Neural circuits in silicon

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Studies of neurally inspired silicon circuits are showing how networks of neurons can multiply and select input signals. They may also provide alternative ways to build computers modelled on biology.

Animal brains form the centrepiece of nature's development of information-processing machines. In attributes such as adaptability and fault tolerance they are likely to remain unsurpassed by any human-built machine in the foreseeable future. But in terms of numerical computation, digital computers are the pinnacle of the past quarter-century's explosion in information technology and have capabilities that far exceed those of animal brains. This dichotomy perplexes us. How do animal brains compute? And if silicon technology is so powerful, why can we not build thinking machines?

Carver Mead, a pioneer in integrated-circuit technology, quipped during a discussion of brains versus computers that "silicon doesn't know anything about bits". The implication is that nothing about silicon itself requires computers to be digital. On page 947 of this issue, Hahnloser *et al.*[1] take this reasoning to its logical conclusion: they have built a cortex-inspired silicon circuit that multiplies and selects features in its input, using a network of neuron-like elements. The theoretical basis for this work is not new: in 1996, Salinas and Abbott[2] reported computer simulations of a network of model neurons, demonstrating that the network could perform these exact tasks. What Hahnloser *et al.* have done is to reproduce the behaviour of such a network in silicon.

The networks studied by Salinas and Abbott and by Hahnloser *et al.* both use recurrent (or feedback) connections that are excitatory for connections between neighbouring neurons and inhibitory at larger distances (Fig. 1a). This pattern of local excitation and long-range inhibition is common in contemporary models of the brain's cortex[3–6]. One attribute of this type of network is that, when a neuron at a given physical location receives an input, the network responds by activating both the stimulated neuron and a cluster of neurons around it (Fig. 1b). Moreover, when the background input to all neurons is increased systematically, this cluster of activity is multiplied by a gain factor that is a linear function of the background input (Fig. 1b). These responses are intriguing from a neurophysiological perspective. Say, for example, we equate the background input to a motor signal representing eye position, then these multiplicative responses are similar to the modulation of neuronal responses by eye position observed in the visual cortex[7].

A second important feature of this type of recurrent network is its ability to select a single stimulus when presented with several competing stimuli. In this way the network exhibits nonlinear behaviour, selecting the strongest of the competing stimuli and suppressing the weaker (Fig. 1c). Such behaviour can be regarded as a simplified form of sensory attention, whereby the network selects the stimulus location based on stimulus strength. From a neurophysiological perspective, the selection of a single target and the suppression of distractors is important, for example, in programming arm or eye movements.

The network's ability to switch between linear and nonlinear behaviour, based on its input, is very different from that of standard electronics. Engineers usually require separate analogue and digital circuits to carry out linear amplification and nonlinear selection, respectively. Hahnloser *et al.* explain their hybrid analogue–digital circuit in terms of the set of neurons that are active in steady state, and a gain response that depends only on the identities of the active neurons and not on their analogue responses. Behaviour that derives from a common set of active neurons is linear in the input, whereas behaviour that derives from a comparison among different sets of active neurons is nonlinear in the input.

Hahnloser *et al.* extend previous studies of this class of recurrent networks by analysing the stability of the dynamical equations that model the network, and show that there are inviolate constraints on the allowed network states. In particular, they show that if no single input can activate a set of neurons (the set cannot form a memory), then no input can activate a supergroup of these same neurons (no supergroup can form a memory). A limitation of the study by Hahnloser *et al.* is the requirement that synaptic connections be symmetric — that is, the strength of the connection from neuron A to neuron B must be the same as that from B to A. This assumption allows them to prove network stability, but is difficult to justify neurobiologically. A fruitful area for future research, therefore, is the study of recurrent cortical networks with non-symmetric synaptic connections (see, for example, refs 8–10 and Supplementary Information[1]).

What do Hahnloser *et al.*, and others like them, hope to accomplish by building silicon circuits modelled on biology? First, they can learn how to map neuronal primitives (such as neurons and synapses) onto silicon, and then how to compute using these primitives (see, for example, refs 10–12). Second, they can investigate how physical and technological limits, such as wire density, signal delays and noise, constrain neuronal computation. And third, they can learn about alternative models of computation. Biology provides examples of non-digital computing machines that are incredibly space- and energy-efficient, and that excel at finding good solutions to ill-posed problems. Scientists may eventually decipher all of nature's electrochemical circuits, but the work of Hahnloser *et al.* demonstrates that we already know enough to begin building integrated circuits that compute like biology. ■

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Figure 1 **Linear and nonlinear behaviour in a silicon circuit inspired by neurobiology.** a, **Neuronal network studied by Salinas and Abbott[2], and built in silicon by Hahnloser *et al.*[1]. Each neuron excites its nearest neighbours, and inhibits neurons further away from it. The artificial neurons, in both cases, use a continuously varying signal to model the firing rate of a cortical neuron. In their numerical simulations, Salinas and Abbott model the strength of synaptic connections from a neuron to its neighbours as a 'Mexican hat' function (shown below the network), whereas Hahnloser *et al.* approximate this function in their silicon circuit.** b, **Example of multiplicative responses (that is, linear gain modulation) in the network. Given three input pulses at the same location but at different background amplitudes (green, blue and red), the network multiplies the output by a gain factor that is a linear function of the background input.** c, **Example of stimulus selection in the network. Given input pulses at two different locations, the network selects the location with the stronger input, suppressing the location with the weaker input. This competitive, nonlinear behaviour is the result of** recurrent excitatory and inhibitory interactions among neurons.