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Model based automatic target recognition from high range resolution radar returns

John S. Baras*
Department of Electrical Engineering
and Institute for Systems Research
University of Maryland
College Park, MD 20742

Sheldon I. Wolk
Code 5750
Tactical Electronic Warfare Division
Naval Research Laboratory
Washington, D.C. 20375

ABSTRACT

Economic descriptions of objects are essential for model-based ATR. We develop economic target descriptions based on high range resolution target returns, utilizing wavelet multiresolution representations and Tree Structured Vector Quantization, in its clustering mode. The algorithm automatically constructs the multi-scale aspect graph of the target, which is a most efficient model that guides the on-line ATR algorithm. This results in a progressive coding of the target model information and in an extremely efficient, hierarchical indexing of the stored target models. As a final outcome we obtain extremely fast recovery, search and matching during the on-line ATR operation. In addition these scale space (or multiresolution) representations can be used to generate target fingerprints across a range of scales, unavailable heretofore, which aid substantially in target recognition even with occluded or spurious data.

We have successfully addressed the problem of reducing the target model representations with respect to viewpoint variations and other sensor parametric variations. Our method can be viewed as a quantization of the space of sensing operations. The resulting aspect graph is a (relational) graph representation of this quantization. Aspect graphs of target radar returns are generated algorithmically. Since our off-line model/parameter tuning methods are based on general vector quantization, our methods extend naturally and efficiently to multi-sensor data: LADAR, TV, mmWave, SAR, etc..

We also investigate, the so-called new target insertion problem in a fielded ATR system, and the required fast reprogrammability of the ATR system. We compare the performance and cost (both computational and hardware) of ATR algorithms based on the parallel use of single target aspect graphs *vs* ATR algorithms using the combined aspect graph for the group of targets under consideration. We show that efficient real-time ATR algorithms can be constructed using the aspect graph of each target in a parallel computation. The resulting architecture includes wavelet preprocessing with neural networks postprocessing. We use synthetic radar returns from ships as the experimental data to demonstrate the performance of the resulting ATR algorithm.

1 INTRODUCTION

High range resolution radar returns contain in their structure substantial information about the target which can be used to better identify complex targets consisting of many scatterers. This applies to many forms of radar signatures, including the amplitude of pulsed radar (PR) returns, the phase of pulsed radar returns, Doppler radars (DR), synthetic aperture radar (SAR) returns, inverse synthetic aperture radar (ISAR) returns, millimeter–wave (MM–wave) radar returns. With the increasing resolution of modern radars it is *at least theoretically* possible to store many of the possible returns (i.e. returns organized according to aspect, elevation, pulsewidth etc.) of a complex target and use them in the field for target identification. The advantage of the increasing radar resolution is the availability of more detailed information, and ultimately of *specific features*, characteristic of the radar return from a specific target. The disadvantage is that these very detailed characteristics require an ever increasing amount of computer memory to be stored. The latter not only results in unfeasible memory requirements but it also slows down the search time in real field operations.

It is therefore important to develop extremely efficient ways to compress the representations of high resolution data returns from real targets, and to design efficient search schemes which operate in a progressive manner on the compressed representations to recover the target identity. Wavelet theory [1]—[9] offers an attractive means for the development of the required multi-resolution representations. This can be roughly explained by the fundamental property of wavelet representations of signals to uncover the superposition of these signals in terms of different structures occurring on different time scales at different times (see [14, 17, 25] for details). Successful methods to provide effective compression of radar returns must address also the substantial variability of the returns with respect to aspect, elevation and radar pulsewidth. It is therefore physically meaningful to cluster the radar returns from various viewpoints into equivalence classes using a measure of similarity. The resulting quantization of the signal space (i.e. of the radar returns) characterizes the limits of discriminating between returns from different targets using information about the viewpoint; in essence if we insist on extremely fine quantization cells we are modeling the radar sensor noise and not the underlying complex target. A systematic application of these two fundamental techniques leads to the development of economic radar target models.

*Also with AIMS, Inc.. Research supported by AIMS, Inc., 6110 Executive Blvd., Suite 850, Rockville, MD 20852.

The problem of automatic target recognition based on high range resolution (HRR) radar returns when a large number of targets is possible, presents formidable algorithmic and computational difficulties. A key step in the design and implementation of high performance ATR algorithms is the organization and construction of efficient and economic target models which will result in significant search speed-up and memory reduction. In this paper we use as target models scale space aspect graphs constructed using the two basic techniques mentioned above (i.e. wavelets and hierarchical clustering) as describe in our work [14, 17, 25].

In addition to economic target models we must address the development of massively parallel algorithms for ATR which efficiently utilize these target models. In this paper we develop such algorithms operating in parallel, where the target data are processed concurrently as they are received by algorithms tuned to a particular target model. We demonstrate that such massively parallel algorithms have superior performance than algorithms based on a compound model of the entire target database constructed with the same efficiency.

Our target representations lead naturally to classification schemes that are progressive. That is, a small amount of information, in the form of a coarse approximation to the return, is used first to provide partial classification and progressively finer details are added until satisfactory performance is obtained. This results in a scheme where small amounts of computation are used initially and additional computations are performed as needed, resulting in extremely fast searches while preserving high fidelity in the search. Each target is reperesented by its multiresolution aspect graph [15], which is a quantization (produced by clustering) of the space of HRR returns and view points. Using an efficient Tree-Structured Vector Quantization (TSVQ) algorithm we cluster the returns from the various viewpoints into equivalence classes according to an appropriate discrimination measure. This approach automatically accounts for the discrimination capability of the sensor and in effect it performs a quantization of the sensory data which reduces the data input to the classification algorithm by orders of magnitude. In each equivalent class a "paradigm" is selected and the collection of these typical pulses arranged in a multi-scale tree constitute the target model that is guiding the on-line classification search. In its parallel version our scheme allows for the comparison of the sensor data to many hypothetical targets at the coarse resolution and to a progressively smaller candidate set as the resolution is refined and more detailed features are revealed. We therefore achieve progressively finer classification with a constant computational resource since the coarse comparisons are faster per target hypothesis as compared to the finer ones.

We demonstrate our results by experiments with highly accurate synthetic returns from the Naval Research Laboratory code 5750 ship radar return simulator. We use a two ship example but the results generalize easily to many ship senarios. We show confusion matrices computed which demonstrate the high performance of the resulting ATR algorithm. In its parallel multi-target model implementation the algorithm also solves the so called "new target" insertion problem. Indeed, the addition of targets is handled by adding the corresponding aspect graphs and by passing the sensor data through these models; no new expensive off-line training of the algorithm is required.

2 EFFICIENT TARGET MODELS FOR RADAR RETURNS

A key construct in our approach to economical target model hierarchies is that of an aspect graph [15], which is a hierarchical data structure, indexed by sections of viewpoint, that stores compressed target formats. A general definition of the aspect graph [15] is that it is a graph structure in which there is a node for each *general view* of the object as seen from some maximal connected cell of *viewpoint space*, and there is an arc for each possible transition across the boundary between the cells of two neighboring general views. A general viewpoint is defined as one from which an infinitesimal movement in any possible direction in viewpoint space results in a view that is equivalent to the original. Under this definition, the aspect graph is complete in that it provides an enumeration of the fundamentally different views of an object, yet is minimal in the sense that the cells of general viewpoint are disjoint. Thus the aspect graph is equivalent to a parcellation (tesselation) of viewpoint space into general views. Considerable research has been performed in recent years on algorithms that compute the aspect graph and its related representations [15]. However, todate these conventional methods have addressed only the ideal case of perfect resolution in object shape, in the viewpoint, and the projected image, leading to a set of important practical difficulties [15], [25].

Almost exclusively, previous work on aspect graphs has focused on computer vision and object geometry [11, 15]. Our notion of the aspect graph as developed in [14, 17, 25] is an extension of these concepts to sensors other than cameras such as radar. Earlier work by one of the authors has addressed these very points successfully for FLIR sensors [18].

The various algorithms that have been developed may be classified using three properties: the object domain, the view representation, and the model of viewpoint space. We use object domain and the 2-D viewing sphere in our algorithms. According to a panel discussion [15] on "Why aspect graphs are not (yet) practical for computer vision" held at the *1991 IEEE Workshop on Directions in Automated CAD-Based Vision* concluded that an important problem has been the fact that aspect graph research has not included the notion of *scale*. Our results reported in [14, 17, 25] and in [18] incorporate scale in the construction of the aspect graph in a manner consistent with the sensor considered. Indeed we have developed an algorithmic construction of *scale space aspect graphs*. Scale space aspect graphs are equivalent to families of viewpoint space tesselations parameterized by scale. It is precisely these scale space aspect graphs that we use in this paper as efficient target models to develop high performance model based ATR algorithms.

The key idea on which our target modeling is based, is the physical principle that the view of the target signature remains invariant over regions of viewpoint and resolution, depending on sensor physics, environmental conditions, etc. The fact that the field sensor data are noisy further reinforces the argument. In our algorithmic construction [25] we first determine viewpoint equivalence classes according to a distortion measure and then identify the significant radar return features that remain invariant in the viewpoint tessels (see Figure 1) determined by the equivalence classes. In this *iterative process*, refinements can result, causing further subdivision of a class. Our algorithms work across multiple resolutions. Furthermore, we can compare characteristic radar returns from each equivalence class of each target to test if the resulting cluster has acceptable classification performance; this brings the characteristics of the sensor directly in the target model hierarchy. Motivated by existing terminology in computer vision [11, 15] we call the resulting viewpoint equivalence classes *aspects*. If we arrange the aspects as nodes in a graph we can connect them with links to obtain what we call the *aspect graph* of the target. The links denote the appearances of new features, or the disappearances of features relating the transitions between various aspects. This precompiled object is then used to guide the target classification process *on-line*.

We now turn to the explicit description of our economical target models. We employ wavelets and Tree Structured Vector Quantization. We refer to [2], [3], [9] for wavelet fundamentals. In such a multiresolution analysis [2] one has *two functions: the mother wavelet* ψ *and a scaling function* ϕ. We denote by f the generic radar pulse, by $\psi_{m,n} = 2^{-m/2}\psi(2^{-m}t - n)$, $\phi_{m,n}(x) = 2^{-m/2}\phi(2^{-m}x - n)$ the functions obtained by dilation and translation from ψ and ϕ. The coefficients of expanding f in terms of the $\psi_{m,n}$ are $c_{m,n}(f)$, while $a_{m,n}(f)$ are the coefficients of expanding f in terms of $\phi_{m,n}$. Usually one denotes by V_m the space spanned by the $\phi_{m,n}$. The spaces V_m describe successive approximation spaces, $\ldots V_2 \subset V_1 \subset V_0 \subset V_{-1} \subset V_{-2}\ldots$, each with resolution 2^m. This sequence of successive approximation spaces V_m constitutes a *multiresolution analysis* [2, 9]. W_m denotes the space which is exactly the orthogonal complement in V_{m-1} of V_m. These concepts result in a fast algorithm for the computation of the $c_{m,n}(f)$ (or $\mathbf{c^m}$) and $a_{m,n}(f)$ (or $\mathbf{a^m}$) [2]. The whole process can also be viewed as the computation of successively coarser approximations of f, together with the "difference in information" between every two successive levels.

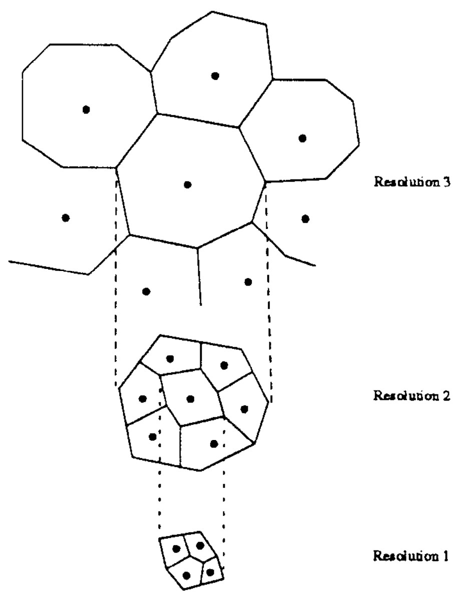

Figure 1: Illustrating a multiresolution TSVQ by splitting Voronoi cells based on different resolution data.

We generated radar return databases for various different ships, utilizing the NRL Code 5750 ship radar return simulator. In generating the synthetic data we kept the radar fixed and turned the ship, including the motion induced by sea waves. We varied the aspect angle from 0° to 360° in increments of 0.5°. This allowed for large variation in the number and appearance of dominant scatterers. Each database contained 720 pulses at fine resolution.

Let S denote the set of discretized radar pulses. The fine resolution data will be denoted by $S^0f(n)$, $n \in I^0$, where $I^0 = \{1, 2, \cdots, 2^7\}$, is the index set of the fine resolution data. We shall let $N = 2^J$ denote the number of samples in the fine resolution data, where J is the maximum possible number of scales that we can consider. In practice one considers scales up to J^* where $J^* < J$. Respectively for each resolution m we denote by I^m the subset of I^0 where sampled values of the m^{th} resolution pulse representation $S^m f$ are computed. I^m is obtained from I^{m-1} by decimation. We used $N = 128$, and $J^* = 3$. This gives us four scales (including the given fine scale) $m = 0, 1, 2, 3$, with vector lengths $128, 64, 32, 16$ and resolutions 10 ns, 20 ns, 40 ns, 80 ns, respectively. We identify $\mathbf{a}^0$ with the vector of sampled data $S^0 f$. Then we use the *pyramid* scheme [2] to recursively compute the successive approximations $S^m f$ to the pulse f at various scales m and the residual pulses $W^m f$. As we proceed with this analysis step from scale m to the coarser scale $m+1$, the space of signals becomes smaller, and the length of vectors is halved. Thus the algorithm recursively splits the initial vector $\mathbf{a}^0$ representing the sampled pulse $S^0 f$ to its components $\mathbf{c}^m$ at different scales indexed by m representing the wavelet residuals $W^m f$; the multiresolution scheme replaces the information in each pulse $f = S^0 f$ with the set $\{W^m f,\ m = 1, 2, \cdots, J^*,\ S^{J^*} f\}$.

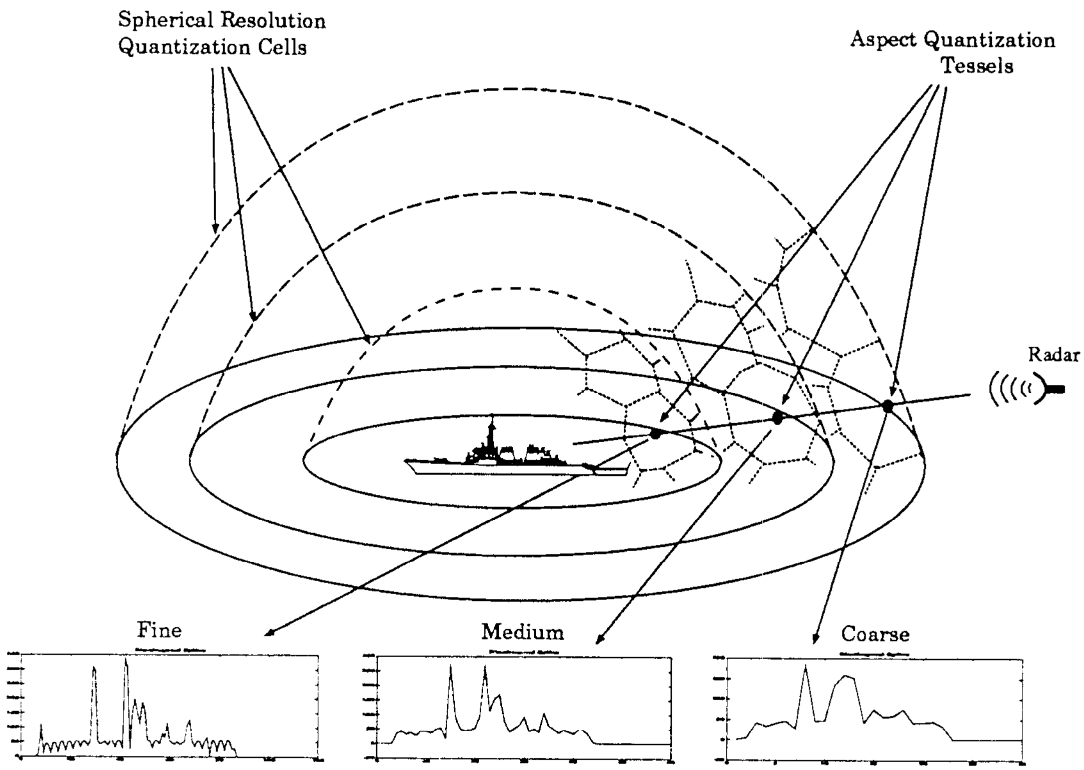

Figure 2: Illustrating a multiresolution aspect graph for radar ship data.

We then construct the scale space aspect graph for each ship target by developing a hierarchical, tree-structured organization of radar returns, which utilizes the multiresolution representations provided by wavelets. Vector Quantization (VQ) is primarily used as a data compression method. By properly defining a rate-distortion measure between the respective sample distributions one can reinterpret the process of vector quantization in the context of optimal decision theory. In fact, this flexibility of the definition and interpretation of rate and distortion in Shannon's theory has recently led to very beneficial cross-fertilization between these two areas, in particular between tree-structured vector quantizers [10] and classification (decision) trees [12]. VQ in addition is a clustering algorithm. Indeed the codewords, represented by the centroids, can be thought of as representatives of the equivalence class represented by each cell of the VQ (each Voronoi cell). It is in this sense that we use VQ in our approach to the problem of hierarchical representations for HRR radar returns.

A useful method for designing the tree structure is based on the application the Linde–Buzo–Gray (LBG) algorithm [10] to successive stages using a training set. We have used a variant of this method which is of the "greedy" [13] variation. We first perform a multiresolution wavelet representation of the radar pulses, based on the selection of a mother wavelet. This allows us to consider each pulse reconstructed at different resolutions $S^0 f,\ S^1 f, \cdots,\ S^{J^*} f$. We then proceed by splitting the signal space at various resolutions in cells as indicated pictorially in Figure 1. The data vector space (signal space) is partitioned into cells, or collections of data vectors which are determined by the repeated application of the Linde-Buzo-Gray (LBG) algorithm. LBG is first applied to the coarsest resolution representation of the data vectors $\{S^{J^*} f,\ f \in \mathcal{S}\}$. The resultant distortion is determined based on a mean squared distance metric, and is computed using the finest resolution representation of the data vectors. The cell (equivalence class of coarse resolution representations) which is the greatest contributor to the total average distortion for the entire partition is the cell which is split in the next application of LBG. A new Voronoi vector is found near the Voronoi vector for the cell to be split and is added to the Voronoi vectors previously used for LBG. LBG is then applied to the entire population of data vectors, again using the coarsest representation of each vector. These steps are repeated until the percentage reduction in distortion for the entire population falls below a predetermined threshold. The partition in the coarsest resolution is then fixed, and further partitioning continues by splitting the cells already obtained based on finer resolution representations of the data vectors in the cell. The algorithm then iterates through these steps until the allotted number of cells have been allocated, or until total average distortion has been reduced to a requisite level. Each new layer in the tree corresponds exactly to partitions based on the next finer resolution representation of the data.

The algorithm constructs a hierarchical organization of the radar return data as a tree, which is conformant with the wavelet multiresolution data representations. This representation can be constructed for a single target or for a collection of targets. In the former case this construction produces a "model" for the target as viewed by the radar sensor. In the later this construction organizes an entire database of target radar returns. The resulting tree is our *aspect graph of the target(s)*. As illustrated in Figure 2 a multiresolution (or scale space) aspect graph for radar ship data results naturally from our construction. Here the concentric spheres designate different resolutions (scales). The cells on these spheres illustrate aspect equivalence classes for the radar signals (returned pulses). These equivalence classes mean that the pulses in these clusters are difficult to discriminate due to their similarity. As we move inwards in this graph, the outside cells split as we can now get further characteristics of the target based on finer resolution information on the pulse. These characteristics are related to dominant scattering centers. To construct the aspect graph we select as the representative from each equivalence class, the radar pulse corresponding to the centroid of the corresponding Voronoi cell. The resulting graph has geometrically the appearance of a tree; a typical one is depicted in Figure 3. The nodes (cells in these figures) correspond to aspect–elevation neighborhoods for which the corresponding returned pulses are too similar to be separated. The nodes are given for various resolutions as well as the percentages of pulses that were clustered in each cell. It is clear from this discussion that the aspect graph

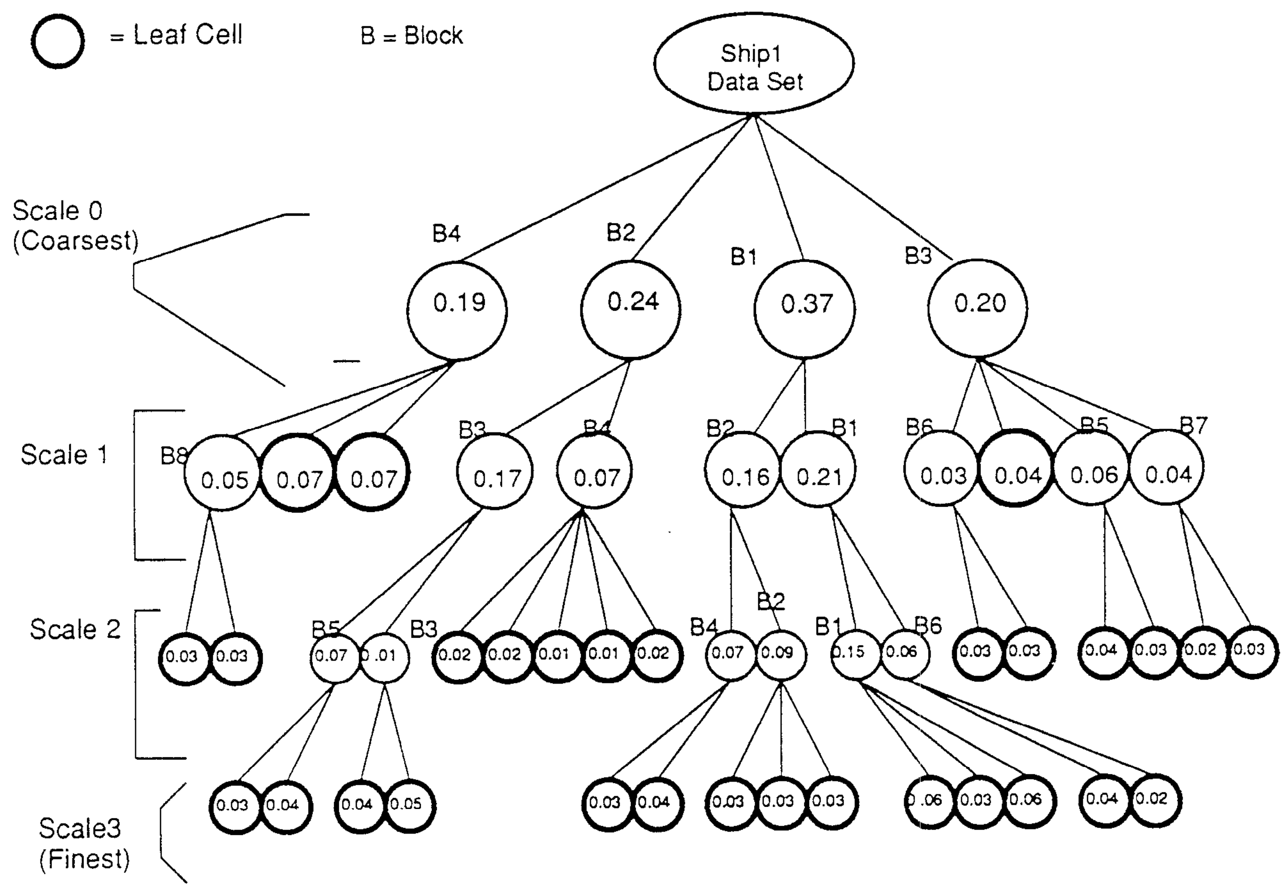

Figure 3: Aspect graph (as a tree) for the ship1 radar data set

is a reduced but accurate model of the target and can be used to guide the ATR process in model–based ATR. In such an application the received pulse is compared with the "canonical" pulse at each node sequentially as the ATR process evolves. As explained and demonstrated in detail in [14, 17, 25] these scale space aspect graph radar target models are not only efficient but very accurate.

3 HIGH PERFORMANCE MODEL BASED ATR ALGORITHMS

The efficient radar target modeling techniques and model database organization described in the earlier sections will be used in this section to design high performance ATR algorithms. As explained in detail in [16, 18] the mulincoming sensor data are first processed by a wavelet preprocessor and then are input to the tree. At each node of the tree, the distance between the sensor data and the Voronoi vectors (i.e. centroid pulses) of the "children nodes" is computed and the input pulse progresses to the node corresponding to the "child" with the smaller distance and the process repeats. When the incoming pulse reaches a leaf node it is declared as Ship1 or Ship2 according to the labeling that has been assigned to that leaf node.

We shall refer to this method as the **Combined Aspect Graph (CAG) Method** in order to emphasize the fact that a single aspect graph is constructed for the entire database. It is a reasonable approximation to the more systematic method described and proposed in [25]. Its advantages are: (i) It includes all relations between the data; (ii) Due to its tree hierarchy it produces decisions in time logarithmic in the number of leaf nodes (roughly); (iii) It is based on an approximation of the multidimensional distribution of the data from all targets. Its disadvantages are: (i) The multidimensional distribution may "hide" the distinguishing characteristics of individual targets; (ii) The leaf labeling is *ad hoc*; (iii) When a new target needs to be encountered a costly redesign and retraining must be performed. The most serious drawback is (iii) which is often unacceptable despite the fact that it is performed off-line.

We have tested this CAG method on high accuracy synthetic data. The NRL Code 5750 digital simulation model is a flexible tool for experimentation, and it has been used as the basic data generation source for the studies reported here. This model has been validated against field returns and provides high accuracy simulations. The digitally simulated ship model consists of over 800 scatterers (for each viewpoint) of a variety of types, including flat plates, point scatterers and dihedrals. These scatterers are distributed in both range and space in accordance with their actual locations on a ship. To capture safely all ship pulses we used a range gate of 128 bins corresponding to a returned signal time duration of 1280 ns. At the finer resolution of 10 ns, and sampling at the corresponding rate produces 2^7 samples per pulse. We generated radar return databases for two different ships, *Ship 1* and *Ship 2*, utilizing the NRL Code 5750 ship radar return simulator. In generating the synthetic data we kept the radar fixed and turned the ship, including the motion induced by sea waves. We varied the aspect angle from $0°$ to $360°$ in increments of $0.5°$. This allowed for large variation in the number and appearance of dominant scatterers.The parameters in the synthetic data were as follows. Radar frequency: 16.25 GHz, Elevation angle: $.023°$, Sea state: 3, Pulsewidth: 10 ns, Pulse Repetition Interval: 120 ms to 1 s. Each database contained 720 pulses at fine resolution (720 for training and 720 for testing for each ship). We did not change the range gate and therefore each pulse in the database has the same time duration. We used different data for designing the aspect graphs and different data for testing the resulting ATR algorithms.

Figure 4 illustrates the combined aspect graph constructed with the CAG method. The tree has 30 leaf nodes and we also indicate in Figure 4 the resulting labeling by majority vote. The small number of elements in some nodes indicates that further study is needed for the optimal construction and labeling of such aspect graphs. This will be addressed elsewhere. The performance of the resulting ATR algorithm is described by the "confusion matrix" depicted in Figure 5.

Confusion Matrix

30 Cells:

	Ship 1	Ship 2
Ship 1	0.751389	0.248611
Ship 2	0.148611	0.851389

Figure 5: Confusion matrix for the ATR algorithm constructed with the CAG method

The second method uses separately the data from each ship to construct an independent scale space aspect graph model for each target. The resulting trees are then used in parallel for the on-line ATR algorithm as follows. The incoming sensor pulse is processed by each tree independently in the usual fashion progressing through the parent to children nodes on the basis of minimum distance. At the end the incoming sensor pulse will reach a leaf node in each tree. If the distance from the Voronoi vector of the leaf node where the pulse ended is smaller in the tree representing Ship1, then a Ship1 classification is declared. In the opposite case a Ship2 classification is declared.

We refer to this method as the **Parallel Aspect Graph (PAG) Method**. Its advantages are: (i) It is extremely fast and maximally parallel; (ii) On-line training can be easily implemented; (iii) It provides an acceptable solution to the "new target" insertion problem. Its disadvantages are: (i) It does not account for correlations between target models; (ii) The decision scheme is *ad hoc*.

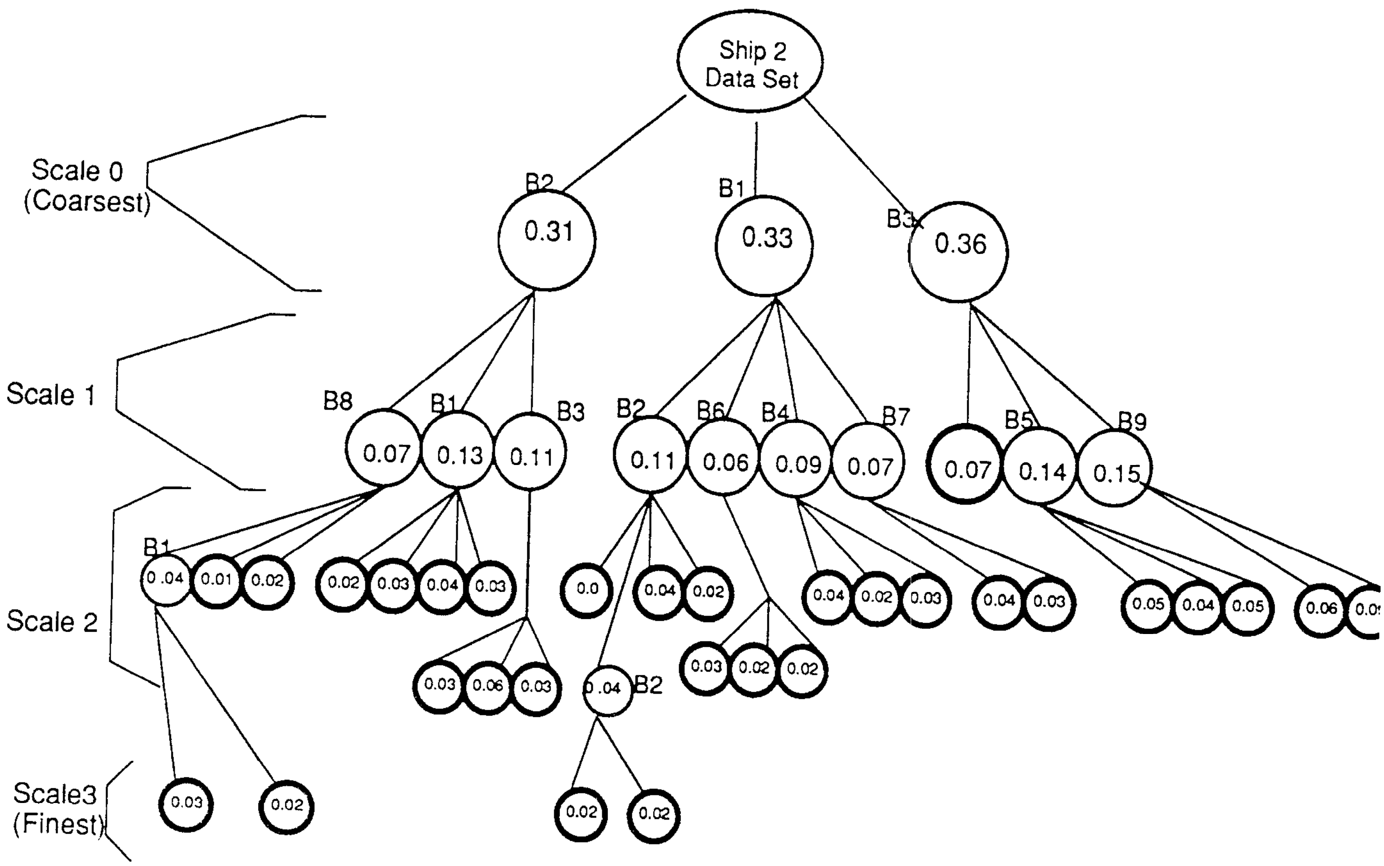

Figure 6: Aspect graph (as a tree) for the ship2 radar data set

We have tested the ATR algorithms constructed with this PAG method using the same data as in the CAG method. The aspect graph constructed for ship1 is depicted in Figure 3, while the spect graph constructed for ship2 is depicted in Figure 6. The resulting confusion matrix is shown in Figure 7.

Confusion Matrix

30 Cells	Ship 1	Ship 2
Ship 1	0.948611	0.051389
Ship 2	0.143056	0.856944

Figure 7: Confusion matrix for the ATR algorithm constructed with the PAG method

Comparing the confusion matrices obtained by the two methods we conclude that the parallel aspect graph method produces higher performance ATR algorithms. This is somewhat surprising. We even reduced the number of leaf nodes in each aspect graph, from 30 to 15, in case some "over training" occured and we obtained similarly excellent confusion matrices from the PAL method, as shown in Figure 8.

Confusion Matrix

15 Cells	Ship 1	Ship 2
Ship 1	0.938889	0.061111
Ship 2	0.168056	0.831944

Figure 8: Confusion matrix for the ATR algorithm, PAG method, 15 cell trees

Further study is needed in order to systematically analyze these promising methods and properly quantify their performance, complexity and trade-offs involved. If these findings hold then we will obtain a superior and systematic method for constructing high performance, maximally parallel model based ATR algorithms. Generalizations and extensions to other sensors and to multi sensor problems will follow easily.

References

[1] I. Daubechies, "Orthonormal Bases of Compactly Supported Wavelets", *Comm. Pure Appl. Math. 41*, pp. 909—996, 1988.

[2] S.G. Mallat, "A Theory for Multiresolution Signal Decomposition: The Wavelet Representation", *IEEE Trans. on Pattern Analysis and Mach. Intel.*, Vol. 11, No. 7, pp. 674—693, 1989.

[3] Y. Meyer, *Ondelettes et Operateurs I, II*, Hermann, Paris, 1990.

[4] J.G. Daugman, "Complete Discrete 2-D Gabor Transforms by Neural Networks for Image Analysis and Compression", *IEEE Trans. on Ac. Sp. and Sign. Process.*, Vol 36, No. 7, pp. 1169—1179, July 1988.

[5] Teuvo Kohonen, *Self-organization and Associative Memory*, Springer-Verlag, New York, 1989.

[6] S.G. Mallat and S. Zhong, " Characterization of Signals From Multiscale Edges", *NYU, Computer Science Technical Report, Nov. 1991*; also in *IEEE Trans. Pattern Anal. Machine Intell*, Vol. 14, No. 7, pp. 710-732, July 1992.

[7] S. Zhong and S.G. Mallat, "Compact Image Representation From Multiscale Edges", *Proc. of 3rd International Conf. on Comp. Vision*, Dec. 1990.

[8] O. Rioul and M. Vetterli, "Wavelets and Signal Processing", *IEEE Signal Processing Magazine*, Vol. 8, No.4, pp.14—38, October 1991.

[9] I. Daubechies, *Ten Lectures on Wavelets*, SIAM, 1992.

[10] A. Gersho and R.M. Gray, *Vector Quantization and Signal Compression*, Kluwer Academic Press, 1991.

[11] K. Bowyer, D. Eggert, J. Stewman, and L. Stark, "Developing the Aspect Graph Representation for Use in Image Understanding", *Proc. DARPA Image Understanding Workshop 1989*, pp.831—849.

[12] L. Breiman, J.H. Friedman, R.A. Olshen and C.J. Stone, *Classification and Regression Trees*, Wadsworth and Brooks, 1984.

[13] E. Riskin, "A Greedy Tree Growing Algorithm for the Design of Variable rate Vector Quantizers", *IEEE Trans. on Signal Process.*, Vol. 39, No. 11, pp. 2500-2507, Nov. 1991.

[14] J.S. Baras and S.I. Wolk, "Hierarchical Wavelet Representations of Ship Radar Returns", submitted for publication to *IEEE Trans. on Signal Process.*, 1993; also *NRL Technical Report* NRL/FR/5755-93-9593.

[15] D.W. Eggert, K.V. Bowyer, C.R. Dyer, H.I. Christensen and D.B. Goldgof, "The Scale Space Aspect Graph", *IEEE Trans. on Pattern Anal. and Mach. Intel.*, Vol. 15, No. 11, pp. 1114-1130, Nov. 1993.

[16] J.S. Baras and J.L. Preston, "Wavelet and Learning Clustering Algorithms for Automatic Target Recognition," AIMS Technical report AIMS-TR-93-04, Final progress report on DARPA SBIR Phase I Contract 92-61, September 1993.

[17] J.S. Baras and S.I. Wolk, "Efficient Organization of Large Ship Radar Databases Using Wavelets and Structured Vector Qantization", *Proc. of the 27th Annual Asilomar Conference on Signals, Systems, and Computers*, Vol 1, pp 491-498, November 1-3, 1993, Pacific Grove, California.

[18] J.S. Baras and D.C. MacEnany, "Model-Based ATR: Algorithms Based on Reduced Target Models, Learning and Probing," *Proceedings of the Second ATR Systems and Technology Conference*, Feb. 1992, Vol. 1, pp. 277-300.

[19] T.F. Knoll and R.C. Jain, " Recognizing Partially Visible Objects Using Feature Indexed Hypotheses", *IEEE J. Robotics and Automation"*, 2(1), 1986, pp. 3-13.

[20] Y. Lamdan and H.J. Wolfson, "Geometric Hashing: A General and Efficient Model-Based Recognition Scheme," *Proc. Second Int. Conf. Comp. Vision*, 1988, pp. 238-249.

[21] K. Ikeuchi and T. Kanade, "Automatic Generation of Object Recognition Programs", *Proc. IEEE*, Vol. 76, No. 8, Aug. 1988, pp. 1016- 1035.

[22] D.E. Dudgeon, J.G. Verly, and R.L. Delanoy, "An Experimental Target Recognition System for Laser Radar Imagery", *Proc. DARPA Image Understanding Workshop 1989*, pp. 479-506.

[23] J.G. Verly and R.L. Delanoy, "Appearance-Model-Based Representation and Matching of 3-D Objects", Proc. of IEEE Computer Society Workshop on Computer Vision, 1990, pp. 248-256.

[24] M. Seibert and A. Waxman, "Adaptive 3-D Object Recognition from Multiple Views", *IEEE Trans. on Pattern Match. and Mach. Intell.*, Vol. 14, 2, pp. 107-124, Feb. 1992.

[25] J.S. Baras and S.I. Wolk, "Wavelet Based Progressive Classification of High Range Resolution Radar Returns", *Proc. of the 1994 SPIE International Symposium on Intelligent Information Systems*, April 1994.