Communicated by Fernando Pineda

Learning State Space Trajectories in Recurrent Neural Networks

Barak A. Pearlmutter
School of Computer Science, Carnegie Mellon University, Pittsburgh, PA 15213, USA

Many neural network learning procedures compute gradients of the errors on the output layer of units after they have settled to their final values. We describe a procedure for finding $\partial E/\partial w_{ij}$ where E is an error functional of the temporal trajectory of the states of a continuous recurrent network and w_{ij} are the weights of that network. Computing these quantities allows one to perform gradient descent in the weights to minimize E. Simulations in which networks are taught to move through limit cycles are shown. This type of recurrent network seems particularly suited for temporally continuous domains, such as signal processing, control, and speech.

1 Introduction

Pineda (1987) has shown how to train the fixpoints of a recurrent temporally continuous generalization of backpropagation networks (Rumelhart et al. 1986). Such networks are governed by the coupled differential equations

$$T_i \frac{dy_i}{dt} = -y_i + \sigma(x_i) + I_i \tag{1.1}$$

where

$$x_i = \sum_j w_{ji} y_j \tag{1.2}$$

is the total input to unit i, y_i is the state of unit i, T_i is the time constant of unit i, σ is an arbitrary differentiable function[1], w_{ij} are the weights, and the initial conditions $y_i(t_0)$ and driving functions $I_i(t)$ are the inputs to the system.

Consider minimizing $E(\mathbf{y})$, some functional of the trajectory taken by $\mathbf{y}$ between t_0 and t_1. For instance, $E = \int_{t_0}^{t_1} (y_0(t) - f(t))^2 dt$ measures the deviation of y_0 from the function f, and minimizing this E would teach the network to have y_0 imitate f. Below, we develop a technique for computing $\partial E(\mathbf{y})/\partial w_{ij}$ and $\partial E(\mathbf{y})/\partial T_i$, thus allowing us to do gradient descent in the weights and time constants so as to minimize E.

[1]Typically $\sigma(\xi) = (1 + e^{-\xi})^{-1}$, in which case $\sigma'(\xi) = \sigma(\xi)(1 - \sigma(\xi))$.

2 A Forward/Backward Technique

Let us define

$$e_i(t) = \frac{\delta E}{\delta y_i(t)}. \tag{2.1}$$

In the usual case E is of the form $\int_{t_0}^{t_1} f(\mathbf{y}(t), t)\, dt$ so $e_i(t) = \partial f(\mathbf{y}(t), t)/\partial y_i(t)$. Intuitively, $e_i(t)$ measures how much a small change to y_i at time t affects E if everything else is left unchanged.

If we define z_i by the differential equation

$$\frac{dz_i}{dt} = \frac{1}{T_i} z_i - e_i - \sum_j \frac{1}{T_j} w_{ij} \sigma'(x_j) z_j \tag{2.2}$$

with boundary conditions $z_i(t_1) = 0$ then

$$\frac{\partial E}{\partial w_{ij}} = \frac{1}{T_j} \int_{t_0}^{t_1} y_i \sigma'(x_j) z_j dt \tag{2.3}$$

and

$$\frac{\partial E}{\partial T_i} = -\frac{1}{T_i} \int_{t_0}^{t_1} z_i \frac{dy_i}{dt} dt. \tag{2.4}$$

These results are derived using a finite difference approximation in (Pearlmutter 1988), and can also be derived using the calculus of variations and Lagrange multipliers (William Skaggs, personal communication) or from the continuous form of dynamic programming (Bryson 1962).

3 Simulation Results

Using first order finite difference approximations, we integrated the system $\mathbf{y}$ forward from t_0 to t_1, set the boundary conditions $z_i(t_1) = 0$, and integrated the system $\mathbf{z}$ backwards from t_1 to t_0 while numerically integrating $z_j\, \sigma'(x_j)\, y_i$ and $z_i\, dy_i/dt$, thus computing $\partial E/\partial w_{ij}$ and $\partial E/\partial T_i$.

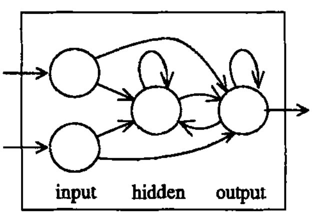

Figure 1: The XOR network.

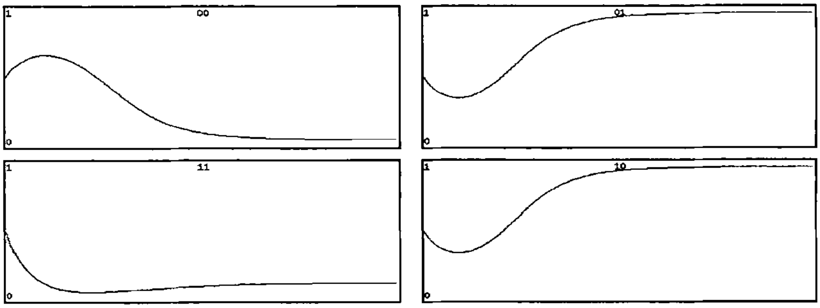

Figure 2: The states of the output unit in the four cases plotted from $t = 0$ to $t = 5$ after 200 epochs of learning. The error was computed only between $t = 2$ and $t = 3$.

Since computing dz_i/dt requires knowing $\sigma'(x_i)$, we stored it and replayed it backwards as well. We also stored and replayed y_i as it is used in expressions being numerically integrated.

We used the error functional

$$E = \frac{1}{2}\sum_i \int_{t_0}^{t_1} s_i(y_i - d_i)^2 dt \tag{3.1}$$

where $d_i(t)$ is the desired state of unit i at time t and $s_i(t)$ is the importance of unit i achieving that state at that time. Throughout, we used $\sigma(\xi) = (1 + e^{-\xi})^{-1}$. Time constants were initialized to 1, weights were initialized to uniform random values between 1 and -1, and the initial values $y_i(t_0)$ were set to $I_i(t_0) + \sigma(0)$. For these simulations we used $\Delta t = 0.1$.

All of these networks have an extra unit which has no incoming connections, an external input of 0.5, and outgoing connections to all other units. This unit provides a bias, which is equivalent to the negative of a threshold. This detail is suppressed below.

3.1 Exclusive Or. The network of figure 1 was trained to solve the XOR problem. Aside from the addition of time constants, the network topology was that used by Pineda in (Pineda 1987). We defined $E = \sum_k \frac{1}{2}\int_2^3 (y_o^{(k)} - d^{(k)})^2 dt$ where k ranges over the four cases, d is the correct output, and y_o is the state of the output unit. The inputs to the net $I_1^{(k)}$ and $I_2^{(k)}$ range over the four possible boolean combinations in the four different cases. With suitable choice of step size and momentum, training

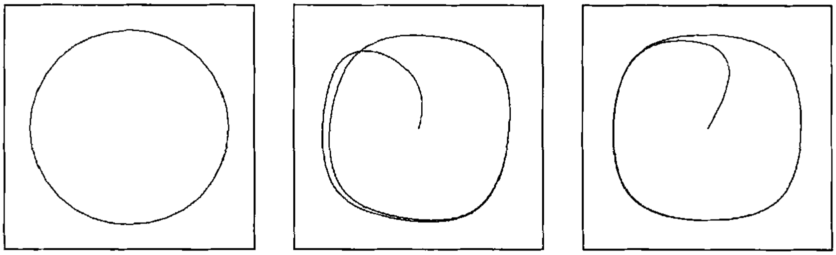

Figure 3: Desired states d_1 and d_2 plotted against each other (left); actual states y_1 and y_2 plotted against each other at epoch 1,500 (center) and 12,000 (right).

time was comparable to standard backpropagation, averaging about one hundred epochs.

It is interesting that even for this binary task, the network made use of dynamical behavior. After extensive training the network behaved as expected, saturating the output unit to the correct value. Earlier in training, however, we occasionally (about one out of every ten training sessions) observed the output unit at nearly the correct value between $t = 2$ and $t = 3$, but then saw it move in the wrong direction at $t = 3$ and end up stabilizing at a wildly incorrect value. Another dynamic effect, which was present in almost every run, is shown in figure 2. Here, the output unit heads in the wrong direction initially and then corrects itself before the error window. A very minor case of diving towards the correct value and then moving away is seen in the lower left-hand corner of figure 2.

3.2 A Circular Trajectory. We trained a network with no input units, four hidden units, and two output units, all fully connected, to follow the circular trajectory of figure 3. It was required to be at the leftmost point on the circle at $t = 5$ and to go around the circle twice, with each circuit taking 16 units of time. While unconstrained by the environment, the network moves from its initial position at $(0.5, 0.5)$ to the correct location at the leftmost point on the circular trajectory. Although the network was run for ten circuits of its cycle, these overlap so closely that the separate circuits are not visible.

Upon examining the network's internals, we found that it devoted three of its hidden units to maintaining and shaping a limit cycle, while the fourth hidden unit decayed away quickly. Before it decayed, it pulled the other units to the appropriate starting point of the limit cycle, and after it decayed it ceased to affect the rest of the network. The network used different units for the limit behavior and the initial behavior, an appropriate modularization.

3.3 A Figure Eight. We were unable to train a network with four hidden units to follow the figure eight shape shown in figure 4, so we used a network with ten hidden units. Since the trajectory of the output units crosses itself, and the units are governed by first order differential equations, hidden units are necessary for this task regardless of the σ function. Training was more difficult than for the circular trajectory, and shaping the network's behavior by gradually extending the length of time of the simulation proved useful.

Before $t = 5$, while unconstrained by the environment, the network moves in a short loop from the initial position at $(0.5, 0.5)$ to where it should sit on the limit cycle at $t = 5$, namely $(0.5, 0.5)$. Although the network was run for ten circuits of its cycle to produce this graph, these overlap so closely that the separate circuits are not visible.

4 Embellishments

Adding time delays to the links simply adds analogous time delays to the differential equation for z. This approach can be used to learn modifiable time delays.

We can avoid the backwards pass by using a shooting method to update guesses for the correct values of $z_i(t_0)$ such that $z_i(t_1) = 0$ and integrating everything in the forward direction. Regretably, the computation required to compute the derivatives required by the shooting method seems excessive, and numeric stability is poor.

We can derive a "teacher forced" variant of our learning algorithm, presumably obtaining speedups similar to those reported by Williams and Zipser (1989).

It would be useful to have some characterization of the class of trajectories that a network can learn as a function of the number of hidden units. These networks have at least the representational power of Fourier decompositions, as one can use a pair of nodes to build an oscillator of arbitrary frequency by making use of the local linearity of the σ function (Furst 1988). We have also found simple bounds on d^2y/dt^2 based on the number of units, the largest weight, and the largest reciprocal time constant.

Experiments with perturbing the cyclic networks of section 3 shows that they have developed true limit cycles which attract neighboring states and pull them into the cycle. The oscillatory behavior of the two output units was not independent, but was coupled by the hidden units, which keep them phase locked even in the face of massive disruptions.

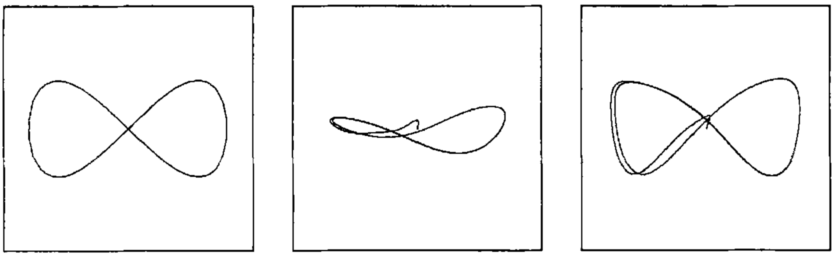

Figure 4: Desired states d_1 and d_2 plotted against each other (left); actual states y_1 and y_2 plotted against each other at epoch 3,182 (center) and 20,000 (right).

Further details on these and other related topics can be found in (Pearlmutter 1988).

5 Related Network Models

We use the same class of networks used by Pineda (1987), but he is concerned only with the limit behavior of these networks, and completely suppresses all other temporal behavior. His learning technique is applicable only when the network has a simple fixpoint; limit cycles or other non-point attractors violate a mathematical assumption upon which his technique is based.

We can derive Pineda's equations from ours. Let I_i be held constant, assume that the network settles to a fixpoint, let the initial conditions be this fixpoint, that is, $y_i(t_0) = y_i(\infty)$, and let E measure Pineda's error integrated over a short interval after t_0, with an appropriate normalization constant. As t_1 tends to infinity, (2.2) and (2.3) reduce to Pineda's equations, so in a sense our equations are a generalization of Pineda's; but these assumptions strain the analogy.

Jordan (1986) uses a conventional backpropagation network with the outputs clocked back to the inputs to generate temporal sequences. The treatment of time is the major difference between Jordan's networks and those in this work. The heart of Jordan's network is atemporal, taking inputs to outputs without reference to time, while an external mechanism is used to clock the network through a sequence of states in much the same way that hardware designers use a clock to drive a piece of combinatorial logic through a sequence of states. In our work, the network is not externally clocked; instead, it evolves continuously through time according to a set of coupled differential equations.

Most recently, Williams and Zipser (1989) have discovered an online learning procedure for networks of this sort. The tradeoffs between this procedure and that of Williams and Zipser is explored in some detail in (Pearlmutter 1988).

6 Acknowledgments

We thank Richard Szeliski for helpful comments and David Touretzky for unflagging support.

This research was sponsored in part by National Science Foundation grant EET-8716324, and by the Office of Naval Research under contract number N00014-86-K-0678. Barak Pearlmutter is a Fannie and John Hertz Foundation fellow.

References

Bryson, A.E., Jr. 1962. A steepest ascent method for solving optimum programming problems. *Journal of Applied Mechanics*, **29(2)**, 247.

Furst, M. 1988. Personal communication.

Jordan, M.I. 1986. Attractor dynamics and parallelism in a connectionist sequential machine. *In:* Proceedings of the 1986 Cognitive Science Conference, 531–546. Lawrence Erlbaum.

Pearlmutter, B. 1988. *Learning state space trajectories in recurrent neural networks.* Technical Report CMU-CS-88-191, School of Computer Science, Carnegie Mellon University, Pittsburgh, PA.

Pineda, F. 1987. Generalization of backpropagation to recurrent neural networks. *Physical Review Letters*, **19(59)**, 2229–2232.

Rumelhart, D.E., G.E. Hinton, and R.J. Williams. 1986. Learning internal representations by error propagation. *In:* Parallel distributed processing: Explorations in the microstructure of cognition. Cambridge, MA: Bradford Books.

Werbos, P.J. 1988. Generalization of backpropagation with application to a recurrent gas market model. *Neural Networks*, **1**, 339-356.

Williams, R.J. and D. Zipser. 1989. A learning algorithm for continually running fully recurrent neural networks. *Neural Computation*, **1**, 270–280.

Received 17 October 1988; accepted 14 March 1989.

This article has been cited by:

1. Samuel J. Cheyette, David C. Plaut. 2017. Modeling the N400 ERP component as transient semantic over-activation within a neural network model of word comprehension. *Cognition* **162**, 153-166. [CrossRef]
2. Alastair C. Smith, Padraic Monaghan, Falk Huettig. 2017. The multimodal nature of spoken word processing in the visual world: Testing the predictions of alternative models of multimodal integration. *Journal of Memory and Language* **93**, 276-303. [CrossRef]
3. Padraic Monaghan. 2017. Canalization of Language Structure From Environmental Constraints: A Computational Model of Word Learning From Multiple Cues. *Topics in Cognitive Science* **9**:1, 21-34. [CrossRef]
4. Rory Finnegan, Mark Shaw, Suzanna Becker. Restricted Boltzmann Machine Models of Hippocampal Coding and Neurogenesis 443-461. [CrossRef]
5. André David Kovac, Maximilian Koall, Gordon Pipa, Hazem Toutounji. 2016. Persistent Memory in Single Node Delay-Coupled Reservoir Computing. *PLOS ONE* **11**:10, e0165170. [CrossRef]
6. Wookyong Kwon, Jaemin Baek, Soohee Han, Sangchul Won. Deep learning based modeling for the lateral movement of a strip in hot finishing mill 1189-1191. [CrossRef]
7. Blair C. Armstrong, David C. Plaut. 2016. Disparate semantic ambiguity effects from semantic processing dynamics rather than qualitative task differences. *Language, Cognition and Neuroscience* **31**:7, 940-966. [CrossRef]
8. Lian Duan, Lihong Huang, Zhenyuan Guo. 2016. Global robust dissipativity of interval recurrent neural networks with time-varying delay and discontinuous activations. *Chaos: An Interdisciplinary Journal of Nonlinear Science* **26**:7, 073101. [CrossRef]
9. Kanaka Rajan, Christopher D. Harvey, David W. Tank. 2016. Recurrent Network Models of Sequence Generation and Memory. *Neuron* **90**:1, 128-142. [CrossRef]
10. Soheil Ganjefar, Sara Rezaei, Mehdi Pourseifi. 2015. Self-adaptive vibration control of simply supported beam under a moving mass using self-recurrent wavelet neural networks via adaptive learning rates. *Meccanica* **50**:12, 2879-2898. [CrossRef]
11. K. Kronander, M. Khansari, A. Billard. 2015. Incremental motion learning with locally modulated dynamical systems. *Robotics and Autonomous Systems* **70**, 52-62. [CrossRef]
12. Jürgen Schmidhuber. 2015. Deep learning in neural networks: An overview. *Neural Networks* **61**, 85-117. [CrossRef]
13. P. Szymczyk, M. Szymczyk. 2015. Classification of geological structure using ground penetrating radar and Laplace transform artificial neural networks. *Neurocomputing* **148**, 354-362. [CrossRef]

14. Nima Mohajerin, Steven L. Waslander. Modular deep Recurrent Neural Network: Application to quadrotors 1374-1379. [CrossRef]

15. Monica Bianchini, Franco Scarselli. 2014. On the Complexity of Neural Network Classifiers: A Comparison Between Shallow and Deep Architectures. *IEEE Transactions on Neural Networks and Learning Systems* **25**:8, 1553-1565. [CrossRef]

16. Andrea Mannarino, Paolo Mantegazza. 2014. Nonlinear aeroelastic reduced order modeling by recurrent neural networks. *Journal of Fluids and Structures* **48**, 103-121. [CrossRef]

17. Luca Consolini, Gabriele Lini. 2014. A Gauss–Newton Method for the Synthesis of Periodic Outputs With Central Pattern Generators. *IEEE Transactions on Neural Networks and Learning Systems* **25**:7, 1394-1400. [CrossRef]

18. S. Mohammad Khansari-Zadeh, Aude Billard. 2014. Learning control Lyapunov function to ensure stability of dynamical system-based robot reaching motions. *Robotics and Autonomous Systems* **62**:6, 752-765. [CrossRef]

19. Michiel Hermans, Benjamin Schrauwen, Peter Bienstman, Joni Dambre. 2014. Automated Design of Complex Dynamic Systems. *PLoS ONE* **9**:1, e86696. [CrossRef]

20. Yongli Song, Yanyan Han, Yahong Peng. 2013. Stability and Hopf bifurcation in an unidirectional ring of n neurons with distributed delays. *Neurocomputing* **121**, 442-452. [CrossRef]

21. Mostafa Ajallooeian, Jesse van den Kieboom, Albert Mukovskiy, Martin A. Giese, Auke J. Ijspeert. 2013. A general family of morphed nonlinear phase oscillators with arbitrary limit cycle shape. *Physica D: Nonlinear Phenomena* **263**, 41-56. [CrossRef]

22. Joanna Tyrcha, John Hertz. 2013. Network inference with hidden units. *Mathematical Biosciences and Engineering* **11**:1, 149-165. [CrossRef]

23. Carl-Johan Thore. 2013. Optimal design of neuro-mechanical oscillators. *Computers & Structures* **119**, 189-202. [CrossRef]

24. Ramazan Coban. 2013. A context layered locally recurrent neural network for dynamic system identification. *Engineering Applications of Artificial Intelligence* **26**:1, 241-250. [CrossRef]

25. Sebastian Bitzer, Stefan J. Kiebel. 2012. Recognizing recurrent neural networks (rRNN): Bayesian inference for recurrent neural networks. *Biological Cybernetics* **106**:4-5, 201-217. [CrossRef]

26. L. Consolini, G. Lini. Limit cycle perturbations for parametric modulation of central pattern generators 6430-6435. [CrossRef]

27. Andre Frank Krause, Volker Durr, Thomas Schack, Holk Cruse. Input compensation learning: Modelling dynamical systems 464-468. [CrossRef]

28. David Sussillo, L.F. Abbott. 2009. Generating Coherent Patterns of Activity from Chaotic Neural Networks. *Neuron* **63**:4, 544-557. [CrossRef]

29. Rodolfo Garcia-Rodriguez, Pablo Zegers, Vicente Parra-Vega. Bounded-time system identification under neuro-sliding training 932-937. [CrossRef]

30. Peter beim Graben, Roland Potthast. 2009. Inverse problems in dynamic cognitive modeling. *Chaos: An Interdisciplinary Journal of Nonlinear Science* **19**:1, 015103. [CrossRef]

31. Roland Potthast, Peter beim Graben. 2009. Inverse Problems in Neural Field Theory. *SIAM Journal on Applied Dynamical Systems* **8**:4, 1405-1433. [CrossRef]

32. Marcus Hutter. 2009. Feature Reinforcement Learning: Part I. Unstructured MDPs. *Journal of Artificial General Intelligence* **1**:1. . [CrossRef]

33. Ruey-Shiang Guh, Yeou-Ren Shiue. 2008. EFFECTIVE PATTERN RECOGNITION OF CONTROL CHARTS USING A DYNAMICALLY TRAINED LEARNING VECTOR QUANTIZATION NETWORK. *Journal of the Chinese Institute of Industrial Engineers* **25**:1, 73-89. [CrossRef]

34. Wei-Po Lee, Kung-Cheng Yang. 2008. A clustering-based approach for inferring recurrent neural networks as gene regulatory networks. *Neurocomputing* **71**:4-6, 600-610. [CrossRef]

35. E. J. Teoh, C. Xiang. A global-local hybrid Evolutionary Strategy (ES) for Recurrent Neural Networks (RNNs) in system identification 1628-1635. [CrossRef]

36. Yasar Becerikli, Yusuf Oysal. 2007. Modeling and prediction with a class of time delay dynamic neural networks. *Applied Soft Computing* **7**:4, 1164-1169. [CrossRef]

37. Suwat Pattamavorakun, Suwarin Pattamavorakun. New Developments on Recurrent Neural Networks Training 169-176. [CrossRef]

38. José Luis Crespo, Marta Zorrilla, Pilar Bernardos, Eduardo Mora. 2007. A new image prediction model based on spatio-temporal techniques. *The Visual Computer* **23**:6, 419-431. [CrossRef]

39. David Braze, Whitney Tabor, Donald P. Shankweiler, W. Einar Mencl. 2007. Speaking Up for Vocabulary. *Journal of Learning Disabilities* **40**:3, 226-243. [CrossRef]

40. L. Leistritz, M. Galicki, E. Kochs, E.B. Zwick, C. Fitzek, J.R. Reichenbach, H. Witte. 2006. Application of Generalized Dynamic Neural Networks to Biomedical Data. *IEEE Transactions on Biomedical Engineering* **53**:11, 2289-2299. [CrossRef]

41. Yusuf Oysal, Yasar Becerikli, A. Ferit Konar. 2005. Phase Portrait Modeling of a Nonlinear System with a Dynamic Fuzzy Network. *Journal of Intelligent Manufacturing* **16**:6, 703-714. [CrossRef]

42. Sahin Yildirim. 2005. Design of Adaptive Robot Control System Using Recurrent Neural Network. *Journal of Intelligent and Robotic Systems* **44**:3, 247-261. [CrossRef]

43. D. L. Yu, T. K. Chang. 2005. Adaptation of diagonal recurrent neural network model. *Neural Computing and Applications* **14**:3, 189-197. [CrossRef]

44. Genci Capi, Kenji Doya. 2005. Evolution of recurrent neural controllers using an extended parallel genetic algorithm. *Robotics and Autonomous Systems* **52**:2-3, 148-159. [CrossRef]

45. Ruey-Shiang Guh *, Yeou-Ren Shiue. 2005. On-line identification of control chart patterns using self-organizing approaches. *International Journal of Production Research* **43**:6, 1225-1254. [CrossRef]

46. Genci Capi, Kenji Doya. 2005. Evolution of Neural Architecture Fitting Environmental Dynamics. *Adaptive Behavior* **13**:1, 53-66. [CrossRef]

47. Xiao Hu, A. Maglia, D.C. Wunsch. A General Recurrent Neural Network Approach to Model Genetic Regulatory Networks 4735-4738. [CrossRef]

48. Yasar Becerikli. 2004. On three intelligent systems: dynamic neural, fuzzy, and wavelet networks for training trajectory. *Neural Computing and Applications* **13**:4, 339-351. [CrossRef]

49. Nejib Smaoui, Suad Al-Enezi. 2004. Modelling the dynamics of nonlinear partial differential equations using neural networks. *Journal of Computational and Applied Mathematics* **170**:1, 27-58. [CrossRef]

50. C.-F. Juang. 2004. A Hybrid of Genetic Algorithm and Particle Swarm Optimization for Recurrent Network Design. *IEEE Transactions on Systems, Man and Cybernetics, Part B (Cybernetics)* **34**:2, 997-1006. [CrossRef]

51. Y. Becerikli, Y. Oysal, A.F. Konar. 2004. Trajectory Priming With Dynamic Fuzzy Networks in Nonlinear Optimal Control. *IEEE Transactions on Neural Networks* **15**:2, 383-394. [CrossRef]

52. Matthew Botvinick, David C. Plaut. 2004. Doing Without Schema Hierarchies: A Recurrent Connectionist Approach to Normal and Impaired Routine Sequential Action. *Psychological Review* **111**:2, 395-429. [CrossRef]

53. Michael W. Harm, Mark S. Seidenberg. 2004. Computing the Meanings of Words in Reading: Cooperative Division of Labor Between Visual and Phonological Processes. *Psychological Review* **111**:3, 662-720. [CrossRef]

54. Isao Tokuda, Ryuji Tokunaga, Kazuyuki Aihara. 2003. Back-propagation learning of infinite-dimensional dynamical systems. *Neural Networks* **16**:8, 1179-1193. [CrossRef]

55. G Cheron, F Leurs, A Bengoetxea, J.P Draye, M Destrée, B Dan. 2003. A dynamic recurrent neural network for multiple muscles electromyographic mapping to elevation angles of the lower limb in human locomotion. *Journal of Neuroscience Methods* **129**:2, 95-104. [CrossRef]

56. Stephan K. Chalup, Alan D. Blair. 2003. Incremental training of first order recurrent neural networks to predict a context-sensitive language. *Neural Networks* **16**:7, 955-972. [CrossRef]

57. Ettore Merlo, Ian McAdam, Renato De Mori. 2003. Feed-forward and recurrent neural networks for source code informal information analysis. *Journal of Software Maintenance and Evolution: Research and Practice* **15**:4, 205-244. [CrossRef]

58. P. Zegers, M.K. Sundareshan. 2003. Trajectory generation and modulation using dynamic neural networks. *IEEE Transactions on Neural Networks* **14**:3, 520-533. [CrossRef]

59. Yaşar Becerikli, Ahmet Ferit Konar, Tarıq Samad. 2003. Intelligent optimal control with dynamic neural networks. *Neural Networks* **16**:2, 251-259. [CrossRef]

60. E. Gelenbe, K.F. Hussain. 2002. Learning in the multiple class random neural network. *IEEE Transactions on Neural Networks* **13**:6, 1257-1267. [CrossRef]

61. David C. Plaut. 2002. Graded modality-specific specialisation in semantics: A computational account of optic aphasia. *Cognitive Neuropsychology* **19**:7, 603-639. [CrossRef]

62. Richard H. R. Hahnloser, Alexay A. Kozhevnikov, Michale S. Fee. 2002. An ultra-sparse code underliesthe generation of neural sequences in a songbird. *Nature* **419**:6902, 65-70. [CrossRef]

63. ROELOF K. BROUWER. 2002. A DISCRETE FULLY RECURRENT NETWORK OF SIGMOID UNITS FOR ASSOCIATIVE MEMORY AND PATTERN CLASSIFICATION. *International Journal of Pattern Recognition and Artificial Intelligence* **16**:05, 527-550. [CrossRef]

64. Douglas L. T. Rohde. 2002. Methods for Binary Multidimensional Scaling. *Neural Computation* **14**:5, 1195-1232. [Abstract] [PDF] [PDF Plus]

65. V. Müller, D. Nelles. 2002. Application of neural networks to static equivalent networks. *European Transactions on Electrical Power* **12**:3, 217-223. [CrossRef]

66. L. Leistritz, M. Galicki, H. Witte, E. Kochs. 2002. Training trajectories by continuous recurrent multilayer networks. *IEEE Transactions on Neural Networks* **13**:2, 283-291. [CrossRef]

67. L. Leistritz, M. Galicki, H. Witte, E. Kochs. 2001. Initial state training procedure improves dynamic recurrent networks with time-dependent weights. *IEEE Transactions on Neural Networks* **12**:6, 1513-1518. [CrossRef]

68. A.G. Parlos, Sanjay Parthasarathy, A.F. Atiya. 2001. Neuro-predictive process control using online controller adaptation. *IEEE Transactions on Control Systems Technology* **9**:5, 741-755. [CrossRef]

69. kei Senda, Tsuyoshi Tanaka. Feedback attitude control of space robot using neural motion generator with oscillator and modulator . [CrossRef]

70. Edmondo Trentin, Marco Gori. 2001. A survey of hybrid ANN/HMM models for automatic speech recognition. *Neurocomputing* **37**:1-4, 91-126. [CrossRef]

71. Kazuhisa Watanabe, Takahiro Haba, Noboru Kudo, Takahumi Oohori. 2001. Fluctuation-driven learning rule for continuous-time recurrent neural networks and its application to dynamical system control. *Systems and Computers in Japan* **32**:3, 14-23. [CrossRef]

72. Michael W. Harm, Mark S. Seidenberg. 2001. Are There Orthographic Impairments in Phonological Dyslexia?. *Cognitive Neuropsychology* **18**:1, 71-92. [CrossRef]

73. Morten H. Christiansen, Nick Chater. 2001. Connectionist psycholinguistics: capturing the empirical data. *Trends in Cognitive Sciences* **5**:2, 82-88. [CrossRef]

74. A. Blanco, M. Delgado, M.C. Pegalajar. 2001. A real-coded genetic algorithm for training recurrent neural networks. *Neural Networks* **14**:1, 93-105. [CrossRef]

75. Lalit Gupta, Mark McAvoy. 2000. Investigating the prediction capabilities of the simple recurrent neural network on real temporal sequences. *Pattern Recognition* **33**:12, 2075-2081. [CrossRef]

76. Lalit Gupta, Mark McAvoy, James Phegley. 2000. Classification of temporal sequences via prediction using the simple recurrent neural network. *Pattern Recognition* **33**:10, 1759-1770. [CrossRef]

77. A.F. Atiya, A.G. Parlos. 2000. New results on recurrent network training: unifying the algorithms and accelerating convergence. *IEEE Transactions on Neural Networks* **11**:3, 697-709. [CrossRef]

78. Masahiro Kimura, Ryohei Nakano. 2000. Dynamical systems produced by recurrent neural networks. *Systems and Computers in Japan* **31**:4, 77-86. [CrossRef]

79. Mikel L. Forcada, Marco Gori. Neural Nets, Recurrent . [CrossRef]

80. Samir Unadkat, Mãlina Ciocoiu, Larry Medsker. Introduction . [CrossRef]

81. Malur Sundareshan, Yee Chin Wong, Thomas Condarcure. Training Algorithms for Recurrent Neural Nets that Eliminate the Need for Computation of Error Gradients with Application to Trajectory Production Problem . [CrossRef]

82. M. Galicki, L. Leistritz, H. Witte. 1999. Learning continuous trajectories in recurrent neural networks with time-dependent weights. *IEEE Transactions on Neural Networks* **10**:4, 741-756. [CrossRef]

83. K.W.C. Ku, Man Wai Mak, Wan Chi Siu. 1999. Adding learning to cellular genetic algorithms for training recurrent neural networks. *IEEE Transactions on Neural Networks* **10**:2, 239-252. [CrossRef]

84. N. Srinivasa, N. Ahuja. 1999. A topological and temporal correlator network for spatiotemporal pattern learning, recognition, and recall. *IEEE Transactions on Neural Networks* **10**:2, 356-371. [CrossRef]

85. S.C. Sivakumar, W. Robertson, W.J. Phillips. 1999. Online stabilization of block-diagonal recurrent neural networks. *IEEE Transactions on Neural Networks* **10**:1, 167-175. [CrossRef]

86. M. Kimura, R. Nakano. 1998. Learning dynamical systems by recurrent neural networks from orbits. *Neural Networks* **11**:9, 1589-1599. [CrossRef]

87. N. Honma, K. Kitagawa, K. Abe. 1998. Effect of complexity on learning ability of recurrent neural networks. *Artificial Life and Robotics* **2**:3, 97-101. [CrossRef]

88. S. Das, O. Olurotimi. 1998. Noisy recurrent neural networks: the continuous-time case. *IEEE Transactions on Neural Networks* **9**:5, 913-936. [CrossRef]
89. R. Silipo, C. Marchesi. 1998. Artificial neural networks for automatic ECG analysis. *IEEE Transactions on Signal Processing* **46**:5, 1417-1425. [CrossRef]
90. M.K. Sudareshan, T.A. Condarcure. 1998. Recurrent neural-network training by a learning automaton approach for trajectory learning and control system design. *IEEE Transactions on Neural Networks* **9**:3, 354-368. [CrossRef]
91. Loo-Nin Teow, Kia-Fock Loe. 1998. Effective learning in recurrent max–min neural networks. *Neural Networks* **11**:3, 535-547. [CrossRef]
92. Noriyasu Honma, Kenichi Abe, Mitsuo Sato, Hiroshi Takeda. 1998. Adaptive evolution of holon networks by an autonomous decentralized method. *Applied Mathematics and Computation* **91**:1, 43-61. [CrossRef]
93. Massimo Buscema. 1998. Self-Recurrent Neural Network. *Substance Use & Misuse* **33**:2, 495-501. [CrossRef]
94. Peter Ford Dominey. 1998. A shared system for learning serial and temporal structure of sensori-motor sequences? Evidence from simulation and human experiments. *Cognitive Brain Research* **6**:3, 163-172. [CrossRef]
95. N. Peterfreund, A. Guez. 1997. Structure-based neural network learning. *IEEE Transactions on Circuits and Systems I: Fundamental Theory and Applications* **44**:12, 1143-1149. [CrossRef]
96. Sepp Hochreiter, Jürgen Schmidhuber. 1997. Long Short-Term Memory. *Neural Computation* **9**:8, 1735-1780. [Abstract] [PDF] [PDF Plus]
97. M. Schuster, K.K. Paliwal. 1997. Bidirectional recurrent neural networks. *IEEE Transactions on Signal Processing* **45**:11, 2673-2681. [CrossRef]
98. S. Haykin, P. Yee, E. Derbez. 1997. Optimum nonlinear filtering. *IEEE Transactions on Signal Processing* **45**:11, 2774-2786. [CrossRef]
99. Binfan Liu, J. Si. 1997. Error estimation of recurrent neural network models trained on a finite set of initial values. *IEEE Transactions on Circuits and Systems I: Fundamental Theory and Applications* **44**:11, 1086-1089. [CrossRef]
100. T. P. Fredman, H. Saxén. 1997. On a Recurrent Neural Network Producing Oscillations. *International Journal of Neural Systems* **08**:05n06, 499-508. [CrossRef]
101. J.P. Draye, D. Pavisic, G. Cheron, G. Libert. 1997. An inhibitory weight initialization improves the speed and quality of recurrent neural networks learning. *Neurocomputing* **16**:3, 207-224. [CrossRef]
102. Peter J. Bolland, Jerome T. Connor. 1997. A Constrained Neural Network Kalman Filter for Price Estimation in High Frequency Financial Data. *International Journal of Neural Systems* **08**:04, 399-415. [CrossRef]
103. Peter F Dominey, Driss Boussaoud. 1997. Encoding behavioral context in recurrent networks of the fronto-striatal system: a simulation study. *Cognitive Brain Research* **6**:1, 53-65. [CrossRef]

104. Masato Koda. 1997. Stochastic sensitivity analysis and Langevin simulation for neural network learning. *Reliability Engineering & System Safety* **57**:1, 71-78. [CrossRef]

105. M. Koda. 1997. Neural network learning based on stochastic sensitivity analysis. *IEEE Transactions on Systems, Man and Cybernetics, Part B (Cybernetics)* **27**:1, 132-135. [CrossRef]

106. Jean-Philippe Draye, Guy Cheron, Marc Bourgeois. 1997. Improved Identification of Complex Temporal Systems with Dynamic Recurrent Neural Networks. Application to the Identification of Electromyography and Human Arm Trajectory Relationship. *Journal of Intelligent Systems* **7**:1-2. . [CrossRef]

107. Barak Cohen, David Saad, Emanuel Marom. 1997. Efficient Training of Recurrent Neural Network with Time Delays. *Neural Networks* **10**:1, 51-59. [CrossRef]

108. Masato Okada. 1996. Notions of Associative Memory and Sparse Coding. *Neural Networks* **9**:8, 1429-1458. [CrossRef]

109. Masahiko Morita. 1996. Memory and Learning of Sequential Patterns by Nonmonotone Neural Networks. *Neural Networks* **9**:8, 1477-1489. [CrossRef]

110. Wang DeLiang, Liu Xiaomei, Stanley C. Ahalt. 1996. On Temporal Generalization of Simple Recurrent Networks. *Neural Networks* **9**:7, 1099-1118. [CrossRef]

111. J.-P.S. Draye, D.A. Pavisic, G.A. Cheron, G.A. Libert. 1996. Dynamic recurrent neural networks: a dynamical analysis. *IEEE Transactions on Systems, Man and Cybernetics, Part B (Cybernetics)* **26**:5, 692-706. [CrossRef]

112. Y. Bengio, P. Frasconi. 1996. Input-output HMMs for sequence processing. *IEEE Transactions on Neural Networks* **7**:5, 1231-1249. [CrossRef]

113. G. Cheron, J.-P. Draye, M. Bourgeios, G. Libert. 1996. A dynamic neural network identification of electromyography and arm trajectory relationship during complex movements. *IEEE Transactions on Biomedical Engineering* **43**:5, 552-558. [CrossRef]

114. G. Cauwenberghs. 1996. An analog VLSI recurrent neural network learning a continuous-time trajectory. *IEEE Transactions on Neural Networks* **7**:2, 346-361. [CrossRef]

115. Kosei Demura, Yuichiro Anzai, Masahiro Kajiura. 1996. Recurrent SOLAR algorithm. *Systems and Computers in Japan* **27**:11, 97-110. [CrossRef]

116. M.J.S. Day, J.S. Payne. The generation of motion kinematics using a time-delay neural network 545-549 vol.4. [CrossRef]

117. Hung-Jen Chang, Walter J. Freeman. 1996. Parameter optimization in models of the olfactory neural system. *Neural Networks* **9**:1, 1-14. [CrossRef]

118. M. Kohata. 1996. Interpolation of LSP coefficients using recurrent neural networks. *Electronics Letters* **32**:16, 1441. [CrossRef]

119. Christopher Miall. Models of neural timing 69-94. [CrossRef]

120. B.A. Pearlmutter. 1995. Gradient calculations for dynamic recurrent neural networks: a survey. *IEEE Transactions on Neural Networks* **6**:5, 1212-1228. [CrossRef]

121. Liang Jin, P.N. Nikiforuk, M.M. Gupta. 1995. Approximation of discrete-time state-space trajectories using dynamic recurrent neural networks. *IEEE Transactions on Automatic Control* **40**:7, 1266-1270. [CrossRef]

122. David William Pearson. 1995. Linear systems equivalent to artificial neural networks via Lie theory. *Neurocomputing* **8**:2, 157-170. [CrossRef]

123. Jean-Philippe Draye, Davor Pavisic, Guy Cheron, Gaëtan Libert. 1995. Adaptative time constants improve the prediction capability of recurrent neural networks. *Neural Processing Letters* **2**:3, 12-16. [CrossRef]

124. P. Frasconi, M. Gori, M. Maggini, G. Soda. 1995. Unified integration of explicit knowledge and learning by example in recurrent networks. *IEEE Transactions on Knowledge and Data Engineering* **7**:2, 340-346. [CrossRef]

125. Koji Nakai, Akio Ushida. 1995. Design technique of cellular neural network. *Electronics and Communications in Japan (Part III: Fundamental Electronic Science)* **78**:3, 97-107. [CrossRef]

126. MASATO KODA. 1995. Stochastic sensitivity analysis method for neural network learning. *International Journal of Systems Science* **26**:3, 703-711. [CrossRef]

127. Gustavo Deco, Bernd Schürmann. 1995. Neural learning of chaotic dynamics. *Neural Processing Letters* **2**:2, 23-26. [CrossRef]

128. D.R. Baughman, Y.A. Liu. Process Forecasting, Modeling, and Control of Time-Dependent Systems 228-364. [CrossRef]

129. Chao-Chee Ku, K.Y. Lee. 1995. Diagonal recurrent neural networks for dynamic systems control. *IEEE Transactions on Neural Networks* **6**:1, 144-156. [CrossRef]

130. Abhay B. Bulsari, Henrik Saxén. 1995. A recurrent network for modeling noisy temporal sequences. *Neurocomputing* **7**:1, 29-40. [CrossRef]

131. Steven K. Rogers, John M. Colombi, Curtis E. Martin, James C. Gainey, Ken H. Fielding, Tom J. Burns, Dennis W. Ruck, Matthew Kabrisky, Mark Oxley. 1995. Neural networks for automatic target recognition. *Neural Networks* **8**:7-8, 1153-1184. [CrossRef]

132. D.R. Baughman, Y.A. Liu. Fundamental and Practical Aspects of Neural Computing 21-109. [CrossRef]

133. P. Baldi. 1995. Gradient descent learning algorithm overview: a general dynamical systems perspective. *IEEE Transactions on Neural Networks* **6**:1, 182-195. [CrossRef]

134. H. Bersini, M. Saerens, L.G. Sotelino. 1994. Hopfield net generation, encoding and classification of temporal trajectories. *IEEE Transactions on Neural Networks* **5**:6, 945-953. [CrossRef]

135. Ronald L. Black, William J.B. Oldham, William M. Marcy. 1994. Training KSIM models from time series data. *Technological Forecasting and Social Change* **47**:3, 293-307. [CrossRef]
136. Hong Liang Hiew, Chi Ping Tsang. 1994. An adaptive fuzzy system for modeling chaos. *Information Sciences* **81**:3-4, 193-212. [CrossRef]
137. J. Ting-Ho Lo. 1994. Synthetic approach to optimal filtering. *IEEE Transactions on Neural Networks* **5**:5, 803-811. [CrossRef]
138. P. Baldi, A.F. Atiya. 1994. How delays affect neural dynamics and learning. *IEEE Transactions on Neural Networks* **5**:4, 612-621. [CrossRef]
139. Leong Kwan Li. 1994. Learning fixed point patterns by recurrent networks. *Journal of Computer and System Sciences* **48**:2, 203-213. [CrossRef]
140. Bard Ermentrout, Nancy Kopell. 1994. Learning of Phase Lags in Coupled Neural Oscillators. *Neural Computation* **6**:2, 225-241. [Abstract] [PDF] [PDF Plus]
141. M. Bianchini, M. Gori, M. Maggini. 1994. On the problem of local minima in recurrent neural networks. *IEEE Transactions on Neural Networks* **5**:2, 167-177. [CrossRef]
142. O. Olurotimi. 1994. Recurrent neural network training with feedforward complexity. *IEEE Transactions on Neural Networks* **5**:2, 185-197. [CrossRef]
143. Alexander V. Lukashin, Apostolos P. Georgopoulos. 1994. A Neural Network for Coding of Trajectories by Time Series of Neuronal Population Vectors. *Neural Computation* **6**:1, 19-28. [Abstract] [PDF] [PDF Plus]
144. MICHAEL C. MOZER. 1994. Neural Network Music Composition by Prediction: Exploring the Benefits of Psychoacoustic Constraints and Multi-scale Processing. *Connection Science* **6**:2-3, 247-280. [CrossRef]
145. Padhraic Smyth. 1994. Hidden Markov models for fault detection in dynamic systems. *Pattern Recognition* **27**:1, 149-164. [CrossRef]
146. Luis Gonzalez Sotelino, Marco Saerens, Hugues Bersini. 1994. Classification of temporal trajectories by continuous-time recurrent nets. *Neural Networks* **7**:5, 767-776. [CrossRef]
147. W.S. Hortos. Application of neural networks to the adaptive routing control and traffic estimation of survivable wireless communication networks 85-91. [CrossRef]
148. Yukio Hayashi. 1994. Oscillatory neural network and learning of continuously transformed patterns. *Neural Networks* **7**:2, 219-231. [CrossRef]
149. David C. Plaut, Tim Shallice. 1993. Deep dyslexia: A case study of connectionist neuropsychology. *Cognitive Neuropsychology* **10**:5, 377-500. [CrossRef]
150. Vicente López, Ramón Huerta, José R. Dorronsoro. 1993. Recurrent and Feedforward Polynomial Modeling of Coupled Time Series. *Neural Computation* **5**:5, 795-811. [Abstract] [PDF] [PDF Plus]

151. A. V. Lukashin, A. P. Georgopoulos. 1993. A dynamical neural network model for motor cortical activity during movement: population coding of movement trajectories. *Biological Cybernetics* **69**:5-6, 517-524. [CrossRef]
152. D. Wang. 1993. Pattern recognition: neural networks in perspective. *IEEE Expert* **8**:4, 52-60. [CrossRef]
153. Shawn R. Lockery, Terrence J. Sejnowski. 1993. The computational leech. *Trends in Neurosciences* **16**:7, 283-290. [CrossRef]
154. Ulrich Ramacher, Jörg Beichter, Nico Brüls. 1993. A general-purpose signal processor architecture for neurocomputing and preprocessing applications. *Journal of VLSI signal processing systems for signal, image and video technology* **6**:1, 45-56. [CrossRef]
155. S.R. Lockery, T.J. Sejnowski. 1993. A lower bound on the detectability of nonassociative learning in the local bending reflex of the medicinal leech. *Behavioral and Neural Biology* **59**:3, 208-224. [CrossRef]
156. Uwe Müller-Wilm. 1993. A neuron-like network with the ability to learn coordinated movement patterns. *Biological Cybernetics* **68**:6, 519-526. [CrossRef]
157. O. Nerrand, P. Roussel-Ragot, L. Personnaz, G. Dreyfus, S. Marcos. 1993. Neural Networks and Nonlinear Adaptive Filtering: Unifying Concepts and New Algorithms. *Neural Computation* **5**:2, 165-199. [Abstract] [PDF] [PDF Plus]
158. James A. Kottas. 1993. Training Periodic Sequences Using Fourier Series Error Criterion. *Neural Computation* **5**:1, 115-131. [Abstract] [PDF] [PDF Plus]
159. Erol Gelenbe. 1993. Learning in the Recurrent Random Neural Network. *Neural Computation* **5**:1, 154-164. [Abstract] [PDF] [PDF Plus]
160. Ulrich Ramacher. HAMILTONIAN DYNAMICS OF NEURAL NETWORKS 61-85. [CrossRef]
161. Erica H. C. Bastiaanssen, Jan Vanderschoot, Johan L. van Leeuwen. 1993. Learning procedure in a neural control model for the urinary bladder. *Neurourology and Urodynamics* **12**:3, 285-288. [CrossRef]
162. Jean-Michel Renders, Hugues Bersini, Marco Saerens. Adaptive NeuroControl: How Black Box and Simple can it be 260-267. [CrossRef]
163. D.R. Hush, B.G. Horne. 1993. Progress in supervised neural networks. *IEEE Signal Processing Magazine* **10**:1, 8-39. [CrossRef]
164. Ulrich Ramacher. 1993. Hamiltonian dynamics of neural networks. *Neural Networks* **6**:4, 547-557. [CrossRef]
165. Ken-ichi Funahashi, Yuichi Nakamura. 1993. Approximation of dynamical systems by continuous time recurrent neural networks. *Neural Networks* **6**:6, 801-806. [CrossRef]
166. K.J. Hunt, D. Sbarbaro, R. Żbikowski, P.J. Gawthrop. 1992. Neural networks for control systems—A survey. *Automatica* **28**:6, 1083-1112. [CrossRef]

167. Erica H. C. Bastiaanssen, Jan Vanderschoot, Johan L. van Leeuwen. Learning procedure in a neural control model for the urinary bladder 1508-1509. [CrossRef]

168. D. Wang, B. Schurmann. 1992. Computer aided analysis and derivation for artificial neural systems. *IEEE Transactions on Software Engineering* **18**:8, 728-735. [CrossRef]

169. A.F. Kohan, R.P.J. Perazzo. 1992. Exact learning and default-rule governed behaviour. *Physica A: Statistical Mechanics and its Applications* **185**:1-4, 417-427. [CrossRef]

170. M.N. Karim, S.L. Rivera. 1992. Comparison of feed-forward and recurrent neural networks for bioprocess state estimation. *Computers & Chemical Engineering* **16**, S369-S377. [CrossRef]

171. Yoshua Bengio, Renato De Mori, Marco Gori. 1992. Learning the dynamic nature of speech with back-propagation for sequences. *Pattern Recognition Letters* **13**:5, 375-385. [CrossRef]

172. Jürgen Schmidhuber. 1992. A Fixed Size Storage O(n3) Time Complexity Learning Algorithm for Fully Recurrent Continually Running Networks. *Neural Computation* **4**:2, 243-248. [Abstract] [PDF] [PDF Plus]

173. S.L. Rivera, M.N. Karim. 1992. On-line Estimation of Bioreactors using Recurrent Neural Networks. *IFAC Proceedings Volumes* **25**:2, 159-162. [CrossRef]

174. S.R. Lockery. 1992. Realistic neural network models using backpropagation: panacea or oxymoron?. *Seminars in Neuroscience* **4**:1, 47-59. [CrossRef]

175. Paolo Frasconi, Marco Gori, Giovanni Soda. 1992. Local Feedback Multilayered Networks. *Neural Computation* **4**:1, 120-130. [Abstract] [PDF] [PDF Plus]

176. Jürgen Schmidhuber. 1992. Learning to Control Fast-Weight Memories: An Alternative to Dynamic Recurrent Networks. *Neural Computation* **4**:1, 131-139. [Abstract] [PDF] [PDF Plus]

177. M.A. Cohen. 1992. The construction of arbitrary stable dynamics in nonlinear neural networks. *Neural Networks* **5**:1, 83-103. [CrossRef]

178. Tatsumi Watanabe, Yoshiki Uchikawa, Kazutoshi Gouhara. 1992. Learning algorithms and the shape of the learning surface in recurrent neural networks. *Systems and Computers in Japan* **23**:13, 90-107. [CrossRef]

179. Erol Gelenbe. Learning in the Recurrent Random Neural Network 1-12. [CrossRef]

180. J.G. Taylor. Temporal sequence storage 841-845. [CrossRef]

181. Abhay B. Bulsari, Henrik Saxén. A Recurrent Neural Network Model 1091-1094. [CrossRef]

182. Nikzad Benny Toomarian, Jacob Barhen. 1992. Learning a trajectory using adjoint functions and teacher forcing. *Neural Networks* **5**:3, 473-484. [CrossRef]

183. Eric Mjolsness, David H. Sharp, John Reinitz. 1991. A connectionist model of development. *Journal of Theoretical Biology* **152**:4, 429-453. [CrossRef]

184. I. Guyon. 1991. Neural networks and applications tutorial. *Physics Reports* **207**:3-5, 215-259. [CrossRef]

185. F. Chapeau-Blondeau, G. Chauvet. 1991. A neural network model of the cerebellar cortex performing dynamic associations. *Biological Cybernetics* **65**:4, 267-279. [CrossRef]

186. G. Taga, Y. Yamaguchi, H. Shimizu. 1991. Self-organized control of bipedal locomotion by neural oscillators in unpredictable environment. *Biological Cybernetics* **65**:3, 147-159. [CrossRef]

187. A. V. M. Herz. 1991. Global analysis of parallel analog networks with retarded feedback. *Physical Review A* **44**:2, 1415-1418. [CrossRef]

188. D. B. Arnold, D. A. Robinson. 1991. A learning network model of the neural integrator of the oculomotor system. *Biological Cybernetics* **64**:6, 447-454. [CrossRef]

189. Kiyotoshi Matsuoka. 1991. Learning of neural networks using their adjoint systems. *Systems and Computers in Japan* **22**:11, 31-41. [CrossRef]

190. N. Toomarian, J. Barhen. 1991. Adjoint-operators and non-adiabatic learning algorithms in neural networks. *Applied Mathematics Letters* **4**:2, 69-73. [CrossRef]

191. H. Behrens, D. Gawronska, J. Hollatz, B. Schürmann. RECURRENT AND FEEDFORWARD BACKPROPAGATION: PERFORMANCE STUDIES 1511-1514. [CrossRef]

192. Jürgen Schmidhuber. Learning Algorithms for Networks with Internal and External Feedback 52-61. [CrossRef]

193. Tadasu Uchiyama, Katsunori Shimohara. 1991. A realtime learning algorithm for recurrent neural networks. *Systems and Computers in Japan* **22**:10, 73-79. [CrossRef]

194. S. Gulati, J. Barhen, S.S. Iyengar. Neurocomputing Formalisms for Computational Learning and Machine Intelligence 173-245. [CrossRef]

195. Ronald J. Williams, Jing Peng. 1990. An Efficient Gradient-Based Algorithm for On-Line Training of Recurrent Network Trajectories. *Neural Computation* **2**:4, 490-501. [Abstract] [PDF] [PDF Plus]

196. Yan Fang, Terrence J. Sejnowski. 1990. Faster Learning for Dynamic Recurrent Backpropagation. *Neural Computation* **2**:3, 270-273. [Citation] [PDF] [PDF Plus]

197. Shawn R. Lockery, Yan Fang, Terrence J. Sejnowski. 1990. A Dynamic Neural Network Model of Sensorimotor Transformations in the Leech. *Neural Computation* **2**:3, 274-282. [Abstract] [PDF] [PDF Plus]

198. S.-i. Amari. 1990. Mathematical foundations of neurocomputing. *Proceedings of the IEEE* **78**:9, 1443-1463. [CrossRef]

199. Steve Renals, Richard Rohwer. 1990. A study of network dynamics. *Journal of Statistical Physics* **58**:5-6, 825-848. [CrossRef]

200. Gary Kuhn, Raymond L. Watrous, Bruce Ladendorf. 1990. Connected recognition with a recurrent network. *Speech Communication* **9**:1, 41-48. [CrossRef]

201. J. Barhen, N. Toomarian, S. Gulati. 1990. Application of adjoint operators to neural learning. *Applied Mathematics Letters* **3**:3, 13-18. [CrossRef]

202. R. Kamimura. Application of temporal supervised learning algorithm to generation of natural language 201-207 vol.1. [CrossRef]

203. M. Sato, K. Joe, T. Hirahara. APOLONN brings us to the real world: learning nonlinear dynamics and fluctuations in nature 581-587 vol.1. [CrossRef]

204. Masa-aki Sato. 1990. A learning algorithm to teach spatiotemporal patterns to recurrent neural networks. *Biological Cybernetics* **62**:3, 259-263. [CrossRef]

205. G.Z. Sun, H.H. Chen, Y.C. Lee, C.L. Giles. Recurrent neural networks, hidden Markov models and stochastic grammars 729-734 vol.1. [CrossRef]

206. Ronald J. Williams, David Zipser. 1989. A Learning Algorithm for Continually Running Fully Recurrent Neural Networks. *Neural Computation* **1**:2, 270-280. [Abstract] [PDF] [PDF Plus]

207. Jyh-Shan Chang, Jenn-Huei Lin, Tzi-Dar Chiueh. Neural networks for truck backer-upper control system 328-334. [CrossRef]

208. R. Zbikowski. State-space approach to continuous recurrent neural networks 152-157. [CrossRef]

209. J. Ludik, W. Prins, K. Meert, T. Catfolis. A comparative study of fully and partially recurrent networks 292-297. [CrossRef]

210. H. Hasegawa, M. Inazumi. Speech recognition by dynamic recurrent neural networks 2219-2222. [CrossRef]

211. R.H.R. Hahnloser. Generating network trajectories using gradient descent in state space 2373-2377. [CrossRef]

212. T. Yokoyama, K. Takeshima, R. Nakano. Model selection and local optimality in learning dynamical systems using recurrent neural networks 1039-1044. [CrossRef]

213. K. Doya, A.I. Selverston. A learning algorithm for Hodgkin-Huxley type neuron models 1108-1111. [CrossRef]

214. H. Takase, K. Gouhara, Y. Uchikawa. Time sequential pattern transformation and attractors of recurrent neural networks 2319-2322. [CrossRef]

215. Chunkai Zhang, Hong Hu. An Evolved Recurrent Neural Network and Its Application in the State Estimation of the CSTR System 2139-2143. [CrossRef]

216. J.G. Schneider, C.M. Brown. Cooperative coaching in robot learning 332-337. [CrossRef]

217. D. Wang, B. Schurmann. Computer aided investigations of artificial neural systems 2325-2330. [CrossRef]

218. K. Gohara, K. Yokoi, Y. Uchikawa. Robustness of recurrent neural networks against deformation of external input patterns 980-985. [CrossRef]

219. Jianjun Xu, M.C.E. Yagoub, Runtao Ding, Q.J. Zhang. Feedforward dynamic neural network technique for modeling and design of nonlinear telecommunication circuits and systems 930-935. [CrossRef]
220. T. Fukuda, T. Kohno, T. Shibata. Heuristic learning by genetic algorithm for recurrent neural network 71-77. [CrossRef]
221. A. Atiya, A. Parlos. An accelerated recurrent network training algorithm 1101-1106. [CrossRef]
222. H. Behrens, D. Gawronska, J. Hollatz, B. Schurmann. Recurrent and feedforward backpropagation for time independent pattern recognition 591-596. [CrossRef]
223. T.A. Condarcure, M.K. Sundareshan. A learning automaton approach to trajectory learning and control system design using dynamic recurrent neural networks 2684-2689. [CrossRef]
224. T. Miyoshi, H. Ichihashi, S. Okamoto, T. Hayakawa. Learning chaotic dynamics in recurrent RBF network 588-593. [CrossRef]
225. D.W. Pearson. Trajectory assignment by output zeroing 417-420. [CrossRef]
226. V. Sterzing, B. Schurmann. Recurrent neural networks for temporal learning of time series 843-850. [CrossRef]
227. A. Ferit Konar, Y. Becerikli, T. Samad. Trajectory tracking with dynamic neural networks 173-180. [CrossRef]
228. P. Frasconi, M. Gori, M. Maggini, G. Soda. An unified approach for integrating explicit knowledge and learning by example in recurrent networks 811-816. [CrossRef]
229. K. Shibata, Y. Okabe, K. Ito. Simple learning algorithm for recurrent networks to realize short-term memories 2367-2372. [CrossRef]
230. J.A. Nossek. Design and learning with cellular neural networks 137-146. [CrossRef]
231. N. Toomarian, J. Barhen. Fast temporal neural learning using teacher forcing 817-822. [CrossRef]
232. J. Schmidhuber. Learning temporary variable binding with dynamic links 2075-2079. [CrossRef]
233. J. Barhen, N. Toomarian, A. Fijany. Learning without local minima 4592-4596. [CrossRef]
234. H. Nakajima, T. Koda, Y. Ueda. A measure theoretical analysis of learning algorithms for recurrent neural networks 2575-2578. [CrossRef]
235. J.-P. Draye, D. Pavisic, G. Cheron, G. Libert. Improved signal processing with dynamic recurrent neural models using ARMA-like units 525-528. [CrossRef]
236. S. Das, O. Olurotimi. An analysis of noisy recurrent neural networks 1297-1301. [CrossRef]

237. R. Petridis, S. Kazaplis, A. Papaikonomou. A genetic algorithm for training recurrent neural networks 2706-2709. [CrossRef]
238. M. Matsuga, Chi-Sang Poon. Recognition of oscillatory signals using a neural network oscillator 115-124. [CrossRef]
239. A.J. Schuler, M. Brabec, D. Schubel, J.A. Nossek. Hardware-oriented learning for cellular neural networks 183-188. [CrossRef]
240. I. Tokuda, Y. Hirai, R. Tokunaga. Back-propagation learning of an infinite-dimensional dynamical system 2271-2275. [CrossRef]
241. H. Magnussen, G. Papoutsis, J.A. Nossek. Continuation-based learning algorithm for discrete-time cellular neural networks 171-176. [CrossRef]
242. B. Liu, J. Si. Error estimation of recurrent neural network models trained on a finite set of initial values 1574-1578. [CrossRef]
243. K. Doya. Bifurcations in the learning of recurrent neural networks 2777-2780. [CrossRef]
244. G.-Z. Sun, H.-H. Chen, Y.-C. Le. A fast online learning algorithm for recurrent neural networks 13-18. [CrossRef]
245. Q. Xu, K. Krishnamurthy, B. McMillin, W. Lu. A recursive least squares training algorithm for multilayer recurrent neural networks 1712-1716. [CrossRef]
246. Yunxian Huang, Wei Yan. Dynamic control of communication systems based on simple recurrent neural networks 254-258. [CrossRef]
247. A.J. Schuler, P. Nachbar, J.A. Nossek, L.O. Chua. Learning state space trajectories in cellular neural networks 68-73. [CrossRef]
248. K. Imai, K. Gouhara, Y. Uchikawa. Recognition of printed sequential plural patterns using the 3-layered BP model with feedback connections 754-759. [CrossRef]
249. M. Sakai, N. Honma, K. Abe. Complexity control method for recurrent neural networks 484-489. [CrossRef]
250. Yee Chin Wong, M.K. Sundareshan. A simplex optimization approach for recurrent neural network training and for learning time-dependent trajectory patterns 353-358. [CrossRef]
251. J. Schmidhuber. A neural network that embeds its own meta-levels 407-412. [CrossRef]
252. K. Gouhara, K. Yokoi, Y. Uchikawa. Valley searching method for recurrent neural networks 972-979. [CrossRef]
253. U. Ramacher, M. Wesseling. Treating weights as dynamical variables-a new approach to neurodynamics 497-503. [CrossRef]
254. M. Kimura, R. Nakano. Learning Dynamical Systems from Trajectories by Continuous Time Recurrent Neural Networks 2992. [CrossRef]

255. Chia-Feng Juang, Yuan-Chang Liou. On the hybrid of genetic algorithm and particle swarm optimization for evolving recurrent neural network 2285-2289. [CrossRef]
256. R. Silipo, C. Marchesi. Neural techniques for ST-T change detection 677-680. [CrossRef]
257. Y. Ajioka, K. Inoue. A simple visual perception model by adaptive junction 73-78. [CrossRef]
258. C.H. Chen, L. Yu. A learning algorithm for improved recurrent neural networks 2198-2202. [CrossRef]
259. C. Coulston, S. Pakzad. A biological-based neural network model of leech reflexive behaviors 32-39. [CrossRef]
260. P. Baldi, N.B. Toomarian. Learning trajectories with a hierarchy of oscillatory modules 1172-1176. [CrossRef]
261. S. Das, O. Olurotimi. Temporal pattern learning in noisy recurrent neural networks 598-600. [CrossRef]
262. Bao Xiaohong, Jia Yingmin. Neural networks trained for associative memory 1783-1787. [CrossRef]
263. S. Ojima, S. Yano. Eye movement model with neural oscillators 2297-2302. [CrossRef]
264. S. Miesbach. Efficient gradient computation for continuous and discrete time-dependent neural networks 2337-2342. [CrossRef]
265. James Ting-Ho Lo. Neural network approach to optimal filtering . [CrossRef]
266. U. Ramacher, P. Nachbar. The Hamiltonian approach to neural networks dynamics 1930-1936. [CrossRef]
267. L.G. Sotelino, H. Bersini. Hopfield net generation and encoding of trajectories in constrained environment 857-862. [CrossRef]
268. E.H.C. Bastiaanssen, J.L. van Leeuwen, J. Vanderschoot. Nested subsystems in a control model for the urinary bladder 93-96. [CrossRef]
269. R.P. Gorman. Neural networks and the classification of complex sonar signals 283-290. [CrossRef]
270. S. Yildirim, V. Aslantas. Feedback error learning for control of a robot using SMENN 518-523. [CrossRef]
271. T. Fukuda, T. Kohno, T. Shibata. Dynamic memory by recurrent neural network and its learning by genetic algorithm 2815-2820. [CrossRef]
272. T. Fukuda, T. Kohno, T. Shibata. Learning scheme for recurrent neural network by genetic algorithm 1756-1761. [CrossRef]
273. L.K. Li. Approximation theory and recurrent networks 266-271. [CrossRef]
274. V. Petridis, A. Papaikonomou. Recurrent neural networks as pattern generators 872-875. [CrossRef]

275. M. Morita. Smooth recollection of a pattern sequence by nonmonotone analog neural networks 1032-1037. [CrossRef]
276. K. Gouhara, T. Watanabe, Y. Uchikawa. Learning process of recurrent neural networks 746-751. [CrossRef]
277. O. Olurotimi, R. McDonald, S. Das. Neural network identification and control in the presence of noise 694-699. [CrossRef]
278. M. Kohata. An application of recurrent neural networks to low bit rate speech coding 314-317. [CrossRef]