

Guest Editorial

Overview of Pulse Coupled Neural Network (PCNN) Special Issue

Abstract— Pulse coupled neural networks (PCNN's) have proven to be highly effective when used in a diverse set of applications. The theory is based on biological studies of pulse synchronization. The editors present this special issue in response to numerous requests from colleagues for more information on PCNN's.

Index Terms— Pulse coupled neural networks.

I. BASIC THEORIES AND REVIEWS

THE premier article in the issue, "Neural Mechanisms of Scene Segmentation," comes from pioneer R. Eckhorn *et al.* The incisively significant results described in this paper could provide the foundation for ten years of research by the community. Firmly based on Eckhorn's early work, which established the foundations for study of pulse coupled neural networks, this paper extends the concepts, while continuing to link the abstracted concepts to the biological investigations undertaken by the lab.

This article contains many new results, both experimental and theoretical, that support and expand his earlier research into pulse synchronization. It discusses new applications for segmentation and activity grouping via medium and far linking; the role of global recursive inhibition; how to achieve zero phase delay correlation; and several new segmentation effects, including the interactions between forced and induced synchronization. The paper moves from a discussion of experimentally observed synchronous pulse activity and its correlation with controlled visual stimuli to a description of the linking field model itself. Eckhorn has used the same basic model since its introduction in 1990: low-pass temporal filters and modulator pulse coupling generate an internal activity that drives a pulse generator. He uses a neuromime generator rather than a more conventional integrate-and-fire model.

Several very significant results are presented in the paper. The first is a demonstration that modulatory coupling is more effective than additive coupling because it better separates the linking versus the nonlinking signals. Another shows a feedback effect that gives an excellent demonstration of the dynamical control (rather than chaotic behavior) obtained by PCNN's. It gives a "snapshot" effect for input distributions, automatically sequences and time-prioritizes different inputs, and improves figure-ground separation. The most important result is a demonstration of zero-delay correlation; an experimental finding that is elegantly supported by Eckhorn's modeling, and fully presented in this paper. Overall, it is a major extension of many of Eckhorn's previous results

and presents an elegant model for the zero-delay correlation. Enough summary material is included to provide a good review of the basic PCNN model, the Eckhorn linking field model.

"PCNN Models and Applications," by Johnson and Padgett, fills gaps in the content of the issue. This review supplies detail needed to provide groundwork for readers new to the field, and explanations to those working in similar but not identical PCNN areas.

"Class 1 Neural Excitability, Conventional Synapses, Weakly Connected Networks, and Mathematical Foundations of Pulse-Coupled Models," by Izhikevich, puts PCNN's on a rigorous yet mathematically tractable basis. It proves that the actual biological cell models discussed are the same as the PCNN model (among others). All are related by what is essentially a change of variables. It is proven that it is not necessary to have the detailed dynamical model in order to get the detailed dynamical behavior. All that is needed are 1) pulses of a class I excitability and 2) weak coupling. The paper is a brief but clear introduction to the phase representation for pulsed systems. It shows on fundamental grounds that a PCNN will spontaneously desynchronize rather than remaining fixed in a synchronization lock for all of time. This allows a PCNN to exhibit many more dynamical regimes, to be a much more complex and versatile processing system. It is thus vital that the information processing view of PCNN's be carefully studied and understood. Overall, this is an exceptional paper that provides a new tool for neurodynamics.

"Weakly Pulse-Coupled Oscillators, FM Interactions, Synchronization, and Oscillatory Associative Memory," also by Izhikevich, gives a new methodology for analytical neurodynamics. It is a powerful paper, picking up where the first one ended, with all the class I neurons mapped to a single phase-based model. After a slight generalization, it shows that it is possible to multiplex neuronal pulse signals. This is an entirely new view. The pulse rate is not the information; it is only the ID tag for the transmission channel. Izhikevich proves that the information is in the phase modulation. This concept is new, and its applications go far beyond neural networks. With it, a true parallel computer can be built.

II. IMPLEMENTATIONS

"An Accelerator for Neural Networks with Pulse-Coded Model Neurons," by Frank *et al.*, describes methods for implementing the Eckhorn linking field model using programmable gate array (FPGA) modules. This is an electronic digital accelerator board architecture. Major points presented are the following: 1) the use of an indirect address (pointer) scheme to

deal with the large interconnect count; 2) a unique list-passing algorithm, chosen for its compatibility with the FPGA units; 3) breakdown of the neural function into three subfunctions; and 4) a VLSI simulation. The neural subfunctions are 1) the decay phase (indexed-decrement phase); 2) pulse propagation (axon-based updates rather than the usual dendritic view); and 3) synaptic adaptation. The final system design is analyzed to show that in VLSI it will have a significant cost and speed advantage over other implementations.

This paper presents a substantial breakthrough in the construction of a useful, potentially real-time simulation of a large set of pulse-coded neurons. This accelerator approach to neural network hardware makes feasible a realistic implementation of the ideas expressed in the Eckhorn paper. Previously available hardware does not provide for such an implementation. Some of the applications that make the pulse-coded approach worthwhile include simulation of motor systems, simulations of space representations, and labeling of visual features by synchronized spikes.

“Analog Hardware Implementation of Pulse-Coupled Neural Networks,” by Ota and Wilamowski, describes simulation of a CMOS architecture that implements a pulse coupled network. The model is not the modulatory Eckhorn linking field. It uses instead a leaky integrate-and-fire pulse generator, adaptive synaptic coupling, and dendritic delay-line propagation. The paper describes the underlying algorithm in detail, and applies it to a sample image, showing that its noise-smoothing capability is, like the Eckhorn model, superior to median filter smoothing and average-filter smoothing. The detailed CMOS design process is constrained in the course of the paper to emphasize small nodal size and high-speed operation. The dynamical properties are 1) threshold-based firing (settable from external controls); 2) some pulse spreading and delay due to axonal propagation; and 3) characteristic autowave behavior of mutual pulse annihilation. The resulting architecture provides a practical near-term implementation leading to greatly enhanced image segmentation capability.

In “Frequency Based Neural Network with On-Chip Learning and Enhanced Neuron Characteristics,” Hikawa presents useful ideas, which should stimulate further research on frequency-based neural networks. First, the digital implementation is justified. Next multilayer neural networks are discussed, with backpropagation learning featured. Then the change to a frequency-based multilayer neural network is described. The model discussed is not an Eckhorn PCNN, and only uses average pulsed frequency. Still, the suggestions made have been implemented and tested. They represent an exciting new architecture, and are a good starting point for a potential implementation of a full PCNN.

The paper “A Retina with Parallel Input and Pulsed Output, Extracting High Resolution Information,” by Wilcox, describes an electronic circuit model that implements the biological networks. The tie with PCNN’s is the way the analog information on location and movement is converted to pulses and used as a contrast detector to provide aperture control. (The biological fly-eye has no iris.) The pulse coupling also gives a logical “exclusive-or” function, which greatly reduces noise problems while giving completed object outlines. The value of this paper

is that it gives the biological architecture in some detail and shows that in nature there is a lot of analog processing as well as pulse interactions. It shows how the pulse signals and the analog signals interact to give each other much better performance than either alone. The discussion of the electronic implementation models is an extra benefit to those interested in fly-eye cameras.

The main benefits of “Implementation of Pulse-Coupled Neural Networks in a CNAPS Environment,” by Kinser and Lindblad, are threefold: 1) A detailed CNAPS-based algorithm for a PCNN makes this paper a very useful development tool. 2) The CNAPS PCNN system (not the simulation) is applied to several good image-processing problems, yielding a quick evaluation of PCNN effectiveness when implemented in hardware. In particular, the results for denoising and for automatically finding outlines are very impressive. 3) The PCNN (as an accelerator board) improves another algorithm, in this case the fractional power (Fourier) filter. This demonstrates that the PCNN can be used in image processing to augment and improve the performance of other algorithms.

III. APPLICATIONS

“Physiologically Motivated Image Fusion for Object Detection Using a Pulse Coupled Neural Network,” by Broussard *et al.*, applies the basic PCNN modulation to an image fusion problem, and demonstrates a dramatic improvement in the reduction of false alarms. The combination of PCNN’s and wavelets is quite effective. Results are presented for application of PCNN’s to mammograms and infrared target images. These new results on two highly significant and very different topics, medical diagnostics, and military targets, show the power of the basic PCNN model.

“Perfect Image Segmentation Using Pulse Coupled Neural Networks, by Kuntimad and Ranganath,” discusses a method for achieving the best possible feature binding or segmentation. A simpler version of the Eckhorn linking field PCNN is chosen: 1) there are no temporal linking synapse filters; 2) the feeding input is static; and 3) the threshold is reset to a high but fixed value rather than being reset by a constant threshold increment. This corresponds to the small-signal limit in the full Eckhorn model. Also, heavy use is made of the linking strength coefficient, something not explicit in the 1990 Eckhorn model. Finally, all the linking receptive fields are very small (2×2 and 3×3).

This paper is a primary model for using the PCNN for image segmentation. It shows how to start with the basic Eckhorn model, tailor it to fit the particular problem, and discusses the improved performance obtained with PCNN’s. It further shows a result unique in image processing. No other segmentation approach has provable conditions for perfect segmentation.

“Range Image Segmentation Using a Relaxation Oscillator Network,” by Liu and Wang, describes a pulse-coupled architecture that is not derived from the Eckhorn linking field model. Instead, the nodes are made up of pairs of excitatory-inhibitory units, which interact competitively to generate the pulse profiles. The excitatory component uses a cubic nullcline and the inhibitory component uses a hyperbolic tangent func-

tion. The coupling in the network among the nodes themselves is entirely additive (no linking modulation). Despite these differences, the paper shows that in slab-scale architecture the dynamical behavior is similar to that of the Eckhorn model. In particular, using the total time-signal slab output as a global inhibitory feedback causes all spatially disjoint regions sharing a common intensity input to automatically space themselves out in equal phase-shift separations throughout their common pulse period. The model algorithm is also used to clean up the noisy range imagery. Range images are well known for having extreme noise problems due to occasional signal dropout, yet the results shown in the paper are very clean. The phase-shift action is highly useful in range imagery, as it allows several spatially disjoint targets at a common range to be dynamically separated and thus automatically interrogated. This paper also presents a successful application to the segmentation of machined parts, using some thresholds and weights, which are not yet automatically determined.

“Smart Adaptive Optic Systems Using Spatial Light Modulators,” by Clark and Ranganath, first describes the optical problem to be addressed, that of mirror figure correction. Next presented is the mathematical tool to be used, phase diversity: given an atmospherically blurred satellite telescope image, correct it by rebending the telescope mirror to compensate for the induced optical wavefront distortions. The approach is basically an optical gradient measurement that is done on a segment-by-segment basis. The key issue resolved by the PCNN is noise propagation in the computations. The mirror corrections depend on dividing up the aperture into subareas. The correction signals from these subareas must be continuous. The noise, expressed as the variance of the correction signal set, increases quickly with the number of subapertures. The PCNN is used to reduce the noise while retaining a large number of subapertures. It improves the performance by a factor of five in the simulations. The PCNN algorithm by Ranganath is shown to be a very desirable choice because it is fast, computationally compact, and low power. These properties are important for satellite applications. It is also extremely effective. This PCNN is highly compatible with the desired MEMS hardware implementation as an adaptive phase-correcting array. Other smoothing algorithms do not share this compatibility.

“Finding the Shortest Path in the Shortest Time Using PCNN’s,” by Caulfield and Kinser, presents a novel and useful application of PCNN. It is a clever approach to a difficult problem. The PCNN is modified so that the output pulses decay in time. The maze is explored by the PCNN and the shortest solution path is found by backtracking the decayed pulses.

“Inherent Features of Wavelets and Pulse Coupled Neural Networks,” by Lindblad and Kinser, presents a useful comparison of pulse coupled neural networks and wavelets.

It demonstrates that in some cases, the two techniques are complementary. On the other hand, there are enough similarities to make the techniques compatible for inclusion in the same system. The real-time implementations are useful illustrations, and the evaluation of hardware available for real-time processing is excellent.

“Object Detection Using Pulse Coupled Neural Networks,” by Ranganath and Kuntimad, uses the PCNN as a component of a larger image processing system. Although it uses imagery of a scene with model vehicles, the algorithm itself is oriented toward medical image diagnostics. It operates in the following way: The image is fully segmented by feature binding. Then those segments that are too large or too long to possibly be a part of the desired target image are discarded. The remaining segments are rapidly combined in various subgroups and each grouping is evaluated. The groups most likely to be the target are the system output. This approach allows multiple PCNN passes with a rule-based system to efficiently determine the best choice of segments matching that of the target.

“Foveation by a Pulse-Coupled Neural Network,” by Kinser, describes an application of PCNN’s that takes advantage of the inherent area-based dynamics of the linking field model. Other segmentation algorithms depend on the establishment of edges or on pure intensity thresholding. The PCNN segmentation action, however, is area-based, and accordingly is partially due to the geometrical and spatial relationships in the underlying imagery. This paper is illustrative of how the PCNN is applied in conjunction with a larger algorithm to solve an otherwise difficult problem. The PCNN’s basic segmentation capability is used on the images, then the rest of the algorithm processes the image based on the PCNN segments. The outstanding feature here is that the desired information (foveation points) is very efficiently extracted by the PCNN with no prior knowledge required by the PCNN. This demonstrates the value of PCNN’s in foveation and target recognition.

Considered together, this combination of basic theory, reviews, implementations, and applications presents the PCNN as a viable and practical approach to the study and application of neural dynamics.

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