A HYBRID STAP APPROACH FOR RADAR TARGET DETECTION IN HETEROGENEOUS ENVIRONMENTS

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ABSTRACT

We address the problem of radar target detection under clutter heterogeneity. Traditional approaches, or two-data set (TDS) algorithms, require a training data set in order to estimate the interference covariance matrix and implement the adaptive filter. When the training data exhibits statistical heterogeneity with respect to the test data, the TDS detectors suffer from a degradation in their performance. The single-data set (SDS) detectors have been proposed to deal with this problem by operating solely on the test data. In this paper, we propose a novel hybrid approach that combines the SDS and TDS algorithms, taking the degree of heterogeneity into account. We derive the hybrid detectors and propose the use of the generalised inner product as a heterogeneity measure. We also give expressions for their probabilities of false alarm and detection under heterogeneous assumptions. Simulation results show that new detectors combine the advantages of both the TDS and SDS algorithms resulting in improved performance in homogeneous interference as well as robustness to heterogeneity.

1. INTRODUCTION

Space-Time Adaptive Processing (STAP) for radar target detection has been heavily researched for over thirty years, [1, 2]. The problem is essentially that of detecting the presence of a signal with a known template embedded in coloured Gaussian interference. Consider a size N_s linear antenna array that collects N_t data snapshots for each range gate. The data matrix of the range gate of interest, say range gate r, is then partitioned with a sliding window of size $M_s \times M_t$ as shown in fig. 1. This results in $K_T = L_s L_t$ sub-matrices that are stacked into column vectors and arranged into a matrix $\mathbf{X}$. The parameters L_s and L_t are clearly given by $L_s = N_s - M_s + 1$ and $L_t = N_t - M_t + 1$. The signal model is given by

$$\mathbf{X} = \alpha \mathbf{S} + \mathbf{N}. \tag{1}$$

Here α is a complex magnitude, $\mathbf{S}$ the template of the signal of interest (SOI), whose k^{th} column is given by $\mathbf{s}_{s,l_s} \otimes \mathbf{s}_{t,l_t}$ and the noise matrix $\mathbf{N}$ consists of zero-mean circular complex Gaussian interference (clutter plus noise) with columns $\mathbf{n}_k \sim \mathcal{CN}_M(\mathbf{0}, \mathbf{C})$. The indices k, l_s and l_t are related by $k = l_s N_s + l_t + 1$ and the symbol $\otimes$ denotes the Kronecker product. The spatial and temporal steering vectors, $\mathbf{s}_{s,l_s}$ and $\mathbf{s}_{t,l_t}$, are respectively given by

$$\mathbf{s}_{s,l_s} = \left[e^{j2\pi l_s f_s} \; e^{j2\pi (l_s+1) f_s} \ldots \; e^{j2\pi (l_s+M_s) f_s} \right]^T, \text{ and,} \tag{2}$$

$$\mathbf{s}_{t,l_t} = \left[e^{j2\pi l_t f_t} \; e^{j2\pi (l_t+1) f_t} \ldots \; e^{j2\pi (l_t+M_t) f_t} \right]^T. \tag{3}$$

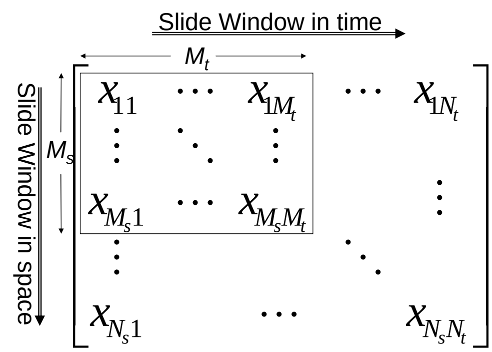

Figure 1: Sliding window partitioning strategy for data matrix of range gate r.

The detection problem is usually treated as a hypothesis test for the presence of the signal. The null and alternative hypotheses are given by $\mathrm{H}_0 : \mathbf{X} = \mathbf{N}$, and $\mathrm{H}_1 : \mathbf{X} = \alpha \mathbf{S} + \mathbf{N}$. It is well known that the optimum processor, $\mathbf{w}_{opt}$, is [3]

$$\mathbf{w}_{opt} = \beta \mathbf{C}^{-1} \mathbf{s}, \tag{4}$$

β being an arbitrary constant and $\mathbf{s}$ the space-time test steering vector of length $M = M_s M_t$, $\mathbf{s} = \mathbf{s}_{s,0} \otimes \mathbf{s}_{t,0}$. The filter output power is compared to a suitably chosen threshold γ,

$$\left| \frac{1}{|\mathbf{t}|} \mathbf{w}_{opt}^H \mathbf{X} \mathbf{t}^* \right|^2 \underset{H_0}{\overset{H_1}{\gtrless}} \gamma. \tag{5}$$

The length K_T space-time steering vector $\mathbf{t}$ corresponds to the frequency pair of $\mathbf{s}$. The superscripts $*$, T and H denote the conjugate, transpose and hermitian respectively.

The optimum processor requires knowledge of the true interference covariance matrix $\mathbf{C}$, which is not usually available. Practical algorithms, such as the GLRT [4] and AMF [5], designated here as the'two-data-set' (TDS) algorithms, replace $\mathbf{C}$ with an estimate obtained from an independent training data set. This training data is usually extracted from adjacent range gates to the test gate.

The training data must be homogeneous with the test data and free from targets. However, it has been recognised for some time that real clutter data can exhibit significant heterogeneity, [6] and [7], a problem that has attracted a significant amount of research. Training data selection strategies such as the non-homogeneity detection (NHD), aimed at improving the quality of the training data set were suggested, e.g. [8, 9]. The generalised inner product (GIP) was a proposed as an

NHD that allows heterogeneous training data snapshots to be excluded. In [10], on the other hand, the authors present the direct data domain (D^3) that processes the test data directly in a deterministic way. The D^3 was used in [11, 12] as a pre-processor and cascaded with an adaptive TDS detector such as the AMF to give a hybrid detection approach that is more robust to heterogeneous clutter. This strategy involves the use of an NHD, such as the GIP, to construct suitable training data sets and to switch between the hybrid detector and a TDS detector.

Recently, an alternative strategy for the detection problem has been put forward in [13] and [14]. In the case where no suitable training data can be obtained, the proposed detectors work solely on the test data and implement a data-adaptive CFAR test. These algorithms, namely the GMLED and MLED, which we designate here as the 'single-data-set' (SDS) algorithms, eliminate the need for independent training data by deriving a covariance matrix estimate from the test data itself. This makes them suitable for application in heterogeneous environments. They differ fundamentally from the TDS algorithms in that they are high-resolution CFAR spectral estimators. In [15] the performance of both the SDS and TDS algorithms under steering vector mismatch was assessed. It was shown that the SDS algorithms enjoy a higher resolution than their TDS counterparts but are less robust to steering vector mismatch.

In this paper, we propose a new hybrid detection strategy that combines the TDS and SDS philosophies, thereby benefitting from the advantages of each. Instead of relying solely on either the test or the training data, we make use of both data sets, at the same time taking into account the degree of heterogeneity. This results in a gain in the homogeneous case due to the increased sample support size, as well as an improvement in the performance in the heterogeneous case due to the scaling of the contribution of the training data according to the measured degree of heterogeneity. The paper is organised as follows: In the following section the hybrid approach is discussed. The algorithm is derived for the homogeneous case in section 2.1 and its statistical properties given in 2.2. In 2.3 the heterogeneous case is dealt with. Simulation results are presented in section 3 and finally some conclusions are given in section 4.

2. HYBRID ALGORITHM

Traditional implementations of the optimal processor, such as the GLRT [4] and AMF [5], assume the availability of an independent training data set that is identically distributed to, in other words homogeneous with, the interference in the test range cell. They use this training data set to obtain a maximum likelihood (ML) estimate, $\mathbf{R}$, of the interference covariance matrix. In the radar context, this training data set is usually drawn from adjacent range cells. Various factors such as terrain type variations, height profile and shadowing, can render the clutter returns range-heterogeneous and hence result in a degradation in the performance of the traditional TDS detectors, [7]. The SDS algorithms, on the other hand, have been proposed to deal with this heterogeneity problem by eliminating the need for a training data set, [13] and [14]. They carry out the processing solely on the test range cell. They obtain a maximum likelihood estimate, $\mathbf{Q}$, of the interference covariance matrix from the test data set. These algorithms are essentially high resolution spectral estimators that have been formulated in such a way as to endow them with the CFAR property under the assumed noise conditions.

When the two data sets are homogeneous with respect to each other, both the SDS and TDS approaches obtain ML estimates of the interference covariance matrix from two statistically independent data sets. Consequently, the estimates themselves are mutually statistically independent. This observation leads us to propose improving the covariance matrix estimation in the homogeneous case by combining the two estimates to obtain a new estimate $\boldsymbol{\Sigma}$. The combined estimate uses a larger amount of data and would be expected to yield a detection performance that is closer to the optimum than the two individual approaches. This case is treated in subsection 2.1. Under heterogeneous conditions, however, the use of the training data set covariance matrix estimate, $\mathbf{R}$, in the total covariance matrix $\boldsymbol{\Sigma}$ leads to a degradation in the performance. As the degree of heterogeneity increases, so does the performance loss. When this loss, with respect to the optimum, surpasses that of the SDS case it becomes desirable to revert to the SDS algorithms and rely solely on $\mathbf{Q}$. Therefore, the general hybrid detector we propose, uses a suitably devised heterogeneity measure to determine the manner in which $\mathbf{R}$ and $\mathbf{Q}$ are combined to give $\boldsymbol{\Sigma}$. This case is dealt with in subsection 2.3.

2.1 Homogeneous Case

Now let us restrict our attention to the homogeneous case and proceed to derive the expression for the hybrid covariance matrix estimate. To this end, we resort to a procedure similar to that established in [14].

Assume that, in addition to the test data set $\mathbf{X}$, we have an independent training data set $\{\mathbf{z}_k\}_{k=1}^{K_t}$, that is homogeneous with the test data. That is $\mathbf{z}_k \sim \mathcal{CN}_M(\mathbf{0}, \mathbf{C})$. Also for the purpose of the analysis, let us assume that, although the test data snapshots were obtained using a sliding window, the columns of $\mathbf{X}$ are statistically independent. The likelihood function of the training data given the covariance matrix is

$$\begin{aligned} f(\mathbf{Z}|\mathbf{C}) &= \left(\frac{1}{\pi^M|\mathbf{C}|}\right)^{K_t} e^{-\sum_{k=1}^{K_t}\mathbf{z}_k^H\mathbf{C}^{-1}\mathbf{z}_k} \\ &= \left(\frac{1}{\pi^M|\mathbf{C}|}\right)^{K_t} \operatorname{etr}\left(-K_t\mathbf{C}^{-1}\mathbf{R}\right), \end{aligned} \quad (6)$$

where $\mathbf{Z}$ is an $M \times K_t$ matrix whose k^{th} column is the vector $\mathbf{z}_k$, $\mathbf{R} = \frac{1}{K_t}\sum_{k=1}^{K_t}\mathbf{z}_k\mathbf{z}_k^H$, and $\operatorname{etr}(-\mathbf{M}) = e^{-\operatorname{tr}(\mathbf{M})}$ with $\operatorname{tr}(\mathbf{M})$ being the trace of $\mathbf{M}$. We have also made use of the identity $\mathbf{v}^H\mathbf{M}\mathbf{v} = \operatorname{tr}\left(\mathbf{M}\mathbf{v}\mathbf{v}^H\right)$. The test data likelihood function not only depends on the covariance matrix $\mathbf{C}$ but also on the parameter α through the data mean. It is, thus, given by

$$f(\mathbf{X}|\mathbf{C},\alpha) = \left(\frac{1}{\pi^M|\mathbf{C}|}\right)^{K_T} \operatorname{etr}\left\{-(K_T-1)\mathbf{C}^{-1}\mathbf{M}_\alpha\right\}, \quad (7)$$

where $\mathbf{M}_\alpha = \frac{1}{K_T-1}\sum_{k=1}^{K_T}(\mathbf{x}_k - \alpha\mathbf{st}(k))(\mathbf{x}_k - \alpha\mathbf{st}(k))^H$, and the subscript α indicates the dependence of $\mathbf{M}$ on α. Since the training and test data sets are independent, their joint likelihood function is obtained from the product of (6) and (7). Thus, setting $K = K_t + K_T$, we have under the null hypothesis

$$f_0(\mathbf{X},\mathbf{Z}|\mathbf{C}) = \left(\frac{1}{\pi^M|\mathbf{C}|}\right)^{K} \operatorname{etr}\left\{-(K-1)\mathbf{C}^{-1}\boldsymbol{\Sigma}_0\right\}. \quad (8)$$

where $\mathbf{\Sigma}_0 = \frac{1}{K-1}\left[(K_T-1)\mathbf{M}_0 + K_t\mathbf{R}\right]$. Similarly, under the alternative hypothesis, the joint likelihood is

$$f_1(\mathbf{X},\mathbf{Z}|\mathbf{C},\alpha) = \left(\frac{1}{\pi^M|\mathbf{C}|}\right)^K \mathrm{etr}\left\{-(K-1)\mathbf{C}^{-1}\mathbf{\Sigma}_\alpha\right\}. \quad (9)$$

Following the procedure of [14], we maximise each of the likelihoods with respect to their parameters and take the ratio of the maxima. Clearly, the maximum of f_0 with respect to $\mathbf{C}$ is obtained when $\mathbf{C} = \mathbf{\Sigma}_0$. Similarly, the maximum of f_1 over the values of $\mathbf{C}$ is obtained when $\mathbf{C} = \mathbf{\Sigma}_\alpha$. It remains for us to maximise the expression of f_1 over α. That is we require

$$\max_\alpha \max_{\mathbf{C}} f_1 = \max_\alpha \left(\frac{1}{(e\pi)^M|\mathbf{\Sigma}_\alpha|}\right)^K. \quad (10)$$

This is equivalent to minimising the determinant expression in the denominator with respect to α. Expanding the expression of $\mathbf{M}_\alpha$ and carrying out the minimisation in a similar manner to the procedure of [14], we arrive at the result

$$\hat{\alpha} = \frac{1}{|\mathbf{t}|}\frac{\mathbf{s}^H\mathbf{\Sigma}^{-1}\mathbf{g}}{\mathbf{s}^H\mathbf{\Sigma}^{-1}\mathbf{s}}, \quad (11)$$

where $\mathbf{\Sigma} = \frac{1}{K-1}\left[K_t\mathbf{R} + (K_T-1)\mathbf{Q}\right]$, $\mathbf{Q} = \frac{1}{K_T-1}\left(\mathbf{X}\mathbf{X}^H - \mathbf{g}\mathbf{g}^H\right)$ and $\mathbf{g} = \frac{1}{|\mathbf{t}|}\mathbf{X}\mathbf{t}^H$. Substituting the various expressions into the likelihood functions and taking the K^{th} root of their ratio, we obtain the desired likelihood ratio test. Thus, we arrive at the following two hybrid statistical tests

$$Y_{H1} = \frac{|\mathbf{s}^H\mathbf{\Sigma}^{-1}\mathbf{g}|^2}{\mathbf{s}^H\mathbf{\Sigma}^{-1}\mathbf{s}\left(1+\frac{1}{K-1}\mathbf{g}^H\mathbf{\Sigma}^{-1}\mathbf{g}\right)} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma, \quad (12)$$

and

$$Y_{H2} = \frac{|\mathbf{s}^H\mathbf{\Sigma}^{-1}\mathbf{g}|^2}{\mathbf{s}^H\mathbf{\Sigma}^{-1}\mathbf{s}} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma. \quad (13)$$

As expected in the homogeneous case, the hybrid detectors have similar expressions to the SDS and TDS detectors but with the covariance matrix estimate $\mathbf{\Sigma}$ obtained from both the training and test data.

2.2 Statistical Analysis

We now proceed to give the expressions for the probabilities of false alarm and detection for the hybrid algorithm. Based on the problem formulation and with reference to [4] and [14], it is straightforward to establish the CFAR property of the Hybrid detectors. Furthermore, we expect that the expressions the P_{fa} and P_d are analogous to those of the TDS and SDS algorithms.

To start we define a new $M \times K$ data matrix $\mathbf{D}$ by concatenating the test and training data, $\mathbf{D} = [\mathbf{X}|\mathbf{Z}]$. Then, the mean vector $\mathbf{g}$ and the covariance matrix estimate can be re-written as

$$\mathbf{g} = \frac{1}{|\mathbf{w}|}\mathbf{D}\mathbf{w}^*, \quad \text{and} \quad \mathbf{\Sigma} = \mathbf{D}\mathbf{W}\mathbf{D}^H, \quad (14)$$

where $\mathbf{w} = \left[\mathbf{0}_{K_t,1}^T \ \mathbf{t}^T\right]^T$ is a length K vector and the matrix $\mathbf{W} = \mathbf{I}_K - \mathbf{w}^*\mathbf{w}^T$. Now observe that $\mathbf{W}$ is idempotent of rank $K-1$ and $\mathbf{W}\mathbf{w}^* = \mathbf{0}$. This implies that $\mathbf{g}$ and $\mathbf{\Sigma}$ are mutually independent and distributed as $g \sim \mathcal{CN}_M(\alpha\mathbf{s},\mathbf{C})$ and $(K-1)\mathbf{\Sigma} \sim \mathcal{CW}_M(\mathbf{C},K-1)$. At this point we see that the problem has a similar formulation to that of the GMLED and MLED in [14]. The resulting expressions of the P_{fa} and P_d are

$$P_{fa}(\gamma) = \int_0^1 (1+\tau)^{-L} f_\beta(\eta; L+1, M-1)d\eta. \quad (15)$$

where $L = K - M$, $f_\beta(\eta; L+1, M-1)$ is the type I beta distribution, and

$$P_d = \int_0^1 h(\eta) f_\beta(\eta; L+1, M-1)d\eta. \quad (16)$$

The function $h(\eta)$ is defined as

$$h(\eta) = 1-(1+\tau)^{-L}\sum_{l=1}^{L}\binom{L}{l}\tau^l e^{-\frac{\eta\rho}{1+\tau}}\sum_{n=0}^{l}\frac{1}{n!}\left(\frac{\eta\rho}{1+\tau}\right)^n. \quad (17)$$

The parameter ρ is the signal to noise ratio, $\rho = |\alpha|^2$. The threshold τ is algorithm dependent and is given by $\tau = \gamma/(K-1-\gamma)$ for Y_{H1}, and $\tau = \eta\gamma/(K-1)$ for Y_{H2}.

2.3 Heterogeneous Case

We now consider the heterogeneous case and modify the hybrid expression of $\mathbf{\Sigma}$, derived above, to take the heterogeneity into account. The algorithm presented here will be referred to as the variable-scale hybrid (VSH). That of the homogeneous case will then be denoted as fixed-scale hybrid (FSH).

As the clutter becomes range-heterogeneous, the training data set $\mathbf{Z}$ becomes less statistically representative of the interference in the test data. This results in a degradation in the performance of the TDS detectors as well as the FSH algorithms. The heterogeneity clearly leaves the SDS algorithms unaffected. As the degree of heterogeneity increases, we desire to rely less on the data set $\mathbf{Z}$ in the covariance matrix estimate. When the performance of the FSH algorithms becomes inferior to that of the SDS detectors, the former should be made identical to the latter by eliminating the contribution of $\mathbf{Z}$ in $\mathbf{\Sigma}$. Thus, we propose the following procedure for estimating the covariance matrix

$$\mathbf{\Sigma} = \frac{1}{K_T + bK_t - 1}\left[(K_T-1)\mathbf{Q} + bK_t\mathbf{R}\right], \quad (18)$$

where b is a suitably chosen constant such that $0 \le b \le 1$, with $b = 1$ corresponding to the homogeneous case. The other limit, $b = 0$ is obtained when the hybrid algorithms deteriorate beyond the SDS detectors.

The formulation just presented can be generalised further by treating each training data snapshot separately and weighing its contribution by its own degree of heterogeneity with respect to the test data. The resulting expression becomes

$$\mathbf{\Sigma} = \frac{1}{K_T - 1 + \mathrm{tr}(\mathbf{B})}\left[(K_T-1)\mathbf{Q} + \mathbf{Z}\mathbf{B}\mathbf{Z}^H\right], \quad (19)$$

where $\mathbf{B}$ is a diagonal matrix with the diagonal elements corresponding to the weights assigned to each training data snapshot and satisfying $0 \le b_{kk} \le 1$,. In the homogeneous case, $\mathbf{B}$ would become identical to the identity matrix and the algorithms correspond to the FSH formulation.

A thorough investigation of the general form of (19) is beyond the scope of this paper, and consequently we restrict ourselves to the case where $b_{kk} \in \{0, 1\}$, where 0 corresponds to $\mathbf{z}_k$ being deemed heterogeneous with the test data.

For our choice of the b_{kk}, we resort to the GIP which has been studied in [9]. Given the covariance matrix estimate, $\mathbf{Q}$, the GIP for the training data snapshot $\mathbf{z}_k$ is

$$p_{kk} = \frac{1}{K_T - 1} \mathbf{z}_k^H \mathbf{Q}^{-1} \mathbf{z}_k. \tag{20}$$

The GIP statistics p_{kk} are mutually independent and are statistically independent of the true covariance matrix. They can be easily shown to have the standard distribution $p \sim \frac{M}{K_T - M} F_{M, K_T - M}$, [16] pp. 74. Now employing a two-sided hypothesis test and setting a (one-sided) type-I error, ϵ, we can then obtain a lower and upper thresholds ν_L and ν_U for rejecting the hypothesis that $\mathbf{z}_k$ and the test data have the same covariance matrix,

$$\epsilon = \Pr(p \leq \nu_L) = 1 - \text{betainc}\left(\frac{1}{\nu_L + 1}, M, K_T - M\right) \tag{21}$$

and

$$\epsilon = \Pr(p \geq \nu_U) = \text{betainc}\left(\frac{1}{\nu_U + 1}, M, K_T - M\right) \tag{22}$$

Finally, b_{kk} is set to 1 if $\nu_L \leq p_{kk} \leq \nu_U$ and to 0 otherwise.

3. SIMULATIONS

To illustrate the performance advantages of the proposed algorithms, they were simulated along with the TDS and SDS detectors in the one dimensional case. For the reader's convenience, we start by summarising The various statistics: All the tests considered here have either the form of equation (12) or that of (13) with the covariance matrix estimate and the training data set size changing between the difference detectors. Thus, for the GLRT, the test statistic is given by (12), but with $\mathbf{\Sigma}$ replaced by $\mathbf{R}$ and $K - 1$ replaced by K_t. Similarly the GMLED statistic is also given by (13) with $\mathbf{Q}$ used instead of $\mathbf{\Sigma}$ and $K_T - 1$ in place of $K - 1$. The AMF and MLED, on the other hand, use the form in (13) but with the variable replacements mirroring those of the GLRT and GMLED respectively.

The parameters used in the simulation were $M = 16$ and $K_T = K_t = 2M$. 10^5 Monte Carlo runs were averaged to obtain the P_d curves for a $P_{fa} = 10^{-3}$. For the interference heterogeneity, we adopted the model of [6] (which we denote as the Nitzberg model). Accordingly, the training data snapshots, $\mathbf{z}_k$, are drawn from the distribution $\mathcal{CN}_M(\mathbf{0}, q\mathbf{C})$, where q is gamma distributed such that the mean interference power is equal to that of the test data and the spread parameter $a = 0.5$. Fig. 2 shows the detection performance under complete homogeneity. Looking at the FSH detectors, we note that their simulated curves agree with the theoretical results. Furthermore, these detectors show the expected gain over the TDS and SDS algorithms. This gain results from the increased sample support obtained from the use of both data sets in the covariance matrix estimation. The FSH curves now correspond to the performance resulting from $4M - 1$ training data snapshots. The figure also shows the performance of the variable scale hybrid algorithms. For these detectors, we have set the test power, $\epsilon = 0.1$. This resulted in lower and upper thresholds $\nu_L = 0.632$ and $\nu_U = 1.582$. Thus, a training data snapshot was accepted only if its GIP fell between these two limits. We can see from the plot that the variable scale detectors show some deterioration with respect to their FSH counterparts. This is due to the occasional rejection of homoegeneous training data snapshots due to their statistical variation which consequently lowers the effective sample support size. However, the loss is small and the VSH detectors still outperform the other algorithms. The theoretical FSH curves were kept in the plot for comparison purposes.

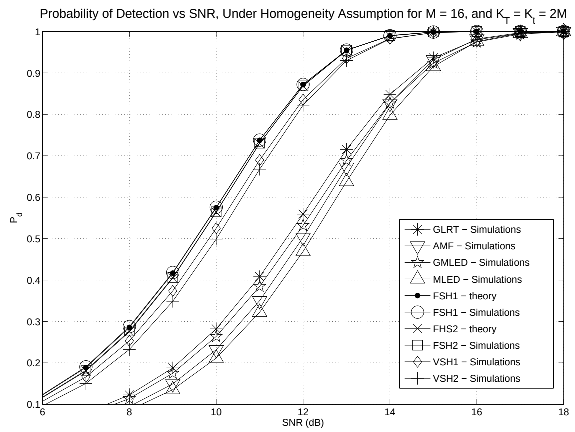

Figure 2: Probability of detection vs SNR for $P_{fa} = 10^{-3}$ with homogeneous training data.

The performance results under the Nitzberg heterogeneity model are shown in fig. 3. Firstly, notice that the performance of the SDS detectors remains exactly the same since they are unaffected by the heterogeneity. The TDS detectors, on the other hand, show severe degradation for the relatively benign heterogeneity model we are considering, in fact the AMF completely fails (which explains why its curve is missing from the plot). The fixed scale hybrid algorithms also deteriorate since they are always incorporating the full training data set in their covariance matrix estimation. The variable scale algorithms, on the other hand, exhibit the robustness that they gain from assessing the degree of heterogeneity of each training data snapshot and rejecting those that exceed the limit we set. The first VS-Hybrid algorithm (VSH1) still enjoys a gain over the SDS algorithms and actually outperforms all of the detectors considered here. The second VS-Hybrid detector matches the performance of the MLED detector, thus withstanding the heterogeneous data effect.

It is worthy of note here that the algorithms were assessed using a benign heterogeneity model. Radar clutter heterogeneity is more likely to exhibit, in addition to power fluctuations, actual covariance matrix structure variations, [7]. Whereas the power fluctuations can be accounted for by the Nitzberg model used above, other heterogeneity types require more complicated models and result in more severe losses. Under these conditions, the advantages of the proposed algorithms would be accentuated.

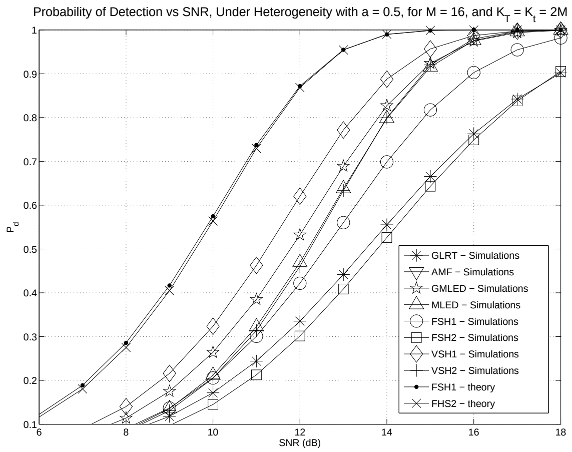

Figure 3: Probability of detection vs SNR for $P_{fa} = 10^{-3}$ with heterogeneous training data. The Nitzberg heterogeneity model was used with a spread parameter $a = 0.5$.

4. CONCLUSIONS

In this paper we have presented a novel hybrid signal detection approach that is robust to the heterogeneity problem that is found to afflict training data in practical radar target detection scenarios. The novel detectors proposed here combine the test and training data to increase the sample support for the covariance matrix estimation. This results in a performance gain under homogeneous interference conditions. The theoretical probabilities of false alarm and detection for the new detectors were also given. The heterogeneity of the training data results in a degradation in performance and must be taken into account. Therefore, a non-homogeneity detector was used to scale the contribution of the training data to the covariance matrix estimation according to the observed degree of heterogeneity. A variable-scale formulation of the hybrid detectors was given and simulated under both homogeneous and heterogeneous interference conditions. It was found to possess a superior performance to the TDS algorithms in both homogeneous and heterogeneous scenarios. Furthermore, it has better detection performance than the SDS algorithms under homogeneity and is comparable to or even can outperform them when applied to heterogeneous data.

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