Journal of Systems Engineering and Electronics
Vol. 34, No. 4, August 2023, pp.873 – 878

A tunable adaptive detector for distributed targets when signal mismatch occurs

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Abstract: Aiming at the problem of detecting a distributed target when signal mismatch occurs, this paper proposes a tunable detector parameterized by an adjustable parameter. By adjusting the parameter, the tunable detector can achieve robust or selective detection of mismatched signals. Moreover, the proposed tunable detector, with a proper tunable parameter, can provide higher detection probability compared with existing detectors in the case of no signal mismatch. In addition, the proposed tunable detector possesses the constant false alarm rate property with the unknown noise covariance matrix.

Keywords: multichannel signal detection, target detection, distributed target, signal mismatch.

DOI: 10.23919/JSEE.2023.000029

1. Introduction

Early radar signal detection theories are based on single-channel data. However, with the appearance of phased array radar, the form of the data received by radar changed from single-channel to multi-channel. The multi-channel model can provide correlation characteristics of signals between different channels, which improves the performance of signal processing. In the case of unknown noise, the multichannel adaptive detectors usually have the characteristics of constant false alarm rate (CFAR) and achieve better detection performance than the filtering-then-CFAR approaches. Recently, the problem of multi-channel adaptive detection has attracted widespread attention [1−6].

There are three commonly used detector design criteria, namely, the generalized likelihood ratio test (GLRT), Rao test, and Wald test. The theory of multichannel adaptive signal detection was first investigated by Professor Kelly of Lincoln Laboratory in 1986 [7]. Based on the GLRT criterion, Kelly proposed the famous Kelly's GLRT (KGLRT) detector [7]. On this basis, adaptive matched filter (AMF) [8], De Maio's Rao detector (DMRao) [9] and the adaptive coherence estimator (ACE) [10] were proposed.

The above-mentioned detectors are all aimed at the rank-one signal, namely, the signal having one known steering vector. However, the signal may be a subspace signal, which is an extension of rank-one signals. The subspace signal refers to a signal that is in a subspace and whose coordinates are unknown. In practice, the model of subspace signal is often utilized for polarization target detection [11−13]. The subspace generalized forms of the KGLRT, AMF, DMRao, and ACE were given in [14−17].

With the development of radar technology, the resolution of radar continues to improve. A single target may occupy multiple range resolution units. Moreover, even when the resolution of the radar is low, a target may occupy multiple range units, for example, a large ship. As a result, the model of the target changes from point target model to distributed target model. It is assumed that the echoes of the distributed target all come from the same direction in [18], where the GLRT is proposed both for homogeneous environment (HE) and partially HE (PHE). In order to estimate the unknown covariance matrix, it is assumed that there are enough training samples. The training samples only contain noise components that obey the complex Gaussian distribution and have the same covariance matrix as the noise in the unit to be detected. The Rao test and the Wald test in the HE were derived in

Manuscript received July 20, 2021.
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This work was supported by the National Natural Science Foundation of China (62071482).

[19], while the corresponding Rao test and the Wald test in PHE were obtained in [20].

Most of the references mentioned above, assume that the steering vector of the actual signal is the same as the assumed one. In other words, the signal mismatch, namely, the actual signal steering vector is not aligned with the nominal one adopted by the radar system, is not considered in these references. However, there is inevitably the influence of element error, mutual coupling, and sidelobe interference, which leads to signal mismatch. According to different detection characteristics for mismatched signals, the detectors can be classified into two basic categories, i.e., robust detectors and selective detectors. When signal mismatch occurs, the robust detector can still detect the target with a higher probability. Selective detectors are opposite to robust detectors. When the signals are mismatched, the probability of detection (PD) of the selective detector decreases rapidly as the amount of mismatch increases. Usually, when the radar is working in the long-range surveillance mode, it needs robust detectors. In contrast, when the radar is working in the tracking mode, it needs selective detectors.

For the problem of detecting point targets in the presence of signal mismatch, several selective detectors were proposed in [21,22] by adding virtual deterministic interference under the null hypothesis. In [23,24], cascaded detectors were proposed, which is formed by cascading two detectors with different detection performance for mismatched signals. The cascaded detectors can achieve flexible detection of mismatched signals by adjusting the threshold pair [25]. In [26,27], several tunable detectors were proposed. Their detection performance for mismatched signals is parameterized by a positive scaling factor, called tunable parameter. The tunable detector can achieve robustness or selectivity for mismatched signals by adjusting the tunable parameter.

The above-mentioned selective detectors, cascaded detectors, and tunable detectors are mainly designed for point targets. However, there are only a few studies on distributed target detection when signal mismatch occurs. Two selective detectors suitable for distributed targets were proposed in [28] by adding virtual deterministic interference under the null hypothesis. Although the selective detector can suppress the mismatched signal very well, it does not have robust characteristics. In [29], a tunable detector was proposed for distributed target detection in the PHE. This tunable detector can achieve robust or selective properties by choosing an appropriate tunable parameter. However, it may suffer from certain performance loss in HE. Given this, this paper proposes a tunable detector suitable for distributed target in HE when signal mismatch occurs. It is shown by Monte Carlo simulations that by choosing an appropriate tunable parameter, the proposed detector can provide improved robustness or selectivity for mismatched signals than existing detectors. Moreover, it can also achieve better or comparable detection performance than existing ones in the absence of signal mismatch.

2. Problem formulation

Suppose that a phased-array radar has N_a antenna elements, and every element transmits N_b pulses. If a distributed target exists, it occupies K range bins, the received data can be denoted by an $N\times K$ matrix $\boldsymbol{X}$, with $N=N_a\times N_b$. The echo signal of the kth range bin can be expressed as a vector with dimension $N\times 1$, i.e., $\boldsymbol{x}_k$ $(k=1,2,\cdots,K)$. Under the null hypothesis, $\boldsymbol{x}_k$ contains the noise $\boldsymbol{n}_k$, which is independent and identically distributed as the complex Gaussian distribution with a mean value of $\boldsymbol{0}$, and covariance matrix $\boldsymbol{R}$, denoted as $\boldsymbol{n}_k\sim \mathrm{CN}_N(\boldsymbol{0}_{N\times 1},\boldsymbol{R})$.

Under the alternative hypothesis H_1, $\boldsymbol{X}$ contains the noise $\boldsymbol{N}$ and the signal $\boldsymbol{s}$, having the form $\boldsymbol{s}=\boldsymbol{h}\boldsymbol{a}^{\mathrm{H}}$, where $\boldsymbol{h}$ is the signal steering vector, $\boldsymbol{a}$ is the signal amplitude, and $(\cdot)^{\mathrm{H}}$ denotes conjugate transpose. However, in the actual environment, the noise covariance matrix $\boldsymbol{R}$ is unknown. To estimate $\boldsymbol{R}$, suppose there are L independent and identically distributed training samples, denoted as $\boldsymbol{x}_{e,l}(l=1,2,\cdots,L)$, which only contain noise $\boldsymbol{n}_{e,l}$, written as $\boldsymbol{n}_{e,l}\sim \mathrm{CN}_N(\boldsymbol{0}_{N\times 1},\boldsymbol{R})$. Therefore, the binary hypothesis test of the problem to be tested can be expressed as

$$\begin{cases} \mathrm{H}_0: \boldsymbol{X}=\boldsymbol{N}, \boldsymbol{X}_L=\boldsymbol{N}_L \\ \mathrm{H}_1: \boldsymbol{X}=\boldsymbol{h}\boldsymbol{a}^{\mathrm{H}}+\boldsymbol{N}, \boldsymbol{X}_L=\boldsymbol{N}_L \end{cases} \tag{1}$$

where $\boldsymbol{X}=[\boldsymbol{x}_1,\boldsymbol{x}_2,\cdots,\boldsymbol{x}_K]$, $\boldsymbol{N}=[\boldsymbol{n}_1,\boldsymbol{n}_2,\cdots,\boldsymbol{n}_K]$, $\boldsymbol{a}=[a_1,a_2,\cdots,a_K]^{\mathrm{T}}$, $\boldsymbol{X}_L=[\boldsymbol{x}_{e,1},\boldsymbol{x}_{e,2},\cdots,\boldsymbol{x}_{e,L}]$, and $\boldsymbol{N}_L=[\boldsymbol{n}_{e,1},\boldsymbol{n}_{e,2},\cdots,\boldsymbol{n}_{e,L}]$.

To design a selective detector, a fictitious interference $\boldsymbol{J}$ is injected into the test data $\boldsymbol{X}$ under the null hypothesis H_0. Therefore, the original binary hypothesis test is modified as

$$\begin{cases} \mathrm{H}_0: \boldsymbol{X}=\boldsymbol{N}+\boldsymbol{J}\boldsymbol{Q}, \boldsymbol{X}_L=\boldsymbol{N}_L \\ \mathrm{H}_1: \boldsymbol{X}=\boldsymbol{h}\boldsymbol{a}^{\mathrm{H}}+\boldsymbol{N}, \boldsymbol{X}_L=\boldsymbol{N}_L \end{cases} \tag{2}$$

where $\boldsymbol{J}$ is an $N\times(N-1)$ dimensional column full-rank matrix, spanning the subspace of the virtual interference. The $(N-1)\times K$ dimensional matrix $\boldsymbol{Q}$ represents the coordinates of the interference. Both $\boldsymbol{J}$ and $\boldsymbol{Q}$ are unknown, and the virtual interference $\boldsymbol{J}$ satisfies the constraint

$$\boldsymbol{J}^{\mathrm{H}}\boldsymbol{S}^{-1}\boldsymbol{h}=\boldsymbol{0}_{(N-1)\times 1} \tag{3}$$

where $\boldsymbol{S}$ is the sample covariance matrix (SCM).

3. Detector design

The GLRT criterion [29] is given as

$$t_{\text{GLRT}} = \frac{\max\limits_{a,R} f_1(\boldsymbol{X}, \boldsymbol{X}_L)}{\max\limits_{Q,R} f_0(\boldsymbol{X}, \boldsymbol{X}_L)} \tag{4}$$

where $f_0(\cdot)$ and $f_1(\cdot)$ are the joint probability density functions (PDF) of $\boldsymbol{X}$ and $\boldsymbol{X}_L$ under H_0 and H_1, respectively.

Aiming at the detection problem in (2), the generalized adaptive beamformer orthogonal rejection test (ABORT) in HE (G-ABORT-HE) was proposed in [30] according to the GLRT criterion, whose expression is

$$t_{\text{G-ABORT-HE}} = \frac{1 + \text{tr}(\tilde{\boldsymbol{X}}^{\text{H}} \boldsymbol{P}_{\tilde{h}} \tilde{\boldsymbol{X}})}{\left|\boldsymbol{I}_K + \tilde{\boldsymbol{X}}^{\text{H}} \tilde{\boldsymbol{X}}\right| \left[1 - \dfrac{\tilde{\boldsymbol{h}}^{\text{H}} \tilde{\boldsymbol{X}} (\boldsymbol{I}_K + \tilde{\boldsymbol{X}}^{\text{H}} \tilde{\boldsymbol{X}})^{-1} \tilde{\boldsymbol{X}}^{\text{H}} \tilde{\boldsymbol{h}}}{\tilde{\boldsymbol{h}}^{\text{H}} \tilde{\boldsymbol{h}}}\right]} \tag{5}$$

where $\text{tr}(\cdot)$ denotes the trace of the matrix, $|\cdot|$ is a determinant of a matrix, $\tilde{\boldsymbol{h}} = \boldsymbol{S}^{-1/2}\boldsymbol{h}$, $\boldsymbol{P}_{\tilde{h}} = \tilde{\boldsymbol{h}}(\tilde{\boldsymbol{h}}^{\text{H}}\tilde{\boldsymbol{h}})^{-1}\tilde{\boldsymbol{h}}^{\text{H}}$, $\tilde{\boldsymbol{X}} = \boldsymbol{S}^{-1/2}\boldsymbol{X}$, $\boldsymbol{S} = \boldsymbol{X}_L\boldsymbol{X}_L^{\text{H}}$ is the SCM, and $\boldsymbol{I}_K$ is the identity matrix of dimension K.

The proposed detector has selective characteristics for mismatched signal but does not have robust characteristics. To manage the tradeoff between robustness and selectivity for mismatched signals, we introduce a tunable detector based on the G-ABORT-HE in (5):

$$t_{\text{T-ABORT-HE}} = \frac{1 + \text{tr}(\tilde{\boldsymbol{X}}^{\text{H}} \boldsymbol{P}_{\tilde{h}} \tilde{\boldsymbol{X}})}{\left|\boldsymbol{I}_K + \tilde{\boldsymbol{X}}^{\text{H}} \tilde{\boldsymbol{X}}\right|^{\gamma} \left[1 - \dfrac{\tilde{\boldsymbol{h}}^{\text{H}} \tilde{\boldsymbol{X}} (\boldsymbol{I}_K + \tilde{\boldsymbol{X}}^{\text{H}} \tilde{\boldsymbol{X}})^{-1} \tilde{\boldsymbol{X}}^{\text{H}} \tilde{\boldsymbol{h}}}{\tilde{\boldsymbol{h}}^{\text{H}} \tilde{\boldsymbol{h}}}\right]} \tag{6}$$

which is denoted as the tunable ABORT in HE (T-ABORT-HE). The non-negative number γ is called the tunable parameter. It is not difficult to infer that the T-ABORT-HE becomes more and more robust as the tunable parameter γ reduces, while the T-ABORT-HE becomes more and more selective as the tunable parameter γ increases. In particular, when $\gamma = 1$, the T-ABORT-HE degenerates into the G-ABORT-HE. In addition, the T-ABORT-HE has the CFAR property, since the statistical properties of the quantities $\tilde{\boldsymbol{X}}^{\text{H}}\tilde{\boldsymbol{X}}$ and $\tilde{\boldsymbol{X}}^{\text{H}}\boldsymbol{P}_{\tilde{h}}\tilde{\boldsymbol{X}}$ do not depend on the noise covariance matrix $\boldsymbol{R}$ under hypothesis H_0 [18].

4. Numerical examples

This section evaluates the detection performance of the T-ABORT-HE. Since the statistical characteristics of the detector are not obtainable, only Monte Carlo simulation is performed here. The detection probabilities are shown both in the presence and absence of signal mismatch. For Monte Carlo simulation, the detection threshold and PD are obtained through 100/PFA and 10^4 Monte Carlo experiments, respectively, where PFA stands for probability of false alarm. The (i, j) element of the $\boldsymbol{R}$ is $\varepsilon^{|i-j|}$ $(i, j = 1, 2, \cdots, N)$. In the simulation, let $N = 8$, $\varepsilon = 0.9$, $\text{PFA} = 10^{-3}$. In practice, PFA is often very low, such as 10^{-6}. The number of secondary data is $L = 2N$. Here, it is set as 10^{-3} to reduce the amount of calculation. When PFA is other values, the change trend of the detector remains unchanged. In the case of signal mismatch, the actual signal steering vector $\boldsymbol{h}_0$ has the form

$$\boldsymbol{h}_0 = \frac{1}{\sqrt{N}}\left[1, \text{e}^{-\text{j}2\pi\bar{f}}, \cdots, \text{e}^{-\text{j}2\pi(N-1)\bar{f}}\right]^{\text{T}} \tag{7}$$

where $\bar{f} \in [-0.5, 0.5]$ is the normalized spatial or temporal frequency of the signal. The amount of mismatch can be measured by

$$\cos^2\phi = \frac{\left|\boldsymbol{h}_0^{\text{H}}\boldsymbol{R}^{-1}\boldsymbol{h}\right|^2}{\boldsymbol{h}_0^{\text{H}}\boldsymbol{R}^{-1}\boldsymbol{h}_0\boldsymbol{h}^{\text{H}}\boldsymbol{R}^{-1}\boldsymbol{h}} \tag{8}$$

which is the cosine squared between the actual signal steering vector $\boldsymbol{h}_0$ and the nominal one $\boldsymbol{h}$ in the whitened space.

The signal to noise ratio (SNR) is defined as

$$\text{SNR} = \boldsymbol{a}^{\text{H}}\boldsymbol{a}\boldsymbol{h}_0^{\text{H}}\boldsymbol{R}^{-1}\boldsymbol{h}_0. \tag{9}$$

4.1 The case of signal mismatch

Fig. 1 and Fig. 2 compare the PD of the T-ABORT-HE under different degrees of signal mismatch with existing detectors, namely, the generalized adaptive matched filter (GAMF), the generalized adaptive subspace detector (GASD) [18], and G-ABORT-HE [29]. The GAMF and GASD are given by

$$t_{\text{GAMF}} = \frac{\tilde{\boldsymbol{h}}^{\text{H}}\tilde{\boldsymbol{X}}\tilde{\boldsymbol{X}}^{\text{H}}\tilde{\boldsymbol{h}}}{\tilde{\boldsymbol{h}}^{\text{H}}\tilde{\boldsymbol{h}}}, \tag{10}$$

$$t_{\text{GASD}} = \frac{\tilde{\boldsymbol{h}}^{\text{H}}\tilde{\boldsymbol{X}}\tilde{\boldsymbol{X}}^{\text{H}}\tilde{\boldsymbol{h}}}{(\tilde{\boldsymbol{h}}^{\text{H}}\tilde{\boldsymbol{h}})\text{tr}(\tilde{\boldsymbol{X}}\tilde{\boldsymbol{X}}^{\text{H}})}. \tag{11}$$

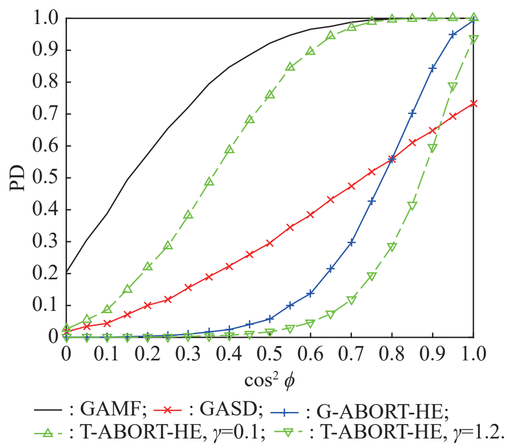

Fig. 1 PD versus $\cos^2\phi$ ($K = 3$, SNR =22 dB)

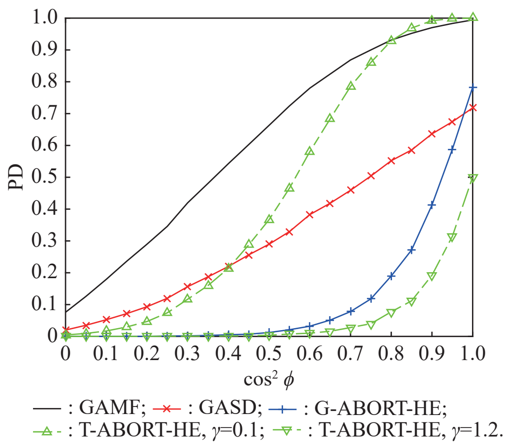

Fig. 2 PD versus $\cos^2\phi$ (K= 8, SNR =22 dB)

The results indicate that the T-ABORT-HE has desirable flexibility in controlling the detection performance for mismatched signals. In particular, the T-ABORT-HE with $\gamma = 1.2$ has the best selectivity characteristics. In contrast, the T-ABORT-HE with $\gamma = 0.1$ has better robustness than the G-ABORT-HE and GASD. Moreover, the GAMF exhibits too much robustness. Even when $\cos^2\phi = 0$, the GAMF can provide a PD greater than zero. This seems unacceptable.

Fig. 3 and Fig. 4 show the contours of the PD of the T-ABORT-HE under different SNRs and $\cos^2\phi$ with the tunable parameters $\gamma = 0.3$ and $\gamma = 1.5$, respectively. It can be seen that when the tunable parameter is small, the T-ABORT-HE has robust characteristics. Specifically, even when the amount of mismatch is large, the target can be detected by the T-ABORT-HE when the SNR is large enough. In contrast, when the adjustable parameter is large, it is impossible to detect a target by the T-ABORT-HE for a signal with a large amount of mismatch, even if the SNR is large enough. Therefore, the flexible detection of mismatched signals can be realized by changing the tunable parameter.

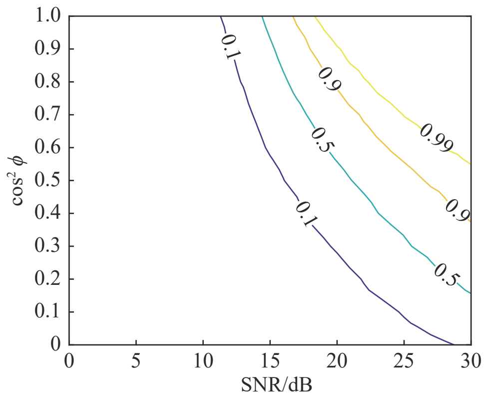

Fig. 3 Contours of the PD of the G-ABORT-HE versus SNR and $\cos^2\phi$ (K=3, γ=0.3)

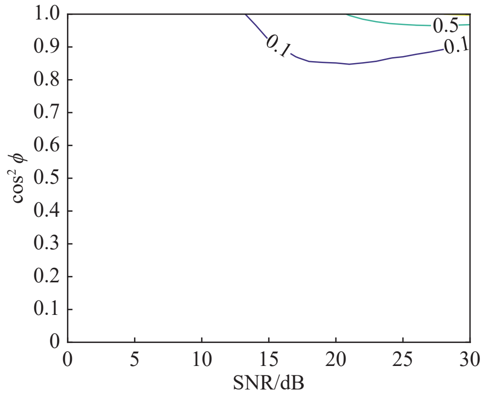

Fig. 4 Contours of the PD of the G-ABORT-HE versus SNR and $\cos^2\phi$ (K=3, γ=1.5)

4.2 The case of no signal mismatch

Fig. 5 and Fig. 6 show the detection performance of the detectors under different SNRs in the absence of signal mismatch. It can be seen that T-ABORT-HE can achieve the best detection performance with an appropriate tunable parameter when the SNR is large.

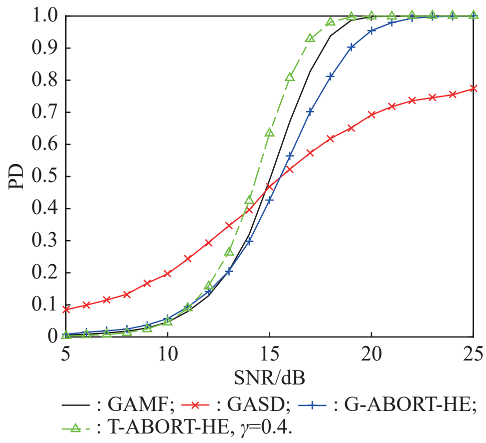

Fig. 5 PD versus SNR (K=3, $\cos^2\phi$=1)

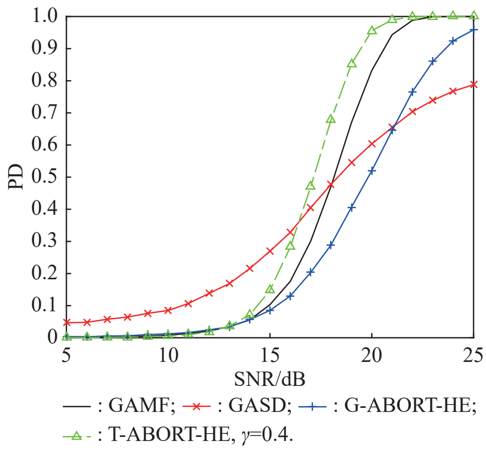

Fig. 6 PD versus SNR (K=8, $\cos^2\phi$=1)

Fig. 7 shows the detection performance of T-ABORT-HE under different tunable parameters without signal mismatch. It can be seen that as the adjustable parameter increases, the PD of the T-ABORT-HE decreases. Remarkably, the T-ABORT-HE can provide a higher PD than the G-ABORT-HE as long as $0 < \gamma < 1$.

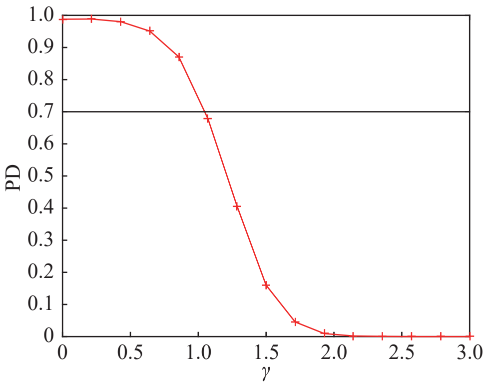

Fig. 7 PD versus γ (K=8, $\cos^2\phi$=1, and SNR =19 dB)

5. Conclusions

Aiming at the detection problem in the presence of distributed target signal mismatch, this paper proposes a TABORT-HE detector with an adjustable parameter, which can achieve robust or selective detection of mismatched distributed target signals by adjusting the tunable parameter according to different system requirements. Moreover, even when there is no signal mismatch, the T-ABORT-HE with a proper tunable parameter can provide a higher PD than the existing detectors.

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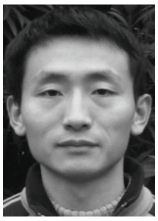

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