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Parametric detection in non-stationary correlated clutter using a sequential approach

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ABSTRACT

Sequential detection provides a powerful solution to minimize the required number of observations for a given performance. Due to the non-stationary nature of clutter, this problem is recurrent in radar applications. In this paper, we develop a sequential parametric adaptive detection algorithm based on the approximation of clutter as an autoregressive process. Stationary segments are considered where both space and time windows are minimized, respectively, by using one secondary cell on each side of the cell under test and by applying a sequential test. We derive the distributions of the considered test statistic and give a closed form expression for the upper threshold whereas, the lower one is given as a simply numerical solution of a proper equation, rather than use the commonly Monte Carlo method based ones. The proposed approach is compared to an existing method based on a fixed sample size. Results obtained using synthetic and real data show that the proposed scheme reduces substantially the required sample size with detection performance close to that of the fixed sample size method.

1. Introduction

Performance of detection in radar and other applications is clearly dependent on noise, in which the received signals are buried. In addition to the thermal noise inherent to any electronic system, the performance is also limited by the environment around the object to be detected. In fact, detection is disturbed by the unwanted echoes stemming from the target background. This is the case in radar, which scans the horizon of the ground or the sea. In such situations, the target background (mountains, rain, sea surface and ground) consists of receivers that provide interfering signals generally considered as random quantities, being added to the thermal noise, and form clutter. In practice, the most important characteristics that describe clutter and its effects on detection are its intensity, its distribution, the associated autocorrelation functions and its stationarity. Detection of signals in non-Gaussian correlated and non-stationary clutter is a problem of interest in radar applications. In fact, recent advances in radar resolution have led to a target-like spiky clutter and the detection of signals embedded in non-Gaussian correlated noise. This problem has been widely studied, not only in the field of radar, but also in the communications and sonar fields [1–3]. Therein, the compound Gaussian model is proposed to model correlated non-Gaussian clutter.

Sub-optimal approximations were derived for signals with unknown parameters [4–7] and led to expressions equivalent to the Normalized Matched Filter (NMF), derived for the Gaussian case. In practice, adaptive techniques are used to estimate the covariance matrix of the clutter (generally unknown and space and time varying), using secondary signal-free data taken from range cells, surrounding the Cell Under Test (CUT), which are assumed to share the same statistical properties. The Adaptive Normalized Matched Filter (ANMF) corresponds to a sub-optimal solution where the unknown covariance matrix of the compound Gaussian clutter is estimated. Two classes of methods are then to be distinguished, nonparametric methods and the parametric ones. In a non-parametric approach, no assumption is made on clutter. However, the number of secondary cells must be at least equal to the sample size. In parametric methods, where the clutter is assumed to belong to a certain model, this condition can be relaxed.

One of the parametric methods consists of modeling clutter, using an autoregressive (AR) process. Several works dealing with such modeling can be found in the literature [8–12], where time varying autoregressive (TVAR) models are used to deal with nonstationary clutter [13–15]. Another solution consists of dividing non-stationary clutter into assumed stationary segments, whose size is to be defined and minimized. Recall that in detection theory, if the decision to accept or reject a considered hypothesis is

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based on a fixed sample size (fixed number of observations), it is impossible to minimize both the error of the first kind (probability of false alarm) and the error of the second kind (probability of miss detection), and the required sample size [16]. This is the case of the Neyman–Pearson criterion, which is the most used in radar [17]. Consequently, in adaptive approaches such as the ANMF detector, where secondary data is used to estimate unknown parameters, the use of a test based on a fixed sample size leads to two major problems, namely the choice of this size in a real-time context and the non-stationarity of the secondary signal-free data. The latter is of a major importance, as it requires the minimization, in both space and time, of the size of the secondary data, which does not always coincide with the desired performance. These two issues can be resolved respectively by taking a minimum number of secondary cells and using a detection criterion based on a time varying sample size.

In this paper, a sequential detection approach is proposed to overcome the two above mentioned problems. This theory, which allows the analysis of an incoming data flow, was developed by Wald [16]. Based on AR modeling, a parametric construction of the unknown clutter covariance matrix is used in the ANMF structure. Secondary cells are assumed to contain clutter only and the detection concerns targets corresponding to a known signal with unknown amplitude in the presence of non-stationary clutter. The detection performance is assessed using simulated targets in both synthetic and real radar clutter.

The remainder of the paper is organized as follows: Section 2 is dedicated to the model setup, the parametric-ANMF (PANMF) definition and the problem formulation. In Section 3, the proposed approach is presented. Section 4 presents some results obtained using synthetic and real data sets. Finally, Section 5 concludes the study.

2. Model setup and detection background

2.1. Model setup

The binary detection problem consists of deciding between two possible statistical hypotheses $\mathcal{H}_0$ and $\mathcal{H}_1$ given a random observation. In the special case of radar detection, the random observation corresponds to the received signal after the transmission of N pulses. The two possible exclusive statistical situations are:

$\mathcal{H}_0$: the hypothesis of the absence of a target,

$\mathcal{H}_1$: the hypothesis of the presence of a target.

The commonly used rank-one model is given by [7]:

$$\begin{cases} \mathcal{H}_0 : \mathbf{x} = \mathbf{c} \\ \mathcal{H}_1 : \mathbf{x} = \delta \mathbf{d} + \mathbf{c} \end{cases} \tag{1}$$

where $\mathbf{x} = [x(0), x(1), \ldots, x(N-1)]^T$ is referred to as the received signal in the cell under test (CUT), $\mathbf{c} = [c(0), c(1), \ldots, c(N-1)]^T$ is clutter, δ is an unknown deterministic amplitude, and $\mathbf{d} = [d(0), d(1), \ldots, d(N-1)]^T$ is the target steering vector with components dependent on f_d, which is the assumed known Doppler frequency normalized with respect to the radar pulse repetition frequency (PRF).

We assume that:

$$d(n) = \exp(j2\pi f_d n), \quad 0 \le n \le N-1 \tag{2}$$

Our work is based on the use of a set of secondary data from L range cells adjacent to the CUT. Secondary signals $\mathbf{c}_k = [c_k(0), c_k(1), \ldots, c_k(N-1)]^T$, $k = 1, \ldots, L$, are approximated in each cell in terms of stationary segments, where in each of them, the clutter is modeled as a stationary AR process. Assuming that the AR order p is known and the L secondary cells around the CUT contain only clutter, the signal $\mathbf{c}_k$ issued from each cell, at a given range bin, can be modeled as an AR process according to the following equation [18]:

$$c_k(n) = -\sum_{i=1}^{p} a(i) c_k(n-i) + w_k(n) \tag{3}$$

for $n = 0, \ldots, N-1$ and $k = 1, \ldots, L$.

Here $a(i)$ is the i-th AR coefficient and w_k denotes white noise driving the AR process (innovations).

The estimation of the AR coefficients is based on minimization of the global forward prediction square error for secondary data, issued from adjacent cells on both sides of the CUT. This ensures that all the background around the CUT is captured. The general form of AR model given in (3) can be rewritten in a matrix form as follows:

$$\mathbf{c}_k = -\mathbf{C}_k \mathbf{a} + \mathbf{w}_k, \quad k = 1, \ldots, L \tag{4}$$

where $\mathbf{a}$ denotes the vector of AR coefficients (VAR) : $\mathbf{a} = [a(1), a(2), \ldots, a(p)]^T$, $\mathbf{w}_k$ is the innovation vector and $\mathbf{C}_k$ is given by:

$$\mathbf{C}_k = \begin{bmatrix} 0 & 0 & \ldots & 0 \\ c_k(0) & 0 & \ldots & 0 \\ c_k(1) & c_k(0) & \ldots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ c_k(p-1) & c_k(p-2) & \ldots & c_k(0) \\ c_k(p) & c_k(p-1) & \ldots & c_k(1) \\ \vdots & \vdots & \vdots & \vdots \\ c_k(N-2) & c_k(N-3) & \ldots & c_k(N-p-1) \end{bmatrix} \tag{5}$$

For each range cell, the forward prediction square error is given by:

$$\rho_k = \sum_{n=0}^{N-1} \left| e_k(n) \right|^2 = \sum_{n=0}^{N-1} \left| c_k(n) - \hat{c}_k(n) \right|^2, \quad k = 1, \ldots, L$$

Here $\hat{c}_k(n) = -\sum_{i=1}^{p} a(i) c_k(n-i)$ is the linear forward prediction of $c_k(n)$. In a compact form, the square error is given by:

$$\rho_k = \mathbf{e}_k^H \mathbf{e}_k = (\mathbf{c}_k - \hat{\mathbf{c}}_k)^H (\mathbf{c}_k - \hat{\mathbf{c}}_k), \quad k = 1, \ldots, L$$

The global square error for all secondary signals, stemming from the L adjacent cells is given by:

$$\rho = \sum_{k=1}^{L} \rho_k = \sum_{k=1}^{L} (\mathbf{c}_k - \hat{\mathbf{c}}_k)^H (\mathbf{c}_k - \hat{\mathbf{c}}_k)$$

Replacing $\hat{\mathbf{c}}_k$ by $-\mathbf{C}_k \mathbf{a}$ in the last expression gives:

$$\rho = \sum_{k=1}^{L} (\mathbf{c}_k + \mathbf{C}_k \mathbf{a})^H (\mathbf{c}_k + \mathbf{C}_k \mathbf{a}) = \sum_{k=1}^{L} \big(\mathbf{c}_k^H \mathbf{c}_k + \mathbf{a}^H \mathbf{C}_k^H \mathbf{c}_k + \mathbf{c}_k^H \mathbf{C}_k \mathbf{a} + \mathbf{a}^H \mathbf{C}_k^H \mathbf{C}_k \mathbf{a} \big)$$

The estimate of the autoregressive vector $\mathbf{a}$ is then obtained by minimizing the global error:

$$\hat{\mathbf{a}} = -\left(\sum_{k=1}^{L} \mathbf{C}_k^H \mathbf{C}_k \right)^{-1} \left(\sum_{k=1}^{L} \mathbf{C}_k^H \mathbf{c}_k \right) \tag{6}$$

The condition of non-singularity of the matrix being inverted in (6) is given by [9]:

$$L \ge \frac{p}{(N-p)}$$