

Robust estimators for frequency offset of OFDM in non-Gaussian noise

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Abstract: This paper addresses robust estimation for the frequency offset of orthogonal frequency division multiplexing in non-Gaussian noise channels. We first propose a maximum-likelihood (ML) estimator in non-Gaussian noise modeled as a complex isotropic Cauchy process, and then present a simpler, yet still robust, estimator based on the ML estimator. From numerical results, it is confirmed that the proposed estimators offer a substantial performance improvement over the conventional estimators in non-Gaussian noise channels.

Keywords: frequency offset estimation, non-Gaussian noise, OFDM

Classification: Wireless communication hardware

References

- [1] R. V. Nee and R. Prasad, *OFDM for Wireless Multimedia Communications*, Boston, MA: Artech House, 2000.
- [2] T. Hwang, C. Yang, G. Wu, S. Li, and G. Y. Li, “OFDM and its wireless applications: a survey,” *IEEE Trans. Veh. Technol.*, vol. 58, no. 4, pp. 1673–1694, May 2009.
- [3] T. M. Schmidl and D. C. Cox, “Robust frequency and timing synchronization for OFDM,” *IEEE Trans. Commun.*, vol. 45, no. 12, pp. 1613–1621, Dec. 1997.
- [4] M. Morelli and U. Mengali, “An improved frequency offset estimator for OFDM applications,” *IEEE Commun. Lett.*, vol. 3, no. 3, pp. 75–77, March 1999.
- [5] J.-W. Choi, J. Lee, Q. Zhao, and H.-L. Lou, “Joint ML estimation of frame timing and carrier frequency offset for OFDM systems employing time-domain repeated preamble,” *IEEE Trans. Wireless Commun.*, vol. 9, no. 1, pp. 311–317, Jan. 2010.
- [6] T. K. Blankenship and T. S. Rappaport, “Characteristics of impulsive noise in the 450-MHz band in hospitals and clinics,” *IEEE Trans. Antennas Propag.*, vol. 46, no. 2, pp. 194–203, Feb. 1998.
- [7] P. Torío and M. G. Sánchez, “A study of the correlation between horizontal and vertical polarizations of impulsive noise in UHF,” *IEEE Trans.*

- Veh. Technol.*, vol. 56, no. 5, pp. 2844–2849, Sept. 2007.
- [8] C. L. Nikias and M. Shao, *Signal Processing With Alpha-Stable Distributions and Applications*, New York, NY: Wiley, 1995.
- [9] H. G. Kang, I. Song, S. Yoon, and Y. H. Kim, “A class of spectrum-sensing schemes for cognitive radio under impulsive noise circumstances: structure and performance in nonfading and fading environments,” *IEEE Trans. Veh. Technol.*, vol. 59, no. 9, pp. 4322–4339, Nov. 2010.
- [10] M. R. Spiegel and J. Liu, *Mathematical Handbook of Formulas and Tables*, New York, NY: McGraw-Hill, 1999.
- [11] T. C. Chuah, B. S. Sharif, and O. R. Hinton, “Nonlinear decorrelator for multiuser detection in non-Gaussian impulsive environments,” *Electron. Lett.*, vol. 36, no. 10, pp. 920–922, May 2000.
- [12] X. Ma and C. L. Nikias, “Parameter estimation and blind channel identification in impulsive signal environments,” *IEEE Trans. Signal Process.*, vol. 43, no. 12, pp. 2884–2897, Dec. 1995.
- [13] S. A. Kassam, *Signal Detection in Non-Gaussian Noise*, New York, NY: Springer-Verlag, 1988.
- [14] I. Song, J. Bae, and S. Y. Kim, *Advanced Theory of Signal Detection*, Berlin, Germany: Springer-Verlag, 2002.

1 Introduction

Due to its high spectral efficiency and immunity to multipath fading, orthogonal frequency division multiplexing (OFDM) has been widely used as a modulation technique for wireless communication systems. However, OFDM is very sensitive to the frequency offset (FO) caused by a Doppler shift or oscillator instabilities: Thus, the FO estimation is one of the most important technical issues in OFDM systems [1]. Specifically, we are concerned about the FO estimation based on training symbols, which provides a better performance than that based on the blind approach [2].

Conventionally, the FO estimation techniques have been proposed under the assumption that the ambient noise is a Gaussian process [3, 4, 5], which is generally justified with the central limit theorem. However, it has been observed that the ambient noise often exhibits non-Gaussian nature in wireless channels, mostly due to the impulsive nature originated from various sources such as car ignitions, moving obstacles, lightning in the atmosphere, and reflections from sea waves [6, 7]. The conventional estimators developed under the Gaussian assumption on the ambient noise could suffer from severe performance degradation under such non-Gaussian noise environments.

In this paper, our goal is to obtain robust FO estimators for OFDM systems in non-Gaussian noise environments. We first derive a maximum-likelihood (ML) estimator in non-Gaussian noise modeled as a complex isotropic Cauchy noise, and then derive a simpler estimator with a lower complexity. From numerical results, the proposed estimators are confirmed to provide a substantial performance improvement over the conventional estimators in non-Gaussian noise environments.

2 Signal model

In the presence of FO, the k th received OFDM sample can be expressed as

$$r(k) = \sum_{l=0}^{L-1} h(l)x(k-l)e^{j2\pi k\varepsilon/N} + n(k) \quad (1)$$

for $k = 0, 1, \dots, N-1$, where $h(l)$ is the l th channel coefficient of a multipath channel with length L , $x(k)$ is the k th sample of the transmitted OFDM symbol generated by the inverse fast Fourier transform (IFFT) of size N , ε is the FO normalized to the subcarrier spacing $1/N$, and $n(k)$ is the k th sample of additive noise.

In this paper, we adopt the complex isotropic symmetric α stable (CIS α S) model for the independent and identically distributed noise samples $\{n(k)\}_{k=0}^{N-1}$; this model has been widely employed due to its strong agreement with experimental data [8, 9]. The probability density function (pdf) of $n(k)$ is then given by [8]

$$f_n(\rho) = \frac{1}{4\pi^2} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \exp \left[-\gamma (u^2 + v^2)^{\frac{\alpha}{2}} - j\Re \{ \rho (u - jv) \} \right] dudv, \quad (2)$$

where $\Re\{\cdot\}$ denotes the real part, the dispersion $\gamma > 0$ is related to the spread of the pdf, and the characteristic exponent $\alpha \in (0, 2]$ is related to the heaviness of the tails of the pdf: A smaller value of α indicates a higher degree of impulsiveness, whereas a value closer to 2 indicates a more Gaussian behavior.

A closed-form expression of (2) is not known to exist except for the special cases of $\alpha = 1$ (complex isotropic Cauchy) and $\alpha = 2$ (complex isotropic Gaussian). In particular, we have

$$f_n(\rho) = \begin{cases} \frac{\gamma}{2\pi} (|\rho|^2 + \gamma^2)^{-\frac{3}{2}}, & \text{when } \alpha = 1 \\ \frac{1}{4\pi\gamma} \exp\left(-\frac{|\rho|^2}{4\gamma}\right), & \text{when } \alpha = 2. \end{cases} \quad (3)$$

Due to such a lack of closed-form expressions, we concentrate on the case of $\alpha = 1$: We shall see in Section 4 that the estimators obtained for $\alpha = 1$ are not only more robust to the variation of α , but they also provide a better performance for most values of α , than the conventional estimators.

3 Proposed estimators

3.1 Cauchy maximum-likelihood estimator

In estimating the FO, we consider a training symbol $\{x(k)\}_{k=0}^{N-1}$ with two identical halves as in [3], i.e., $x(k) = x(k + N/2)$ for $k = 0, 1, \dots, \frac{N}{2} - 1$. Then, from (1), we have

$$r(k + N/2) - r(k)e^{j\pi\varepsilon} = n(k + N/2) - n(k)e^{j\pi\varepsilon} \quad (4)$$

for $k = 0, 1, \dots, \frac{N}{2} - 1$. Observing that $n(k + N/2) - n(k)e^{j\pi\varepsilon}$ obeys the complex isotropic Cauchy distribution with dispersion 2γ (since the distribution

of $-n(k)e^{j\pi\varepsilon}$ is the same as that of $n(k)$, we obtain the pdf

$$f_{\mathbf{r}}(\mathbf{r}|\varepsilon) = \prod_{k=0}^{\frac{N}{2}-1} \frac{\gamma}{\pi \left(|r(k+N/2) - r(k)e^{j\pi\varepsilon}|^2 + 4\gamma^2 \right)^{\frac{3}{2}}} \quad (5)$$

of $\mathbf{r} = \{r(k+N/2) - r(k)e^{j\pi\varepsilon}\}_{k=0}^{N/2-1}$ conditioned on ε . The ML estimation is then to choose $\hat{\varepsilon}$ such that

$$\begin{aligned} \hat{\varepsilon} &= \arg \max_{\tilde{\varepsilon}} [\log f_{\mathbf{r}}(\mathbf{r}|\tilde{\varepsilon})] \\ &= \arg \min_{\tilde{\varepsilon}} \Lambda(\tilde{\varepsilon}), \end{aligned} \quad (6)$$

where $\tilde{\varepsilon}$ denotes the candidate value of ε and the log-likelihood function $\Lambda(\tilde{\varepsilon}) = \sum_{k=0}^{N/2-1} \log \left\{ |r(k+N/2) - r(k)e^{j\pi\tilde{\varepsilon}}|^2 + 4\gamma^2 \right\}$ is a periodic function of $\tilde{\varepsilon}$ with period 2: The minima of $\Lambda(\tilde{\varepsilon})$ occur at a distance of 2 from each other, causing an ambiguity in estimation. Assuming that ε is distributed equally over positive and negative sides around zero, the valid estimation range of the ML estimator can be set to $-1 < \varepsilon \leq 1$, as in [3].

From the fact that $|r(k+N/2) - r(k)e^{j\pi\tilde{\varepsilon}}|^2 = 4 \left| \sum_{l=0}^{L-1} h(l)x(k-l) \right|^2 \sin^2(\pi(\tilde{\varepsilon} - \varepsilon)/2)$ in the absence of noise, and that the logarithm is an increasing function, it is straightforward to see that $\Lambda(\tilde{\varepsilon})$ in the absence of noise is convex in each interval $\varepsilon + 2z - 1 < \tilde{\varepsilon} \leq \varepsilon + 2z + 1$, where z is an integer. Thus, the ML estimate $\hat{\varepsilon}$ in (6) can be found by solving $\frac{d\Lambda(\tilde{\varepsilon})}{d\tilde{\varepsilon}} \Big|_{\tilde{\varepsilon}=\hat{\varepsilon}} = 0$ for $\hat{\varepsilon}$: After some algebraic manipulations, we get

$$\hat{\varepsilon} = \frac{1}{\pi} \angle \left(\sum_{k=0}^{\frac{N}{2}-1} \frac{r^*(k)r(k+\frac{N}{2})}{4\gamma^2 + |r(k)|^2 + |r(k+\frac{N}{2})|^2 - 2|r(k)r(k+\frac{N}{2})| \cos(\pi\hat{\varepsilon} + \theta_k)} \right), \quad (7)$$

where $\theta_k = \angle(r(k)r^*(k+N/2))$ with \angle denoting the phase angle in $(-\pi, \pi]$ of a complex number. The estimator (7) will be called the Cauchy ML estimator (CME): The ML estimate $\hat{\varepsilon}$ can be acquired, for example, via an iterative procedure.

3.2 Simplified Cauchy maximum-likelihood estimator

As the signal-to-noise ratio (SNR) gets smaller, the CME would require more iterations to produce a reliable estimate. To avoid the iteration, by assuming that $\hat{\varepsilon}$ is uniformly distributed over $(-1, 1]$ (note that such an assumption is the ‘worst-case’ when the distribution of $\hat{\varepsilon}$ is unknown) and then taking the expectation of the argument of \angle in (7) with respect to $\hat{\varepsilon}$, we can obtain a simplified estimator

$$\begin{aligned} \hat{\varepsilon}_s &= \frac{1}{\pi} \angle \left(\sum_{k=0}^{\frac{N}{2}-1} \frac{1}{2} \int_{-1}^1 \frac{r^*(k)r(k+N/2)}{A + B \cos(\pi\hat{\varepsilon} + \theta_k)} d\hat{\varepsilon} \right) \\ &= \frac{1}{\pi} \angle \left(\sum_{k=0}^{\frac{N}{2}-1} \frac{r^*(k)r(k+N/2)}{\sqrt{\{4\gamma^2 + (|r(k)| + |r(k+N/2)|)^2\} \{4\gamma^2 + (|r(k)| - |r(k+N/2)|)^2\}}} \right), \end{aligned} \quad (8)$$

where $A = 4\gamma^2 + |r(k)|^2 + |r(k + N/2)|^2$, $B = -2|r(k)r(k + N/2)|$, and the second equality is obtained using $\int_{-\pi}^{\pi} \frac{1}{a+b \cos x} dx = \frac{2\pi}{\sqrt{a^2-b^2}}$ [10]. The estimator (8) will be referred to as the simplified Cauchy ML estimator (SCME).

4 Numerical results

The mean square error (MSE) performances of the proposed estimators CME and SCME are compared with those of the conventional estimators [3, 4, 5]. We assume the following parameters: The IFFT size $N = 64$, FO $\varepsilon = 0.25$, iteration number of 20 with an initial value zero for the CME, and a multipath Rayleigh fading channel with length $L = 8$ and an exponential power delay profile of $\mathbf{E}[|h(l)|^2] = \exp(-l/L) / \left\{ \sum_{l=0}^{L-1} \exp(-l/L) \right\}$ for $l = 0, 1, \dots, 7$, where $\mathbf{E}[\cdot]$ denotes the statistical expectation. Since a CIS α S noise with $\alpha < 2$ does not assume a variance, the standard SNR becomes meaningless for such a noise. We thus employ the geometric SNR (GSNR) [11] defined as $\mathbf{E}[|x(k)|^2] / (4C^{-1+2/\alpha}\gamma^{2/\alpha})$, where $C = \exp\{\lim_{m \rightarrow \infty} (\sum_{i=1}^m \frac{1}{i} - \ln m)\} \simeq 1.78$ is the exponential of the Euler constant. The GSNR indicates the relative strength between the information-bearing signal and the CIS α S noise with $\alpha < 2$. Clearly, the GSNR becomes the standard SNR when $\alpha = 2$. Since γ can be easily and exactly estimated using only the sample mean and variance of the received samples [12], it may be regarded as a known value: Thus, γ is set to 1 without loss of generality.

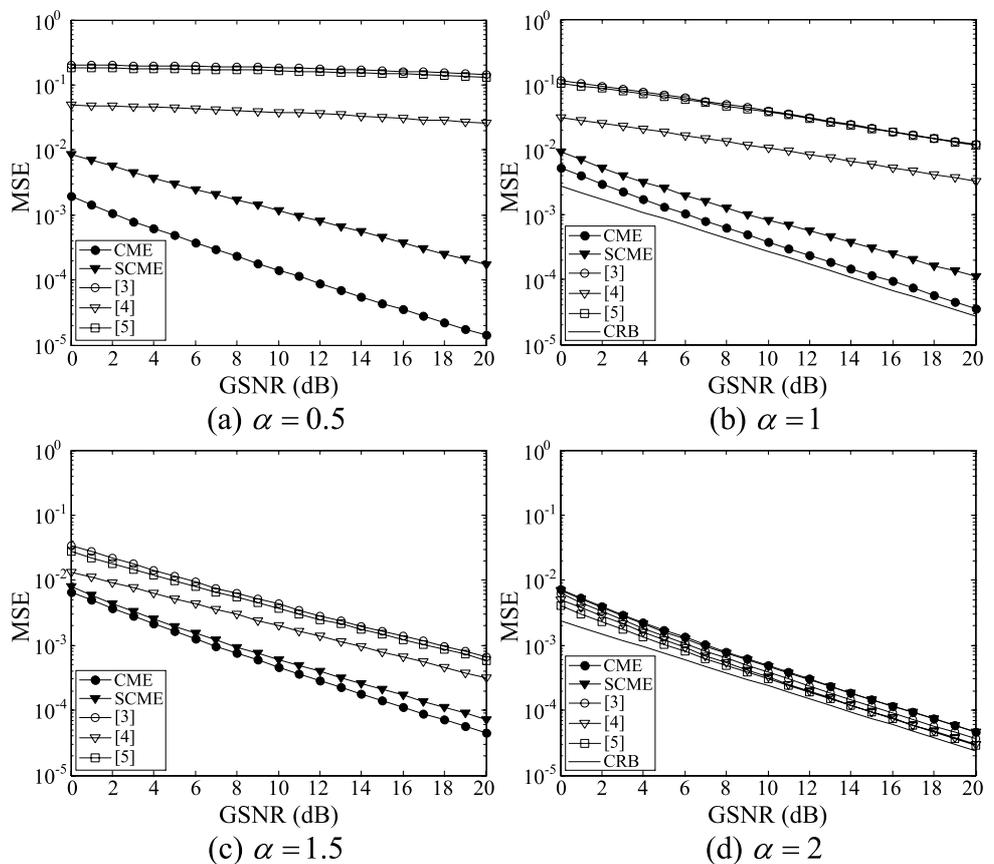


Fig. 1. The MSE performances of the proposed and conventional estimators as a function of the GSNR.

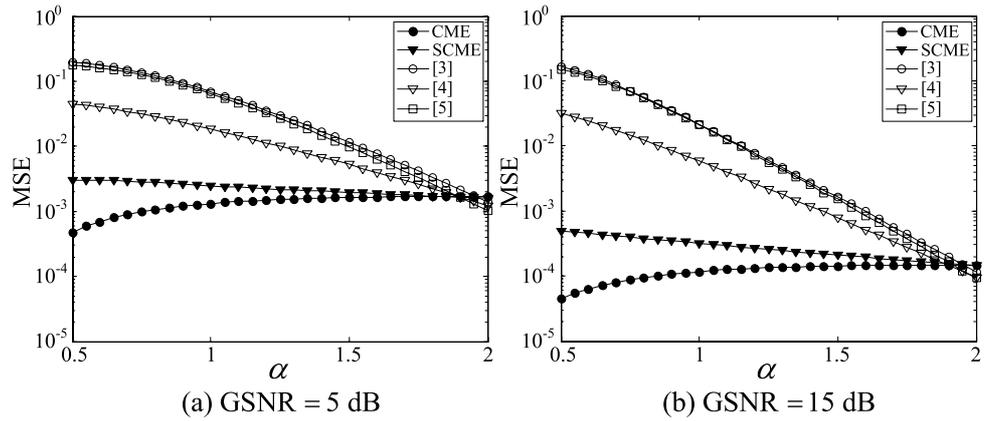


Fig. 2. The MSE performances of the proposed and conventional estimators as a function of α .

Table I. Correlation operations of the received OFDM samples in the proposed and conventional estimators.

Estimator	Correlation operation
CME	$\sum_{k=0}^{\frac{N}{2}-1} \frac{r^*(k)r(k+N/2)}{4\gamma^2 + r(k) ^2 + r(k+N/2) ^2 - 2 r(k)r(k+N/2) \cos(\pi\epsilon + \theta_k)}$
SCME	$\sum_{k=0}^{\frac{N}{2}-1} \frac{r^*(k)r(k+N/2)}{\sqrt{\{4\gamma^2 + (r(k) + r(k+N/2))^2\} \{4\gamma^2 + (r(k) - r(k+N/2))^2\}}}$
[3]	$\sum_{k=0}^{\frac{N}{2}-1} r^*(k)r(k+N/2)$
[4]	$\sum_{k=\frac{mN}{4}}^{N-1} r^*(k - mN/4)r(k), \text{ for } m = 0, 1, 2$
[5]	$\sum_{z=1}^{\frac{N}{16}-1} \left \sum_{m=0}^{\frac{N}{16}-z-1} \sum_{k=0}^{\frac{N}{4}-1} zr(k+mN/4)r^*(k+(m+z)N/4) \right $

Figure 1 shows the MSE performances of the proposed and conventional estimators as a function of the GSNR when $\alpha = 0.5, 1, 1.5,$ and 2 . Similarly, Figure 2 shows the MSE performances as a function of α when the GSNR is 5 and 15 dB. The Cramér-Rao bounds (CRBs) $\frac{15N^2}{32\pi^4 C(N^2-1)(\text{GSNR})}$ and $\frac{3N}{2\pi^2(N^2-1)(\text{GSNR})}$ [4, 8] for FO estimation when $\alpha = 1$ and 2 , respectively, are shown in Figures 1 (b) and (d) for reference.

From the figures, we can clearly observe that the proposed estimators not only outperform the conventional estimators for most values of α , except for those close to 2, but also provide a robustness to the variation of the value of α . This can be explained from Table I showing the correlation operations

of the received OFDM samples in the proposed and conventional estimators. The correlation operations of the received OFDM samples in the proposed estimators involve sample-by-sample normalization by the terms including the magnitude of the received OFDM samples. As it is well-known in signal detection theory [13, 14], such normalization can effectively alleviate the erroneous increase of the correlation due to noise samples of large magnitudes arising frequently in non-Gaussian noise environments, and allows the proposed estimators to yield more reliable estimates than the conventional estimators in impulsive (non-Gaussian) environments.

5 Conclusion

In this paper, we have proposed robust FO estimators for OFDM systems in non-Gaussian noise environments. Modeling the non-Gaussian noise as a complex isotropic Cauchy process, an ML estimator using an iterative procedure has been first derived. A simpler estimator has then been proposed based on the ML estimator. From numerical results, we have confirmed that the proposed estimators not only outperform the conventional estimators, but also provide a robustness in non-Gaussian noise environments.

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