Knowledge Based Map Space Time Adaptive Processing (KBMapSTAP)

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Abstract - The secondary data for estimating the clutter covariance matrix in space-time adaptive processing (STAP) is normally obtained from range rings surrounding the test range ring. The assumption is that near-by range rings are representative of the test range ring. However, this is not always true. A clutter model was developed and the condition necessary for obtaining a good estimate of the clutter covariance matrix is presented. A theoretical basis for choosing reference rings, which contain clutter patches that are representative of one or two patches within the test range ring, is provided. An algorithm for using a priori map data to classify clutter patches based upon the type of land features contained within them is presented. It is conjectured that patches with equivalent classifications will have representative radar returns. Applications to post-Doppler processing are presented and positive results are provided using radar data.

Keywords: Signal Processing, Adaptive Processing, Terrain Databases, Airborne Radar.

1. Introduction

Space-time adaptive processing (STAP) is viewed as a potentially effective means for suppressing ground clutter received by an airborne radar. However, a serious problem with any STAP approach involves the accurate estimation of unknown clutter statistics. This problem is further complicated by the fact that airborne radars are likely to encounter non-homogeneous clutter environments. Previous efforts [1,2] have recognized this problem and have shown the benefits of using a priori data to increase performance in non-homogeneous clutter environments for Constant False Alarm Rate (CFAR) processing and pre-adaptive filtering with STAP.

This paper documents the results of our effort to develop, implement and test a computer-based algorithm to utilize a priori terrain data in order to improve target detection. Our approach was to leverage existing terrain datasets to help selectively choose secondary data for estimating the clutter covariance matrix needed for post-Doppler radar processing. In so doing we will show that performance can be improved. This use of terrain data provides insight into how to build one aspect of the next generation signal processing algorithm and to possibly extend its use to other areas such as tracking and identification.

Section 2 of the paper provides a description of our clutter model. Section 3 discusses the difficulty in choosing secondary data for the estimation of a clutter covariance matrix in a non-homogeneous environment and an approach for easing this difficulty with adaptive post-Doppler processing. Section 4 departs from theory-based discussion and presents a brief description of an airborne radar measurement program used in testing our methodology. Section 5 describes our a priori data approach to estimate the clutter covariance matrix in non-homogeneous environments. Section 6 presents our results and Section 7 presents our conclusions and recommended future work.

2. Clutter Model

Ward's clutter model [3] is employed to determine whether or not available secondary data may be useful in estimating the clutter covariance matrix of a test cell. Ward approximates a continuous field of clutter by modeling the clutter

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return from each range ring as the superposition of a large number of independent point scatters or clutter patches evenly distributed in azimuth about the radar. For simplicity, we assume unambiguous range. Then the clutter return at any instant is from a single range ring.

If we divide the range ring into a total of N_c clutter patches, each patch has an angular extent given by $\Delta\theta = 2\pi/N_c$. The response in the n^{th} channel, due to the m^{th} pulse, in the l^{th} range ring, after summing over all k patches is

$$x_{nm\ell} = \sum_{k=1}^{N_c} \alpha_{\ell k}\, e^{j2\pi(m\bar{\varpi}_{\ell k} + n\nu_{\ell k})} \qquad (1)$$

where ϖ_{lk} is the normalized Doppler frequency, ν_{lk} is the normalized spatial frequency, and α_{lk} is the complex received signal amplitude. From this equation the clutter covariance matrix for the l^{th} range ring can be expressed as

$$M_\ell = \sum_{k=1}^{N_c} E[|\alpha_{\ell k}|^2]\, \underline{v}_{\ell k}\, \underline{v}_{\ell k}^H \qquad (2)$$

where $E[|\alpha_{\ell k}|^2]$ is the estimation of the mean-square value of the complex amplitude magnitude for each of the N_c clutter patches in the range ring and $\underline{v}_{\ell k}$ is the space-time steering vector. Since the space-time steering vector can be specified a priori the estimation of the clutter covariance matrix reduces to the estimation of $E[|\alpha_{\ell k}|^2]$. Therefore, it is important to have a good method for estimating this value by properly choosing representative clutter data.

3. Representative Secondary Clutter

Assume the test cell in which a target is to be detected is located in the l^{th} range ring. Since M_l, the clutter covariance matrix of the l^{th} range ring is unknown, the objective is to select secondary data from other range rings in order to estimate M_l. Suppose attention is focused on the $(l')^{th}$ range ring where $l' \neq l$. The question that arises is, "Is the clutter in the $(l')^{th}$ range ring representative of the clutter in the l^{th} range ring?"

This is true provided each clutter patch in the l^{th} range ring having a specific mean-square complex amplitude magnitude and a specific pair of normalized Doppler and spatial frequencies has a corresponding clutter patch in the $(l')^{th}$ range ring having approximately the same mean-square complex amplitude and approximately the same normalized Doppler and spatial frequencies.

Even though the pairs of normalized Doppler and spatial frequencies remain invariant from one range ring to another, it is unlikely in a non-homogeneous clutter environment that $E[|\alpha_{l'k'}|^2] = E[|\alpha_{lk}|^2]$ for all N_c pairs of clutter patches in the two range rings. In fact, unless the clutter is entirely homogeneous throughout both range rings, it is unlikely that the clutter in the $(l')^{th}$ range ring will be representative of the clutter in the l^{th} range ring over the entire clutter ridge.

However, the concept of representative secondary clutter data may be meaningful on a selective basis. For example, consider post-Doppler adaptive beamforming in which non-adaptive Doppler filtering is first performed separately on the M pulses from each array element. In effect, this produces at each array element the output of M Doppler filters that subdivide the normalized Doppler frequency interval into M contiguous Doppler bins. The basic idea is that a Doppler filter, with the capability for very low Doppler sidelobes, rejects the clutter whose Doppler frequencies fall outside of its passband. In this way, the residual clutter along the clutter ridge is localized in terms of its normalized spatial frequencies. Adaptive spatial filtering is subsequently performed to reduce the residual clutter. This is repeated for each of the M Doppler filters. Because the residual clutter in normalized Doppler and spatial frequencies is confined to a localized region along the clutter ridge, it is no longer necessary that the range ring from which secondary data is being collected be equivalent in its entirety to the range ring in which the test cell is located. Now the clutter in only a few patches of each range ring need be equivalent i.e. those that lie along the same iso-Doppler ridge.

4. Airborne Radar Data

To assist us in building and testing our methodology for selecting equivalent range rings we used data gathered under a U. S. Air Force program. The AFRL Sensors Directorate Multi-channel Airborne Radar Measurements (MCARM) program was designed to collect multi-channel clutter data from an airborne platform with a side looking radar [4]. Northrop Grumman collected MCARM data during flights over the Delmarva Peninsula and the east coast of the United States. A Northrop Grumman owned BAC 1-11 was used as a platform for the L-Band radar data collection system. The radar consisted of 32 sub-apertures combined into 22 adaptive channel elements. The elements were arranged in a 2 by 11 array. Data was collected at a variety of pulse repetition frequencies (PRFs) over various terrain including mountains, rural, urban, and land/sea interfaces. There were a total of eleven flights with more than 50 Gigabytes of data collected and additional flights planned. We chose this data because of its varied and heterogeneous clutter environment.

5. A Priori Data

Digital terrain data was obtained from the United States Geological Survey (USGS) to classify the ground environment that the MCARM radar was irradiating. Since the Delmarva Peninsula has little variation in elevation we decided not to incorporate digital elevation data that would provide a measure of the angular reflection back to the antenna. Instead, we chose Land Use and Land Cover (LULC) data that classifies terrain using a grid of 200 by 200 meter cells and codes that describe the terrain in each cell. There are 9 major codes and 38 minor codes that have a more detailed description. The LULC data provides a measure of the amount of radar reflection and absorption from the ground. In order to simplify our approach we only used the major codes and, if deemed necessary, planned on using the minor codes later. An example of LULC major codes are: Urban Areas, Agricultural Land, Water, etc.

6. Research Problem, Hypothesis, and Preliminary Findings

Can post-Doppler STAP performance be improved by choosing secondary data based upon a priori map data? To determine the answer to this question we compared our results with what we call the standard algorithm or sliding window algorithm. The sliding window algorithm chooses N/2 range rings above and below the test ring minus two guard rings (N is twice the number of independent channels of the MCARM radar which is 22.) see Figure 1. The sliding window algorithm has an implicit assumption that the range rings near the test ring are homogeneous and are representative of the test ring. Our algorithm chooses secondary data by comparing the LULC codes of the Doppler patch that interferes with the test patch in the same range ring and all of the patches that lie on the same iso-Doppler curve of interest. Our assumption is that the major interferer after range and Doppler filtering will be the clutter due to the ground within the same range ring as the test cell.

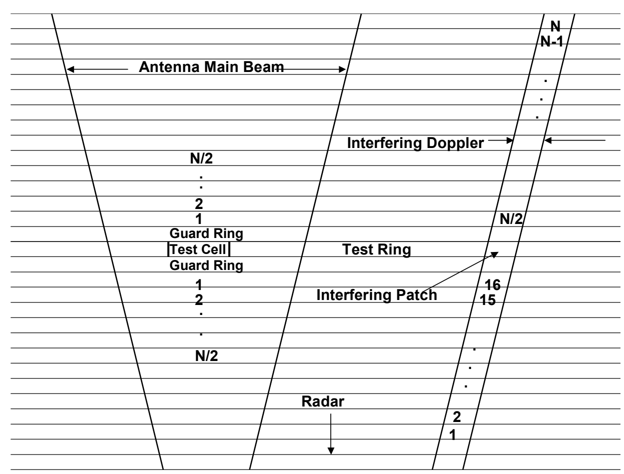

Figure 1. Sliding Window and KBMapSTAP Secondary Data Selection

It was our hypothesis that our algorithm (KBMapSTAP) would do as well as the sliding window algorithm where the test and surrounding area are homogeneous and KBMapSTAP would do better than the sliding window algorithm for areas where the ground is heterogeneous. To test our hypothesis we injected a target at different range rings with the same radial velocity and

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power. The only difference in the implementation of the two algorithms was the choice of the secondary range rings. After Doppler processing, we calculated a Modified Sample Matrix Inversion (MSMI) statistic for each range ring of interest [1,5].

$$\mathrm{MSMI_i} = \frac{\left|s^H \hat{R}^{-1} x_i\right|^2}{s^H \hat{R}^{-1} s} \qquad (3)$$

where s is the space-time steering vector, $\hat{R}$ is the estimate of the clutter covariance matrix and x_i is the radar return vector for the i^{th} range ring. It can be seen that the MSMI has a thresholding or detection quality similar to a constant false alarm rate (CFAR) property. That is, a MSMI threshold can be chosen y such that those radar returns, x_i, that have an MSMI that exceeds y may be considered as potential targets.

Figures 2 and 3 represent the MSMI results for the two algorithms without an injected target. The mean and variance of the results are slightly smaller for KBMapSTAP than for the sliding window algorithm. If a threshold of 20 db were chosen, then the KBMapSTAP would detect fewer false alarms than the sliding window algorithm.

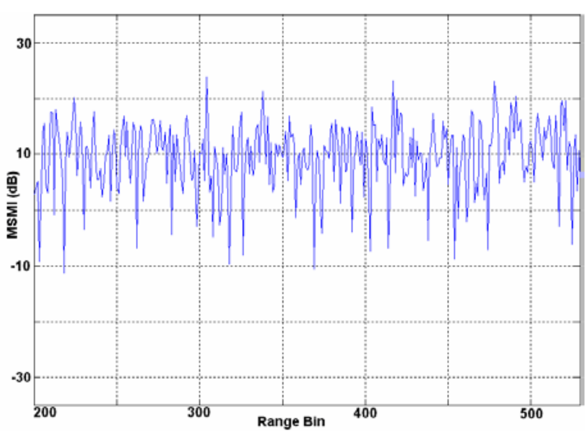

Figure 2. Sliding Window – No Injected Target
(Mean MSMI = 12.9, Var MSMI = 28.9)

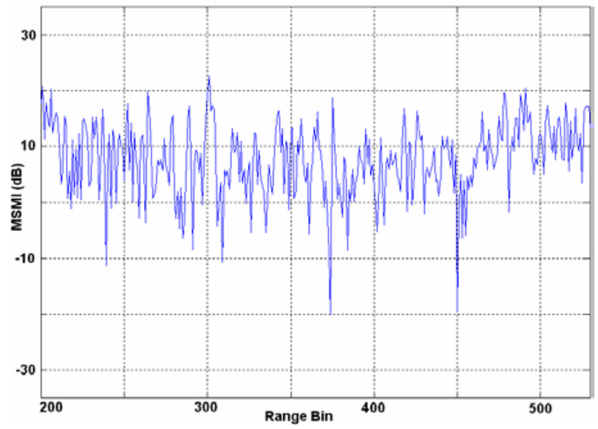

Figure 3. KBMapSTAP – No Injected Target
(Mean MSMI = 11.7, Var MSMI = 26.6)

In heterogeneous environments, KBMapSTAP did consistently better than the sliding window algorithm. For example, Figures 4 and 5 have a target injected at the same power at range bin 296 and show the MSMI output from each algorithm. If a threshold is chosen at 25 dB we can see that the sliding window algorithm wouldn't detect the target. However, KBMapSTAP would clearly detect it at 5 dB above the threshold.

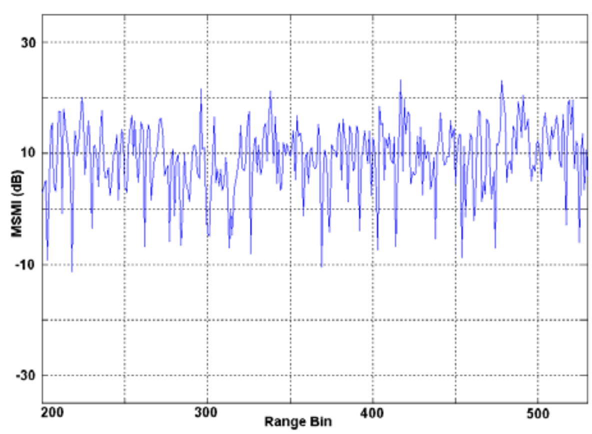

Figure 4. Sliding Window – Target Injected at Range Bin 296
(Mean MSMI = 12.7, Var MSMI = 28.3)

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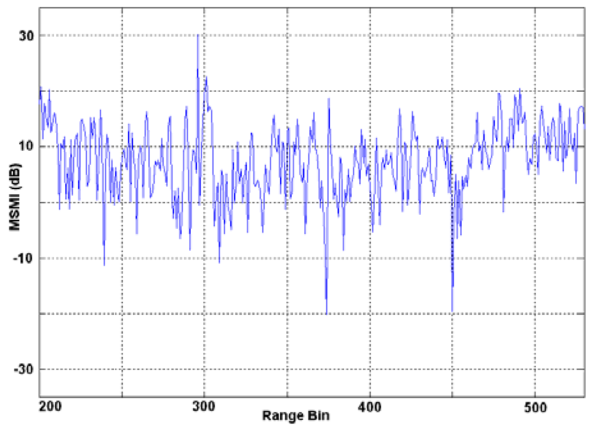

Figure 5. KBMapSTAP – Target Injected at Range Bin 296
(Mean MSMI = 12.3, Var MSMI = 35.4)

To test our hypothesis that the KBMapSTAP algorithm would perform the same as the standard algorithm when a target occurred in a homogeneous clutter environment, we injected a target in range bin 475. This range is in water and is surrounded by water such that the major ground clutter is due also to water. Figure 6 shows the result of the sliding window algorithm and Figure 7 the result for KBMapSTAP. It was conjectured that the KBMapSTAP would do as well as the sliding window algorithm and it did. One could argue however, that it did better considering the lower mean and variance clutter levels.

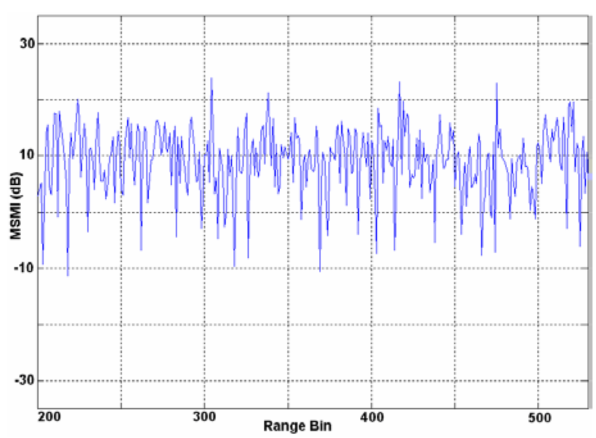

Figure 6. Sliding Window – Target Injected at Range Bin 475
(Mean MSMI = 12.4, Var MSMI = 28.5)

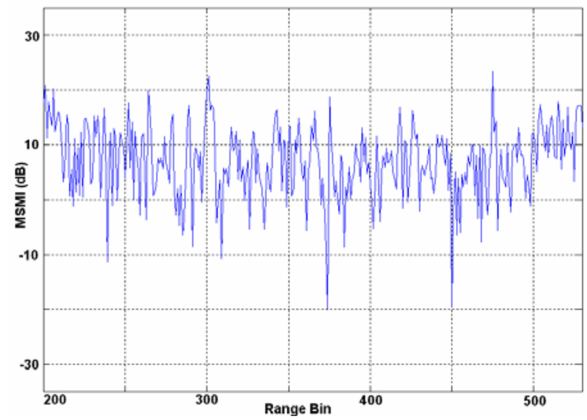

Figure 7. KBMapSTAP – Target Injected at Range Bin 475
(Mean MSMI = 11.2, Var MSMI = 26.9)

7. Conclusions and Future Work

From our limited analysis it can be concluded that the KBMapSTAP algorithm outperforms the standard or sliding window algorithm for heterogeneous clutter environments and performs approximately the same for homogeneous clutter environments. Post-Doppler STAP performance can be improved. The data presented here are limited. More analysis and development is required before a quantitative measure of performance can be obtained.

There are some issues that also need to be explored. The data from the USGS database were collected approximately 10 years before the radar data was obtained. It is likely that some of the USGS data was not current when the radar data were collected. Techniques to validate map data with the radar need to be explored for those cases where recent map data are not available and when weather and environmental conditions have changed, e.g. snow and flooding.

Map precision is important when the radar's range and angle resolution is significantly different from the map data precision. For our experiment the range resolution of the radar was 120 meters and the LULC data points were at a resolution of 200 meters by 200 meters. Even with this difference in precision the KBMapSTAP algorithm performed well. A sensitivity analysis should be performed and the clutter patch characterization portion of the algorithm modified

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for varying precision permutations between the radar and the available map data.

The Delmarva area is relatively flat and using LULC data worked well. If however, the terrain is mountainous then the algorithm must include digital elevation model data. This area needs further investigation along with tests to evaluate its performance.

Finally, the LULC data we used does not contain explicit information about man-made features such as railroads, roads, bridges, power lines, etc. The USGS does offer Digital Line Graph data that maps these features. Future work should be done to incorporate this data into the KBMapSTAP algorithm and tests done to measure improvement.

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9. References

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