Proceedings of the 30th Conference
on Decision and Control
Brighton, England • December 1991

SENSORY-MOTOR CONTROL OF INTELLIGENT ROBOTS USING OSCILLATORY NEURAL NETWORKS

M J Denham*, S Patel**, L J Troup* and M P Norman*
*Department of Computing, Polytechnic South West, Plymouth, PL4 8AA, UK
**Unilever Research, Port Sunlight Laboratory, Wirral, L63 3JW, UK

Abstract

We describe some preliminary results on the application of oscillatory artificial neural networks to the coordination and control of nonrhythmic, sensor induced, free movement in intelligent adaptive industrial robots. In such devices, as appears to be the case in living creatures, sensory stimuli arrive at specific sensors and generate oscillatory space-time neural activity which results in recognition, association and generation of corresponding motor trajectories. In this paper, we describe some preliminary results from network simulations which demonstrate this type of behaviour and attempt to relate them to recent experimental results from neurophysiological studies of visual perception.

Background

Recent studies of the naturally occurring mechanism by which neural activity is coordinated in space and time in response to sensory stimuli have revealed the existence of stimulus-specific oscillatory responses of local groups of neurons, with synchrony as the coordination mechanism. In particular, Gray and Singer [1] have studied neuronal activity in the visual cortex of the cat in response to the visual presentation of aligned light bars and identified a rhythmic pattern of firing of neurons. The study also suggests that the presence of this coherent, periodic activity, resulting from the interactions between local clusters of neurons, leads to the conclusion that the phase of the oscillatory response may be used, in addition to the amplitude and and duration of neural firing activity, to encode information about the visual stimulus. Such a coding mechanism could lead to a solution to the problem of associating activities in different parts of the brain representing different attributes of the stimulus and to the problem of associating sensory stimuli with corresponding motor actions.

Evidence for this form of visual binding is provided by further studies by Gray et al [2], in which they demonstrate that, remarkably, neurons in spatially separate columns of the cat visual cortex can synchronize their oscillatory responses and that the degree of synchronization is dependent on the global nature of the stimulus, eg continuity of the stimulus between the two sectors of the visual field and coherence of the motion of the stimulus in the two sectors. Thus a single long light bar which simultaneously stimulated both receptive fields resulted in a strong synchronization, two short colinear light bars moved in the same direction resulted in weak synchronization, and no synchrony resulted if the two short bars were moved in opposite directions.

Further similar studies have been reported by Engel et al [3], Gray et al [4], Eckhorn et al [5], Engel et al [6].

Preliminary Results

Each neuron in our simulated networks is modelled by the leaky integrator shunting differential equation, as proposed by Grossberg [7] and Bressloff and Taylor [8]:

$$\frac{d}{dt}v_i(t) = -\frac{1}{\tau_i}v_i(t) + \sum_{1}^{N} a_{ij}(t)[s_{ij} - v_i(t)] \qquad (1)$$

where v_i is the membrane potential of the ith neuron in a network of N neurons, s_{ij} is the membrane reversal potential at the ijth synapse, and a_{ij} is the input signal at neuron i from neuron j, which takes the form of a sequence of impulses:

$$a_{ij}(t+t_d) = g_{ij}\sum_{1}^{N} \delta(t-T_n^j)q_{ij}(T_n^j) \qquad (2)$$

In equation (2), t_d is the synaptic time delay, g_{ij} is a constant related to the synaptic efficiency and $q_{ij}(T_n^j)$ is the magnitude of the impulse coming from neuron j at time T_n^j, the time at which neuron j fires for the nth time. These firing times are determined by the iterative threshold condition:

$$T_n^j = \inf\,\{t \mid v_j(t) \geq K_j,\ t \geq T_{n-1}^j + t_R\} \qquad (3)$$

where t_R is the refractory period and K_j is the threshold.

Our simulation results have shown that it is possible to replicate some of the results of the neurophysiological experiments described above in respect of the effect of external stimulus and coupling in the network on synchronization of the oscillatory response of individual, or clusters of, neurons. A similar set of experiments has recently been described by Grossberg [9] using a different, but related, model.

For example, Figure 1 shows the response of six unconnected dipoles (pairs of mutually connected neurons) to a constant external stimulus on four of the dipoles. As expected, starting from random initial conditions, the four stimulated dipoles oscillate with random phase and the unstimulated dipoles decay. Figure 2 shows the result of connecting the dipoles in a ring, each dipole being connected to its immediate right and left neighbour. The four stimulated neurons now oscillate in phase and low level oscillations are induced in the unstimulated neurons. Note that the nature of the interconnections between dipoles is identical to that within a dipole, ie via impulse trains.

Figure 3 shows the response of a 3x6 array of neurons with each neuron connected to its four immediate neighbours, resulting in a torus (and thus eliminating boundary effects), as a result of stimulating three neurons in one row with a constant external excitation. Note that before onset of the stimulus, the neurons are oscillating with a broad spectrum of frequencies. After onset, the oscillations focus on a narrower frequency range and are approximately in phase. Little or no response to the external stimulus is evoked in the unstimulated neurons.

This example appears to correspond in principle to the results of Eckhorn et al [5], in that the stimulus evoked response of the network is to move from a broad band oscillation to a narrow band for the stimulated neurons, and for approximate phase locking between the responses of stimulated neurons.

Figure 4 shows the response of the 3x6 torus network to external stimulation of two separate sets of pairs of neurons in one row, ie analogous to the case of stimulation by two short colinear light bars. The same kind of response is evoked in the stimulated neurons, but significantly, the intermediate neuron is also stimulated, although at a lower level. This corresponds in principle to the global stimulus properties observed by Gray et al [2], also observed in model simulations by Grossberg [9].

Sensory-motor coordination and control

The initial outline scheme which we have adopted is based on that described by Eckmiller [10]. The main feature of this scheme is a dynamic neural network, the "motor network" which will generate a space-time trajectory of neural activity from which the appropriate motor trajectory can be derived. The behaviour of this network is controlled or modulated by another network, "the motor modulation network". Connections from this network to the motor network cause inhibition or excitation of selected neurons which determines the form and timing of the space-time trajectory on the motor network. The motor modulation network is itself stimulated via connections to the "pattern recognition network" which itself responds directly to the external stimulus.

Each of these networks takes the form of an network of neurons modelled by leaky integrator shunting equations of the form described above. We have experimented via simulation with various topologies for the motor network in particular. Unfortunately, space limitations prevent a graphic description here of the spatio-temporal behaviour of this network. However we have successfully demonstrated that such networks are capable of generating trajectories of space-time oscillatory activity and that the activity can be modulated or controlled by another external network.

References

[1] Gray C M and Singer W, 1989, Proc. Natl. Acad. Sci. USA, 86, 1698-1702.

[2] Gray C M et al, 1989, Nature, 338, 334-337

[3] Engel A K et al, 1990, Eur. J. Neurosci., 2, 588-606.

[4] Gray C M et al, 1990, Eur. J. Neurosci., 2, 607-619.

[5] Eckhorn R et al, 1988, Biol. Cybern., 60, 121-130.

[6] Engel A K et al, 1991, Science, 252, 1177-1179.

[7] Grossberg S, 1988, Neural Networks, 1, 17-61.

[8] Bressloff P C and Taylor J G, 1990, Proc Int. Neural Network Conf., Paris, 1009-1012.

[9] Grossberg S and Somers D, 1991, Proc Int. Neural Network Conf., Helsinki, 3-8.

[10] Eckmiller R, 1989, IEEE Control Systems Magazine, April, 53-59.

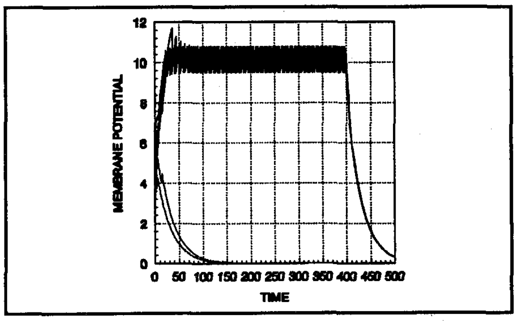

Figure 1

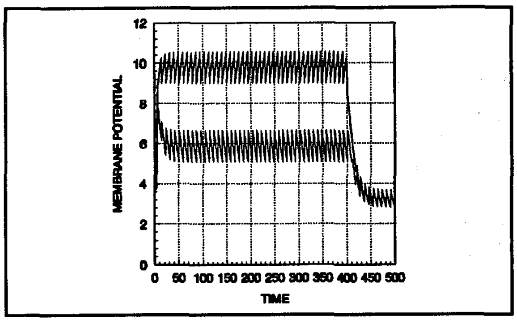

Figure 2

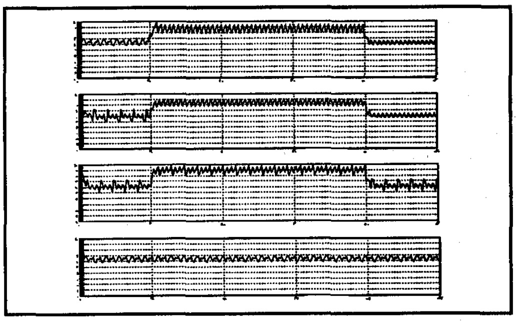

Figure 3

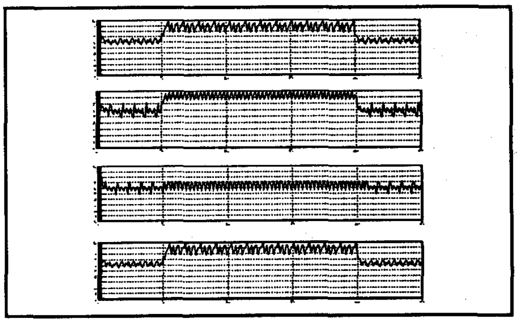

Figure 4