REPORT DOCUMENTATION PAGE

AD-A247 081

Public reporting burden... to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, ... Office of Management and Budget, Paperwork Reduction Project (0704-0188), Washington, DC 20503.

1. AGENCY USE ONLY	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
		Annual - 1 Sep 89 - 31 Aug 90

4. TITLE AND SUBTITLE
INVESTIGATION OF DYNAMIC ALGORITHMS FOR PATTERN
RECOGNITION IDENTIFIED IN CEREBRAL CORTEX

5. FUNDING NUMBERS
AFOSR-88-0268
PE - 61102F
PR - 2305
TA - B3

6. AUTHOR(S)
Dr Walter J. Freeman

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
University of California
Molecular & Cell Biology
Division of Neurobiology
Berkeley, CA 94720

8. PERFORMING ORGANIZATION REPORT NUMBER

AFOSR-TR- 92 0137

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Dr Haddad
AFOSR/NL
Building 410
Bolling AFB, DC 20332-6448

10. SPONSORING / MONITORING AGENCY REPORT NUMBER

DTIC
ELECTE
MAR 0 6 1992
S D

11. SUPPLEMENTARY NOTES

12a. DISTRIBUTION / AVAILABILITY STATEMENT

Approved for public release;
distribution unlimited.

12b. DISTRIBUTION CODE

13. ABSTRACT (Maximum 200 words)
Patterns of 40 to 80 Hz oscillation have been observed by researchers of this
laboratory in the large scale activity not only of olfactory cortex, but also
visual neocortex, and shown to predict the olfactory and visual pattern recognition
responses of a trained animal. Similar observations of 40 Hz oscillation in auditory
and motor cortex, and in the retina and EMG have been reported. It thus appears
that cortical computaiton in general may occur by dynamical interaction of resonant
modes, as we have long thought to be the case in the olfactory system. The
oscillation can serve a macroscopic clocking function and entrain or "bind" the
relevant microscopic activity of disparate cortical regions into a well defined
phase coherent collective state of "gestalt". This can override irrelevant micro-
scopic activity and produce coordinated motor output. We have further evidence that
the oscillatory activity is roughly periodic, but actually appears to be chaotic
(nonperiodic) when examined in detail. If this view is correct, then networks with
oscillatory and possibly chaotic activity form the actual cortical substrate of the
diverse sensory, motor, and cognitive operations now studied in static networks. It
must then be shown how those functions can be accomplished with oscillatory and

14. SUBJECT TERMS

15. NUMBER OF PAGES

16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
(U)	(U)	(U)	(U)

chaotic dynamics. It is our expectation that nature makes good use of this dynamical complexity, and our intent has been to search here for novel design principles that may underly the superior performance of biological systems in pattern recognition. These may then be applied in artificial systems to engineering problems.

Accesion For		
NTIS CRA&I	☑	
DTIC TAB	☐	
Unannounced	☐	
Justification		
By		
Distribution /		
Availability Codes		
Dist	Avail and / or Special	
A-1		

92 3 03 157

92-05630

Annual

~~FINAL~~ TECHNICAL REPORT

Grant No. AFOSR-88-0286

2 December 1991

1 Introduction

Patterns of 40 to 80 Hz oscillation have been observed by researchers of
this laboratory in the large scale activity not only of olfactory cortex, but
also visual neocortex, and shown to predict the olfactory and visual pattern
recognition responses of a trained animal. Similar observations of 40 Hz
oscillation in auditory and motor cortex, and in the retina and EMG have
been reported.

It thus appears that cortical computation in general may occur by dy-
namical interaction of resonant modes, as we have long thought to be the
case in the olfactory system. The oscillation can serve a macroscopic clocking
function and entrain or "bind" the relevant microscopic activity of disparate
cortical regions into a well defined phase coherent collective state or "gestalt".
This can overide irrelevant microscopic activity and produce coordinated mo-
tor output. We have further evidence that the oscillatory activity is roughly
periodic, but actually appears to be chaotic (nonperiodic) when examined in
detail.

If this view is correct, then networks with oscillatory and possibly chaotic
activity form the actual cortical substrate of the diverse sensory, motor, and
cognitive operations now studied in static networks. It must then be shown
how those functions can be accomplished with oscillatory and chaotic dy-
namics. It is our expectation that nature makes good use of this dynamical
complexity, and our intent has been to search here for novel design principles
that may underly the superior performance of biological systems in pattern
recognition. These may then be applied in artificial systems to engineering
problems.

The focus of our work was to characterize mathematically the essential mechanisms and principles of operation of the mamalian olfactory neural network and evaluate its computation and pattern recognition capabilities. In this endeavor we have indeed discovered novel and powerful network architectures and learning algorithms.

Over the three and a half years of the grant, we published 13 papers, and gave presentations at 16 conferences. Network algorithms and architectures for pattern recognition have been constructed from neural models of the olfactory system, using the mathematical tools of dynamicl systems theory. These span a range from highly abstract to physiologically detailed, and employ the kind of dynamical complexity observed in olfactory cortex, ranging from oscillation to chaos.

2   Theoretical Work

A new class of learning algorithms for the storage of static and periodic attractors in recurrent analog neural networks was developed. Over the grant period, the original projection algorithm has been extended and refined in many ways. The seminal mathematical insight of the algorithm was that techniques of bifurcation theory for analysis of nonlinear dynamical systems could be inverted to produce precise techniques for synthesis of dynamical neural networks like that of the olfactory system.

A key feature of a net constructed by this algorithm is that the underlying dynamics is explicitly isomorphic to any of a class of standard, well understood nonlinear dynamical systems - a "normal form". This system is chosen in advance, independent of both the patterns to be stored and the learning algorithm to be used. This control over the dynamics permits the design of important aspects of the network dynamics independent of the particular patterns to be stored. Stability, basin geometry, and rates of convergence to attractors can be programmed in the standard dynamical system.

We were able to derive learning algorithms for content addressable memory storage of static and oscillatory attractors with analytically guaranteed storage capacity of N static and N/2 oscillatory attractors in an N node network. This is in contrast to the ESTIMATES of 4 N/ log N static attractors for an AVERAGE Hopfield network (nothing precise can be said for any individual Hopfield network). This was done with a simple learning rule

2

- a formula requiring a matrix inversion - for first and third order weights in a recurrent network architecture. There are no spurious attractors, and there is a Liapunov function in a special coordinate system which governs the approach of transient states to stored patterns.

Later work extended these results to allow guaranteed storage of multiple periodic spatiotemporal sequences of up to $N/2$ total Fourier components. We showed also that for orthogonal patterns, the projection learning rule reduced to a Hebbian outer product rule that allowed local incremental learning. In this last year we have shown that $N/3$ chaotic attractors may be stored in an N node network, and constructed networks with multiple static, periodic, and chaotic attractors all in the same network.

A new architecture called the projection network was developed that did not require the higher order weights (only 3 X N squared weights instead of N fourth) yet retained all the mathematically demonstrable capabilities of the previous architecture. This net was thus more suited to engineering applications. Unsupervised or supervised incremental learning algorithms for pattern classification, such as competitive learning or bootstrap Widrow-Hoff can easily be implemented in this architecture.

Network performance was demonstrated by application to the problem of real time handwritten digit recognition. An effective system with on line learning was written for the Macintosh. It utilizes static, oscillatory, and/or chaotic attractors of three kinds - Lorenz attractors, Roessler attractors, or attractors resulting from chaotically interacting oscillatory modes, which we call Ruelle-Takens attractors. This appears to be the first system which can use exclusively chaotic dynamics to accomplish pattern recognition.

On the more scientific front of biological modeling, the higher order network was refined into a biologically minimal network model of olfactory cortex with explicit excitatory and inhibitory neurons. This model assumed the least of known biological connections, and was shown to have the associative memory capacity of the systems above. We showed also that only N squared of the higher order weights between excitatory neurons were reqired for approximate pattern storage in this system.

3   An Industrial Application

In a parallel development by Freeman and Yao, a physiologically detailed
olfactory system model was developed in software and hardware versions. Its
features were derived from biological studies and bring the model closely into
conformance with biological constraints. This model, which we call a KIII
set, was tested in respect to artificially generated data set and then with a
data set derived from an industrial source. The KIII model was "instructed"
with examples from groups of objects to be classified, with use of a form of
the Hebb rule to modify the connection weights. The interconnections were
designed in accordance with the time multiplexing operation that enables
connections to be made in large arrays of N coupled oscillators with 2-N
rather than N-square connections.

The performance of the KIII model in classification of the members of
this data set was compared with the performance of a Bayesian statistical
approach, the Hopfield model, and a back-propagation model. Of the three
classes of objects, those having a relatively high degree of symmetry were
classified equally well by all of the approaches. The most difficult set of
objects, which had a high degree of asymmetry and therefore a large amount
of extraneous variance, were successfully classified only by the KIII model
operating in a chaotic domain and not in a limit cycle domain. The results
indicate that exploration of chaotic dynamics may be crucially important for
the preprocessing of complex high-dimensional data sets prior to attempts
at classification.

B,ll Baird

Invited Talks and Conferences*

1988

First Annual INNS Meeting, Boston, Mass., September

Neural Information Processing Systems - Natural and Synthetic, Denver, Colo., November

1989

U.C. San Diego, Cognitive Science Dept., January

Chairman of session, Workshop on Neural Networks as Dynamical Systems, U.C., San Diego, Ca., February

Emergent Computation - Self-Organizing, Collective, and Cooperative Phenomena in Natural and Artificial Computing Networks, Center for Nonlinear Science, Los Alamos, N.M., May

International Joint Conference on Neural Networks, Wash. D.C., June

Neural Information Processing Systems - Natural and Synthetic, Denver, Colo., November

1990

Stanford University, Chemistry Dept., Palo Alto, Ca., March

Lawrence Livermore National Laboratory, Institute for Scientific Computing, Livermore, Ca., April

Chairman of session, International Joint Conference on Neural Networks, San Diego, Ca., June

Analysis and Modeling of Neural Systems 1, U.C. Berkeley, Ca., July

U.C. Santa Cruz, Mathematics Dept., September

Neural Information Processing Systems - Natural and Synthetic, Denver, Colo., November

1991

Plenary talk, Applications of Artificial Intelligence and Neural Networks, SPIE, Orlando, Fla., April

Stanford University, Artificial Networks Group, Palo Alto, Ca., April

Invited Speaker, Workshop on Complex Dynamics in Neural Networks, Vietri, Italy, June

*talk or poster given at all conferences listed

Bill Baird - Publications for AFOSR

References

[1] B. Baird. A bifurcation theory approach to the programming of periodic attractors in network models of olfactory system. In D. S. Touretsky, editor, *Advances in Neural Information Processing Systems 1*, pages 459–467. Morgan Kaufman, 1988.

[2] B. Baird. Biologically applied neural networks may foster the co-evolution of neurobiology and cognitive psychology. *Brain and Behavioral Sciences*, 37:436–438, 1988.

[3] B Baird. A bifurcation theory approach to vector field programming for periodic attractors. In *Proc. Int. Joint Conf. on Neural Networks, Wash. D.C.*, pages 1:381–388, June 1989.

[4] B. Baird. Associative memory in a simple model of oscillating cortex. In D. S. Touretsky, editor, *Advances in Neural Information Processing Systems 2*, pages 68–75. Morgan Kaufman, 1990.

[5] B. Baird. Bifurcation and learning in network models of oscillating cortex. In S. Forest, editor, *Emergent Computation*, pages 365–384. North Holland, 1990. also in Physica D, 42.

[6] B. Baird. A learning rule for cam storage of continuous periodic sequences. In *Proc. Int. Joint Conf. on Neural Networks, San Diego*, pages 3: 493–498, June 1990.

[7] B. Baird. Cam storage of analog patterns and continuous sequences with $3n^2$ weights. In D. S. Touretsky, editor, *Advances in Neural Information Processing Systems 3*, pages 192–198. Morgan Kaufman, 1991.

[8] B. Baird. Learning with synaptic nonlinearities in a coupled oscillator model of olfactory cortex. In F. Eeckman, editor, *Analysis and Modeling of Neural Systems*, 1991. in press.

[9] B. Baird, W. Freeman, F. Eeckman, and Y. Yao. Applications of chaotic neurodynamics in pattern recognition. In *SPIE Proceedings Vol. 1469*, pages 12–23, 1991.

Eisenberg J, Freeman WJ, Burke B (1989) Hardware architecture of a neural network model simulating pattern recognition by the olfactory bulb. Neural Networks 2: 315-325.

Freeman WJ, Yao Y. Chaos in the biodynamics of pattern recognition by neural networks. Proc IJCNN I: 243-246, 1990.

Freeman WJ (1991) Colligation of coupled cortical oscillators.by the collapse of the distributions of amplitude-dependent characteristic frequencies Chapter 5 in: Gear, C.W. (ed.) First NEC Research Symposium. Philadelphia, SIAM, pages 69-103.

Freeman WJ (1991) Nonlinear dynamics in olfactory information processing. Chapter 9 in: Davis JL, Eichenbaum HB (eds.) Olfaction: A Model System for Computational Neuroscience. Cambridge MA, MIT Press, 225-250.

Freeman WJ (1991) What are the state variables for modeling brain dynamics with neural networks? Chapter 22 in: Schuster HG (ed) Nonlinear Dynamics and Neuronal Networks. Berlin, Springer-Verlag. pp. 243-256.

Yao, Y, Freeman WJ (1989) Pattern recognition in olfactory systems: modeling and simulation. Proceedings IJCNN I: 699-704.

Yao Y, Freeman WJ (1990) Model of biological pattern recognition with spatially chaotic dynamics. Neural Networks 3: 153-170.

Yao, Y., Freeman WJ, Burke, B., Yang, Q. (1991) Pattern recognition by a distributed neural network: An industrial application. Neural Networks 4: 103-121.