Chapter 7

Conclusions

The spirit within nourishes, and mind instilled
Throughout the living parts activates the whole mass
And mingles with the vast frame.
Virgil

Life is not so simple, man!
B. Uma Shankar

We have presented in this thesis some results of investigations, both theoretical and computational, which demonstrate some of the features of simple networks of excitatory and inhibitory neuron-type elements. The main goal was to study the behavior of the simplest network model capable of producing chaotic behavior. Initially, a single pair of an excitatory and an inhibitory neuron is described and analyzed in detail. Then small networks of such pairs are studied in the context of control and synchronization of their activity. Finally, an attempt is made to utilize such networks for some image processing tasks, specifically, segmentation and adaptive smoothing.

In the following section, the most important results are briefly summarized, while the final section provides an outlook to further problems which can be looked at in the future, as an extension to the investigation reported here.

7.1 Summary of Main Results

- The intrinsic properties of an excitatory-inhibitory neural pair have been studied with four types of nonlinear activation functions, distinct from each other in terms of their (*i*) asymmetric or anti-symmetric nature and (*ii*) sigmoid or piecewise linear characteristics. Fixed point, oscillatory and chaotic behaviors have been found to occur for various parameter values for these different types of functions, leading to the conclusion that this wide range of dynamics is a generic feature of excitatory-inhibitory neural pairs, evolving in discrete time.

- In addition to generic features, behavior specific to each type of transfer function has also been observed. For example, in the case of the piecewise linear functions, the presence of border-collision bifurcations and multifractal fragmentation of the phase space are noted. Neural pairs with sigmoidal activation functions exhibit a period-doubling route to chaos, which is an universal feature of unimodal one-dimensional chaotic maps [134, 188]. The anti-symmetric activation functions show a transition from symmetry-broken chaos (with multiple coexisting but disconnected chaotic attractors) to symmetric chaos (when only a single chaotic attractor exists).

- Varying a *threshold/ bias* parameter or equivalently, introducing a constant amplitude external stimulus, leads either to transition between chaos and periodic behavior or to coexistence of multiple attractors, depending on the nature of the variation. In the case of anti-symmetric functions, this causes previously distinct attractors to be dynamically connected. *Hysteresis* effect, a possible mechanism for short-term memory, is observed as the parameter is varied.

- Networks composed of elements having piecewise linear activation functions are found to be amenable to analytical treatment under some simplifying assumptions. This makes the resultant dynamics effectively equivalent to that of an one-dimensional piecewise linear map with multiple "folds". These "folds" permit the creation and maintenance of localized coherent structures within a global chaotic activity. This is of relevance to the use of such networks for information processing. Applications to problems of auto-associative recall, pattern classification, nonlinear function approximation and periodic sequence generation are outlined. This serves to indicate the versatility of such networks and possible areas where they maybe successfully used.

- In the presence of low-amplitude, low-frequency external stimulation, the chaotic neural pair with anti-symmetric activation function is found to exhibit a type of *nonlinear resonance* phenomenon, which can be looked upon as a deterministic analogue of "stochastic resonance" (SR) [59]. By introducing a piecewise linear system to study this phenomenon, a detailed understanding of the resonance process is obtained. The chaotic trajectory of the system is found to switch between two halves of the phase space at a rate which 'resonates' with the frequency of an externally applied periodic perturbation (both multiplicative and additive). By periodically modulating the parameter at a specific frequency, we observe the existence of resonance where the response of the system (in terms of the residence-time distribution) is maximum. The possible application of nonlinear resonance for the enhancement of subthreshold signals is indicated by showing that the excitatory- inhibitory neural pair shows similar resonance behavior when the external input is a small amplitude periodic signal. The "characteristic frequency" at which the system response is maximum is obtained explicitly in terms of the network parameters, in the case of the piecewise linear activation function. It is found that as the amplitude of the signal increases, the response of the system also increases up to a limit. An expression for the "critical signal amplitude", above which the response saturates, is also obtained.

- Control mechanisms for the chaos observed in excitatory-inhibitory neural pairs have been studied. Two types of control have been proposed: (*i*) proportional variable feedback and (*ii*) small-amplitude periodic forcing. A physical understanding of the control mechanism is obtained in the case of a single excitatory-inhibitory pair. Control of a 3-neuron pair network has been studied through computer simulations. A possible connection between undesirable stabilization of periodic cycles by external periodic stimulus and the phenomenon of epileptic hallucination is suggested.

- Collective dynamics and synchronization of small assemblies of neural pairs are analyzed. Both unidirectional and bidirectional couplings between the neural pairs have been studied. For bidirectional coupling, intermittent synchronization is observed in the case of two coupled neural pairs, while the case of three coupled neural pairs show the more interesting feature of "mediated" synchronization. For unidirectional coupling, the phenomena of "frustrated synchronization" has been studied in detail. The well-known Lorenz system of equations has been used as a model system for ease of theoretical analysis. A 'desynchronization' parameter has been defined, which shows a scaling relation with the scaled coupling parameter.

- The utility of chaotic dynamics in certain image processing tasks such as, segmentation and adaptive smoothing, has been studied. A two-dimensional network of locally coupled excitatory-inhibitory pairs is used to study *segmentation.* Bilevel segmentation is achieved through different dynamical responses of neural pairs corresponding to "object" and "background". An approximate expression for the critical input stimulus magnitude, that leads to transition between the two different dynamical responses, is obtained in the case of an isolated neural pair. Noisy, synthetic images as well as "real-life" images are used to show the effectiveness of the segmentation procedure.

- *Adaptive smoothing* of gray-level images is achieved with a three layer network of excitatory, inhibitory and excitatory neurons, respectively. The output of this network is then used to find the edges of the input image by using a standard difference operator. The network has been used on several "real-life" images, and the results compare favorably to those of some standard methods of edge detection. The network architecture has been inspired by the structure of the outer plexiform layer of the retina and it has been proposed as a model for retinal information processing.

7.2 Outlook

In this work, we have stressed on 'simple' network models: 'simple' not only in terms of the size of the networks considered when compared to the brain (consisting of $\sim 10^{11}$ neurons and $\sim 10^{15}$ synapses), but 'simple' also in terms of the properties of the constituent elements (i.e., the 'neurons') themselves, in that, most of the physiological details of real neurons are ignored. Biological neurons are far more complicated, and a lot of computation is achieved at the level of the single neuron itself [105].

The point is to see what is essential and what is unnecessary detail for the proper functioning of biological neuronal networks. To do that one has to throw away as much of the complexity as possible to make the model tractable - while at the same time retaining those features of the system which make it interesting. So, while our modeling is indeed inspired by neuroscience, we are not concerned with actually mimicking the activity of real neuronal systems.

Our prime concern is what functional role chaos might be playing in the brain. As the brain itself is still a relatively poorly understood system, we have instead tried to look at what *artificial* networks can do with chaos. Hopefully, this will give us a clearer understanding of how chaos might actually be used in the brain to perform cognitive tasks. By resorting to a simple model, where we can perform detailed theoretical analysis, we can obtain a deep understanding of its behavior. This can then be used fruitfully to study the more complex entity, that is the brain.

In the work reported here, many interesting features were observed. However, to see their relevance to the actual biological situation, we have to make a connection between our results and the behavior of the brain. Such attempts have already been made, as for example, in Chapter 4, where, undesired control of neurobiological chaos is sought to be connected to the phenomenon of epileptic hallucinations. However, to take these efforts further, the complexity of the model needs to be increased systematically in a step-by-step manner, with detailed analysis of the new features thus revealed, in each step of the way.

For example, in this work we have been concerned exclusively with 'neurons' evolving in discrete time intervals. Biological neurons are better modeled by differential equations which evolve in continuous time. However, this is not really a limitation as any N-dimensional discrete-time dynamical system may be related to a corresponding $(N+1)$-dimensional continuous-time dynamical system through the concept of *Poincare sections* [188]. It follows that the discrete-time model we have studied has a higher dimensional differential equation analogue, which will show qualitatively similar behavior. Several differential equation models already exist which describe the activity of single neurons, with varying degrees of fidelity. A popular model which is biologically motivated and yet simple enough for ease of analysis is the Bonhoeffer-van der Pol (BVP) system of equations. Such systems have been shown to exhibit chaos when subjected to forced oscillations of specific amplitude and frequency [148].

However, large networks of BVP or similar systems have, as yet, not been studied in detail. Investigation of the collective behavior of such continuous-time neural network models, and linking the results to those reported here, should go a long way in establishing the genericity of our findings.

Real biological systems reside in an extremely noisy environment. This is incorporated in neural models by using stochastic updating rule and/or explicit introduction of a term representing external noise. The former can be represented as a form of multiplicative noise, whereas the latter is a strictly additive form of noise [192]. Physiologically, additive noise may originate from threshold fluctuations of a dendritic potential, while multiplicative noise could be due to stimulus-induced stochastic release of vescicles, containing neurotransmitter chemicals, from the synapses. We plan to introduce similar features in our model in the future. In dissipative chaotic systems, the effect of external noise seems to be limited to destroying the fine structure of the bifurcation sequence [41]. The interaction of deterministic chaos and stochastic noise in the network will be interesting to study.

One important point not addressed here is the issue of *learning.* The connection weights $\{ W_{ij} \}$ have been assumed constant, as they change at a much slower time scale compared to that of the neural activation states. However, modification of the weights due to learning will also cause changes in the dynamics. Such bifurcation behavior, induced by weight changes, will have to be taken into account when devising learning rules for specific purposes. The interaction of chaotic activation dynamics at a fast time scale and learning dynamics on a slower time scale might yield richer behavior than that seen in the present model [47]. The first step towards such a program would be to incorporate time-varying connection weights in the model. In [196], time-dependence of a suitable system parameter was shown to give rise to interesting dynamical behaviors, e.g., transition between periodic oscillations and chaos. This suggests that varying the environment can facilitate memory retrieval if dynamic states are used for storing information in a neural network. The introduction of temporal variation in the connection weights, independent of the neural state dynamics, should allow us to develop an understanding of how the dynamics at two time-scales interact with each other.

Parallel to this we have to look at the *learning dynamics* itself. Freeman [54], among others, has suggested an important role of chaos in the Hebbian model of learning [84]. This is one of the most popular learning models in the neural network community and is based on the following principle postulated by Hebb [84] in 1949:

> When an axon of cell A is near enough to excite cell B and repeatedly or consistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased.

According to the principle known as *synaptic plasticity*, the synapse between neurons A and B increase its "weight", if the neurons are simultaneously active. By invoking an "adiabatic approximation", we can separate the time scale of updating the connection weights from that of neural state updating. This will allow us to study the dynamics of the connection weights in isolation.

The final step will be to remove the "adiabatic approximation", so that the neural states will evolve, guided by the connection weights (as studied in the thesis), while the connection weights themselves will also evolve, depending on the activation states of the neurons, as:

$$W_{ij}(n+1) = \mathcal{F}_\epsilon(W_{ij}(n), X_i(n), X_j(n)),$$

where $X(n)$ and $W(n)$ denote the neuron state and connection weight at the nth instant, $\mathcal{F}$ is a nonlinear function that specifies the learning rule, and ϵ is related to the time-scale of the synaptic dynamics. The cross-level effects of such synaptic dynamics interacting with the chaotic network dynamics might lead to significant departure from the overall behavior of the network described here.

The proposed extensions and modifications of the neural network model presented here will most probably lead to behavior yet unexpected. Considering that the model already exhibits such complex behavior, the incorporation of the details suggested above should provide results, which will be comparable to actual neurobiological data.

On a broader front, chaos may play a substantial role in resolving the *stability-plasticity dilemma* that confronts a wide range of complex adaptive systems, including neural networks. This dilemma can be framed in terms of the following questions:

- How can a learning system be designed to remain plastic (adaptive) in response to significant events and yet remain stable in response to irrelevant events ?
- How does the system know when to switch between its stable and plastic modes to achieve stability without rigidity and plasticity without disorder ?

Transitions between chaotic and ordered behavior are a general feature of complex adaptive systems and form the subject matter of the recently emerged discipline of Artificial Life (A-Life). It studies how local rules of interaction between elements of a complex system can give rise to collectively emergent global behavior of the system. This phenomena has been studied in the relatively simple system of cellular automata (CA) models by Langton [109]. CA are rule driven systems, defined by specifying the transformation rules that map a given initial state of the system to the final state. They can show a wide variety of behavior, ranging from highly ordered to totally chaotic. By using a variable parameter, changing which alters the behavior of the system, it has been seen that, at the region where transition from ordered to chaotic behavior occurs, the system exhibits complexity in the sense that it is capable of universal computation. Langton has extended this finding to the generalization that *"complexity occurs at the edge of chaos"*. The substance of this assertion is that while an ordered system is too rigid to learn from experience, and chaotic systems are too unstable to exist in a competitive environment, complexity arises only in those systems having the right blend of order and chaos. Only systems poised at the "edge of chaos" , the critical state at which complexity is most likely to emerge, are rigid enough to survive, while being capable of suitably adapting themselves to a changing environment. While these findings are only for the specific system of CA, and not yet universally accepted, they are nonetheless highly suggestive. The brain, being a complex adaptive system also, might be indulging in a similar kind of tradeoff between order and chaos. Studying chaotic models of neural activity thus might provide us with an an understanding of how complexity emerges not only in the brain, but in a broad family of complex adaptive systems, of which it is a member.

Bibliography

[1] M. Adachi and K. Aihara. Associative dynamics in a chaotic neural network. *Neural Networks*, 10:83–98, 1997.

[2] R. D. Adams and M. Victor. *Principles of Neurology.* McGraw-Hill, New York, 1977.

[3] K. Aihara, G. Matsumoto, and Y. Ikegaya. Periodic and non-periodic responses of a periodically forced Hodgkin-Huxley oscillator. *J. Theo. Biol.*, 109:249–269, 1984.

[4] K. Aihara, T. Takabe, and M. Toyoda. Chaotic neural networks. *Phys. Lett. A*, 144:333–340, 1990.

[5] S. Amari. Characteristics of random nets of analog neuron-like elements. *IEEE Trans. Systems, Man and Cybernetics*, 2:643–657, 1972.

[6] S. Amari and M. Arbib, editors. *Competition and Cooperation in Neural Nets.* Springer-Verlag, New York, 1982.

[7] S. Amari and K. Maginu. Statistical neurodynamics of associative memory. *Neural Networks*, 1:63–73, 1988.

[8] D. J. Amit. *Modeling Brain Function.* Cambridge University Press, Cambridge, 1989.

[9] Y. V. Andreyev, Y. L. Belsky, A. S. Dmitriev, and D. A. Kuminov. Information processing using dynamical chaos: neural networks implementation. *IEEE Trans. Neural Networks*, 7:290–299, 1996.

[10] Y. V. Andreyev, A. S. Dmitriev, and S. O. Starkov. Information processing in one-dimensional systems with chaos. *IEEE Trans. Circuits and Systems - I*, 44:21–28, 1997.

[11] V. S. Anishchenko, A. B. Neiman, and M. A. Safanova. Stochastic resonance in chaotic systems. *J. Stat. Phys.*, 70:183–196, 1993.

[12] P. Ashwin, J. Buescu, and I. Stewart. Bubbling of attractors and synchronisation of chaotic oscillators. *Phys. Lett. A*, 193:126–139, 1994.

[13] A. Atiya and P. Baldi. Oscillations and synchronizations in neural networks: An exploration of the labeling hypothesis. *Int. J. Neural Systems*, 1:103–124, 1989.

[14] A. Babloyantz and A. Destexhe. Low-dimensional chaos in an instance of epilepsy. *Proc. Natl. Acad. Sci. USA*, 83:3513–3517, 1986.

[15] A. Babloyantz, J. M. Salazar, and C. Nicolis. Evidence of chaotic dynamics of brain activity during the sleep cycle. *Phys. Lett. A*, 111:152–156, 1985.

[16] P. Baldi and A. Atiya. How delays affect neural dynamics and learning. *IEEE Trans. Neural Networks*, 5:612–621, 1994.

[17] J. Basak. *Connectionist models for certain tasks related to object recognition.* PhD thesis, Indian Statistical Institute, Calcutta, 1994.

[18] C. Beck and F. Schlögl. *Thermodynamics of Chaotic Systems.* Cambridge University Press, Cambridge, 1993.

[19] R. Benzi, A. Sutera, and A. Vulpiani. The mechanism of stochastic resonance. *J. Phys. A*, 14:L453–L457, 1981.

[20] H. Bersini and V. Calenbuhr. Frustrated chaos in biological networks. *J. Theo. Biol.*, 188:187–200, 1997.

[21] S. Biswas, N. R. Pal, and S. K. Pal. Smoothing of digital images using the concept of diffusion process. *Pattern Recognition*, 29:497–510, 1996.

[22] S. N. Biswas and B. B. Chaudhuri. On the generation of discrete circular objects and their properties. *Computer Vision, Graphics and Image Processing*, 32:158–170, 1985.

[23] A. Blake and A. Zisserman. *Visual Reconstruction.* MIT Press, Cambridge, Mass., 1987.

[24] E. K. Blum and X. Wang. Stability of fixed points and periodic orbits and bifurcations in analog neural networks. *Neural Networks*, 5:577–587, 1992.

[25] Y. Braiman and I. Goldhirsch. Taming chaotic dynamics with weak periodic perturbations. *Phys. Rev. Lett.*, 66:2545–2548, 1991.

[26] Y. Braiman, J. F. Lindner, and W. L. Ditto. Taming spatiotemporal chaos with disorder. *Nature*, 378:465–467, 1995.

[27] D. S. Broomhead and R. Jones. Time-series analysis. *Proc. Roy. Soc. Lond. A*, 423:103–121, 1989.

[28] S. Campbell and D. L. Wang. Synchronization and desynchronization in a network of locally coupled Wilson-Cowan oscillators. *IEEE Trans. Neural Networks*, 7:541–554, 1996.

[29] J. Canny. A computational approach to edge detection. *IEEE Trans. Pattern Analysis and Machine Intelligence*, 8:679–698, 1986.

[30] T. W. Carr and I. B. Schwartz. Controlling high-dimensional unstable steady states using delay, duration and feedback. *Physica D*, 96:17–25, 1996.

[31] T. L. Carroll and L. M. Pecora. Stochastic resonance and crises. *Phys. Rev. Lett.*, 70:576–579, 1993.

[32] F. Catté, P. L. Lions, J. M. Morel, and T. Coll. Image selective smoothing and edge detection by nonlinear diffusion. *SIAM J. Num. Anal.*, 29:182–193, 1992.

[33] Z. Chang-song, C. Tian-lun, and H. Wu-qun. Chaotic neural network with nonlinear self-feedback and its application to optimization. *Neurocomputing*, 14:209–222, 1997.

[34] T. R. Chay. Chaos in a three-variable model of an excitable cell. *Physica D*, 16:233–242, 1985.

[35] L. Chen and K. Aihara. Chaotic simulated annealing by a neural network model with transient chaos. *Neural Networks*, 8:915–930, 1995.

[36] M. Y. Choi and B. A. Huberman. Digital dynamics and the simulation of magnetic systems. *Phys. Rev. B*, 28:2547–2554, 1983.

[37] D. J. Christini and J. J. Collins. Controlling nonchaotic neuronal noise using chaos control techniques. *Phys. Rev. Lett.*, 75:2782–2785, 1995.

[38] M. Conrad. What is the use of chaos ? In A. V. Holden, editor, *Chaos*, pages 3–14. Manchester University Press, Manchester, 1986.

[39] M. Cosnard and D. Moumida. Dynamical properties of an automaton with memory. In F. Fogelman Soulié, Y. Robert, and M. Tchuente, editors, *Automata Networks in Computer Science*, pages 82–100. Manchester University Press, Manchester, 1987.

[40] A. Crisanti, M. Falcioni, G. Paladin, and A. Vulpiani. Stochastic resonance in deterministic chaotic systems. *J. Phys. A*, 27:L597–L603, 1994.

[41] J. Crutchfield, M. Nauenberg, and J. Rudnick. Scaling for external noise at the onset of chaos. *Phys. Rev. Lett.*, 46:933–935, 1981.

[42] K. M. Cuomo, A. V. Oppenheim, and S. H. Strogatz. Synchronization of Lorenz-based chaotic circuits with applications to communications. *IEEE Trans. Circuits & Systems II*, 40:626–633, 1993.

[43] V. Deshpande and C. Dasgupta. A neural network storing individual patterns in a limit cycle. *J. Phys. A*, 24:5105–5119, 1991.

[44] A. Destexhe. Oscillations, complex spatiotemporal behavior and information transport in networks of excitatory and inhibitory neurons. *Phys. Rev. E*, 50:1594–1606, 1994.

[45] M. Ding and W. Yang. Stability of synchronous chaos and on-off intermittency in coupled map lattices. *Phys. Rev. E*, 56:4009–4016, 1997.

[46] A. S. Dmitriev, M. Shirokov, and S. O. Starkov. Chaotic synchronization in ensembles of coupled maps. *IEEE Trans. Circuits and Systems-I*, 44:918–926, 1997.

[47] D. Dong. *Dynamic properties of neural networks*. PhD thesis, California Institute of Technology, 1991.

[48] J. K. Douglass, L. Wilkens, E. Pantazelou, and F. Moss. Noise enhancement of information transfer in crayfish mechanoreceptors by stochastic resonance. *Nature*, 365:337–340, 1993.

[49] B. Doyon, B. Cessac, M. Quoy, and M. Samuelides. Control of the transition to chaos in neural networks with random connectivity. *Int. J. Bif. Chaos*, 3:279–291, 1993.

[50] R. M. Everson. Scaling of intermittency period with dimension of a partition boundary. *Phys. Lett. A*, 122:471-475, 1987.

[51] W. J. Freeman. Simulation of chaotic EEG patterns with a dynamic model of the olfactory system. *Biol. Cybern.*, 56:139–150, 1987.

[52] W. J. Freeman. The physiology of perception. *Scientific American*, 264 (2):78–85, 1991.

[53] W. J. Freeman. Tutorial on neurobiology: From single neurons to brain chaos. *Int. J. Bif. Chaos*, 2:451–482, 1992.

[54] W. J. Freeman. Chaos in the brain: Possible roles in biological intelligence. *Int. J. Intelligent Systems*, 10:71–88, 1995.

[55] H. Fujisaka and T. Yamada. Stability theory of synchronized motion in coupled-oscillator systems. *Prog. Theor. Phys.*, 69:32–47, 1983.

[56] H. Fujisaka and T. Yamada. Stability theory of synchronized motion in coupled-oscillator systems IV. Instability of synchronized chaos and new intermittency. *Prog. Theor. Phys.*, 75:1087–1104, 1986.

[57] T. Fukai and M. Shiino. Asymmetric neural networks incorporating the Dale hypothesis and noise-driven chaos. *Phys. Rev. Lett.*, 64:1465–1468, 1990.

[58] P. M. Gade, R. Rai, and H. Singh. Stochastic resonance in maps and coupled map lattices. *Phys. Rev. E*, 56:2518–2526, 1997.

[59] L. Gammaitoni, P. Hänggi, P. Jung, and F. Marchesoni. Stochastic resonance. *Rev. Mod. Phys.*, 70:223–287, 1998.

[60] L. Gammaitoni, F. Marchesoni, and S. Santucci. Stochastic resonance as a *bona fide* resonance. *Phys. Rev. Lett.*, 74:1052–1055, 1995.

[61] A. Ghosh, N. R. Pal, and S. K. Pal. Object-background classification using Hopfield type neural network. *Int. J. Patt. Rec. Artif. Int.*, 6:989–1008, 1992.

[62] L. Glass and M. C. Mackey. *From Clocks to Chaos: The Rhythms of Life.* Princeton University Press, Princeton, N. J., 1988.

[63] L. Glass and C. P. Malta. Chaos in multilooped negative feedback systems. *J. Theo. Biol.*, 145:217–223, 1990.

[64] R. C. Gonzalez and R. E. Woods. *Digital Image Processing.* Addison-Wesley, Reading, Mass., 1992.

[65] P. Grassberger. Generalized dimensions of strange attractors. *Phys. Lett. A*, 97:227–230, 1983.

[66] P. Grassberger. New mechanism for deterministic diffusion. *Phys. Rev. A*, 28:3666–3667, 1983.

[67] P. Grassberger and I. Procaccia. Characterization of strange attractors. *Phys. Rev. Lett.*, 50:346–349, 1983.

[68] C. M. Gray, P. König, A. K. Engel, and W. Singer. Oscillatory responses in cat visual cortex exhibit inter-columnar synchronization which reflects global stimulus properties. *Nature*, 338:334–337, 1989.

[69] C. Grebogi, E. Ott, and J. A. Yorke. Crises, sudden changes in chaotic attractors and chaotic transients. *Physica D*, 7:181–200, 1983.

[70] S. Grossberg and D. Somers. Synchronized oscillations during cooperative feature linking in a cortical model of visual perception. *Neural Networks*, 4:453–466, 1991.

[71] S. Grossman and H. Fujisaka. Diffusion in discrete nonlinear dynamical systems. *Phys. Rev. A*, 26:1779–1782, 1982.

[72] M. R. Guevara, L. Glass, M. C. Mackey, and A. Shrier. Chaos in neurobiology. *IEEE Trans. Systems, Man and Cybernetics*, 13:790–798, 1983.

[73] S. K. Han, W. S. Kim, and H. Kook. Temporal segmentation of the stochastic oscillator neural network. *Phys. Rev. E*, 58:2325–2334, 1998.

[74] D. Hansel and H. Sompolinsky. Synchronization and computation in a chaotic neural network. *Phys. Rev. Lett.*, 68:718–721, 1992.

[75] E. Harth. Order and chaos in neural systems: An approach to the dynamics of higher brain functions. *IEEE Trans. Systems, Man and Cybernetics*, 13:782–789, 1983.

[76] E. Harth and G. Pertile. The role of inhibition and adaptation in sensory information processing. *Kybernetik*, 10:32–37, 1972.

[77] M. Hasegawa, T. Ikeguchi, T. Matozaki, and K. Aihara. Improving image segmentation by chaotic neurodynamics. *IEICE Trans. Fundamentals E*, 79-A:1630–1637, 1996.

[78] M. Hasler and Y. L. Maistrenko. An introduction to the synchronization of chaotic systems: coupled skew tent maps. *IEEE Trans. Circuits and Systems -I*, 44:856–866, 1997.

[79] H. Hayashi, M. Nakao, and K. Hirakawa. Chaos in the self-sustained oscillation of an excitable biological membrane under sinusoidal stimulation. *Physics Letters A*, 88:265–266, 1982.

[80] Y. Hayashi. Oscillatory neural network and learning of continuously transformed patterns. *Neural Networks*, 7:219–231, 1994.

[81] R. He and P. G. Vaidya. Analysis and synthesis of synchronous periodic and chaotic systems. *Phys. Rev. A*, 46:7387–7392, 1992.

[82] J. F. Heagy, T. L. Carroll, and L. M. Pecora. Desynchronization by periodic orbits. *Phys. Rev. E*, 52:R1253-R1256, 1995.

[83] J. F. Heagy, N. Platt, and S. M. Hammel. Characterization of on-off intermittency. *Phys. Rev. E*, 49:1140–1150, 1994.

[84] D. O. Hebb. *The Organization of Behavior.* Wiley, New York, 1949.

[85] J. Hertz, A. Krogh, and R. G. Palmer. *Introduction to the Theory of Neural Computation.* Addison-Wesley, Reading, Mass., 1991.

[86] M. W. Hirsch. Convergent activation dynamics in continuous time networks. *Neural Networks*, 2:331–349, 1989.

[87] A. V. Holden, editor. *Chaos.* Manchester University Press, Manchester, 1986.

[88] A. V. Holden, W. Winlow, and P. G. Haydon. The induction of periodic and chaotic activity in a molluscan neuron. *Biol. Cybern.*, 43:169–173, 1982.

[89] D. Holton and R. May. The chaos of disease response and competition. In T. Mullin, editor, *The Nature of Chaos*, pages 183–200. Oxford University Press, Oxford, 1993.

[90] J. J. Hopfield. Neural networks and physical systems with emergent collective computational abilities. *Proc. Natl. Acad. Sci. (USA)*, 79:2554–2558, 1982.

[91] J. J. Hopfield. Neurons with graded response have collective computational properties like those of two-state neurons. *Proc. Natl. Acad. Sci. (USA)*, 81:3088–3092, 1984.

[92] G. Hu, Z. Qu, and K. He. Feedback control of chaos in spatiotemporal systems. *Int. J. Bif. Chaos*, 5:901–936, 1995.

[93] E. R. Hunt. Stabilizing high-period orbits in a chaotic system: The diode resonator. *Phys. Rev. Lett.*, 67:1953–1955, 1991.

[94] M. Inoue and S. Fukushima. A neural network of chaotic oscillators. *Prog. Theor. Phys.*, 87:771–774, 1992.

[95] E. Ippen, J. Lindner, and W. L. Ditto. Chaotic resonance: a simulation. *J. Stat. Phys.*, 70:437–450, 1993.

[96] S. Ishii, K. Fukumizu, and S. Watanbe. A network of chaotic elements for information processing. *Neural Networks*, 9:25–40, 1996.

[97] L. Jin, P. N. Nikiforuk, and M. M. Gupta. Absolute stability conditions for discrete-time recurrent neural networks. *IEEE Trans. Neural Networks*, 5:954–964, 1994.

[98] L. Jin, P. N. Nikiforuk, and M. M. Gupta. Approximation of discrete-time state space trajectories using dynamic recurrent neural networks. *IEEE Trans. Automatic Control*, 40:169–176, 1995.

[99] K. Kaneko. Pattern dynamics in spatiotemporal chaos. *Physica D*, 34:1–41, 1989.

[100] K. Kaneko. Spatiotemporal chaos in one- and two-dimensional coupled map lattices. *Physica D*, 37:60–82, 1989.

[101] K. Kaneko. Clustering, coding, switching, hierarchical ordering and control in a network of chaotic elements. *Physica D*, 41:137–172, 1990.

[102] O. Kinouchi and M. H. R. Tragtenberg. Modeling neurons by simple maps. *Int. J. Bif. Chaos*, 6:2343–2360, 1996.

[103] S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi. Optimization by simulated annealing. *Science*, 220:671–680, 1983.

[104] R. Klages. *Deterministic diffusion in one-dimensional chaotic dynamical systems.* PhD thesis, Technische Universitat Berlin, 1995.

[105] C. Koch. Computation and the single neuron. *Nature*, 385:207–210, 1997.

[106] J. M. Kowalski, G. L. Albert, and G. W. Gross. Asymptotically synchronous chaotic orbits in systems of excitable elements. *Phys. Rev. A*, 42:6260–6263, 1990.

[107] M. K. Kundu and S. K. Pal. Edge detection based on human visual response. *Int. J. Systems Sci.*, 19:2523–2542, 1988.

[108] K. E. Kurten and J. W. Clark. Chaos in neural systems. *Phys. Lett. A*, 114:413–418, 1986.

[109] C. G. Langton. Computation at the edge of chaos: phase transitions and emergent computation. *Physica D*, 42:12–37, 1990.

[110] T. Y. Li and J. A. Yorke. Period three implies chaos. *Am. Math. Monthly*, 82:985 – 992, 1975.

[111] T. Lindeberg. Scale-space for discrete signals. *IEEE Trans. Pattern Analysis and Machine Intelligence*, 12:234–254, 1990.

[112] J. F. Lindner, B. K. Meadows, W. L. Ditto, M. E. Inchiosa, and A. R. Bulsara. Array enhanced stochastic resonance and spatiotemporal synchronization. *Phys. Rev. Lett.*, 75:3–6, 1995.

[113] W. A. Little. The existence of persistent states in the brain. *Math. Biosci.*, 19:101–120, 1974.

[114] E. N. Lorenz. Deterministic nonperiodic flow. *J. Atm. Sci.*, 20:130–141, 1963.

[115] J. Losson and M. C. Mackey. Coupling induced statistical cycling in two diffusively coupled maps. *Physica D*, 72:324–342, 1994.

[116] P. K. Maiti, P. K. Dasgupta, and B. K. Chakrabarti. Improved performance of the Hopfield and Little neural network models with time delayed dynamics. *Int. J. Mod. Phys. B*, 9:3025–3037, 1995.

[117] C. M. Marcus and R. M. Westervelt. Dynamics of iterated-map neural networks. *Phys. Rev. A*, 40:501–504, 1989.

[118] D. Marr. *Vision: A computational investigation into the human representation and processing of visual information.* W. H. Freeman, New York, 1982.

[119] D. Marr and E. Hildreth. Theory of edge-detection. *Proc. Roy. Soc. Lond. B*, 207:187–217, 1980.

[120] M. A. Matias and J. Güemez. Stabilization of chaos by proportional pulses in the system variables. *Phys. Rev. Lett.*, 72:1455–1458, 1994.

[121] G. Matsumoto, K. Aihara, Y. Hanyu, N. Takahashi, S. Yoshizawa, and J. Nagumo. Chaos and phase locking in normal squid axons. *Phys. Lett. A*, 123:162–166, 1987.

[122] R. M. May. Bifurcations and dynamic complexity in ecological systems. *Ann. N. Y. Acad. Sci.*, 316:517–529, 1978.

[123] J. L. McCauley. *Chaos, Dynamics and Fractals.* Cambridge University Press, Cambridge, 1993.

[124] W. S. McCulloch and W. Pitts. A logical calculus of the ideas immanent in nervous activity. *Bull. Math. Biophys.*, 5:115–133, 1943.

[125] B. McNamara and K. Wiesenfeld. Theory of stochastic resonance. *Phys. Rev. A*, 39:4854–4869, 1989.

[126] M. Mezard, G. Parisi, and M. A. Virasoro. *Spin Glass Theory and Beyond.* World Scientific, Singapore, 1987.

[127] J. Nagumo and S. Sato. On a response characteristic of a mathematical neuron model. *Kybernetik*, 10:155–164, 1972.

[128] G. Nicolis, C. Nicolis, and D. McKernan. Stochastic resonance in chaotic dynamics. *J. Stat. Phys.*, 70:125–139, 1993.

[129] J. S. Nicolis. Should a reliable information processor be chaotic ? *Kybernetes*, 11:269–274, 1982.

[130] J. S. Nicolis and I. Tsuda. Chaotic dynamics of information processing: The magic number "seven plus minus two" revisited. *Bull. Math. Biol.*, 47:343–365, 1985.

[131] K. N. Nordström. Biased anisotropic diffusion – A unified regularization and diffusion approach to edge detection. Technical Report CSD-89-514, Dept. of Computer Science, Univ. of California, Berkeley, 1989.

[132] H. E. Nusse and J. A. Yorke. Border-collision bifurcations including "period-two to period-three" for piecewise smooth systems. *Physica D*, 57:39–57, 1992.

[133] H. E. Nusse and J. A. Yorke. Border-collision bifurcations for piecewise smooth one-dimensional maps. *Int. J. Bif. Chaos*, 5:189–207, 1995.

[134] E. Ott. *Chaos in Dynamical Systems.* Cambridge University Press, Cambridge, 1993.

[135] E. Ott, C. Grebogi, and J. A. Yorke. Controlling chaos. *Phys. Rev. Lett.*, 64:1196–1199, 1990.

[136] E. Ott and J. C. Sommerer. Blowout bifurcations: The occurrence of riddled basins and on-off intermittency. *Phys. Lett. A*, 188:39–47, 1994.

[137] D. Ottoson. *Physiology of the Nervous System.* Macmillan, London, 1983.

[138] N. H. Packard, J. P. Crutchfield, J. D. Farmer, and R. S. Shaw. Geometry from a time series. *Phys. Rev. Lett.*, 47:712–715, 1980.

[139] N. R. Pal and S. K. Pal. A review of image segmentation techniques. *Pattern Recognition*, 26:1277–1294, 1993.

[140] L. M. Pecora and T. L. Carroll. Synchronization in chaotic systems. *Phys. Rev. Lett.*, 64:821–824, 1990.

[141] L. M. Pecora and T. L. Carroll. Driving systems with chaotic signals. *Phys. Rev. A*, 44:2374–2383, 1991.

[142] X. Pei and F. Moss. Characterization of low-dimensional dynamics in the crayfish caudal photoreceptor. *Nature*, 379:618–621, 1996.

[143] C. J. Perez, A. Corral, A. Diaz-Guilera, K. Christensen, and A. Arenas. On self-organized criticality and synchronization in lattice models of coupled dynamical systems. *Int. J. Mod. Phys. B*, 10:1111–1151, 1996.

[144] P. Perona and J. Malik. Scale-space and edge detection using anisotropic diffusion. *IEEE Trans. Pattern Analysis and Machine Intelligence*, 12:629–639, 1990.

[145] J. P. Pijn, J. Van Neerven, A. Noest, and F. H. Lopes da Silva. Chaos or noise in EEG signals: Dependence on state and brain site. *Electroenceph. Clin. Neuropsych.*, 79:371–381, 1991.

[146] A. S. Pikovsky and P. Grassberger. Symmetry breaking bifurcation for coupled chaotic attractors. *J. Phys. A*, 24:4587–4597, 1991.

[147] N. Platt, S. M. Hammel, and J. F. Heagy. Effects of additive noise on on-off intermittency. *Phys. Rev. Lett.*, 72:3498–3501, 1994.

[148] S. Rajasekar and M. Lakshmanan. Period-doubling bifurcations, chaos, phase-locking and devil's staircase in a Bonhoeffer - Van der Pol oscillator. *Physica D*, 32:146–152, 1988.

[149] D. H. Rao and M. M. Gupta. Chaotic behavior of a dynamic neural network. In *Proc. Third Int. Conf. Fuzzy Logic, Neural Nets and Soft Computing, (IIZUKA-94)*, pages 533–534, 1994.

[150] E. Reibold, W. Just, J. Becker, and H. Benner. Stochastic resonance in chaotic spin-wave dynamics. *Phys. Rev. Lett.*, 78:3101–3104, 1997.

[151] P. Saint-Marc, J. S. Chen, and G. Medioni. Adaptive smoothing : a general tool for early vision. *IEEE Trans. Pattern Analysis and Machine Intelligence*, 13:514–529, 1991.

[152] H. Sakaguchi and K. Tomita. Bifurcations of the coupled logistic map. *Prog. Theo. Phys.*, 78:305–315, 1987.

[153] P. P. Saratchandran, V. M. Nandakumaran, and G. Ambika. Dynamics of the logistic map under discrete parametric perturbation. *Pramana - J. Phys.*, 47:339–345, 1996.

[154] J. Sarraille and Peter DiFalco. FD3, ver 0.3 (fractal dimension estimation software), 1992. (available at ftp:// ftp.immt.pwr.wroc.pl/ pub/ fractal).

[155] S. J. Schiff, K. Jerger, D. H. Duong, T. Chang, M. L. Spano, and W. L. Ditto. Controlling chaos in the brain. *Nature*, 370:615–620, 1994.

[156] T. B. Schillen and P. König. Binding by temporal structure in multiple feature domains of an oscillatory neuronal network. *Biol. Cybern.*, 70:397–405, 1994.

[157] N. J. Schulmann. Chaos in piecewise linear systems. *Phys. Rev. A*, 28:477–479, 1983.

[158] C. Seko and K. Takatsuka. Rhythmic hopping in a one-dimensional crisis map. *Phys. Rev. E*, 54:956–959, 1996.

[159] D. Sherrington. Spin glasses and neural networks. In J. G. Taylor and C. L. T. Mannion, editors, *New Developments in Neural Computing*, pages 15–30. Adam Hilger, Bristol, 1989.

[160] I. Shimada and T. Nagashima. A numerical approach to ergodic problems of dissipative dynamical systems. *Prog. Theor. Phys.*, 61:1605–1616, 1979.

[161] T. Shinbrot, C. Grebogi, E. Ott, and J. A. Yorke. Using small perturbations to control chaos. *Nature*, 363:411–417, 1993.

[162] T. Shinbrot and J. M. Ottino. Using horseshoes to create coherent structures. *Phys. Rev. Lett.*, 71:843–846, 1993.

[163] S. W. Sides, R. A. Ramos, P. A. Rikvold, and M. A. Novotny. Kinetic Ising system in an oscillating external field: stochastic resonance and residence-time distributions. *J. Appl. Phys.*, 81:5597–5599, 1997.

[164] S. W. Sides, P. A. Rikvold, and M. A. Novotny. Stochastic hysteresis and resonance in a kinetic Ising system. *Phys. Rev E* (to appear), 1998. (http:// xxx.lanl.gov/ abs/ cond-mat/ 9712021).

[165] S. Sinha. Unidirectional adaptive dynamics. *Phys. Rev. E*, 49:4832–4842, 1994.

[166] S. Sinha. Chaos control in an oscillatory neural network model. *J. IETE*, 42:205–213, 1996.

[167] S. Sinha. Controlled transition from chaos to periodic oscillations in a neural network model. *Physica A*, 224:433–446, 1996.

[168] S. Sinha. Geometry of chaos control in a one-dimensional map. In *Proc. Int. Conf. Dynamical Systems, Bangalore*, page 61, 1997.

[169] S. Sinha. Chaos and synchronization in simple excitatory-inhibitory neural network models. In *Proc. Int. Conf. Nonlinear Dynamics and Brain Functioning, Bangalore*, page 54, 1998.

[170] S. Sinha. Chaotic dynamics in iterated map neural networks with piecewise linear activation function. *Fundamenta Informaticae* (to appear), 1998.

[171] S. Sinha. Frustrated synchronization in competing drive-response coupled chaotic systems. LANL e-print, 1998. (http:// xxx.lanl.gov/ abs/ chao-dyn/ 9808017).

[172] S. Sinha and J. Basak. Response of an excitatory-inhibitory neural network to external stimulation: An application to image segmentation. LANL e-print, 1998. (http:// xxx.lanl.gov/ abs/ cond-mat/).

[173] S. Sinha and S. Biswas. Associative memory for gray-level images. In *Proc. IEEE Int. Conf. Image Processing,* Santa Barbara, Calif., pages 871–873, 1997.

[174] S. Sinha and B. K. Chakrabarti. Deterministic SR in a piecewise linear chaotic map. *Phys. Rev. E* (to appear), 1998. (available at http:// xxx.lanl.gov/ abs/ chao-dyn/ 9803033).

[175] S. Sinha and P. K. Das. Dynamics of simple one-dimensional maps under perturbation. *Pramana - J. Phys.*, 48:87–98, 1997.

[176] S. Sinha and S. Kar. Competition among synchronizing chaotic systems: Implications for neural computation. In T. Yamakawa and G. Matsumoto, editors, *Methodologies for the conception, design and application of intelligent systems*, pages 700–703. World Scientific, Singapore, 1996.

[177] C. A. Skarda and W. J. Freeman. How brains make chaos in order to make sense of the world. *Behavioral and Brain Sciences*, 10:161–195, 1987.

[178] S. M. Smirnakis, M. J. Berry, D. K. Wayland, W. Bialek, and M. Meister. Adaptation of retinal processing to image contrast and spatial scale. *Nature*, 386:69–73, 1997.

[179] R. V. Sole and L. M. de la Prida. Controlling chaos in discrete neural networks. *Phys. Lett. A*, 199:65–69, 1995.

[180] H. Sompolinsky, A. Crisanti, and H. J. Sommers. Chaos in random neural networks. *Phys. Rev. Lett.*, 61:259–262, 1988.

[181] H. Sompolinsky, D. Golomb, and D. Kleinfeld. Global processing of visual stimuli in a neural network of coupled oscillators. *Proc. Natl. Acad. Sci. USA*, 87:7200–7204, 1990.

[182] C. Sparrow. *The Lorenz Equations: Bifurcations, Chaos, and Strange Attractors.* Springer-Verlag, New York, 1982.

[183] O. Sporns, G. Tononi, and G. M. Edelman. Modeling perceptual grouping and figure-ground segregation by means of active reentrant connections. *Proc. Natl. Acad. Sci. USA*, 88:129–133, 1991.

[184] V. Srinivasan, P. Bhatia, and S. H. Ong. Edge detection using a neural network. *Pattern Recognition*, 27:1653–1662, 1994.

[185] P. Sterling. The Retina. In G. M. Shepherd, editor, *The Synaptic Organization of the Brain*, pages 170–213. Oxford University Press, Oxford, 1990.

[186] N. Stollenwerk. Self-controlling chaos in neuromodules. In H. Herrmann, E. Pöppel, and D. Wolf, editors, *Supercomputing in Brain Research: From Tomography to Neural Networks*, pages 421–426. World Scientific, Singapore, 1995.

[187] L. Stone. Period-doubling reversals and chaos in simple ecological models. *Nature*, 365:617–620, 1993.

[188] S. H. Strogatz. *Nonlinear Dynamics and Chaos.* Addison-Wesley, Reading, Mass., 1994.

[189] M. M. Sushchik, N. F. Rulkov, and H. D. I. Abarbanel. Robustness and stability of synchronized chaos: An illustrative model. *IEEE Trans. Circuits and Systems-I*, 44:867–873, 1997.

[190] J. Testa and G. A. Held. Study of a one-dimensional map with multiple basins. *Phys. Rev. A*, 28:3085–3089, 1983.

[191] C. M. Thomas, W. G. Gibson, and J. Robinson. Stability and bifurcations in an associative memory model. *Neural Networks*, 9:53–66, 1996.

[192] I. Tsuda. Dynamic link of memory: Chaotic memory map in nonequilibrium neural networks. *Neural Networks*, 5:313–326, 1992.

[193] E. Vaadia, I. Haalman, M. Abeles, H. Bergman, Y. Prut, H. Slovin, and A. Aertsen. Dynamics of neuronal interactions in monkey cortex in relation to behavioral events. *Nature*, 373:515–518, 1995.

[194] C. von der Malsburg and J. Buhmann. Sensory segmentation with coupled neural oscillators. *Biol. Cybern.*, 67:233–242, 1992.

[195] D. L. Wang. Emergent synchrony in locally coupled neural oscillators. *IEEE Trans. Neural Networks*, 6:941–948, 1995.

[196] L. Wang. Oscillatory and chaotic dynamics in neural networks under varying operating conditions. *IEEE Trans. Neural Networks*, 7:1382–1388, 1996.

[197] X. Wang. Period-doublings to chaos in a simple neural network: An analytical proof. *Complex Systems*, 5:425–441, 1991.

[198] X. Wang and E. K. Blum. Discrete time vs continuous time models of neural networks. *J. Comp. Syst. Sci.*, 45:1–19, 1992.

[199] J. Weickert and B. Benhamouda. Why the Perona-Malik filter works. Technical Report DIKU-TR-97/22, Dept. of Computer Science, Univ. of Copenhagen, 1997. (available at http:// www.diku.dk/ users/ joachim/).

[200] F. S. Werblin. Functional organization of a vertebrate retina: sharpening up in space and intensity. *Ann. N. Y. Acad. Sci.*, 190:75–85, 1972.

[201] F. S. Werblin. The control of sensitivity in the retina. *Sci. Am.*, 228 (1):71–79, 1973.

[202] R. T. Whitaker and S. M. Pizer. A multi-scale approach to nonuniform diffusion. *CVGIP: Image Understanding*, 57:99–110, 1993.

[203] I. C. Whitfield. *Neurocommunications: An Introduction.* John Wiley, Chichester, 1984.

[204] H. R. Wilson and J. D. Cowan. Excitatory and inhibitory interactions in localized populations of model neurons. *Biophys. J.*, 12:1–24, 1972.

[205] T. Yamakawa, M. Shimono, and T. Miki. Design criteria for robust associative memory employing non-equilibrium network. In T. Yamakawa and G. Matsumoto, editors, *Methodologies for the conception, design and application of intelligent systems*, pages 688–691. World Scientific, Singapore, 1996.

[206] T. Yoshida, H. Mori, and H. Shigematsu. Analytic study of the tent map: band structures, power spectra and critical behaviors. *J. Stat. Phys.*, 31:279–308, 1983.

[207] Y. H. Yu, K. Kwak, and T. K. Lim. On-off intermittency in an experimental synchronization process. *Phys. Lett. A*, 198:34–38, 1995.

LIST OF PUBLICATIONS OF THE AUTHOR

1. S. Sinha, "Influence of asymmetric initial configurations on the recall properties of the Hopfield net", *J. IE(I)*, vol. 74, pp. 28–31, 1993.

2. S. Sinha, "The evolution of adaptability: the artificial life approach", *Ind. J. Phys.*, vol. 69 B, pp. 625–640, 1995.

3. S. Sinha, "Controlled transition from chaos to periodic oscillations in a neural network model", *Physica A*, vol. 224, pp. 433–446, 1996.

4. S. Sinha, "Chaos control in an oscillatory neural network model", *J. IETE*, vol. 42, pp. 205–213, 1996.

5. S. Sinha and S. Kar, "Competition among synchronizing chaotic systems: Implications for neural computation", in T. Yamakawa and G. Matsumoto (eds.), *Methodologies for the conception, design and application of intelligent systems*, pp. 700–703, (World Scientific, Singapore) 1996.

6. S. Sinha, "Adaptive walks in fitness landscapes", *Ind. J. Theo. Phys.*, vol. 44, pp. 63–73, 1996.

7. S. Sinha, "Geometry of chaos control in a one-dimensional map", in *Proc. Int. Conf. Dynamical Systems, Bangalore*, pg. 61, 1997.

8. S. Sinha and S. Biswas, "Associative memory for gray-level images", in *Proc. IEEE Int. Conf. Image Processing, Santa Barbara, Calif.*, pp. 871–873, 1997.

9. S. Sinha and B. K. Chakrabarti, "Deterministic stochastic resonance in a piecewise linear chaotic map", *Phys. Rev. E* (to appear), 1998.

10. S. Sinha, "Chaotic dynamics in iterated map neural networks with piecewise linear activation function", *Fundamenta Informaticae* (to appear), 1998.

11. S. Sinha, "Chaos and synchronization in simple excitatory-inhibitory neural network models", in *Proc. Int. Conf. Nonlinear Dynamics and Brain Functioning, Bangalore*, pg. 54, 1998.

12. S. Sinha, "Frustrated synchronization in competing drive-response coupled chaotic systems", LANL e-print (http:// xxx.lanl.gov/ abs/ chao-dyn/ 9808017), 1998.

13. S. Sinha and J. Basak, "Response of an excitatory-inhibitory neural network to external stimulation: An application to image segmentation", LANL e-print (http:// xxx.lanl.gov/ abs/ cond-mat/), 1998.