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Adaptive detection and estimation for an unknown occurring interval signal in correlated Gaussian noise

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ABSTRACT

This paper considers the problem of detecting and estimating an unknown occurring interval signal in correlated Gaussian noise, which is often arisen in signal processing society, e.g., identifying the onset times of a seismic wave and detecting a distributed target in unknown occurring range cells. We propose the novel Generalized Likelihood Ratio Test (GLRT) algorithm, where the Maximum Likelihood Estimations (MLEs) of the unknown occurring interval are obtained through a Dynamic Programming (DP) method adaptively without the secondary data. Unlike the classic Sequential Probability Ratio Test (SPRT) methods which consist of an on-line detector before an off-line estimator, the proposed GLRT outputs the decision result and the estimations at the same time. The performances of the proposed algorithm are evaluated by numerical simulations as well as the applications of detecting and suppressing the transient interference in a radar operated on High-Frequency (HF) band with real data.

1. Introduction

A signal with unknown occurring interval is often arisen in earthquake wave, radar signal, and many other signal families. For example, in the earthquake monitoring, the seismic waves with unknown onset time and duration are with respect to the earthquake randomly [1]; in the High Resolution Radars (HRRs), the returns of targets, e.g., aircrafts, are often distributed in multiple range cells [2]; in the sky-wave Over the Horizonal Radars (OTHRs), the random occurring transient interferences in the ionosphere hold a few seconds during the Coherent Pulse Interval (CPI) [3], and so on.

To detect and estimate the signal with unknown occurring interval is an important issue and has received considerable attention recently. According to the mathematics approach, these works can be classified into three categories summarily. The first category works adopt the Sequential Probability Ratio Test (SPRT),[1] which generally assumes that the interesting signal resulted in only one change of the observations sequence [5]. In the case that the change is in the mean value, i.e., *the additive change*, the on-line Cumulative Sum (CUSUM) detector and its off-line change time estimator are developed in [6,7]. Although the CUSUM is still with crucial interest, it will be invalid when the change is in the behavior of spectrum [8], i.e., *the non-additive change*.[2] Then, by modeling the non-additive change to a small-disturbance Auto-Regressive (AR) process, the Local Linear Hypotheses CUSUM (LLH-CUSUM) [10] and the Local Composite Hypotheses CUSUM (LCH$-\chi^2$ $-$CUSUM, also called LCH-GLRT) [11] with their off-line estimators are proposed. As the local approximation SPRT methods, they are more suitable for the low Signal-Noise-Ratio (SNR) [12].

The second category works employ the Optimal Stopping (OS) approach, which is a method to find the supremum of a

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[1] The details of the SPRT can be referred to [4].

[2] In this paper, the definitions of the *additive change* and *non-additive change* are referred to [9].

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stochastic process on a filtered probability space [13], for example, portfolio re-balancing and choosing optimal moments of time to sell or buy stock in finance application [14]. The OS extended the problem to detect a moment of time when the probabilistic structure of the observation changes but still not suitable for the multiple change case [13].

The third category works address the Multi-Family Likelihood Ratio Test (MFLRT). In [15], based on the multiple signal model, the MFLRT is proposed to solve the multiple change problem, but it only considers the additive change and the white Gaussian noise.

In practical applications, the multiple non-additive change in the correlated Gaussian noise is often inevitable. For example, the true seismic waves are with time-varying spectrum and contain many other nuisance signals from the environment [16]; the transient meteor trail interferences in OTHRs often show spread spectrum in the heterogeneous clutter [17]; the recognition-oriented signals are often with segment spectrum structure in correlated Gaussian noise [18].

In this paper, we investigate the double nonadditive change problem in the correlated Gaussian noise. First, we parameterize the observations sequence to a double change AR process. In fact, almost all Wide-Sense Stationary (WSS) Gaussian processes can be expressed as the response of an AR process steered by a white Gaussian noise [19] and the nonadditive change can be simplified to the parameters change of the AR model [9]. Based on the AR process, we design a Generalized Likelihood Ratio Test (GLRT) without any secondary data. More specifically, the GLRT is derived by comparing the Logarithm Maximum Likelihood Functions (Log-MLFs) under the changed and non-changed AR processes. Meanwhile, the estimations of the unknown parameters of the signal and noise are obtained through a Dynamic Programming (DP) method, which minimizes the signal projection on the noise-subspace with respect to the parameters recursively and avoids searching all possible solutions in the parameter-space. Thus, all parameter's estimations are obtained together with the decision result without any off-line estimator.

The rest of the paper is organized as follows. In Section 2, we formulate the problem in a binary hypothesis. In Section 3, the proposed DP-GLRT is developed. Then, we evaluate the performances of the proposed DP-GLRT as well as the LLH-CUSUM, LCH-GLRT, Ext-LLH-CUSUM and Ext-LCH-GLRT algorithms by computer simulations and real data in Section 4 and 5. Finally, conclusions and further work are provided in Section 6.

2. Problem formulation

Letting $\mathbf{x}$ be the K-dimensional complex received vector, the detection problem with unknown occurring interval signal can be formulated in terms of the following binary hypothesis:

$$\begin{cases} \mathrm{H}_0: \mathbf{x} = \mathbf{n} \\ \mathrm{H}_1: \mathbf{x} = \boldsymbol{\alpha}\mathbf{q} + \mathbf{n}, \end{cases} \tag{1}$$

where

- α denotes the unknown complex amplitude;
- $\mathbf{q}$ consists of three sub-vectors as in [15], given by

$$\mathbf{q} = \left[\mathbf{0}_{L_1}^T \ \bar{\mathbf{q}}_{L_2}^T \ \mathbf{0}_{L_3}^T\right]^T, \tag{2}$$

where the superscript $[.]^T$ denotes the vector transpose operator; $\bar{\mathbf{q}}_{L_2}$ is a deterministic steering vector of interest, which occurs within the unknown interval $[k_1+1, k_2], 1 \le k_1 \le k_2 \le K$ with unknown length $L_2 = k_2 - k_1$; $\mathbf{0}_{L_1}$ and $\mathbf{0}_{L_3}$ are respectively the zero vectors within the intervals $[1, k_1]$ and $[k_2+1, K]$ with length $L_1 = k_1$ and $L_3 = K - K_2$, while $L_1 + L_2 + L_3 = K$.
- $\mathbf{n}$ is the K-dimensional zero-mean circular complex Gaussian random vector with covariance matrix $\mathbf{C}$, which can be modeled as an AR parametric process [19], i.e.,

$$\mathbf{n}(k) = \sum_{i=1}^{P} \mathbf{a}(i)\mathbf{n}(k-i) + \mathbf{w}(k), \tag{3}$$

where $\mathbf{a} = [\mathbf{a}(1), \mathbf{a}(2), \ldots, \mathbf{a}(P)]^T$ is the P-dimensional unknown complex AR coefficient vector, while P, for $P \ll K$, denotes the order of the AR process which is assumed to be known, $\mathbf{w}$ is the K-dimensional zero-mean circular Gaussian random vector with covariance $\sigma^2\mathbf{I}$ ($\mathbf{I}$ is the K-dimensional identity matrix), i.e.,

$$\mathbf{w} \sim N(0, \sigma^2\mathbf{I}). \tag{4}$$

3. The DP-GLRT algorithm

According to the Neyman–Pearson (NP) criteria, the optimum detector is the Logarithm Likelihood Ratio Test (Log-LRT) [20]:

$$\Lambda = \log \frac{p(\mathbf{x}; k_1, k_2, \mathbf{a}, \sigma, \alpha | H_1)}{p(\mathbf{x}; \mathbf{a}, \sigma | H_0)} \underset{H_0}{\overset{H_1}{\gtrless}} \eta, \tag{5}$$

where $p(\mathbf{x}; k_1, k_2, \mathbf{a}, \sigma, \alpha | H_1)$ and $p(\mathbf{x}; \mathbf{a}, \sigma | H_0)$ denote respectively the likelihood functions under H_1 and H_0, η denotes the detection threshold setting to be a function of the noise level in order to maintain a constant false alarm probability (P_{FA}) [20]. For $P \ll K$, they can be expressed as [2,21]

$$p(\mathbf{x}; k_1, k_2, \mathbf{a}, \sigma, \boldsymbol{\alpha} | H_1) \approx \frac{1}{(\pi\sigma^2)^{K-P}} \prod_{i=0}^{2} \exp\left\{ -\frac{\left\| \left[\left(\mathbf{x}_{k_i+P+1}^{k_{i+1}} - \mathbf{X}_{k_i,P}^{k_{i+1}}\mathbf{a} \right) - \alpha\left(\mathbf{q}_{k_i+P+1}^{k_{i+1}} - \mathbf{Q}_{k_i,P}^{k_{i+1}}\mathbf{a} \right) \right] \right\|^2}{\sigma^2} \right\}, \tag{6}$$

under H_1 with $k_0 = 0; k_3 = K; P+1 \le k_1 \le K-2P-2$; $2P+2 \le k_2 \le K-P-1$ and

$$p(\mathbf{x}; \mathbf{a}, \boldsymbol{\sigma} | H_0) \approx \frac{1}{(\pi\sigma^2)^{K-P}} \exp\left\{ -\frac{\left\| \left(\mathbf{x}_{P+1}^K - \mathbf{X}_{0,P}^K\mathbf{a} \right) \right\|^2}{\sigma^2} \right\}, \tag{7}$$

under H_0 respectively, where

$$\mathbf{x}_i^j = [\mathbf{x}(i), \mathbf{x}(i+1), \ldots, \mathbf{x}(j)]^T; \\ \mathbf{q}_i^j = [\mathbf{q}(i), \mathbf{q}(i+1), \ldots, \mathbf{q}(j)]^T, \tag{8}$$

for $i \le j$ and

$$\mathbf{X}_{i,P}^j = [\mathbf{x}_{i+P}^{j-1}, \mathbf{x}_{i+P-1}^{j-2}, \ldots, \mathbf{x}_{i+1}^{j-P}]; \\ \mathbf{Q}_{i,P}^j = [\mathbf{q}_{i+P}^{j-1}, \mathbf{q}_{i+P-1}^{j-2}, \ldots, \mathbf{q}_{i+1}^{j-P}], \tag{9}$$