STATISTICAL SPACE-TIME ADAPTIVE PROCESSING ALGORITHM¹

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Abstract For the slowly changed environment-range-dependent non-homogeneity, a new statistical space-time adaptive processing algorithm is proposed, which uses the statistical methods, such as Bayes or likelihood criterion to estimate the approximative covariance matrix in the non-homogeneous condition. According to the statistical characteristics of the space-time snapshot data, via defining the aggregate snapshot data and corresponding events, the conditional probability of the space-time snapshot data which is the effective training data is given, then the weighting coefficients are obtained for the weighting method. The theory analysis indicates that the statistical methods of the Bayes and likelihood criterion for covariance matrix estimation are more reasonable than other methods that estimate the covariance matrix with the use of training data except the detected outliers. The last simulations attest that the proposed algorithms can estimate the covariance in the non-homogeneous condition exactly and have favorable characteristics.

Key words Space-Time Adaptive Processing (STAP); Non-homogeneous condition; Bayes and likelihood criterion; Data weighting

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I. Introduction

Space-Time Adaptive Processing (STAP) technique is a well-established technique for the detection of moving targets by an airborne radar. Following the landmark publication by Brenna and Reed in 1973³, researchs on STAP evolved rapidly. It takes advantage of joint spatial and time domain processing, which can compete with any other combination of adaptive array algorithms and a Moving Target Indication (MTI) technique³–⁴. A crucial aspect of the effectiveness of any STAP system is the training data selection and the clutter covariance matrix estimation. Most of the reported advantages of a STAP system accrue from an appropriate knowledge of this matrix. In herein its estimation is assumptions about the homogeneity of the clutter.

When using secondary data in the covariance matrix estimation, all the secondary data must be identical and independently distributed (i.i.d), the number of these i.i.d secondary data should be at least twice the dimension of the covariance matrix to avoid severe estimation loss.

These two conditions are not always guaranteed on a practical level, especially for an airborne radar scenario. The i.i.d assumption is not true because radar echoes are easily contaminated by not only natural clutter but also any man-made non-homogeneity. The number of secondary data required to support a STAP-based airborne radar system could still be a vital concern when we need a large array to achieve a higher gain or we need a long Coherent Processing Interval (CPI) to get a better Doppler resolution. Accordingly, we will encounter either a non-homogeneous situation (non i.i.d secondary data) or a limited number of available secondary data cases. Actually, these two situations are relevant because a non-homogeneous environment automatically implies that the available number of secondary data is small.

Understandably, the covariance matrix estima-

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tion is a problem in the non-homogeneous condition. As long as the covariance matrix estimation problem is, as it was, unsolved, the implementation of a STAP-based radar system is virtually impossible. At present, the common method for covariance matrix estimation is the sample selection approach, such as the covariance matrix estimated with the training data which discards the outliers, the common Non-Homogeneous Detection (NHD) method is Generalized Inner Products[5,6], and there are other methods, but the effect of NHD depends on the covariance matrix of sample data by Maximum Likelihood (ML) algorithm, hence the selected training data are not excellent for covariance estimation.

Sample selection is proper especially for discrete-type non-homogeneity, where only a few data are non-homogeneous. In this case, we can easily detect and drop them out. However, for a slowly changed environment, take range-dependent non-homogeneity for example, there can be no distinct boundary between homogeneity and non-homogeneity. Consequently, we may drop too many good data when we should avoid including the likely non-homogeneity data, which is absolutely not worthwhile. We can not afford to lose many data because the secondary data are already limited. In this respect, we prefer to find a weighting function to compensate this range-dependent parameter. We consider applying weighting function to the parts or the whole set of the secondary data to improve covariance estimation. We call this method data weighting. The merit of data weighting comes from the fact that we can weight the likely non-homogeneous data with less weighting than the homogeneous data, which consequently reduces the existing overall error caused by non-homogeneity.

In this paper, a new statistical space-time adaptive processing algorithm is proposed, which uses the statistical methods, such as Bayes[7,8] or likelihood[9] criterion to estimate the approximative covariance matrix in the non-homogeneous condition. The statistical methods of the Bayes and likelihood criterion for covariance matrix estimation are more reasonable than other methods that estimating the covariance matrix with the use of training data except of the detected outliers, and the detection results are not reliable, and usually depend on the deciding criterion. The statistical methods make use of the likelihood of the effective training data, if the likelihood value is large, its contribution to the covariance matrix estimation will be large, whereas if the likelihood value is small, its contribution to the covariance matrix estimation will also be small. Therefore, the statistical methods are the most reasonable and optimal methods for STAP covariance matrix estimation. Simulation results indicate that the proposed algorithm can estimate the covariance in the non-homogeneous condition exactly and has favourable characteristics.

II. Problem Statement

Consider a radar system utilizing an N-element array with inter-element spacing d. the radar transmits an M-pulse waveform in its Coherent Processing Interval (CPI). The received data for each range gate can be organized into an \( NM \times 1 \) space-time snapshot \( x \) by stacking the spatial snapshots from each pulse. The space-time (signal + clutter + noise) covariance matrix is defined as \( R \), where \( R = E\{xx^H\} \), and the \( E\{\} \) is the expectation operator. Under the assumption of Gaussian clutter/interference, the optimum processor (Wiener filter) is

\[
w_{opt} = R^{-1}s
\]

where \( s \) is the \( NM \times 1 \) signal-steering vector.

In practice, the exact covariance matrix \( R \) is unknown and needs to be estimated from the data, which will result in some performance loss. In addition, the clutter statistics of the test range gate may be unknown. The data from the adjacent range gates, conventionally referred to as the training data, are then used for the estimation of the covariance matrix. The training data (assumed to be target-free and derived from a homogeneous clutter environment) consist of only the clutter/interference and noise components. They are assumed to be independent and identical distributed (i.i.d.) but possess the same statistics as the primary data.

When the above two restrictions are present, the estimated covariance matrix \( \hat{R} \) obtained from the Maximum Likelihood Estimator (MLE)[10] is then given by