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Joint estimation of time difference of arrival and frequency difference of arrival for cyclostationary signals under impulsive noise

Yang Liu [a,*], Tianshuang Qiu [b], Jingchun Li [c]

[a] College of Electronic Information Engineering, Inner Mongolia University, Hohhot, 010021, China
[b] Faculty of Electronic Information and Electrical Engineering, Dalian University of Technology, Dalian, 116024, China
[c] The State Radio Monitoring Center, Beijing, 100037, China

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ABSTRACT

The problem of jointly estimating time difference of arrival (TDOA) and frequency difference of arrival (FDOA) or Doppler has a variety of practical applications. The conventional cyclic ambiguity function and the fractional lower-order ambiguity function suffer performance degradation in the presence of non-Gaussian α-stable impulsive noise and corruptive interference. To overcome these drawbacks, a new robust signal-selective algorithm for cyclostationary signals based on the fractional lower-order cyclostationarity is proposed. The new method makes use of cyclostationarity features and fractional lower-order statistics, and is highly tolerant to interference and robust to both Gaussian noise and non-Gaussian α-stable impulsive noise. The robustness and effectiveness of the proposed method in the presence of impulsive noise and interference are demonstrated by comparing it with the cyclostationarity-based and fractional lower-order statistics (FLOS)-based methods.

1. Introduction

The problem of locating a signal source has many civilian and military applications, such as communication regulation enforcement, military reconnaissance, and search and rescue operations. A variety of wireless location schemes have been extensively investigated [1]. One typical method used to estimate the mobile location is time difference of arrival (TDOA), which does not require knowledge of the transmit time of the received signal from the transmitter, and has better accuracy than angle of arrival (AOA) [2,3]. Often, at least one of the receivers is located on a moving platform resulting in relative motion between the emitter and one or more of the receivers. This relative motion results in a Doppler shift or frequency difference of arrival (FDOA), which can be measured and exploited along with TDOA measurements to locate an emitter [4–6]. The accuracy of emitter location methods relies on the accurate and robust estimation of the TDOA and FDOA. Although several techniques are used to reduce the effects of interference and noise, it is necessary to develop effective TDOA and FDOA estimation algorithms.

Many of the conventional methods for estimating TDOA are based on coherence and time delay estimation techniques that were developed within the radar and sonar research communities. A popular conventional method for jointly estimating TDOA and FDOA is using the ambiguity function (AF) [7], and it has been widely used for location and radar applications [8]. These methods have many variations and can be robust TDOA and FDOA estimation techniques in some applications [9]. However, it has been demonstrated that they perform poorly against spectrally overlapping signals, and they are unable to produce separate unbiased TDOA and FDOA estimates when multiple emitters are located spatially close to each other [10]. The limitations of conventional methods motivate the need for new TDOA and FDOA estimation algorithms that can produce unbiased estimates from spectral overlapping signals. Many man-made modulated signals encountered in communications, radar and sonar are appropriately modeled as cyclostationary time series [11,12]. A class of cyclostationarity-based signal-selective TDOA methods for passive location is introduced by Gardner et al. in [13–17]. An asymptotic cyclic correlation-based Cramér–Rao bound (CRBCRB) and an approximate maximum-likelihood estimator in the AWGN environment are presented in [18]. In many cases, the Doppler shift needs to be estimated for moving targets, and thus a new method based on cyclic cross-ambiguity function for jointly estimating TDOA and FDOA is presented in [10,19,20]. Since most of the cyclostationary signals have more than one cycle frequency, several modified multi-cycle algorithms which exploit more than one cycle frequency are developed in [21,22]. Moreover, by utilizing the information of both the cyclic correlation and the cyclic conjugate

* Corresponding author.
E-mail address: yangliuimu@163.com (Y. Liu).

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correlation functions, the improved signal selective direction finding algorithm delivers better performance than the conventional cyclic-MUSIC and cyclic-ESPRIT [23]. The new cyclostationarity-based signal processing algorithms have been shown to significantly outperform classical algorithms based on a stationary model for signals in severe noise and interference environments [7,14,22].

However, the primary single-cycle and multi-cycle TDOA and FDOA estimation methods focus on the case where the environmental noises are assumed to follow the Gaussian distribution model. Generally, it is reasonable to assume the noise is Gaussian distribution with finite second-order statistics, because it may lead to closed-form solution; however, studies and experimental measurements have shown that the noise components in communication, telemetry, radar and sonar systems often exhibit non-Gaussian properties [24–30]. It is for this type of noise that the non-Gaussian models provide a useful theoretical tool. In [27] and [28], the convolutional noise at the early stage of the deconvolution process is represented by the edgeworth expansion based model and the maximum entropy model, respectively. These models improve the performance of the deconvolution process for 16 Quadrature Amplitude Modulation (QAM) inputs. The generalized Gaussian distribution (GGD) provides a flexible and suitable tool for data modeling in signal processing and communications. A complex generalized Gaussian distribution (CGGD) is defined in [29]. The GGD describes a wide range of super-Gaussian to sub-Gaussian densities including specific densities such as Laplacian and Gaussian distributions. Since the new generalized Gaussian kernel encompasses Gaussian, Laplacian and Uniform as special cases, it provides more flexibility [29]. By using the generalized Gaussian kernel, a new detector for amplify-and-forward (AF) relaying cooperative system is proposed [30]. The bit error rate performance of the receiver is improved by this new detector.

One important class of non-Gaussian noise that is frequently encountered in many practical applications is impulsive noise. In [31], the contaminated Gaussian noise which is derived from the Gaussian mixture model is adopted to model the impulsive noise. The impulsive noise is usually of short time duration and time varying, its statistics are rather difficult to estimate accurately. The α-stable distribution is more suitable for modeling noise of impulsive nature than Gaussian distribution in communication, telemetry, radar and sonar systems [32–36]. Since stable distribution does not have finite second-order moments (except for $\alpha = 2$) [25], or even first-order moment ($\alpha < 1$) [26], conventional cyclostationarity-based signal processing algorithms will be considerably weakened in additive impulsive noise environments [34]. Several TDOA and FDOA estimation algorithms have been introduced in [35] and [36], which take account the impulsive noise using fractional lower-order statistics (FLOS). Although the FLOS-based methods are robust to both Gaussian noise and non-Gaussian impulsive noise, the interfering signals that occupy the same spectral band as the signal of interest can severely degrade the performance of these methods. To overcome the limitations of conventional cyclostationarity-based and FLOS-based algorithms, it is necessary to develop a new signal-selective method that is substantial tolerance to interference, Gaussian noise and non-Gaussian impulsive noise.

In this paper, we address the problem of jointly estimating the TDOA and FDOA of cyclostationary signals in the presence of interference and impulsive noise. To achieve high accuracy estimates of TDOA and Doppler, a robust fractional lower-order cyclostationarity-based method is presented. The proposed fractional lower-order cyclic cross-ambiguity function approach exploits fractional lower-order cyclostationarity to overcome the limitations of conventional methods.

The paper is organized as follows. Section 2 outlines the signal model and provides a brief review of the conventional cyclic cross-ambiguity function method. Details of the proposed fractional lower-order cyclostationarity-based method are presented in Section 3. Numerical results are carried out to corroborate the effectiveness and robustness of the proposed algorithm in Section 4. Finally, conclusions are drawn in Section 5.

2. Problem formulation

2.1. Signal model

In general, for a signal radiating from a remote source through a channel with interfering signals and noise, the model for TDOA and FDOA estimation between received signals at two receivers is given by

$$x(t) = r_1 s(t) + n(t) \tag{1}$$

$$y(t) = r_2 s(t-D) e^{j2\pi f_d t} + m(t) \tag{2}$$

where $s(t)$ is the signal of interest (SOI), $n(t)$ and $m(t)$ are the signals not of interest (SNOI) which include interference and noise, D and f_d are the TDOA and FDOA to be estimated, and r_1 and r_2 represent the magnitude mismatch between two receivers. To simplify the problem, it is assumed that $s(t)$ is statistically independent of the SNOI, and interfering signals exhibit no cyclostationarity at cycle frequency of the SOI. Since $n(t)$ and $m(t)$ may contain the same interfering signals, they can be statistically dependent [13,19].

2.2. Cyclostationarity-based TDOA-FDOA estimation method

The problem of cyclostationarity-exploiting TDOA and FDOA estimation has been studied in [10,19,21], and a cyclic cross-ambiguity function for joint TDOA and FDOA estimation was developed, which is defined as

$$C^{\varepsilon}_{yx}(\tau, f) \triangleq \int R^{\varepsilon-f}_{yx}(u)\big(R^{\varepsilon}_{x}(u-\tau)\big)^{*} e^{j\pi f u} du \tag{3}$$

Note that $R^{\varepsilon}_{x}(\tau)$ and $R^{\varepsilon}_{yx}(\tau)$ are the cyclic autocorrelation function and cyclic cross-correlation function, respectively. According to the definition in [11], the cyclic autocorrelation function of $x(t)$ at certain cycle frequency ε is given by

$$R^{\varepsilon}_{x}(\tau) \triangleq \big\langle x(t+\tau/2)x^{*}(t-\tau/2)e^{-j2\pi\varepsilon t}\big\rangle \tag{4}$$

where $\langle\cdot\rangle = \lim_{T\to\infty}(1/T)\int_{-T/2}^{T/2}(\cdot)dt$ is the time-averaging operation, and "$*$" denotes the conjugation. Using the signal model in (1) and (2), the cyclic autocorrelation and cross-correlation functions can be expanded to

$$R^{\varepsilon}_{x}(\tau) = |r_1|^2 R^{\varepsilon}_{s}(\tau) \tag{5}$$

$$R^{\varepsilon}_{yx}(\tau) = r_2 r_1^{*} e^{-j\pi f_d \tau} e^{-j\pi(\varepsilon - f + f_d)D} R^{\varepsilon - f + f_d}_{s}(\tau - D) \tag{6}$$

Substitution of (5) and (6) into (3) results in,

$$C^{\varepsilon}_{yx}(\tau, f) = |r_1|^2 r_1^{*} r_2 e^{-j\pi\varepsilon D} \int R^{\varepsilon - f + f_d}_{s}(u-D)\big(R^{\varepsilon}_{s}(u-\tau)\big)^{*} \times e^{j\pi(f-f_d)(u+D)} du \tag{7}$$

From the Schwartz inequality, we can see that

$$\big|C^{\varepsilon}_{yx}(\tau, f)\big| \le |r_2||r_1|^3 \left|\int \big|R^{\varepsilon}_{s}(u)\big|^2 du\right| \tag{8}$$

and only if $\tau = D$ and $f = f_d$ can the equality in (8) hold. Thus, the estimates of TDOA and Doppler shift can be obtained by

$$(D, f_d) = \arg\Big(\max_{\tau, f}\big(\big|C^{\varepsilon}_{yx}(\tau, f)\big|\big)\Big) \tag{9}$$