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SAMPLE SELECTION FOR COVARIANCE ESTIMATION IN PRACTICAL AIRBORNE ENVIRONMENTS

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13. ABSTRACT (Maximum 200 words)
In this technical memorandum, a significant observation on a fundamental limitation to space-time adaptive processing in practical airborne environments is briefly discussed. This observation is a result of extensive analysis of measured airborne data from the Multichannel Airborne Radar Measurements (MCARMS) program. In particular, the problem of nonhomogeneous data and its impact on the estimation of the interference covariance matrix, a critical operation in space-time adaptive processing, is considered.

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Abstract

In this technical memo a significant observation on a fundamental limitation to space-time adaptive processing in practical airborne environments is briefly discussed. This observation is a result of extensive analysis of measured airborne data from the Multichannel Airborne Radar Measurements program. In particular, the problem of nonhomogeneous data and its impact on the estimation of the interference covariance matrix, a critical operation in space-time adaptive processing, is considered.

1.0 Background

Excellent overviews of space-time adaptive processing (STAP) are given in [1-3]. In short, STAP is the practical implementation of an optimum two-dimensional filter in the angle-Doppler domain. Degrees of freedom in both space (angle) and time (Doppler) are employed to maximize signal-to-interference ratio (SIR) to improve detection of weak and/or low velocity targets by an airborne surveillance radar.

Optimum filtering implies known statistics a priori, a situation only valid in a theoretical study. In practice, unknown statistics are estimated from available data, leading to the adaptive processor. The adaptive weights are computed via

$$\hat{w}_k = s^H \hat{R}_k^{-1} \qquad (1)$$

for range cell, k, where s and $\hat{R}_k$ are the space-time steering vector and sample interference covariance matrix, respectively [1]. Note that the optimum weights follow from (1) by replacing the sample interference covariance matrix, $\hat{R}_k$, with the known interference covariance matrix, R_k, for range cell k. Thus, the critical unknown in the adaptive implementation is the interference covariance matrix. The maximum likelihood estimate is commonly used to estimate $\hat{R}_k$ as [2-3]

$$\hat{R}_k = \frac{1}{K}\sum_{i=0}^{K} X_k X_k^H \; ; \quad i \neq k \tag{2}$$

where X_i are space-time data vectors assumed to be independent and identically distributed (iid).

While theory and computer simulations assume a sufficient quantity of iid data to accurately compute (2), such that averaging over larger K leads to convergence between optimal and adaptive implementations, preliminary analysis of measured multichannel airborne data from the Multichannel Airborne Radar Measurements (MCARM) program indicates that nonhomogeneous features of the actual airborne environment force (2) to converge to an "average" value which may differ significantly from the true interference covariance matrix characterizing range cell, k. See reference [4] for a brief description of the MCARM program. This "averaging" limits the detection performance potential improvement of STAP previously identified through extensive computer simulations using modeled, homogeneous, iid data. One approach to improving STAP performance is careful selection of the secondary data, X_i, used to compute (2).

2.0 Observations From Analysis of Measured Airborne Data

In this section, brief analysis of MCARM data is discussed to better understand the impact of nonhomogeneous interference and data selection for sample covariance matrix formulation on

STAP performance. For example, Figure 1 shows a plot of the modified sample matrix inversion (MSMI) test statistic [5],

$$\eta_k = \frac{\left| s^H \hat{R}_k^{-1} X_k \right|^2}{s^H \hat{R}_k^{-1} s} \tag{3}$$

versus range for Doppler filter 10 using measured MCARM data from file "t3r40575". This analysis uses the Factored Time-Space (FTS) architecture, which amounts to Doppler processing followed by adaptive beamforming [2-3]. The interference covariance matrix is computed via (2) for all three curves in Figure 1, where the only difference is the selection of secondary data, X_i. The interference covariance matrix is computed using $2N_s = 44$ data vectors, where N_s is the number of spatial channels, symmetrically windowed about the range cell under test to arrive at the solid line labeled "2N_SW". This symmetric windowing approach is depicted in Figure 2. Alternately, the dotted curve labeled "2N_NHD" is computed using a single interference covariance matrix estimate for all range cells shown. In this case, the interference covariance matrix estimate is computed via (2) by selecting 44 nonconsecutive data vectors determined to be most homogeneous in covariance structure to each other. The "generalized inner product",

$$\hat{\Xi}_k = X_k^H \hat{R}_k^{-1} X_k \tag{4}$$

is employed to test the homogeneity of the Doppler-filtered data vector from range cell k, as described in [6]. Nonconsecutive selection of secondary data is depicted in Figure 3. Finally, the dashed curve labeled "2N_HP" is computed using a single covariance matrix over all indicated range by selecting 44 data vectors with the highest estimated power content (inner product),

$$\gamma_k = X_k^H X_k \ , \tag{5}$$

to compute (2). In all three covariance estimation methods, the same superset of secondary data is used in the computation of (2) for a fair comparison.

A synthetic target has been injected into range bin 290, Doppler 10, broadside (0 degrees azimuth). Applying a fixed threshold to the data, recalling that the MSMI test statistic has an embedded constant false alarm rate (CFAR) characteristic [5], one observes that the false alarms increase dramatically for the case where a unique interference covariance matrix is estimated for each range cell by symmetric windowing (solid curve, "2N_SW"). The performance improves greatly for the dotted and dashed curves, where the injected target is readily identified and clutter suppression is improved merely by differing the training strategy (secondary data selection) used to compute the sample interference covariance matrix via (2).

To further understand the previous results and their impact on STAP performance, consider Figure 4 showing estimates of the interference at Doppler 10 versus azimuth for four range cells spaced roughly 0.5 nmi apart. A one-dimensional slice through the two-dimensional transformed data (ie., 2-D FFT) produces the results in Figure 4. No averaging over range has been applied to preserve local interference characteristics. Note that the peaks of the interference move several degrees from range cell to range cell, indicating nonhomogeneity. Thus, both null depth and null placement are critical issues impacted by the averaging process in (2) used to estimate the interference covariance matrix.

Next, consider the adapted filter spatial response patterns for range cell 290, Doppler 10, resulting from the three different covariance matrix training strategies previously discussed, as shown in Figure 5. All three filter responses vary considerably even though the adaptive weights were computed from the same superset of secondary, further confirming the effects of nonhomogeneous data and the potential impact of training data selection schemes. The solid line shows the spatial response for the symmetric windowing method. The wider notch centered just right of 20 degrees roughly corresponds to averaging all interference peaks shown in Figure 4 and yields the poorest performance. Of the four cells shown, only range cell 300 has been identified as "homogeneous", via (4), to a majority of the surrounding cells in its covariance structure, thereby explaining the shift of the main null slightly to the left of 20 degrees when the most "homogeneous" data is used for covariance estimation (dotted line, "2N_NHD"). Also note that mainbeam gain has not diminished. Finally, range cells 290, 295 and 300 have been identified as including the highest power content, and thus the "average" of their peaks explains the slight migration of the main null slightly further left when cells with highest power content are used to estimate the covariance matrix (dashed line, "2N_HP"). Note, however, the significant loss of mainbeam gain in the look direction of zero degrees.

3.0 Conclusions

The conclusions are twofold. First, in a nonhomogeneous environment, the averaging process used to compute (2) leads to "average" performance for the range cells under consideration, which may differ significantly from the optimum scenario. This averaging process limits the effectiveness of STAP, where the adaptive processor no longer converges to the optimum filter, but to some average filter response based on the varying characteristics of the nonhomogeneous secondary data. Secondly, secondary data selection greatly affects the adaptive filter performance in a practical, nonhomogeneous environment, as demonstrated through the analysis of a specific MCARM data file. Thus, it appears that development of better training strategies is essential to improved STAP detection performance potential in practical situations. Furthermore, these improved training strategies may greatly impact STAP performance in the presence of electronic warfare [7].

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Figures

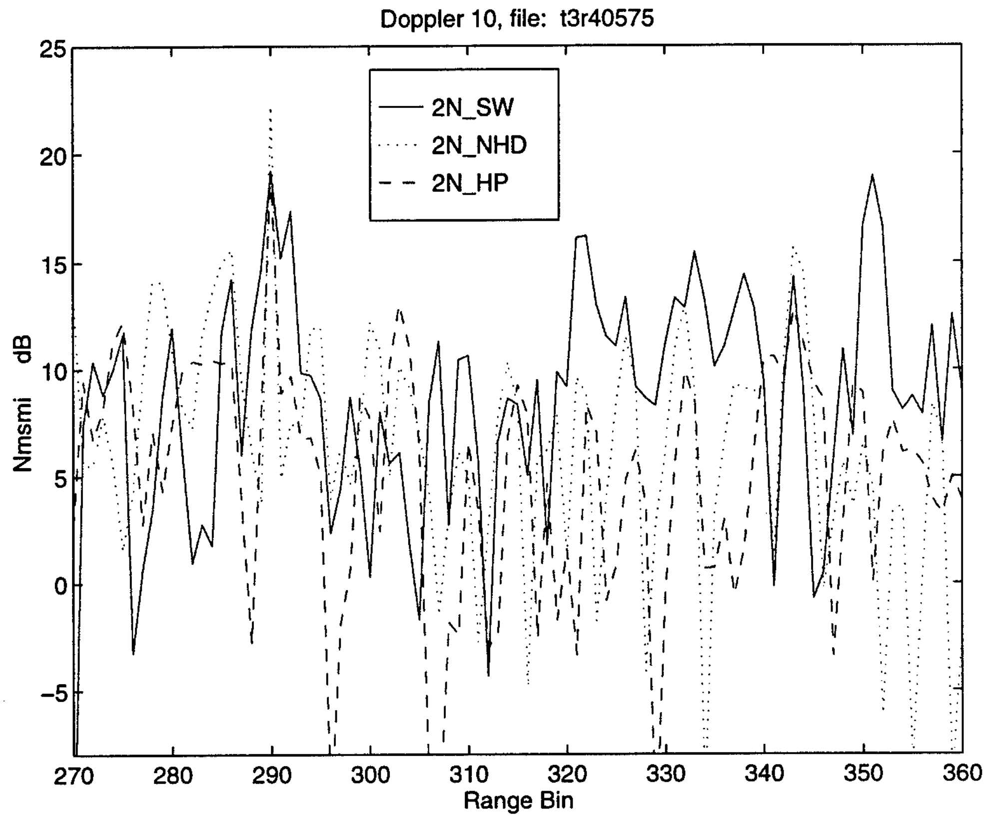

Figure 1 MSMI Test Statistic versus Range, Doppler 10, FTS Architecture.

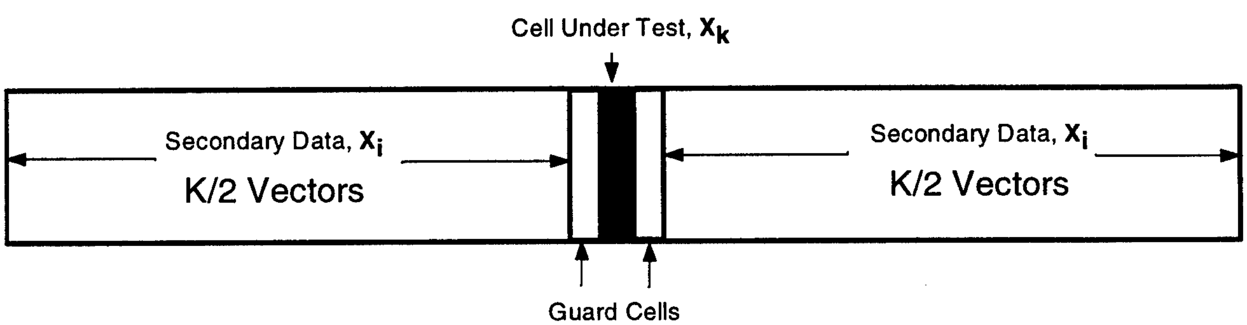

Figure 2 Symmetric Windowing Approach to Secondary Data Selection and Interference Covariance Estimation for Range Cell k.

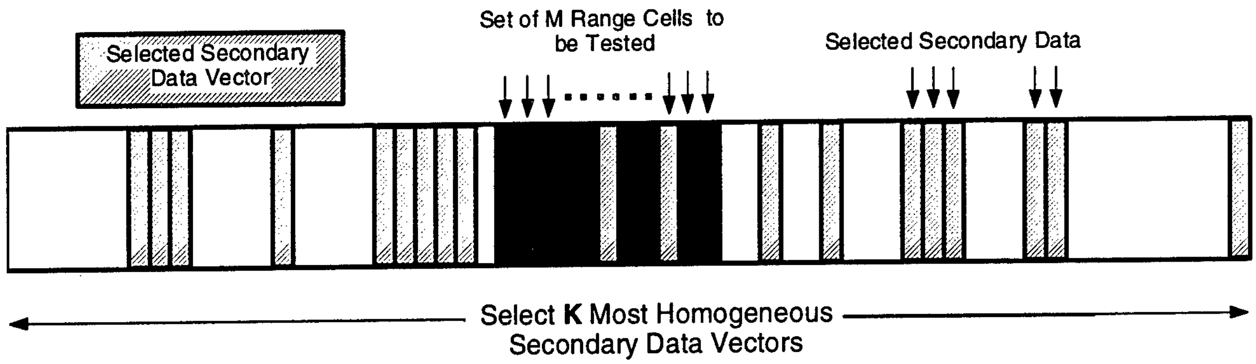

Figure 3 Nonconsecutive Selection of Secondary Data Based on (4) or (5) to Compute a Single Covariance Matrix Applied to all M Range Cells Under Test.

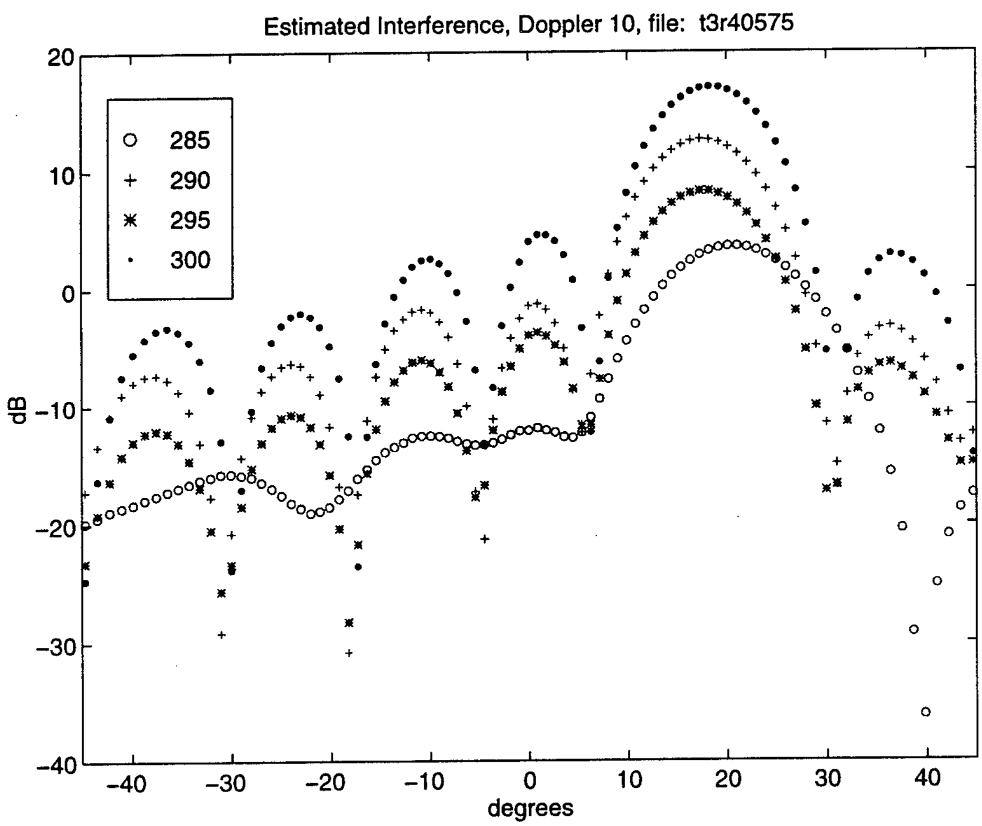

Figure 4 Estimates of Interference Vs. Azimuth Over Range, Doppler 10 (5 Bins~0.5 nmi).

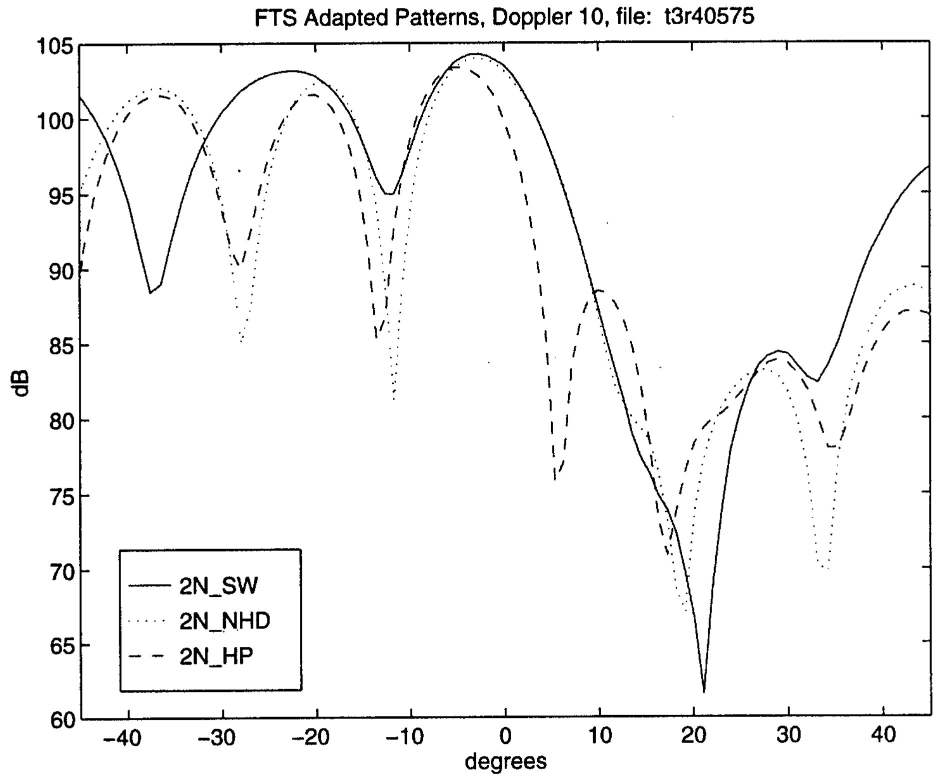

Figure 5 Adapted Spatial Response Patterns, Doppler 10, Range 290.

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