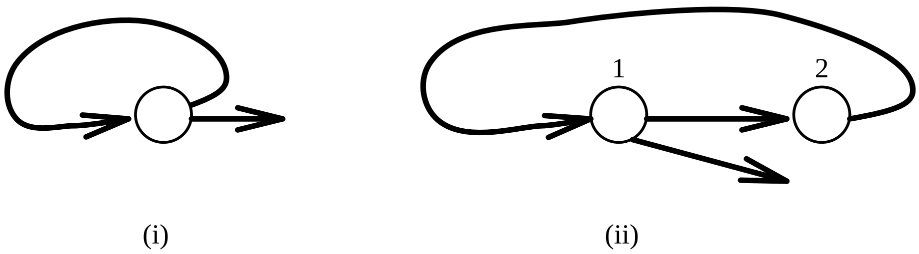


Figure 2: Generator feedback loops.

will refer to such neurons as *generator units* and will now analyse their properties in detail. These are not entirely obvious since internal noise is uniformly distributed with mean zero. In the following all connections have unit time delays, which is the case for all the experiments described in this paper.

Consider the single neuron feeding back onto itself as shown in Figure 2(i). The input at time t, I_t, is related to the output at time $t-1$, O_{t-1}, by $I_t = \ (O_{t-1} + n_t)$, where   is the transfer function of equation 1 and n_t is the noise injected by the unit at time t. Ignoring the threshold terms for the moment, and concentrating on the linear part of the function, we can write:

$$O_t = k(O_{t-1} + n_t) \tag{2}$$

where k is the slope of the linear part of   . Hence,

$$O_0 = kn_0 \tag{3}$$

$$O_1 = k(kn_0 + n_1) \tag{4}$$

$$\cdots O_t =$$

$1/2N$. Using elementary probability theory, it can be shown that they each have mean $\mu_{n_i} = 0$ and variance $\sigma^2_{n_i} = N^2/3$ (Meyer (4)). The linear relationships between the a_is and n_is means that the a_is can be regarded as independent random variables with mean $\mu_{a_i} = 0$ and variance $\sigma^2_{a_i} = k^{t+1-i}N^2/3$. In other words the output of the unit can be regarded as the sum of a series of independent random variables. To return to the temporarily ignored threshold conditions of , because O_t can never become negative (lower threshold condition), we can use a version of the central limit theorem to guarantee that the distribution of the random variable Z given below,

$$Z = \frac{O_t - \sum_{i=0}^{t} \mu_{a_i}}{\sqrt{\sum_{i=0}^{t} \sigma^2_{a_i}}} \tag{7}$$

is closely approximated by the *positive* half of the standardized normal distribution $\mathcal{N}(0,1)$. Now, $\sum_{i=0}^{t} \mu_{a_i} = 0$ and $\sum_{i=0}^{t} \sigma^2_{a_i} = \sum_{i=0}^{t} k^{t+1-i}\frac{N^2}{3} = \frac{N^2}{3} \times \frac{k-k^{t+2}}{1-k}$, hence:

$$Z = \frac{O_t}{\frac{N}{\sqrt{3}} \times \sqrt{\frac{k-k^{t+2}}{1-k}}} \tag{8}$$

This result can be used to estimate the expected time for O_t to reach the upp kTh,k,erer thebles.en

5 Experimental Setup

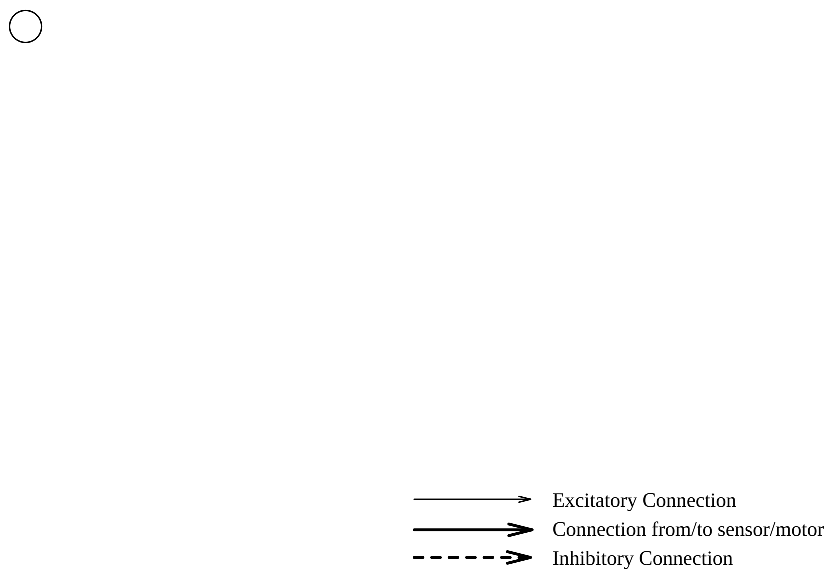
We started our research program by successfully evolving networks to generate obstacle avoidance behaviours in cluttered environments (1), but recently we have concentrated on uncluttered minimalist environments to allow a very close focus on the neural basis of simple robot behaviours. However, these environments are still noisy as are the (realistically) simulated robot kinematics. The results included in this paper are derived from experiments in which the robot moves in a cylindrical arena (see Figure 4). Populations of size 100 were evolved for 100 generations under the following evaluation function:

$$\mathcal{E} = \sum_{\forall t} \exp(-s|\mathbf{r}(t)|^2) \tag{10}$$

Where $\mathbf{r}(t)$ is the 2D vector from the robot's position at time t to the centre of the arena, and $\forall t$ denotes the duration of the evaluation run. $\mathcal{E}$ drops off very rapidly the more time the robots spend near the walls. On each evaluation run the robot was started in a random position close to the wall. This implicit evaluation function was chosen to study, with different sensor configurations, how well artificial evolution produced networks to keep the robots as far away from the walls as possible for as long as possible.

6 Network Controller Analysis

Figure 3 shows a typical network controller that evolved after about 20 generations under fitness function $\mathcal{E}$, and with unit time delays on all links. In this case the robot only had the tactile sensors mentioned earlier. Figure 4 shows the behaviour generated by this network. After eliminating those units with no output links and by using time plots of sensor, neuron and motor activities to further eliminate units which play no role in this behaviour, it is a straightforward matter to arrive at the reduced network shown in Figure 5 as the essential behaviour generator. Its operation can be readily understood. In the absence of sensory input the right motor is jammed on full forwards due to high activity in unit 12 which is a generator unit as explained above. The left motor maintains half speed forwards by virtue of an input of value 1.0 from unit 12. The neuron transfer function halves this signal, and noise can never be sufficient to shift the signal out of the half forwards range. Hence the basic behaviour is to move in a wide circle. This is a reasonable strategy to score on the $\mathcal{E}$ fitness function. It can be seen that the robot moves sharply away from the wall on contact, which again is a useful strategy given the fitness function. For the behaviour shown, triggering of the back bumper or front right whisker produces the tight turn away from the wall.



Excitatory Connection
Connection from/to sensor/motor
Inhibitory Connection

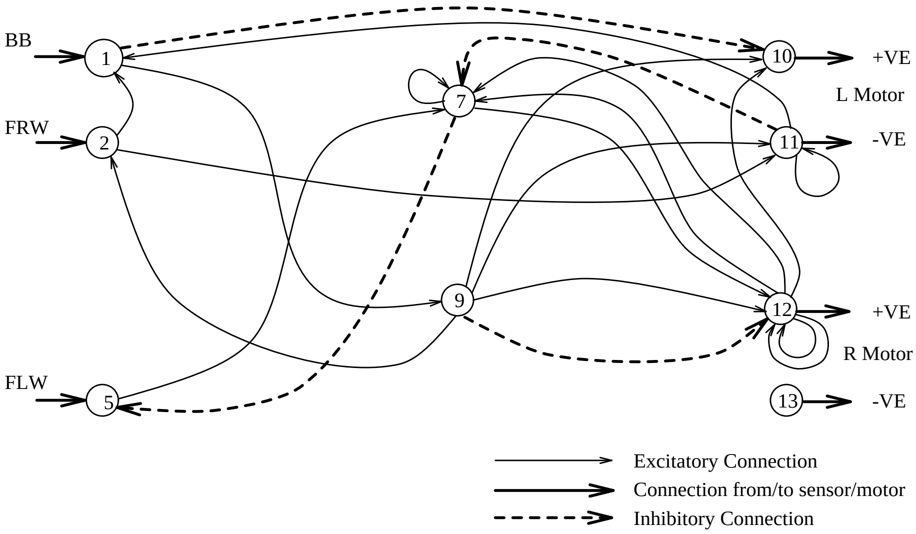
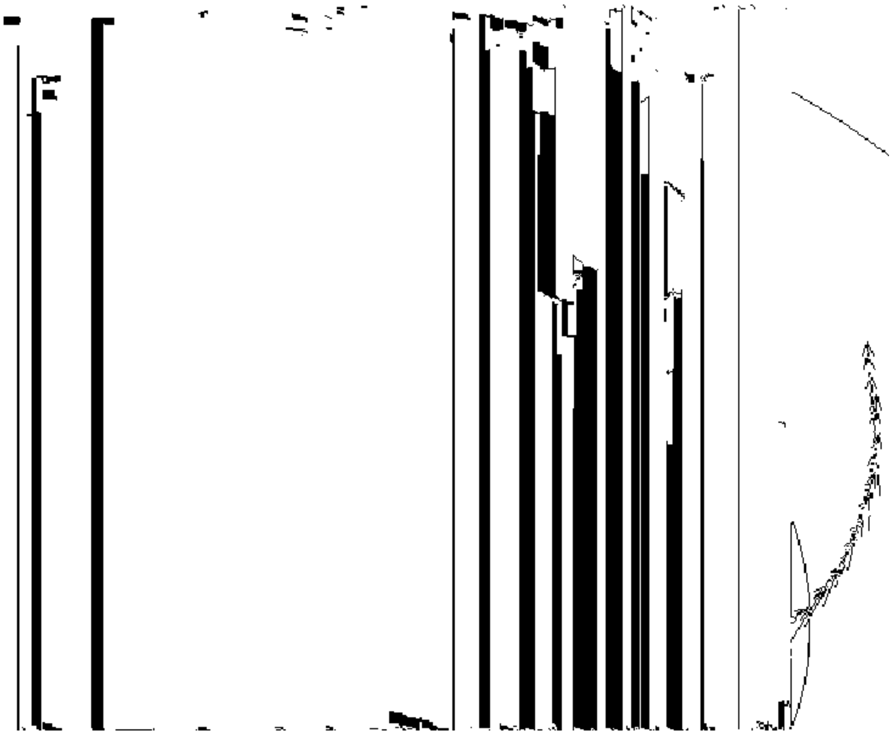


Figure 5: Reduced network which is essentially responsible for generating the behaviour shown.

70 generations. It can be seen that the path is wider than for the earlier behaviours and is able to reliably score higher on $\mathcal{E}$. The path is achieved by oscillating between straight line motion and the previous circling behaviour. This is caused by the oscillating right motor signal as can be seen from the activity plots shown in Figure 7.

Analysis of the full network reveals that the circuits for turning away from the walls on contact are still present but the reduced network responsible for the wide path behaviour is now as shown in Figure 8. Unit 12 is no longer a generator unit but unit 8 essentially is, being involved in two mutual feedback loops with unit 12 and one with unit 10, as well as having



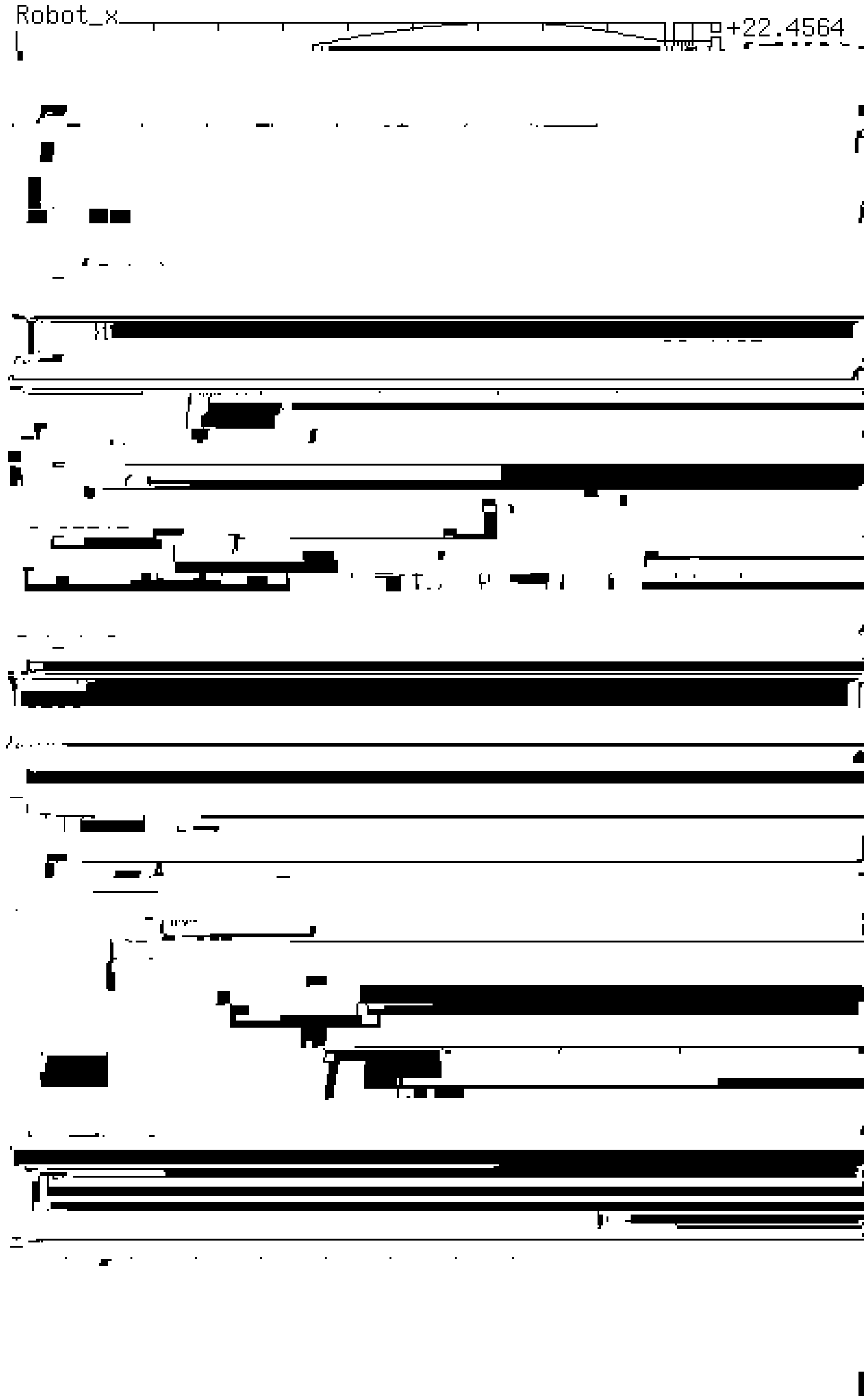


Figure 7: Activity plots for behaviour shown in figure 6

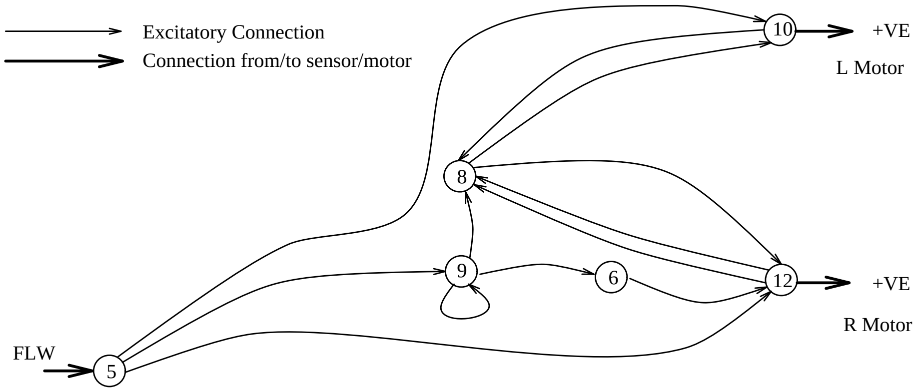


Figure 8: Reduced network responsible for generating behaviour shown in Figure 6

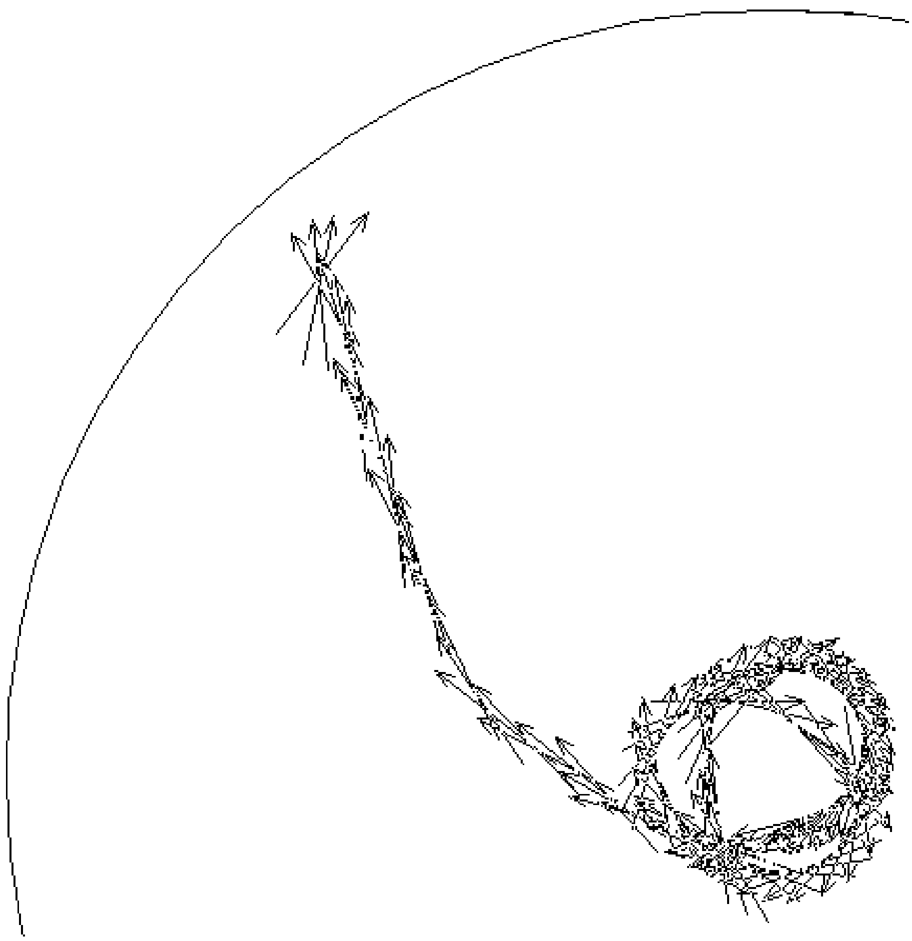


Figure 9: Evolved behaviour for robot with visual input under evaluation function $\mathcal{E}$.