

# Spike-time robotics: a rapid response circuit for a robot that seeks temporally varying stimuli

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## Abstract

In this paper we describe a spiking neural circuit inspired by the pyramidal-interneuron network gamma (PING) circuit modeled by Whittington and colleagues [1]. The spiking network controls a rat animat – a rodent-inspired robot that can autonomously explore and map its environment. We demonstrate how the neural controller directs the rat animat’s movement towards temporal stimuli of the appropriate frequency using an approach based on Braitenberg Vehicles. The circuit responds robustly (after four cycles) when first detecting a light pulsing at 1 Hz, and rapidly (after one-to-three cycles) when primed by recent experiences with the same frequency. This study is the first to demonstrate a biologically-inspired spike-based robot that is both robust and rapid in detecting and responding to temporal dynamics in the environment. It provides the basis for further studies of biologically-inspired spike-based robotics.

**Keywords:** spiking neural networks, resonating circuits, autonomous robotics, rat animat, Braitenberg Vehicles, neurorobotics, spike-time robotics

## 1 Introduction

The goal of our research program is to study issues in systems neuroscience using neural circuits implemented in a biologically-inspired autonomous robot. This program is part of a growing movement of roboticists [2], computational modelers and neuroscientists interested in brain-based devices [3], neurorobotics [4], and bio-inspired computation [5]. Neural networks as reactive controllers for robots can provide a set of low-level robust behaviours on which higher order complex controllers can be developed [6]. The majority of neurorobotic studies have used rate coded neural networks as controllers as they are theoretically more tractable as well as easier to develop and (until recently) have been easier to simulate and to train (e.g. [7, 8]).

In the past decade spiking neural circuits have begun to be studied in a variety of research laboratories [5, 9, 10]. Real-world stimuli are inherently temporal and spike-timed networks have a significant advantage over rate-coded networks in their ability

to sense and process precise timing in tasks involving temporal stimuli (for example, the silicon retina has achieved sub-millisecond response times by processing individual spikes asynchronously [11]). Learning rules based on spike-time dependent plasticity (STDP) have been developed to learn temporal patterns [12] and evolutionary algorithms (EAs) have been used to evolve spiking neural circuits [4, 13-15]. French and Damber [9] studied phototaxis and phonotaxis using a robot that was attracted to a light flashing with one frequency, and avoided another one with a different frequency. They evolved a feedforward spiking neural circuit, in which the neurons acted as integrators of the input signals, driving the wheels of the robots directly.

As French and Damber have observed, temporal dynamics are inherent in tasks such as phonotaxis. It is less well appreciated that vision also has inherently temporal properties. A particularly interesting aspect of spiking networks as controllers for embodied systems is the interaction between external and intrinsic dynamics (if an image is stabilised on the (human) retina, it fades from view [16]). The simplest such interactions occur when the spiking network resonates with temporal patterns in the environment, and there is an inherent trade off between rapid responses to temporal changes and the robustness of their detection.

Challenges for robust and rapid detection of temporal stimuli are present even in the simplest temporal stimulus provided by a periodically flashing light. The theoretically minimum time in which a sensory system can detect a specific frequency,  $f$ , is given by the period,  $1/f$ . However, a system tuned to respond immediately to the detection of a pair of light pulses with a given period would be prone to error, responding to many temporal sequences. For robust detection, several periods are required in any practical implementation. A productive compromise between speed and robustness observed in biological systems is to respond conservatively when initially detecting a pattern of interest, then respond more rapidly when primed by recent observations of the pattern [17].

In this study, we explored the resonant abilities of a recurrent spiking neural network acting as an embodied controller for a fully embodied bio-inspired robot, called the *rat animat* [18] (see Fig 1).



Fig 1. The rat animat and temporal dynamics of its visual environment. The rat animat (left, photo source [18]) moves autonomously through its office environment (typical camera view, centre). The average ambient light levels were recorded while the rat animat rotated 360 deg (right, green trace). With high gain the signal derivative shows fast oscillations (blue trace). A monitor flashing at 1 Hz superimposed an additional dynamic on the ambient light, and could be seen for 110 degrees.

Real neural systems exhibit intrinsic oscillations through all ranges of frequencies [19]. One simple spiking network uses excitatory-inhibitory feedback – the pyramidal-interneuron network gamma (PING) circuit [1]. Since biological evolution has already evolved the PING circuit, we implemented the network directly without the need for a genetic algorithm and with only minor adaptation and tuning of parameters (see Section 2). We replaced the rat animat's onboard navigation system with the spiking neural controller, and following French and Damper [9], we tested the ability of the spike-time rat animat to seek lights flashing with different frequencies. Our studies extend their results which were based on feedforward spiking networks, to the use of bio-inspired recurrent spiking networks, based on the PING circuit which has an intrinsic oscillation frequency (Study 1), and testing for robust and rapid detection of temporal stimuli with intrinsic oscillation frequencies (Study 2).

## 2 Neuron and synapse models

The network was constructed using leaky integrate-and-fire (LIF) model neurons [20] (for network architecture see Figure 3 and for parameters see Table 1). The membrane time constant ( $\tau_{\text{memb}}$ ) was set to 1.5 times the desired resonant period of the network, which then dictated the required membrane resistance ( $R_{\text{memb}}$ ).

Table 1: Leaky integrate-and-fire cell parameters.

$V_{\text{rest}}$	Resting potential	-60 mV
$V_{\text{thresh}}$	Spike threshold	-45 mV
$V_{\text{reset}}$	Spike reset potential	-60 mV
$t_{\text{refract}}$	Refractory period	3 ms
$C_{\text{memb}}$	Membrane capacitance	10 nF
$\tau_{\text{reson}}$	Desired resonant period ( <i>variable</i> )	$x$ sec
$\tau_{\text{memb}}$	Membrane time constant	$1.5\tau_{\text{reson}}$
$R_{\text{memb}}$	Membrane resistance	$\tau_{\text{memb}}/C_{\text{memb}}$ $\Omega$
$R_{\text{e\_memb}}$	Membrane resistance (edge detector cells)	1 M $\Omega$

The synapses were modelled as a postsynaptic current initiated by a presynaptic spike that decayed with a characteristic time constant. Synaptic parameters varied depending on the type of cell and the type of synapse (for a full list of parameters see Table 2). Synapses were either static or dynamic; static synapses had fixed weight and dynamic synapses were subject to usage-dependent synaptic depression [21]. The synapses were conductance-based, meaning they had an equilibrium potential which might be different from zero due to ionic concentration differences inside and outside the cells, maintained by ionic pumps in the cell membranes.

For static synapses (which in the current model applied to just the connections to the edge detector neurons) the magnitude of the synaptic current  $I_{\text{static}}$  induced when a presynaptic spike occurred was proportional to the synaptic weight  $w$ . The rate of change,  $\dot{I}_{\text{static}}$ , was given by:

$$\dot{I}_{static} = \sum_i \left[ \delta(t - t_i) w_i - \frac{I_i}{c_i} \right] \quad \dots(1)$$

where  $\delta$  is the Dirac delta function,  $t_i$  is the time of the last spike from presynaptic neuron  $i$ ,  $w_i$  is the constant synaptic weight, and  $c_i$  is the synaptic current time constant.

To implement short term synaptic depression (which in the current model applied to all synapses except the connections to the edge detector neurons), all of the currently-available proportion of neurotransmitter  $p$  at each synapse was released at the occurrence of each spike;  $p$  recovered back to unity with time constant  $d$ . The rate of change of  $p$  for neuron  $i$ ,  $\dot{p}_i$ , was given by:

$$\dot{p}_i = -\delta(t - t_i) p_i + \frac{(1 - p_i)}{d_i} \quad \dots(2)$$

With dynamic synapses the calculation for synaptic current,  $I_{dynamic}$ , becomes:

$$I_{dynamic} = \sum_i w_i p_i \quad \dots(3)$$

The synaptic depression recovery time constant  $d$  was set equal to the synaptic time constant  $\tau$  for each synapse, except where noted in Table 2 and Figure 3.

All simulations were conducted using the Parallel Circuit Simulator (PCSIM) [22], a comprehensive, well-supported software package for the simulation of large neural networks.

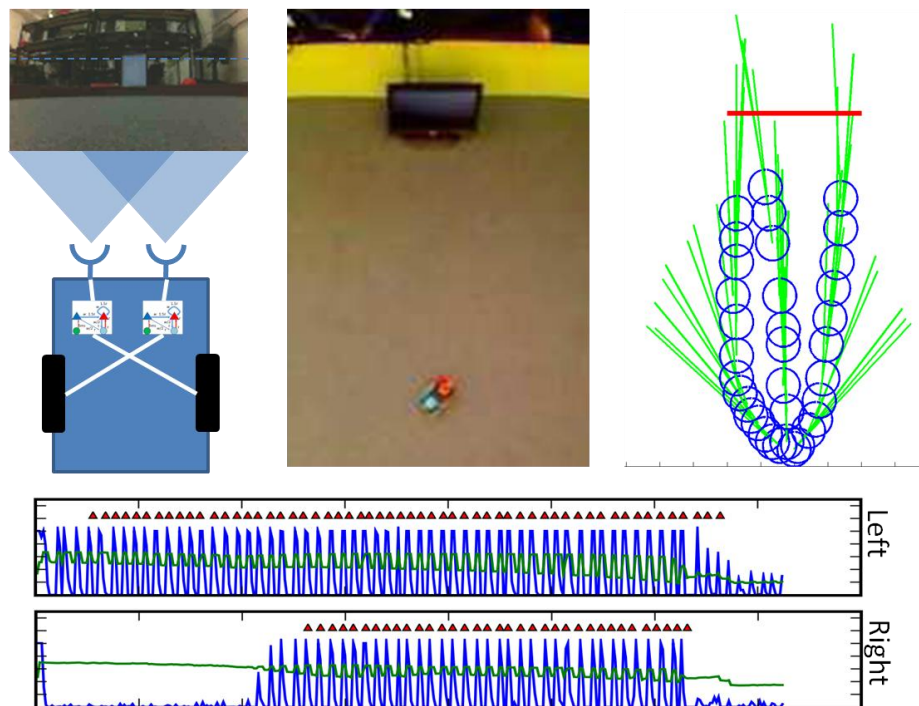
Table 2: Synapse parameters

$E_e$	Excitatory equilibrium potential	0 mV
$E_i$	Inhibitory equilibrium potential	-70 mV
$\tau_e$	Excitatory time constant	$\tau_{memb}$
$w_e$	Excitatory conductance	$5/\tau_e$ nS
$\tau_i$	Inhibitory time constant	$\tau_{reson}$
$w_i$	Inhibitory conductance	$2.5/\tau_i$ nS
$w_{ei}$	Edge detector to inhibitory conductance	$3/\tau_i$ nS
$d_{ei}$	Edge detector to inhibitory depression time constant	$\tau_{reson}/2$
$w_{pe}$	Input to edge detector conductance	50 nS
$\tau_{eii}$	Edge detector inhibition time constant	3 ms
$w_{eii}$	Edge detector inhibition conductance	$40/\tau_{eii}$ nS
$t_{syn}$	Synaptic delay	1 ms

### 3 Spike-time robot performing phototaxis

The aim of the studies was to explore the rat animat's ability to perform phototaxis to a flashing light source in the fully embodied system, and also understand the behavior of the underlying circuit in detail.

The set-up and practical abilities of the rat animat are illustrated in Fig 2. The animat received input from an onboard camera and a single scan line was extracted just above the midline (Fig 2 top left, dashed line in camera image). A monitor presenting a flashing stimulus at 1Hz was visible as a grey square in the centre of the image. The left light sensor summed pixel intensities from the left-most two thirds of the scan line and the right sensor from the right-most two thirds, resulting in the sensors overlapping in the middle third of the image (shaded triangles). Each sensor was connected to a resonating neural circuit (see Fig 3 for circuit details). The output from each oscillator drove the wheel actuator on the opposite side of the vehicle, causing the vehicle to display seeking behavior to 1Hz flashes.



**Fig 2:** Study set up. Rat animat location and spiking network output while tracking a 1Hz flashing stimulus. (top left) Rat animat showing two light sensors, their respective resonant circuits and crossed connections to the wheels. (top middle) Tracking camera view. (top right) Tracking data showing three trials, first with the robot directly facing the flashing stimulus, then rotated approximately  $45^\circ$  to the left and right. (bottom) Left and right sensor responses (see text for details).

The position and orientation (i.e. *pose*) of the rat animat was tracked with an overhead camera and the locations digitized. Fig 2 centre shows the tracking view, and the cover attached to the rat animat's top with a red dot at the front and a blue dot behind. Fig 2 top right shows tracked positions with circles (approximately the same size as the robot) marking the robot's position and the emanating directional lines indicating the robot's corresponding heading. The thick horizontal line shows the size and

placement of the LCD monitor used as the light source. The light grey axes show a 1x1m square. In all cases the robot successfully oriented to and approached the stimulus. Typical sensor responses can be seen in Fig 2 (bottom panel “Left”). When the robot was oriented 45° to the right of the monitor, the robot’s left sensor responded first. Triangles show firing times of the resonator neuron, the small amplitude oscillation signal is the summed camera pixel intensities, and the large amplitude oscillation signal is the same signal with a high gain applied to enhance rising edge detection. The left sensor’s connection to the right wheel induced an initial left turn towards the stimulus. Once the stimulus also came into view of the right sensor (bottom panel “Right”), the robot travelled directly towards the stimulus since the resonators were driving both wheels.

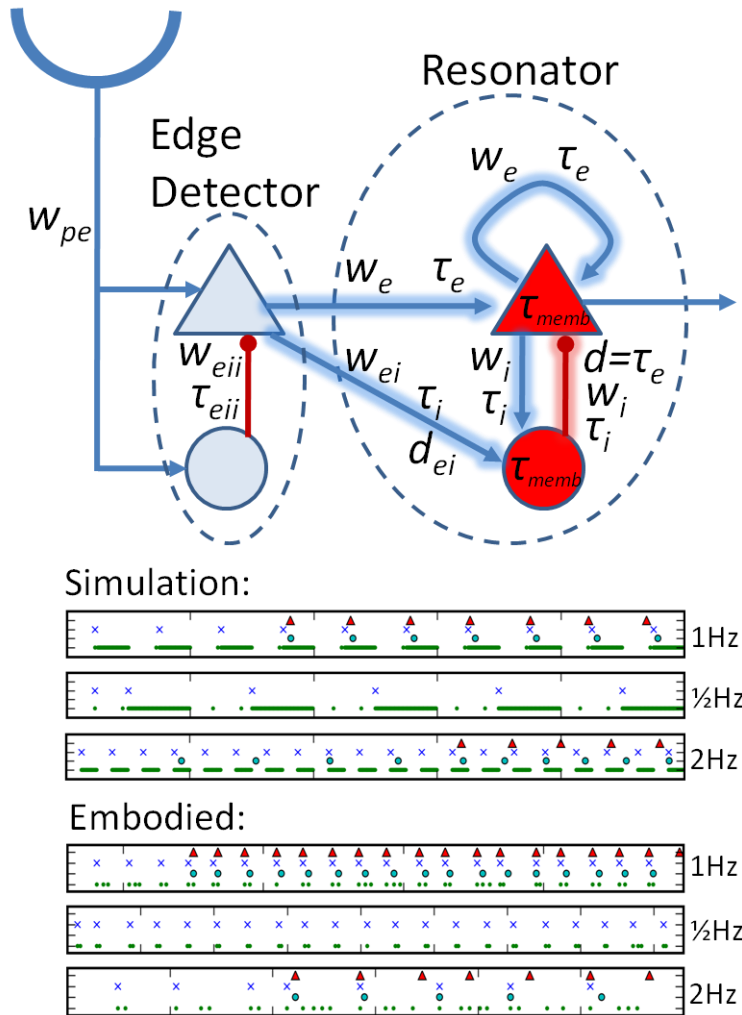
In a range of pilot studies, the rat animat’s behavior in an office environment with and without a flashing light was observed. When it observed a light flashing with its preferred frequency, it moved towards the light (analogous to Braitenberg’s Vehicle 2b [6]). The behavior was reliably observed from any starting configuration at distances up to two meters. The rat animat also generalized its behavior to orient towards other temporal stimuli, including on one occasion moving towards a person as they walked past.

### **Study 1. Spiking neural network responses to oscillating stimuli**

The first study systematically tested the range of responses of the circuit to different frequencies (see Fig 3). The animat was placed directly facing the light source at one meter distance, with the default behavior set to remain still when no oscillations were detected. The circuit was first tested in simulation (Fig 3 centre) and then on the rat animat (Fig 3 bottom). The rising edge detector circuit responded with a single spike when a rapid increase was detected in the light level. The output from the edge detector was directed to the resonator, which responded with single spikes at its own resonant frequency if the input spikes from the edge detector arrived at times appropriate for causing resonance. The connection weights, connection time constants and membrane time constants are shown in Fig 3 (top).

The time-to-first-spike was recorded for a range of frequencies from 0.1 to 2.4 Hz. Each frequency was shown for 20 cycles followed by a 10 second delay during which the light source was constant. When exposed to a stimulus at its preferred frequency of 1 Hz (top panel), responses were initially only observed from the rising edge detector neurons (excitatory neuron - blue crosses; inhibitory neurons – small green dots/dashes). The resonator neuron spikes after the fourth flash (red triangles), rapidly followed by the inhibitory neurons (large dots). For input at half the preferred frequency (0.5 Hz, second panel), only the rising edge detector neurons fire, and no resonating response occurs. For input at 2 Hz (third panel), the network responds but at a much longer delay, with the first resonating spike occurring after the thirteenth edge input spike.

From a resting state, the fastest response was 4 cycles, which occurred for input near the resonant frequency (0.7-1.0 Hz). As expected, the resonator did not respond to frequencies close to zero (0-0.6 Hz) or just above the resonant frequency (1.1-1.6 Hz). All frequencies above 1.6 Hz elicited a response from the resonator, albeit with latencies longer than 10 cycles. Responses to such higher frequencies are likely due to the broad tuning of the resonator.

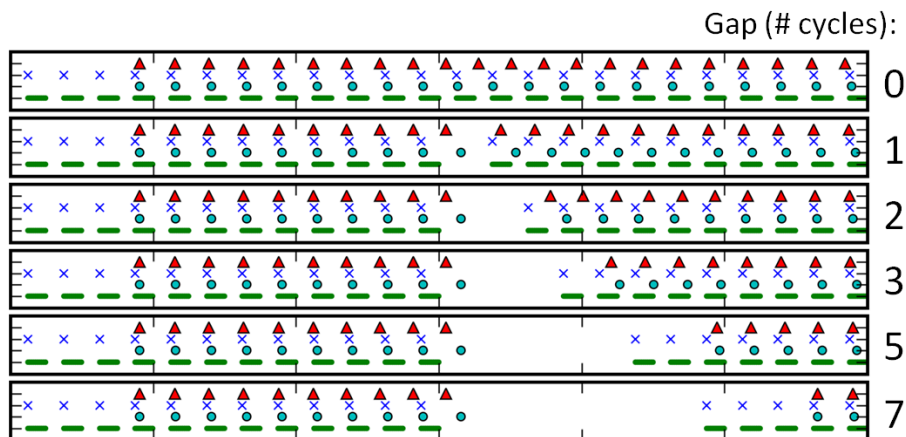


**Fig. 3.** Study 1. Spike-time controller during phototaxis. (top) The spiking circuit has two components: a rising edge detector (light/blue spiking neurons) and the PING-inspired resonator (dark/red spiking neurons; excitatory neurons are triangles, inhibitory are circles, excitatory connections are arrowed, inhibitory connections are capped with a dot). (centre) Simulation results for flashing stimuli of various frequencies. Each panel shows the responses of the four main neurons in the network (y-axis) over 10 seconds (x-axis, tick marks every 2 seconds). (bottom) Embodied (real) robot results. The response of the circuit embodied on the rat animat is similar to the simulation at both 1 and 0.5Hz (1<sup>st</sup> and 2<sup>nd</sup> panels, tick marks every 5 seconds); at 2Hz the edge detector does not respond to some of the input flashes due to a combination of circuit properties and camera input sampling frequency (3<sup>rd</sup> panel, tick marks every 2 seconds).

### Study 2. From robust to rapid responding

It was observed in the pilot studies and circuit investigations that the resonator neuron responded faster if it had already been responding in the past. If the break was short, it could respond on the first next detected edge. The second study explored in simulation how rapidly the circuit could detect the resonant frequency after an interruption to the signal. The stimuli consisted of 12 seconds of a light flashing at 1 Hz, followed by a period with no light of 1-7 seconds, then the flashing light resumed again at 1 Hz. The behavior of interest was the time taken for the circuit to recommence spiking after the interruption.

The results demonstrate the circuit's systematic response to the interruption. Initially, the circuit took 4 cycles to respond. After a single missing flash, the circuit responded immediately after the next flash. As the gap increased, the time to spike also increased, returning to normal after a 7-second delay (see Fig 4). The rapid response to recommencing stimuli occurs for two reasons. Firstly, the excitatory synaptic currents to the resonator neuron (from both the edge detector and from itself) decay over time rather than falling instantly to zero (see Fig 3 top and Table 1). This exponential decay means that residual excitatory current from previous oscillations remains in the circuit for some time. Secondly, the resonator neuron membrane time constant causes the membrane to return to its resting potential over a similar timeframe. The combination of decaying synaptic currents and membrane potential decaying to rest with appropriate time constants causes the circuit to retain a 'memory' of recent past firing, with a consequent rapid recommencement of resonating response even after input interruptions of several cycles.



**Fig 4.** Study 2: Resonator recovery from interrupted input cycles. The resonator initially took 4 input flashes (3 full cycles) to respond (top panel), resonator neuron spikes are marked with triangles, rising edge neuron spikes with crosses, inhibitory neurons are large and small dots for the resonator and edge detector circuits respectively. For a gap of 1 or 2 cycles, the resonator responded after the first subsequent input flash. For a gap of 3 or 4 cycles (4 cycles not shown), the resonator responded after the second subsequent input flash, and for 5 or 6 cycles after 3 flashes. After a 7-cycle gap, the resonator required the full 4 input flashes to respond.



## 4 Conclusions and future work

The studies reported in this paper demonstrate that a spiking neural circuit inspired by the pyramidal-interneuron network gamma (PING) circuit can be used to control a fully embodied rat animat performing phototaxis. The system demonstrates robust detection of an oscillating light, and rapid detection of a light that has recently been active. With the use of PING circuits, these studies add a new level of biological fidelity to spike-based robotic methods, and enable the study of interactions between the inherent dynamics of spiking neural circuits with the external dynamics from embodied action.

For the studies reported in this paper, the results were collected in a 1m x 1m area, which is comparable to the size in which rodent studies are performed. Larger studies are also possible as the rat animat is autonomous with onboard power, and is able to move through the office environment using reactive abilities to avoid walls. Its abilities to deal with real world stimuli, including fluctuating ambient light and changing configurations of objects and barriers makes it a useful tool for extending the neurobotic studies. In future studies we intend to extend the controller to add learning based on spike-time dependent plasticity to learn a range of temporal patterns.

**Acknowledgments.** This work was supported by an Australian Research Council (ARC) and National Health and Medical Research Council (NHMRC) Thinking Systems Grant (Special Research Initiative: Thinking Systems; Grant number: TS0669699) and a Tony Murphy Postgraduate Scholarship to CN.

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