Iterated Wavelet Transformation and Signal Discrimination for HRR Radar Target Recognition

Dale E. Nelson, *Senior Member, IEEE*, Janusz A. Starzyk, *Senior Member, IEEE*, and D. David Ensley

***Abstract*—This paper explores the use of wavelets to improve the selection of discriminant features in the target recognition problem using high range resolution (HRR) radar signals in an air to air scenario. We show that there is statistically no difference among four different wavelet families in extracting discriminatory features. Since similar results can be obtained from any of the four wavelet families and wavelets within the families, the simplest wavelet (Haar) should be used. We use the box classifier to select the 128 most salient pseudo range bins and then apply the wavelet transform to this reduced set of bins. We show that by iteratively applying this approach, classifier performance is improved. We call this the iterated wavelet transform. The number of times the feature reduction and transformation can be performed while producing improved classifier performance is small and the transformed features are shown to quickly cause the performance to approach an asymptote.**

***Index Terms*—Automatic target resolution, feature selection, high range resolution radar, rough sets, wavelets.**

I. Introduction

Most of the work in high range resolution (HRR) target recognition has been done by or sponsored by the military. The approaches taken by various researchers as summarized by [1] appear to ignore the benefits that can be gained by proper transformations of the input signal. The wavelet transform [2]–[4] is a new tool that has been used in image compression, edge detection, image classification, and more recently, in target recognition. When wavelet transforms are used for image compression the most important goal is to minimize the loss of information. In automatic target recognition (ATR) the most important objective is to separate the various target classes [5]. Some researchers have explored the use of wavelets to provide a richer feature space [5]–[8]. However there is little evidence of widespread use of this technique.

Famili [9] found that preprocessing the data allows easier subsequent feature extraction and increased resolution. In the past, engineers have used transforms such as the fourier transform to transform the signal from a time base to a frequency base [10]. Although this is useful for some applications, target recognition of HRR signals improved only a little under this transform. The reason for this lies in the fact that the fourier transform tells us that a feature occurs somewhere in the signal, but not where. Wavelets bring a new tool to HRR signal classification. The benefits of using wavelets [11] are that the new transforms are local; i.e., the event is connected to the time when it occurs. Researchers who have used wavelets for target recognition (especially for HRR) have found that the original feature space can be augmented by the wavelet coefficients and will yield a smaller set of more robust features in the final classifier [7], [12], [13]. In addition to computational savings [8], investigators have also found that wavelet methods can improve the probability of correct classification (P_{cc}) [6], [7]. However, even with improvement in P_{cc} there can be a bias of the wavelets toward one or two classes to the detriment of others [7].

In considering wavelets for ATR, serious consideration must be given to the selection of a wavelet family and a wavelet in the family. Lu [14] explored this issue in the context of image coders. In his paper, Lu compared two wavelets, one from the Biorthogonal family and the other from the Daubechies family. Using two different metrics, Lu observed a slight advantage of the biorthogonal versus the Daubechies. In this paper, using the criterion of improving the probability of correct classification, we show that there is no statistical advantage of one family (out of four) over any other family. Any difference in performance that can be observed in a particular application is due to the statistical nature of normal variations in the data. Stirman, using wavelets for ATR, explored the use of different wavelets from the Daubechies family, and found that the results were similar among the three wavelets [7]. In this paper we show that there is no statistical advantage of one wavelet in a family over another in the same family, thus generalizing Stirman's observation.

Other researchers have employed wavelets to assist in HRR target identification [8], [13]. Devaney's approach used a sequential decision process where the log likelihood ratios are computed at each scale in the discrete wavelet transform (DWT) and then hypothesis testing is applied at each scale to yield the target identification. Etemad [13] used the multiscale DWT to reduce the dimensionality of the classification problem. He used the coefficients to build a set of basis functions which yield the largest class separability. These basis functions result in simple and efficient algorithms for classification. The work presented here differs from the efforts of these two researchers. We employ a classifier in this work, but the focus is *not* on the classifier but on a method to improve upon the DWT itself. Etemad and Devaney applied the multiscale DWT one time we apply it many times. After the first application of the DWT we down-select, using the box classifier, a number of coefficients equal to the orignial number of range bins in the signal. Doing this many

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D. E. Nelson is with the Air Force Research Laboratory, Wright Patterson AFB, OH 45433-7321, USA (e-mail: Dale.Nelson@wpafb.af.mil).

J. A. Starzyk is with the Department of Computer Engineering, Russ College of Engineering and Technology, Ohio University, Athens, OH 45701, USA.

D. D. Ensley is with Warner Robins Air Logistics Center-US Air Force, Robins AFB, GA 31098-1622, USA.

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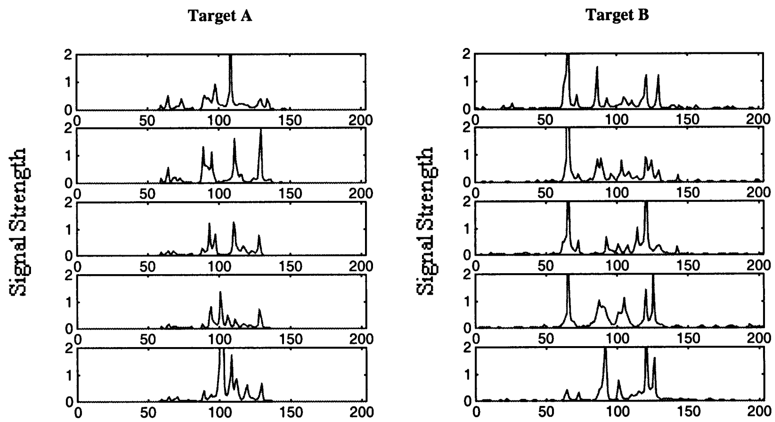

Fig. 1. Comparison of two HRR target signals.

times yields a new pseudo wavelet (**iterated wavelet transform**) constructed for the problem presented by the training data.

It is not the purpose of this paper to explore the development of a classifier. However, in order to have a means to test the usefulness of the data transforms, we must have a classifier to test the performance and determine which features to select for further transformation. We have chosen to use the simple generalized box classifier [15]–[17] from which to evaluate the results. Our main objective was to determine which, if any, family of wavelets provided the best feature set for a classifier. A secondary objective was to determine if further wavelet transformations would produce even better classification results. This required the use of a method for down selecting features from which to perform further wavelet analysis. In this paper, using wavelet transformations, we will show the following:

1) wavelets are useful for generating features that improve classifier performance;
2) what family and which wavelet in the family is best;
3) how to mitigate or eliminate wavelet bias toward some target classes.

II. Problem Specification

A. Signal and Its Transform

This paper uses HRR radar signals. A HRR signal is an n-dimensional vector $x = (a_1, a_2, \ldots, a_n)$, where $a_i \in \{0, 1, \ldots, 255\}$. The HRR radar provides a one–dimensional (1–D) picture of what the sensor is looking at. HRR signals are particularly hard to use for target recognition, partly because the three-dimensional (3-D) world is projected on to just one dimension. When this is done, there are many ambiguities created which must be resolved. A further complication is that when HRR data is plotted as signal strength vs. range bin, the resulting graph is almost impossible for a human to use for target recognition, mostly because it is a visual 1-D image we have no experience interpreting [18]. A better representation would be to present the HRR signal as an audio signal (similar to sonar) because humans have experience interpreting or recognizing this kind of 1-D signal. Szu points out that the human auditory system uses wavelets [5] that aid in the recognition process.

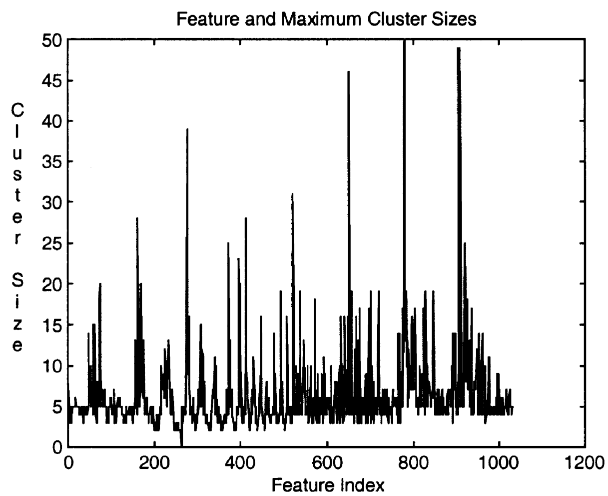

Fig. 2. Maximum Cluster Sizes.

A further complication to target identification using HRR is that the signals change considerably with only a small change in azimuth and elevation. This is illustrated in Fig. 1.

The signals shown in Fig. 1 are from two different targets. The signals shown for each target were taken at 200 msec intervals. Their significant variations in a short time span illustrate how difficult it would be to construct a target identification system based on these signals.

Wavelet transforms have been found useful in a variety of applications. This is because they provide the analyst with an approximation of the signal and a detail of the signal as well. This helps to identify small anomalies which might be useful. A complete description of wavelet packet analysis also known as multilevel wavelet analysis as used in this research may be found in [10] and [11]. Graphs of the wavelets used are presented in [10].

Prior to selecting features for the target classifier, it is useful to preprocess the original signal. Any operation which increases our ability to separate the classes is desirable. In this paper, we base feature selection on transformations derived from wavelets. Training and test sets were constructed using each of the functions. The utility of each of these wavelets for enhancing the performance of a classifier was then analyzed. An example of the power of a wavelet transformation is illustrated in Fig. 2 using the Haar wavelet transform on the original signal.

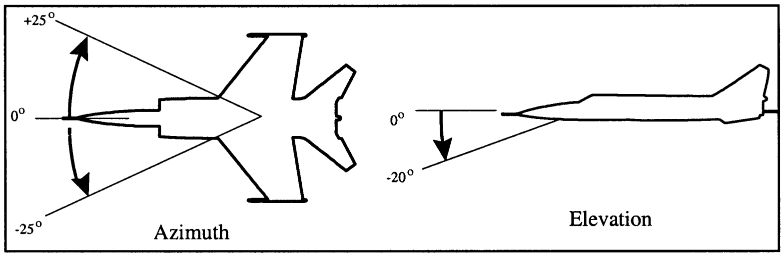

Fig. 3. Azimuth and elevation ranges.

In Fig. 2, the original signal is contained in the first 128 feature index points. The coefficients of the Haar transform are contained in the remaining feature index points. The original signal features show that the largest number of signals in the training set that can be classified by a single feature is 20 out of a maximum of 60. Selecting a single feature from the wavelet coefficients, it is possible to classify 50 out of 60 signals. This is a significant improvement!

B. Training and Test Data Sets

The data set used in this research consists of synthetic HRR returns on six targets. This data was generated using XPATCH, a state of the art electromagnetic modeling program. For each target there are 1071 range profiles consisting of 128 range bins. The value of each range bin is an integer between 0 and 255. The pose of the target is head-on with an azimuth range of $\pm 25^\circ$ and elevations of -20° to 0° in one degree increments as illustrated in Fig. 3.

This data is divided into two sets, one for training and the other one for testing. The training set consists of 25% of the data and the test set 75% of the data (the remaining data), randomly selected. The small training set permits faster training, facilitating algorithm development and debugging. The training set was constructed by using a random number generator to select 25% of the azimuth and elevation angles and then by selecting signals from each target class with these angles. All remaining signals were placed into the test set.

We have illustrated that wavelets provide a powerful way of looking at the original signal so it makes sense to incorporate wavelet transforms and some statistical properties into the training and test set. The first step toward creating the training and test set is to normalize the original signal x_i using the l_2 norm yielding $\bar{x_i}$. We next calculate six values that characterize the data (2-norm, mean, infinity norm, standard deviation, 1-norm, and the Euclidean norm)$Q(\bar{x_i}) = (q_{1i}(\bar{x_i}), q_{2i}(\bar{x_i}), \ldots, q_{6i}(\bar{x_i}))$ where Q represents these vectors. Using similar notation, the wavelet transforms $W(\bar{x_i})$ are constructed as described in [10]. The rows in the training set S are defined as the tuple $S_i = (Q(\bar{x_i}), \bar{x_i}, W(\bar{x_i}))$ where each $S_{ij} \in [0,1] \in \Re$. The training and test sets are conveniently represented as a matrix

$$S = \begin{bmatrix} \vdots \\ S_i \\ \vdots \end{bmatrix}$$

We refer to each row of the training and test sets as a signal. The training set S consists of signals having 1030 pseudo range bins.

III. Classifier Description

The classifier used in this paper is a version of the generalized box classifier [15]. The training set produced as described previously is used to construct the classifier. The first step in constructing the classifier is to sort each column of S from the smallest value to largest value creating a new matrix $\bar{S}$. A matrix $\bar{M}$ is constructed with each element of $\bar{M}$ corresponding to the target type of each element of $\bar{S}$.

The algorithm determining a target classifier is as follows: Let i denote the target class, and j the feature number. Set $i = j = 1$.

Step 1. Search all columns of $\bar{M}$ to find the column with the largest contiguous cluster of the selected target class i. Let $\sigma(j)$ denote the column determined by this procedure (σ is a permutation of the columns of $\bar{S}$). Let $\bar{S}_{n,\sigma(j)}$ denote the minimum value in the contiguous cluster and let $\bar{S}_{k,\sigma(j)}$ denote the maximum value in the contiguous cluster.
The indices n and k correspond to the row indices of $\bar{S}$ with the minimum and maximum values. All signals contained in this cluster are removed from further consideration.
Step 2. Define the jth feature of target class i as the set $f_{ij} = (\bar{S}_{n,\sigma(j)}, \bar{S}_{k,\sigma(j)})$. Set $j = j + 1$ and repeat this process (go to step 1) until there are no more training signals from target class i.
Step 3. Increment target class i and set $j = 1$. Repeat this process (go to step 1) until all target classes are accounted for.

The elements of f_{ij} are called individual features. The feature set F is defined as the set of all f_{ij}. A transformed signal z is said to be classified as target class i when there exists a feature f_{ij} such that $z \in f_{ij}$.

A classifier is tested by classifying each of the transformed test signals, z. An *n* x *n* confusion matrix C is constructed to represent the results. To construct the confusion matrix, we first set $C = [0]$. Each test signal is classified and C is modified as follows. If the ith test signal, known to be of class j is classified as the target type j then $C_{jj} = C_{jj} + 1$. If the ith test signal known to be of class j is classified as target type k, then

TABLE I
PERFORMANCE OF WAVELETS

Wavelet Name	P_{cc}	Wavelet Name	P_{cc}	Wavelet Name	P_{cc}	Wavelet Name	P_{cc}
Bior1.3	0.72488	Haar	0.77130	Coif1	0.76115	Sym2	0.79153
Bior1.5	0.78045	Db2	0.79576	Coif2	0.78231	Sym3	0.75886
Bior2.2	0.75760	Db3	0.75886	Coif3	0.77133	Sym4	0.77458
Bior2.4	0.78150	Db4	0.79160	Coif4	0.78770	Sym5	0.75800
Bior2.6	0.77400	Db5	0.77567	Coif5	0.76943	Sym6	0.76345
Bior2.8	0.78600	Db6	0.78120			Sym7	0.76591
Bior3.1	0.70550	Db7	0.77460			Sym8	0.78275
Bior3.3	0.77030	Db8	0.76760				
Bior3.5	0.78020	Db9	0.79410				
Bior3.7	0.79410	Db10	0.77630				
Bior3.9	0.79290	Db11	0.75598				
Bior4.4	0.72990	Db12	0.76300				
Bior5.5	0.74150						
Bior6.8	0.73010						
Mean	0.76064		0.77550		0.77438		0.77073
Standard Deviation	0.02890		0.01329		0.01060		0.01272

$C_{jk} = C_{jk} + 1$. In other words, the diagonal represents the correctly classified targets. The off-diagonal elements represent misclassification. This process continues until all transformed test signals are classified. In this paper we used equal numbers of signals to represent each target class for both training and test. Therefore, to obtain the final confusion matrix, each element of C is divided by the number of signals for a target class. It should be noted that some test signals might not be classified as any target type. Therefore, it is possible that the rows and columns of the confusion matrix will not sum to one. To evaluate the overall performance of the classifier the probability of correct classification, P_{cc}, is calculated. P_{cc} is defined for n target classes as $P_{cc} = 1/n \sum_{i=1}^{n} C_{ii}$.

IV. WAVELET SIGNAL DISCRIMINATION PROPERTIES

As observed in the previous discussion, a wavelet transform improves feature selection for target recognition. The natural question is to identify which wavelet improves target recognition the most. In this section we demonstrate that there is no single wavelet that outperforms all others in this task.

Conjecture 1: No single wavelet transform has a statistically significant advantage over other wavelets in extracting features for the target classification.

To verify conjecture 1, classifiers were constructed using training sets from all the wavelet families. Table I shows the results obtained upon testing the classifier built from the original signal and the associated wavelet transform. In addition, the mean and standard deviation of P_{cc} for the wavelet family are presented in Table I. To compare if there is any significant difference among the families we use hypothesis testing of the means [19]. The mean, μ, and the standard deviation, σ, of the population are calculated using

$$\mu = \frac{1}{n}\sum_{i=1}^{n} P_{CCi} \quad \sigma = \sqrt{\frac{n\sum\limits_{i=1}^{n} P_{CCi}^2 - \left(\sum\limits_{i=1}^{n} P_{CCi}\right)^2}{n(n-1)}}.$$

When the mean and standard deviation are computed from samples, μ is replaced by $\bar{x}$ and σ is replaced by s, respectively.

TABLE II
WAVELET FAMILY HYPOTHESIS TEST

Wavelet Name	Wavelet Name	$\|Z\|$	Accept or Reject H0
Biorthogonal	Daubechies	1.723060	Accept
Biorthogonal	Coiflet	1.516130	Accept
Biorthogonal	Symlet	1.109050	Accept
Daubechies	Coiflet	0.183654	Accept
Daubechies	Symlet	0.775505	Accept
Coiflet	Symlet	0.540601	Accept

We are testing the hypothesis; H_0: $\mu_1 = \mu_2$ against the alternative hypothesis; H_1: $\mu_1 \neq \mu_2$. We compute the test statistic as follows:

$$Z = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{\sigma_1^2}{n_1} + \frac{\sigma_2^2}{n_2}}}$$

We will reject H_0 if $|Z| > 1.96$ (1.96 is for a two-tailed test where the results are significant at a level of 0.05). The results of this hypothesis testing are presented in Table II.

From the analysis presented we must accept the null hypothesis, that there is no difference in the mean values. This means that there is no statistically significant difference in the performance of the classifiers when different families of wavelets are used to transform the input data. It would be best (from a computational standpoint) to use the simplest form of a wavelet possible. Since there is no difference *among* the families, the question arises is there any significant difference *within* each family? By examining the size of the mean and the size of the standard deviation, we see that there is no significant difference among the wavelets within the families. It is safe to conclude that classifier performance would be the same no matter which wavelet we choose. Therefore, it benefits us to use the simplest form of wavelet possible, the Haar (Db1) wavelet.

Normally this type of analysis is limited to large samples where the standard deviations of the samples are known. A t-test was also performed which gave the same results. This indicates

TABLE III
RESULTS OF ITERATIVE APPLICATION OF HAAR TRANSFORM

Iteration	P_{CC}	Target 1	Target 2	Target 3	Target 4	Target 5	Target 6
0	.7713	.9490	.6219	.8219	.6853	.8134	.7363
1	.81361	.9552	.6741	.8555	.6692	.8893	.8383
2	.84762	.9552	.7724	.9128	.7027	.9104	.8321
3	.86421	.9453	.7823	.9452	.7363	.9154	.8607
4	.87976	.9453	.7935	.9465	.7774	.9328	.8831
5	.88618	.9453	.8172	.9552	.7550	.9316	.9129
6	.88453	.9453	.8197	.9601	.7376	.9316	.9129
7	.89095	.9391	.8507	.9664	.7450	.9316	.9129
8	.89261	.9391	.8246	.9664	.7799	.9316	.9142
9	.88867	.9391	.8346	.9651	.7488	.9316	.9129
10	.89717	.9391	.8706	.9639	.7512	.9391	.9192
11	.89365	.9353	.8570	.9639	.7512	.9391	.9154
12	.90049	.9353	.8483	.9689	.7749	.9465	.9291

that the small number of samples did not give us a false acceptance of H_0.

V. ITERATED WAVELET TRANSFORM

If the original signals are transformed and then 128 of the most informative pseudo range bins (original signal's range bins augmented by the wavelet coefficients) selected for further transformation, a new linear transformation of the input data is created [16]. This process can be repeated many times and is called the **iterated wavelet transform**. This is similar to the basic assumption of genetic programming where new generations of features related to the most successful features from prior generations may show better qualities than their parents. For any learning process based on a fixed set of data the increase in information represented by learning features is getting smaller as progress toward the optimum is made. At some point there will be no increase, at which point the learning process must stop.

Conjecture 2: By iteratively selecting the most informative pseudo range bins and transforming them, the informative value of the range bins in general may increase yielding a better classifier.

An experiment was performed to verify this conjecture. The original 128 range bin signal was transformed (using the Haar wavelet) as previously discussed creating 1024 pseudo range bins. A box classifier was constructed. The range bins used as features were chosen for further transformation. If there are more than 128 pseudo range bin features, then the features which classify the most training signals are selected. If there are fewer than 128 features, then additional pseudo range bins are selected from the middle of the pseudo signal. These 128 range bins were wavelet transformed, a classifier was constructed and tested. This procedure was repeated twelve times and the results are presented in Table III and Fig. 4.

When using just one wavelet transform on the original signal Stirman showed an increase in P_{cc} of six percentage points [6] and 7.53 percentage points over the baseline classifier [7]. This difference, over the baseline classifier, may have resulted from changing the type of classifier or the use of wavelets. Stirman did not attribute the increase in performance to one or the other, neither did he analyze the significance of using the wavelet transform. In the results presented here, we find that using the same classifier, the improvement in P_{cc} after one application of

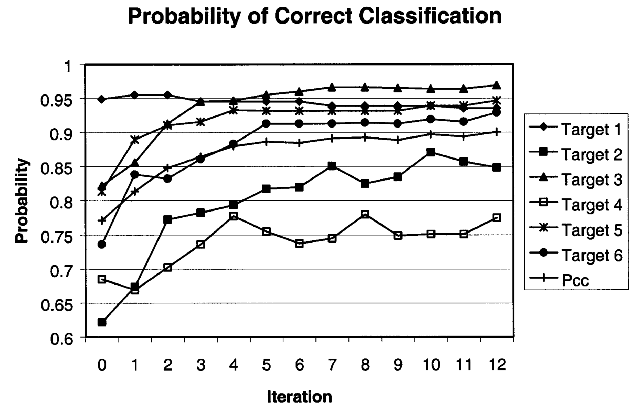

Fig. 4. Classification improvement with iterated wavelet transforms.

the wavelet transform is 4.2 percentage points. This improvement is smaller than the one observed by Stirman, but we can attribute this difference to our use of a different classifier and wavelet (Haar).

The most important curve in Fig. 4 is the one for P_{cc} that represents the performance of the classifier for all target classes at each iteration of the iterated wavelet transform. In this figure, iterations 2–12 demonstrate the benefits of the iterated wavelet transform over the use of a single transform. This curve shows an increase in overall classifier performance from 0.7713 to 0.897 17 by iteration 10. This represents an improvement of 12 percentage points. Furthermore, Target 2 improved by 25 percentage points and Target 6 by 18 percentage points. This is a significant improvement in performance over a single wavelet transform and confirms the benefit of using the iterated wavelet transform.

We questioned why there would be a decrease in performance on some of the targets such as seen on Target 2 between iterations 7 and 8. It is apparent that the iterated wavelet transforms yield an increasing performance in the entire classifier. Individual targets may sacrifice performance while overall performance increases. In general, the momentary decreases are recovered in later iterations. This may be a manifestation of the biasing problem reported by Stirman [7]. If so, by iterating the wavelet transform this problem appears to either be mitigated or eliminated. For our problem, the maximum advantage of iterating the wavelets happens at about ten iterations.

VI. SUMMARY OF RESULTS

The contribution of this paper is the **iterated wavelet transformation** that was used to enrich the feature space and improve classifier performance. Our conjectures were verified using statistical hypothesis testing on synthetic HRR data. An information entropy approach for the down select of the pseudo range bins has shown similar improvement in classification performance.

We have shown that there is no statistically significant difference in performance of the classifier when different wavelets are chosen. This means that the simplest wavelet to implement will do as good a job as any other wavelet, at least for the HRR target recognition problem.

The application of the **iterated wavelet transformation** method used here to improve performance could potentially be used in classification of any 1-D signal such as found in echo cardiograms, seismology, sonar, and economic analysis.

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Dale E. Nelson (SM'02) received the B.S. degree in aeronautical engineering from Tri-State University, Angola, IN in 1969, the M.S. degree in computer science from Wright State University (WSU), Dayton, OH, in 1981 and the Ph.D. degree in electrical engineering in 2001 from Ohio University, Athens, OH.

From 1969 to 1972, he was a Structural Fatigue Engineer at Cessna Aircraft, Wichita, KS. In 1972, he joined the Air Force Flight Dynamics Laboratory, where he worked in the preliminary aircraft design group. In 1986 he was promoted into the Aeronautical Systems Division (ASD) Deputy for Development Planning, where he was the database administrator responsible for the budgeting submission of ASD to HQ AFMC. In 1989, he became the supervisor of the Advanced Systems Research Group responsible for performing machine intelligence research. He is currently chief of the ATR and Fusion Algorithms Branch of the Sensors Directorate. He is leading a group doing basic research into advanced algorithms for target identification. He is also serving as an adjunct faculty member at WSU. His current research interests are in the area of rough set theory, automatic target recognition, and machine intelligence.

Janusz A. Starzyk (SM'83) received the M.S. degree in applied mathematics and the Ph.D. degree in electrical engineering from Warsaw University of Technology (WUT), Warsaw, Poland, in 1971 and 1976, respectively.

From 1977 to 1981, he was an Assistant Professor at the Institute of Electronics Fundamentals, WUT. From 1981 to 1983, he was a Post-Doctorate Fellow and Research Engineer at McMaster University, Hamilton, Canada. In 1983, he joined the Department of Electrical and Computer Engineering, Ohio University, Athens, Ohio, where he is currently a professor of EECS. He has cooperated with the National Institute of Standards and Technology in the area of testing and mixed signal fault diagnosis. He has been a consultant to AT&T Bell Laboratories, Sverdrup Technology, and Magnetek Corporation. In 1991, he was a Visiting Professor at University of Florence, Italy. He was a visiting researcher at Redstone Arsenal—U.S. Army Test, Measurement, and Diagnostic Activity and at the Air Force Research Laboratory—Advanced Systems Research and Sensor ATR Technology Development. His current research is in the areas of neural networks, rough sets, VLSI design and test of mixed signal MOS circuits, and reconfigurable design for wireless communication systems.

D. David Ensley received the B.E.E. degree in 1989 and the M.S. degree in 1992, both from Auburn University, Auburn, AL.

From 1992 to 1998, he researched computer intelligence and automatic target recognition algorithms with the U.S. Air Force Research Laboratory. He is currently with the U.S. Air Force Special Operations Forces System Program Office where he manages software and avionics projects on the most technologically advanced helicopters in the world