

Applications of Artificial Neural Networks



73277003
A652

PROCEEDINGS
SPE—The International Society for Optical Engineering

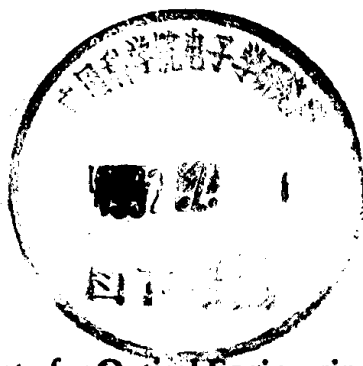
Applications of Artificial Neural Networks

Steven K. Rogers
Chair/Editor

18-20 April 1990
Orlando, Florida

Sponsored by
SPE—The International Society for Optical Engineering

Cooperating Organization
CREOL/University of Central Florida



Published by
SPE—The International Society for Optical Engineering
P.O. Box 10, Bellingham, Washington 98227-0010 USA



Volume 1294

9250099
SPE (The Society of Photo-Optical Instrumentation Engineers) is a nonprofit society dedicated to advancing engineering and scientific applications of optical, electro-optical, and optoelectronic instrumentation, systems, and technology.

9250099



2082/23

The papers appearing in this book comprise the proceedings of the meeting mentioned on the cover and title page. They reflect the authors' opinions and are published as presented and without change, in the interests of timely dissemination. Their inclusion in this publication does not necessarily constitute endorsement by the editors or by SPIE.

Please use the following format to cite material from this book:

Author(s), "Title of Paper," *Applications of Artificial Neural Networks*, Steven K. Rogers, Editor, Proc. SPIE 1294, page numbers (1990).

Library of Congress Catalog Card No. 90-52796
ISBN 0-8194-0345-8

Published by
SPIE—The International Society for Optical Engineering
P.O. Box 10, Bellingham, Washington 98227-0010 USA
Telephone 206/676-3290 (Pacific Time) • Fax 206/647-1445

Copyright © 1990, The Society of Photo-Optical Instrumentation Engineers.

Copying of material in this book for sale or for internal or personal use beyond the fair use provisions granted by the U.S. Copyright Law is subject to payment of copying fees. The Transactional Reporting Service base fee for this volume is \$2.00 per article and should be paid directly to Copyright Clearance Center, 27 Congress Street, Salem, MA 01970. For those organizations that have been granted a photocopy license by CCC, a separate system of payment has been arranged. The fee code for users of the Transactional Reporting Service is 0-8194-0345-8/90/\$2.00.

Individual readers of this book and nonprofit libraries acting for them are permitted to make fair use of the material in it, such as to copy an article for teaching or research, without payment of a fee. Republication or systematic or multiple reproduction of any material in this book (including abstracts) is prohibited except with the permission of SPIE and one of the authors.

Permission is granted to quote excerpts from articles in this book in other scientific or technical works with acknowledgment of the source, including the author's name, the title of the book, SPIE volume number, page number(s), and year. Reproduction of figures and tables is likewise permitted in other articles and books provided that the same acknowledgment of the source is printed with them, permission of one of the original authors is obtained, and notification is given to SPIE.

In the case of authors who are employees of the United States government, its contractors or grantees, SPIE recognizes the right of the United States government to retain a nonexclusive, royalty-free license to use the author's copyrighted article for United States government purposes.

Printed in the United States of America

APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS

Volume 1294

CONFERENCE COMMITTEE

Conference Chair

Steven K. Rogers, U.S. Air Force Institute of Technology

Cochairs

Gerard J. Montgomery, AbTech Corporation
Dennis W. Ruck, U.S. Air Force Institute of Technology
Patrick K. Simpson, General Dynamics Corporation
Barbara Yoon, Defense Advanced Research Projects Agency

Session Chairs

Session 1—Plenary Session

Steven K. Rogers, U.S. Air Force Institute of Technology

Session 2—Pattern Recognition I

Steven K. Rogers, U.S. Air Force Institute of Technology

Session 3—Pattern Recognition II

Steven K. Rogers, U.S. Air Force Institute of Technology

Session 4—Pattern Recognition III

Dennis W. Ruck, U.S. Air Force Institute of Technology

Session 5—Implementations

Dennis W. Ruck, U.S. Air Force Institute of Technology

Session 6—Neural Networks for Control

Dennis W. Ruck, U.S. Air Force Institute of Technology

Session 7—Novel Networks

Dennis W. Ruck, U.S. Air Force Institute of Technology

Session 8—Novel Neural Networks

Patrick K. Simpson, General Dynamics Corporation

Session 9—Special Applications

Patrick K. Simpson, General Dynamics Corporation

(continued)

APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS

Volume 1294

Session 10—Environments and Special Applications
Gerard J. Montgomery, AbTech Corporation

Session 11—Theory
Gerard J. Montgomery, AbTech Corporation

Conference 1294, *Applications of Artificial Neural Networks*, was part of a two-conference program on Optical/Neural Image and Information Processing held at the 1990 SPIE Technical Symposium on Optical Engineering and Photonics in Aerospace Sensing, 16-20 April 1990, in Orlando, Florida. The other conference was:

Conference 1296, *Advances in Optical Information Processing IV*.

Program Chair: **Anthony VanderLugt**, North Carolina State University

viii/ SPIE Vol. 1294 Applications of Artificial Neural Networks (1990)

INTRODUCTION

Welcome to SPIE's first conference on Applications of Artificial Neural Networks. This conference was conceived in 1989 as a logical outgrowth of the Applications of Artificial Intelligence Series. This meeting included one day of tutorials and sixty papers presented over three days.

The goal of this conference was to provide a forum for presentation and discussion of applications work. The focus was on high-quality applications work that clearly identifies contributions other applications engineers might be able to apply. The applications areas include image processing for object recognition, control, hardware implementations, defense applications, and development tools. There were also papers from academic researchers on algorithms and novel networks.

The conference will have a similar format next year. I would like to thank all of my cochairs, especially Dennis Ruck, who aided me greatly in the preparation of the technical program. I also wish to thank my wife/secretary, Debbie Rogers, whose administrative assistance assured the success of this conference.

Steven K. Rogers
U.S. Air Force Institute of Technology

APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS

Volume 1294

CONTENTS

	Conference Committee	vii
	Introduction	ix
SESSION 1	PLENARY SESSION	
1294-01	Artificial neural networks for automatic target recognition S. K. Rogers, D. W. Ruck, M. Kabrisky, G. L. Tarr, U.S. Air Force Institute of Technology.	2
1294-02	Adaptive inverse control B. Widrow, Stanford Univ.	13
1294-03	Theory of networks for learning B. Moore, Massachusetts Institute of Technology.	22
1294-04	Multifunctional hybrid optical/digital neural net D. P. Casasent, Carnegie Mellon Univ.	31
1294-05	Investigation of neural networks for F-16 fault diagnosis: II. System performance R. J. McDuff, P. K. Simpson, General Dynamics Corp.	42
1294-06	Abductive networks G. J. Montgomery, K. C. Drake, AbTech Corp.	56
1294-07	Neural network technology for automatic target recognition M. W. Roth, Johns Hopkins Univ.	65
1294-08	Neural network training using the bimodal optical computer M. A. Abushagur, A. M. Helaly, H. J. Caulfield, Univ. of Alabama in Huntsville.	77
SESSION 2	PATTERN RECOGNITION I	
1294-09	Neural networks in scene analysis C. Koutsougeras, H. S. Barad, A. B. Martinez, Tulane Univ.	86
1294-10	Target recognition in parallel networks R. Raghavan, F. W. Adams, Jr., H. T. Nguyen, Lockheed Missiles and Space Co., Inc.	94
1294-11	Neural network target tracker C. Narathong, Univ. of Wisconsin/Platteville; R. M. Inigo, Univ. of Virginia.	110
1294-12	Segmentation using neural networks for automatic thresholding A. V. Scherf, G. A. Roberts, Ford Aerospace Corp.	118
1294-13	Position-invariant target detection by a neural net J. P. Davis, W. A. Schmidt, Naval Air Development Ctr.	125
SESSION 3	PATTERN RECOGNITION II	
1294-14	Machine recognition of atomic and molecular species using artificial neural networks A. L. Sumner, S. K. Rogers, G. L. Tarr, M. Kabrisky, D. Norman, U.S. Air Force Institute of Technology.	138
1294-15	Application of neural networks to pattern recognition problems in remote sensing and medical imagery J. Parikh, J. S. DaPonte, Southern Connecticut State Univ.; M. Damodaran, P. Sherman, Univ. of Bridgeport.	146

(continued)

APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS

Volume 1294

1294-16	Enhanced neural net learning algorithms for classification problems B. Aazhang, Rice Univ.; T. F. Henson, IBM Corp.	161
1294-17	Neural networks with optical-correlation inputs for recognizing rotated targets S. C. Gustafson, D. L. Flannery, D. M. Simon, Univ. of Dayton Research Institute.	171
1294-18	Multispectral-image fusion using neural networks J. H. Kagel, C. A. Platt, T. W. Donaven, E. A. Samstad, McDonnell Douglas Electronic Systems Co.	180
1294-19	Region growing and object classification using a neural network P. T. Gaughan, G. M. Flachs, New Mexico State Univ.	187
SESSION 4 PATTERN RECOGNITION III		
1294-20	Radar classification using a neural network G. B. Willson, HRB Systems, Inc.	200
1294-21	Radar-warning-receiver emitter-identification processing utilizing artificial neural networks I. L. Howitt, Georgia Tech Research Institute.	211
1294-22	Comparison of two neural net classifiers to a quadratic classifier for millimeter-wave radar J. R. Brown, M. R. Bower, H. E. Beck, S. J. Archer, Martin Marietta Corp.	217
1294-23	Automatic description of the Gulf Stream from IR images using neural networks M. Lybanon, Naval Oceanographic and Atmospheric Research Lab.; E. Molinelli, M. Flanigan, Planning Systems Inc.	225
1294-24	Infrared target motion estimation using a neural network R. A. Samy, Société Anonyme des Télécommunications (France).	238
SESSION 5 IMPLEMENTATIONS		
1294-26	Analog hardware implementation of neocognitron networks R. M. Iñigo, A. Bonde, Jr., B. Holcombe, Univ. of Virginia.	248
1294-27	Application of the Lockheed programmable analog neural network breadboard to the real-time adaptive mirror control problem W. A. Fisher, R. Fujimoto, J. R. Roehrig, R. C. Smithson, Lockheed Palo Alto Research Lab.	260
1294-28	Multidimensional Kohonen net on a HyperCube B. A. Conway, M. Kabrisky, S. K. Rogers, G. B. Lamont, U.S. Air Force Institute of Technology.	269
1294-29	Application of a neural network model to sensor data fusion G. Whittington, T. Spracklen, Univ. of Aberdeen (UK).	276
1294-30	Optimization of magneto-optical spatial light modulators for neural networks V. I. Chani, General Physics Institute (USSR); A. Y. Chervonenkis, N. N. Kiryukhin, Scientific and Research Ctr. of Physics and Technology (USSR).	284
SESSION 6 NEURAL NETWORKS FOR CONTROL		
1294-31	Can robots learn like people do? S. H. Lane, D. A. Handelman, J. J. Gelfand, Princeton Univ.	296
1294-32	DC motor speed control using neural networks H. Tai, J. Wang, K. Ashenayi, Univ. of Tulsa.	310
1294-34	Payload-invariant servo control using artificial neural networks M. A. Johnson, M. B. Leahy, Jr., S. K. Rogers, U.S. Air Force Institute of Technology.	319

APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS

Volume 1294

1294-35	Feasibility of automating printed circuit board assembly using artificial neural networks C. H. Dagli, M. Vellanki, Univ. of Missouri/Rolla.	331
SESSION 7 NOVEL NETWORKS		
1294-36	Applications of probabilistic neural networks D. F. Specht, Lockheed Palo Alto Research Lab.	344
1294-37	Improved probabilistic neural network and its performance relative to other models J. B. Cain, Harris Corp.	354
1294-38	Use of probabilistic neural networks for emitter correlation P. S. Maloney, Lockheed Missiles & Space Co., Inc.	366
1294-39	Neural hypercolumn architecture for the preprocessing of radiographic weld images A. Gaillard, D. C. Wunsch II, R. A. Escobedo, Boeing Co.	378
1294-40	Neural network for interpolation and extrapolation S. C. Gustafson, G. R. Little, D. M. Simon, Univ. of Dayton Research Institute.	389
1294-41	Implementation of the Hopfield model with excitatory and inhibitory synapses and static thresholding A. J. Breese, J. MacDonald, Univ. of Reading (UK).	396
SESSION 8 NOVEL NEURAL NETWORKS		
1294-42	Knowledge-base browsing: an application of hybrid distributed/local connectionist networks T. Sanjadh, Honeywell, Inc.; P. Israel, Tulane Univ.	404
1294-43	Predicate calculus for an architecture of multiple neural networks R. H. Consoli, GTE Government Systems Corp.	416
1294-44	Novel geometrical supervised-learning scheme C. J. Hu, Southern Illinois Univ.	426
1294-45	Multiple neural network approaches to clinical expert systems D. F. Stubbs, Upjohn Co.	433
1294-46	Modular neural networks and distributed adaptive search for traveling salesman algorithms K. E. Nygard, N. Kadaba, North Dakota State Univ.	442
SESSION 9 SPECIAL APPLICATIONS		
1294-47	Abductive networks applied to electronic combat G. J. Montgomery, P. Hess, AbTech Corp.; J. S. Hwang, Wright Research and Development Ctr. ...	454
1294-48	Applications of neural nets to munition systems K. Min, H. L. Min, U.S. Air Force Armament Lab.	466
1294-49	Self-training inspection system for the on-line inspection of printed material H. E. Beck, Martin Marietta Corp.; D. W. McDonald, Oak Ridge National Lab.; D. Brzakovic, Univ. of Tennessee/Knoxville.	478
1294-50	Sensor calibration methods: performance study O. Masory, A. L. Aguirre, Florida Atlantic Univ.	490
1294-51	Neural network application to error control coding M. Hussain, J. Song, J. S. Bedi, Wayne State Univ.	502
1294-52	High-order neural models for error-correcting code C. Jeffries, Clemson Univ.; P. Proetzl, NASA/Langley Research Ctr.	510

(continued)

APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS

Volume 1294

1294-63	Optical multistage networks with reversible nonlinear devices R. Golshan, J. S. Bedi, Wayne State Univ.	518
SESSION 10	ENVIRONMENTS AND SPECIAL APPLICATIONS	
1294-53	AFIT neural network development tools and techniques for modeling artificial neural networks G. L. Tarr, D. W. Ruck, S. K. Rogers, M. Kabrisky, U.S. Air Force Institute of Technology.	524
1294-54	Neural network simulation environment A. Zell, T. Korb, T. Sommer, R. Bayer, Univ. Stuttgart (FRG).	535
1294-55	Classification of acoustic-emission waveforms for nondestructive evaluation using neural networks R. S. Barga, M. A. Friesel, R. B. Melton, Battelle/Pacific Northwest Lab.	545
1294-56	Comparison of Mahalanobis distance, polynomial, and neural net classifiers J. H. Hughen, K. R. Hollon, D. C. Lai, Martin Marietta Corp.	557
1294-57	Exploration of temporal processing of a sequential network for speech parameter estimation H. Ye, ICP/Univ. Stendhal (France); S. Wang, TIM3 (France); G. Bailly, ICP/Univ. Stendhal (France); F. Robert, TIM3 (France).	570
SESSION 11	THEORY	
1294-58	Classification power of multiple-layer artificial neural networks E. R. McCurley, K. R. Miller, R. Shonkwiler, Georgia Institute of Technology.	577
1294-59	Uncertainty computations in neural networks L. S. Hsu, H. H. Teh, S. C. Chan, K. F. Loe, National Univ. of Singapore (Singapore).	588
1294-60	Removing and adding network connections with recursive-error-minimization equations W. E. Simon, J. R. Carter, Martin Marietta Astronautics Group.	600
1294-61	Statistical learning from nonrecurrent experience with discrete input variables and recursive-error-minimization equations J. R. Carter, W. E. Simon, Martin Marietta Astronautics Group.	607
1294-62	Monte Carlo learning algorithm for clipped neural networks W. Huang, Y. Zhang, Nankai Univ. (China).	612
	Addendum.	617
	Author Index.	618

APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS

Volume 1294

SESSION 1

Plenary Session

Chair

Steven K. Rogers

U.S. Air Force Institute of Technology

9250099

ARTIFICIAL NEURAL NETWORKS FOR AUTOMATIC TARGET RECOGNITION

Steven K. Rogers

Dennis W. Ruck

Matthew Kabrisky

Gregory L. Tarr

Department of Electrical and Computer Engineering

Air Force Institute of Technology

AFIT/ENG, Wright-Patterson AFB, OH 45433

Published in Proceedings of SPIE Conference on Applications of Artificial Neural Networks, Orlando, Florida April 1990 (Paper Number 1294-01)

Abstract

This paper will review recent advances in the applications of artificial neural network technology to problems in automatic target recognition. The application of feedforward networks for segmentation, feature extraction, and classification of targets in Forward Looking Infrared (FLIR) and laser radar range scenes will be presented. Biologically inspired Gabor functions will be shown to be a viable alternative to heuristic image processing techniques for segmentation. The use of local transforms, such as the Gabor transform, fed into a feedforward network is proposed as an architecture for neural based segmentation. Techniques for classification of segmented blobs will be reviewed along with neural network procedures for determining relevant features. A brief review of previous work on comparing neural network based classifiers to conventional Bayesian and K-nearest neighbor techniques will be presented. Results from testing several alternative learning algorithms for these neural network classifiers are presented. A technique for fusing information from multiple sensors using neural networks is presented and conclusions are made.

1 Introduction

Autonomous object recognition is an active area of interest for military and commercial applications. The Air Force Institute of Technology (AFIT) has been researching this area for the past twenty-five years. This paper reports on the recent work in the application of artificial neural network technology to problems in automatic target recognition (ATR). Given an input image from an infra-red or range sensor, the problem is to find interesting objects in those images and then classify those objects according to their type. For example, to find the tanks, trucks and jeeps as opposed to rocks, trees and hills. This is sometimes called the target/non-target problem. More specific classification problems, where targets types must be determined will also be considered. This problem is related to the general purpose robotic vision problem, but without the common constraints, such as controlled range, light or even aspect, available to those systems. Throughout this paper results are presented as found using a neural network development environment. This environment is the subject of a companion paper and was found to be critical to advances in artificial neural network applications to the target recognition problem. The system allows the display of the images and the workings of the networks to educate the users and allow creative insights to the workings of the system for subsequent modifications. The next section will address segmentation of images followed by a discussion of feature extraction. Classification alternatives are then presented followed by a neural network sensor fusion system. Experimental results and conclusions are presented. The authors do not necessarily feel that ATR systems must be all neural networks, but can in fact be hybrid systems with existing or other emerging technologies combined to make an automatic target recognizer. With this philosophy many of the neural network results will be shown wedged in between other technologies. The hope is to find the advantages/disadvantages of artificial neural networks in an ATR system.

2 Segmentation

Visual cortex, area 17 or sometimes called V1, can be modeled as a multiple image display screen which contains many images. In V1 there are the color images of the world, so called RGB images, texture images and also motion maps. Using these multiple cues, mammals can segment the world. We will ignore arguments that some mammals don't have color vision, such as dogs, since the argument is basically a matter of degree. A reasonable quality color system seems to have been retrofitted onto the lower mammal visual system for primates. It should be noted that many infra-primates have better color systems than we do. In either case the use of color, texture and motion to find lumps in the world is a cue that automatic target recognition systems should heed. For now let's restrict our attention to the texture analysis system. In the section on fusion, ideas that have an obvious relation to using multiple colors will be presented as well as ideas on how to combine these multiple views into a single or multiple competing hypotheses.

The texture map can be modeled as a Gabor function. Figure 1 shows some examples of Gabor functions. The reason some people believe that the cortical texture map can be modeled as a Gabor representation is because experiments have shown the receptive fields match to a high degree an appropriate parameterized Gabor function [4]. This work is not in complete disagreement with the earlier work of Hubel and Wiesel which proposed the existence of bar detectors [3]. At a recent neural network conference, IJCNN 90, Hubel still insisted that the appropriate model was bar-detectors and not smoothed bars as could be explained with Gabor functions. The use of Hough transform techniques which can be thought of as breaking the image up into its component bars is also being investigated and will be reported on separately in an article on processing synthetic aperture radar images. Let's return to the idea of a Gabor function as a model of how a neuron's receptive field is modulated. If these Gabor functions are correlated with an input image, the pixels in the resulting correlation image are a measure of the similarity of that part of the image with that Gabor function. If the output images from these correlations are then combined, a segmented image results. Figure 2 shows an example FLIR scene and the result of correlating four Gabor functions with that scene and then adding the resulting correlation images and thresholded. This is the simplest of the ideas of combining these correlation images. We have also tested a gating idea where only the maximum amplitude pixel from all of the correlations is maintained in the output image. The figure clearly shows this technique can segment blobs from the original FLIR image. Figure 3 shows a similar FLIR image segmented using conventional image processing techniques that work on the histogram of the pixel values. The quality of the segmentation is similar with the advantage going to the artificial neural network solution for ease of implementation and execution speed. Specifically, the Gabor transform can be implemented in an artificial neural network [1] or even in an optical system [8] which might be called an optical neural network.

As a side point many current researchers are developing front end vision systems that purport to model biological vision systems. It seems that a driving factor in this research is the ability of these models to reproduce common illusions. In the early 1960's Kabrisky proposed using low frequency Fourier transforms for understanding much of human visual information processing [5]. It was later shown by one of his students that common illusions could be explained with this Fourier model [2]. Recent work at AFIT has shown that the Gabor transform can also account for these common illusions [6]. Much of the rationale of these systems is to faithfully reproduce the type of processing that is going on in animals. For example, at a recent conference it was said that animal visual systems must be able to complete partially occluded boundaries because in the retina the light gets blocked by the blood vessels and interconnections of neurons prior to detection by the rods and the cones at the back of the eye. This logic shows a fundamental misunderstanding of how the visual system works. All static information is lost in the transmission of the image information back to the cortex. Anything frozen in the image, external or internal to the eye, is not mapped onto the cortex. Saccadic movements prevent external objects from being frozen in the image unless some perverted measures are taken by an experimental psychologist in order to study vision. The bottom line is even if such a phenomenon were going on in the visual system, why should an artificial system incorporate processing which by these researchers own arguments only exists to

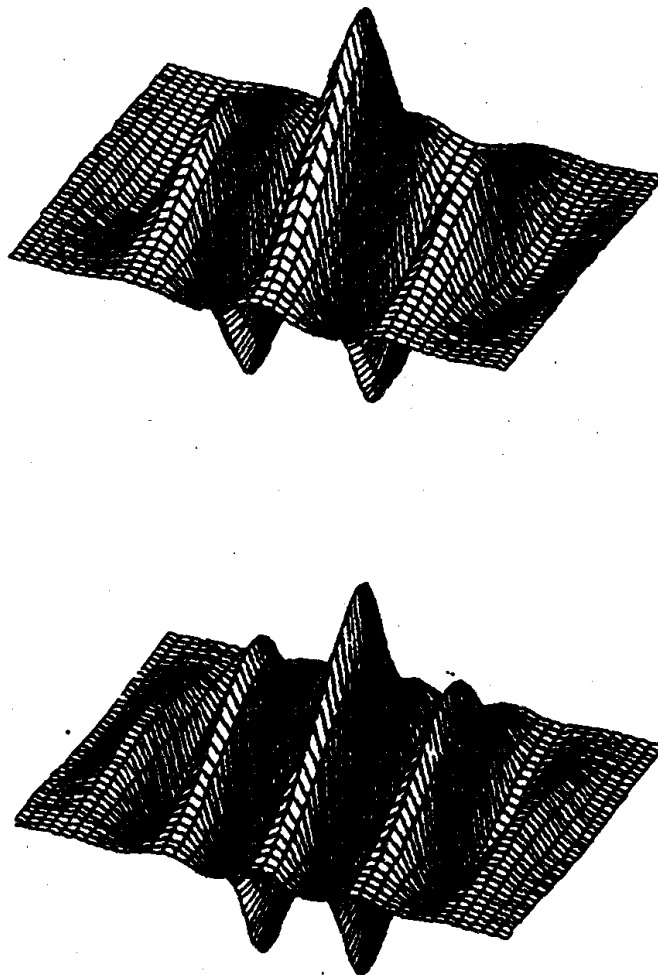


Figure 1: Gabor Function Examples

overcome the present implementation in the wetware?

Let's continue our design of the general purpose front end system. Implementing these local transforms in neural networks, either Gabors or Fourier or even Houghs, some means of determining whether the local area should pass a segmentation step must be accomplished. We propose a system that would take the transform information from little local windows and feed that information into a feedforward network. This network could be either an unsupervised or a supervised network. In the unsupervised case lots of images are passed through the system and the nodes organize to respond according to the density of the input in the transform spaces used. A subsequent calibration of the self-organized network could determine the classification of the nodes as representing regions that should pass the segmentation step. Currently we are testing our variations of the Kohonen Learning Vector Quantization techniques.

For the supervised network case, the local transform information is fed to a network along with a user classification of that region of the input image. By the supervisor feeding enough data through the network it should converge, learning to discriminate regions of interest from similar images. Techniques to determine which of the transforms are important to the segmentation process can be determined either after the training or during learning [9].

3 Feature Extraction

As the old adage goes, Good Features make Good Recognizers. This is true whether your recognizer is using an artificial network or whether it is using some statistical based decision mechanism. The purpose of this section is to demonstrate that from a set of features input to either a conventional or a neural

11 + 01250 0

Table 1: FLIR Features Evaluated

Feature	Description
Complexity	Ratio of points given to total object pixels
Contrast	Ratio of object to background
Length	Ratio of maximum brightness to total object pixels
Width	Ratio of number of pixels in object to number of pixels in background

Figure 2: Original FLIR and Gabor Segmentation

Table 2: Ranking of FLIR Features

Feature	Rank	Importance Measure Rank
Complexity	1	1
Length/Width	2	2
Mean Contrast	3	3
Maximum Brightness	4	4
Contrast Ratio	5	5
Difference of Means	6	6
Standard Deviation	7	7

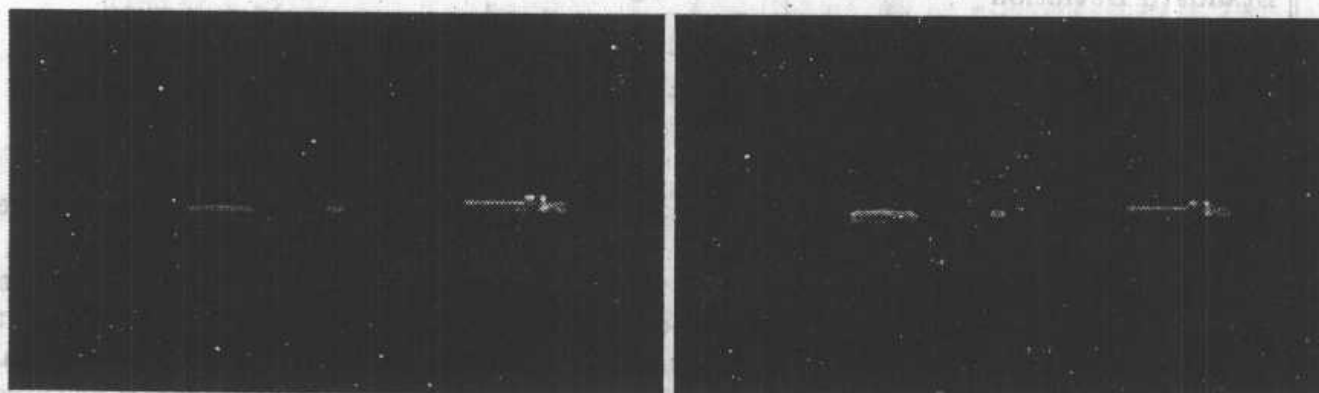


Figure 3: Conventional Heuristic Segmentation

Table 1: FLIR Features Evaluated

Feature	Description
Complexity	Ratio of border pixels to total object pixels
Length/Width	Ratio of object length to width
Mean Contrast	Contrast ratio of object's mean to local background mean
Maximum Brightness	Maximum brightness on object
Contrast Ratio	Contrast ratio of object's highest pixel to its lowest
Difference of Means	Difference of object and local background means
Standard Deviation	Standard deviation of pixel values on object
Ratio Bright Pixels/Total Pixels	Ratio of number of pixels on object within 10% of maximum brightness to total object pixels
Compactness	Ratio of number of pixels on object to number of pixels in rectangle which bounds object

Table 2: Ranking of FLIR Features

Feature	P_e Criterion Rank	Saliency Measure Rank
Complexity	8	8
Length/Width	7	7
Mean Contrast	6	3
Maximum Brightness	5	2
Contrast Ratio	4	4
Difference of Means	3	6
Standard Deviation	2	5
Ratio Bright Pixels/Total Pixels	1	0
Compactness	0	1

network based recognizer the same level of accuracies can be obtained and in fact the features are used in a similar manner.

The last statement should be qualified somewhat. If we use a conventional statistical based classification criterion, such as Bayesian, then some determination can be made on how important each of the input features are to reducing the probability of error. Specifically, using the set of features in Table 1, and ranking those features by individually testing the probability of error if only that feature is used, the features are ordered as shown. The question becomes when these same features are used by an artificial neural network for classification which are the important features. By using a simple definition for saliency, or importance, of a given feature we have shown that the artificial neural network finds basically the same importance of features [9]. The determination of the importance of a given feature turns out to be independent of the network starting conditions and consistent with the order of importance determined by the minimum probability of error used to rank importance by the Bayesian technique. Table 2 shows the features used for a FLIR classification problem and the order of importance as determined by the statistical approach and the artificial neural network classifier.

Further testing using only the most important features for classification demonstrated that these are

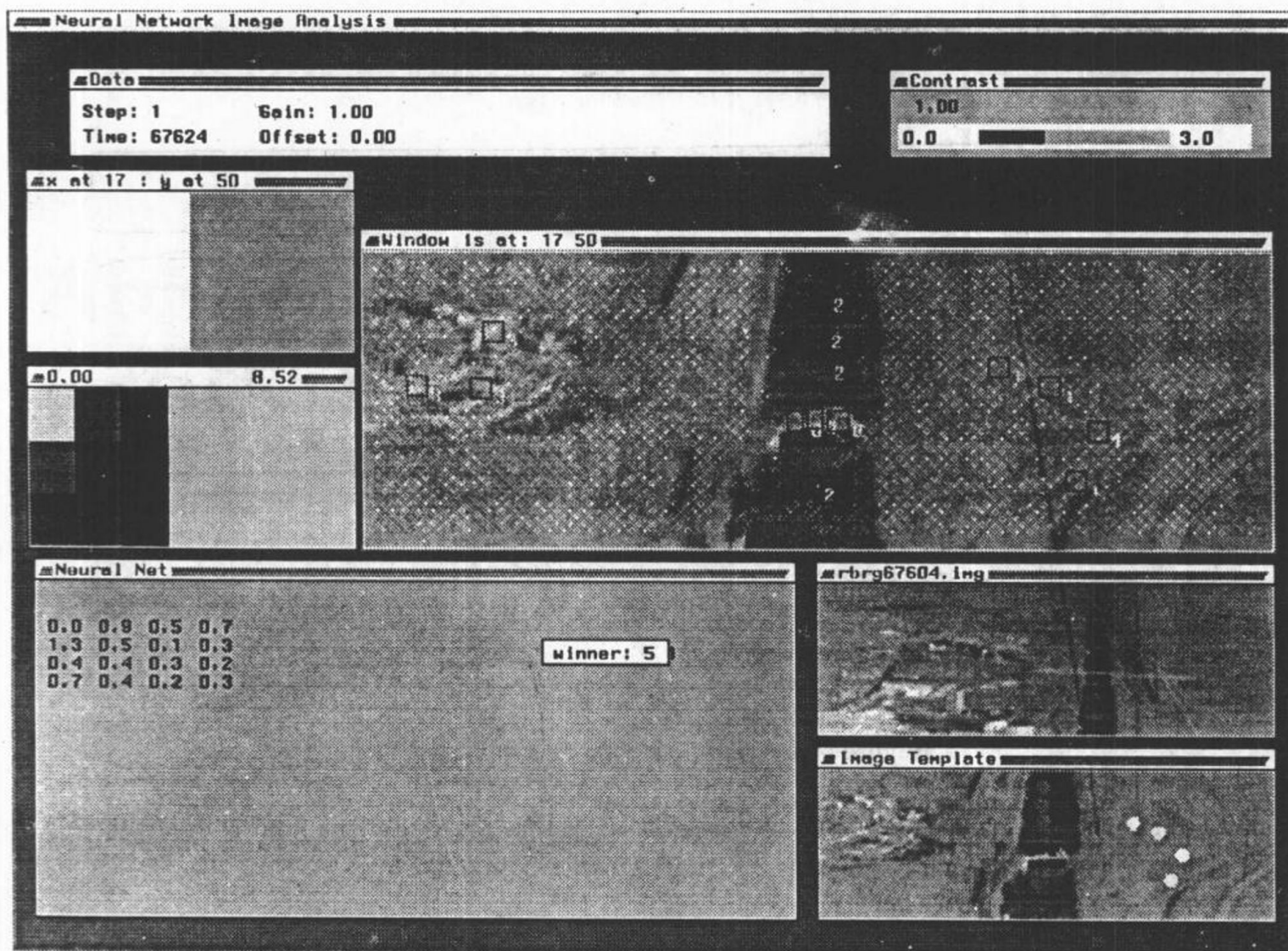


Figure 4: Neural Segmentation/Feature Extraction

in fact the important features. It also demonstrated that irrelevant of which variation of training rule that was used to learn, the same relative order of importance was found. Variations of the training rules is discussed in the next section. Even though the investigation that demonstrated the importance of the features to an artificial neural network was conducted after training, the technique could be incorporated during learning to automatically structure the network including the number of inputs.

The features shown above came from conventional techniques of identification of objects. These features were extracted with conventional image processing algorithms. Could a neural network be used on the front end to process the incoming image and automatically extract the features as well as segment? Since in the first section we proposed a neural based segmentation using the local transforms that could be implemented in artificial neural networks, could these coefficients then be used for classification by either a neural network or conventional classifier? Research into using the byproducts of the neural based segmentation, the local transform coefficients, can now be conducted since we can now determine which of the features, the coefficients, are important for classification via our saliency metric. An early version of that type of system is demonstrated below in Figure 4.

In Figure 4 a FLIR scene is shown with small boxes that represent areas where some teacher has denoted classification for segmentation. The system then computes local transforms, Hough/Fourier/Gabor, and a network determines which type of area is in that region of the picture. In the development system a color