AD-A195 631 STORING AND RETRIEVING DATA IN A PARALLEL DISTRIBUTED 1/1
MEMORY SYSTEM(U) BROWN UNIV PROVIDENCE RI CENTER FOR
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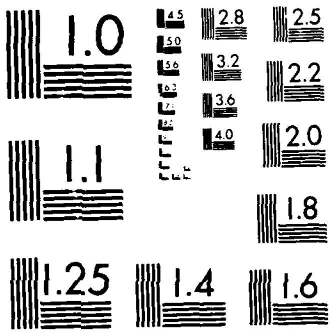
UNCLASSIFIED N00014-86-K-0041 F/G 12/6 NL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REPORT DOCUMENTATION PAGE — READ INSTRUCTIONS BEFORE COMPLETING FORM

1. REPORT NUMBER #45	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) STORING AND RETRIEVING DATA IN A PARALLEL DISTRIBUTED MEMORY SYSTEM (PH.D. THESIS)		5. TYPE OF REPORT & PERIOD COVERED TECHNICAL REPORT 6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s) Terry Wayne Potter		8. CONTRACT OR GRANT NUMBER(s) N00014-86-K-0041
9. PERFORMING ORGANIZATION NAME AND ADDRESS Center for Neural Science Brown University Providence, Rhode Island 02912		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS N-201-484
11. CONTROLLING OFFICE NAME AND ADDRESS Personnel and Training Rsch. Program Office of Naval Research, Code 442PT Arlington, Virginia 32217		12. REPORT DATE June 24, 1988 13. NUMBER OF PAGES 11 pages
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office)		15. SECURITY CLASS. (of this report) 15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

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17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

DTIC ELECTE JUL 0 1 1988 S D E

18. SUPPLEMENTARY NOTES

Ph.D. Thesis, State University of New York at Binghamton

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

Hopfield Model
Modified Energy Contour
Distributed Memory
Error Correction

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

The storage and retrieval of patterns in a Hopfield-like Parallel Distributed Memory is investigated experimentally with a view toward increasing its storage capacity. The first two Chapters give an overview of distributed memories and in particular the Hopfield distributed memory. This is followed by a Chapter which experimentally identifies the basic storage capacity of the original Hopfield memory when using text patterns.

The dissertation then experimentally investigates new and untested methods to

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S/N 0102-LF-014-6601

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

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20. ABSTRACT CONTINUED

increase the storage capabilities of a Hopfield-like neural net. Increasing the storage capacity by using the continuous-valued Hopfield memory is explored in Chapter 3 and the impact on capacity of data representation is experimentally investigated in Chapter 4. We then focus on new ways of storing data (changing the interconnect strengths) including in Chapter 7 developing a new method called Modifying the Energy Contour or MEC. In addition, this Chapter also outlines how to increase error-tolerance through the use of noisy patterns.

The Hopfield distributed memory is then contrasted to another intelligent memory subsystem based on more of a traditional computer technology. In Chapter 8 we see that traditional computer technology using data-parallel techniques has a greater storage efficiency than possible with current Hopfield-like distributed memories. The design of this data-parallel memory is based in part on what is learned experimentally from the preceding Chapters on the Hopfield-like distributed memory. This fast data-parallel approach also supports retrieval of data patterns with noisy inputs although it does not have all the functionality of the Hopfield-like distributed memory.

STORING & RETRIEVING DATA IN A PARALLEL DISTRIBUTED MEMORY SYSTEM

BY

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B.S., Math, Kent State University, 1970
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DISSERTATION

Submitted in partial fulfillment of the requirements for the degree
of Doctor of Philosophy in Advanced Technology
in the Graduate School of the
State University of New York
at Binghamton
1987

ABSTRACT

The storage and retrieval of patterns in a Hopfield-like Parallel Distributed Memory is investigated experimentally with a view toward increasing its storage capacity.

The first two Chapters give an overview of *distributed memories* and in particular the Hopfield distributed memory. This is followed by a Chapter which experimentally identifies the basic storage capacity of the original Hopfield memory when using text patterns.

This *dissertation* then experimentally investigates new and untested methods to increase the storage capabilities of a Hopfield-like neural net. Increasing the storage capacity by using the continuous-valued Hopfield memory is explored in Chapter 3 and the impact on capacity of data representation is experimentally investigated in Chapter 4. We then focus on new ways of storing data (changing the interconnect *strengths*) including in Chapter 7 developing a new method called Modifying the Energy Contour or *MEC*. In addition, this Chapter also outlines how to increase error-tolerance through the use of noisy patterns. [illegible] error correction (KR),

The Hopfield distributed memory is then contrasted to another intelligent memory subsystem based on more of a traditional computer technology. In Chapter 8 we see that traditional computer technology using data-parallel techniques has a greater storage efficiency than possible with current Hopfield-like distributed memories. The design of this data-parallel memory is based in part on what is learned experimentally from the preceding Chapters on the Hopfield-like distributed mem-

ory. This fast data-parallel approach also supports retrieval of data patterns with noisy inputs although it does not have all the functionality of the Hopfield-like distributed memory.

The following three results are the most significant outcomes of this dissertation. Experimentally, it was determined that:

- The Hopfield memory would support new methods for adaptation or learning of patterns and that recall was done by a parallel, nearest-neighbor pattern search procedure.
- The storage capacity of the Hopfield-like memory can be improved but the storage efficiency is far less than data-parallel based associative memories. In addition, experiments show that:
  - the way in which data is represented can greatly impact storage capacity and error-tolerance in Hopfield distributed memories,
  - a single layered fully connected Hopfield-like memory can have more than n stored stable states when using the *Modified Energy Contour* storage process to develop the interconnect *strenghts* (where n is the dimensionality of stored patterns), and
  - when storing 200 randomly generated 96-bit *balanced* coded patterns, 34% of the recall patterns with up to 5% error were still completely correctable when using the *MEC* process and training with noisy patterns.
- A data-parallel implementation of the Nearest-Neighbor Rule provides for fast parallel search of pattern space and can support software-based learning procedures. This implementation can then behave as a Parallel Associative Memory dealing with inexact data in the recall key.

ACKNOWLEDGEMENTS

I would like to acknowledge the many that have in one way or another played a significant role in the completion of this work. Probably most importantly is my family who contributed in ways they will never imagine.

Next, I would like to thank Dr. Cooper and his graduate students at the Neuroscience Lab at Brown University for the many hours of discussion about these neural models as well as for a quiet intellectual environment. In particular, I was helped by Chip Bachman who became very involved in looking at Hopfield's work as well as other models and provided an excellent bouncing board for ideas. This group is supported in part by the Office of Naval Research under contract N00014-86-K-0041 and the Army Research Office under contract DAAG-29-84-K-0262.

I would also like to thank Dr. James Anderson of the Cognitive Science Department at Brown for the many hours of discussions on how such Neural Models could be used. Another helpful individual at Brown, Dr. Stuart Geman who questioned how a more traditional Computer Science approach would compare to the Neural approach. This led to the development of Chapter 8 in this work.

Dr. Howard Pattee, a theoretical Biologist in the System Science Department at SUNY was co-chairman of my Dissertation committee. Dr. Pattee spent a great deal of time reviewing my work and becoming familiar with this field of Research. His influence has been significant. Thanks also to Dr. George Klir, Chairman of the System Science Department and co-chairman of my Dissertation committee, whose interest in the study of Systems allowed him the time to review and influence this work.

Dr. Robert Orchard, Chairman of the Computer Science Department at the

City University of New York acted as motivator and councelor. As a member of my Dissertation committee, he continued to help me keep focused on the objective and provided hours of review and comments.

I would also like to thanks the many students who I have introduced to neural models of associative memory over the years, expecially, Jim Hutchinson and Ruby Li from MIT, Stephen Smith from Cornell, Brian Nelson from the University of Lowell and a host of students from the Computer Science Department at the City University of New York. I would also like to thank Mike Hudak from SUNY-Binghamton, who asked a lot of good questions about the Hopfield memory.

Last but not least, I would like to thank Digital Equipment Corporation for its support of this work. In addition, several key people there and especially Gary Carpenter helped me obtain appropriate computational resources.

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