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NEW DIRECTIONS IN MISSILE GUIDANCE: SIGNAL PROCESSING BASED ON NEURAL NETWORKS AND FRACTAL MODELING

New research in missile guidance and navigation at APL is concentrating on two areas of the science of complexity: neural networks and fractal scene modeling. Requirements for autonomous target recognition and scene matching are major considerations in evaluating this emerging technology. Ongoing APL investigations are directed toward the recognition of ships using back propagation neural networks, and the representation of ship targets using approaches such as Fourier descriptors and primitive structural features. New work involves investigating the utility of fractal models as the basis of natural scene rendering for evaluating both target recognition and scene-matching navigation systems. This article discusses two internally funded APL projects to investigate the above-mentioned approaches for advanced missile guidance.

INTRODUCTION AND BACKGROUND

Practical development of new tactical missile guidance systems has reached the threshold of a new paradigm, which requires a radical shift of intellectual perspective. The system designer can no longer view the development of missile guidance solely as a problem in search, detection, and tracking for terminal engagement with an arbitrary target. Future missile systems operating in a complex and cluttered environment must be able to control adaptively the outcome as if possessed of intelligent reactions, which means that future missiles will be programmed to hit only desired targets. This seemingly innocuous tactical requirement of "target selection" has enormous implications and in its essential form translates into target recognition. Furthermore, *autonomous* target recognition (ATR) requires a leap of trust on the part of the tactical system user. No one will use a weapon system, however sophisticated, that is not reliable. Since the tactical environment is so inherently unpredictable, a high degree of fault tolerance (and fault avoidance) is therefore needed in the maintenance and operation of ATR systems. Neural networks offer the prospect of robust or fault-tolerant performance for future missiles used in a variety of tactical scenarios requiring reliable target selection.[1,2]

As the adversary has become more sophisticated in his responses and as threats have proliferated, weapons that respond effectively have increased in complexity, and the concomitant signal requirements have become more challenging in terms of bandwidth, dynamic range, sensitivity, and adaptability. For instance, it is no longer satisfactory that we detect point targets, reject homogeneous clutter, and track targets via centroid or even correlation estimation. We must now detect extended and often complex targets embedded in inhomogeneous and even statistically nonstationary scenes. Multiple threats must be tracked, and false identifications are a major concern and a tactical liability. System developers who wish to push the state of the art of missile guidance beyond present limits increasingly demand synthetic models that take proper account of the real world, both target *and* background. Investigators are now addressing the applicability of fractal-based scene modeling to image-matching-based navigation systems (Constantikes, unpublished data) and to the modeling of cloud clutter.[3] These models and the contemplated solutions to the guidance problems now encountered share a common relationship.

Heinz Pagels recently captured the essence of this new paradigm that underpins the relationship between the real-world models that support tactical missile performance prediction, and effective solutions to missile guidance derived from the models. Speaking in more general terms than the context of missile guidance, he describes the rise of the sciences of complexity in quoting Peter Lax of New York University, who says:

> The traditional branches of science, the experimental and the theoretical, correspond to the traditional sources of knowledge. In the last two decades a third branch, the computational, has joined the other two, and is rapidly approaching its older sisters in importance and intellectual respectability . . . This rapid rise of computing was made possible by striking improvements in computer hardware and software, and by equally striking improvements in the discretizations of the equations that model the physical phenomena, as well as clever algorithms to solve the discretized equations.[4]

Pagels goes on to emphasize the importance of various emergent disciplines within the new "sciences of complexity," among which are biologically inspired connections/neural networks and nonlinear/chaotic dynamical systems. In fact, there is a close relationship among chaotic dynamical systems, fractal models of nature, and the behavior of neural networks. For pattern recognition and scene representation—two fundamental requirements for intelligent missile guidance—these emergent and novel aspects that make up the science of complexity appear promising and worthy of investigation.

An internally funded special-interest project, under way for the last two years at APL, is addressing signal enhancement and target classification as it pertains to tactical missile guidance. Neural network and parallel computational solutions to particular mission requirements, especially antiship missiles, have come into focus in two projects. In addition, a new initiative that investigates scene representation using fractal modeling is also planned. In the following sections, these efforts are described and some of the progress is highlighted.

PRIOR ART AND KEY ISSUES

An ATR system can be defined as "a class of equipment consisting of sensors and processors (hardware and embedded software) [that] . . . accepts data from other sources and functions to sense and process scenarios of military interest . . . independent of human intervention."[5] This definition makes clear that ATR design and analysis are classic systems problems. *A priori* information provided to the missile at launch is used to bound and define the expected ATR target set. For example, signals of interest, such as target radar transmitter characteristics, could be defined at launch for a missile that performed ATR using a passive RF receiver. It is clear that the range of choices available to the developer of recognition algorithms is limited by the choice of sensor, the computing power and time available to perform the recognition task, and environmental considerations. Table 1 lists some common techniques investigated by APL for antiship applications and associated with various types of sensors.

In developing future ATR systems, there are two different philosophies: design ATR algorithms to fit existing sensors, and create new, multisensor suites to obviate the limitations of current sensor technology and therefore exploit multispectral signatures and propagation trade-offs. Either way, the objective is to gather as much invariant and reliable information on the target as possible. The information should be invariant with respect to target aspect, kinematics, clutter, noise, interference, weather, and time of day or year.

To be robust, ATR algorithms have certain key needs[1] that include high-fidelity modeling of targets and clutter to assist the algorithm training process, a capability for adaptation to variable tactical environments in real time (in-flight) or near real time (preflight), generation and selection of invariant target features (as mentioned above), and the use of *a priori* and/or contextual knowledge (e.g., threat priority, countermeasure response or potential, disposition of alternate threats, and the possibility for coordinated reaction). Neural network tools offer potential solutions to these ATR needs. Learning algorithms, such as back propagation and variations of it, can be used to address all the ATR needs. Background and clutter characteristics may be more accurately modeled using fractal-based approaches. Good target features can be found by neural-network-inspired feature selection. For "higher vision" functions that establish context or use *a priori* knowledge, expert systems approaches may be used, although generally these rule-based artificial intelligence systems are "brittle," that is, not very fault-tolerant. Two APL internal research and development projects are under way to investigate these ATR needs.

Table 1. Autonomous target recognition techniques for antiship applications.

Sensor	ATR techniques (preprocessing/classification)
Noncoherent (RF) radar	Use of *a priori* target geospecific location Coarse sorting by size and/or length Feature extraction using fast Fourier transform Statistical classification of returned pulse shape
Synthetic aperture radar	Coarse sorting by aspect ratio Collapsing target image into longitudinal profile Reconstruction using maximum entropy method Maximum likelihood estimation of radar scatterer distributions
Forward-looking infrared	Walsh–Hadamard, Fourier boundary, and moment descriptors Nearest-neighbor classifiers Binary template correlation

NEW APPROACHES TO TARGET RECOGNITION AND SCENE-MATCHING DEVELOPMENT

To lend some perspective to the target recognition and scene-matching problems, consider the system-level functional diagrams shown in Figures 1A and 1B. Figure 1A relates to the antiship problem in which a radar-based ATR system views the target, processes the signal (effectively reducing the input data bandwidth without loss of important invariant information), and subsequently classifies the target according to some predetermined algorithm embedded in a digital post-processor. In the process of training, the preprocessor (or feature selector) may be determined by a neural network designed to find a good (but not necessarily the best) representation of the

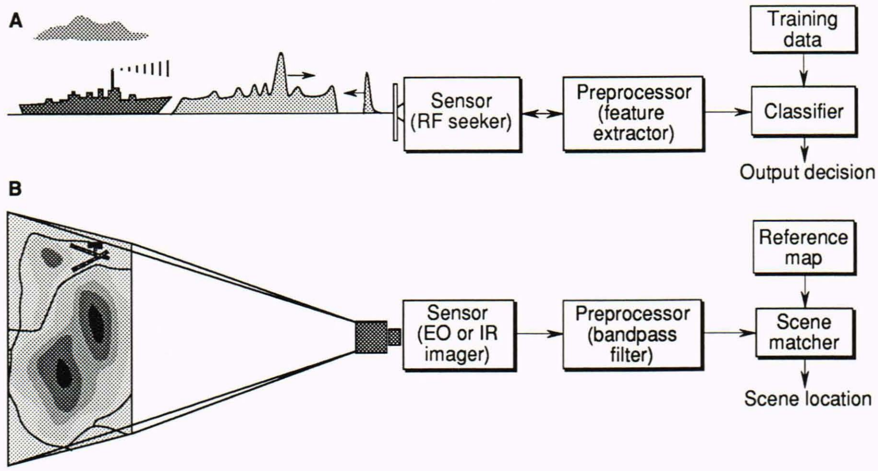

Figure 1. Basic architectural components and scenarios. **A.** Active RF antiship sensor/ATR system. **B.** Passive infrared (IR) or electro-optical (EO) sensor/scene-matcher system.

target. ("Best" in only one set of conditions is not necessarily better than "good" under most conditions.) Traditionally, classical statistical ATR algorithms such as Bayesian and nearest-neighbor classifiers have been used. These classical methods were not very successful, particularly at broadside aspect, because of the limited spatial resolution of current radar seeker data. Recently, back propagation neural networks have been evaluated and compared against these standard statistical classifiers under a limited set of conditions.[6] This will be described in the section titled Neural Network Training, where emphasis will be placed on the training phase and the various alternatives to target representation.

For almost a decade, APL has also investigated the performance and characteristics of image-based scene matchers. Enroute navigation updates are required for the inertial guidance of land-strike missiles using such scene matchers (see Fig. 1B). The surface of the Earth represents an extended "target" that is periodically sampled by an electro-optical (EO) or infrared (IR) sensor. The sensor video snapshots are preprocessed by bandpass filtering before correlation with a larger reference map. Then the correlation peak height and position are used to determine the quality of match and the location offset relative to a predetermined missile flight path. Significant concerns include what types of imagery are suitable for accurate performance as measured by correlation, and what models incorporate the statistical properties needed to optimize system performance. These and other concerns will be considered in the discussion of fractal scene modeling.

NEW MODELS AND REPRESENTATIONS FOR MISSILE GUIDANCE

Neural networks can contribute at two levels in a tactical missile guidance system. At the first level, neural networks can interface to the missile sensor outputs. The interface can be either direct or via an intermediate bandwidth-reduction and/or feature-extraction layer. The second level consists of a single neural network that integrates the outputs of the lower-level networks or other subsystems with other known missile information to either carry out or direct missile guidance. These two levels should work together to provide a robust, wide bandwidth, and fault-tolerant missile guidance technology.

Neural networks that interface to missile sensors provide a first level of bandwidth reduction and decision-making. Networks operating at this level must compare sensor information with internally stored target models via an associative memory operation. Associative memory operations operate in reverse to standard computer random access memory, which requires that the computer find the value at a specified memory location. In contrast, accessing associative memory requires finding the information distributed in the memory that most closely matches a given value. Networks functioning at this level serve to reduce the typically wide-bandwidth signals derived from missile sensors and to make decisions regarding the nature of the data.

The second and topmost network level accepts decisions from the lower neural network components and other known missile parameters, such as inertial systems outputs, flight path perturbations, and factors such as electronic countermeasures. This level effectively combines or "fuses" this information to make high-level decisions regarding flight path modification, aimpoint selection, and fault recovery.

The following discussion will concentrate on the first level of neural networks, which are used specifically for pattern recognition.

Neural Network Training

There exists a rich class of neural network models, each of which is applicable to particular sets of problems in pattern recognition.[7] The models can be divided into supervised and unsupervised learning categories. The unsupervised learning models include the adaptive resonance theory model,[8] self-organizing feature maps,[9] and the adaptive bidirectional associative memory.[10] The supervised learning models include the associative memory models (including the Hopfield model,[11] Hamming net,[12] and bidirectional associative memory[13]) and feed-forward nets (such as the back-propagation net,[14] among others). Network models have evolved that con-

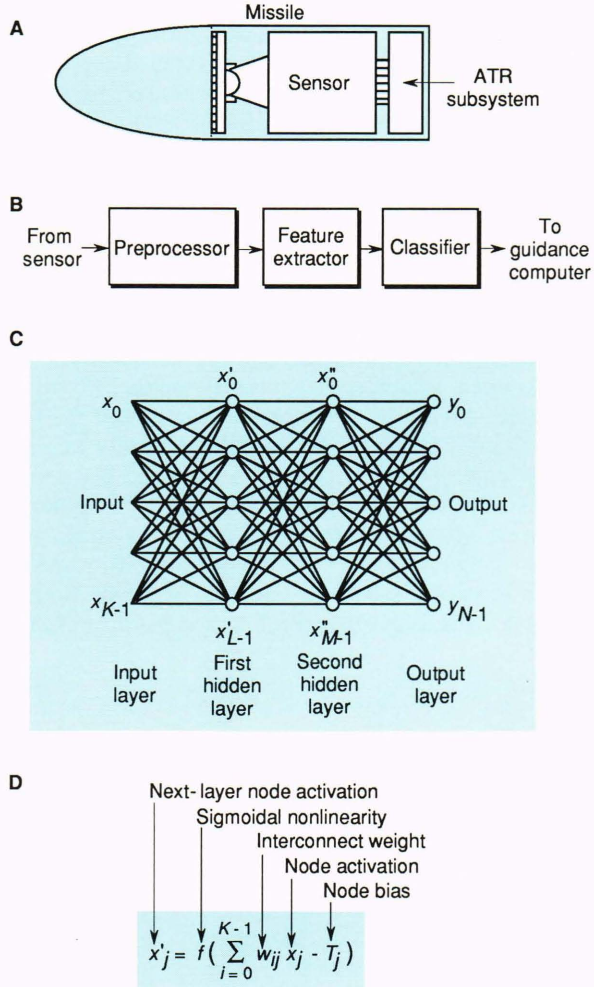

Figure 2. Structure of a two-hidden-layer neural network (**C**), which is embedded in the classifier portion (**B**) of an ATR subsystem that could be interfaced to a radar sensor (**A**). The relationship between the input layer and the first hidden layer shown in the equation (**D**) is similar to the corresponding relationship between all layers of the network.

sist of modules of different neural network paradigms (e.g., a hybrid system consisting of a self-organizing feature map net to perform clustering on the front end and a back-propagation network to perform classification on the back end).[15] The associative memory models provide content-addressable memory, which is robust with respect to incomplete or noisy inputs, and essentially memorize the training data. The back-propagation model, on the other hand, generalizes in a statistical sense over the inputs and, with two hidden layers and a sufficient number of nodes in the hidden layers, can generate decision surfaces of arbitrary complexity. Figure 2 illustrates the typical structure of such a feed-forward network. Individual processing elements in a given node are connected with each of the processing elements in the preceding or succeeding layer and are not connected with any other processing element in the same layer.

In each of the neural network approaches, a critical issue is the representation of the information. An ideal representation is one that is invariant to all relevant parameters, such as aspect angle, kinematics, and noise, and is also a strong discriminant. For example, the Fourier–polar transform has provided a translation and rotation invariant representation for a problem involving the recognition of infrared aircraft images.[16] Other examples are shown in Table 2. For many problems that are not well-posed or are hard to predict on a statistical basis, it is difficult to arrive at a good representation. For such problems, invariance over only a few parameters or over a limited range of variation of any given parameter is achievable; it is then necessary for the training set to span the remaining variability that is not embodied in the representation. The selection of a suitable (invariant) representation often is done independently of the choice of a particular ATR (classifier) algorithm. Multiple redundant representations are often more effective than separate representations.[17] The extraction of features suitable for pattern recognition, however, is a natural function of neural networks.

An APL investigation of the recognition of range-profile ship signatures using a back-propagation neural net with comparisons to baseline statistical classifiers[6] will now be described. These signatures exhibit scintillation effects and varying specular contributions from individual flat-plate and dihedral reflectors that result from aspect-angle variations caused by ship motion and missile line-of-sight dynamics. These variations are of key concern in our studies. In the APL classification experiments, the training set consisted of data taken over a time span during which the target underwent one or more roll cycles. Neural net performance was evaluated by processing data at different target aspects: bow, quarter, and beam. The magnitude of the fast Fourier transform (FFT) provides a target signature representation that is invariant to translation and range but not to ship motion, aspect angle, or noise. For example, if the variations seen in the original data were due to profile scale compression only, the Fourier–Mellin transform would theoretically provide a representation invariant to aspect angle as well. The Fourier–Mellin transform, however, is not suitable for this problem, because of insufficient range resolution and because the variability observed is

Table 2. Selected feature representations and their invariance characteristics.

Representation	Invariance properties
Fast Fourier transform magnitudes	Translation
Fourier–Mellin transform	Translation and scale
Fourier–polar transform	Translation, scale, and rotation
Hu moments	Scale, translation, and rotation
Walsh–Hadamard transform	Translation

not simply due to profile scale compression. Moreover, other information, such as the location of individual peaks, is not encoded in the magnitude of the Fourier coefficients. By using complex FFT features, we include magnitude and phase. Phase information improves performance because it accounts for structural information versus position, although at the expense of invariance with respect to the range translation (jitter) of the profile within the data acquisition window.

The most robust single representation discovered in these neural network studies consisted of five profile shape descriptors (PSD's). As shown in Figure 3, these parameters include the number of peaks, area under the profile, apparent length, separation between the two highest peaks normalized to the apparent length, and the location of the highest peak normalized to the apparent length. Figure 4 shows that PSD's provided better overall classification performance than the FFT magnitudes; they were also more robust with respect to aspect angle and, as shown in Figure 5, more robust with respect to the addition of noise to the test set. As shown in Figure 4, individual PSD's, when combined with the FFT magnitudes, do not significantly improve performance and, in some cases, degrade performance. The combination of the FFT magnitudes and all of the PSD's provided the best overall performance.

The weight matrix between the inputs and the first hidden layer of the network was trained with both the FFT magnitudes and the PSD's to determine how the various features were weighted. Figure 6 details the mean abso-

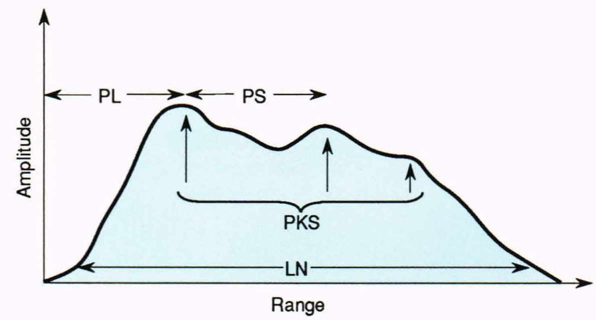

Figure 3. Definition of profile shape descriptors for a typical range-only radar profile. LN is length (range bins); area is the area under the profile; PKS is the number of peaks; PL is the location of the absolute peak; and PS is the separation between the two highest peaks.

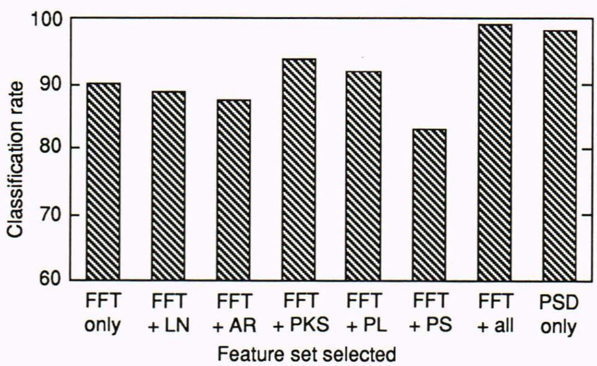

Figure 4. Performance of a neural network trained with the back propagation learning algorithm for various choices of a feature set consisting of different combinations of FFT and PSD features. Results are for a network tested against an Ex-DD at bow aspect. FFT = fast Fourier transform; PSD = profile shape descriptor; LN is length; AR is area under the profile; PKS is the number of peaks; PL is the location of the absolute peak; and PS is the separation between the two highest peaks.

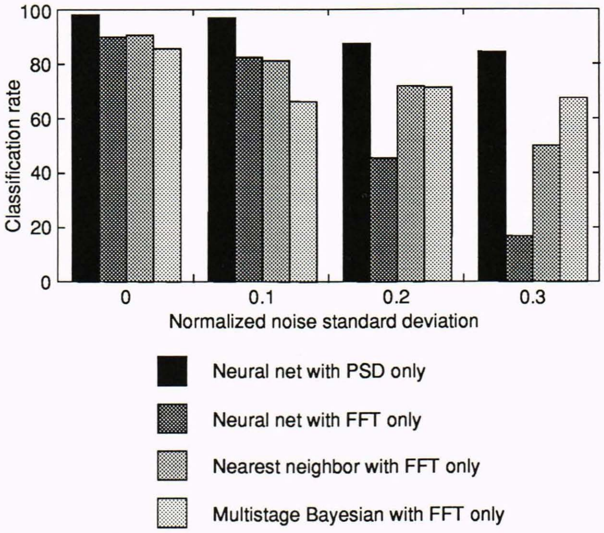

Figure 5. Robustness of neural network (trained by back propagation) and conventional statistical classifiers (nearest-neighbor and hierarchical Bayesian) with respect to the noise degradation of the test set. The abscissa is the standard deviation of a band-limited Gaussian zero mean process, which is used to degrade each raw test profile (before feature extraction). Each profile is normalized so that its peak amplitude is unity. The performance of the neural network is shown for two choices of the feature set when tested against an Ex-DD at bow aspect. FFT = fast Fourier transform; PSD = profile shape descriptor.

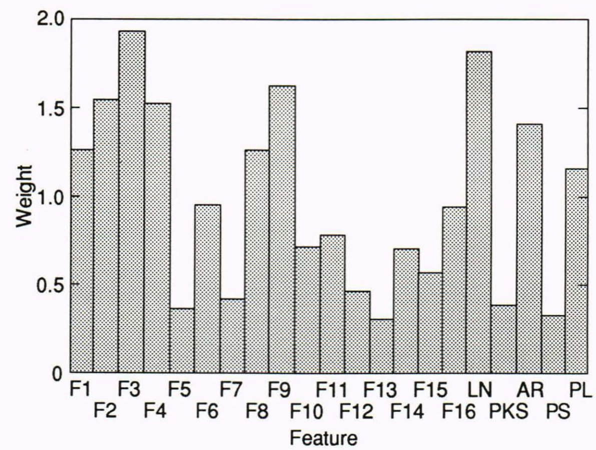

Figure 6. The level of importance of each feature as interpreted by a neural network (trained by back propagation), given a feature set consisting of 16 FFT magnitudes and 5 PSD's. The weight matrix is the connection matrix between the input and first hidden layers. FFT = fast Fourier transform; PSD = profile shape descriptor; LN = apparent length; AR = area under profile; PKS = number of peaks; PS = normalized separation between the two highest peaks; and PL = normalized location of the highest peak.

lute weights for each of the 21 features (16 FFT's and 5 PSD's). It shows that the 10 most heavily weighted features consisted of four low-frequency FFT magnitudes (frequency bins 1 through 4), three middle-frequency FFT bins (bins 6, 8, and 9), and three PSD's (length, area under the pulse, and relative position of the highest peak). The neural network provides an effective means of combining and evaluating dissimilar feature representations for which a suitable metric is not apparent. The neural network simply learns which features or combination of features are good discriminants.

Fractal Scene Modeling

The ATR systems rely on knowledge of target geometry to distinguish target from nontarget. Yet these systems often operate in environments with natural clutter backgrounds. Thus, investigators are prompted to ask how knowledge of natural geometry can be embedded in these systems. Autonomous scene-matching navigation systems compare the geometry of an observed scene to a stored scene to determine position. When the scene geometry is Euclidean, we can match on the basis of simple geometric primitives such as spheres, prisms, etc. How do we represent the geometry of natural scenes? What geometric statistics are appropriate to modeling the detection and false alarm performance of scene-correlation navigators? These questions are complex and not well-understood. However, as Mandelbrot shows in his manifesto,[18] nature has fractal geometry. We are beginning an investigation into the application of fractal scene representations for design and performance analysis of the new generation of ATR and scene-matching navigation systems.

A fractal can be defined as "a shape made of parts similar to the whole."[19] This first definition makes explicit the idea of scaling in fractals. The scaling property is essentially how a fractal may capture the geometry of an object. Figure 7 illustrates that fractals may be computed by geometric procedures (Fig. 7A), or as a section of the phase-space attractor of a dynamical system (Fig. 7B), or as random processes (Fig. 7C).[20] Random fractals are self-similar in distribution, while deterministic fractals are self-similar sets.[21] The mathematics and geometry of fractals, fractal dimension, lacunarity, etc., are too rich for a discussion here (see the boxed insert for an introductory lexicon). References 18 and 19 provide a comprehensive treatment.

The desirable properties of a scene model are that it have few parameters, built-in assumptions about the geometry of scene, and stable estimation techniques for extracting parameters from data. It should also be constructive as well as analytic; that is, the analyst should be able to synthesize a realization of a scene as well as to characterize its geometry. Note that different geometries require different models, for example, forest versus tundra. The models can be directly applied to the design of nonlinear whitening filters that decorrelate the higher-order moments of a scene or they can provide statistical models for detection of signals in natural noises. Estimated fractal dimension and lacunarity might be used for the

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Fractals

Shapes with fragmented and irregular patterns that tend to have the same degree of irregularity and/or fragmentation at all scales. "Fractal" is a Mandelbrot neologism from the Latin "fractus," or broken. Fractals have fractional dimension (formally, Hausdorff–Besicovitch dimension[19]) or self-similarity.

Fractal dimension

Defined in a variety of ways using fractal similarity, clusters, mass, etc., the fractal dimension describes the rate at which some measurement of the set diverges as the scale of the measure decreases. The usual example is a coastline: we measure the length using a set of dividers. The fractal dimension describes the way that measured length increases as the divider interval decreases.

Lacunarity

Mandelbrot neologism from the Latin "lacuna," or gap. Lacunar fractals are fractal sets interspersed with gaps. Lacunarity has not been quantified *per se*, although measures such as the variance of mass distribution have been used profitably.[22]

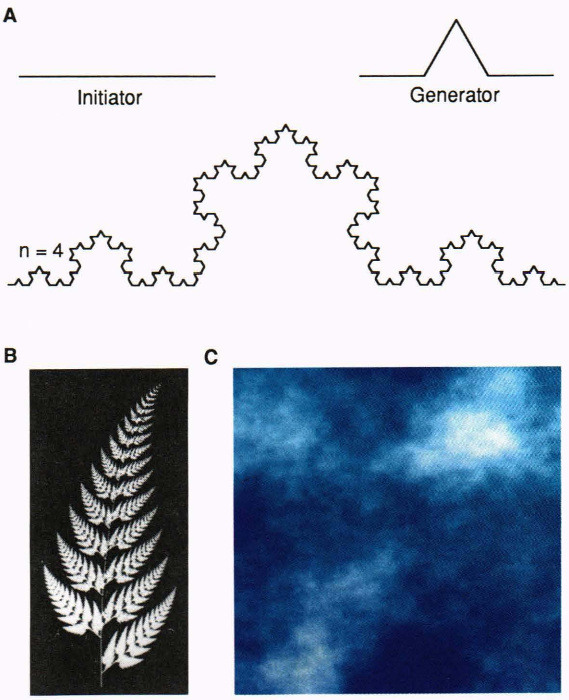

Figure 7. Examples of different fractals. **A**. A Koch curve, where line segments are replaced iteratively by the generator. A straight line initiates the curve. The curve shown results after four applications of the generator. **B**. The attractor of an iterated function system, where affine transforms are applied iteratively to an initial condition. The affine transforms are selected randomly from a set. **C**. Fractional Brownian motion rendered as a cloud. Fractional Brownian motion can be computed by synthesizing a frequency domain representation with random phase and power-law decreasing magnitudes.

segmentation of natural scenes into morphologically consistent regions, and for discrimination of natural (fractal) objects from manmade (Euclidean) objects (Fig. 8). When the models are used with image-rendering algorithms, we may study the effect that shadowing in a natural scene has on ATR and on scene-matching algorithms or synthesize data sets for ATR and scene-matcher algorithm performance studies.

Next, consider a scaling deterministic fractal, such as the Koch curve in Figure 7A. If we know the scaling relationship for the fractal and we know a fragment of the curve, we know the curve everywhere.[19] Thus, the scaling relationship and a fragment of the curve also define all of the moments of the curve in a simple way. Fractional Brownian motion as illustrated in Figure 7C, a stochastic fractal, is also defined in part by a scaling relationship.[18] Thus, fractal models include the higher-order moments that can be used by neural networks as features for classification or correlation.

An analytic fractal model might be used to predict system performance or to perform some recognition task. In matched filters, peak-to-sidelobe ratio is often used as a figure of performance. Sidelobe variance is a function of fourth-order sidelobe moments, but statistical models of scenes usually incorporate only up to second-order moments, that is, variance and correlation length.[23] Scene texture has been used as a sidelobe variance predictor, and some researchers have found that texture is well-described by fractal dimension and lacunarity, which correspond approximately to roughness and periodicity.[24] Figure 9 shows an example of Weierstrass–Mandelbrot functions with different lacunarity and fractal dimension.

Pentland[22] has shown that local estimates of fractal dimension can be used to segment images. This kind of segmentation could be used to control a multimode target-acquisition algorithm. The input scene (of Fig. 8) could be segmented into regions of solar sea glint and cloud and land clutter, as well as regions of no clutter, on the basis of local fractal dimension estimates. The target acquisition system could then process each region on the basis of the local statistics of clutter, thereby achieving better performance.

The fractal literature is rich in estimates of fractal dimension of natural objects.[18,19] Burrough[19] has tabulated fractal dimension estimates for a variety of environmental data, Voss and Mandelbrot[19] have made numerous convincing forgeries of landscapes, and Lovejoy[19] has shown that fractal dimension is an invariant of clouds. Recent investigations, however, suggest that estimating dimension must be done with some care.[3]

The APL initiative in fractal scene modeling will begin with a careful model-based estimation of the dimension and lacunarity of land-scene intensity images (intensity images of illuminated fractal objects are in themselves fractal[22]). These models can then be applied to problems such as clutter discriminants and detection statistics. In the longer term, we hope to synthesize three-dimensional scene models and use computer graphic rendering techniques[25] to study how ATR and scene-matching navigation systems perform when environmental changes occur, such as when lighting changes cause moving shadows, when snowfall causes partial contrast reversal of scenes, and when seasonal foliage causes shape changes.

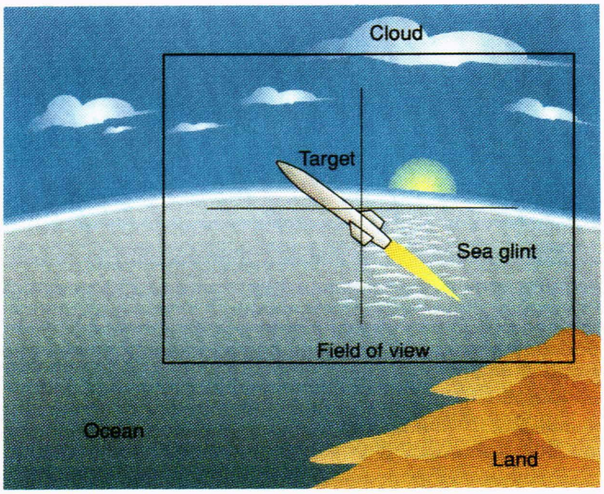

Figure 8. A target acquisition system may have to operate in structurally varied clutter backgrounds. Each clutter type may require a different acquisition algorithm. Natural clutters can be distinguished by fractal dimension, and fractal models of clutter may provide geometrical statistics for system design.

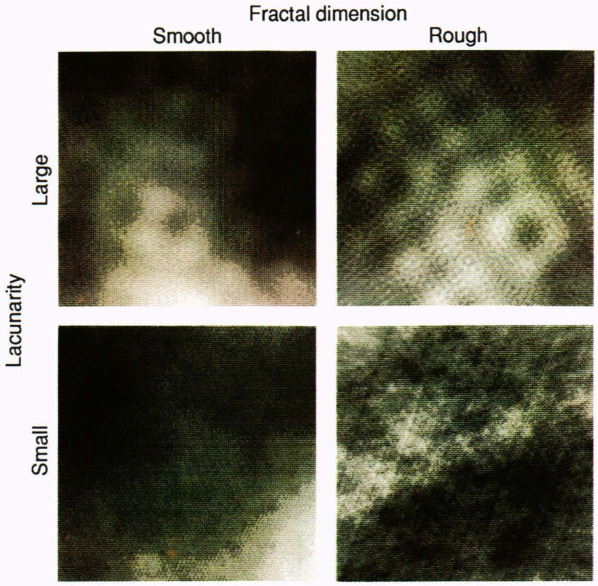

Figure 9. Examples of random fractal images that illustrate combinations of lacunarity and fractal dimension. The images were synthesized by successively adding the real part of randomly rotated one-dimensional Weierstrass–Mandelbrot functions, previously extended in the orthogonal direction.[19]

PROSPECTS FOR FUTURE WORK

Ongoing efforts in pattern recognition at APL will continue to exploit the new set of computational tools offered by neural network models. These tools will be applied to a broader set of classification problems than considered previously, including high-resolution range-only radar data and synthetic aperture radar imaging data. Some of the demonstrated capabilities of neural networks include fast optimization for image processing, knowledge encoding and fusion of diverse features, feature extraction and clustering, robust classification, and inclusion of *a priori* information. Issues that must be considered in these approaches include the choice of neural network paradigms, architecture, learning algorithms, and learning parameters, as well as feature representation, dimensionality reduction, and other preprocessing steps. It is imperative in these empirical investigations to establish a baseline of optimal statistical pattern classification approaches; relative performance is more informative than is absolute performance in limited empirical studies. The synthesis of effective modules from neural network and more conventional classical approaches into a hybrid classifier will also be a consideration. The optimal solution, as in many difficult problems, will probably not involve any single breakthrough in a single field such as that of neural networks, but may involve several incremental developments throughout the entire field of pattern recognition, including neural networks.

A new effort in ATR—target acquisition—and scene-matching navigation will apply fractal geometric approximations of natural clutter and ray-tracing algorithms to the development of image clutter models and image synthesis. It is hoped that such models will contain more complete knowledge of image structure than models currently used, and thereby provide a means for better assessment of systems performance. Image synthesis of shadowed scenes, for example, will permit a detailed study of scene-matcher sensitivity to illumination instability over a range of scene geometries. New systems designs may use the models for obtaining more optimal performance in structurally varied clutter backgrounds. Issues include the development of robust fractal dimension estimators, lacunarity measures and estimators, and parametric scaling statistics for scenes. Computational complexity of estimation and synthesis is also a prime concern. Models will be evaluated against measured image data to determine the higher-order correlation fidelity and the ability to segment images into morphologically consistent regions.

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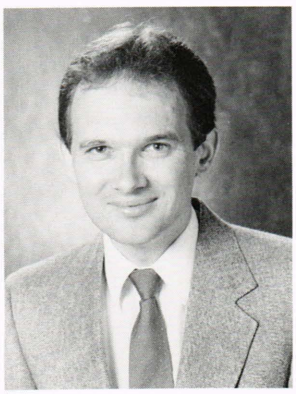

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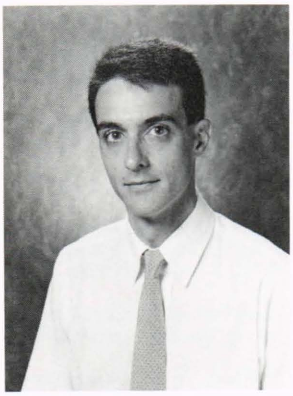

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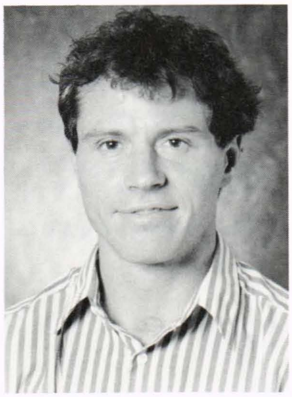

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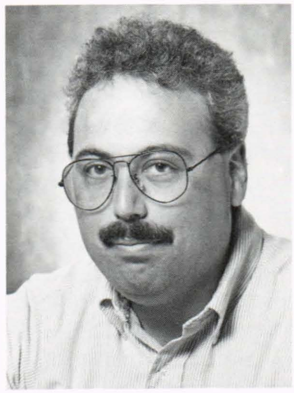

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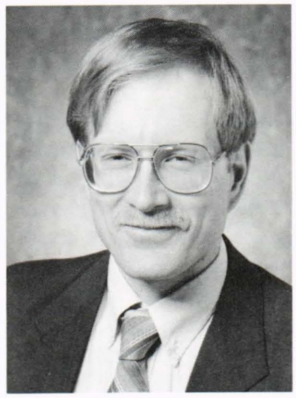

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