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SIGNAL PROCESSING FOR MISSILE GUIDANCE: PROSPECTS FOR THE FUTURE

The future of missile guidance will depend heavily on signal processing technology. Expected mission requirements will demand autonomous weapons. APL has set the pace for developments in this area, taking the approach that missiles must use image-based signal processing and intelligent sensors. Current missile-guidance functions such as detection and tracking of point targets already have been developed successfully. New signal processing developments must meet new system requirements to resolve accurately the location and physical structure of targets. These processors also must decide what action to take on the basis of target identification. We present in this article two advanced concepts under investigation at APL that promise to support future missile-guidance needs.

INTRODUCTION

Of the many missions using guided missiles, those that have been the focus of work at APL include anti-surface, anti-air, and land-strike warfare. We emphasize in this article the anti-surface mission, and particularly the anti-ship role.

In anti-surface warfare, the prototypical scheme is represented by the "war-at-sea" engagement concept, in which the missile encounters a variety of surface combatants and must select a high-value target from less important ones. Although this is a relatively small "closed-set" classification problem, it is surprisingly difficult. Natural and man-made signal degradations together require sophisticated seeker processing. For radar sensors, target motion and aspect changes are unpredictable. For imaging infrared sensors, signal degradation results from inherently low target contrast, which varies with target thermal signature, and from atmospheric propagation loss, which increases with range. These are the classical problems frequently faced by weapon system developers.

Figure 1 shows the most important signal processing subsystems of a generic, advanced missile-guidance system. The sensor suite can be a radio-frequency imaging

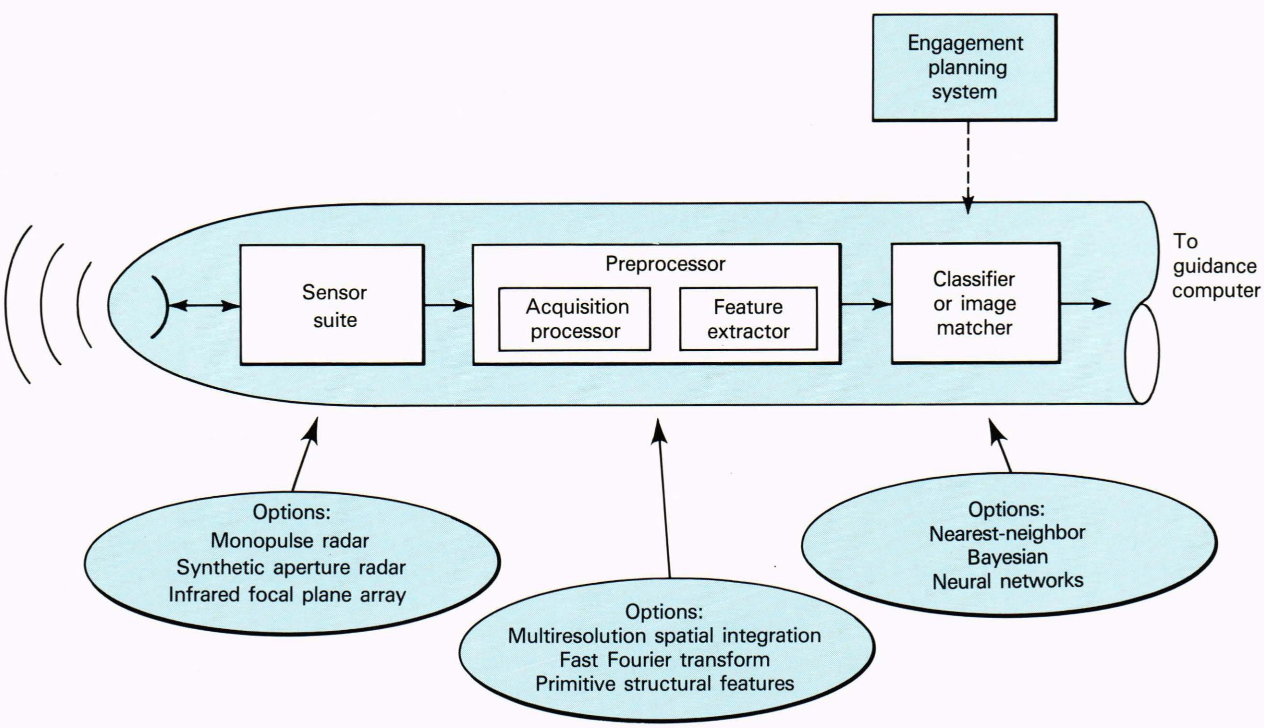

Figure 1—Signal processing subsystems for advanced anti-ship missile guidance.

radar (e.g., monopulse and synthetic aperture radar), an imaging infrared (or optical) focal plane array, or a combination of both. Other key subsystems are the preprocessor—which usually performs signal conditioning and feature extraction or segmentation—and the classifier. Important adjuncts to the system include a post-processor for decision integration and a physically separate engagement (or mission) planning system that includes a mechanism for generating reference data for classification. Preprocessor architectures are more likely to be parallel, classifiers sequential, and post-processors symbolic.

We present below two representative examples of advanced signal and image processing algorithms for missile guidance. A new approach to ship recognition now being applied to monopulse radar-derived range profiles will be described. Here, we focus on neural-network-based classification algorithms. In the area of electro-optical systems, we present a multiresolution spatial integration technique for extended target detection and segmentation applicable to imaging infrared seekers.

NEURAL-NETWORK-BASED TARGET RECOGNITION ALGORITHMS

Current anti-ship missile seekers use conventional (real-beam) monopulse radar, which yields range profiles (i.e., one-dimensional functions of target radar cross-section versus range). At longer ranges, inverse synthetic aperture radar can be used for stand-off ship classification, but its imagery varies considerably over successive looks, producing various perspectives such as plan and side views. Future anti-ship missile seekers may use synthetic aperture radar or monopulse imaging to generate ship images, which essentially are plan views of the radar-scatterer distribution of the illuminated targets. Using any of these sensor options, we envision the need for target recognition in future anti-ship missiles.

For survivability, total look time required for imaging and recognition always is limited to durations on the order of the motion cycle of the targets. During terminal engagement, radical changes in missile–target geometry also occur, and missile ingress relative to target bearing varies unpredictably from mission to mission. Thus, target signatures presented to a typical anti-ship missile will vary considerably. Classifier performance, therefore, must be robust, and the training of such classifiers must include representative looks. APL has developed a systematic methodology[1] for classifier training that incorporates various databases (both measured and synthetic) and several feature extraction and classification algorithms, including traditional (statistical) and neural-network-based algorithms.

When using radar-range profiles, the performance of conventional classifiers degrades substantially at the broadside aspect or near-broadside, since range-only profiles (having relatively low spatial resolution) will have few range cells on ship targets, especially at broadside. Sensitivity to target aspect can be determined by training a given classifier at a particular aspect and then testing it within an angular sector spanning the training point. The larger the angular sector over which the probability of correct classification remains high ($\geq 90\%$), the better the performance. Also, there will be less data to store in the missile-guidance computer memory for real-time operation. Increased classifier robustness versus aspect, therefore, translates into less training data and smaller computer memory needs. Neural networks offer the hope that greater robustness can be achieved.

During times of signal acquisition, targets exhibit varying signatures. For real-beam radar, which provides range profiles, the time interval over which signatures must be collected to achieve an adequate signal-to-noise ratio for classification (≥ 20 dB) is usually well below 1 s. But over longer, multilook intervals (>10 s) required, for example, for decision integration, variation of the range-profile structure can be substantial, as shown in Fig. 2. For synthetic aperture radar, image frame times are on the order of 1 s, but then target motion may blur the detailed radar cross-section structure of the desired target. Also, look times for inverse synthetic aperture radar required to capture the best representative image of a target can easily be 10 s or more. An effective classifier should accommodate these changes in target signature for any possible seeker type within the appropriate look time, without substantial performance degradation. Hence, the features chosen to enable classification (i.e., the input to the classifier) should always be separable in feature space so that the output decision can be made with a high degree of confidence.

Optimization of classifier performance is an important design goal. Performance depends on the spatial resolution of the sensor, the features extracted from the signatures, the mathematical structure of the classifier, and the type of decision-integration scheme used. Performance versus resolution is particularly important to target aspect when using range-only profiles. For feature extraction, Fourier harmonics of the range profile are typically used, since they reveal how rapidly the radar cross section of the target varies and which spectral components of the radar are dominant. For neural networks, optimizing the network structure in terms of the learning algorithm (e.g., backpropagation, as described below) and the number of connections is also important. Optimization with respect to the choice of a decision-integration rule is desirable when considering long dwells on the intended target. By integrating sequential output decisions, greater confidence can be achieved.

Neural Network Algorithms

The neural network approach is based on a metaphor of the information processing capacity of the human brain (see the articles by Roth and Jenkins elsewhere in this issue). Among the many options in neural networks, APL is focusing on the multilayer perceptron, or backpropagation-based algorithm.[2] Although such algorithms take longer to train, the time to classify is relatively short. This represents a significant tactical advantage for a missile having little time to classify multiple targets in a typical war-at-sea scenario. (For current missile-engagement planning, which occurs before mis-

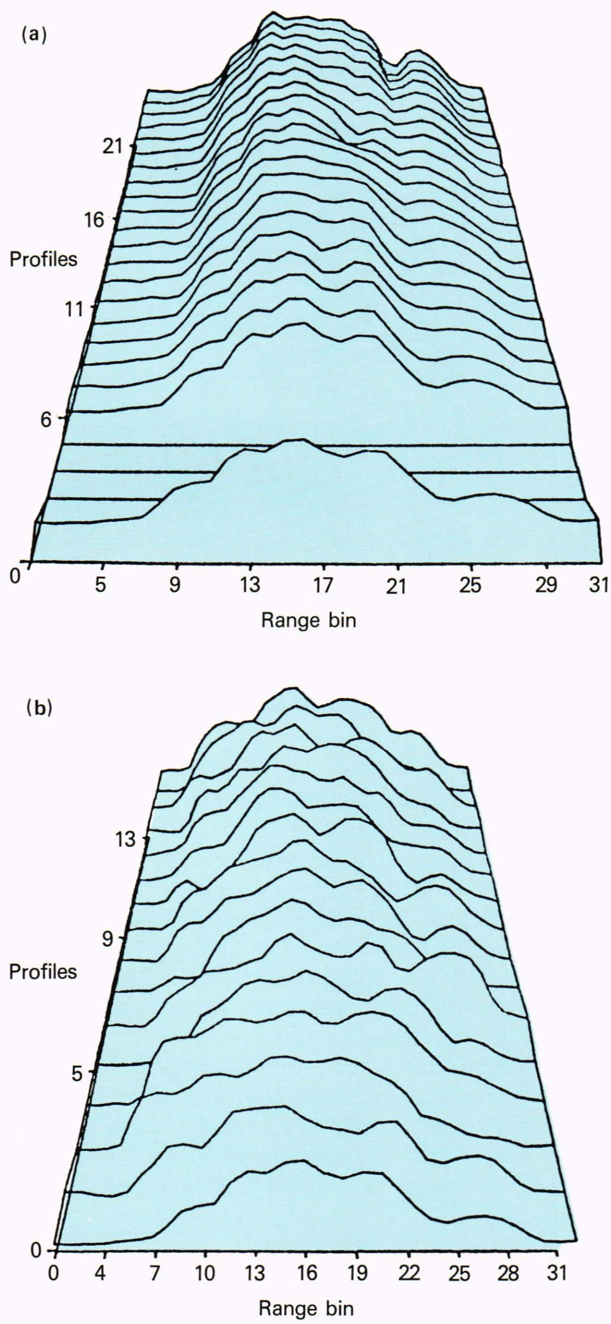

Figure 2—The variation of radar-range profiles for durations of (a) 100 ms and (b) 16 s.

sile launch, the longer time required for training is acceptable.) Classification time is short for backpropagation because the algorithm requires only one pass to classify, rather than an iteration required by other types (e.g., the Hopfield net).[3]

The implementation of a multilayer perceptron via backpropagation for the recognition of ship radar signatures is shown in Fig. 3. A received ship signature is conditioned, digitized, and fast-Fourier-transformed. The first few harmonics of the transform are chosen on the basis of the sensor resolution and signal-to-noise ratio. The number of input layers to the perceptron equals the number of harmonics. The hidden layer typically will have three times the number of nodes of the input layer, enough to allow for effective separation of the classes in feature space. The number of output nodes corresponds to the number of classes. The connections between nodes are weighted. At each node, a summation of the weighted inputs is subjected to a sigmoidal nonlinearity. During training, the weights are adapted using a heuristic rule derived from the classical Widrow–Hoff technique,[4] and the weight changes are updated, working backward from the output layer to the input layer. Subsequently, when classification occurs in real time on board the missile, the particular output node corresponding to the input class will be activated.

Comparisons of Classifier Performance

When comparing neural network classifiers with conventional ones, it is important to consider a given neural net algorithm with its appropriate conventional counterpart. Lippman suggests that the single-layer perceptron is analogous to the Bayesian classifier, and the multilayer perceptron is analogous to the k-nearest-neighbor classifier.[5] Thus, Bayesian and k-nearest-neighbor classifiers become the natural baseline with which to compare neural network classifiers. Not surprisingly, most previous efforts have been devoted to training and testing Bayesian and k-nearest-neighbor algorithms.

Classifiers traditionally are evaluated on the basis of a single-look probability of correct classification, a number derived from a "confusion matrix," for example,

$$
\begin{array}{cc}
 & \text{Testing target} \\
 & \begin{array}{ccc} 1 & 2 & 3 \end{array} \\
\text{Training target}\;\begin{array}{c} 1 \\ 2 \\ 3 \end{array} & \begin{bmatrix} P_{11} & P_{12} & P_{13} \\ P_{21} & P_{22} & P_{23} \\ P_{31} & P_{32} & P_{33} \end{bmatrix}
\end{array}
$$

This matrix contains the probabilities of correctly classifying (P_{ii}) and misclassifying (P_{ij}, $i \neq j$) a set of targets. Obviously, we desire unity diagonal terms (correct decisions) and zero off-diagonal terms (incorrect decisions) with high confidence. In practice, we must maximize the trace of the matrix and minimize the sum of all off-diagonal terms. A range of cost functions might weight off-diagonal terms differently, depending on the particular situation. Presently, we cannot assign an appropriate weighting for the off-diagonal terms. The average probability of correct classification is, therefore, the only measure of effectiveness. More importantly, for comparing algorithm performance, the average probability of correct classification should attenuate as distance from the training point increases. This attenuation function may be more gradual for neural networks than for conventional classifiers.

Typical radar-range profiles for a decommissioned U.S. naval combatant are displayed in Fig. 2, and a representative set of features is shown as an input to the

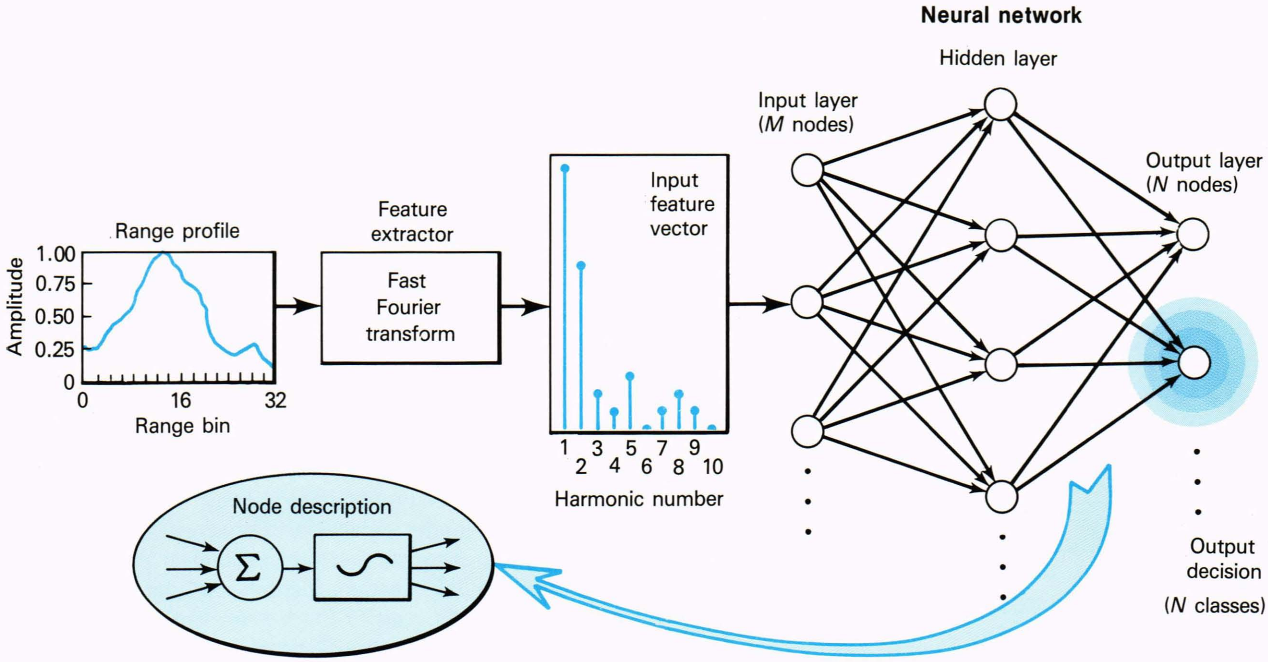

Figure 3—Information processing flow, showing range profile, feature extraction, and neural network architecture.

schematic of the neural network of Fig. 3. When this and several other combatants are used for training and testing, the average probability of correct classification is derived from the single-look confusion matrices. Results for Bayesian, nearest-neighbor, and backpropagation-based algorithms at various aspects are then compared, and the degradation of those single-look results versus distance from the training point is determined. Those results suggest that neural networks may perform very well in some cases, but we cannot draw any firm conclusions, because the algorithm, features, and decision-integration rule have not been optimized.

The algorithms described above have been applied to a very limited closed-set classification problem, so more extensive data sets must be used for training. One approach for generating such data sets (now undergoing validation at APL) is a synthetic radar-signatures simulation model developed by Georgia Tech Research Institute.[6] With such a tool, we can accomplish extensive optimization of classical as well as neural network algorithms. These algorithms also can be extended to synthetic aperture radar, inverse synthetic aperture radar, and monopulse imaging radar.

EXTENDED TARGET DETECTION AND SEGMENTATION

In addition to radio-frequency seekers, infrared seekers are being considered for current and future missile-guidance roles. Expected missions include both anti-surface and land-strike warfare.

Advantages of infrared technology for anti-ship missile application include passive operation, good resistance to jamming, and high spatial resolution. The need for the latter follows from potential operational requirements for target classification; assuming an adequate signal-to-noise ratio (*S/N*), high classification accuracy requires high spatial resolution, whether the imagery is interpreted by a human[7] or processed by a computer.[8] Perhaps the key drawback of infrared anti-ship missile seekers is limited range performance under conditions of poor atmospheric visibility. The purpose of the signal processor described below[9] is to optimize the detection range of infrared sensors against ship targets.

The single-frame signal processing approach we have developed for maximizing infrared sensor *S/N* is complementary to earlier approaches for *S/N* optimizations, such as waveband optimization, advanced infrared detector developments, and multiframe image processing.

Human Vision System Model

The idea for our new signal processing concept was anticipated by a brief study indicating that detection ranges obtained by human observers of visual displays could, under a broad variety of conditions, greatly exceed ranges obtained by a hot-spot detection algorithm. Thus, the predicted performance of an archetypal human observer became the standard against which to gauge the performance of proposed ship-detection algorithms.

Seeker spatial resolution, or "pixel size," is important in determining both acquisition range against ship targets and classification accuracy. The *S/N* (and, hence, detection range) is maximized by matching the pixel size to the target size. But high classification accuracy (assuming an adequate signal-to-noise ratio) requires making the pixel size much smaller than the target size. If the pixel size is chosen to maximize detection range, the resolution will be inadequate for classification; if the pixel size is made as small as possible to facilitate accurate classification, the initial detection range will be very poor. Clearly, spatial resolution requirements for detection are in conflict with those for classification.

These conflicting requirements have been resolved by image processing methods based on a model of the human vision system that in the past has been used widely by electro-optics engineers to predict the performance of human operators of thermal imaging equipment and televisions.[7] The model comprises an infinite-dimensional bank of spatial filters, with each filter in the array corresponding to a possible target shape. Every possible shape is represented in the filter bank, as well as all variants of each shape obtainable by the processes of translation, rotation, and scaling.

Although the original human vision system model (Fig. 4) is not directly amenable to digital realization, APL developed a suboptimal image processing architecture called the multiresolution spatial integrator (MRSI), which approximates the human vision system in performing detections of targets seen against uncomplicated (uncluttered) backgrounds, such as those likely to occur at sea.[10]

MRSI Performance

Like the human vision system model that preceded it, the MRSI detection algorithm comprises a bank of spatial filters tuned for maximum response to objects of various sizes and shapes. Recalling that the human model is infinite-dimensional, and, therefore, nonrealizable, a key challenge in designing the MRSI was to achieve detection performance comparable to the human system, with a low-dimensional filter bank.

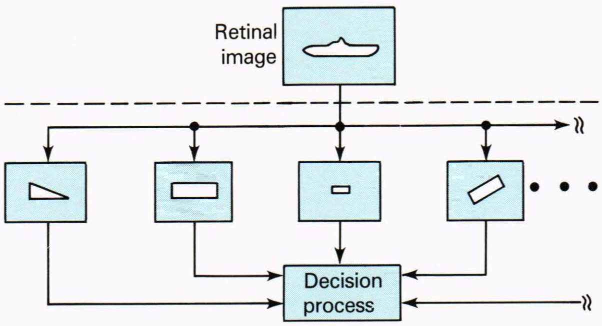

Figure 4—A conceptual model of the human vision system detection process, based on an infinite-dimensional array of spatial matched filters.

Since the noise-reducing characteristics of MRSI processing are generally impossible to calculate analytically, a computer program was developed for numerically evaluating the effectiveness of the processor.

Initial computer simulations used measured ship imagery as input. The results were very encouraging (e.g., Fig. 5) but not always easy to interpret, since the ship images were recorded under uncertain conditions. Most calculations were performed subsequently using artificial black/white silhouettes,[8] which, while deficient in certain real-world characteristics, were obtained under completely controlled conditions.

The probability of detection (P_D) versus S/N for three ship profiles was determined using computer simulation. We found that the S/N improvement provided by MRSI processing can be estimated as $G = 0.8\sqrt{A}$,

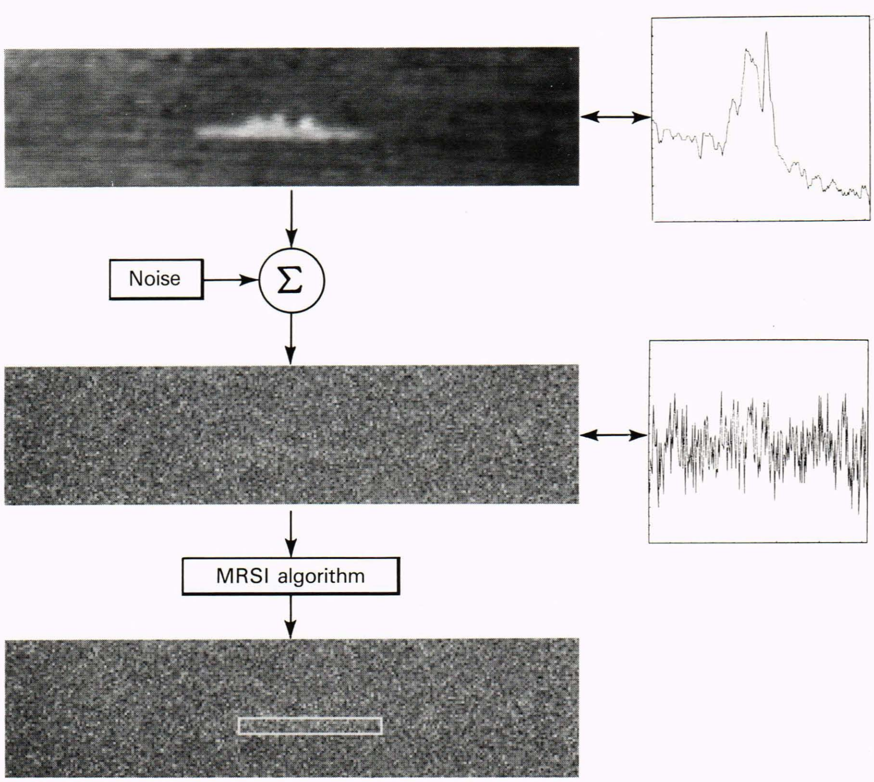

Figure 5—Initial qualitative evidence of correct simulation performance. A measured ship image with high S/N (top) was degraded to $S/N = 0.2$ (center) to simulate observation in a less favorable atmosphere. To the right of these images are scan lines obtained at the elevation indicated by the horizontal arrows. The degraded image (bottom) was input to FORTRAN simulation, and the ship was subsequently detected and sized (range to ship = 13.5 nmi).

where A is the area of the target (in pixels). Our main results are shown in Fig. 6 as plots of P_D versus S/N_{det}, where $S/N_{det} = G\ S/N$.

The symbols on Fig. 6 were obtained from our computer simulations of the MRSI processor; the curve is an analytical fit to experimental psychovisual data[7] (i.e., experiments performed with human operators of television displays). We see from this figure that MRSI performance is nearly invariant with aspect angle and in close agreement with the psychovisual data.

Experiments applying the MRSI iteratively suggest that multiple passes through the algorithm result in the extraction of a series of rectangles that may be assembled into a ship-like composite (Fig. 7). A simple classification algorithm can then help to ensure against false alarms induced by cloud reflections from the sea.

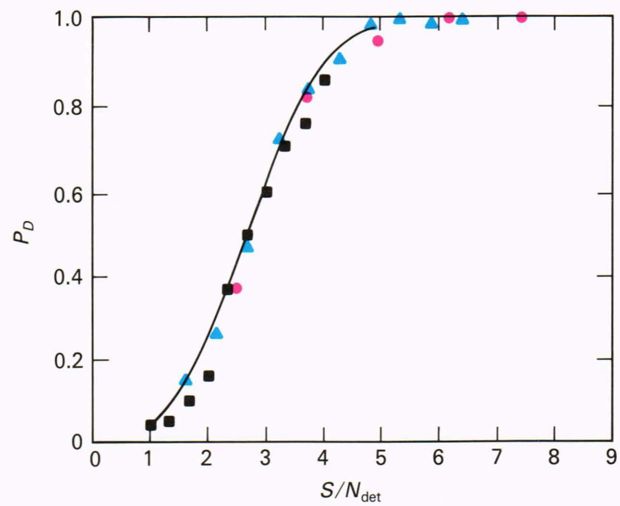

Figure 6—Detection probability (P_D) versus detection S/N (S/N_{det}) for a ship silhouette with a range-resolution product of 1.3 m. The three symbol types correspond to different viewing aspects: • = 90°, ▲ = 45°, ■ = 10°. The curve is an analytical fit to experimental psychovisual data.[14]

SUMMARY

Advances in autonomous target recognition algorithm development will enhance our use of current and future missile radars and infrared seekers. More optimal and robust approaches based on neural networks and multiple spatial resolution may be developed. The trend to significantly more parallel digital signal processing will encourage this development.

The ultimate system envisioned for missile signal processing could have multiple sensors integrated via sensor fusion techniques based on artificial intelligence principles. Here, the organization of the brain will likely have an impact on the system architecture design. Within this organization, algorithms for target recognition based on neural networks will probably be the most natural and robust approach.

To complement radar sensor imaging, infrared sensors also will be used. MRSI processing is one approach based on a model of the human vision system that is applicable to image detection and segmentation. It can be developed for different anti-ship missile concepts: completely autonomous seekers or man-aided image processing. In the man-in-the-loop system, MRSI processing could perform target cueing, which would relieve the human image interpreter from the need to search visually over a wide field of view. In combination with neural-network-based recognition schemes, MRSI processing could well become a missile signal processor entirely based on the human intelligence paradigm.

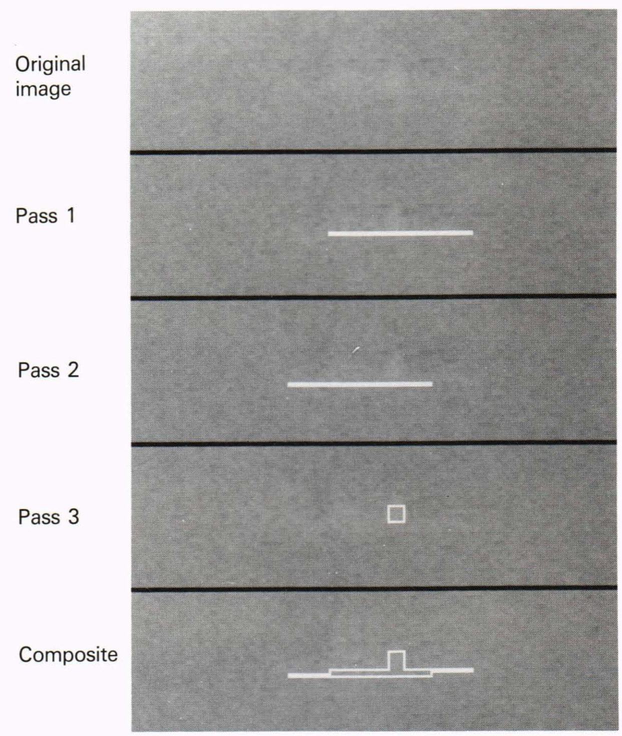

Figure 7—The multipass MRSI processing of a low-contrast thermal image provides shape information. The original image is shown at the top; a composite product of three-pass MRSI processing is shown at the bottom (range to ship = 10 nmi).

REFERENCES

[1] B. G. Boone, "Signal Enhancement and Target Classification," JHU/APL IR&D Site Review (8 Mar 1988).

[2] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning Internal Representations by Error Propagation," in *Parallel Distributed Processing: Explorations in the Microstructure of Cognition,* MIT Press, Cambridge (1986).

[3] J. J. Hopfield, "Neural Networks and Physical Systems with Emergent Collective Computational Abilities," *Proc. Natl. Acad. Sci. USA* **79,** 2554–2558 (1982).

[4] G. Widrow and M. E. Hoff, "Adaptive Switching Circuits," *IRE Western Electronic Show and Convention Record,* Pt. 4, pp. 96–104 (1960).

[5] R. P. Lippman, "An Introduction to Computing with Neural Nets," *IEEE ASSP Magazine,* pp. 4–22 (Apr 1987).

[6] M. T. Tuley, M. M. Horst, and J. W. Peifer, *Development and Validation of a Track Point Model for an Anti-Ship Missile Simulation,* Georgia Tech Research Institute Project A3417 Final Technical Report (Apr 1985).

[7] F. A. Rosell and R. H. Willson, "Recent Psychophysical Experiments and the Display of Signal-to-Noise Concept," Chap. 5 in *Perception of Displayed Information,* L. M. Biberman, ed., Plenum Press, New York (1973).

[8]F. W. Riedel and D. K. White, Jr., "A Comparison of Pattern Recognition Discriminant Sets for Autonomous Ship Target Classification," JHU/APL FS-83-202 (1983).

[9]R. A. Steinberg and J. J. Rivera, "Infrared Ship Detection at Low Signal-to-Noise," JHU/APL FS-87-193 (1987).

[10]R. F. Gasparovic, "Airborne Measurements of Sea Surface Temperature Variability with a Two-Wavelength Infrared Radiometer," American Geophysical Union Meeting, Philadelphia, Pa. (Jun 1982).

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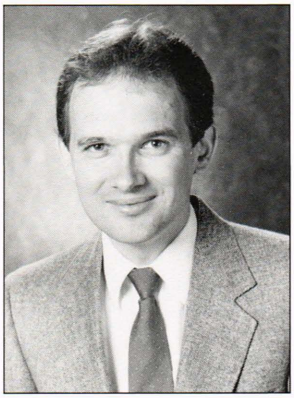

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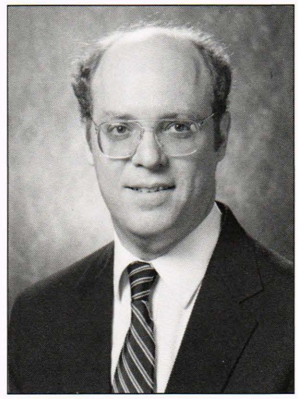

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