Rochester Connectionist Papers: 1979-1984

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Appendix A: Errata Sheet for "Dynamic Connections in Neural Networks"
**Report Number**: TR 124 revised

**Title (and Subtitle)**: Rochester Connectionist Papers: 1979-1984

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1. Background Papers


A primordial paper which introduces generalized voting and the idea of voting to detect shape invariance.


Examples of the general shape recognition scheme in action. Subsequently, much more detailed experiments have been carried out at SRI International.


This is the first attempt at formulating what would now be called a localist connection model. Surprisingly enough, none of the informal discussion needs to be recanted (yet), and several topics discussed generally here have not yet received systematic treatment.


A preliminary version of the above, which has no current value.
2. Definitional Papers


The basic reference. It contains definitions, generally useful constructs, and a variety of examples.


This differs from the above mainly in the inclusion of an eigenvalue stability theorem for the special case of symmetric inhibitory-excitatory arrays.


This is the draft from which the two above papers derive. It is much rougher and not to be believed. The one thing that has not appeared elsewhere is a detailed treatment of symmetric mutual inhibition (winner-take-all) networks.


This is the basic reference for short- and long-term memory change, dynamic links, and recruiting of concept nodes. It is riddled with misprints; an errata sheet is Appendix A of this report.


The draft report for the article above. It contains a good deal of motivating discussion missing from the *Biological Cybernetics* piece, and more technical details in several places.
3. Intrinsic Images and Visual Gestalts

Ballard, D.H., "Parameter networks," *Artificial Intelligence Journal* 22, 235-267, 1984. (An early version of this paper was presented at the 7th International Joint Conference on Artificial Intelligence; a later revision is TR 75.)

The first paper which lays out a parameter-space theory of visual gestalts. This theory focuses on problems of computing intrinsic images and global organizations in patterns.


Shows how rigid body motion parameters can be detected from a depth map and optic flow field. Further elaboration of the subspaces concept.


First demonstration of the concept of coupled computations, whereby a global parameter (sun angle) is estimated concurrently with surface normals via parallel-iterative Hough/relaxation.


Shows how unit-value concept (and others in [Feldman and Ballard, 1982]) constrains cortical anatomy.


Enunciates the continuing hope that multiple intrinsic images are easier to calculate together than separately. Several evocative examples but few new hard results. Not connectionist except for use of Hough transform.
4. General Vision


An attempt to provide an account of the overall functioning of the visual system in connectionist terms. Three of the four coordinate frames are based on the eye, the head, and extra-personal space, while the fourth is general world knowledge and non-spatial. The model purports to be consistent with all behavioral, biological, and computational constraints.

Ballard, D.H. and D. Sabbah, "View-invariant shape detection," to appear, IEEE Trans. on Pattern Analysis and Machine Intelligence. (Also appeared as TR 92, which has some minor bugs.)

Introduces the idea of detecting high-dimensional features by using subspaces. In the context of view transforms, rotation and scale are shown to be computable before translation.


Extends previous work in connectionist form perception to deal with many additional concepts, including image noise, patterns, moving shapes, space-time issues, and hierarchical shape representation. (An early version of some of the topics appeared in the IEEE Computer Vision Workshop, Ringe, NH, 1982.)


An overview of work at several labs.


Tutorial and introduction to current ideas behind computer vision systems. Has faint connectionist bias.


Working out the details of spatial visual perception in connectionist terms.


This is a much reduced version of TR 99, with explicit links to other papers in the Conference.

This forthcoming technical report exhibits a detailed connectionist solution to a technical problem in the Four Frames model (TR 99). Indexing (categorization) in that model works in parallel, but can be confused by scrambled images. This paper describes a sequential verification algorithm that prevents these confusions, using techniques similar to those of Hrechanyk and Ballard.
5. Applications to Natural Language


This short paper sets forth our initial thoughts on the construction of connectionist models of natural language parsing. Each of the authors worked independently to model the word sense discrimination required to analyze the sentence "A man threw up a ball" using massively distributed networks. The results of these studies were put together into this brief description of how it might be possible to build a detailed and accurate model of human sentence comprehension.


Each of these papers contains an introduction to the problems of connectionist parsing of natural language, and either would be a good starting point on the connectionist approach to the computational modeling of natural language comprehension. The papers contend that the differences between traditional computer programs and human computation make the use of highly parallel networks the most fruitful way to go about modeling human language processing. Scientific constraints on such models are presented, along with an initial model that meets many of these constraints. Problems with the existing model and research questions within the overall framework are discussed. The second paper contains some material on syntax not included in the first paper.


This short paper contains some imprecise thoughts on the exploded nature of human schematic knowledge. It argues that the chunking of knowledge into scripts (frames) may not be the best way to look at the organization of information in a model of human memory, especially in keeping an eye on the problems of word sense discrimination, anaphoric reference, and discourse cohesion for natural language understanding. The paper explains why the connectionist approach might be advantageous for studying memory and gives some examples illustrating how some classical problems can be looked at differently.


A connectionist model of access of information about words which corresponds to current psychological data, explains some anomalies in that data, and makes empirically verifiable predictions.
6. Motor Control


The first attempt at using connectionism to model a real neural control system. The model developed appears to satisfy much of current experimental data, and raises several issues about the structure of the oculomotor control system.


An analysis of connectionism as a computational paradigm for the analysis and synthesis of control systems.


Hierarchical representation of spatial and mechanical information for robot manipulation.
7. Knowledge Representation and Inference


This paper develops a completely parallel connectionist inference mechanism. The mechanism handles obvious inferences, where each clause is only used once, but may be extendable to harder cases.


Connected networks of nodes representing conceptual knowledge are widely employed in artificial intelligence and cognitive science. This report describes a direct way of realizing these semantic networks with neuron-like computing units. The proposed framework appears to offer several advantages over previous work. It obviates the need for a centralized knowledge base interpreter, thereby partially solving the problem of computational effectiveness, and also embodies an evidential semantics for knowledge that provides a natural treatment of defaults, exceptions, and "inconsistent" or conflicting information. The model employs a class of inference that may be characterized as working with a set of competing hypotheses, gathering evidence for each hypothesis, and selecting the best among these. The resulting system has been simulated and is capable of supporting existing semantic network applications dealing with problems of recognition and recall in a uniform manner.


A very reduced version of TR 131 that is intended to allow people to assess whether they want to approach the full paper.
8. Simulation


Our first large program in the connectionist paradigm. It simulates a multi-layer network for recognizing line drawings of Origami figures. The program successfully deals with noise and simple occlusion and the thesis incorporates many key ideas on designing and running large models.


This paper describes the organization and use of the connectionist network construction and simulation program that currently runs in Franz Lisp on our Vax 780 under Unix. The program (ISCON) aids the user in building connection networks and then simulating their activity with graphical illustration. The user and the program interact to build up networks that would be complicated to do by hand; simple ISCON commands cause some complex (but schematic) connection network patterns to be incorporated at particular points in the user’s network design. Unfortunately, this report currently takes the form of a user’s manual that is not organized well enough to be terribly useful to interested persons outside the local community. Since the simulator project will be ongoing for some time, it might be helpful to take a look at this first version of the manual, but at the same time to await the next version before blaming yourself for not understanding it.
9. Hough Transform Developments


Experimental study of using a small context-addressable cache to accumulate HT votes. Presents a heavily parameterized model and many statistics of its performance in various configurations.


A precis of TR 105 and TR 114.


A quad-tree structure is implemented in a cache hierarchy. Flushing can then be based on properties of volumes of accumulator space.


Description of a VLSI circuit that implements content-addressable cache for use as accumulator cache in Hough transform.


Presents a cache-flushing scheme that uses information about the vote distribution to increase the reliability of peak-finding algorithms.


Combinatorial investigation of peak-finding with no information about the underlying distribution.
Appendix A: Errata Sheet for "Dynamic Connections in Neural Networks"

ERRATA

Figure 4 (p. 31), Figure 7 (p. 33), and Figure 8 (p. 35) are incomplete as published. The correct versions of these Figures appear below and overleaf. In addition there are the following typographical errors.

p. 28, second column, line 11, should read 'v+ if p > 0 ...'

p. 30, second column, line -13, should read 'stimulate A and not B.'

p. 33, line -10, formula should be \( P = (1-F)^B \).

p. 35, line -12, formula should be \( v + 2p \)

p. 36, line 16, formula should be \( Pr(k \text{ links}) = \binom{d}{k} \).

- Figure 4 (p. 31)
- Figure 7 (p. 33)
- Figure 8 (p. 35)

\[
F = (1-F)^B
\]

- \( F \) = Probability that there is no link from \( x \) to \( y \)
- \( N \) = Number of units in a "Layer"
- \( B \) = Number of Randomly Outgoing Branches/Unit = \( \sqrt{N} \)
- \( F = B/N \) (Branching Factor)
- \( K \) = Number of Intermediate Levels (2 in diagram above)

| \( F \) for \( B = 1000 \); different numbers of levels and units |
|---|---|---|---|
| \( B \) | \( 10^6 \) | \( 10^7 \) | \( 10^8 \) |
| 0 | .999 | .9999 | .99999 |
| 1 | .957 | .905 | .889 |
| 2 | .10^440 | \( 10^54 \) | \( 10^6 \) |
Random Networks:
H nodes each connected to \( \sqrt{H} \) others

Assume \( v = 2 \) * potential, Decay is 2

| T = 0 | F | I | G | L | O | A | R |...
|------|---|---|---|---|---|---|---|...
| 1    | 10| 10| 0 | 0 | 0 | 0 | 0 |...
| 2    | 10| 10| 0 | 2 | 4 | 2 | 2 |...
| 3    | 10| 10| 0 | 2.8| 6 | 2 | 2 |...
| 4    | 10| 10| 1 | 4 | 8.6| 2 | 2 |...
| 5    | 10| 10| 1 | 6.3| 10| 2 | 2 |...

Figure 8: Random Churning Network