

Estimation of Channel Transfer Function and Carrier Frequency Offset for OFDM Systems With Phase Noise

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Abstract—The joint estimation of carrier frequency offset (CFO) and channel transfer function (CTF) for orthogonal frequency-division multiplexing (OFDM) systems with phase noise is discussed in this paper. A CFO estimation algorithm is developed by exploring the time–frequency structure of specially designed training symbols, and it provides a very accurate estimation of the CFO in the presence of both unknown frequency-selective fading and phase noise. Based on the estimated CFO, phase noise and frequency-selective fading are jointly estimated by employing the maximum *a posteriori* (MAP) criterion. Specifically, the fading channel is estimated in the form of the frequency-domain CTF. The estimation of the CTF eliminates the requirement of *a priori* knowledge of channel length, and it is simpler compared with the time-domain channel impulse response (CIR) estimation methods used in the literature. Theoretical analysis with the Cramer–Rao lower bound (CRLB) demonstrates that the proposed CFO and CTF estimation algorithms can achieve near-optimum performance.

Index Terms—Carrier frequency offset (CFO), channel estimation, channel transfer function (CTF), maximum *a posteriori* (MAP), orthogonal frequency-division multiplexing (OFDM), phase noise.

I. INTRODUCTION

THE orthogonal frequency-division multiplexing (OFDM) system has emerged as one of the most promising communication technologies for both wireless and wireline communications [1]–[5]. OFDM achieves broadband communication by multiplexing a large number of narrow-band data streams onto mutually orthogonal subcarriers via fast Fourier transform (FFT). The adoption of FFT greatly reduces implementation costs due to the advancement in digital signal processing and the very large scale integrated circuit. Compared with the single-carrier system, OFDM has higher spectral efficiency and

is less sensitive to intersymbol interference (ISI). However, the performance of OFDM systems is very sensitive to the carrier frequency offset (CFO) and phase noise. The CFO is caused by the Doppler shift and/or frequency mismatch between oscillators at the transmitter and the receiver; phase noise is the phase difference between the carrier and the local oscillator [6]. The CFO and phase noise, if not properly estimated and compensated, will cause amplitude reduction and phase drift in equalized symbols and introduce intercarrier interference, thus degrading the performance of OFDM systems [7]–[16].

CFO and phase noise estimations for OFDM systems have attracted considerable attention during the past decade [7]–[16]. A large number of algorithms have been developed for CFO estimation, where the CFO can be estimated by utilizing either specially designed training symbols [7], [8], redundant information contained in the cyclic prefix (CP) [9], [10], or null subcarriers embedded in one OFDM symbol [11], [12]. Works on phase noise estimation and suppression for OFDM systems can be found in [13]–[16]. In [13], a carrier recovery (CR) scheme is performed in the time domain with the aid of CR pilot tones for the estimation and compensation of phase noise. In [14] and [15], phase noise is estimated by using a parametric frequency-domain model of the received OFDM signal. In [16], phase noise cancellation is achieved via approximate probabilistic inference.

The proper operation of coherent OFDM systems demands the joint estimation of CFO, phase noise, and channel state information. In [17], the CFO is estimated and compensated before channel estimation, and phase noise is suppressed by passing the estimated channel impulse response (CIR) through a low-pass filter originally designed for additive noise suppression. In [18], joint CFO and channel estimation for multi-input–multi-output (MIMO) OFDM systems is performed by relying on null subcarriers and nonzero pilot symbols hopping from block to block. This specifically designed pilot pattern enables decoupling of CFO estimation and channel estimation. However, the optimum solution in [18] requires an exhaustive line search, which leads to high computational complexity. The CFO, timing error, and CIR for a multiuser orthogonal frequency-division multiple-access (OFDMA) uplink transmission are estimated in [19] with a maximum-likelihood (ML) criterion. Again, the ML solution in [19] requires an exhaustive search over a multidimensional grid spanned by CFOs and timing errors from multiple users. Although simplifications can be performed to reduce the search effort for the optimum

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solutions, the computational complexity is still high. A joint CFO/phase noise/CIR estimator (JCPCE) is presented in [20]. Similar to [18] and [19], the JCPCE suffers from high computational complexity due to the nonclosed-form estimation of the CFO. To reduce the complexity of the JCPCE, a modified JCPCE (MJCPCE) algorithm with closed-form CFO estimation is developed in [20] by adopting a special training symbol structure, as proposed in [7]. The MJCPCE algorithm requires knowledge of channel length, which is usually not available at the receiver before channel estimation. In addition, its practical value is seriously limited by the fact that it can only estimate the CFO with a value less than the frequency space between two adjacent subcarriers.

We present in this paper an enhanced algorithm for the efficient estimation of CFO, phase noise, and channel state information. The new algorithm does not suffer from any of the aforementioned limitations. CFO estimation is developed by exploring the time–frequency properties of two consecutive training symbols with structures similar to those used in [8]. The new method renders an accurate estimation of the CFO in the presence of both unknown frequency-selective fading and phase noise. More importantly, the CFO can take arbitrary values, as against the limitation imposed by the MJCPCE that the CFO must be less than the subcarrier space [20]. With the estimated CFO, phase noise and frequency-selective fading are jointly estimated based on the maximum *a posteriori* (MAP) criterion. In particular, the channel is estimated in terms of the frequency-domain channel transfer function (CTF), and it is different from the time-domain CIR estimation method used in the MJCPCE. The adoption of the CTF instead of the CIR leads to an estimator with lower complexity and better accuracy. In addition, it eliminates the requirement for *a priori* knowledge of channel length, which is usually unavailable at the receiver before channel estimation. The Cramer–Rao lower bound (CRLB) for the mean square error (MSE) of CTF estimation is derived to benchmark the performance of the proposed algorithm. Simulation results show that the new channel estimator can achieve performance close to the CRLB.

The remainder of this paper is organized as follows: In Section II, an OFDM system model with CFO and phase noise distortion is presented. In Section III, a CFO estimation method is first developed by exploring the time–frequency structure of the training symbols, and then, a joint phase noise and CTF estimation algorithm is developed based on the CFO-compensated signals. Simulation results are presented in Section V, and Section VI concludes this paper.

II. SYSTEM MODEL

A baseband OFDM signal can be obtained by performing normalized inverse discrete Fourier transform (IDFT) on a group of modulated symbols $s = [s_0, s_1, \dots, s_{N-1}] \in \mathcal{C}^{1 \times N}$ at the transmitter, i.e.,

$$x_n = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} s_k e^{j2\pi \frac{kn}{N}}, \quad -N_p \leq n < N \quad (1)$$

where N is the number of subcarriers, and $N_p \geq L$ is the length of the CP, with L being the length of the equivalent discrete-time CIR $\{h_l\}_{l=0}^{L-1}$. The adoption of the CP removes ISI, and it enables the conversion of linear channel convolution to circular convolution, which leads to simple equalization at the receiver.

We consider slow frequency-selective fading in this paper. The CIR is assumed to be constant over one slot duration, which contains two OFDM training symbols, followed by multiple OFDM data symbols [20]. The OFDM training symbol is generated by alternatively transmitting pilot symbols and zeros in the frequency domain. Without loss of generality, it is assumed that $N/2$ pilot symbols are transmitted on the even-indexed subcarriers and zeros on the odd-indexed subcarriers. The time-domain representation of the OFDM training symbol can then be expressed as

$$x_n = \frac{1}{\sqrt{N/2}} \sum_{k=0}^{N/2-1} s_{2k} e^{j2\pi \frac{kn}{N/2}}, \quad -N_p \leq n < N \quad (2)$$

where $\{s_{2k}\}_{k=0}^{N/2-1}$ are pilot symbols, and the normalization factor $1/\sqrt{N/2}$ is used in (2) to maintain constant OFDM symbol energy. The transmission of zeros on odd-indexed subcarriers results in $(N/2)$ -point IDFT in (2). In addition, it is clear from (2) that the time-domain OFDM training symbol has two identical halves, i.e., $\{x_n\}_{n=0}^{N/2-1}$ is exactly the same as $\{x_n\}_{n=N/2}^{N-1}$. This property of the training symbol will be exploited to assist CFO estimation.

At the receiver, after the removal of the CP, we have the time-domain samples of the received OFDM training symbol as

$$\begin{aligned} y_n &= e^{j(2\pi \frac{n\epsilon}{N} + \phi_n)} (h_n \otimes x_n) + v_n \\ &= e^{j(2\pi \frac{n\epsilon}{N} + \phi_n)} \frac{1}{\sqrt{N/2}} \sum_{k=0}^{N/2-1} s_{2k} H_{2k} e^{j2\pi \frac{kn}{N/2}} + v_n \end{aligned} \quad (3)$$

where $n = 0, 1, \dots, N-1$; \otimes denotes circular convolution; v_n is the additive white Gaussian noise (AWGN) with variance σ^2 ; ϵ is the CFO normalized with respect to the subcarrier space $1/(NT_s)$, with T_s being the sampling period at the receiver; ϕ_n is the phase noise distortion; and the frequency-domain CTF H_{2k} is defined as

$$H_{2k} = \sum_{l=0}^{L-1} h_l e^{-j2\pi \frac{2kl}{N}}, \quad 0 \leq k \leq N/2 - 1. \quad (4)$$

It should be noted that the circular convolution in the first equality of (3) is due to the insertion of the CP, and the relationship described in (3) is valid as long as $N_p \geq L$.

Defining $\mathbf{E} = \text{diag}\{1, e^{j2\pi\epsilon/N}, \dots, e^{j2\pi(N-1)\epsilon/N}\}$, $\mathbf{P} = \text{diag}\{e^{j\phi_0}, e^{j\phi_1}, \dots, e^{j\phi_{N-1}}\}$, $\mathbf{S} = \text{diag}\{s_0, s_2, \dots, s_{N-2}\}$, and $\mathbf{H} = [H_0, H_2, \dots, H_{N-2}]^t$, (3) can then be represented in matrix format as

$$\mathbf{y} = \mathbf{E}\mathbf{P}\tilde{\mathbf{H}}\mathbf{S}\mathbf{H} + \mathbf{v} \quad (5)$$

where $\mathbf{y} = [y_0, y_1, \dots, y_{N-1}]^t$; $\mathbf{v} = [v_0, v_1, \dots, v_{N-1}]^t$; $(\cdot)^t$ and $(\cdot)^h$ stand for transpose and Hermitian transpose, respectively; and $\tilde{\mathbf{H}} = [\mathbf{F}_{N/2}, \mathbf{F}_{N/2}] \in \mathcal{C}^{(N/2) \times N}$, with $\mathbf{F}_{N/2}$ being

the $(N/2)$ -point normalized DFT matrix. The (k, l) th element of $\mathbf{F}_{N/2}$ is $(\mathbf{F}_{N/2})_{k,l} = (1/\sqrt{N/2})e^{-j2\pi(k-1)(l-1)/(N/2)}$.

The statistical properties of phase noise depend on specific receiver implementations [6]. For a receiver equipped with a phase-locked loop (PLL), phase noise can be modeled as a zero-mean colored stationary Gaussian process [6]. When the system is only frequency locked, phase noise is modeled as a zero-mean nonstationary Wiener process [21]. Since the PLL is necessary for a coherent receiver, the stationary Gaussian process model, which has extensively been used in the literature [13], [16], [20], [22], is adopted in this paper. In this case, $\phi = [\phi_0, \phi_1, \dots, \phi_{N-1}]^t$ has a multivariate Gaussian distribution of $\phi \sim \mathcal{N}(\mathbf{0}_N, \mathbf{R}_\phi)$, where the mean vector $\mathbf{0}_N$ is a size $N \times 1$ all-zero vector, and \mathbf{R}_ϕ is the covariance matrix of ϕ . The value of \mathbf{R}_ϕ can be calculated with the specifications of a phase-locked voltage-controlled oscillator [21].

III. DEVELOPMENT OF THE ESTIMATION ALGORITHM

A. CFO Estimation in the Presence of Unknown Fading and Phase Noise

Based on the training symbol property $x_n = x_{n+N/2}$, for $n = 0, \dots, N/2 - 1$, the received time-domain training samples y_n and $y_{n+N/2}$ are the same, except for a phase difference in the absence of additive noise and phase noise [cf. (3)], i.e.,

$$y_n^* y_{n+N/2} = |y_n|^2 e^{j\pi\epsilon}. \quad (6)$$

Obviously, (6) is a periodic function of ϵ with period $2z$, where z is an integer. Thus, the CFO can be estimated by measuring the phase difference between $\mathbf{y}_1 = [y_0, y_1, \dots, y_{N/2-1}]^t$ and $\mathbf{y}_2 = [y_{N/2}, y_{N/2+1}, \dots, y_{N-1}]^t$, up to an ambiguity $2z$. In [20], CFO estimation with additive noise and phase noise rejection is performed in the time domain by measuring the phase difference between \mathbf{y}_1 and \mathbf{y}_2 , and the result can be written as

$$\hat{\epsilon} = \frac{1}{\pi} \angle \left[\mathbf{y}_1^h (\mathbf{Y}_1 \mathbf{R}_\Delta \mathbf{Y}_1^h + 2\sigma^2 \mathbf{I}_{N/2})^{-1} \mathbf{y}_2 \right] \quad (7)$$

where $\angle a \in (-\pi, \pi]$ returns the phase of the complex-valued number a ; $\mathbf{Y}_1 = \text{diag}\{\mathbf{y}_1\}$, with $\text{diag}\{\mathbf{a}\}$ being a diagonal matrix with the vector \mathbf{a} on its diagonal; $\mathbf{I}_{N/2}$ is a size $N/2$ identity matrix; and $\mathbf{R}_\Delta = 2\mathbf{R}_{N/2} - \mathbf{Y} - \mathbf{Y}^t$, with $\mathbf{R}_{N/2} \in \mathcal{C}^{(N/2) \times (N/2)}$ and $\mathbf{Y} \in \mathcal{C}^{(N/2) \times (N/2)}$ being submatrices of \mathbf{R}_ϕ , which is expressed as follows:

$$\mathbf{R}_\phi = \begin{bmatrix} \mathbf{R}_{N/2} & \mathbf{Y} \\ \mathbf{Y}^t & \mathbf{R}_{N/2} \end{bmatrix}. \quad (8)$$

The CFO estimation described in (7) implies that the estimated CFO satisfies $|\hat{\epsilon}| < 1$. When the actual CFO is larger than the subcarrier space, or $|\epsilon| > 1$, it fails to solve the ambiguity $2z$, with z being a nonzero integer, as indicated by (6). In other words, if we denote the CFO by $\epsilon = \epsilon_0 + 2z$, with $|\epsilon_0| < 1$, then only the fractional CFO ϵ_0 is estimated from (7).

We propose to estimate the integer part of the CFO, i.e., $2z$, in the frequency domain by utilizing two consecutive OFDM

training symbols. From (3), the received samples of the first and second OFDM training symbols can be written as

$$y_{1,n} = \sqrt{\frac{2}{N}} e^{j2\pi \frac{n\epsilon}{N}} e^{j\phi_n} \sum_{k=0}^{N/2-1} s_{1,2k} H_{2k} e^{j2\pi \frac{kn}{N/2}} + v_{1,n} \quad (9a)$$

$$y_{2,n} = \sqrt{\frac{2}{N}} e^{j2\pi \frac{(n+N+N_p)\epsilon}{N}} e^{j\phi_{n+N+N_p}} \times \sum_{k=0}^{N/2-1} s_{2,2k} H_{2k} e^{j2\pi \frac{kn}{N/2}} + v_{2,n} \quad (9b)$$

where $n = 0, 1, \dots, N-1$ for both $y_{1,n}$ and $y_{2,n}$. The ratio of the two training sequences $\{s_{1,2k}\}_{k=0}^{N/2-1}$ and $\{s_{2,2k}\}_{k=0}^{N/2-1}$ is set to be equal to a predefined pseudonoise (PN) sequence $\{\alpha_k\}_{k=0}^{N/2-1}$, i.e., $s_{2,2k}/s_{1,2k} = \alpha_k$.

The fractional CFO ϵ_0 is estimated with (7) and then compensated in $y_{1,n}$ and $y_{2,n}$, respectively, leading to the following approximation:

$$\hat{y}_{1,n} \approx \sqrt{\frac{2}{N}} \sum_{k=0}^{N/2-1} s_{1,2k} H_{2k} e^{j2\pi \frac{(k+z)n}{N/2}} + \hat{v}_{1,n} \quad (10a)$$

$$\hat{y}_{2,n} \approx \sqrt{\frac{2}{N}} e^{j4\pi \frac{zN_p}{N}} \sum_{k=0}^{N/2-1} s_{2,2k} H_{2k} e^{j2\pi \frac{(k+z)n}{N/2}} + \hat{v}_{2,n} \quad (10b)$$

where $\hat{v}_{1,n}$ and $\hat{v}_{2,n}$ are the noise components after fractional CFO compensation, and the approximation $e^{j[\phi_n + 2\pi n(\epsilon_0 - \hat{\epsilon}_0)/N]} \approx 1$ is used in the preceding equations based on the fact that the combined disturbance of the phase noise and residual CFO is usually small in practice [13]. It should be noted that the approximation used in (10) is only for the convenience of integer CFO estimation. The actual phase noise will be estimated and compensated during channel estimation described in the next section. It will be shown in simulation that the integer CFO $2z$ can accurately be estimated, even with the approximation used in (10).

The estimation of $2z$ is performed in the frequency domain. Performing N -point DFT on $\hat{y}_{1,n}$ and $\hat{y}_{2,n}$ leads to

$$\hat{Y}_{1,k} = \sqrt{2} s_{1,(k-2z)_N} H_{(k-2z)_N} + \hat{V}_{1,k} \quad (11a)$$

$$\hat{Y}_{2,k} = \sqrt{2} e^{j4\pi z N_p / N} s_{2,(k-2z)_N} H_{(k-2z)_N} + \hat{V}_{2,k} \quad (11b)$$

where $(\cdot)_N$ denotes modulus N operation, and $\hat{Y}_{i,k}$ and $\hat{V}_{i,k}$ are the DFTs of $\hat{y}_{i,n}$ and $\hat{v}_{i,n}$, respectively, for $i = 1$ and 2 . There is a phase difference $e^{j4\pi z N_p / N}$ between $\hat{Y}_{1,k}$ and $\hat{Y}_{2,k}$ in the frequency domain, and the phase difference is independent of the subcarrier index k . Define the metric used to estimate z as

$$\mathcal{M}(z) = \left| \sum_{k=0}^{N/2-1} \hat{Y}_{1,2k+2z}^* \alpha_k^* \hat{Y}_{2,2k+2z} \right| \quad (12)$$

where $(\cdot)^*$ denotes complex conjugate. With $\mathcal{M}(z)$ defined in (12), the estimated value of z is obtained as

$$\hat{z} = \arg \max_{z \in \mathcal{I}} \mathcal{M}(z). \quad (13)$$

The estimation of the CFO, i.e., $\epsilon = \epsilon_0 + 2z$, can then be expressed as $\hat{\epsilon} = \hat{\epsilon}_0 + 2\hat{z}$.

It should be noted that with the estimation method derived from (11) and (12), the value of the integer CFO z must satisfy $|z| < N/4$, due to the fact that both $\hat{Y}_{1,k}$ and $\hat{Y}_{2,k}$ in (11) are periodic functions of z with period $N/2$. In a practical OFDM system, it is reasonable to assume that the CFO (proportional to $2z$) is much less compared with the OFDM signal bandwidth (proportional to N). Therefore, the additional restriction of $|z| < N/4$ can be met in most practical OFDM systems.

An alternative null-subcarrier-based suboptimum integer CFO estimation algorithm was presented in [11] by transmitting zeros not only on odd subcarriers but on part of the even subcarriers of the OFDM training symbol as well. While the method requires only one OFDM training symbol, the reduction in the number of nonnull even-indexed subcarriers leads to inferior estimation of the overall CIR. Simulation results show that the algorithm proposed in this paper obtains a more accurate estimation of the CFO compared with that in [11] at a low signal-to-noise ratio (SNR).

B. Joint Phase Noise and CTF Estimation

With the estimated CFO $\hat{\epsilon}$, we are able to construct $\hat{\mathbf{E}} = \text{diag}\{1, e^{j2\pi\hat{\epsilon}/N}, \dots, e^{j2\pi\hat{\epsilon}(N-1)/N}\}$ as the CFO compensation matrix. Multiplying both sides of (5) with $\hat{\mathbf{E}}^h$ leads to

$$\tilde{\mathbf{y}} = \mathbf{P}_{\text{eff}} \tilde{\mathbf{F}}^h \mathbf{S} \mathbf{H} + \tilde{\mathbf{v}} \quad (14)$$

where $\tilde{\mathbf{y}} = \hat{\mathbf{E}}^h \mathbf{y}$, and $\mathbf{P}_{\text{eff}} = (\Delta \mathbf{E}) \mathbf{P}$ is the effective phase noise matrix after CFO compensation, with $\Delta \mathbf{E} = \text{diag}\{1, e^{j2\pi\Delta\epsilon/N}, \dots, e^{j2\pi\Delta\epsilon(N-1)/N}\}$ being a phase rotation matrix due to the CFO estimation error $\Delta\epsilon = \epsilon - \hat{\epsilon}$. The equivalent noise $\tilde{\mathbf{v}} = \hat{\mathbf{E}}^h \mathbf{v}$ is still the AWGN with a covariance matrix $\sigma^2 \mathbf{I}$.

The effective phase noise matrix can alternatively be represented as $\mathbf{P}_{\text{eff}} = \text{diag}\{\phi_{\text{eff}}\}$, where $\phi_{\text{eff}} = [\phi_0, \phi_1 + 2\pi(\Delta\epsilon/N), \dots, \phi_{N-1} + 2\pi(\Delta\epsilon(N-1)/N)]^t$. The vector ϕ_{eff} has a multivariate Gaussian distribution of $\phi_{\text{eff}} \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_{\phi_{\text{eff}}})$. The covariance matrix $\mathbf{R}_{\phi_{\text{eff}}}$ depends on the variance of the residual CFO $\Delta\epsilon$. At a high SNR, the variance of $\Delta\epsilon$ can be approximated by [7], [8]

$$\sigma_{\Delta\epsilon}^2 = \frac{1}{\pi^2 \cdot (N/2) \cdot \gamma} \quad (15)$$

where γ denotes the SNR in linear scale. Therefore, the covariance matrix of ϕ_{eff} can accurately be approximated as $\mathbf{R}_{\phi_{\text{eff}}} = \mathbf{R}_{\phi} + (8/(N^3\gamma)) \mathbf{T}$, where $\mathbf{T} = \mathbf{b}\mathbf{b}^t$, with $\mathbf{b} = [0, 1, \dots, N-1]^t$. Noting the fact that the scaling factor $8/(N^3\gamma)$ of \mathbf{T} is inversely proportional to N^3 , whereas the maximum element in \mathbf{T} is on the order of N^2 , we conclude that the effect of the residual CFO on phase noise is negligible for practical values of N . As a result, it is reasonable to assume that ϕ_{eff} has the same distribution as ϕ , i.e., $\phi_{\text{eff}} \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_{\phi})$. Simulation results show that the assumption of $\phi_{\text{eff}} \sim \mathcal{N}(\mathbf{0}, \mathbf{R}_{\phi})$ is valid under both low and high SNRs, and it does not apparently affect the accuracy of the proposed channel estimation method.

The MAP criterion is adopted for the joint estimation of ϕ_{eff} and \mathbf{H} . From (14), the *a posteriori* probability density of ϕ_{eff}

and \mathbf{H} can be written as

$$p(\phi_{\text{eff}}, \mathbf{H} | \tilde{\mathbf{y}}) = p(\tilde{\mathbf{y}} | \phi_{\text{eff}}, \mathbf{H}) p(\phi_{\text{eff}}) p(\mathbf{H}) / p(\tilde{\mathbf{y}}) \quad (16)$$

where it is assumed that ϕ_{eff} and \mathbf{H} are mutually independent. In practice, *a priori* knowledge of channel is usually unavailable; therefore, it is reasonable to treat \mathbf{H} as an unknown constant during channel estimation. Thus, $p(\mathbf{H}) = 1$. From (16), the negative log-likelihood function can be written as

$$\begin{aligned} \mathcal{L}(\phi_{\text{eff}}, \mathbf{H}) &= -\log p(\phi_{\text{eff}}, \mathbf{H} | \tilde{\mathbf{y}}) \\ &= -\log p(\tilde{\mathbf{y}} | \phi_{\text{eff}}, \mathbf{H}) - \log p(\phi_{\text{eff}}) + \log p(\tilde{\mathbf{y}}). \end{aligned} \quad (17)$$

Discarding irrelevant constants and noting that $p(\tilde{\mathbf{y}})$ is irrelevant to specific values of ϕ_{eff} and \mathbf{H} , we define the cost function for the MAP criterion as

$$\mathcal{J}(\phi_{\text{eff}}, \mathbf{H}) = \frac{1}{\sigma^2} \|\tilde{\mathbf{y}} - \mathbf{P}_{\text{eff}} \tilde{\mathbf{F}}^h \mathbf{S} \mathbf{H}\|^2 + \frac{1}{2} \phi_{\text{eff}}^t \mathbf{R}_{\phi}^{-1} \phi_{\text{eff}} \quad (18)$$

where $\|\mathbf{a}\|^2 = \mathbf{a}^h \mathbf{a}$ for a column vector \mathbf{a} .

Solving $\partial \mathcal{J}(\phi_{\text{eff}}, \mathbf{H}) / \partial \mathbf{H}^* = 0$ leads to the optimal estimation of the CTF vector \mathbf{H} , i.e.,

$$\hat{\mathbf{H}} = \frac{1}{2} \mathbf{S}^{-1} \tilde{\mathbf{F}} \mathbf{P}_{\text{eff}}^h \tilde{\mathbf{y}}. \quad (19)$$

The solution in (19) requires knowledge of effective phase noise matrix \mathbf{P}_{eff} . When \mathbf{P}_{eff} is ideally estimated, the channel estimator given by (19) is a minimum variance unbiased estimator (MVUE) for \mathbf{H} [23].

To estimate \mathbf{P}_{eff} , substituting (19) into (18) yields

$$\mathcal{J}(\phi_{\text{eff}}) = \frac{1}{\sigma^2} \mathbf{p}^t \mathbf{B} \mathbf{p}^* + \frac{1}{2} \phi_{\text{eff}}^t \mathbf{R}_{\phi}^{-1} \phi_{\text{eff}} \quad (20)$$

where $\mathbf{p} = e^{j\phi_{\text{eff}}}$, $\mathbf{B} = \tilde{\mathbf{Y}}^h (\mathbf{I}_N - (1/2) \tilde{\mathbf{F}}^h \tilde{\mathbf{F}}) \tilde{\mathbf{Y}}$, and $\tilde{\mathbf{Y}} = \text{diag}\{\tilde{\mathbf{y}}\}$. Using the approximation of $\mathbf{p} = e^{j\phi_{\text{eff}}} \approx \mathbf{1}_N + j\phi_{\text{eff}}$ for small ϕ_{eff} [13] and solving $\partial \mathcal{J}(\phi_{\text{eff}}) / \partial \phi_{\text{eff}} = 0$, we have the optimal estimation of ϕ_{eff} as

$$\hat{\phi}_{\text{eff}} = \left[\text{Re}(\mathbf{B}) + (\sigma^2/2) \mathbf{R}_{\phi}^{-1} \right]^{-1} \text{Im}(\mathbf{B}) \mathbf{1}_N \quad (21)$$

where $\text{Re}(\cdot)$ and $\text{Im}(\cdot)$ are the real and imaginary part operators, respectively, and $\mathbf{1}_N$ denotes an $N \times 1$ all-one column vector. Obviously, the estimation of $\hat{\phi}_{\text{eff}}$ is independent of the modulation data matrix \mathbf{S} , which, on the other hand, is required by the MJCPCE method in [20]. The independence of the estimation on \mathbf{S} leads to a much simpler form of the estimator, which requires less computational complexity and no *a priori* knowledge of transmitted modulation symbols, as compared with the phase noise estimator provided by MJCPCE method.

The estimated value of $\hat{\phi}_{\text{eff}}$ can then be substituted back into (19) to obtain an estimate of the CTF vector $\hat{\mathbf{H}}$. Equation (19) provides an estimation of $\mathbf{H} \in \mathcal{C}^{(N/2) \times 1}$, which is the CTF of even-indexed subcarriers. The estimation of the normalized CTF on all subcarriers can be calculated from $\hat{\mathbf{H}}$ as

$$\hat{\mathbf{H}}_{\text{full}} = \sqrt{2/N} \mathbf{F}_N \left[\left(\mathbf{F}_{N/2}^h \hat{\mathbf{H}} \right)^t \mathbf{0}_{N/2}^t \right]^t \quad (22)$$

where \mathbf{F}_N is the N -point normalized DFT matrix, with the (k, l) th element being $(\mathbf{F}_N)_{k,l} = (1/\sqrt{N})e^{-j2\pi(k-1)(l-1)/N}$; and $\mathbf{0}_{N/2}$ is an all-zero column vector with size $N/2$. Furthermore, the time-domain channel CIR $\mathbf{h} = [h_0, h_1, \dots, h_{L-1}]^t$ can be estimated by performing IDFT over the estimated CTF vector $\hat{\mathbf{H}}$ as [cf. (4)]

$$\hat{\mathbf{h}} = \sqrt{2/N}\mathbf{F}_{1:L}^h \hat{\mathbf{H}} \quad (23)$$

where $\mathbf{F}_{1:L} \in \mathcal{C}^{(N/2) \times L}$ contains the first L columns of the $(N/2)$ -point DFT matrix $\mathbf{F}_{N/2}$. In the case that the channel length L is unknown, the matrix $\mathbf{F}_{1:L}$ can be replaced by $\mathbf{F}_{N/2}$. Replacing $\mathbf{F}_{1:L}$ with $\mathbf{F}_{N/2}$ leads to an estimated CIR with $N/2$ channel taps, where the first L channel taps are exactly the same as those estimated by using $\mathbf{F}_{1:L}$, and the remaining $N/2 - L$ channel taps contain pure noise. In this case, the estimation accuracy can be improved by either directly discarding channel taps with negligible power [24] or applying the noise-reduction algorithm [25].

Compared with the MJCPCE method presented in [20], the algorithm proposed in this paper has three main advantages: First, the new algorithm can accurately estimate the CFO with arbitrary values, whereas the method in [20] can only estimate the CFO with a value less than the subcarrier space. Second, estimating the frequency-domain CTF instead of the time-domain CIR leads to a simpler estimator with lower computational complexity. Third, knowledge of channel length L is not required during CTF estimation, whereas the estimation procedure in [20] depends on L . The newly presented estimation method can easily be extended to single-input-multiple-output (SIMO) systems with independent CFO, phase noise, and fading channel on different receive antennas.

IV. CRLB FOR OFDM CHANNEL ESTIMATION

The CRLBs of the MSE for the estimation of the frequency-domain CTF, i.e., \mathbf{H} and \mathbf{H}_{full} , and the time-domain CIR, i.e., \mathbf{h} , are derived in this section.

In the absence of CFO and phase noise, the log-likelihood function $\log p(\mathbf{y}|\mathbf{H})$ can be calculated from (5) as

$$\log p(\mathbf{y}|\mathbf{H}) = c - \frac{1}{\sigma^2} (\mathbf{y} - \tilde{\mathbf{F}}^h \mathbf{S} \mathbf{H})^h (\mathbf{y} - \tilde{\mathbf{F}}^h \mathbf{S} \mathbf{H}) \quad (24)$$

where c is a constant, independent of \mathbf{y} and \mathbf{H} . The CRLB for the estimation of \mathbf{H} can then be calculated as

$$\begin{aligned} \text{CRLB}(\mathbf{H}) &= \text{tr} \left\{ \left[\mathbb{E} \left\{ \left[\frac{\partial}{\partial \mathbf{H}^*} [\log p(\mathbf{y}|\mathbf{H})] \right] \right. \right. \right. \\ &\quad \left. \left. \left. \times \left[\frac{\partial}{\partial \mathbf{H}^*} [\log p(\mathbf{y}|\mathbf{H})] \right]^h \right] \right\}^{-1} \right\} \\ &= \frac{\sigma^2}{2} \text{tr} \left\{ \left\{ \mathbb{E}[\mathbf{S}^h \mathbf{S}] \right\}^{-1} \right\} \end{aligned} \quad (25)$$

where $\text{tr}\{\cdot\}$ denotes the trace of a square matrix, and $\mathbb{E}\{\cdot\}$ denotes the mathematical expectation. Based on (22) and (25),

it is easy to obtain the CRLB for the estimation of normalized \mathbf{H}_{full} as

$$\text{CRLB}(\mathbf{H}_{\text{full}}) = \frac{2}{N} \times \text{CRLB}(\mathbf{H}) = \frac{\sigma^2}{N} \text{tr} \left\{ \left\{ \mathbb{E}[\mathbf{S}^h \mathbf{S}] \right\}^{-1} \right\}. \quad (26)$$

Similarly, from (23) and (25), the CRLB for the estimation of the CIR vector \mathbf{h} is obtained as

$$\text{CRLB}(\mathbf{h}) = \frac{\sigma^2}{N} \text{tr} \left\{ \left\{ \mathbf{F}_{1:L}^h \mathbb{E}[\mathbf{S}^h \mathbf{S}] \mathbf{F}_{1:L} \right\}^{-1} \right\}. \quad (27)$$

If the modulation symbols are equiprobable and independent, i.e., $\mathbb{E}[\mathbf{S}^h \mathbf{S}] = \sigma_s^2 \mathbf{I}$, then (26) and (27) can be simplified to

$$\text{CRLB}(\mathbf{H}_{\text{full}}) = \frac{1}{2} \cdot \frac{\sigma^2}{\sigma_s^2} \quad (28)$$

$$\text{CRLB}(\mathbf{h}) = \frac{L}{N} \cdot \frac{\sigma^2}{\sigma_s^2}. \quad (29)$$

We conclude this section with the following two remarks.

Remark 1: From (28) and (29), we find $\text{CRLB}(\mathbf{H}_{\text{full}}) \neq \text{CRLB}(\mathbf{h})$ when $N \neq 2L$. The difference is due to the fact that the estimation of \mathbf{h} in (23) depends on knowledge of channel length L , whereas \mathbf{H}_{full} is estimated without knowledge of L .

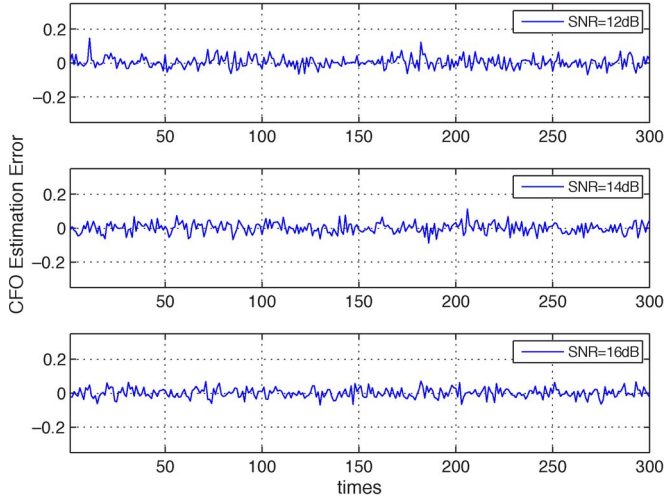
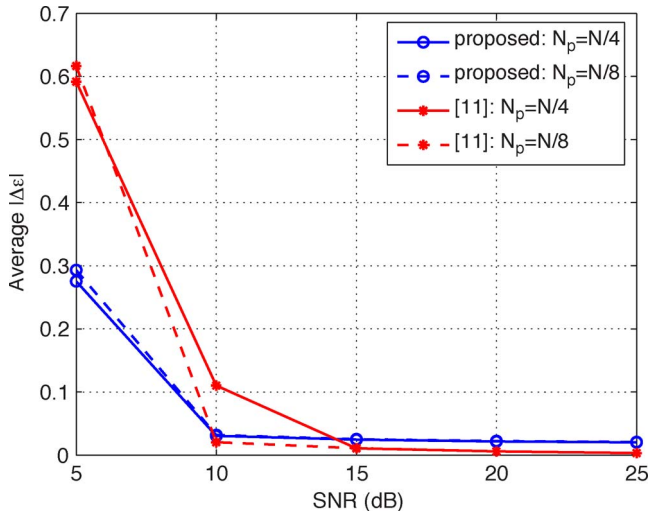
Remark 2: From (19), the channel-estimation MSE can be evaluated as

$$\mathbb{E} \left[\|\mathbf{H} - \hat{\mathbf{H}}\|^2 \right] = \frac{\sigma^2}{2} \text{tr} \left\{ \mathbb{E} \left[(\mathbf{S} \mathbf{S}^h)^{-1} \right] \right\} \quad (30)$$

which is equal to the CRLB given by (25) when the constant modulus modulation scheme, such as phase-shift keying (PSK), is adopted. In other words, if \mathbf{P}_{eff} is ideally estimated, then the CRLB for the estimation of \mathbf{H} can be achieved for systems with constant modulus modulation. On the other hand, for a nonconstant modulus-modulation scheme, the MSE in (30) is always larger than the CRLB bound in (25). This means that even if the obtained estimator is still the MVUE, the CRLB can never be reached for systems with nonconstant modulus-modulation schemes. Therefore, in terms of channel estimation, constant modulus-modulation schemes are preferable compared with nonconstant modulus-modulation schemes under the same energy constraint.

V. SIMULATION

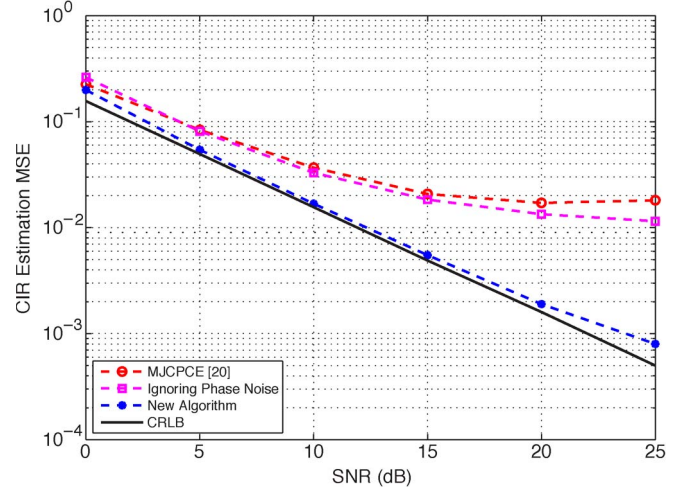
Simulation results are presented in this section to verify the performance of the proposed algorithm. System parameters similar to those used in [20] are adopted here for comparison purposes: The number of subcarriers is $N = 64$, and the system sampling rate is $f_s = 1/T_s = 20$ MHz, leading to a subcarrier space of $\Delta f = f_s/N = 312.5$ kHz. Phase noise is simulated by passing a white Gaussian process through a one-pole Butterworth low-pass filter with a 3-dB bandwidth $f_o = 100$ kHz. The covariance matrix of phase noise \mathbf{R}_ϕ is calculated as $(\mathbf{R}_\phi)_{m,n} = (\pi \phi_{\text{rms}}/180)^2 \exp\{-2\pi f_o |m - n|/f_s\}$. The fractional CFO ϵ_0 is generated as a uniform distribution over $(-1, 1)$, and the integer CFO z is randomly taken from $[-z_m, z_m]$, with $|z_m| < N/4$. Frequency-selective fading has a power

Fig. 1. CFO estimation error ($\epsilon_0 \in (-1, 1)$, $z \in [-14, 14]$, QPSK).Fig. 2. Average $|\Delta\epsilon|$ versus SNR ($\epsilon_0 \in (-1, 1)$, $z \in [-14, 14]$, QPSK).

delay profile of $1.2257 \times e^{-0.8l}$ ($0 \leq l < L$), which is normalized to unit energy. The CP length N_p is selected so that ISI is avoided among OFDM symbols. Unless otherwise specified, QPSK modulation is adopted, and ϕ_{rms} is set to 6° in the simulations. The PN sequence $\{\alpha_k\}_{k=0}^{N/2-1}$ is randomly generated from the set $\{1, j, -j, -1\}$.

We first investigate the accuracy of CFO estimation. The channel length is chosen as $L = 8$. The integer CFO is in the range of $[-14, 14] \subset [-(N/4 - 1), N/4 - 1]$, with $N/4 - 1$ being the maximum integer CFO that can be estimated by the proposed method. Fig. 1 plots the residual CFO $\Delta\epsilon = \epsilon - \hat{\epsilon}$ at different SNRs. For each SNR, 300 independent CFO estimations are performed at the presence of phase noise. From the figure, it is obvious that the residual CFO $\Delta\epsilon$ is consistently less than 0.2. This observation indicates that the proposed algorithm can accurately estimate the integer part of the CFO without error, i.e., $\hat{z} = z$, at the presence of unknown frequency-selective fading and phase noise.

The 1000-times averaged absolute residual CFO $|\Delta\epsilon|$ is shown in Fig. 2 as a function of the SNR, with $N_p = N/4$ and $N_p = N/8$, respectively. For comparison purposes, the results

Fig. 3. CTF estimation MSE versus SNR (QPSK, $\epsilon_0 \in (-1, 1)$, $z = 0$).

obtained with the CFO estimation method in [11] are also shown in this figure. For fairness of comparison, the power of the pilot symbol used in the method of [11] is maintained to be the same as the pilot symbol in our proposed method. As expected, the average absolute CFO estimation error for both methods monotonically decreases with the increase of the SNR. The proposed method is better than [11] at a low SNR. When the SNR is high, the residual CFO $|\Delta\epsilon|$ from both methods is very small and, thus, has a negligible impact on the subsequent channel estimation.

The performance of the joint phase noise and CTF estimation algorithm is studied in the next example, where the channel length is set as $L = 10$, and $N_p = N/4$. We first consider the case when $|\epsilon| < 1$, and the performance of systems with arbitrary ϵ is discussed in the next example. Fig. 3 illustrates the MSE and the corresponding CRLB of the estimated normalized CTF \hat{H}_{full} in the presence of phase noise. The results from the MJCPCE method [20] and the proposed algorithm neglecting phase noise are also shown in the figure for comparison. Obviously, the new algorithm achieves performance that is very close to the CRLB. As expected, the estimation performance degrades when phase noise is ignored. For the MJCPCE method, it has been shown in [20] that its MSE performance is very close to the CRLB when $|\epsilon| < 0.4$. However, its performance degrades when the range of ϵ is extended to $(-1, 1)$, as evidenced in Fig. 3. The performance degradation of the MJCPCE method is caused by phase flipping introduced during CFO estimation. Phase flipping refers to the case when $-\pi$ is estimated as π , or *vice versa*, when the phase difference $\pi\epsilon$ in (6) approaches $-\pi$ or π . The performance of the MJCPCE method greatly suffers from phase flipping, even in systems with only fractional CFO. Due to phase flipping, the inclusion of CFO estimation and compensation in the MJCPCE results in worse performance compared with the case when the CFO is not estimated at all. Phase flipping also happens in the proposed method. However, the incorrectly estimated fractional CFO caused by phase flipping can easily be corrected by integer CFO estimation. Therefore, the performance of the proposed method is not affected by phase flipping. Similar results are observed for CIR estimation, as shown in Fig. 4. We repeat

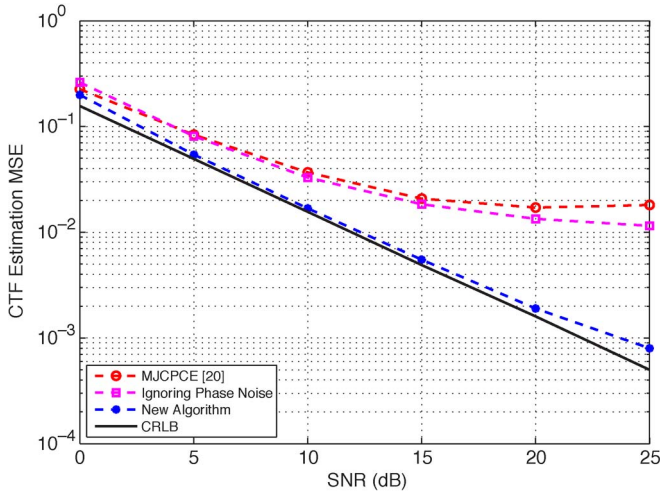


Fig. 4. CIR estimation MSE versus SNR (QPSK, $\epsilon_0 \in (-1, 1)$, $z = 0$).

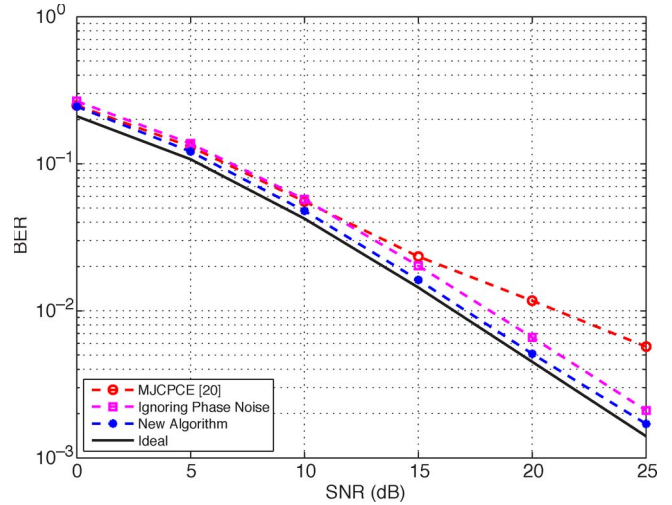


Fig. 6. BER versus SNR ($\epsilon_0 \in (-1, 1)$, $z = 0$, QPSK).

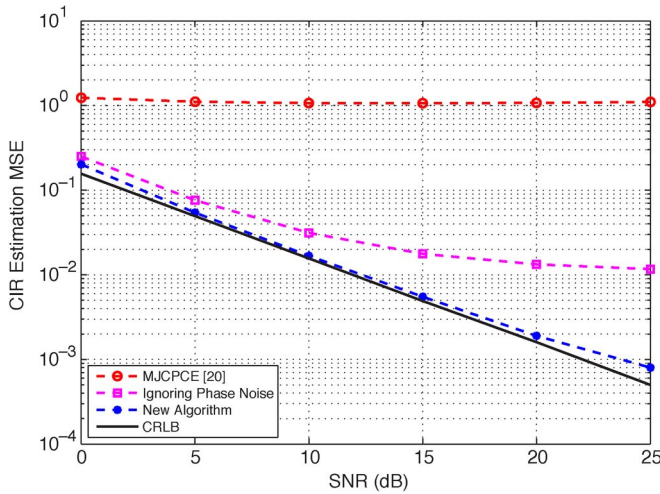


Fig. 5. CIR estimation MSE versus SNR (QPSK, $\epsilon_0 \in (-1, 1)$, $z \in [-4, 4]$).

the simulations for systems with 8PSK modulation and observe that the proposed algorithm performs consistently well and has better performance than the MJCPCE method. Finally, we note that the unresolvable residual common-phase rotation (RCPR), which means that phase noise can accurately be estimated but differs from that of the actual by a constant phase rotation, also exists in the proposed method, as in [20]. Detailed analysis of the cause of the RCPR is given in [20].

The next example demonstrates channel estimation performance when the integer CFO z is introduced, in addition to the fractional CFO ϵ_0 . The maximum integer CFO is set as $z_m = 4$. The MSE results, along with the CRLB of CIR estimation, are presented in Fig. 5. As expected, the MJCPCE method, which neglects the integer CFO, does not properly function under such a system configuration. The proposed scheme, on the other hand, consistently works well, regardless of the presence of the integer CFO.

The uncoded bit error rates (BERs) obtained from different channel-estimation algorithms are compared in Fig. 6. Phase noise has a standard deviation of $\phi_{\text{rms}} = 10^\circ$. Each slot consists of 52 OFDM symbols, with the first two as training symbols. Each BER point is obtained by simulating 1000 slots. The

BER curve for the system with ideal channel estimation is plotted as a reference. The performance of the system with the proposed channel-estimation method is only 0.5 dB away from the system with ideal channel estimation. This corroborates the MSE results presented in the previous figures.

VI. CONCLUSION

A new channel-estimation algorithm for OFDM systems with CFO and phase noise has been presented in this paper. The CFO was estimated by a hybrid time–frequency estimation method. Specifically, the fractional part of the CFO was estimated by identifying the phase difference between the time-domain samples from the same training symbol, whereas the integer part of the CFO was estimated by utilizing the frequency-domain samples residing on the same subcarrier but belonging to different training symbols. Simulation results show that the integer part of the CFO can be estimated without error, even at a low SNR. With the CFO-compensated signal, a joint phase noise and CTF estimation algorithm was developed by employing the MAP criterion over the time-domain samples. Compared with the CIR estimation algorithm in the literature, the new algorithm has lower complexity and better accuracy, and it can operate without knowledge of channel length in the time domain. Simulation results show that the joint phase noise and CTF estimation algorithm achieves MSE performance close to the CRLB. The proposed estimation method can easily be extended to SIMO OFDM systems with independent fading channels.

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