CLASSIFICATION OF RADAR SIGNALS USING THE BISPECTRUM

I. Jouny — Dept. of Elec. Eng., Lafayette College, Easton, PA 18042

R. L. Moses — Dept. of Elec. Eng., Ohio State University, Columbus, OH 43210

F. D. Garber — Dept. of Elec. Eng., Wright State University, Dayton, OH, 45435

ABSTRACT

This paper uses features extracted from the bispectrum of radar signals for classification of unknown radar targets. The classification performance is compared with the performance of other classifiers that are not based on higher order spectral processing of the measured radar data. The radar signals used in this study are experimental measurements that correspond to scattering from real radar targets. The data is corrupted with different types of disturbances that are likely to occur in a typical radar system.

INTRODUCTION

This paper presents a comparison of the classification performance of target recognition systems that are based on bispectral features of unknown targets and those based on spectral features. There are two reasons for using bispectral features of radar targets for classification purposes. First, the bispectrum suppresses additive disturbances that are zero mean with symmetric probability density functions. Second, bispectral processing detects implicit correlations between spectral components that may be present in the data and that are not recovered using spectral processing; this property has been investigated in [1], where it is shown that the bispectrum of radar signals can be used to detect multiple interactions between scatterers.

Classification performance using bispectral features is compared with that obtained using spectral features and time-domain scattering features. Although the classifiers used are suboptimal, their performance provides significant information about the quality of features used and the robustness of such features under different data conditions. The data conditions investigated in this study include classification of noisy signals where the additive noise is modeled as Gaussian, and Weibull. The case where the azimuth position of the target is unknown is also examined.

II. TIME DOMAIN BISPECTRAL FEATURES

The bispectrum is defined as the Fourier transform of the third order cumulant of the data. Cumulants represent the triple correlation of the data sequence and are usually a function of time, and the bispectrum is then a function of frequency. In radar signal processing, the third order cumulant is defined as

$$R(f_1,f_2)=E[H^*(f)H(f+f_1)H(f+f_2)] \quad (1)$$

where H(f) is complex and represent the backscatter response of the target at frequency f, and E[.] denotes the expectation. The bispectrum is then obtained as a function of time

$$B(t_1,t_2)=\sum_{f_1}\sum_{f_2}R(f_1,f_2)\exp[-j(t_1f_1+t_2f_2)]$$

The bispectrum can also be expressed as a function of range using 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 term "bispectrum" is somewhat misleading in this application, as it is a function of time, not frequency, however, we will use this term because it has become standard terminology.

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

$$B(t_1,t_2)=\langle h(t_1)h(t_2)h(t_1+t_2)\rangle \quad \text{--}(2)$$

where <,> denotes the ensemble average.

The above definition of the bispectrum has been used to detect implicit dependencies between the different responses that appear 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 (t1,t2) indicates that an implicit coupling is detected be-

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tween the time response at instant t1 and the time response at instant t2 [1]. Note that neither the spectrum nor the impulse response of the target 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.

III. TYPES OF CLASSIFIERS USED

The classifiers simulated in this study do not require any prior information about the statistical properties of the measured data. These classifiers either measure the Euclidean distance between the signatures of the unknown target and the signatures of the catalog target or measure the cross-correlation between the two. For computational efficiency reasons, 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.
1) Bispectrum Classifier:
The goal is to find a catalog element (i) whose bispectral response matches the bispectral response of an unknown target (u). That is one wishes to minimze

$$\min_i \int_{t_1}\int_{t_2} (B_i(t_1,t_2)-B_u(t_1,t_2))^2 dt_1 dt_2$$

If the first two terms are fixed, then this entails maximizing

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

and since the target zero-reference is assumed to be known, this is equivalent to maximizing the normalized cross-correlation between the catalog target bispectral response, and the unknown target response. Using Fourier transform identities and Parseval's theorem, we find that the cross-correlation can be written as (for the discrete frequency case)
The test target is classified to catalog c

$$\Gamma^B_{iu}(0,0) \equiv$$

$$\frac{IDFT[R_i(f_1,f_2)\,R_u^*(f_1,f_2)]}{\sum_{f_1}\sum_{f_2}|R_i(f_1,f_2)|^2]^{\frac{1}{2}}[\sum_{f_1}\sum_{f_2}|R_u(f_1,f_2)|^2]}$$

if

$$\Gamma^B_{cu}(0,0)=\max_i[\Gamma^B_{iu}(0,0)],\ i=1,\ldots,M$$

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

2) Nearest Neighbor Rule: This classifier is used to identify an unknown target based on the backscatter data without employing any signal processing. Given that the measured backscatter is

$$H_u=[H_u(1),H_u(2),\ldots,H_u(K)]$$

where K is the number of frequencies used. A target (i) is chosen if

$$(H_u-H_i)^T(H_u-H_i)=\min_j[(H_u-H_j)^T(H_u-H_j)]$$

for j=1,..,M, where M is the number of targets.

3) Cross-correlation of Impulse Responses: This classifier identifies an unknown target based on its time-domain response h(k) where k is a time index. A target (i) is chosen such that

$$\Gamma^I_{iu}=\max_j \frac{\sum_k h_u(k)\,h_j(k)}{\sqrt{\sum_m |h_u(m)|^2 \sum_n |h_j(n)|^2}}$$

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

IV. CLASSIFICATION PERFORMANCE

A comparison between the performance of the bispectrum based cross-correlation classifier and the performance of the other classifiers is summarized in this section. 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 probability of occurrence. Thus, N sample tests are drawn randomly and then used to determine whether the classifier gives the correct decision for these samples or not.

The performance of the cross-correlation classifier using bispectral features is dependent on the bispectral estimation procedure (or the estimation of the triple correlation, see [1]). The level of segmentation used to compute 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.

The data base used in the classification examples consists of experimental measurements in the frequency band from 1-12 GHz of scale models of commercial aircraft [3]. 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.

Decision statistics for each experiment 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 target (for a total of 500 experiments). The 95% confidence interval for these experiments at a missclassification probability of 30% is 4%. The entire test is repeated at different noise levels. Finally, the missclassification percentage (error) is plotted versus signal-to-noise ratio. It was experimentally found that segmenting the data into five records of 21 samples each with a correlation lag of 10 points, gave nearly the best classification performance of the cases considered.

Figure 1 shows the classification performance for five commercial aircraft with complete azimuth information using additive white Gaussian noise. The catalog consists of scattering data for five commercial aircraft at 0, 10, and 20 degrees azimuth. The performance of the nearest neighbor algorithm (NN) is optimal in this case. The bispectrum classifier is outperformed by the impulse response classifier by a small margin. *This figure shows that bispectral features can be used effectively in radar* target identification. Increasing the number of data samples and employing an optimized classification scheme may improve the performance of the bispectrum classifier.

Figure 2 shows the classification performance obtained when additive colored noise generated using AR filtering of white noise (the AR filter coefficients can be found in [4]). The nearest neighbor rule (which is suboptimal in this case) applied to the frequency-domain data outperforms both time-domain classifiers. Also, the performance of the bispectrum classifier compares favorably with the performance of the impulse response classifier and is not as degraded as the additive white Gaussian noise case, which may indicate that the bispectrum can produce favorable results under other colored noise conditions. Figure 3 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 the quadrature component of the data. The performance of the bispectrum classifier has improved even better than the previous two cases. Figure 4 shows the classification performance when the azimuth of the target is not exactly known and an error of 10 degrees is permitted. The nearest neighbor classifier outperforms the other classifiers in this case, and the performance of the bispectrum classifier degrades significantly compared to the impulse response classifier. This figure shows that the bispectrum is sensitive to changes in the aspect angle of the target. This sensitivity may be explained by the fact that changing the azimuth position of the target may introduce additional multiple interactions and eliminate others. Although these interactions do appear in the impulse response, they appear more strongly in the bispectrum [1].

Figure 5 shows the classification performance when the classifier is mis-informed about the target azimuth position with an error margin of 10 degrees. That is a target at azimuth A degrees is always compared with a catalog target at A + 10, or A - 10 degrees. This type of mismatch in design specifications affects the classification performance of all classifiers including the bispectrum classifier.

V. CONCLUSIONS

The performance of radar target identification systems based on the bispectrum is examined in this paper. Although, the number of data samples is relatively small and may be insufficient to produce very accurate bispectral estimates, one may conclude that the bispectrum classifier may outperform other known classifiers under conditions of colored noise and non-Gaussian noise. Further, it seems that the bispectral signatures of radar signals are sensitive to changes in the target aspect angle. Recently, we have been studying classification in the presence of extraneous uncataloged objects, and the performance of the bispectrum classifier seems very encouraging.

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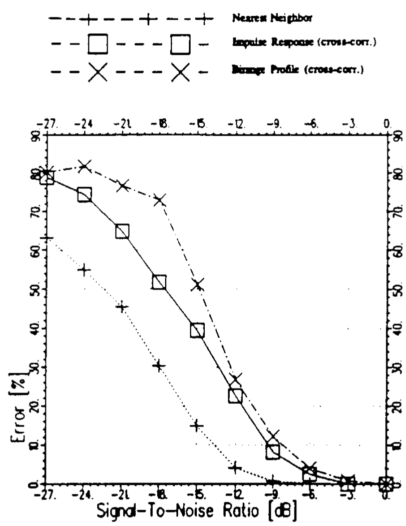

Figure 1: Classification performance (known azimuth and additive white Gaussian noise).

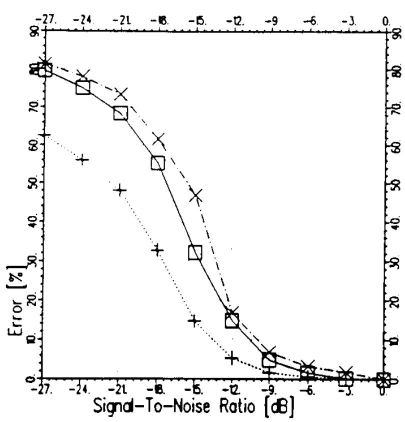

Figure 2: Classification performance (known azimuth and additive colored noise).

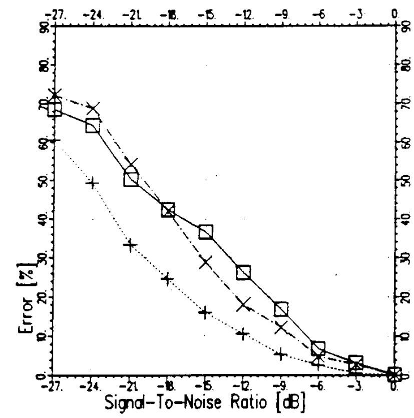

Figure 3: Classification performance (known azimuth and additive non-Gaussian noise).

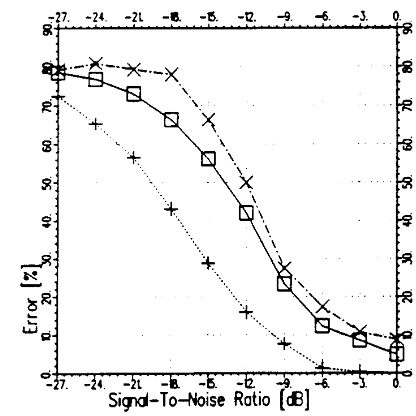

Figure 4: Classification performance (azimuth known within 10 degrees and additive white Gaussian noise).

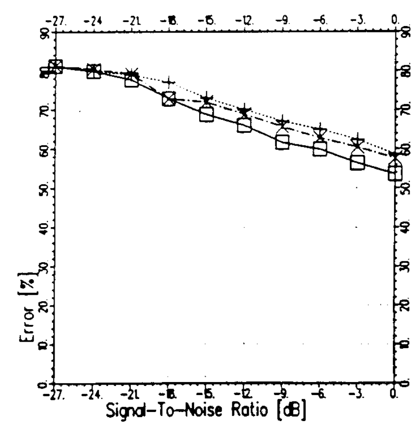

Figure 5: Classification performance (radar mis-informed about target aspect with 10 degrees error and additive white Gaussian noise).