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OPTICAL NEURAL NETS FOR SCENE ANALYSIS

David Casasent (PI)
Carnegie Mellon University
Center for Excellence in Optical Data Processing
Department of Electrical and Computer Engineering
Pittsburgh, PA 15213
(412) 268-2464

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Date 25 Nov 90

D. Casasent(PI)

Semiannual Report (April-September 1990)

OPTICAL NEURAL NETS FOR SCENE ANALYSIS

1.2 APPROACH

Our approach is hybrid and multidisciplinary. We marry pattern recognition and neural net techniques. We also marry optical and digital technologies. A hybrid neural net thus results. We also concentrate on the use of one basic hybrid architecture that is useful for implementing various optimization and adaptive neural nets. Our work thus distinguishes between these two general classes of neural nets (optimization and adaptive) with both being realizable on the same basic hybrid architecture.

1.3 SUMMARY OF NEURAL NETS (NNs) CONSIDERED

The seven neural nets we have considered are now briefly summarized.

The input neurons to the production system NN are facts (antecedents and consequents). Objects and object parts are used in our initial work. Surface types for object parts (cylinder, sphere, valley, ridge, etc.) can also be used in future work. The objects are typical of those present in various scenes. The weights define the rules. These are initially posed as if-then statements, with all rules written as the AND of several antecedents and the OR of several such sets of antecedents. The output neurons that fire represent the new facts that are now learned to be true. As the system iterates, it learns new rules and infers new results on the present input data. We initially consider a propositional calculus system (with all parameters being exact terms) and then plan to address a predicate calculus system (with parameters being variables) that is much more powerful.

The E input neurons in our mixture NN each correspond to the fractional amounts of E elements present in a mixture of elements within one region of an input scene. The outputs from two matrix-vector multiplications are combined to form the new neuron states. After a number of iterations, the final neuron states denote the fractional amount of each element present in the input mixture.

The matrix inversion NN produces the inverse of a matrix that is given to the processor. To calculate the inverse $\underline{X}$ of a matrix $\underline{Q}$, we realize that $\underline{QX} = \underline{I}$. We formulate the solution (the elements of the inverse of Q) as the minimization of an energy function . We solve for the X that minimizes the energy function on a neural net. The matrix elements (weights) in this NN have an attractive block Toeplitz form and thus acousto-optic (AO) architectures should be very suitable for implementing this NN. This represents the first AO NN. Since matrix inversions are required in many pattern recognition linear discriminant function designs and in most adaptive algorithms, this NN should have general computational use in image processing (as well as in adaptive radar, control, etc.).

The cubic energy NN for MTT takes measurements on objects in each of three frames and it assigns one target per measurement and time frame. This is useful for time sequential scene analysis to associate objects (or object parts) in several time frames.

A-1

The quadratic energy MTT NN is a simplified version of the cubic energy NN. It processes pairs of time frames. The resultant optical architecture is much simpler than the cubic energy NN and significantly reduces component requirements.

The symbolic NN combines a symbolic correlator, production system NN, feature extractor and image processing NN. Its major advantage is the ability to process multiple objects in the field of view (this is achieved by the symbolic correlator). No other NN has this ability. It outputs a symbolic description of each region of the input that denotes which generic shapes are present and their location. These data are then symbolically encoded and fed to an NN. The NN is unique because of its symbolic input neuron representation. Alternatively, the locations of regions of interest in the input scene are used to guide the positioning of window functions (for segmentation) from which input features are extracted and subsequently fed to an NN for object classification. These NNs again combine pattern recognition and NN techniques.

The adaptive clustering NN is our major effort. The input neurons are features, the hidden layer neurons are prototypes of the various classes of objects and the output neurons denote the class of the input object. Clustering techniques are used to select the original hidden layer neurons (we allow several neurons or clusters per object class) and hence the initial input to hidden layer weights. These represent a set of linear discriminant functions (LDFs). The output neurons define the class of the input. The hidden to output layer weights map the clusters to classes. Our study of criterion functions determined the type of error function used to train the NN. Thus, advanced pattern recognition techniques are used to initialize the set of NN weights. A new adaptive NN learning algorithm is then used to refine and improve the initial weight estimates and to produce the LDF combinations that provide the nonlinear piecewise discriminant surfaces finally used. This is the adaptive learning stage. This new NN combines pattern recognition and NN techniques.

1.4 YEAR 1 SUMMARY

In Year 1 (April 1989 - March 1990), we advanced six new optimization neural nets (NNs). These include: a mixture NN (with an imaging spectrometer case study), a cubic energy multitarget tracking (MTT) NN, a quadratic energy MTT NN, a symbolic correlator NN, a production system NN, and a matrix inversion NN. We also advanced a new adaptive clustering neural net (ACNN).

We devised a hybrid optical/digital NN hardware architecture and began fabrication of it. It employs a digital HNC NN, and an optical NN with electronic support.

The key feature of this NN hardware is that it is multifunctional and able to realize all seven of our optimization and adaptive NNs.

2. YEAR 2 EFFORT (6 Month Summary)

2.1 YEAR 2 TASKS

The eight Year 2 tasks to be considered follow. These are briefly discussed in Section 2.2.

- **TASK 1:** Fabricate initial laboratory hardware system (film mask).
- **TASK 2:** Demonstrate initial laboratory hardware system for selected associative processor, optimization and our adaptive NNs.
- **TASK 3:** Perfect the new error diffusion computer generated hologram (CGH) interconnection concept.
- **TASK 4:** Address capacity and real time extensions of the laboratory NN.
- **TASK 5:** ACNN distortion-invariant feature space.
- **TASK 6:** ACNN extensions.
- **TASK 7:** New matrix inversion NN algorithm studies.
- **TASK 8:** New predicate calculus NN algorithm studies.

2.2 OVERVIEW

Tasks 1, 3, and 4 address the fabrication of our laboratory hardware. Task 1 refers to the initial system. Task 3 addresses the interconnection mask. Task 4 involves new components.

Task 2 considers laboratory demonstrations

Tasks 7 and 8 represent brief studies of 2 aspects (specific applications) of our ANN.

Tasks 5 and 6 consider the ACNN and are our major emphasis.

The thrust of our approach has been to assemble a multifunctional ANN (capable of solving a variety of NN problems). We have achieved this by simulation and have produced several laboratory examples.

2.3 FUTURE PLANS

This present approach results in a project with many aspects (many different ANNs) and many new NN algorithms. To provide more focus, our remaining Year 2 effort (and all of Year 3) will emphasize laboratory hardware and adaptive learning ANNs (the ACNN and variations of it).

2.4 PUBLICATIONS (DOCUMENTATION)

We have provided a plethora of papers on the various new aspects of our NN work. These are noted here, summarized in subsequent subsections with all references (papers) sent earlier.

Our multifunctional ANN [1] (Section 2.5) is hybrid optical/digital hardware and provides a system that solves all major types of ANN problems. Other optical NNs are not multifunctional.

The hardware for our system [2] (Section 2.6) is detailed (circa January 1990).

Most ANNs cannot accommodate multiple objects in the field of view. The Neocognitron cannot easily and cost-effectively achieve this [3]. Our symbolic correlator ANN (Section 2.7) can achieve this and is the most efficient type of ANN for this vital case. Its concept [4], simulation [5], and laboratory verification [6] have been obtained. This task has been terminated due to funding constraints.

Our associative processor (AP) ANN work resulted in a new H-K AP and robust versions of it [7]. These aspects are presently not being pursued under our DARPA contract, due to budget and research direction constraints (see Section 2.8).

Our optimization ANN work has resulted in new formulations of these NNs as a matrix times a vector plus a vector. In this area of ANNs, we have considered image spectrometry [2] and multitarget tracking ANNs, plus matrix-inversion ANNs. Our matrix-inversion ANN study resulted in <u>very new</u> and significant algorithms [8] that insure that an NN is used and that its number of computations is competitive with other techniques (Section 2.9).

Our ACNN work has involved 4 papers. These involved new feature spaces [9,10] (Section 2.10) and our ACNN algorithm [11,12] (Section 2.11). This algorithm removes ad hoc parameters present in most NNs and combines pattern recognition and neural net techniques with a vastly more efficient number of iterations resulting.

Our software now includes the calibration and control for our hybrid optical/digital NN (Section 2.12) and all input neuron representation spaces and classifiers plus our ACNN (Section 2.13).

Our new predicate calculus NN concepts have been advanced (Section 2.14) and placed on hold pending laboratory and ACNN results.

Our optical laboratory results on the initial laboratory system include new associative processors (with storage greater than any other associative processor) and multitarget tracker optimization ANN laboratory results [7] (Section 2.15).

2.5 MULTIFUNCTIONAL ANN [1]

Reference [1] details our architecture, how it combines optical and digital NN hardware, and how it allows solutions of all major NNs on one hybrid processor.

2.6 HYBRID OPTICAL/DIGITAL HARDWARE [2]

Reference [2] details our hybrid hardware. It consists of a digital NN interfaced to an optical NN with a control computer providing versatility.

2.7 SYMBOLIC CORRELATOR ANN [3,4,5,6]

This most unique ANN uses an optical correlator interfaced to a production system [4] ANN with symbolic encoded ANN inputs. For the specific case we considered, the multiple correlation filters were formed from generic object parts. We provided simulations [5] and laboratory [6] results. We also showed [3] how other ANNs (such as the Neocognitron) cannot easily address this problem of processing multiple objects in the field of view in parallel.

2.8 ASSOCIATIVE PROCESSOR ANNs [7]

We have developed new associative processor (AP) ANN algorithms with larger storage capacity than any other AP. We have also demonstrated their optical realization on our initial hardware [7].

2.9 OPTIMIZATION ANNs [7,8]

We have formulated new optimization ANN algorithms (matrix times vector plus vector) for 3 different optimization NNs. We have demonstrated the multitarget version of this new NN algorithm [7], analyzed an imaging spectrometer optimization NN [2], and developed new and practical matrix-inversion ANN algorithms [8].

2.10 ACNN FEATURE SPACES [9,10]

A new feature space NN input with reduced dimensionality and improved invariance and performance has been devised [9] and tested [10].

2.11 ACNN [11,12]

Our ACNN has been detailed and demonstrated [11,12]. It performs as well as the backpropagation ANN with no ad hoc parameters and with about 1000 times fewer iterations. It is characterized by the hybrid combination of pattern recognition and neural net techniques with new linear algebra algorithms used to provide better performance and convergence.

2.12 SOFTWARE SUPPORT (June 1990 Report)

The software support for our hybrid optical/digital NN has been produced and documented.

2.13 ALGORITHMS/TRAINING/FEATURE SPACES ON DIGITAL NN (October 1990 Report)

We have encoded all major feature space generation and our ACNN algori .m in digital NN hardware.

2.14 PREDICATE CALCULUS ANN (October 1990 Report)

This significant advancement to our original propositional calculus ANN has been detailed. The steps and remaining work in it have been described and new ideas generated. This task is presently on hold.

2.15 OPTICAL LABORATORY RESULTS [7]

These laboratory results on our initial laboratory system included our new associative processors (with larger storage than any other associative processor) and one of our new optimization NNs (for multitarget tracking).

PUBLISHED PAPERS

1. D. Casasent, "A Multi-Functional Hybrid Optical/Digital Neural Net", Proc. SPIE, Vol. 1294, pp. 31-41, April 1990.

2. D. Casasent and T. Slagle, "A Hybrid Optical/Digital Neural Network", Proc. SPIE, Vol. 1215, pp. 434-443, January 1990.

3. E. Barnard and D. Casasent, "Shift Invariance and the Neocognitron", Neural Networks, Vol. 3, No. 4, pp. 403-410.

4. E. Botha, D. Casasent and E. Barnard, "Optical Production Systems Using Neural Networks and Symbolic Substitution", Applied Optics, Vol. 27, pp. 5185-5193, 15 December 1988.

5. D. Casasent and E. Botha, "A Symbolic Neural Net Production System: Obstacle Avoidance, Navigation, Shift-Invariance and Multiple Objects", Proc. SPIE, Vol. 1195, pp. 280-290, November 1989.

6. D. Casasent, E. Botha, J.Y. Wang and R.C. Ye, "Optical Laboratory Realization of a Symbolic Production System", Proc. SPIE, Vol. 1295, pp. 199-210, April 1990.

7. S. Natarajan and D. Casasent, "Optical Test Results on the CMU Multifunctional Hybrid Optical/Digital Neural Network", Proc. SPIE, Vol. 1347, July 1990.

8. D. Casasent and J-S. Smokelin, "Analog Optical Matrix Inversion", Applied Optics, submitted September 1990.

9. E. Barnard and D. Casasent, "Trajectories and Constraint-Based Distortion-Invariance", Proc. SPIE, Vol. 1295, pp. 39-44, April 1990.

10. E. Barnard and D. Casasent, "Invariance and Neural Nets", IEEE Trans. on Neural Networks, submitted September 1990.

11. D. Casasent and E. Barnard, "Adaptive Clustering Optical Neural Net", Applied Optics, Vol. 29, pp. 2603-2615, 10 June 1990.

12. D. Casasent and E. Barnard, "Adaptive Clustering Neural Net for Piecewise Nonlinear Discriminant Surfaces", IJCNN'90 (*International Joint Conference on Neural Networks*), IEEE Catalog No. 90CH2879-5, June 1990, San Diego, Vol. I, pp. I-423 - I-428.

Carnegie Mellon

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Optical Data Processing
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Dr. Robert D. Burnham
Technical Director, Integrated Optoelectronics Devices Group
AMOCO Technology Company
AMOCO Research Center
Warrenville Road and Mill Street
P.O. Box 3011, F-4
Naperville, IL 60566

Dear Bob,

Things are really proceeding well here. There are 3 items that need immediate attention.

1. I don't have a new 1990-1991 consulting agreement effective 1 September 1990.
2. Don Holmgren and you have to make a choice on the LD focusing/collimation specs to aim for and the LDs to be used. This has to be done pretty soon We need the LD angle and spacing specs (we can't 1-D collimate the present 10 stripe array as the LDs are too close together, thus your IQ 1991 goal must change) especially for the 200 μm wide aperture LD array, and the entrance angle for the FO and crystal.
3. We need 10K to cover clean room etc. overruns we discussed and need a decision on (2) to proceed. When (2) is done, I can send you a new P.O. from my company for these CGHs.

As Always,

David Casasent
George Westinghouse Professor
Director, CEODP

cc: E. Schlesinger, CMU

DC:mjl
Encl.