Radar Target Identification Using the Bispectrum: A Comparative Study

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Radar target identification is performed using time-domain bispectral features. The classification performance is compared with the performance of other classifiers that use either the impulse response or frequency domain response of the unknown target. The classification algorithms developed here are based on the spectral or the bispectral energy of the received backscatter signal. Classification results are obtained using simulated radar returns derived from measured scattering data from real radar targets. The performance of classifiers in the presence of additive Gaussian (colored or white), exponential noise, and Weibull noise are considered, along with cases where the azimuth position of the target is unknown. Finally, the effect on classification performance of responses from extraneous point scatterers is investigated.

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I. INTRODUCTION

Considered here is the formulation and performance of features extracted from the bispectrum of radar signals for classification of unknown radar targets. The performance of the bispectrum features is compared with that of classifiers that are not based on bispectral processing of the measured radar data. The radar signals used in this study are compact range measurements of scale model aircraft. Several observation scenarios are simulated by altering the measured data in accordance with the type of disturbances that are likely to occur in a real radar system.

There are two reasons for considering bispectral features for the classification of radar targets. First, the bispectrum suppresses additive disturbances that are described by symmetric probability density functions. Second, bispectral processing can exploit the inter-relations that may be present in the data [1]. In particular, the bispectrum of a set of data recovers implicit relationships between the spectral components that cannot be recovered using spectral analysis. Specifically, the bispectrum can be used to detect multiple interactions between scatterers [1–5].

The classifiers used in this study are nonparametric in the sense that no prior information about the underlying distribution of radar measurements and the probability of occurrence of each target is needed. These classifiers either measure the "distance" between the signal of the unknown target and that of the catalog or compare the energy of the unknown signal with that of the catalog. Even though these classifiers are suboptimal, their performance provides significant information about the quality of the features used and the robustness of these features under different data conditions. The conditions investigated in this study include classification of noisy signals where the additive noise is modeled as Gaussian, exponential, or Weibull, and include classification of signals corrupted with scattering from extraneous scatterers.

The bispectrum of radar signals is considered in Section II, where an interpretation of the bispectral features is presented. Section III is concerned with the type of classifiers used in this study. The performance evaluations of these classifiers using real radar data is presented in Section IV. Finally, Section V addresses the problem of identifying radar targets in the presence of extraneous scatterers.

II. TIME-DOMAIN BISPECTRAL FEATURES

The bispectrum is defined as the Fourier transform of the third-order cumulant of the data [1–5]. Cumulants represent the triple correlation of the data sequence and are usually a function of time, so that the bispectrum is a function of frequency. In radar signal processing, however, the data are often observed as a function of frequency. The third-order cumulant is then defined as

$$R(f_1,f_2) = E\{H^*(f)H(f+f_1)H(f+f_2)\} \tag{1}$$

where $\{H(f)\}$ is the complex-valued coherent backscatter response of the radar target at frequency f, and $E\{\ \}$ denotes the expectation. The bispectrum is obtained, as a function of time, as

$$B(t_1,t_2) = \sum_{f_1}\sum_{f_2} R(f_1,f_2)\exp\{-j(t_1 f_1 + t_2 f_2)\}. \tag{2}$$

The term "bispectrum" is somewhat misleading in this application, as it is a function of time, not frequency. However, we use this term because it has become standard terminology [6–9]. The bispectrum, in our case, can be expressed as a function of range (r_1,r_2) using the radar range relationship $t = 2r/c$, where c denotes the speed of light. If the data $H(f)$ is deterministic then the expectation in the third-order cumulant is replaced by a summation.

The bispectrum can be explicitly defined in terms of the time components of the data, thus providing some intuition to bispectral processing. For the radar signal processing problem, the spectral components simply denote the impulse response of the target as seen by the radar, and the bispectrum is defined as

$$B(t_1,t_2) = \langle h(t_1)h(t_2)h(t_1+t_2)\rangle \tag{3}$$

where $\langle\cdot\rangle$ denote the ensemble average.

The above definition of the bispectrum has been used to detect implicit dependencies between different responses in the target impulse response [1]. These dependencies can be related to multiple interactions between scattering subcomponents along the target. Therefore, a peak in the bispectrum at (t_i,t_j) indicates that implicit coupling is detected between the time response at t_i and the time response at time t_j (see [1] for additional details).

We are concerned here with the classification aspect of bispectral features of radar targets as defined above. Note that neither the spectrum nor the impulse response can recover the information made available through bispectral processing. Therefore, the key to a radar target recognition system based on time-domain scattering features is to use both the impulse response and the bispectrum features in a single pattern recognition machine. The focus here, however, is on the feasibility of classification using bispectral features as compared with using other target features.

III. TYPES OF CLASSIFIERS USED

Assume we have stepped-frequency measurements of a set of M radar targets. Each frequency set is denoted $H_i(f)$, and is collected at stepped frequencies $f = f_0, f_{0+\Delta f},\ldots,f_{0+(K-1)\Delta f}$. These M sets of K data points form the catalog measurements. An unknown target measurement is obtained by computing a catalog vector with extraneous scattering terms

$$H_u(f_k) = H_i(f_k) + n(f_k) \qquad 0 \le k \le K-1 \tag{4}$$

for some $i \in \{1,\ldots,M\}$, where $n(f_k)$ represents the complex additive noise term. From $H_i(f_k)$ at $H_u(f_k)$ we can compute the impulse response $h_i(k)$ and $h_u(k)$ (where k is the time index) using the discrete Fourier transform. We can also compute the bispectrum $B_i(t_1,t_2)$ and $B_u(t_1,t_2)$ using the method described in [5]. It is these latter terms which are used for classification.

The classifiers simulated here do not require any prior information about the statistical properties of the measured data. These classifiers either measure the Euclidean distance between the unknown and the catalog or measure the cross correlation between the two. For computational efficiency, these classifiers assume that the unknown target zero-time response is fixed and known with respect to that of the catalog.

This study considers three classifiers as described below. The classifiers used can be summarized as follows.

A. Classification Using Cross Correlation

The goal of this algorithm is to identify that catalog element (i) whose bispectral response $B_i(t_1,t_2)$ most closely matches the bispectral response derived from the backscatter measurements of an unknown target $B_u(t_1,t_2)$. That is one wishes to minimize

$$\begin{aligned}\min_i&\left\{\int_{t_1}\int_{t_2}(B_i(t_1,t_2)-B_u(t_1,t_2))^2\,dt_1\,dt_2\right\}\\ &=\min_i\left\{\iint B_i^2(t_1,t_2)\,dt_1\,dt_2+\iint B_u^2(t_1,t_2)\,dt_1\,dt_2\right.\\ &\qquad\left.-\iint B_i(t_1,t_2)B_u(t_1,t_2)\,dt_1\,dt_2\right\}.\end{aligned} \tag{5}$$

Since the first two terms in (5) are fixed, this entails maximizing

$$\int_{t_1}\int_{t_2} B_i(t_1,t_2)B_u(t_1,t_2)\,dt_1\,dt_2 \tag{6}$$

and since the target zero-phase reference is assumed to be known, this is equivalent to maximizing

$$\Gamma_{iu}(0,0) = \frac{\int_{t_1}\int_{t_2} B_i(t_1,t_2)B_u(t_1,t_2)\,dt_1\,dt_2}{\left[\int_{t_1}\int_{t_2}|B_u(t_1,t_2)|^2\,dt_1\,dt_2\right]^{1/2}\left[\int_{t_1}\int_{t_2}|B_i(t_1,t_2)|^2\,dt_1\,dt_2\right]^{1/2}} \tag{7}$$

where $\Gamma_{iu}(0,0)$, for $i = 1,2,\ldots,M$ is the normalized cross correlation of the catalog target bispectral response and the test target response u. Using Fourier transform identities and Parseval's Theorem, we find that this cross correlation can be written (for the discrete frequency case)

$$\Gamma_{iu}(0,0) = \frac{I2FFT\{R_i(f_1,f_2)R_u^*(f_1,f_2)\}}{\left[\sum_{f_1}\sum_{f_2}|R_i(f_1,f_2)|^2\right]^{1/2}\left[\sum_{f_1}\sum_{f_2}|R_u(f_1,f_2)|^2\right]^{1/2}}. \tag{8}$$

The test target is classified to catalog c if

$$\Gamma_{cu}(0,0) = \max_i\{\Gamma_{iu}(0,0)\} \qquad i = 1,\ldots,M. \tag{9}$$

This classifier is reasonably computationally efficient and uses all bispectral information available.

B. Nearest Neighbor Rule

This nearest neighbor (NN) classifier is used to identify an unknown target based on the backscatter data without employing any signal processing. Given that the measured backscatter is $H_u = [H_u(f_0),\ldots,H_u(f_{K-1})]$ (where K is the number of frequencies used) then choose target (i) such that

$$(H_u - H_i)^T(H_u - H_i) = \min_j\{(H_u - H_j)^T(H_u - H_j)\} \qquad j = 1,\ldots,M \tag{10}$$

where M is the number of targets.

C. Cross Correlation of Impulse Responses

The cross-correlation classifier identifies an unknown target based on its time-domain response $h_u(k)$ where k is a time index. A target (i) is chosen such that

$$\Gamma_{iu}^I = \max_j\left[\left|\frac{\sum_k h_u(k)h_j(k)}{\sqrt{\sum_m |h_u(m)|^2\sum_n |h_j(n)|^2}}\right|\right], \qquad j = 1,\ldots,M. \tag{11}$$

This is equivalent to maximizing the cross correlation between the unknown target impulse response and the catalog impulse response.

IV. CLASSIFICATION PERFORMANCE OF NOISY RADAR SIGNALS

A comparison between the performance of the cross-correlation classifier using the bispectrum and the performance of other optimal and suboptimal classifiers is given below. The comparison includes classification in additive white Gaussian noise, additive colored Gaussian noise, and additive non-Gaussian noise. Classification with azimuth ambiguity is also investigated. Also a test where the azimuth of the catalog target differs from the azimuth of the unknown by 10° is presented.

The probabilities of target misclassification at different signal-to-noise ratios are estimated using Monte-Carlo simulations. It is assumed that the targets have equal *a priori* probabilities of occurrence. Thus, N test samples are drawn randomly and then used to determine whether the classifier gives the correct decisions for these samples or not.

The data base used in the classification examples has been frequently used in radar target identification studies [10]. The data base consists of experimental measurements in the frequency band from 1–12 GHz of scale models of commercial aircraft. The scaled data corresponds to measurements of the radar cross section (RCS) of full scale aircraft in the HF/VHF frequency band (8–58 MHz). Details of these measurements can be found in [10].

Decision statistics for each target are computed at a fixed noise level, and total statistics of classification error for all targets are obtained. One hundred experiments were performed for each test target (for a total of 500 experiments). For this experiment, a 95% confidence interval for a misclassification probability of 30% is 4%. The entire test is repeated at different noise levels. Finally the misclassification (error) percentage is plotted versus the signal-to-noise ratio. The performance of the cross-correlation classifier using bispectral features is dependent on the bispectral estimation procedure (or the estimation of triple correlation, see [5].

The amount of segmentation used in computing the triple correlation has a significant effect on the performance of the classifier. The triple correlation lag used and the number of data points also influence the performance of the classifier. Finally, removing the average from both the unknown and the catalog improves the classifier performance. It was experimentally found that segmenting the data into 5 records of 21 samples each with a correlation lag 10 (see [5]) gave nearly the best classification performance over the cases considered, so these values were used in the examples shown below.

Fig. 1 shows the classification performance for five commercial aircraft with complete azimith information using additive white Gaussian noise. The catalog consists of scattering data for five commercial aircraft at 0°, 10°, and 20° azimuth, and 0° elevation. The performance of the NN algorithm is optimal for this case. The bispectrum classifier is outperformed by the impulse response classifier, by a small margin. This performance figure shows that bispectral features can be used in radar target identification but not as effectively as using the target frequency response. Increasing the number of data samples and employing an optimized classification scheme may improve the performance of the bispectrum classifier and reduces its sensitivity to the triple correlation estimation procedure.

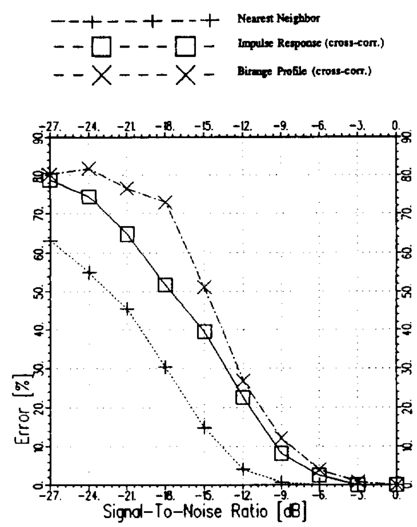


Fig. 1. Classification performance of five commercial aircraft with known azimuth and additive white Gaussian noise.

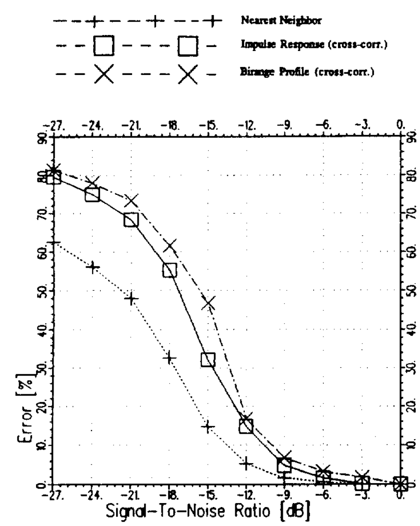


Fig. 2. Classification performance of five commercial aircraft with known azimuth and additive colored Gaussian noise generated by AR filter.

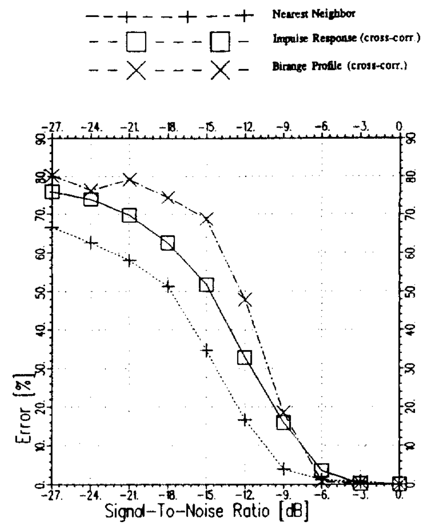


Fig. 3. Classification performance of five commercial aircraft with known azimuth and additive colored Gaussian noise generated by MA filter.

Figs. 2 and 3 show the classification performance when additive colored noise generated by passing white Gaussian noise through an autoregressive (AR) or moving average (MA) filter, respectively. The AR filter coefficients $\{a_i\}_{i=0}^{15}$ are [0.5,0.6,0.7,0.8,0.7,0.6,0.5,0,0, 0.5,0.6,0.7,0.8,0.7,0.6,0.5] (see [9] for the autocorrelation of the noise generated using this filter), and the MA filter has coefficients [1,0.8]. The target azimuth is assumed to be completely known.

The NN rule (which is suboptimal in this case) applied to the frequency-domain data outperforms the time-domain classifiers. Also, the performance of the bispectrum classifier is comparable with the performance of the impulse response classifier. The degradation of the time-domain classifiers compared with the NN rule is slightly lower than the additive white noise case, which may suggest a comparable performance of all classifiers under other colored noise conditions.

Fig. 4 shows the classification performance when additive non-Gaussian noise is used (the square root of a Weibull distributed random variable added to both the in-phase and quadrature components of the data). The azimuth is assumed to be completely known. The performance of the bispectrum classifier is improved but still outperformed by other classifiers, which may indicate a significant role for the bispectrum in classification of unknown targets in a non-Gaussian noise environment.

Figs. 5 and 6 show the classification performance when the azimuth is only known to within $\pm 10°$ (Fig. 5) and $\pm 20°$ (Fig. 6). Although the NN rule is not optimal in this case, it outperforms the time-domain classifiers. Further, the performance of the bispectrum classifier degrades compared with the impulse response classifier when the azimuth ambiguity range increases. In fact, if the target is assumed to be known within $\pm 30°$ (not shown in the Figures) then the performance of the bispectrum classifier degrades significantly compared with the impulse response classifier.

These figures show that the bispectrum is sensitive to changes in target azimuth position. This sensitivity may be explained by the fact that changing the azimuth may introduce additional multiple interactions and delete others. Although these interactions do appear in the impulse response, they appear more strongly in the bispectrum [1].

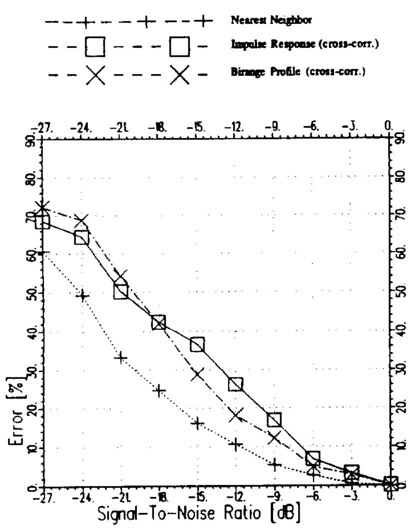


Fig. 4. Classification performance of five commercial aircraft with known azimuth and additive non-Gaussian noise.

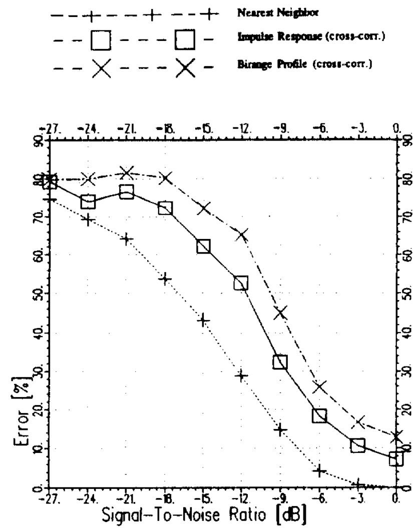


Fig. 6. Classification performance of five commercial aircraft with known azimuth within ±20° and additive white Gaussian noise.

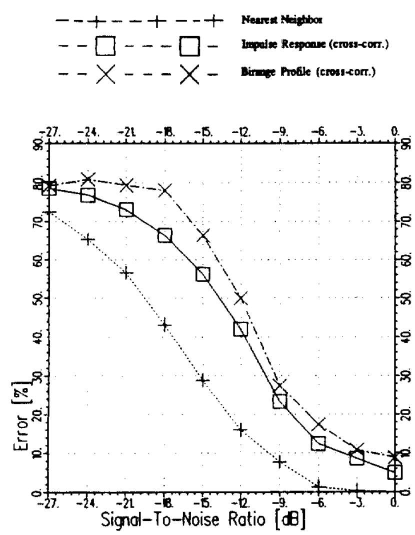


Fig. 5. Classification performance of five commercial aircraft with known azimuth within ±10° and additive white Gaussian noise.

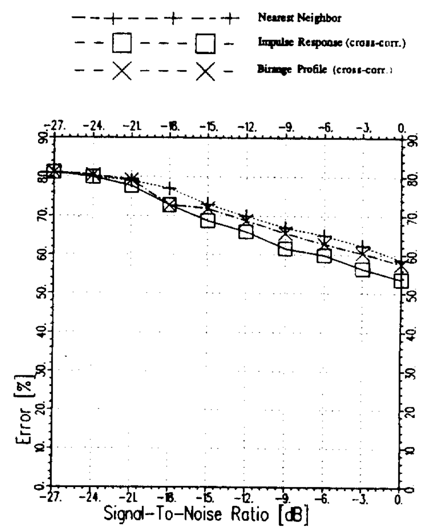


Fig. 7. Classification performance of five commercial aircraft when inaccurate azimuth information (within ±10°) is given to classifier with additive white Gaussian noise.

Fig. 7 shows the classification performance when the classifier is misinformed about the target azimuth position with an error of ±10°. That is, a target at azimuth $A°$ is cross correlated with the catalog targets at azimuth $A° \pm 10°$. This type of mismatch in design specifications affects the classification performance of all classifiers including the bispectrum classifier.

It is clear from Fig. 7 that time-domain classification techniques outperform the NN classifier in this case. Although the bispectrum classifier is sensitive to changes in target azimuth, Fig. 7 shows that the bispectrum classifier is slightly less affected by inaccurate *a priori* azimuth information than is the NN classifier.

V. CLASSIFICATION OF RESPONSES CONTAINING EXTRANEOUS SCATTERERS

In this section, we discuss the effect of adding extraneous scatterers to the unknown target frequency response (scatterers not included in the catalog) on the performance of the classifiers under investigation. This type of classification problem may occur when clutter (in the form of point scatterers with or without interactions) is detected, or when the catalog target model is inaccurate or incomplete. The effect of this type of disturbance is simulated as additive point scatterers with variable scattering magnitude and located at different positions with respect to the target.

TABLE I
Classification Error Rate When Single Extraneous Point Target is Placed at −2 ns (Within Nose Area)

SER [dB]	Frequency Response	Impulse Response	Bispectrum
1	0	0	0
-4	20	0	20
-9	40	20	40
-12	40	20	40
-15	60	40	40

TABLE II
Classification Error Rate When Single Extraneous Point Target is Placed at 0 ns (Within Wing Area)

SER [dB]	Frequency Response	Impulse Response	Bispectrum
1	0	0	0
-4	0	0	0
-9	0	20	20
-12	20	60	20
-15	40	60	40

TABLE III
Classification Error Rate When Single Extraneous Point Target is Placed at 1.2 ns (Within Tail Area)

SER [dB]	Frequency Response	Impulse Response	Bispectrum
1	0	0	0
-4	0	0	0
-9	40	40	0
-12	40	40	0
-15	60	40	20

The ratio of scattering from the target plus extraneous scatterers to scattering from the extraneous scatterers only is denoted by the SER (signal-to-extraneous signal ratio).

Tables I–X show classification results obtained for different scenarios of extraneous scatterers added at different positions with respect to the target. The error rates shown in these tables represent the percentage of misclassification when scattering from extraneous point scatterers (these scatterers are described in the captions) is added to the frequency response of all five targets.

Scattering from the unknown targets is assumed noise-free because the purpose of these experiments is to test the performance of the bispectrum classifier when backscattered signals include uncataloged responses. Therefore, five experiments are conducted for each position of the extraneous scatterer, thus the error is a multiple of 20%. The extraneous scatterers used to generate the results in Tables VII and IX include an interaction whose response appears at −0.8 ns, and those used to generate the results in

TABLE IV
Classification Error Rate When Two Extraneous Point Targets are Placed at −2 ns and 0 ns, Respectively

SER [dB]	Frequency Response	Impulse Response	Bispectrum
-2	0	0	0
-8	0	20	20
-12	40	40	40
-14	40	60	40
-16	60	40	60

TABLE V
Classification Error Rate When Two Extraneous Point Targets are Placed at −2 ns and 1.2 ns, Respectively

SER [dB]	Frequency Response	Impulse Response	Bispectrum
-2	0	0	0
-8	40	20	20
-12	60	20	20
-14	80	40	40
-16	80	40	40

TABLE VI
Classification Error Rate When Two Extraneous Point Targets are Placed at 0 ns and 1.2 ns, Respectively

SER [dB]	Frequency Response	Impulse Response	Bispectrum
-2	0	0	0
-8	0	20	20
-12	40	60	40
-14	40	80	40
-16	40	80	40

TABLE VII
Classification Error Rate When Three Extraneous Point Targets are Placed at −2 ns, 0 ns, and 1.2 ns, Respectively

SER [dB]	Frequency Response	Impulse Response	Bispectrum
-4	0	0	0
-10	60	20	20
-13	60	20	20
-16	80	40	60
-18	80	60	60

Tables VIII and X include an interaction whose response appears at 0 ns.

The following can be concluded from these experimental outcomes.

1) Classification with NN rule is the most sensitive to the presence of extraneous uncataloged scatterers. Changing the location of the scatterers does not increase or decrease the sensitivity of the NN algorithm.

TABLE VIII
Classification Error Rate When Three Extraneous Point Targets are Placed at −3 ns, 2 ns, and 3 ns, Respectively

SER [dB]	Frequency Response	Impulse Response	Bispectrum
-4	0	0	0
-10	20	20	20
-13	20	40	20
-16	40	60	40
-18	60	60	40

TABLE IX
Classification Error Rate When Three Extraneous Point Targets are Placed at −2 ns, 0 ns, and 1.2 ns, Respectively, With Partial Azimuth Information (Within 20°)

SER [dB]	Frequency Response	Impulse Response	Bispectrum
-4	0	0	0
-10	20	30	20
-13	40	60	40
-16	60	60	60
-18	60	60	80

TABLE X
Classification Error Rate When Three Extraneous Point Targets are Placed at −3 ns, 2 ns, and 3 ns, Respectively, With Partial Azimuth Information (Within 20°)

SER [dB]	Frequency Response	Impulse Response	Bispectrum
-4	0	10	0
-10	40	20	0
-13	60	30	20
-16	60	40	40
-18	60	40	40

2) Classification with impulse response is less sensitive to extraneous scatterers than the NN classifier but unaffected by changing the position of extraneous scatterers.

3) Classification with the bispectrum is less sensitive to the presence of extraneous scatterers than the NN classifier. The bispectrum classifier is even less sensitive to uncataloged scatterers if the responses from such extraneous scatterers do not coincide with the response of the unknown target. This makes sense as the presence of extraneous scatterers produces additional peaks in the impulse response, but it takes three extraneous scatterers with interaction to produce a peak in the bispectral response of the unknown target.

The bispectrum classifier outperforms other methods when the number of extraneous scatterers is in the order of the number of scattering centers along the target (up to 5 extraneous scatterers for the target models used in this study). In general target classification degrades as the number of extraneous scatterers increases. When the number of extraneous objects exceeds the number of target scattering components then the bispectrum-based classifier is outperformed by the impulse response classifier.

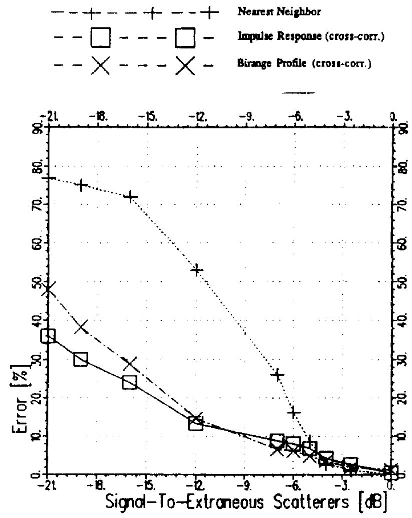


Fig. 8. Comparison between classification using measured data (using NN), impulse response, bispectral response as SER changes with complete azimuth information (three extraneous scatterers used).

Figs. 8 and 9 show a comparison between classification results (plotted as probability of misclassification versus SER). It is clear from these figures that classification using the bispectrum features outperforms classification using the RCS measurements (using NN) even when the azimuth of the unknown target is partially known (or known within a certain azimuth range).

The extraneous signatures used in these figures are three point scatterers where the location of the response due to each scatterer is random and uniformly distributed over $[-T/2, T/2]$, where $T = 1/\Delta f$, (where Δf is the frequency increment of the measured data). The locations of the responses of the extraneous scatterers are independent identically distributed. Two hundred experiments for each of the five targets are simulated for each SER ratio.

Fig. 10 shows classification results obtained when the frequency response of nine extraneous scatterers is added to the frequency responses of the five aircraft. The location of the response due to each scatterer is random and uniformly distributed over $[-T/2, T/2]$. Figs. 8 and 10 show that classification using the impulse response outperforms classification using the bispectrum by about 3 dB when the number of extraneous scatterers is increased from three to nine.

This result can be explained as follows. By adding the responses of nine extraneous scatterers to the data, the likelihood of having a bispectral peak due

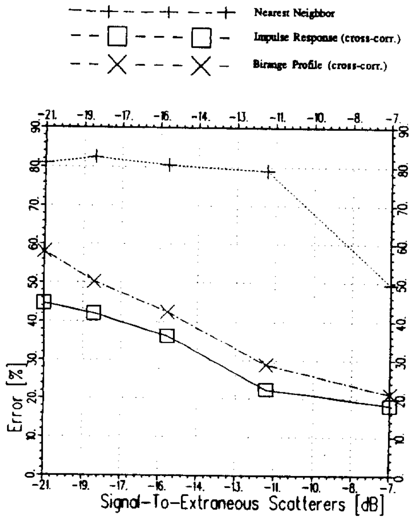


Fig. 9. Comparison between classification using measured data (using NN), impulse response, and bispectral response as SER changes with partial azimuth information $\pm 10°$ (three extraneous scatterers used).

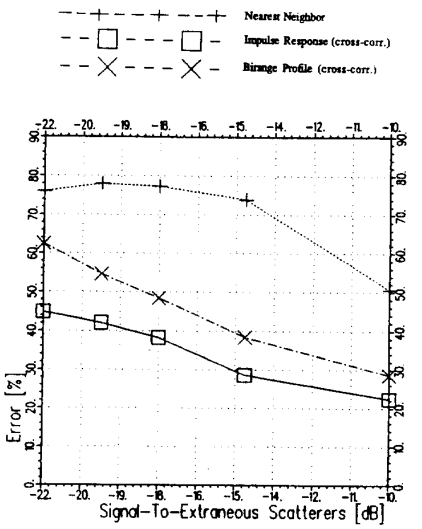


Fig. 10. Comparison between classification using measured data (using NN), impulse response, and bispectral response as SER changes with complete azimuth information (nine extraneous scatterers used).

to extraneous scatterers is higher than that when only three extraneous scatterers are present. Further, each of the five targets has less than nine dominant scattering centers, which indicates that if the number of the extraneous scatterers exceeds the number of scattering centers then the impulse response classifier outperforms the bispectrum classifier by a large margin. Figs. 8 and 10 also show that the performance of the NN classifier is inadequate whether the number of extraneous scatterers exceeds the number of scattering centers or not.

VI. CONCLUSIONS

Target classification using bispectral features is performed and compared with classification using spectral responses and time-domain responses. The results in this paper show that bispectral processing of radar signatures may enhance the target identification process under conditions such as additive colored noise, additive non-Gaussian noise and scattering from extraneous scatterers. Even though the classifiers used in this study are suboptimal, it is evident that bispectral features of unknown radar targets may be less sensitive to scattering from extraneous scatterers, so long as the number of extraneous scatterers is small relative to the number of target scatterers. The presence of large number of extraneous scatterers degrades the performance of the bispectrum classifier in comparison with the performance of the impulse response classifier. Furthermore, it appears that classification using bispectral features is outperformed by other known classifiers when the radar measurement environment is characterized by additive Gaussian noise. The results of this investigation are intended to help identify circumstances under which bispectral processing of radar signals may enhance target recognition.

REFERENCES

[1] Walton, E. K., and Jouny, I. (1989)
Application of bispectral techniques to radar signature analysis.
In *Proceedings of the Workshop on Higher-Order Spectral Analysis*, Vail, CO, June 1989, 56–61.

[2] Brillinger, D. R., and Rosenblatt, M. (1967)
Computation and interpretation of kth order spectra.
In B. Harris (Ed.), *Spectral Analysis of Time Series*.
New York: Wiley, 1967, 189–232.

[3] Rao, T. S., and Gabr, M. M. (1984)
An introduction to bispectral analysis and bilinear time series models.
In E. A. D. Brillinger (Ed.), *Lecture Notes in Statistics*.
New York: Springer-Verlag, 1984.

[4] Hinich, M. J. (1985)
Evidence of nonlinearity in daily stock returns.
Journal of Business and Economic Statistics, **3**, 1 (1985), 69–77.

[5] Nikias, C. L., and Raghuveer, M. R. (1987)
Bispectrum estimation: A digital signal processing framework.
Proceedings of the IEEE, **75**, 7 (July 1987), 869–891.

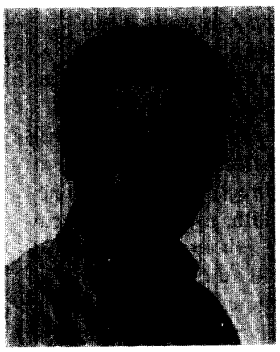
[6] Kletter, D., and Messer, H. (1990)
Suboptimal detection of non-Gaussian signals by third-order spectral analysis.
IEEE Transactions on Acoustics, Speech, and Signal Processing, **38**, 6 (June 1990), 901–909.

[7] Giannakis, G. B., and Tsatsanis, M. K. (1990)
Signal detection and classification using matched filtering and higher-order statistics.
IEEE Transactions on Acoustics, Speech, and Signal Processing, **38**, 7 (July 1990), 1284–1296.

[8] Nielson, P. A., and Thomas, J. B. (1990)
Detection of a constant signal using the bicovariance function.
In *Proceedings of the International Conference on Acoustics, Speech, and Signal Processing*, Albuquerque, NM, Apr. 1990.

[9] Papadopoulos, C. K., and Nikias, C. L. (1990)
Parameter estimation of exponentially damped sinusoids using higher order statistics.
IEEE Transactions on Acoustics, Speech, and Signal Processing, **38**, 8 (Aug. 1990), 1424–1435.

[10] Chamberlain, N. F., Walton, E. K., and Garber, F. D. (1991)
Radar target identification of aircraft using polarization-diverse features.
IEEE Transactions on Aerospace and Electronic Systems, **27**, 1 (Jan. 1991), 58–67.



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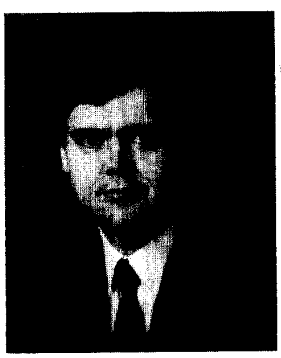

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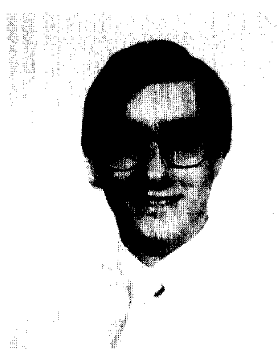

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