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ADAPTIVE RADAR DETECTION WITHOUT SECONDARY DATA: EXPLOITING A DIVERSITY IDEA

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ABSTRACT

This paper addresses adaptive detection of possibly range-spread targets without resorting to secondary data, namely data free of signal components, but sharing the spectral properties of those under test. More precisely, detection of coherent target echoes embedded in Gaussian noise with unknown covariance matrix has been attacked by approximating the covariance matrix of the noise as a block diagonal one with identical diagonal blocks; moreover, each block is estimated from a set of subvectors obtained by filtering out possible signal components from data under test. The proposed detector guarantees the Constant False Alarm Rate (CFAR) property with respect to the noise power. In addition, its threshold setting seems not very sensitive to the actual structure of covariance matrix. Finally, a preliminary performance assessment, also conducted using real high range resolution radar data from an urban scene, has shown that it might be a viable means to deal with uncertain scenarios.

1. INTRODUCTION

Synthetic Aperture Radar (SAR) has opened new interesting research fields in both military and civil contexts. In particular, SAR imaging of urban areas has recently taken on increased significance. The nature of urban environments presents specific problems for a radar surveillance system, since it produces a wide range of different scattering mechanisms. Radar phenomena such as layover, shadowing, and multipath are commonplace and make analysis of urban scenes a challenging problem.

Target detection from SAR images has been considered by many authors. For instance, detection algorithms based on the Generalized Likelihood Ratio Test (GLRT) have been derived in [1]. Therein, the disturbance is assumed to be Gaussian distributed and outliers are eliminated through coherent subtraction between two complex SAR images of the same area of interest. In [2] a feature detector, exploiting the presence of the target shadow together with its bright pixels, is discussed and applied to real SAR data. In [3] the authors address Constant False Alarm Rate (CFAR) detection of targets embedded in Weibull background from spotlight SAR images. Moreover, radar detection during image formation has been proposed in [4], but therein the detection problem is encapsulated in SAR processing.

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Herein, we investigate the potential of implementing a detector fed by high range resolution data whereby the data is obtained from a SAR system prior to any azimuth compression.

Most algorithms proposed in the array processing literature assume that a set of secondary data is available, namely a set of range cells free of signal components, but sharing the covariance matrix of data under test.

An adaptive detector for possibly range-spread targets which does not resort to secondary data has been proposed in [5]. A CFAR detection algorithm has also been proposed in [6, and references therein]. It exploits a signature diversity idea in order to get rid of secondary data. Herein, we follow the lead of [6] and resort to the two-step GLRT design procedure to come up with an ad hoc detector for real beam systems. In order to make the detector fully adaptive, we propose an estimator of the covariance matrix which relies on the assumption that the matrix can be approximated by a block-diagonal one with identical diagonal blocks. Thus, estimation of the covariance matrix reduces to that of a block. The proposed detector is CFAR with respect to the unknown noise power. The performance assessment is conducted by Monte Carlo simulation using either simulated or real data collected by QinetiQ's X-band Enhanced Surveillance Radar (ESR) from an urban scene (where no azimuth compression has been performed).

The paper is organized as follows. Next section, Section 2, is devoted to the derivation of adaptive detector for possibly range-spread targets based upon range compressed SAR data while Section 3 contains the performance assessment and some concluding remarks.

2. PROBLEM FORMULATION AND DETECTOR DESIGN

Assume that the radar platform moves with a velocity v along a straight line and that the antenna transmits a pulse every $1/PRF$ s, where PRF is the Pulse Repetition Frequency of the radar. We want to detect the presence of possible targets within H consecutive range cells. Suppose that the cells under test are the ones labeled by $i = i_0, \ldots, i_0 + H - 1$ within the SAR swath shown in Figure 1 and that the possible target's scatterers have zero azimuth coordinates independent of the range cell they belong to. Finally, assume that the antenna transmits one of the pulses when its azimuth coordinate is equal to zero. As a consequence, the "n-th transmitted pulse" corresponds to an azimuth position of the radar

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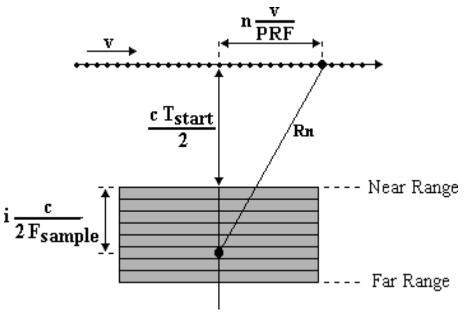

Figure 1: Geometry of the system.

antenna equal to nv/PRF. In order to decide if possible targets are present or not we can process the N pulses with $n = -N/2+1, \ldots, N/2$, where N is such that the antenna footprint covers the zero azimuth position for all values of n, or, otherwise stated, that N is less than or equal to the total number of pulses in one synthetic aperture.

Denote by $\boldsymbol{r}_i$ the N-dimensional vector whose entries are returns, corresponding to the N consecutive transmitted pulses, from the i-th range cell; such vector can be thought of as the signal received by an array of N antennas, spaced v/PRF apart. The possible useful signal received from the i-th range cell can be modeled as a coherent pulse train known up to a complex amplitude, namely as $\alpha_i \boldsymbol{s}_i$, where $\boldsymbol{s}_i$ is the N-dimensional steering vector and α_i an unknown complex factor, accounting for both the target and the channel effects. As to the expression of $\boldsymbol{s}_i$, its k-th entry, $k = 1, \ldots, N$, is given by

$$\exp\left(-j\frac{4\pi}{\lambda}R_{(-N/2+1)+(k-1),i}\right), \quad (1)$$

where j denotes the imaginary unit, λ is the wavelength of the transmitted electromagnetic wave, and

$$R_{(-N/2+1)+(k-1),i}$$

the distance between the possible target scatterer (with zero azimuth) within the i-th range cell and the n-th antenna position ($n = (-N/2+1)+(k-1)$). In particular, as $R_{n,i}$ does not significatively change as i varies over H consecutive values (in the order of a few dozens), we assume that

$$R_{n,i} \approx \sqrt{\left(n\frac{v}{PRF}\right)^2 + \left[\frac{c}{2}\left(T_{start} + \frac{i_0 + \frac{H-1}{2}}{F_{sample}}\right)\right]^2}, \quad (2)$$

where T_{start} is the interval between pulse transmission and the beginning of echo recording and F_{sample} is the sampling rate of the output of the filter matched to the transmitted waveform[1]. Otherwise stated, we will assume $\boldsymbol{s}_i = \boldsymbol{s}$, $i = i_0, \ldots, i_0+H-1$.

[1]Alternatively, $R_{n,i}$ is also given by

$$R_{n,i} = \sqrt{(nS_a)^2 + \left(D_{start} + \left(i_0 + \frac{H-1}{2}\right)S_r\right)^2},$$

where S_a and S_r denote the azimuth pixel spacing and the range pixel spacing of the SAR compressed data image under test, respectively, and D_{start} is the distance between the radar platform at zero azimuth position and the near range.

Detection of possibly extended targets within the H range cells under test can be recast in terms of the following binary hypotheses test:

$$\begin{cases} H_0: & \boldsymbol{r}_i = \boldsymbol{n}_i, & i = i_0, \ldots, i_0+H-1, \\ H_1: & \boldsymbol{r}_i = \alpha_i \boldsymbol{s} + \boldsymbol{n}_i, & i = i_0, \ldots, i_0+H-1. \end{cases} \quad (3)$$

As to $\boldsymbol{n}_i \in \mathbb{C}^{N\times 1}$, it denotes the vector whose entries are noise returns from the i-th cell under test. We suppose that the $\boldsymbol{n}_i$'s, $i = i_0, \ldots, i_0+H-1$, are independent and identically-distributed complex normal random vectors, i.e., $\boldsymbol{n}_i \sim \mathcal{CN}_N(\boldsymbol{0}, \boldsymbol{M})$. In particular, independence is justified by the fact that clutter contribution to different vectors is due to reflections from different ground positions. In order to solve the hypothesis test (3) we resort to the so-called two-step GLRT-based design procedure. First, we derive the GLRT assuming that the covariance matrix $\boldsymbol{M}$ is known; then, we come up with a fully-adaptive detector by replacing the unknown matrix with a suitable estimate.

Step 1. Subsequent developments require specifying the complex multivariate probability density function (pdf) of the $\boldsymbol{r}_i$'s under both hypotheses. Denote by $\boldsymbol{R} = [\boldsymbol{r}_1 \cdots \boldsymbol{r}_H]$ the data matrix and by $\boldsymbol{\alpha} = [\alpha_1 \cdots \alpha_H]^T$ the vector of the possible target (or targets) amplitudes with ^{T} denoting, in turn, transpose. Previous assumptions imply that the pdf of $\boldsymbol{R}$ may be written as

$$f_0(\boldsymbol{R};\boldsymbol{M}) = \frac{1}{[\pi^N \det(\boldsymbol{M})]^H} e^{-\mathrm{tr}\left(\boldsymbol{M}^{-1}\boldsymbol{T}_0\right)},$$

under H_0, and

$$f_1(\boldsymbol{R};\boldsymbol{M},\boldsymbol{\alpha}) = \frac{1}{[\pi^N \det(\boldsymbol{M})]^H} e^{-\mathrm{tr}\left(\boldsymbol{M}^{-1}\boldsymbol{T}_1\right)},$$

under H_1, with, in turn, $\boldsymbol{T}_0$ and $\boldsymbol{T}_1$ given by

$$\boldsymbol{T}_0 = \sum_{i=i_0}^{i_0+H-1} \boldsymbol{r}_i \boldsymbol{r}_i^\dagger$$

and

$$\boldsymbol{T}_1 = \sum_{i=i_0}^{i_0+H-1} (\boldsymbol{r}_i - \alpha_i \boldsymbol{s})(\boldsymbol{r}_i - \alpha_i \boldsymbol{s})^\dagger,$$

respectively, where $\det(\cdot)$ denotes the determinant and $\mathrm{tr}(\cdot)$ the trace of a square matrix; as to the superscript $\dagger$, it indicates conjugate transpose.

The GLRT for known $\boldsymbol{M}$ is given by

$$\frac{\max_{\boldsymbol{\alpha}} f_1(\boldsymbol{R};\boldsymbol{M},\boldsymbol{\alpha})}{f_0(\boldsymbol{R};\boldsymbol{M})} = \frac{\max_{\boldsymbol{\alpha}} \exp\left[-\mathrm{tr}\left(\boldsymbol{M}^{-1}\boldsymbol{T}_1\right)\right]}{\exp\left[-\mathrm{tr}\left(\boldsymbol{M}^{-1}\boldsymbol{T}_0\right)\right]} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma,$$

where γ is the threshold value to be set in order to ensure the desired Probability of False Alarm (P_{fa}).

Moreover, performing the required maximization yields

$$\sum_{i=i_0}^{i_0+H-1} \frac{\left|\boldsymbol{s}^\dagger \boldsymbol{M}^{-1}\boldsymbol{r}_i\right|^2}{\boldsymbol{s}^\dagger \boldsymbol{M}^{-1}\boldsymbol{s}} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma, \quad (4)$$

with $|\cdot|$ denoting the modulus of a complex number.

Step 2. We can make detector (4) fully adaptive, namely capable of operating when $\boldsymbol{M}$ is an unknown covariance matrix, by replacing it with a suitable estimate, $\widehat{\boldsymbol{M}}$ say. Assume that K and $L = N/K$ are integers and suppose that $\boldsymbol{M}$ can be approximated by a block-diagonal matrix with L identical diagonal blocks, $\boldsymbol{B} \in \mathbb{C}^{K\times K}$, i.e.,

$$\boldsymbol{M} = \begin{pmatrix} \boldsymbol{B} & \boldsymbol{0} & \dots & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{B} & \boldsymbol{0} & \dots \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{0} & \dots & \dots & \boldsymbol{B} \end{pmatrix}.$$

Now estimating the noise covariance matrix amounts to estimating $\boldsymbol{B}$. To this end, we can get rid of useful target echoes by projecting the subvector

$$\boldsymbol{z}_{i,l} = \boldsymbol{r}_i\Big((-N/2+1)+(l-1)K : (-N/2+1)+lK-1\Big)$$

onto the orthogonal complement of the subsignature

$$\boldsymbol{p}_l = \boldsymbol{s}\Big((-N/2+1)+(l-1)K : (-N/2+1)+lK-1\Big),$$

$i = i_0, \dots, i_0+H-1$, $l = 1, \dots, L$, namely constructing the "training vectors"

$$\boldsymbol{v}_{i,l} = \left(\boldsymbol{I}_K - \frac{\boldsymbol{p}_l\boldsymbol{p}_l^\dagger}{\|\boldsymbol{p}_l\|^2}\right)\boldsymbol{z}_{i,l}, \qquad \begin{array}{l} i = i_0, \dots, i_0+H-1, \\ l = 1, \dots, L, \end{array}$$

where $\boldsymbol{I}_K$ is the $(K\times K)$-dimensional identity matrix. Then, we estimate $\boldsymbol{B}$ (with $NH \geq 2K^2$) as

$$\widehat{\boldsymbol{B}} = \frac{1}{L}\sum_{l=1}^{L}\frac{1}{H}\sum_{i=i_0}^{i_0+H-1}\boldsymbol{v}_{i,l}\boldsymbol{v}_{i,l}^\dagger$$

and, hence,

$$\widehat{\boldsymbol{M}} = \begin{pmatrix} \widehat{\boldsymbol{B}} & \boldsymbol{0} & \dots & \boldsymbol{0} \\ \boldsymbol{0} & \widehat{\boldsymbol{B}} & \boldsymbol{0} & \dots \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{0} & \dots & \dots & \widehat{\boldsymbol{B}} \end{pmatrix}. \tag{5}$$

If $\boldsymbol{M}$ is Toeplitz it is also possible to increase the sample size by resorting to overlapped subvectors at the price of an increased complexity (since each of them has to be projected onto the orthogonal complement of the corresponding subsignature). Note though that the effectiveness of this approach is partially limited by the correlation between subvectors.

The fully adaptive test is thus given by

$$\sum_{i=i_0}^{i_0+H-1}\frac{\left|\boldsymbol{s}^\dagger\widehat{\boldsymbol{M}}^{-1}\boldsymbol{r}_i\right|^2}{\boldsymbol{s}^\dagger\widehat{\boldsymbol{M}}^{-1}\boldsymbol{s}} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma. \tag{6}$$

A few remarks are now in order. First observe that, due to the projection operations, the proposed estimator of the covariance matrix is a biased one. More generally, it is important to assess its properties for finite sample sizes and, eventually, the performance of the corresponding adaptive detector. This is the object of the next section. Finally, observe that (6) ensures the CFAR property with respect to the noise power although it does not guarantee the generalized CFAR property (with respect to $\boldsymbol{M}$).

i_0	$\widehat{\boldsymbol{M}}$		B-$\boldsymbol{S}$	
	$\rho = 0.995$	$\rho = 0.9$	$\rho = 0.995$	$\rho = 0.9$
1	0.8340	0.1876	0.8246	0.1526
2481	0.8409	0.2141	0.8250	0.1522

Table 1: Values of V for $\widehat{\boldsymbol{M}}$ and B-$\boldsymbol{S}$: $N = 512$, $K = 32$, $H = 16$, ρ as parameter.

3. PERFORMANCE ASSESSMENT

This section is devoted to the performance assessment of the estimator (5) and of the corresponding adaptive decision scheme (6).

The behavior of the estimator has been studied evaluating a normalized mean square error defined as

$$V = \frac{E\Big[\,\big\|\boldsymbol{M} - \widehat{\boldsymbol{M}}\big\|^2\Big]}{\|\boldsymbol{M}\|^2}$$

where E denotes statistical expectation while $\|\cdot\|$ is the Frobenius norm. V has been calculated by Monte Carlo simulation over 10^3 independent trials. Note that V is independent of the actual noise power. For simulation purposes, a clutter-dominated scenario has been considered: the $\boldsymbol{n}_i$'s have been generated as zero-mean, complex normal random vectors with an exponentially-shaped covariance matrix, namely with (i,j)-th entry given by $\sigma^2\rho^{|i-j|}$, where σ^2 is the variance of the complex noise samples and ρ is the one-lag correlation coefficient.

Results are reported in Table 1 for $N = 512$, $K = 32$, $H = 16$, ρ as parameter. For comparison purposes the table also contains the values of V obtained by resorting to sample covariance. More precisely, the proposed estimator is compared to the block-diagonal matrix obtained "replicating" the sample covariance of the $K\times K$ principal submatrix of $\boldsymbol{M}$ that lies in the first K rows and K columns (based upon LH data generated under the H_0 hypothesis). Such an estimator will be referred to as B-$\boldsymbol{S}$. The comparisons show that the values of V obtained by resorting to $\widehat{\boldsymbol{M}}$ are always greater than those achievable resorting to B-$\boldsymbol{S}$; however, for the considered parameters, corresponding values of V are not significantly different. Note also that the floor on the values of V is equal to 0.8207 and 0.1391 for exponentially correlated noise with $\rho = 0.995$ and $\rho = 0.9$, respectively.

For our purposes it is also important to assess the performance of the adaptive detector. To this end, we have estimated the threshold necessary to ensure a preassigned P_{fa} and the Probability of detection (P_d) by resorting to Monte Carlo simulations based on $100/P_{fa}$ and 10^3 independent trials, respectively. In Figure 2 we plot P_d of proposed detector vs the (input) Signal-to-Noise-Ratio (SNR), defined as

$$SNR = \frac{\sum_{i=1}^{H}|\alpha_i|^2\|\boldsymbol{s}\|^2/(HN)}{\sigma^2}. \tag{7}$$

Signals backscattered from target's scatterers have been generated as non-fluctuating pulse trains; in particular, the

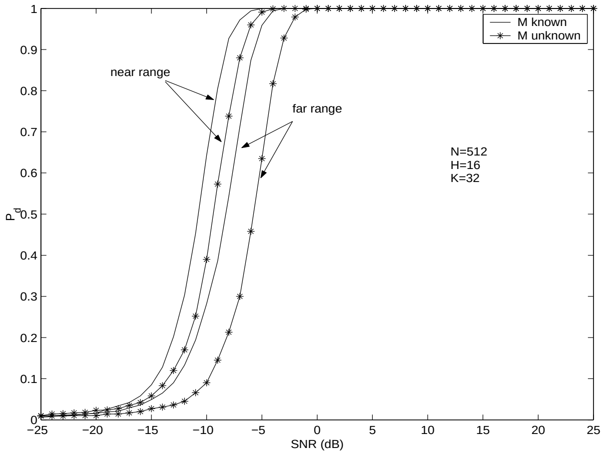

Figure 2: P_d versus SNR for the adaptive detector and the GLRT for known covariance matrix with $N = 512, H = 16, K = 32$, $P_{fa} = 10^{-2}$.

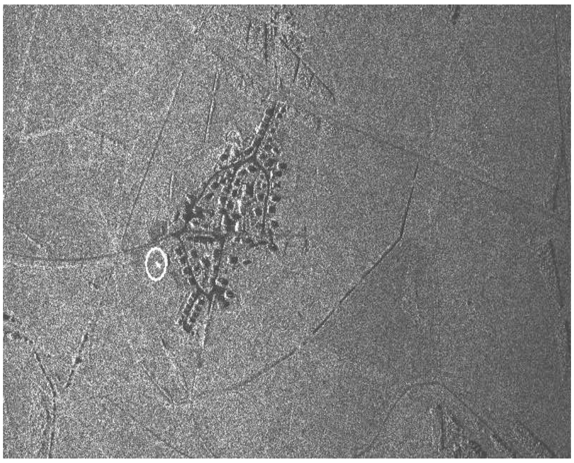

Figure 3: SAR image of the urban area under test.

α_i's have deterministic amplitudes and independent phases, uniformly-distributed in $(0, 2\pi)$. In addition, all of the H cells contain a scatterer and the scatterers possess the same radar cross section. The signatures have been constructed through equation (1), resorting to the QinetiQ's X-band ESR parameters. For comparison purposes, performance of a GLRT, which assumes knowledge of the clutter covariance matrix $\boldsymbol{M}$, has been plotted too. The figure highlights that the adaptive receiver experiences acceptable, although not negligible, losses with respect to its non-adaptive counterpart.

We have also assessed the performance of the proposed strategy fed by range-compressed SAR data from an urban scene. Data have been collected using QinetiQ's X-band ESR and are displayed in Figure 3. Note that Figure 3 shows the SAR image whilst the detector operates on the data prior to the SAR azimuth compression. The region under test is centered on a target spread over about 20 pixels in range and 20 pixels in azimuth and highlighted by a circle in Figure 3. We have chosen this target since it is apart from interfering targets in range and in azimuth. The rest of the imagery contains several other buildings; in particular, there are other buildings with the same azimuth. Range migration has not been corrected due to the relatively short range of the processed data. We have set the threshold γ in order to ensure $P_{fa} = 10^{-2}$ based upon an exponentially-shaped covariance matrix with $\rho = 0.995$ and the signatures corresponding to the far range. Figure 4 shows results obtained running the proposed adaptive detector on the region under test with $N = 512$, $H = 16$, and K as a parameter. The test is repeated over non-overlapping range data. Note that our reference target is detected (detection No.1) and that other detections could come from buildings located near the white line in Figure 4; the number of false alarms is limited. As a final comment note that, although the proposed detector does not possess the generalized CFAR property (i.e., with respect to $\boldsymbol{M}$), it seems not very sensitive to a mismatch between actual and nominal values of $\boldsymbol{M}$. A definite validation of the results is part of current research activity.

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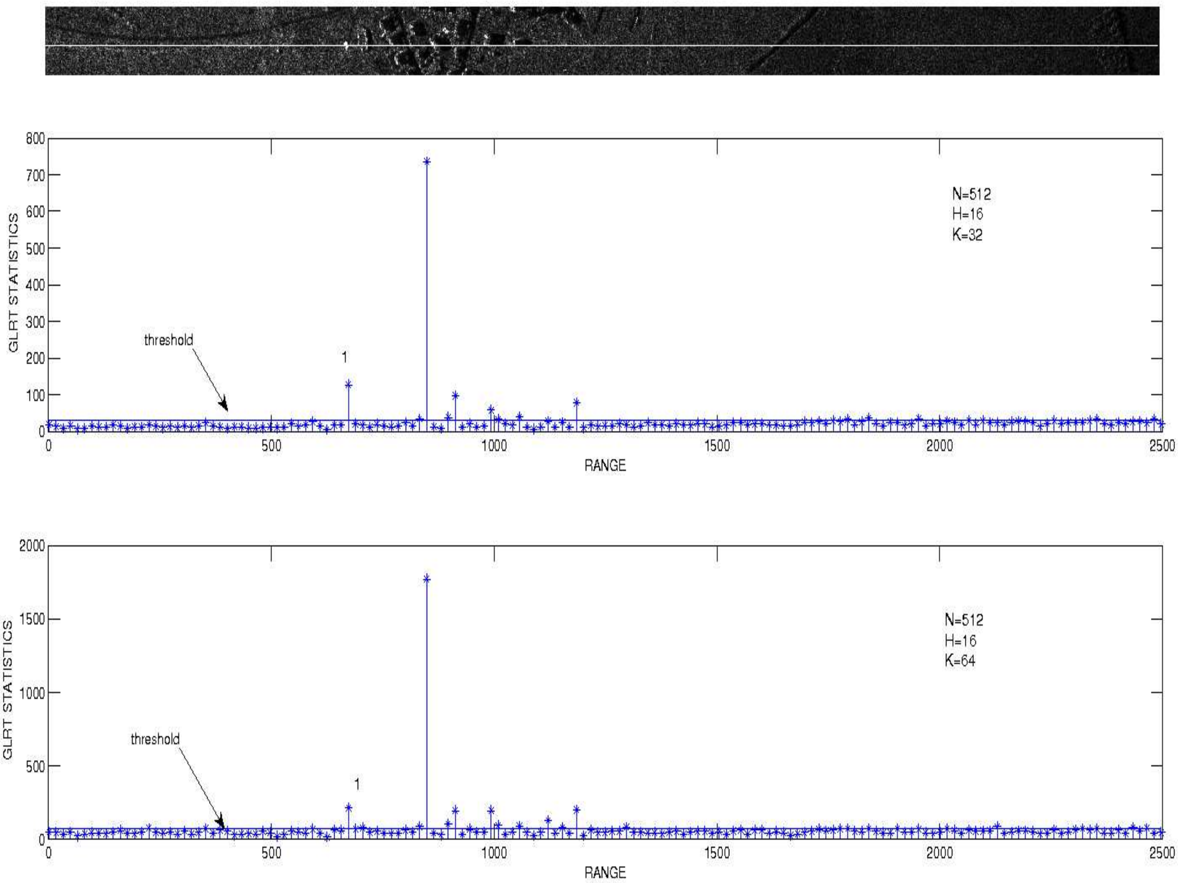

Figure 4: Results obtained resorting to the proposed adaptive detector to scan the urban area under test.