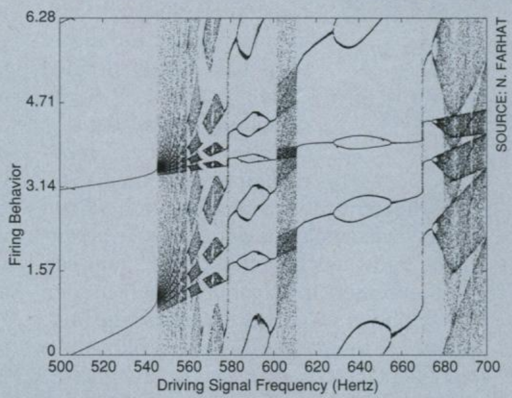
A Subtler Silicon Cell for Neural Networks

Nature is the model for artificial neural networks. These networks of processors—either real or simulated on a conventional computer—"learn" from experience by adjusting the strength of their connections, much like networks of real neurons. Small neural nets have become commonplace, doing tasks such as predicting how stock prices may fluctuate and recognizing handwritten characters. But Nabil Farhat of the University of Pennsylvania, Philadelphia, thinks he can build a better neural net by making its constituent neurons even closer to biology.

Neural nets traditionally consist of so-called sigmoidal neurons, circuits that add up incoming signals until they reach a fixed threshold and then fire themselves. Farhat's so-called bifurcation neurons, in contrast, switch between different modes of operation—between regular and chaotic firing, for example—depending on subtler factors. These include not just the value of a particular train of incoming signals, but also the interaction between many incoming signals and the neuron's recent history. So far, Farhat has made only single neurons, and he hasn't linked them together into a complete network. But his latest simulations suggest, he says, that they could yield neural nets with more lifelike behavior than has been seen in networks to date, such as the ability to see, recognize, and even react to the world in real time.



Nervous behavior. The bifurcation neuron switches among many different firing modes, depending on the frequency of the signal it receives.

Whether he will succeed is still an open question, says Daniel Collobert, a neural net expert at France Telecom. But he notes that Farhat's bifurcating neuron provides a level of behavioral complexity "that [artificial] neural networks could not previously [show], and I guess never will, because of the functional simplicity of [their] neurons."

The neurons in traditional nets sacrifice important information, because they know only how many spikes reached them in a given period, but not when each spike arrived. To an ordinary neuron, the periodic signal 110110110 (where a 1 is a spike) would be exactly the same as 101101101.

Yet real neuronal nets, in the brain, capture this timing information. A neuron fires because incoming signals cumulatively depolarize the excitable membrane of the neuron's output device, the axon. Afterward, there follows a period when the membrane cannot respond at all to an incoming signal, which gives way to another slow buildup. A pulse arriving immediately after firing will have a completely different effect on the output of the neuron from one that arrives immediately before.

Real neurons also respond differently to signals when they are correlated than when they arrive separately. Farhat explains that signals arriving simultaneously through different dendrites produce a periodic modulation of the neuron's electrically excitable membrane, just as two beams of light from the same source produce a periodic pattern of light and dark patches when they interfere with each other. The oscillation modulates the neuron's response to later inputs.

Conventional digital circuitry, with its arrays of on-off switches, can't efficiently mimic this kind of behavior. So Farhat has been combining resistors, capacitors, and other components into so-called analog circuits, which can adopt any intermediate state between "on" and "off." One proof-of-principle design incorporated two capacitors, which charge up in parallel as incoming signals build up. Eventually, one capacitor "breaks down," allowing current to flow, which switches on a light-emitting diode. The diode discharges both capacitors, reversing the breakdown and allowing the charging to begin again. This behavior makes the circuit time-sensitive: Signals arriving when the capacitors have just been discharged have a different effect from signals arriving earlier or later.

The latest incarnations of Farhat's neurons display more complex behavior (see diagram). When many neural inputs (spike trains) arrive at the same time, they interact to generate an electrical oscillation, which affects the neuron's firing. Small changes in the frequency of this oscillation, caused by varying input signals, produce huge shifts in the output behavior. For instance, oscillation frequencies below about 550 hertz produce periodic firing with two spikes per cycle. Just above this frequency, the output rapidly changes to chaotic firing.

Farhat and his colleagues are now planning to link such neurons into a full array using optical signals, which should allow them to create the dense thicket of interconnections needed for a large neural net. In a paper to be published in the *Journal of Intelligent and Robotic Systems* early next year, Farhat describes a computer simulation that offers a glimpse of how such a network would behave. The bifurcation neurons seem to form "netlets"—subsets of the neurons that work together. In an even more recent simulation, Farhat found that the netlets formed a kind of neuroanatomy, with different clusters of netlets responding to stimuli from different sources in the environment. "That's exactly the same as people observe when they look at functional MRI [magnetic resonance imaging] and PET [positron emission tomography] scans of the brain," Farhat says. "Depending on the inputs, the stimulus from the outside, or the cognitive task that the person is engaged in, we see different parts of the brain firing." It's that kind of complexity, Farhat thinks, that could make his networks of bifurcation neurons capable of simple abilities that we take for granted. **–Sunny Bains**

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mimic some aspects of the brain in so-called neural nets, networks of "processors" linked by "synapses"—connections that strengthen or weaken depending on activity, enabling the net to learn from experience. But these neural nets generally aren't real physical devices—instead, they are simulated ones, running as software on conventional computers. What's more, their neurons are, with few exceptions (see sidebar), generally much simplified versions of the real thing. Neuromorphics, on the other hand, is an effort to capture some of the richness of actual neurons in hardware—transistors, capacitors, and resistors, all fabricated onto silicon chips—in what is called analog VLSI, or simply AVLSI.

Besides allowing transistors to operate at many different voltage levels, neuromorphic engineers are designing them to serve as both calculation and memory elements. Work by Lance Glasser at the Massachusetts Institute of Technology, and by Mead and his team at Caltech, has led to the design of a new type of transistor, the floating gate transistor, which