Applications of Artificial Neural Networks

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Applications of Artificial Neural Networks

Steven K. Rogers
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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

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SESSION 1

Plenary Session

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ARTIFICIAL NEURAL NETWORKS FOR AUTOMATIC TARGET RECOGNITION

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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. Sacadic 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

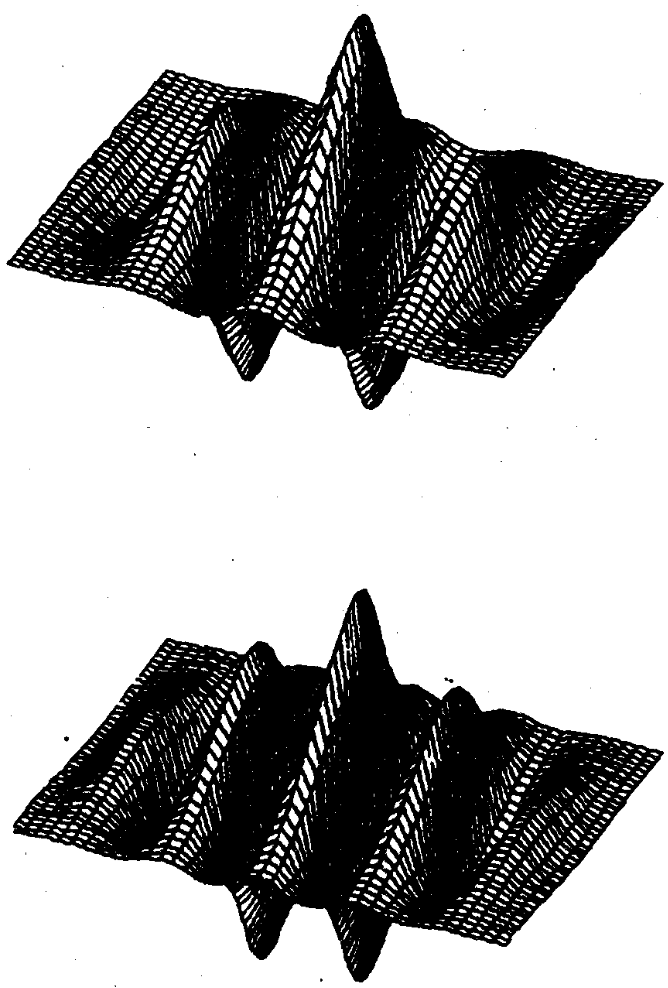

Figure 1: Gabor Function Examples

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 Recongizers. 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

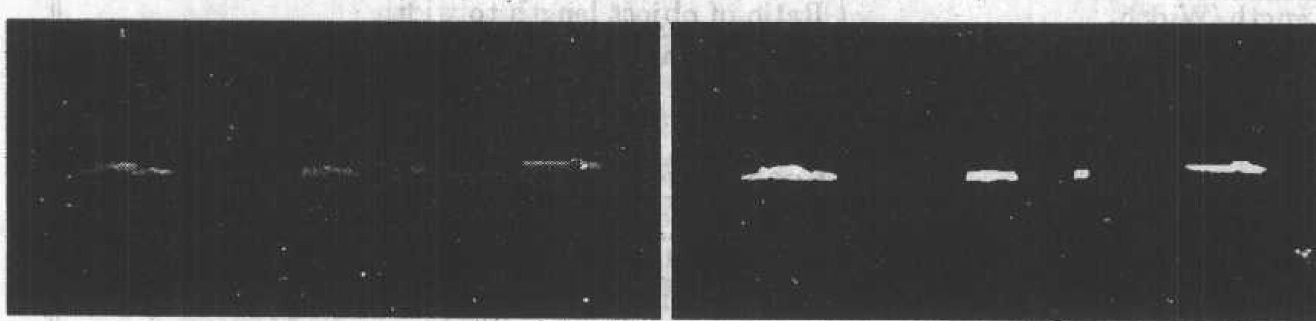

Figure 2: Original FLIR and Gabor Segmentation

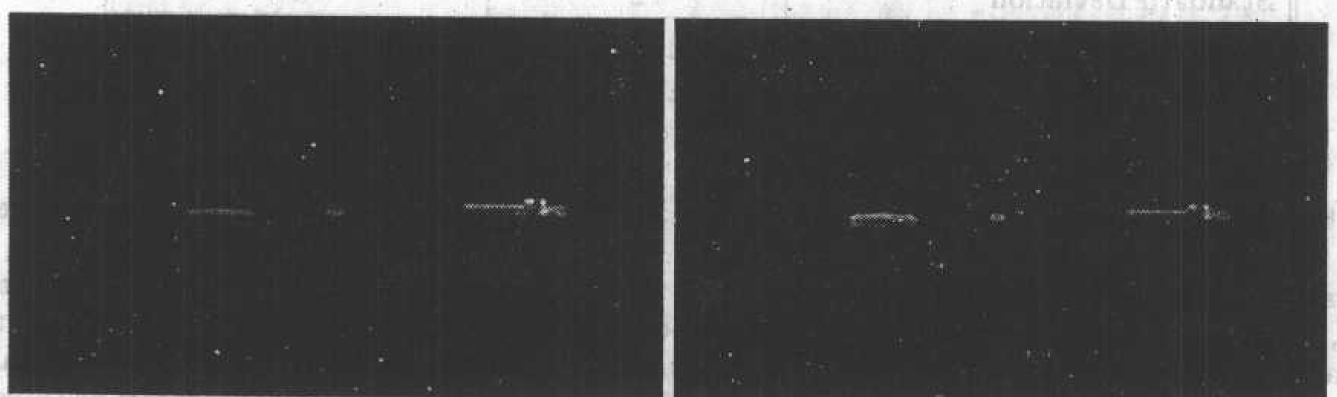

Figure 3: Conventional Heuristic Segmentation

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

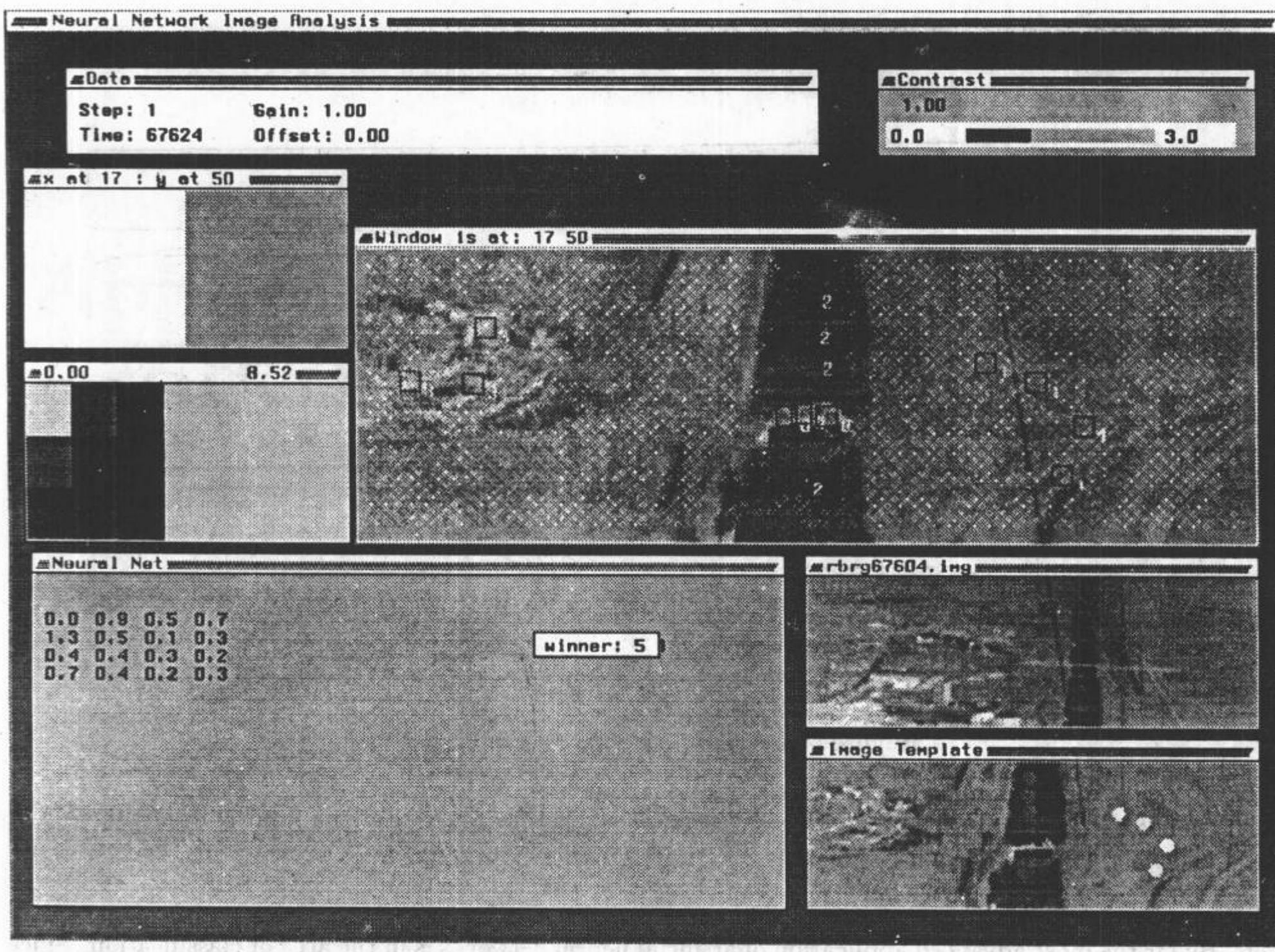

Figure 4: Neural Segmentation/Feature Extraction

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

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