Signal Processing 108 (2015) 389–399

Contents lists available at ScienceDirect

Signal Processing

journal homepage: www.elsevier.com/locate/sigpro

Signal detection with noisy reference for passive sensing ☆

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ARTICLE INFO

Article history:
Received 30 April 2014
Received in revised form
6 August 2014
Accepted 25 September 2014
Available online 8 October 2014

Keywords:
Cross-correlation detector
Generalized likelihood ratio test (GLRT)
Matched filter detector
Reference signal

ABSTRACT

In many detection applications, the signal to be detected, referred to as *target signal*, is not directly available. A reference channel (RC) is often deployed to collect a noise-contaminated version of the target signal to serve as a reference, which is then used to assist detecting the presence/absence of the target signal in a test channel (TC). A standard approach is to cross-correlate (CC) the signals received in the TC and RC, respectively. When the signal-to-noise ratio (SNR) in the RC is high, the CC behaves like the optimum matched filter. However, when the SNR in the RC is low, the CC detector suffers significant degradation. This paper considers the above detection problem with a noisy reference signal. We propose four detectors based on the generalized likelihood ratio test principle, by treating the unknown target signal to be deterministic or stochastic and under conditions whether the noise variance is known or unknown. Our results demonstrate that the noise in the RC has an impact on the achievable detection performance. However, when the reference signal is noisy, three of the proposed detectors offer substantial improvements in detection performance over the CC detector.

1. Introduction

Detection of a signal in noise has been a topic of long-standing interest in sensing and communications. If the signal to be detected is perfectly known and the noise is stationary with zero-mean and white power spectral density, the optimal detector is the matched filter (MF) which maximizes the output signal-to-noise ratio (SNR) [1]. However, the signal may not be known in many practical applications, such as underwater acoustics [2–5], seismology [6–9], neurophysiology [10,11], and passive radar [12–16]. Consider for example passive radar. Unlike its active counterpart, a passive radar does not transmit a known waveform and then listen for echos. Instead, it utilizes commercial RF signals from TV stations or cellular towers as sources to illuminate potential targets of interest. The RF source waveforms are generally unknown to the passive radar receiver.

A conventional approach to the unknown signal detection problem is to deploy a reference channel (RC) for collecting the unknown transmitted signal to serve as a reference. In passive radar, a reference signal can be obtained by using a directive antenna pointing toward the commercial RF source with a known location. Given the availability of the reference signal, a natural solution is to mimic the MF processing, i.e., cross-correlate (CC) the reference and the test signal observed in a test channel (TC). Nevertheless, the reference signal is inevitably contaminated by noise. Under the condition that the SNR in the RC is high, the noise is negligible and the CC detector behaves like the MF. However, the detection performance of the CC detector would be significantly degraded, when

☆ This work was supported in part by a subcontract with Dynetics, Inc. for research sponsored by the Air Force Research Laboratory (AFRL) under Contract FA8650-08-D-1303.

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http://dx.doi.org/10.1016/j.sigpro.2014.09.034
0165-1684/

the SNR in the RC is low. In such cases, improved detection performance is possible, if the noise in the reference signal is properly taken into account. In this paper, we consider signal detection with a noisy reference.

Specifically, the detection problem in the presence of a noisy reference signal can be formulated as the following binary hypothesis test:

$$H_0: \begin{cases} \boldsymbol{x}_r = \beta \boldsymbol{s} + \boldsymbol{v}, \\ \boldsymbol{x}_t = \boldsymbol{w}, \end{cases} \tag{1a}$$

$$H_1: \begin{cases} \boldsymbol{x}_r = \beta \boldsymbol{s} + \boldsymbol{v}, \\ \boldsymbol{x}_t = \alpha \boldsymbol{s} + \boldsymbol{w}, \end{cases} \tag{1b}$$

where $\boldsymbol{x}_r$ and $\boldsymbol{x}_t$ denote $N \times 1$ vectors composed of complex (baseband equivalent) samples received in the RC and TC, respectively; $\boldsymbol{s}$ is an $N \times 1$ vector containing samples of the unknown transmitted signal waveform; α and β are unknown scaling parameters accounting for the channel propagation effects; $\boldsymbol{w}$ and $\boldsymbol{v}$ are noise vectors in the TC and RC, respectively, which are modeled as independent circular[1] complex Gaussian vectors with zero mean and covariance matrix $\eta \mathbf{I}_N$, where η denotes the noise power and $\mathbf{I}_N$ stands for an N-dimensional identity matrix. The problem of interest is to decide between hypotheses H_1 and H_0 given observations of $\boldsymbol{x}_r$ and $\boldsymbol{x}_t$ made over the RC and TC channels.

We employ two models to describe the unknown transmitted signal $\boldsymbol{s}$, namely, a deterministic model where $\boldsymbol{s}$ is deterministic but unknown, and a stochastic model in which $\boldsymbol{s}$ is a complex Gaussian vector. The stochastic model is suitable for signal sources involving multiplexing techniques, such as the orthogonal frequency division multiplexing (OFDM) as used in digital audio broadcasting [17], which use multiple random information streams to form a composite communication signal that can be adequately modeled as a Gaussian process due to the central limit theorem (CLT).

In this paper, we develop four generalized likelihood ratio test (GLRT) detectors for both models under the assumption of known and unknown noise power. In particular, cyclic iteration algorithms are proposed to obtain the maximum likelihood estimates (MLEs) of unknown parameters. Numerical simulations are presented to illustrate the detection performance of these proposed detectors. It is shown that the proposed GLRT detectors, except the one developed under the assumption of unknown noise power in the stochastic model, outperforms the CC detector, especially when the noise in the RC is not negligible.

A comment on the model in (1) for passive sensing is now in order. In passive radar, since the target location is unknown, there is an unknown delay of the waveform $\boldsymbol{s}$ observed at the TC relative to that observed at the RC. In practical sensing scenarios, the delay is within a known interval (i.e., the target is located within a range specified by a minimum and a maximum detection distance), which is discretized into a number of small sub-intervals called *range bins*. The hypothesis in (1) is tested on each bin one by one, whereby the RC and TC observations are aligned according to the delay of the tested range bin and detection is performed by using, e.g., any detector discussed in this paper. Presumably, the test result will be positive with a high probability only when the tested range bin matches the true unknown delay. For simplicity (and also as in the standard radar signal detection literature), we assume that the delay alignment has already been accomplished, and the observations in (1) have already been delay compensated. Likewise, when detecting a moving target, there is a Doppler uncertainty which can be handled by discretizing the Doppler frequency into Doppler bins and running the test on each Doppler bin one by one. It should be noted that delay and Doppler uncertainties are present in active radar as well, and they are often handled in a similar manner there.

The remainder of the paper is organized as follows. In Section 2, two GLRT-based detectors are devised under the deterministic model. In Section 3, we design two GLRT-based detectors under the stochastic model. In Section 4, computer simulations are offered. Finally, we provide concluding remarks and possible future research tracks in Section 5.

Notation: Vectors (matrices) are denoted by boldface lower (upper) case letters. Superscripts $(\cdot)^T$, $(\cdot)^*$, and $(\cdot)^\dagger$ denote transpose, complex conjugate, and complex conjugate transpose, respectively. $\mathbf{I}_p$ stands for a p-dimensional identity matrix. $\|\cdot\|$ is the Frobenius norm. $|\cdot|$, $\angle(\cdot)$, and $\Re(\cdot)$ denote the modulus, the phase, and the real part of a complex number, respectively. $\lambda_{\max}(\cdot)$ and $\lambda_{\min}(\cdot)$ represent the largest eigenvalue and the smallest eigenvalue of an argument, respectively. $\det(\cdot)$ denotes the determinant operation. $\mathrm{var}(\cdot)$ and $E(\cdot)$ are the variance and the statistical expectation, respectively. $\Pr\{\cdot\}$ denotes the probability of a random variable.

2. Deterministic model based detectors

The *Neyman–Pearson* criterion is widely used for signal detection, which enables us to obtain the maximum probability of detection while not allowing the probability of false alarm to exceed a certain value [1]. According to the *Neyman–Pearson* criterion, the optimum solution to the hypothesis testing problem in (1) is obtained by comparing the ratio of the likelihood of the received data under hypothesis over that under hypothesis with an appropriate detection threshold, i.e.,

$$\Lambda(\boldsymbol{x}_t, \boldsymbol{x}_r) = \frac{f_{H_1}(\boldsymbol{x}_t, \boldsymbol{x}_r)}{f_{H_0}(\boldsymbol{x}_t, \boldsymbol{x}_r)} \underset{H_0}{\overset{H_1}{\gtrless}} \gamma, \tag{2}$$

where $f_{H_0}(\boldsymbol{x}_t, \boldsymbol{x}_r)$ and $f_{H_1}(\boldsymbol{x}_t, \boldsymbol{x}_r)$ are the likelihood functions under H_0 and H_1, respectively, and γ denotes the detection threshold. Based on the Gaussian assumptions on $\boldsymbol{v}$ and $\boldsymbol{w}$, the probability density functions (PDFs) for deterministic $\boldsymbol{s}$ can be written as

$$f_{H_0}(\boldsymbol{x}_t, \boldsymbol{x}_r) = \frac{1}{\pi^{2N} \eta^{2N}} \exp\left(-\frac{\|\boldsymbol{x}_r - \beta \boldsymbol{s}\|^2 + \|\boldsymbol{x}_t\|^2}{\eta} \right), \tag{3}$$

and

$$f_{H_1}(\boldsymbol{x}_t, \boldsymbol{x}_r) = \frac{1}{\pi^{2N} \eta^{2N}} \exp\left(-\frac{\|\boldsymbol{x}_r - \beta \boldsymbol{s}\|^2 + \|\boldsymbol{x}_t - \alpha \boldsymbol{s}\|^2}{\eta} \right), \tag{4}$$

[1] A circular complex random variable indicates that its real part and imaginary part are independent and identically distributed random variables.