A Blind Carrier Frequency Offset Estimation Scheme for OFDM Systems via Hybrid-ICA algorithm

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ABSTRACT

This paper addresses a new iterative blind carrier frequency offset (CFO) estimator in orthogonal frequency-division multiplexing (OFDM) systems. In our scenario, relying on a hybrid independent component analysis (ICA) scheme, a blind frequency offset estimator is proposed for OFDM systems employing single antenna. The proposed estimator is a combination of the fast fixed-point ICA (FastICA) algorithm and the natural-gradient ICA algorithm, which inherits the fast convergence and high accuracy of these algorithms, respectively. As a major advantage, the proposed estimator works in an efficient way in practical high-data-rate OFDM systems especially with large number of subcarriers. To demonstrate the efficiency of our proposed algorithm, numerical results are provided from computer simulations and comparisons are made with other existing CFO estimators in the literature. It is shown that by applying our proposed algorithm, the normalized mean-square error of the CFO estimator is decreased to a high extent.

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1. INTRODUCTION

Orthogonal frequency division multiplexing (OFDM) has received considerable attention in the last decade as an efficient transmission technique for wireless communications. It has been adopted in different broadband communication systems including European digital audio broadcasting systems (DAB), Digital Multimedia Broadcasting (DMB), Digital Video Broadcast-Handheld (DVB-H), Media Forward Link Only (MediaFLO) and Wireless Local Area Networks (WLANs) due to its immunity to frequency selective multipath fading channel, along with high frequency spectral efficiency [1], [2]. As a brief look, OFDM divides a wideband frequency selective channel into multiple narrow band flat fading sub-channels in which the information bits can be transmitted in parallel through a large number of orthogonal subcarriers and the bandwidth of each subcarrier is much less than the channel coherence bandwidth [3]. In addition, a cyclic prefix (CP) is inserted in each OFDM symbol to combat hostile effect of inter-symbol interference (ISI) caused by dispersive environment. However, OFDM is highly vulnerable to carrier frequency offset (CFO) due to oscillator mismatch, Doppler frequency spread and phase noise at both the transmitter and the receiver [4]. This phenomenon causes a loss of subcarrier orthogonality and leads to inter carrier interference (ICI) between the subcarriers and hence CFO greatly deteriorates the performance of OFDM systems. Therefore, it seems necessary to cancel the CFO effect through an accurate estimation in practical OFDM systems.
There are different classes of blind CFO estimators. One approach has been proposed by utilizing null subcarriers existing in many practical OFDM systems [7]. This scheme provides robustness against channel multipath, but the computational complexity is relatively high. A constant modulus (CM)-based scheme is proposed in [8]. This scheme exploits the correlation of the squared amplitude spectrum of the channels by using the gradient descent method for minimizing the cost function, which makes it complex. Another blind (CM)-based scheme by using the circular shifts of OFDM blocks is proposed in [9]. This scheme, first the covariance matrix is calculated by the circular shifts of the received signal and second from the banded structure of the covariance matrix in the absence of CFO, the CFO is estimated through minimization of the powers outside the band. On the other hand, blind estimators using the cyclic prefix or the cyclostationarity (CS) of the OFDM transmissions [9], [10] have lower complexity, but their performance degrades as the frequency selectivity becomes more noticeable. The blind algorithm for joint ST and CFO estimation proposed in [11] is based on conjugate-symmetry property that approximately holds in the beginning of a burst of OFDM/OQAM symbols which provides acceptable performance for reasonable values of the signal-to-noise ratio. In [13], a kurtosis-based blind CFO estimator is exploited for OFDM systems. The kurtosis metric is used to construct a kurtosis-type cost function for fine CFO estimation. Although this scheme has the advantage of low complexity, its estimation accuracy requires a large number of OFDM blocks which causes processing delay. In [13], [14], two blind iterative CFO estimators based on ICA approach for SISO-OFDM are proposed which are suffering from estimation accuracy and fast convergence rate, respectively.

The rest of this paper is organized as follows. Section 2 provides a brief description of a SISO-OFDM model in the presence of CFO. The theoretical analysis of the proposed CFO estimator is described in section 3. In section 4 the performance of the suggested algorithm will be analyzed, and will be compared with other methods through simulation results. Finally, concluding remarks will be presented in section 5.

![Figure 1. The architecture of SISO-OFDM system model](image)

## 2. SYSTEM MODEL AND INTER-CARRIER INTERFERENCE PROBLEM

### 2.1. Input-Output Relations

The structure of a typical SISO-OFDM transceiver system used in this paper is illustrated in Fig. 2. At the transmitter, the input binary source data are first converted into many parallel data streams, each with symbol period $T_s$, which are subsequently mapped to modulate synchronous subcarriers within one OFDM symbol. Let $N$ be the number of orthogonal subcarriers which are spaced by $1/NT_s$ in the frequency domain. The $q$'th OFDM symbol is written as $X(q) = \{X_0(q), X_1(q), \ldots, X_{N-1}(q)\}$, a vector of $N$ symbols, which are fed into an $N$ point inverse discrete Fourier transform (IDFT) unit to obtain the digital time domain signal $x(q) = \{x_0(q), x_1(q), \ldots, x_{N-1}(q)\}$ as

$$x_m(q) = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} X_k(q) \exp\left(\frac{j2\pi km}{N}\right)$$  \hspace{1cm} (1)

here $m = 0, 1, \ldots, N-1$. In order to avoid Inter-symbol Interference (ISI) due to channel dispersion, a cyclic prefix, whose length is longer than the maximum delay of the fading channel, is inserted between successive OFDM symbols. The channel $h = \{h_0, h_1, \ldots, h_{N-1}\}$ is defined as $T_s$ spaced complex gains of a multipath A Blind Carrier Frequency Offset Estimation Scheme for OFDM Systems via Hybrid-ICA algorithm (A Jalili)
Rayleigh fading channel. We assume the channel is quasi-stationary during CFO estimation and its transfer function at the frequency of the $k$'th subcarrier is defined as

$$h_k = \sum_{p=0}^{P-1} \eta_p \exp\left(\frac{j2\pi kp}{N}\right)$$

(2)

where $P$ is the total number of fading paths and $\eta_p$ is the magnitude of the $p$'th multipath component. We assume that the channel is quasi-stationary during CFO estimation i.e., channel variances are negligible during one OFDM symbol but are present between successive OFDM symbols.

At the receiver, after sampling the OFDM signal, serial-to-parallel conversion, and the removal of CP, the complex envelope of the received signal in the time can be expressed as

$$y_m(q) = \frac{1}{N} \sum_{k=0}^{N-1} \eta_k X_k(q) \exp\left[\frac{j2\pi m(k + \varepsilon)}{N}\right] + w_m(q)$$

(3)

where $w_m(q)$ is the complex envelope of the additive white Gaussian noise (AWGN) with zero mean and variance $\sigma_w^2$, and $\varepsilon$ is the normalized CFO which is defined as

$$\varepsilon = \frac{f_A}{\Delta f}$$

(4)

where $f_A$ is the frequency offset between the local oscillators of the transmitter and the receiver and $\Delta f$ is the subcarrier spacing.

The received signal in the frequency domain $Y(q) = [Y_0(q), Y_1(q), \ldots, Y_{N-1}(q)]^T$ in the presence of CFO can be expressed as

$$Y_s(q) = \frac{1}{\sqrt{N}} \sum_{m=0}^{N-1} y_m(q) \exp(-j2\pi mn/N)$$

$$= \frac{1}{N} \sum_{k=0}^{N-1} \sum_{m=0}^{N-1} \eta_k X_k(q) \exp\left[\frac{j2\pi m(k - n + \varepsilon)}{N}\right] + N_s(q)$$

$$= \frac{1}{N} \left\{ H_s X_s(q) \sin\frac{\pi\varepsilon}{\sin(\pi\varepsilon/N)} \exp[(N - 1)\pi\varepsilon/N] + I_s(\varepsilon) \right\} + N_s(q)$$

(5)

The first element corresponds to the modulation value of the original transmitted data $X_s(q)$ modified by the channel transfer function $H$. This element suffers from an amplitude reduction and phase shift due to the frequency offset. The second element corresponds to the ICI caused by the frequency offset and is given by

$$I_s(\varepsilon) = \sum_{k=0}^{N-1} \sum_{m=0}^{N-1} \eta_k X_k(q) \exp\left[\frac{j2\pi m(k - n + \varepsilon)}{N}\right]$$

(6)

which are actually the interfering signals transmitted on subcarriers other than the desired subcarrier and the third element $N_s(q)$ is the additive noise in the frequency domain.

To gain more insight, (5) can be rewritten in the matrix-vector model as

$$Y(q) = G(\varepsilon)H\vec{X}(q) + N(q).$$

(7)

here $H = \sqrt{N}Fh$ is the channel response in the absence of CFO, $G(\varepsilon)$ is the CFO matrix, $\vec{X}(q) = \text{diag}(X_0(q), X_1(q), \ldots, X_{N-1}(q))$, and $F$ is a unitary DFT matrix which is expressed by

$$F_{r,s} = \frac{1}{\sqrt{N}} e^{-\frac{j2\pi rs}{N}} ; \quad r,s = 0,1,\ldots,N-1.$$
2.2. The CFO Matrix in Detail

As it is clear from (5), the CFO is modeled as a multiplicative factor introduced in the channel and hence the \((n,k)\) entry of the CFO matrix \(G(\epsilon)\) can be defined as

\[
g_{n,k}(\epsilon) = \frac{1}{N} \sum_{m=0}^{N-1} \exp \left( jm \frac{\phi_{n,k}}{N} \right)
\]

(9)

where \(\phi_{n,k} = 2\pi n + \theta_{n,k}\) and \(\theta_{n,k} = 2\pi (k-n)\). It can be clearly observed that \(\theta_{n,k}\) is the multiplication of constant phase value with the index of the component. The eigenvalue decomposition of \(G(\epsilon)\) is given by

\[
[E_G, V_G] = FC(\epsilon) F^T
\]

(10)

where \(V_G\) is the orthogonal matrix of its eigenvectors and \(E_G\) is the diagonal matrix of eigenvalues of \(G(\epsilon)\) which can be shown as

\[
C(\epsilon) = \text{diag} \{c_e\}
\]

(11)

with \(c_e = [1, \exp(j2\pi \epsilon/N), \ldots, \exp(j2\pi (N-1)\epsilon/N)]\) depicts frequency shifts of each subcarrier. As it will be shown in the next section, our proposed algorithm for CFO estimation is based on the estimation of the inverse of CFO matrix. Hence, the inverse of CFO matrix is obtained by applying an inverse operation on (10), we have

\[
W(\epsilon) = G^{-1}(\epsilon) = FC^{-1}(\epsilon) F^n.
\]

(12)

it can be easily shown that

\[
W(\epsilon) = G^n(\epsilon).
\]

(13)

and hence \(G(\epsilon)\) is a unitary matrix. Thus, the \((n,k)\) entry of inverse of the CFO matrix can be obtained after straightforward calculations as

\[
w_{n,k}(\epsilon) = \frac{1}{N} \sum_{m=0}^{N-1} \exp \left( -jm \frac{\phi_{n,k}}{N} \right)
\]

(14)

we can simplify (14) as

\[
w_{n,k}(\epsilon) = \frac{1}{N} \left[ \cos \left( \frac{(N-1)\phi_{n,k}}{2N} \right) - j \sin \left( \frac{(N-1)\phi_{n,k}}{2N} \right) \right] \sin \left( \frac{\phi_{n,k}}{2N} \right)
\]

(15)

It can be easily proved from (15) that the inverse of CFO matrix \(W(\epsilon)\) is a circulant matrix i.e.,

\[
w_{n,k}(\epsilon) = w_{0, (k-n) \mod N}(\epsilon)
\]

(16)

and in order to clearly visualize this property, the inverse of CFO matrix \(W(\epsilon)\) can be shown as

\[
W(\epsilon) = \begin{bmatrix}
w_0 & w_{N-1} & \ldots & w_1 \\
w_1 & w_0 & \ldots & w_2 \\
& \vdots & \ddots & \vdots \\
w_{N-1} & w_{N-2} & \ldots & w_0
\end{bmatrix}.
\]

(17)
In order to mitigate the ICI effect, the normalized carrier frequency offset $\varepsilon$ needs to be estimated. There is an efficient recursive function based on ICA algorithm for noisy systems in [15], hence, we neglect the noise term in (7) for simplicity. Under this assumption, (7) can be rewritten as

$$Y(q) = G(\varepsilon) \Gamma(q)$$

(18)

where $\Gamma(q) = HX(q)$ is defined as the desired signals matrix. Here, as the most practical systems, the essential assumptions are that the components of desired signal are mutually independent, complex valued, zero mean, stationary, and non-Gaussian distributed. According to the Central Limit Theorem, the distribution of $Y(q)$ which is the linear combination of desired signals is more Gaussian than the distribution of any individual component. Thus, the distribution of desired signals tends to be more non-Gaussian when the estimated value of normalized CFO, $\hat{\varepsilon}$, approaches the $\varepsilon$. In other words, we can reach $\Gamma(q)$ by estimating the inverse of $G(\varepsilon)$ which will maximize the non-Gaussianity of $G^{-1}(\varepsilon)Y(q)$. Therefore, (20) resembles the ICA equation and can be applied for CFO cancellation.

3. THEORETICAL ANALYSIS OF THE PROPOSED SCHEME

3.1. Preliminaries

Before running the algorithm, it will be very helpful to apply two crucial pre-processing steps which are generally carried out before typical ICA algorithms. As a first step, the received signal is centered as

$$\bar{Y}(q) = Y(q) - E[Y(q)]$$

(19)

The second step is whitening the received signal which involves linearly transforming the measured signal in which case the mixing matrix is made unitary and the convergence of the subsequent ICA algorithm is accelerated. Hence, whitening transform $V$ and whitened received signal $Z$ is obtained respectively, as

$$V = D^{-1/2}E^T$$

$$Z(q) = \sqrt{V}\Gamma(q).$$

(20)

(21)

where $D$ and $E$ are eigen values and eigen vectors of received signal, respectively. Hence, (23) is obtained as an ICA equation from (21) after pre-processing implementations. In the following section, separating matrix $W(\varepsilon)$ will be estimated.

3.2. Our FastICA-Based Algorithm

The FastICA is an efficient and popular algorithm for independent component analysis invented by Aapo Hyvärinen et al. in 1997. This algorithm is a very successful fast converged batch algorithm that can be derived either from a fixed-point iteration or as an approximate Newton method and can be used to estimate the components either one-by-one by maximizing non-Gaussianity as a measurement of statistical independence [16]. By using the kurtosis as a cost function we can obtain the fundamental recursive function in FastICA after straightforward calculations as

$$w_j(i + 1) = E[Z(q)g[w_j^T(i)Z(q)] - E[g[w_j^T(i)Z(q)]]w_j(i)$$

(22)

where the nonlinearity $g$ can be almost any smooth function with different choices such as cubic Gaussian and hyperbolic tangent function and $w_j$ is the $j$’th column of the separating matrix.

Just like the other algorithms based on ICA, the estimated column of the separating matrix through the FastICA algorithm is still suffered from the permutation ambiguity i.e., the order of independent components cannot be uniquely determined. We employ effective strategy by using an optimization process to solve this permutation ambiguity in the estimated column of the separating matrix. To do so, a cost function is built to estimate the CFO through the minimization of initially estimated column of the separating matrix. Through the harmonious issue in the inverse of CFO matrix relating to the phase of its components which is expressed in (16), the cost function in the optimization process is written as
\[ J_k(\varepsilon) = \frac{1}{N-1} \tan^{-1} \Phi_k. \]  

(23)  

where \( \tan^{-1}\Phi_k \) is the phase of \( k \)’th column of separating matrix, and an \( N \times 1 \) vector \( \Phi_k(i) \) is given by

\[ \Phi_k = \frac{3[w_{n,k}(\varepsilon)]}{\Re[w_{n,k}(\varepsilon)]}; \quad n = 0,1,\ldots,N-1. \]  

(24)  

Let \( \hat{\varepsilon} \) denotes a candidate estimate of the CFO which is found through minimization of \( J_k(\varepsilon) \) as

\[ \hat{\varepsilon} = \frac{1}{\pi} \arg \min_n |J_k(\varepsilon)| \]  

(25)  

If we assume \( 2\pi \varepsilon < \theta_{\Delta} \), the minimum value of \( J(\varepsilon) \) is satisfied when \( \theta_{\Delta,k} = 0 \), i.e. \( J(\varepsilon) = 2\pi \varepsilon \). Hence, we can reach \( \hat{\varepsilon} \) from one arbitrary column of \( \hat{W}(\varepsilon) \) without any information about the value of \( \theta_{\Delta} \), i.e., without knowing the index of estimated column of the separating matrix. Since \( \tan^{-1}(.) \) is a monolithic function and \( N \) is a constant value, we can simplify (26) as

\[ \hat{\varepsilon} = \frac{1}{\pi} \arg \min_n \frac{1}{N-1} \tan^{-1} \frac{3[w_{n,k}(\varepsilon)]}{\Re[w_{n,k}(\varepsilon)]}; \quad n = 0,1,\ldots,N-1. \]  

(26)  

After eliminating the permutation ambiguity from the estimated column the whole separating matrix \( \hat{W}(\hat{\varepsilon}) \) can be reconstructed. Hence the inverse of CFO matrix \( \hat{W}(\hat{\varepsilon}) \) is completely estimated by using the FastICA algorithm.

3.3. The Proposed Hybrid-ICA Scheme

In this sub-section we propose a fast convergence high accurate algorithm for CFO estimation which is based on the combination of the basic conventional FastICA and the natural gradient ICA algorithm. The natural-gradient direction uses the knowledge of the Riemannian distance structure of the parameter space to alter the gradient direction and hence, the natural-gradient method provides fast and accurate adaptation behavior [18]. By using the natural gradient ICA algorithm to update the separation matrix \( W \), we have

\[ W(i+1) = W(i) + \mu \left( \mathbf{I} - \mathbf{E}[\mathbf{I}W(i)Z(q)]^T g[W(i)Z(q)] \right) W(i) \]  

(27)  

where \( \mu \) is the convergence factor and \( \mathbf{I} \) is the identity matrix. Here, in the hybrid-ICA scheme, the initial value for \( W(i) \) is the separating matrix which is estimated through the FastICA algorithm in the previous sub-section. When the (28) is converged, the separating matrix \( \hat{W}(\hat{\varepsilon}) \) is completely estimated by using the hybrid-ICA scheme.

4. ANALYSIS AND SIMULATION RESULTS

In this section, simulation results are presented to demonstrate the effectiveness of our proposed algorithm in comparison with other algorithms via Monte Carlo simulations. Table I represents the simulation parameters which are mainly chosen according to [18]. In all experiments, the basic simulation parameters are as follows: the modulation scheme is quadrature-phase-shift-keying (QPSK), the size of OFDM block \( N \), and the length of cyclic prefix are set to be 128 and 16, respectively. We consider a frequency-selective multipath fading channel with five independent Rayleigh-fading taps. For each path, the amplitude varies independently and follows Rayleigh distribution with exponentially decaying power delay profile \( \mathbf{R}_p = \exp(-p/3) \sum_{p} \exp(-p/3) \) where \( p \) is the number of paths. Furthermore, the Signal to Noise Ratio (SNR) is assumed to be 15dB and the simulation results are averaged over 10000 realizations.

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Table 1. Simulation Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
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</thead>
<tbody>
<tr>
<td>Modulation scheme</td>
<td>QPSK</td>
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<tr>
<td>Subcarrier number</td>
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</tr>
<tr>
<td>Subcarrier spacing [kHz]</td>
<td>15</td>
</tr>
<tr>
<td>CP length</td>
<td>16</td>
</tr>
<tr>
<td>Signal to Noise Ratio [dB]</td>
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</tr>
<tr>
<td>Simulation realizations</td>
<td>10000</td>
</tr>
<tr>
<td>Path number</td>
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</tr>
<tr>
<td>Doppler frequency [Hz]</td>
<td>100</td>
</tr>
<tr>
<td>Normalized frequency offset</td>
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</tr>
<tr>
<td>Total bandwidth [MHz]</td>
<td>10</td>
</tr>
</tbody>
</table>

In Figure 3, we plot the normalized MSE performance of the proposed scheme, the kurtosis-based algorithm of [13], the original CP-based algorithm of [11], the CS-based algorithm of [10], and the modified CP-based algorithm in [18]. As can be seen in Figure 3, our proposed hybrid-ICA scheme outperforms all other algorithms especially the FastICA-based algorithm with less computational requirements. The modified CP-based method, which requires knowledge of the channel order and a longer than necessary CP, presents moderate performance in comparison with other algorithms. The CS-based algorithm performs worse than all other algorithms, and will not be simulated further.

Figure 2. Normalized MSE of different blind CFO estimators in a SISO-OFDM system versus SNR

The bit-error rate (BER) performance of the simulated OFDM system using the proposed CFO estimator to compensate the CFO effect is illustrated in Figure 4. For comparison, we also plot the BER performance of the same system with no CFO compensation, with kurtosis-based CFO estimation, and with CP-based CFO estimation. As expected, without CFO compensation, the system performance suffers serious degradation due to inter-carrier interference (ICI). Whereas the CP based estimator shows a serious error floor phenomenon in high SNR values, the proposed scheme outperforms all the other algorithms for the wide range of SNR. In the high SNR zone, the BER of the simulated OFDM system is primarily due to CFO effects, and the performance improvement of the hybrid-ICA scheme is substantial. On the other hand, in the low SNR range, the BER is mainly because of noise effects, and the improvement of the hybrid-ICA scheme is slight.

Fig. 4 depicts the crosstalk error learning curve of the hybrid-ICA scheme under two typical SNR levels SNR = 10 dB, SNR = 30 dB and different choices of the nonlinearity $g$. As can be seen, the performance of the system is improved as the SNR value increases. Indeed, the additive noise slightly degrades the performance of the proposed estimator which means that the proposed hybrid-ICA scheme is robust against noise.
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Figure 3. BER of the simulated OFDM system employing the hybrid-ICA scheme and different CFO estimators versus SNR

Figure 4. Crosstalk error evolution versus iteration number under different SNR values

As illustrated in Fig. 5, on the contrary to the general ICA separation case where the ICA algorithm converges in thousands of iterations, the hybrid-ICA scheme uniformly converges after around 160 iterations. This occurs because of two main reasons; first the separating matrix only depends on the CFO, second this scheme employs the FastICA with cubic nonlinearity. This fact shows that the proposed scheme converges faster in comparison with the other CFO estimators. This scheme can be implemented in practical high-data-rate OFDM systems with a moderate increase of computational requirements.

5. CONCLUSION

In this paper, we investigated the estimation of CFO effect in the SISO-OFDM systems. According to the mentioned mathematical modeling of the ICI problem, it was shown that the received signal in the frequency domain is the multiplication of the CFO matrix and the transmitted signal. To estimate the CFO effect, we proposed a blind estimator based on the combination of the FastICA algorithm and the natural-gradient ICA algorithm. The major point behind our proposed algorithm is that the CFO matrix is a circulant matrix with only $N$ different values. After an initial estimation of the separating matrix through the FastICA algorithm, the estimated value is used as the initial value for the natural-gradient ICA algorithm. The proposed algorithm has a notable advantage: it converges very fast with high estimation accuracy which provides practicability for OFDM systems with large number of subcarriers. Simulation results illustrated that our proposed algorithm has better BER performance in comparison with those of other algorithms but the performance efficiency cannot reach the perfect point. Finally a more accurate algorithm with a lower complexity for cooperative communication systems can be investigated further in the future.
REFERENCES


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