Information Sciences

Spiking Neurons for Analysis of Patterns
High-performance pattern-analysis systems could be implemented as analog VLSI circuits.

NASA's Jet Propulsion Laboratory, Pasadena, California

Artificial neural networks comprising spiking neurons of a novel type have been conceived as improved pattern-analysis and pattern-recognition computational systems. These neurons are represented by a mathematical model denoted the state-variable model (SVM), which among other things, exploits a computational parallelism inherent in spiking-neuron geometry. Networks of SVM neurons offer advantages of speed and computational efficiency, relative to traditional artificial neural networks. The SVM also overcomes some of the limitations of prior spiking-neuron models. There are numerous potential pattern-recognition, tracking, and data-reduction (data preprocessing) applications for these SVM neural networks on Earth and in exploration of remote planets.

Spiking neurons imitate biological neurons more closely than do the neurons of traditional artificial neural networks. A spiking neuron includes a central cell body (soma) surrounded by a treelike interconnection network (dendrites). Spiking neurons are so named because they generate trains of output pulses (spikes) in response to inputs received from sensors or from other neurons. They gain their speed advantage over traditional neural networks by using the timing of individual spikes for

computation, whereas traditional artificial neurons use averages of activity levels over time. Moreover, spiking neurons use the delays inherent in dendritic processing in order to efficiently encode the information content of incoming signals. Because traditional artificial neurons fail to capture this encoding, they have less processing capability, and so it is necessary to use more gates when implementing traditional artificial neurons in electronic circuitry. Such higher-order functions as dynamic tasking are effected by use of pools (collections) of spiking neurons interconnected by spike-transmitting fibers.

The SVM includes adaptive thresholds and submodels of transport of ions (in imitation of such transport in biological neurons). These features enable the neurons to adapt their responses to high-rate inputs from sensors, and to adapt their firing thresholds to mitigate noise or effects of potential sensor failure. The mathematical derivation of the SVM starts from a prior model, known in the art as the point soma model, which captures all of the salient properties of neuronal response while keeping the computational cost low. The point-soma latency time is modified to be an exponentially decaying function of the strength of the applied potential.

Choosing computational efficiency over biological fidelity, the dendrites surrounding a neuron are represented by simplified compartmental submodels and there are no dendritic spines. Updates to the dendritic potential, calcium-ion concentrations and conductances, and potassium-ion conductances are done by use of equations similar to those of the point soma. Diffusion processes in dendrites are modeled by averaging among nearest-neighbor compartments. Inputs to each of the dendritic compartments come from sensors. Alternatively or in addition, when an affected neuron is part of a pool, inputs can come from other spiking neurons.

At present, SVM neural networks are implemented by computational simulation, using algorithms that encode the SVM and its submodels. However, it should be possible to implement these neural networks in hardware: The differential equations for the dendritic and cellular processes in the SVM model of spiking neurons map to equivalent circuits that can be implemented directly in analog very-large-scale integrated (VLSI) circuits.

This work was done by Terrance Huntsberger of Caltech for NASA's Jet Propulsion Laboratory. Further information is contained in a TSP (see page 1). NPO-40945

Symmetric Phase-Only Filtering in Particle-Image Velocimetry
Performance is enhanced significantly with little increase in computation time.

John H. Glenn Research Center, Cleveland, Ohio

Symmetrical phase-only filtering (SPOF) can be exploited to obtain substantial improvements in the results of data processing in particle-image velocimetry (PIV). In comparison with traditional PIV data processing, SPOF PIV data processing yields narrower and larger amplitude correlation peaks, thereby providing more-accurate velocity estimates. The higher signal-to-noise ratios associated with the higher amplitude correlation peaks afford greater robust-

ness and reliability of processing. SPOF also affords superior performance in the presence of surface flare light and/or background light. SPOF algorithms can readily be incorporated into pre-existing algorithms used to process digitized image data in PIV, without significantly increasing processing times.

A summary of PIV and traditional PIV data processing is prerequisite to a meaningful description of SPOF PIV processing. In PIV, a pulsed laser is used to illuminate

a substantially planar region of a flowing fluid in which particles are entrained. An electronic camera records digital images of the particles at two instants of time. The components of velocity of the fluid in the illuminated plane can be obtained by determining the displacements of particles between the two illumination pulses.

The objective in PIV data processing is to compute the particle displacements from the digitital image data. In traditional PIV data processing, to which the