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NEURAL NETWORKS FOR AUTOMATIC TARGET RECOGNITION

Developments in neural network technology have provided several tools that can be used to solve the problem of automatic target recognition. Those tools include collective computation for implementing a variety of computational vision techniques, learning and adaptation for pattern recognition, knowledge integration for expert-system capabilities, and hardware beyond the supercomputer level. This article summarizes some of APL's contributions and continuing efforts.

INTRODUCTION

Automatic target recognition (ATR) is the process of recognizing high-value targets in noisy environments and discriminating them from low-value objects and false alarms. The problem is challenging and has significant potential applications for the national defense. An example of a possible application is an infrared or radar system for recognizing tanks, ships, or airplanes. Although significant progress has been made toward ATR, substantial developments are still needed to make it operationally usable.

Neural networks represent a developing technology that can provide solutions to a wide variety of scientific and engineering problems involving extraction of useful information from complex and uncertain data.[1] The approach uses the massively parallel distributed-processing capabilities of computational hardware that can now be realized. Neural networks are models and algorithms that can be simulated on conventional computers but are best implemented on special-purpose computational hardware known as neurocomputers.

Neural networks and neurocomputers are radical departures from traditional digital computer algorithms and architectures. They are "neuron-inspired," using processing elements that mimic some of the properties of biological nervous systems. Neural networks do not accurately simulate real neurons; instead, they approximate the useful computational properties exhibited by biological nervous systems. The result is that neural networks exhibit characteristics not readily available in other types of systems.

Researchers at APL have been applying neural network technology to the ATR problem, with both application-oriented studies and theoretical and hardware developments. This article presents a brief summary of APL's contributions and continuing efforts.

ISSUES, NEEDS, AND NEURAL NETWORK TOOLS

One issue with current ATR systems is their high false-alarm rates, which is influenced by the high variability of target signatures and backgrounds that results from effects such as variation in illumination and aspect angles. Other important effects, primarily for ground targets, include occlusion (one target behind another) and obscuration (a target behind an environmental object).

A framework (Fig. 1) has been developed showing how neural network technology can provide several significant tools that can be directly applied to the ATR problem.[2] Automatic target recognition needs methods for representing targets and backgrounds that are sufficiently descriptive yet resistant to variations in signature and environment. Neural networks offer powerful collective computation techniques for implementing special-purpose hardware that can achieve fast optimization for several potential computational vision and multisensor fusion methods. It must be able to adapt to additional targets and environments. The existence of powerful learning algorithms is one of the main strengths of the neural network approach. Systems for ATR need to construct a compact set of maximally discriminating target features. Several techniques inspired by neural networks can be used for the selection or development of such a feature set. Finally, effective ATR performance can be enhanced if *a priori* knowledge about target signatures and backgrounds is used. Although previous techniques for integrating diverse forms of knowledge were limited, neural network technology provides expert-system capabilities for automatic integration.

One technique for achieving robust representations of signatures and backgrounds is to estimate geometric shapes accurately. The geometric shape of an object is invariant with respect to lighting variations and is also invariant with respect to aspect angle if the object is rotated to a coordinate system corresponding to the same aspect angle. One way of estimating geometric shape from image data is to perform stereopsis (estimation of depth information from images of the same scene taken at two or more aspect angles). We are examining this approach.

Figure 2 shows a binocular stereo displacement map that was produced using model images[3] and the Drumheller–Poggio stereo algorithm[4] on the Connec-

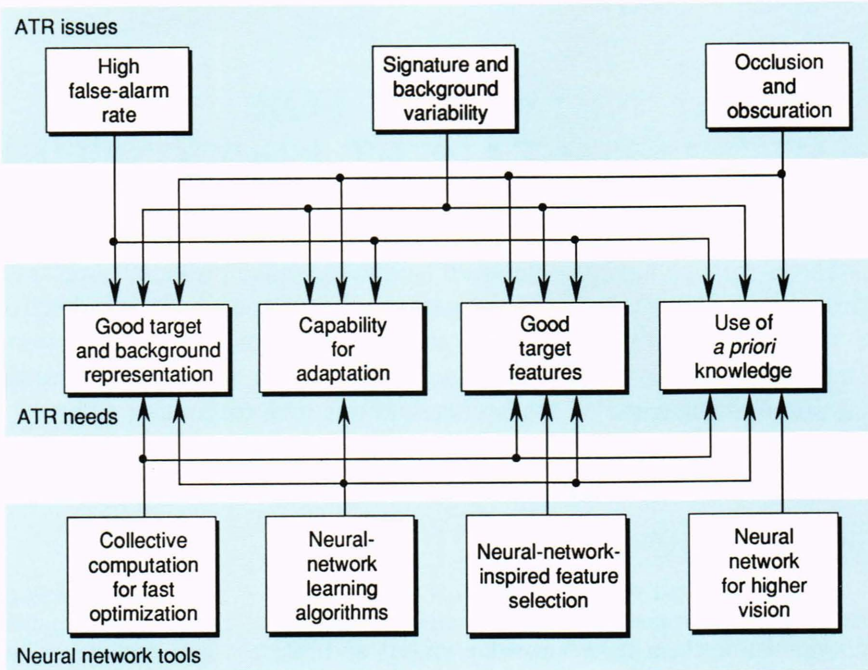

Figure 1. Critical ATR issues. Neural network technology can provide a variety of tools to meet the needs of the ATR problem. See text for discussion.

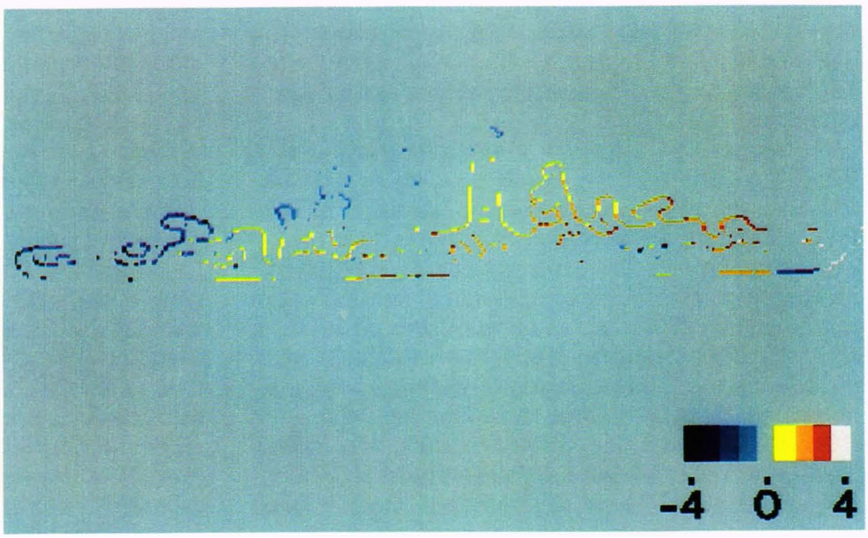

Figure 2. Example of preliminary stereo calculations on the Connection Machine. The original stereo pair consisted of images of ship models at 75° and 85° aspect angles. The displacement map shown is the amount (in pixels) that one image is displaced from the other at isolated features. If the remaining displacement map can be filled in, detailed three-dimensional shape data can be calculated. Implementation of algorithms producing improved displacement maps is in progress.

tion Machine at the Naval Research Laboratory.[5] The figure was computed by first taking the digitized images of a ship model viewed at two different aspect angles (75° and 85°). The depth of an object in the image is estimated by matching features from the object, calculating the relative displacement between them, and then computing the depth to the features. The algorithm used detected edges as features. The figure shows the displacement in pixels from the edges in one image to the matched edges in the other image in false-color coding, which explains why the maximum displacements occur at the bow and the stern of the ship model. Although the features are relatively sparse, techniques exist for filling in objects where there are no features (i.e., using Markov random fields). We are working on the development of such improved techniques. Although this approach of calculating geometrical shape is computationally intensive, the potential of neurocomputer hardware to implement such calculations as neural-network collective computations implies that the neural network approach could lead to real-time implementations.

Neural network learning could facilitate two main advances for ATR: automatic knowledge acquisition and continuous system refinement. The use of learning in system construction would save the user from spending the enormous amount of time necessary to derive rule-based databases for targets and environments. System refinement could then be incorporated to make necessary changes that would improve the performance of the recognition system. These two modifications alone could significantly advance the present abilities of ATR systems.

While at APL, Fernando J. Pineda developed an important learning algorithm for recursive neural networks.[6] Since stereo algorithms can be implemented by recursive neural networks, Pineda's algorithm provides a means for learning the parameters from examples. The algorithm has already been demonstrated for random-dot stereograms.[7]

Selection of appropriate target features is one of the most important tasks for ATR algorithm development. It is impractical to match a given input image (or image representation) with the image templates of all possible targets and their variations. Therefore, it is necessary to find a compact set of features that can represent the critical aspects of a target. The selection of the feature set is linked to the classification task because the feature set must be complete enough to discriminate targets from nontargets. Features that are invariant with respect to target and environmental variations (e.g., translation, rotation, scale, context) are of more interest than noninvariant features. Neural network technology can simplify feature selection in several ways.

Neural networks can use optimum feature receivers to extract weak features from high-clutter environments.[8] In general, detection devices must set high thresholds to achieve a reasonable false-alarm rate; this is especially true for environments where the clutter distributions have long tails, such as those produced by radar at low elevation angles. The problem with setting a high threshold to cut down on false alarms is that small and medium-size features can go undetected. A previously impractical idea for solving this problem was to use a large bank of matched filters to cover the feature variations. Because neural network hardware is precisely designed to use massively parallel computations, it offers new opportunities for such previously impractical ideas. In particular, a recursive neural network can make an optimum post-detection target feature receiver possible. Simulations have shown that considerable (more than 12 dB) improvement in the signal-to-noise ratio can be achieved.

Previously, it was believed that neural networks could implement only limited kinds of feature detectors. Although feedforward neural networks can perform several computationally significant operations, some computational operations cannot be performed by a feedforward network with a finite number of layers. An example of such an operation is the determination of whether a given figure is connected. Such a restriction, however, does not apply to recursive or feedback networks. In particular, a three-layer network with two recursive layers can compute the connectedness of a figure.[1]

Neural networks can contribute to the generation of expert systems for higher vision computations because they can automatically integrate a diverse set of features. *A priori* knowledge may suggest that a specific set of diverse features (i.e., size, Fourier-polar coefficients, presence of hot spots, etc.) is important for the classification problem. There is a significant problem of combining such diverse features into an effective classifier, however, especially when there is no obvious metric available. Neural-network learning algorithms, combined with appropriate training sets, can be an effective way to integrate automatically such diverse features into a classification system.[9] Analysis of the resulting neural network weights can then determine whether a particular feature has effectively participated in the classification task.[10] Otherwise, it can be removed without loss of overall performance.

Neural network models and algorithms are computationally intensive on general-purpose computers. Because of the computational simplicity of the basic processing element, however, neural networks can be implemented on special-purpose massively parallel hardware that can vastly outperform implementations on even the most powerful serial computers. Consequently, several groups are developing such special-purpose neurocomputer hardware for neural network applications. Such neurocomputers have been an essential ingredient for the development of practical applications of neural network technology. The ATR problem also requires that computational hardware be configurable into a reasonably compact volume. Several research efforts on neural network hardware promise to provide both high performance and compact design.[11] For example, a very large scale integration (VLSI) chip has been developed to implement the previously described technique for extracting weak features in high clutter environments; wafer-scale designs are in progress.[12]

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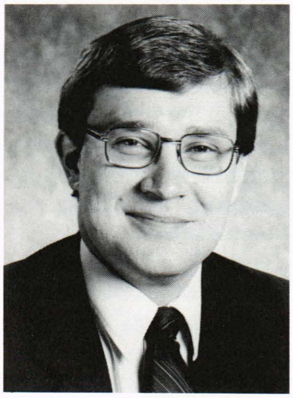

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