A network of spiking neurons develops sensorimotor mechanisms while guiding behavior.

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Abstract
Practical, artificial nervous systems can be realized with spiking neurons fabricated by VLSI. To explore ways of developing networks of such units through sensorimotor experience, a simulated vehicle, equipped with whiskers and compound eye was trained, using biologically realistic Hebbian mechanisms to navigate an obstacle course. Starting with a simple tactile reflex, networks developed visual guidance mechanisms based on the detection of luminance and motion.

Keywords: Vision, development, Hebbian learning, avoidance

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1. Introduction

Emulating the grace and efficiency of animal movement in artificial models may be informative about brain organization as well as useful. An application of neuromorphic engineering is in the control of small, maneuverable robots using compact, low power circuits fabricated in VLSI. The silicon "neuromorph" developed in our laboratory is a neuron analog with a branched dendritic tree, studded with synaptic sites [4]. The dendrites respond to incoming spikes with postsynaptic potentials that diffuse towards a spike-generating soma. Networks are made by a digital spike-routing system that allows real-time modification of connection patterns, weights and delays. The problem is how to set up such networks to perform behavioral tasks, given the richness of potential connections and choice of synaptic and other neuronal mechanisms. The objective, then, is to explore self-organization in a neuromorphically-controlled vehicle, much as animal nervous systems self-organize during development. The biological prototype for this effort is the retino-tectal-motor system of fishes, which start life as free-swimming embryos whose brains grow throughout life while behaving adaptively [1]. If successful, the vehicle's neuromorphic network will extract the necessary information from the environment for its navigation, with minimal recourse to connection design. The present results are computer simulations, but there is no reason to suppose that they could not be achieved by existing neuromorphic hardware.

2. The model

The sensors and neural system controlling the vehicle are shown in Fig.1. The external environment is sensed by an array of 6 whiskers and an array of 21 photoreceptors forming a compound eye. Both whiskers and eye span 120˚ of frontal space in the horizontal plane. Each whisker responds to contact with an object by firing trains of spikes at a frequency proportional to the whisker's overlap with the object. The photoreceptors have Gaussian receptive field profiles of 6˚ halfwidth and spacing – similar to the eye of *Limulus* but without the lateral inhibition [6] - and generate non-adapting analog signals proportional to their light capture. These photoreceptor signals are connected topographically to two layers of "retinal ganglion cells", the sustained and transient layers, each with 21 spiking neurons. Upon luminance increment, the sustained layer responds with trains of spikes; the transient layer with one spike or a brief spike burst. All sensory spikes project to a layer of 8-10 spiking neurons - the "tectum". In fishes, this important midbrain structure is a multimodal sensory analyzer that commands locomotory movements. In the model tectum, units of each half elicit contraversive turns. The difference in the rate of spiking between the two halves determines the angle turned through in each simulation step.

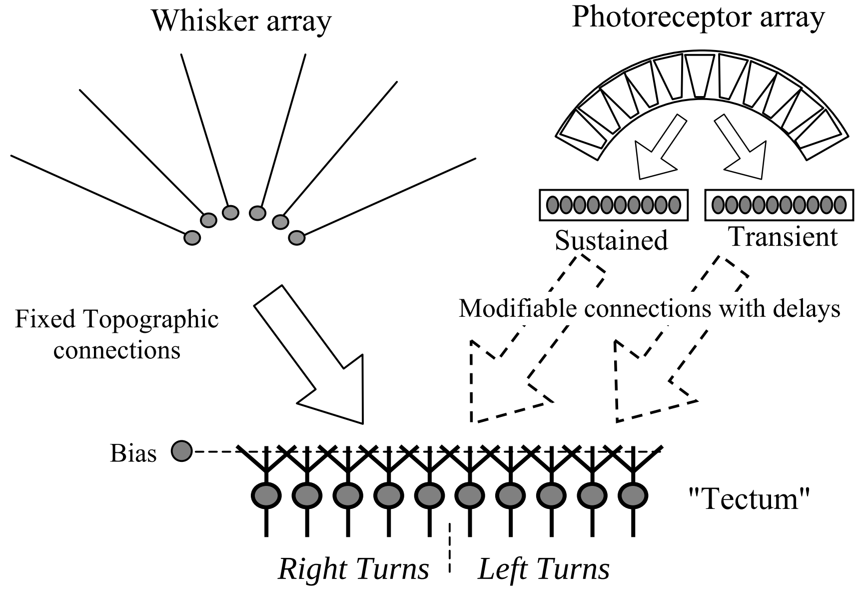

Fig. 1. Schematic of the model. See text for details.

Compared to dendritic tree neuromorphs [4], the units of the model tectum have simplified properties, implemented by a Spike Response Model [2]. A spike incoming to a tectal unit generates a postsynaptic potential of a double exponential form whose amplitude depends on a synaptic weight. Fig. 2A shows a postsynaptic potential generated by a positive weight. (A negative weight generates a negative-going potential.) Synaptic potentials evoked by spikes occurring within the integration time of the neuron sum; when the result exceeds a threshold, the unit fires a spike. A time-dependant threshold (dashed curve in Fig. 2A) provides refractoriness. The excitability of the tectal units is controlled by a constant, negative bias, to prevent firing when unstimulated.

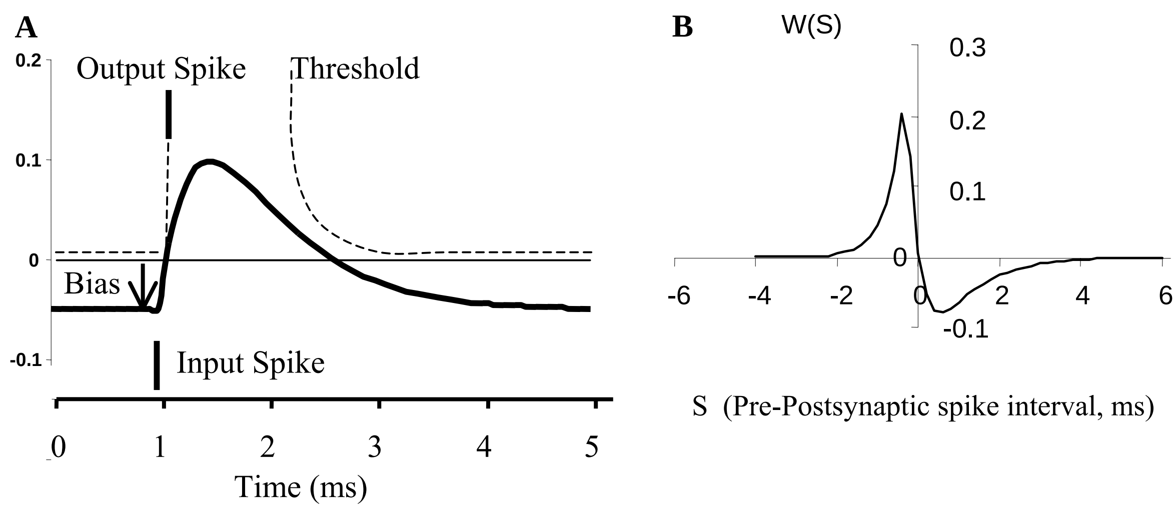

Fig. 2. A. An excitatory postsynaptic potential (heavy curve) evoked by an input spike. Spike firing threshold shown by dashed curve. Output spike generated when potential exceeds threshold. B. The function W(s) used for Hebbian weight updates. S on the abscissa, is the time interval $t_{pre} - t_{post}$.

The weights of the synaptic connections of the retinal units onto the “tectal” units are changed by a Hebbian plasticity rule that depends upon spike timing, similar to the rule operating at retinotectal synapses in Xenopus [9, 2]. The synaptic weight, w_{ij} , from unit *j* onto unit *i,* assuming the latter has fired recently, is updated by an amount Δw_{ij} according to the rule: $\Delta w_{ij} = \varepsilon(W(s_{ij}) - w_{ij})$, where ε is the learning rate, s_{ij} is the time interval $(t_j - t_i)$ between the firing of units *j* and *i*, and W(s) is the biphasic function shown in Fig. 2B. Subtraction of the existing weight, w_{ij}, ensures that weights do not grow without limits [5]. The application of this rule continuously over time leads to stable weights but an excess of excitatory drive to the tectal units. To maintain an equitable balance between excitation and inhibition, weight normalization is applied to make all the weights onto each tectal unit sum to 1.

Training and testing takes place within an environment populated with white cylindrical obstacles of various diameters, randomly distributed in the vehicle’s path. The vehicle’s task is to navigate in a northerly direction at a constant speed through the obstacles without colliding with them. A pass through a 7-obstacle course takes 20-30 ms at 10 simulation steps per ms.

3. Results

Developmental training starts with excursions through the obstacles using a tactile reflex. The whiskers are topographically connected to the tectal units via the weight matrix shown in Fig. 3A. Then, when a whisker is stimulated, it elicits contraversive turning, steering the vehicle safely between obstacles. In this noiseless system, head-on approach to an obstacle may lead to perfectly balanced activation of the two tectal halves, and finally, collision. The introduction of noise and special connections may be required to deal with such indecision, but will not be considered further here. The likelihood of collision is strongly influenced by the bias applied to all the tectal units. Lowering bias makes the vehicle more economical in its turning movements but less reactive to the point of carelessness; raising bias makes it more jittery and liable to execute wide avoidance detours. Bias can be analogized with “level of arousal”. A measure of performance depending on the costs of collision and detouring yields a Yerkes-Dodson [3] or U-shaped relationship with bias (see Fig. 5 for definition of cost).

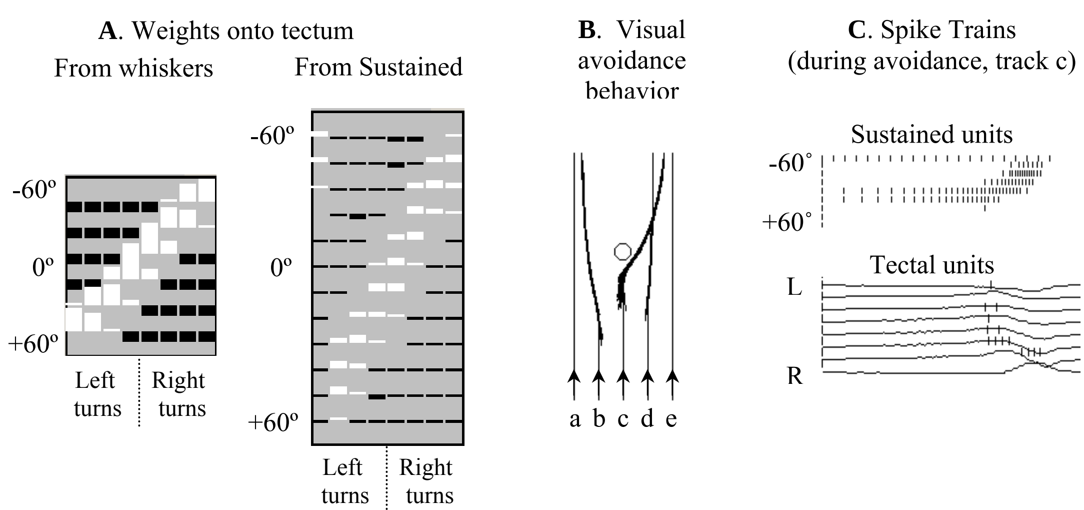

Fig. 3. A. Weight matrices connecting whiskers and visual sustained units to an 8 unit tectum. Excitatory weights are shown in white, inhibitory in black. Height of bars represent weight values. Inputs in vehicle centered space from -60º (left) to +60º (right), are represented along rows; the different tectal units down columns. Half of the tectal units contribute to left turning, half to right turning as shown. The weights from the sustained units were learned during movement through a multi-obstacle course. B. Visual avoidance behavior shows vehicle trajectories without whiskers, after training. C. Spike trains of the sustained visual units and the tectal units are shown for avoidance trajectory c. Time markers are at intervals of 10 simulations steps or 1 ms.

Developing a simple form of vision, involves converging the visually-evoked spikes from the sustained layer together with the whisker spikes onto the tectal units. As before, the whiskers are projected in a fixed topographic map onto tectum, while the sustained units are initially unconnected. The latter synapse weights are modified according to the Hebbian rule, resulting in a visuotopic map across the tectum (Fig. 3A). It develops over a few 10's of excursions in the obstacle course, irrespective of the number of obstacles, their size, and whether or not avoidance movements actually occur. During development of the visuotopic map, given appropriate biasing, the visual input alone becomes capable of guiding the vehicle through the obstacles with more anticipation than with whiskers alone (Fig 3B).

Although luminance information provided by the sustained layer may be sufficient for simple obstacle avoidance, navigation through more complex environments requires motion cues. The velocity of images over the retina of a moving animal can, in principle, give the relative location of objects in space. Therefore, the vehicle needs to determine whether an obstacle is close enough to its present path to warrant avoidance. The distance, X, from a straight path in the frontal plane can be estimated from $X = v.\ \mathrm{Sin}^2\ \omega / \acute{\omega}$, where v is the vehicle's velocity, ω the obstacle's azimuth, and $\acute{\omega}$ the angular velocity of the obstacle's image. Therefore velocity detectors should be developed across tectum that respond to centrifugal image motion, firing at low speeds close to the center of the field of view and to progressively higher speeds farther out. In animals, transient visual units provide input to motion processing areas in brains [3,7] because their spikes signal precisely where and when elementary image motion occurs. Also essential for velocity detection are delays. The next objective is to bootstrap the primitive luminance visual system into learning the weights and delays for motion processing and to see if they can control avoidance in a more powerful fashion.

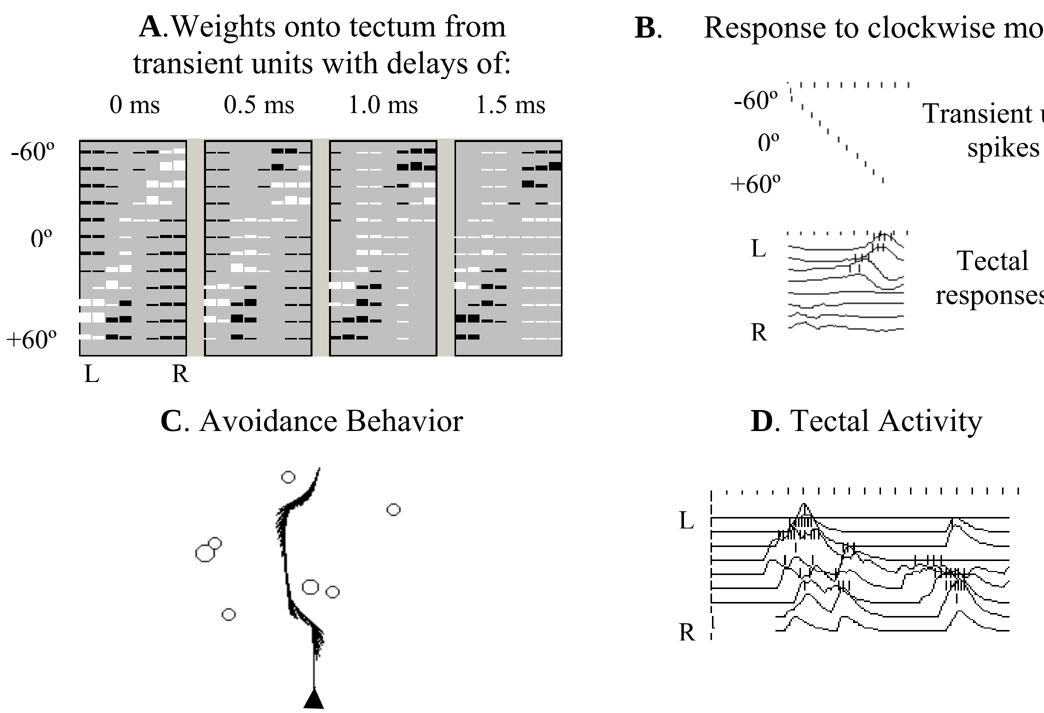

Fig. 4. **A**. Weight matrices of 4 delayed connections between transient units and tectum, resulting from training with a single obstacle while the vehicle was avoiding using the sustained unit connections shown in Fig. 3. **B**. The delayed connections of transients conferred directional selectivity on tectum. Clockwise motion of a stimulus excited only the upper 4 tectal units. **C**. Vehicle trajectory through an obstacle course under control of transient units only. **D**. Tectal unit potentials and spike responses during the maneuver shown in **C**. Time markers are at intervals of 1 ms.

In the next phase of development, the whiskers are disabled, so that only the sustained and transient visual units are allowed to drive the tectal units and control behavior. The sustained units are connected via the matrix of weights already learned (Fig. 3A) and are not further modified. Each transient unit is potentially connected to all tectal units via several discrete delays (0, 0.5, 1.0, 1.5 ms, in Fig.4). The weight matrix for each delay is initialized to zero and allowed to learn during excursions through random obstacle courses using the same weight update algorithm. During training, the bias is adjusted so that the sustained units drive the tectal units to fire in a topographic fashion. The transient units then develop connections with the pattern shown in Fig. 4A : diagonal bands of excitatory weights, flattened with increasing delay. This weight pattern produces directionally selective responses such that a stimulus rotating clockwise through the entire visual field activates only the right half tectum (Fig. 4B). It also produces speed selectivity across tectal cells such that those serving the central field are tuned for lower speeds than those serving the peripheral field, an arrangement required for estimating X, an object's distance perpendicular to the path of advance. The following results (Fig. 5) show that the addition of this motion selectivity assists the vehicle in weaving through obstacles.

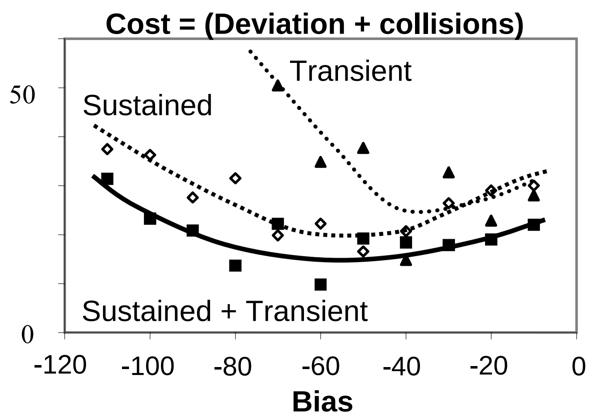

Fig. 5. Visual obstacle avoidance performance after training, using (a) only transient units, (b) only sustained units, and (c) both sustained and transient units. Vehicle was run through random obstacle courses of 7 objects 50 times at each bias. Cost was calculated as (mean path deviation) + (% collision rate). Collision rates fell from ca. 50% to 0% as bias was increased. Curves drawn through data by eye.

Avoidance behavior is quantified by a cost (see Fig. 5 caption), averaged over at least 50 passes through random obstacle fields. Since performance depends upon the bias applied to the tectal units, different training or testing conditions are compared by plotting cost over a range of biases (Fig. 5). After developmental training, the use of sustained units alone is superior to transients alone; but sustained and transient together generally result in the best performance.

4. Conclusions

A start has been made in developing behaving artificial systems, by combining neuron-like units, spiking intercommunication, and a spike-time-dependent Hebbian plasticity rule. The system, although miniature, behaves adaptively in a biologically realistic way, acquiring sensorimotor capabilities accretively, by interaction with its environment.

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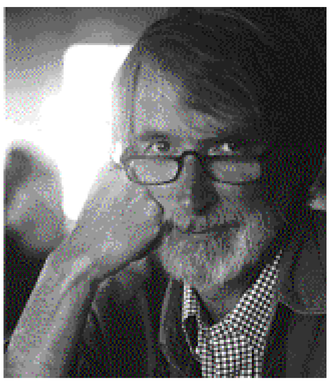

David Northmore. Stimulated by Grey Walter's "The Living Brain", and against all advice, he abandoned physics for psychology and physiology at Oxford. Following a D.Phil. from Sussex University, he migrated to Delaware and continued studies of the visual systems of obscure nonmammalian species. A preoccupation has been the optic tectum, studied electrophysiologically. Walterian interests resurfaced during collaboration on neuromorphs with John Elias, opening vistas on silicon-powered behavior.