GROUND MOVING TARGET INDICATION USING KNOWLEDGE BASED SPACE TIME ADAPTIVE PROCESSING

Raviraj S. Adve, Air Force Research Laboratory (AFRL/SNRT), Rome, NY, USA
Michael C. Wicks, Air Force Research Laboratory (AFRL/SNRT), Rome, NY, USA
Todd B. Hale, Air Force Institute of Technology (AFIT), Dayton, OH, USA
Paul Antonik, Air Force Research Laboratory (AFRL/SNRT), Rome, NY, USA

Introduction

Space-Time Adaptive Processing (STAP) techniques promise to offer the best means to detect weak targets in severe, dynamic, interference scenarios. Traditionally, STAP techniques were developed for the detection of low RCS, high velocity airborne targets, well removed from mainbeam clutter in Doppler. STAP algorithms are only now being used for Ground Moving Target Indication (GMTI) from an airborne reconnaissance platform.

The motion of an airborne platform, including crab and yaw, tends to spread the clutter in Doppler. Low velocity ground targets are therefore buried within mainbeam clutter, making detection difficult. Non-adaptive techniques, such as the two-pulse canceller including motion compensation, are usually able to detect only large ground targets or must deal with several false alarms. This problem is worsened by electronic countermeasures such as jamming. The need to detect small ground targets or targets under cover while minimizing false alarms leads to research in applying adaptive processing to GMTI.

Classical STAP algorithms achieve interference suppression within a primary range cell using an estimated interference covariance matrix. The estimate is typically formed using secondary data from range cells symmetrically placed about the range cell under test. The underlying assumption is that the secondary data samples are an accurate statistical representation of the interference in the primary range cell, i.e. the data is homogeneous. Statistical algorithms suffer from significant loss in performance when this assumption is violated. Non-homogeneous data occurs in many practical situations such as airborne surveillance over land-sea interfaces, urban terrain, etc.

To minimize the loss in performance due to non-homogeneous sample support, a Non-Homogeneity Detector (NHD) [1, 2] can be used to separate the range cells into homogeneous cells and non-homogeneous cells. Within the homogeneous cells a statistical algorithm may be applied using other homogeneous cells as secondary data. These algorithms were originally developed for proof of concept, assuming an idealized linear array of equispaced, isotropic, point sensors. To fully exploit the capabilities of STAP algorithms applied to measured data, attention must be paid to real world issues such as non-linear arrays, mutual coupling between elements, and channel mismatch [3].

Within the cells declared to be non-homogeneous, correlated and uncorrelated interference hinders target detection. For these cells, purely statistical algorithms are inappropriate because the surrounding range cells help suppress correlated interference, but do not possess information about the uncorrelated interference. Statistical algorithms based purely on secondary data therefore cannot suppress a discrete non-homogeneity within a single range cell.

The need for adaptive processing within a non-homogeneous range cell leads to a new class of direct data domain (D^3) algorithms. These algorithms use data from the primary range cell only and make no attempt to estimate a covariance matrix. The performance of D^3 algorithms in countering correlated interference is enhanced by implementing a second stage of adaptive statistical processing; i.e following D^3 adaptive processing with adaptive statistical processing [4]. The second stage of this hybrid algorithm uses homogeneous cells as the secondary data.

In this paper, we present a practical approach to STAP incorporating the three components mentioned: non-homogeneity detection, statistical processing of measured data, and hybrid processing. This combined approach ties together previous research in different aspects of STAP into one algorithm. The algorithm is tested using measured data from the Multi-Channel Airborne Radar Measurements program with particular interest in Ground Moving Target Detection.

Practical STAP for GMTI

A practical application of STAP for weak target detection requires at least three components: a NHD, a statistical algorithm for use within homogeneous cells, and the hybrid algorithm for use within non-homogeneous cells. This minimal approach is illustrated in Fig. 1. This section presents these components in some detail and the advantages of using the described approach.

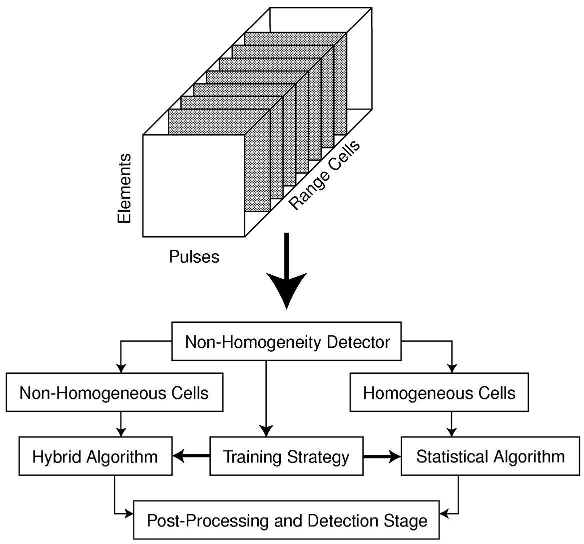

Fig. 1. Practical Space-Time Adaptive Processing

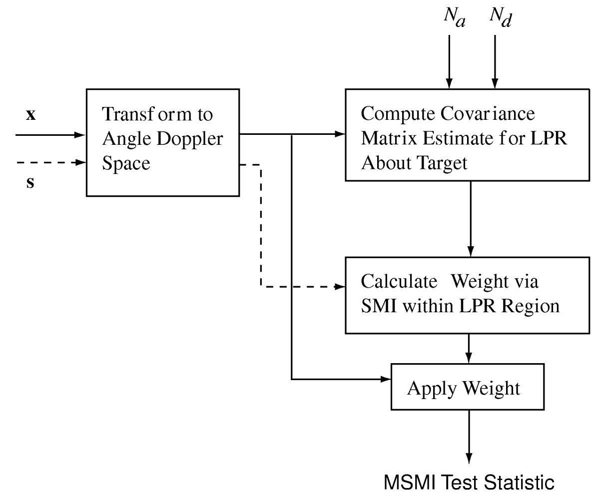

Fig. 2. JDL algorithm used as a NHD.

Non-Homogeneity Detection

The first step in adaptive processing is to distinguish between homogeneous and non-homogeneous range cells, i.e. the first step is a non-homogeneity detector. The problems associated with non-homogeneities and the resulting need for a NHD are described in detail elsewhere and are not repeated here [1, 2].

It must be noted that non-homogeneities may be distributed or localized. Distributed non-homogeneity occurs when two or more kinds of terrain are illuminated, for example at a land-sea interface. The statistics of sea clutter are significantly different from those of land. This sort of non-homogeneity can be countered by developing a knowledge base of the illuminated terrain. This knowledge base may be informed by *a-priori* information such as map data, previous passes over the surveillance volume or information from other sensors. For example, if flying near a land-sea interface, a knowledge based controller can split the data cube into land-only and sea-only data. The STAP algorithm then uses secondary data only from the set to which the primary data belongs.

This paper, on the other hand, addresses the issue of discrete non-homogeneities. Discretes may arise in urban and spiky clutter scenarios due to natural and man-made features or be caused by large targets in the transmit sidelobes. A target in the primary range cell, but not at the look angle-Doppler, is effectively discrete interference. True targets must also be considered discrete interference - when the range bin containing the target is a secondary data sample for other range cells.

The NHD obtains a statistic for each range cell in the radar data cube, which is used to determine if the range cell is to be considered homogeneous or not. Several NHD formulations are possible, such as the Generalized Inner Product (GIP) [1] and the Joint Domain Localized-NHD [2]. The rationale behind these approaches is that with known covariance, the matched filter case, the detection statistic only contains residual thermal noise. Any significant deviations from the mean are caused by localized non-homogeneities such as targets and discretes.

This paper is based on the JDL-NHD as illustrated in Fig. 2. In the figure, $\mathbf{x}$ represents the data and $\mathbf{s}$ the space-time steering vector. N_a and N_d refer to the number of angle and Doppler bins within the Localized Processing Region (LPR). In the angle-Doppler domain, adaptivity is restricted to within the LPR. The JDL-NHD evaluates the modified sample matrix inversion (MSMI) statistic using the JDL algorithm of [3], *assuming* homogeneous interference. A range bin is considered to be non-homogeneous if the JDL-MSMI statistic is above a chosen threshold. The choice of threshold is described later. This approach is closely related to that taken for detection declarations in a traditional application of STAP. However, range bins that traditionally would be declared to contain targets are now considered to be non-homogeneous. In this multi-pass approach, the first pass of STAP serves as a NHD.

As formulated above, the NHD yields two advantages to the next stage of adaptive processing. One, identifying all threshold crossings as non-homogeneities allows the hybrid algorithm to distinguish between true targets and false alarms: applying the hybrid algorithm in these range cells reduces false alarms. Secondly, since even true targets are considered non-homogeneities in the estimation of a sample covariance matrix, any weak targets suppressed by the presence of a target in the secondary data can now be detected: the NHD yields improved detection performance.

Processing in Homogeneous Range Cells: JDL

In the second stage of adaptive processing, range cells declared to be homogeneous are processed using a statistical STAP algorithm. Here the algorithm of choice is the same JDL algorithm used for the NHD. The difference arises from using only homogeneous range cells for the required secondary data sample support.

The basic formulation of the JDL algorithm is illustrated in Fig. 2. When applied to real arrays, the transformation from the element domain to the angle domain is based on the measured spatial steering vectors. For example, if the LPR covers 3 angle bins ($\phi_{-1},\ \phi_0,\ \phi_1; N_a = 3$) and 3 Doppler frequencies ($f_{-1},\ f_0,\ f_1; N_d = 3$) the transformation process is

$$\tilde{\mathbf{x}}_{\mathrm{LPR}} = \mathbf{T}^H \mathbf{x}, \tag{1}$$

where $\mathbf{x}$ is a received space-time data vector. The primary and secondary data is transformed to the angle-Doppler domain using this transformation process. The transformation matrix $\mathbf{T}$ is given by

$$\begin{aligned} \mathbf{T} &= [\mathbf{b}(f_{-1})\ \ \mathbf{b}(f_0)\ \ \mathbf{b}(f_1)] \\ &\quad \otimes [\mathbf{a}_m(\phi_{-1})\ \ \mathbf{a}_m(\phi_0)\ \ \mathbf{a}_m(\phi_1)], \end{aligned} \tag{2}$$

where $\mathbf{a}_m(\phi)$ is the measured spatial steering vector corresponding to angle ϕ, $\mathbf{b}(f)$ is the temporal steering vector corresponding to Doppler frequency f and $\otimes$ represents the Kronecker product. $\mathbf{b}(f) \otimes \mathbf{a}_m(\phi)$ therefore represents the spatial-temporal steering vector corresponding to (ϕ, f). The space-time steering vector is also transformed using the same process, hence matching the angle-Doppler steering vector in the transform domain to the transformation used for the data.

The use of measured steering vectors, instead of ideal steering vectors, accounts for real world array effects such as non-linear arrays, mutual coupling and channel mismatch. The resulting performance improvements, using this enhanced JDL algorithm, are significant [3].

Hybrid Processing in Non-homogeneous Range Cells

In range cells declared to be non-homogeneous, the interference has both discrete and correlated components. Forming a covariance matrix suppresses the correlated interference, but the secondary data has no information about the discrete interference and this component cannot be suppressed. Purely statistical algorithms are therefore not applicable to these range cells. The need for adaptive processing within a non-homogeneous range cell leads to a new class of direct data domain (D^3) algorithms. Originally introduced for spatial adaptivity [5], these algorithms use data from the primary range cell only and make no attempt to estimate a covariance matrix.

The D^3 approach implemented here minimizes the interference within the primary range cell in a least squares sense while maximizing the gain of the array at the look angle/Doppler. D^3 approaches work particularly well against discrete interference, but fail to suppress range and/or Doppler spread interference to the degree possible with statistical algorithms. To overcome these problems, a two-stage algorithm has been developed using a stage of statistical adaptive processing to follow the D^3 stage of processing [4]. The second stage of this hybrid algorithm uses homogeneous cells as the secondary data to suppress correlated interference not suppressed by the first stage D^3 processing.

Consider the general framework of any STAP algorithm. The algorithm processes received data to obtain a complex weight vector for each range bin and each look angle/Doppler. The weight vector then multiplies the primary data vector to yield a complex number. The process of obtaining a real scalar from this number for threshold comparison is part of the post-processing and is not inherent to the algorithm itself. The adaptive process estimates the signal component in the look angle/Doppler and may therefore be viewed as a transform to this angle-Doppler point. These weights play a role similar to the non-adaptive steering vectors used in Eqn. (2) to transform the space-time data to the angle-Doppler domain.

The hybrid algorithm is therefore based on the formulation of the JDL algorithm given by Eqns. (1-2). The non-adaptive steering vectors in matrix $\mathbf{T}$ are replaced by the adaptive weights obtained from a repeated application of the D^3 algorithm. If $\mathbf{w}(\phi, f)$ represents the adaptive D^3 weights corresponding to look angle ϕ and Doppler f, the transformation matrix for the 3×3 LPR is given by

$$\begin{aligned} \mathbf{T} = [&\mathbf{w}(\phi_{-1}, f_{-1})\ \ \mathbf{w}(\phi_0, f_{-1})\ \ \mathbf{w}(\phi_1, f_{-1}) \\ &\mathbf{w}(\phi_{-1}, f_0)\ \ \mathbf{w}(\phi_0, f_0)\ \ \mathbf{w}(\phi_1, f_0) \\ &\mathbf{w}(\phi_{-1}, f_1)\ \ \mathbf{w}(\phi_0, f_1)\ \ \mathbf{w}(\phi_1, f_1)] \end{aligned} \tag{3}$$

for an LPR covering angles $\{\phi_{-1}, \phi_0, \phi_1\}$ and Dopplers $\{f_{-1}, f_0, f_1\}$.

Using Eqns. (1) and (3), the transformed data $\tilde{\mathbf{x}}$ is used to calculate a new set of adaptive weights within the LPR. The secondary data is drawn from the range cells declared to be homogeneous. The secondary data is also transformed to the angle-Doppler domain using Eqns. (1) and (3).

The hybrid algorithm has been shown to combine the benefits of D^3 and statistical processing [4]. The D^3 stage suppresses discrete interference. The statistical processing in the second stage then suppresses any residual correlated interference.

Advantages

The formulation described above incorporating the JDL-NHD, the JDL algorithm, and hybrid processing yields several advantages for implementation. To quote Chang [6], "*A data set is termed wide sense homogeneous if the system performance loss can be ignored or is acceptable for a given STAP algorithm. A data set is said to be wide sense non-homogeneous if it is not wide sense homogeneous*". This definition implies that discrete interference affecting one STAP algorithm *may not* affect another. For example, a sidelobe discrete that falls in a natural null of the transform to the angle-Doppler domain is not relevant to the performance of the JDL algorithm. By using the JDL-NHD, only non-homogeneities that are relevant to the JDL algorithm are identified as such.

All three components are based on the JDL algorithm. The hybrid algorithm uses a D^3 algorithm for the first stage in the transformation from the space-time domain to the angle-Doppler domain. This is in contrast to traditional JDL where non-adaptive spatial-temporal steering vectors are used. Otherwise, the formulation is the same as in JDL.

The transformation described localizes the interference in the angle-Doppler domain, while retaining maximal gain against thermal noise. The size of the LPR can be picked independently of the number of elements or pulses. The number of secondary data vectors required is dependent on the chosen size of the LPR. In severely non-homogeneous regions, the size of the LPR can therefore be reduced to match the secondary data available. In an extreme case, no secondary data may be available and a pure direct data domain algorithm may be used, effectively setting the size of the LPR to 1×1, the look angle-Doppler.

Numerical Example

The combined approach above is tested using measured data from the Multi-Channel Airborne Radar Measurements (MCARM) database [7]. The database is a vast collection of clutter and target measurements collected by an airborne radar over many flights with multiple acquisitions on each flight. The radar antenna is a 22 element (2x11) rectangular array of reduced depth notch radiators. Each acquisition comprises a coherent processing interval (CPI) of 128 pulses at a pulse repetition frequency of 1984 Hz. Each CPI comprises 630 range bins sampled at 0.8μs. Each range bin, therefore, corresponds to 0.075 miles. The array operates at a center frequency of 1.24 GHz. Included with each CPI is information regarding the position, aspect, velocity, and mainbeam transmit direction. This information is used to correlate target detections with ground features. Also included with the database is a set of measured steering vectors which account for the mutual coupling and channel mismatch.

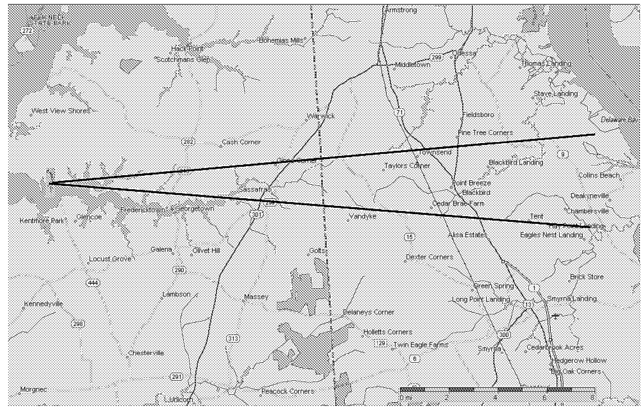

Fig. 3. Location and transmit direction of the MCARM airplane during acquisition 575.

The example illustrates the issues addressed in this paper, namely non-homogeneities and the use of the appropriate processing algorithm in appropriate sections of the radar data cube. This example uses data from acquisition 575 on flight 5. While recording this acquisition the radar platform was at latitude-longitude coordinates of (39.379^o,-75.972^o), placing the aircraft close to Chesapeake Haven, Maryland. The plane was flying mainly south with velocity 223.78 mph and east with velocity 26.48 mph. The aircraft location and the transmit mainbeam are shown in Fig. 3. The mainbeam is close to broadside. Note that the mainbeam illuminates several major highways.

To illustrate the effects of non-homogeneities in secondary training data we inject two targets at closely spaced range bins. These artificial targets are in addition to the ground targets of opportunity on the roadways illuminated by the array. Based on the measured steering vectors and chosen Doppler shifts the response of the two simulated targets may be calculated. The artificial targets are injected in range bins 290 and 295. In this acquisition, the zero range is referenced to range bin 74 and so the targets are injected at ranges of 16.2 miles and 16.575 miles respectively. The parameters of the injected targets are given in Table I. Note that the two targets are at the same look angle and Doppler frequency. Also note that the second target is 20dB stronger than the first.

TABLE I

PARAMETERS DEFINING THE INJECTED TARGETS.

	Target 1	Target 2
Ampl	1×10^{-4}	1×10^{-3}
Angle bin	1^o	1^o
Doppler	-9 $\equiv$ -139.5 Hz	-9 $\equiv$ -139.5 Hz
Range bin	290 $\equiv$ 16.2 mi	295 $\equiv$ 16.575 mi

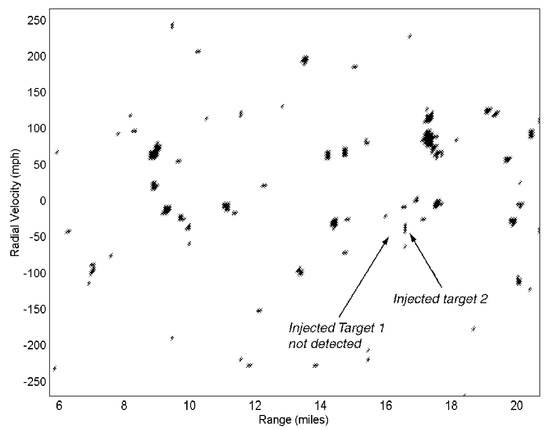

Fig. 4. JDL Processing ignoring non-homogeneities.

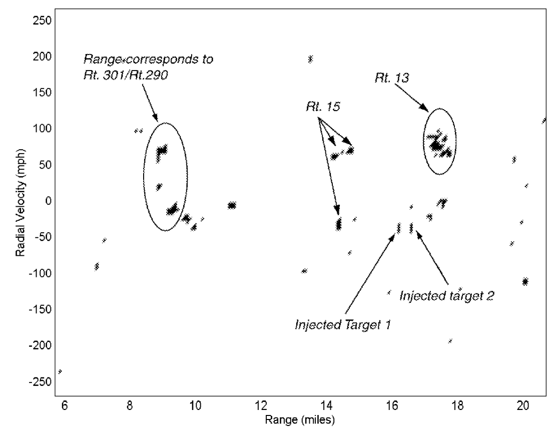

Fig. 5. Combined Processing for GMTI.

This example uses 3 angle bins and 3 Doppler bins (a 3×3 LPR) in all stages of adaptive processing, including the JDL-NHD. Thirty six secondary data vectors are used to estimate the 9×9 angle-Doppler LPR covariance matrix. In addition, two guard cells are used on either side of the primary data vector. Based on these numbers, without a NHD stage, range bin 295 would be used as a secondary data vector for detection within range bin 290. The example compares the results of using the enhanced JDL algorithm without non-homogeneity detection of [3] and the combined approach of this paper illustrated in Fig. 1.

Figure 4 presents the results of using the enhanced JDL algorithm without any attempt to remove non-homogeneities from the secondary data. The range-Doppler plot is of the modified sample matrix inverse (MSMI) statistic after applying a threshold. In producing this figure, a threshold of 40 is used, i.e. any Doppler-range bin with a MSMI statistic greater than 40 (not in dB) is said to contain a target while any Doppler-range bin with a statistic below 40 is declared target free. For Gaussian interference, using 36 secondary data vectors to estimate a 9×9 covariance matrix a threshold of 40 corresponds to a false alarm rate of $P_{fa} = 5 \times 10^{-8}$. Note that the true false alarm rate for measured data is significantly higher. The plot is for adaptive processing between range bins 150 and 350, corresponding to ranges between 5.7 and 20.6 miles and all 128 Doppler bins. Due to platform motion the radar is approaching these targets at a speed of 26.48mph.

As is shown later, certain range bins that are declared to contain a target can be correlated with the map in Fig. 3 as corresponding to roadways. However, not using a NHD results in many false alarms including several at extremely high radial velocities. In addition, the first injected target at range bin 290 is not detected. This is because of the presence of the larger target at range bin 295 in the secondary data when range bin 290 is the primary range bin.

Figure 4 clearly illustrates the need for a stage to identify non-homogeneities and eliminate them from the secondary data set. Applying STAP to measured data results in several false alarms and the possibility of targets in the secondary data masking weak targets. The processing structure detailed in this paper addresses this need.

In the implementation presented in this paper, a JDL-NHD is used to identify non-homogeneous range cells. A range cell is considered to be non-homogeneous if the JDL-MSMI statistic is above 18.52, significantly lower than the threshold of 40 used to produce the results presented in Fig. 4. Assuming Gaussian interference, using 36 secondary data vectors to estimate a 9×9 covariance matrix to obtain an MSMI statistic, this threshold corresponds to a false alarm rate of $P_{fa} = 10^{-4}$. In this acquisition, approximately 5% of the test statistics fall above this threshold.

The combined algorithm uses JDL processing in those cells declared homogeneous and hybrid processing in those cells declared non-homogeneous. Again a 3×3 LPR is used, both in the JDL algorithm and in the hybrid algorithm. In the second application of the JDL algorithm in homogeneous range cells, only similar homogeneous cells are used for sample support. Within the non-homogeneous cells, a hybrid algorithm is used. The D^3 algorithm is applied a total of 9 times corresponding to the 3 angle and 3 Doppler look directions, *using the same primary data*. The angle-Doppler data so obtained using the D^3 adaptive transformation is used for further JDL processing. Homogeneous cells are used to obtain sample support for the second stage JDL processing.

Figure 5 shows the result obtained using this combined approach. Again a detection is declared in any range/Doppler bin with a statistic greater than 40. Notice the significantly fewer false alarms than in Fig. 4. In essence the hybrid algorithm has been applied to all those range/Doppler bins where the JDL-MSMI statistic is greater than 18.52. The use of the hybrid algorithm suppresses non-homogeneities, significantly reducing false alarms.

In addition, the weaker injected target is detected because the stronger target at range bin 295 is eliminated from the sample support. Furthermore, the range bins of most target detections can be directly correlated with the state highways in Maryland and Delaware. Routes 290 and 301 in Maryland are closely spaced at a range of 9.0 and 9.8 miles. Accounting for the platform motion, the ground speed of the target(s) is approximately 50 mph towards (and away) from the aircraft.

The target detections at the far range shown in the plot are between 19.4 and 20.4 miles. The range to Route 9 varies between 19.1 and 21.1 miles within the transmit mainbeam. These far range detections therefore correspond to Route 9. The targets detected at these ranges are present in both Figs. 4 and 5.

Summary and Conclusions

This paper presents a practical approach to Space-Time Adaptive Processing, incorporating previous research into different aspects of STAP. The paper illustrates the use of the appropriate adaptive algorithm within the appropriate range bin. The approach presented incorporates non-homogeneity detection, statistical processing using homogeneous data only, and direct data domain processing within non-homogeneous range cells. Each of these aspects of STAP has been addressed separately before, but never tied together into a single, comprehensive adaptive algorithm.

The algorithm presented has been tested using measured data from the MCARM program. The results prove the importance of non-homogeneity detection and hybrid processing within non-homogeneous range cells. By combining these aspects of STAP our comprehensive approach achieves a significant reduction in the number of false alarms and increased probability of detecting weak targets in multiple target scenarios.

The work presented in this paper helps in moving STAP from theory to practice. In this regard, this research is part of a broader knowledge based space-time adaptive processing (KB-STAP) approach [8]. Knowledge based control provides for selection amongst several different algorithms, *a-priori* knowledge of terrain and interference, knowledge from other sensors, information from previous flights/passes, and feedback from other stages in the adaptive processing chain. With respect to Fig. 1, the knowledge base would aid in non-homogeneity detection, training strategy, and choice of STAP algorithm. The goal of knowledge based control is to match the processing to the environment.

Future Work

The implementation of KB-STAP in a practical manner is still an open research problem. One issue to be addressed is which algorithm to use under what conditions. Here we choose between only two algorithms on the basis of a non-homogeneity detector. Even this simple implementation results in vastly improved performance.

Another area of growing importance to the user community is the application of STAP to non-planar arrays, especially circular arrays. While such arrays yield significant advantages in angular coverage and reduced scanning requirements, the resulting change in interference spectrum with range requires a reformulation of adaptive processing.

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References

[1] M. C. Wicks, W. L. Melvin, and P. Chen, “An efficient architecture for nonhomogeneity detection in space-time adaptive processing airborne early warning radar,” in *Proc. of the 1997 Int. Radar Conf.*, pp. 295–299, October 1997. Edinburgh, UK.

[2] R. S. Adve, T. B. Hale, and M. C. Wicks, “Transform domain localized processig using measured steering vectors and non-homogeneity detection,” in *Proc. of the 1999 IEEE National Radar Conf.*, pp. 285–290, Apr. 1999. Boston, MA.

[3] R. S. Adve and M. C. Wicks, “Joint domain localized processing using measured spatial steering vectors,” in *Proc. of the 1998 IEEE National Radar Conf.*, pp. 165–170, May 1998. Dallas, TX.

[4] R. S. Adve, T. B. Hale, and M. C. Wicks, “A two-stage hybrid space-time adaptive processing algorithm,” in *Proc. of the 1999 IEEE Radar Conf.*, pp. 279–284, Apr. 1999. Boston, MA.

[5] T. K. Sarkar and N. Sangruji, “An adaptive nulling system for a narrow-band signal with a look-direction constraint utilizing the conjugate gradient method,” *IEEE Trans. on AP*, vol. 37, pp. 940–944, July 1989.

[6] H.-H. Chang, *Improving Space-Time Adaptive Processing (STAP) Radar Performance in Nonhomogeneous Clutter*. PhD thesis, Syracuse University, August 1997.

[7] D. Sloper, D. Fenner, J. Arntz, and E. Fogle, “Multi-channel airborne radar measurement (MCARM), MCARM flight test,” Contract F30602-92-C-0161, Westinghouse Electronic Systems, April 1996.

[8] P. Antonik, M. C. Wicks, and Y. Salama, “Knowledge based radar signal and data processing,” in *Proc. of the 5th Int. Conf. on Radar Sys.*, May 1999. Brest, France.