A Low Complex Receiver with Interference Cancellation for Power-Controlled MC-CDMA Downlink Transmissions

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SUMMARY

We consider the downlink of a power-controlled MC-CDMA system in which the near-far effect limits the performance of single-user receivers and calls for interference cancellation (IC)-based schemes. The latter provide enhanced error rate performance but are not suited for downlink applications due to their relatively large complexity. To overcome this problem, we present a novel reduced-complexity IC-based detector in which interfering signals are canceled provided that their estimated power exceeds a given threshold. In addition to the channel response, the proposed scheme requires knowledge of the amplitudes of the users’ signals. The latter are estimated using two different methods that exploit some pilot blocks placed at the beginning of the downlink frame. Numerical results are given to highlight the effectiveness of the proposed scheme and to make comparisons with other existing IC-based solutions.

1. INTRODUCTION

Multi-Carrier Code-Division Multiple-Access (MC-CDMA) has gained increased interest in the last few years as a promising candidate for the downlink of future wireless communication systems [1]-[2]. In these applications the use of orthogonal spreading codes can provide intrinsic protection against co-channel interference. In the presence of multipath propagation, however, the code orthogonality is lost and multiple-access interference (MAI) arises.

A key issue in cellular communication networks is power control. In downlink applications this technique is used to improve the geographical fairness in data reception. This is commonly achieved by transmitting more power to the users located near the cell boundaries since they experience a higher path loss compared to the users close to the base station (BS) [3]-[5]. On the other hand, allocating the transmit power according to the base-to-mobile distance makes the terminals near the BS more exposed to the near-far effect. This limits the performance of conventional single-user receivers and calls for interference cancellation (IC) techniques [6]-[8], where interfering signals are detected and subtracted from the received waveform before

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detection of the desired user’s data. In spite of their effectiveness, however, IC-based schemes are quite unattractive for downlink applications due to their relatively large complexity. To overcome this problem, in this work we propose a reduced complexity IC-based receiver that operates in two steps. First, an initial estimate of the interference is obtained through a single-user minimum-mean-square-error (MMSE) detector [2]. Then, the interfering signals with amplitude above a specified threshold are canceled out in parallel. A similar approach has been adopted in [8], where interfering signals are canceled provided that the corresponding decision variables are sufficiently reliable. The main difference between our approach and [8] is that in our scheme we employ the estimate of the signal amplitude as a reliability measure rather than the decision statistic. As shown later, this improves the error rate performance without increasing the system complexity. Compared with the partial parallel interference cancellation (PPIC) receivers discussed in [9]-[10], our scheme is different in two aspects. First, an interfering signal is either totally canceled or retained depending on its specific reliability measure (i.e., the estimated signal amplitude). Vice versa, in [9]-[10] all interfering signals are partially subtracted from the received waveform, irrespective of their relative power levels. Second, our scheme employs a single stage of cancellation whereas the detectors in [9]-[10] are inherently multistage receivers (hence, not suited for downlink applications).

In addition to channel state information, the proposed IC-based detector requires knowledge of the number of active users and their corresponding power levels. Therefore, we derive two different methods for estimating the amplitudes of the users’ signals by exploiting some training blocks placed at the beginning of each downlink frame. The first scheme is based on maximum likelihood (ML) reasoning and employs orthogonal training sequences of length equal to the spreading gain. A possible drawback of this approach is that it may entail an excessive overhead for applications with large spreading gains. Hence, we also propose an alternative solution based on heuristic arguments that can be used with training sequences of arbitrary length.

2. SYSTEM MODEL

We consider the downlink of a power-controlled MC-CDMA network in which the total number of subcarriers, \( N \), is divided into smaller groups of \( Q \) elements [2]. The BS employs the subcarriers of a given group to communicate with \( K \leq Q \) users, which are separated by means of orthogonal Walsh-Hadamard (WH) codes of length \( Q \). We call \( c_k = [c_k(1), c_k(2), \ldots, c_k(Q)]^T \) the code sequence assigned to the \( k \)th user, where \( c_k(n) \in \{\pm 1/\sqrt{Q}\} \) and \((\cdot)^T\) is the transpose operator. Without loss of generality, we concentrate on a single group and denote \( \{i_n: 1 \leq n \leq Q\} \) the corresponding subcarrier indices, with \( i_n = 1 + (n-1)N/Q \). Calling \( X(m) = [X(m,i_1), X(m,i_2), \ldots, X(m,i_Q)]^T \) the output from the discrete Fourier transform (DFT) unit at a given MT over the considered group of subcarriers and during the \( m \)th MC-CDMA block, we may write [2]

\[
X(m) = \sum_{k=1}^{K} \gamma_k a_k(m) u_k(m) + w(m). 
\] (1)

In the above equation \( a_k(m) \) is the symbol transmitted to the \( k \)th user while \( u_k(m) \) is a \( Q \)-dimensional vector with entries \( u_k(m,n) = H(m,i_n)c_k(n) \), where \( H(m,i_n) \) denotes the channel frequency response over the \( i_n \)th subcarrier. Vector \( w(m) \) represents thermal noise, and its
entries are modeled as statistically independent Gaussian random variables with zero mean and variance \( \sigma^2 = E\{|w(m, i_n)|^2\} \). Finally, \( \gamma_k \) are non-negative and real-valued quantities that allow the BS to perform power control. We adopt the power allocation scheme discussed in [4], where a common power level is assigned to those users whose distance from the BS is less than a certain minimum value \( d_{\text{min}} \). This is tantamount to setting

\[
\gamma_k = \begin{cases} 
(d_{\text{min}}/R)^{n/2} & \text{if } d_k \leq d_{\text{min}} \\
(d_k/R)^{n/2} & \text{if } d_k > d_{\text{min}}
\end{cases} \quad k = 1, 2, \ldots, K
\]  

where \( d_k \) is the distance between the \( k \)th MT and the BS, \( R \) is the cell radius and \( n \) is the path loss exponent.

3. RELIABILITY-BASED IC DETECTOR

The need to keep the remote units as simple and power efficient as possible makes the PPIC receiver discussed in [9] quite unattractive for downlink applications. As an alternative, we propose a novel scheme employing a single stage of cancellation in which interfering signals are subtracted from the DFT output provided that they are sufficiently reliable. Without loss of generality, we concentrate on the \( j \)th MT. Then, the \( k \)th interfering signal is cancelled from the DFT output provided that

\[
\lambda_k / \lambda_j \geq \gamma
\]  

where the threshold \( \gamma \) is a design parameter. This leads to the following expurgated vector

\[
Z'_j(m) = X(m) - \sum_{k \in I_c} \lambda_k \hat{a}_k(m) u_k(m)
\]  

where \( I_C \) is the set of indices \( k \) (with \( k \neq j \)) satisfying (3) and \( \hat{a}_k(m) \) is an estimate of \( a_k(m) \). The entries of \( Z'_j(m) \) are then exploited to detect the useful symbol \( a_j(m) \). For this purpose we observe that, even assuming ideal data decisions (i.e., \( \hat{a}_k(m) = a_k(m) \)), \( Z'_j(m) \) is still affected by residual MAI due to the relatively weak users that are not cancelled. Therefore, instead of combining the elements of \( Z'_j(m) \) using the maximum-ratio-combining (MRC) strategy (which gives the best results in the MAI-free case), we adopt the minimum-mean-square-error (MMSE) approach. Hence, the decision statistic for \( a_j(m) \) is given by

\[
v_j(m) = \sum_{n=1}^{Q} \xi_j(m, n)c_j(n)[Z'_j(m)]_n
\]  

in which \([Z'_j(m)]_n\) denotes the \( n \)th entry of \( Z'_j(m) \) and

\[
\xi_j(m, n) = \frac{\lambda_j H^* (m, i_n)}{|\lambda_j H (m, i_n)|^2 + \sigma^2} \quad n = 1, 2, \ldots, Q.
\]  

Finally, passing \( v_j(m) \) to a threshold device produces the estimate of \( a_j(m) \). In the sequel, the proposed scheme is referred to as the reliability-based IC (RBIC) detector. To summarize, the RBIC operates through the following steps:

1) Select the interfering users that must be cancelled, i.e., those satisfying the constraint (3);
2) Compute the corresponding data decisions \( \hat{a}_k(m) \) using the following single-user (SU)-MMSE decisions statistics

\[
y_k(m) = \sum_{n=1}^{Q} \xi_k(m,n) c_k(n) X(m,i_n) \quad k \in I_c.
\]

(7)

3) Compute the expurgated vector \( Z'_j(m) \) in (4);

4) Use \( v_j(m) \) in (5) to estimate \( a_j(m) \).

Intuitively, we expect that RBIC can achieve a good trade-off between performance and complexity. On one hand, it mitigates the near-far problem by canceling the strongest interfering signals. On the other, it employs a single-stage of cancellation and, accordingly, it is much simpler to implement than conventional multi-stage schemes based on parallel or successive IC. It is fair to say that RBIC has similarities with the detector proposed by Ochiai and Imai (OID) in [8]. The main difference is that in [8] the \( k \)th signal is subtracted from the DFT output provided that \(|y_k(m)| > |y_j(m)|\) whereas in our scheme we take the amplitude of the interfering signal as an indicator of reliability. As shown later, this leads to better error rate performance.

4. ESTIMATION OF THE SIGNALS’ AMPLITUDES

From (6), we see that RBIC requires knowledge of \( \{H(m, i_n)\}, \{\gamma_k\} \) and \( \sigma^2 \) which must be estimated in some manner. The problem of channel estimation in MC-CDMA downlink transmissions has received much attention in the last few years and several solutions are now available [11]-[13]. Hence, in the following we only concentrate on the estimation of \( \{\gamma_k\} \) and assume that channel and noise power estimates are obtained as indicated in [13] by exploiting pilot blocks multiplexed into the frame structure.

Two different schemes are proposed for estimating the quantities \( \{\gamma_k\} \). The first is based on maximum likelihood reasoning while the second is derived from an ad hoc argument. Both schemes exploit \( N_T \) training blocks located at the beginning of the frame, just after the first pilot block (which is employed to estimate the channel response and noise power [13]).

4.1. Maximum likelihood estimation

We begin by rewriting (1) in the equivalent form

\[
X(m) = H(m) \sum_{k=1}^{Q} \gamma_k a_k(m) c_k + w(m) \quad m = 1, 2, \ldots, N_T
\]

(8)

where \( H(m) = \text{diag}\{H(m, i_1), H(m, i_2), \ldots, H(m, i_Q)\} \) while \( \{a_k(m) : m = 1, 2, \ldots, N_T\} \) is the training sequence of the \( k \)th user (belonging to a PSK constellation, i.e., \(|a_k(m)| = 1\)). Note that the summation index in (1) counts the active users whereas in (8) it counts the potentially active codes and spans the interval \( 1 \leq k \leq Q \) (recall that \( Q \) is the maximum number of active codes within a group of subcarriers). The reason for this apparent discrepancy is that in practical applications only the BS knows which codes are effectively employed in the current frame. This means that each MT must estimate the amplitudes \( \Gamma = [\gamma_1, \gamma_2, \ldots, \gamma_Q]^T \) corresponding to the complete set \( \{c_1, c_2, \ldots, c_Q\} \) of potentially active codes. However, it is worth noting that (8) is perfectly equivalent to (1) since \( \lambda_k = 0 \) if the \( k \)th user is turned off.
To proceed further, we rewrite (8) as
\[ X(m) = B(m)\Gamma + w(m) \quad m = 1, 2, \ldots, N_T \] (9)
where \( B(m) \) is the following \( Q \times Q \) matrix
\[ B(m) = H(m)[a_1(m) c_1 \quad a_2(m) c_2 \quad \cdots \quad a_Q(m) c_Q], \] (10)
Thus, recalling that \( \{\gamma_k\} \) are real-valued parameters, the ML estimate of \( \Gamma \) is found to be [14]
\[ \hat{\Gamma}_{ML} = R^{-1} \sum_{m=1}^{N_T} \Re\{B^H(m)X(m)\} \] (11)
with \( R = \sum_{m=1}^{N_T} \Re\{B^H(m)B(m)\} \). In the sequel, equation (11) is referred to as the maximum likelihood estimator (MLE) of the signals' amplitudes. Using standard computations, it can be shown that \( \hat{\Gamma}_{ML} \) is unbiased and has the following mean square estimation error (MSEE)
\[ E\left\{ \|\hat{\Gamma}_{ML} - \Gamma\|^2 \right\} = \frac{\sigma^2}{2\text{tr}\{R^{-1}\}} \] (12)
where \( \|\cdot\| \) is the Euclidean norm and \( \text{tr}\{\cdot\} \) denotes the trace of a matrix. The following remarks are of interest.

i) From (10) we see that computing \( B(m) \) requires channel state information. As mentioned previously, an estimate of the channel response is obtained from the first pilot block using the estimator discussed in [13]. The channel estimate is exploited to compute an estimate of \( B(m) \), say \( \hat{B}(m) \), which is then used in place of the true \( B(m) \).

ii) From (11) we see that the crux in the calculations is the inversion of \( R \), which becomes more and more cumbersome as \( Q \) increases. Note that \( R^{-1} \) cannot be pre-computed and stored at the receiver as it depends on the actual channel realization. The complexity of MLE can be greatly reduced if the channel variations are negligible for \( m = 1, 2, \ldots, N_T \) and the training sequences are orthogonal, i.e., they satisfy the identity \( \sum_{m=1}^{N_T} a^*_k(m)a_\ell(m) = N_T \cdot \delta(k-\ell) \), where \( \delta(\ell) \) is the Kronecker delta function. In these circumstances \( R \) reduces to \( N_T E_H \cdot I_Q \) with
\[ E_H = \frac{1}{Q} \sum_{n=1}^{Q} |H(i_n)|^2, \] and MLE becomes
\[ \hat{\Gamma}_{ML} = \frac{1}{N_T E_H} \sum_{m=1}^{N_T} \Re\{B^H(m)X(m)\}. \] (13)
Also, substituting \( R = N_T E_H \cdot I_Q \) into (12) yields
\[ E\left\{ |\hat{\gamma}_k - \gamma_k|^2 \right\} = \frac{\sigma^2}{2N_T E_H}. \] (14)

4.2. Ad hoc estimation

As shown previously, employing orthogonal training sequences is a viable method to reduce the complexity of MLE. In these circumstances, however, the number \( N_T \) of training blocks
cannot be less than $Q$ since it is not possible to find any set of $Q$ orthogonal sequences with length $N_T < Q$. This may entail an excessive overhead when $Q$ is large. For this reason it is worth looking for an alternative solution. For this purpose, we consider the ML estimate of $\gamma_k$, say $\hat{\gamma}_k^{(ML)}(m)$, based on the observation of a single vector $X(m)$. Then, from (10)-(11) it follows that

$$\hat{\gamma}_k^{(ML)}(m) = a_k(m) \sum_{n=1}^{Q} \Re \{ c_k^*(n) G_{ZF}(m, i_n) X(m, i_n) \}$$

where $G_{ZF}(m, i_n) \ (n = 1, 2, \ldots, Q)$ are Zero-Forcing (ZF) equalizer coefficients, i.e., $G_{ZF}(m, i_n) = \frac{1}{H(m, i_n)}$. It can be shown that $\hat{\gamma}_k^{(ML)}(m)$ is unbiased with variance

$$\mathbb{E} \left\{ \left| \hat{\gamma}_k^{(ML)}(m) - \gamma_k \right|^2 \right\} = \frac{\sigma^2}{2Q} \sum_{n=1}^{Q} \frac{1}{|H(m, i_n)|^2}$$

from which it follows that the accuracy of $\hat{\gamma}_k^{(ML)}(m)$ degrades substantially when $|H(m, i_n)|$ is much less than unity, i.e., in the presence of deeply faded subcarriers. This is a consequence of the noise enhancement phenomenon caused by ZF equalization. To alleviate this drawback, we propose to put the ZF approach aside and equalize the DFT output according to the MMSE criterion. This is tantamount to replacing $G_{ZF}(m, i_n)$ in (15) with

$$G_{MMSE}(m, i_n) = \frac{H^*(m, i_n)}{|H(m, i_n)|^2 + \sigma^2} \quad n = 1, 2, \ldots, Q.$$  

(17)

Also, averaging over the available training blocks (to improve the estimation accuracy) produces the following estimate of $\gamma_k$

$$\hat{\gamma}_k^{(AH)} = \frac{1}{N_T} \sum_{m=1}^{N_T} a_k(m) \sum_{n=1}^{Q} \Re \{ c_k^*(n) G_{MMSE}(m, i_n) X(m, i_n) \}.$$  

(18)

Since (18) has been derived using heuristic arguments, in the sequel it is referred to as the ad hoc estimator (AHE). Skipping the details, it can be shown that AHE has the following bias and variance

$$\mathbb{E}\{\gamma_k - \hat{\gamma}_k^{(AH)}\} = \frac{\sigma^2}{N_T} \sum_{m=1}^{N_T} a_k(m) \sum_{\ell=1}^{K} \gamma_{\ell} a_{\ell}(m) \sum_{n=1}^{Q} \frac{\Re \{ c_k^*(n) c_{\ell}(n) \}}{|H(m, i_n)|^2 + \sigma^2}$$

(19)

$$\text{var}\{\hat{\gamma}_k^{(AH)}\} = \frac{\sigma^2}{2N_T Q} \sum_{n=1}^{Q} |G_{MMSE}(m, i_n)|^2.$$  

(20)

The main advantage of AHE is that it dispenses with any matrix inversion, independently of the number $N_T$ of training blocks.

5. SIMULATION RESULTS

5.1. System parameters

The investigated system operates over a typical urban area with a cell radius $R$ of 1 km. The BS allocates the transmit power as indicated in (2) with $d_{\min} = 0.55 \cdot R$ and $n = 5$. 
The transmitted symbols belong to a QPSK constellation. The total number of subcarriers is \( N = 64 \) and WH codes of length \( Q = 8 \) are used. The signal bandwidth is \( B = 20 \) MHz, so that the useful part of each MC-CDMA block has length \( T = N/B = 8 \) µs. The sampling period is \( T_s = T/N = 0.125 \) µs and a cyclic prefix of \( T_C = 2 \) µs is adopted to eliminate inter-block interference. This corresponds to an extended block (including the cyclic prefix) of 10 µs. Each frame has 128 blocks and a duration of 1.28 ms.

The channel is characterized by 8 independent paths and its impulse response \( h(m) = [h(m, 1), h(m, 2), \ldots, h(m, L)]^T \) over the \( m \)th MC-CDMA block is given by

\[
h(m, q) = \sum_{\ell=0}^{7} \alpha_\ell(m) g(qT_s - \tau_\ell) \quad (21)
\]

where \( g(t) \) is a raised-cosine function with roll-off 0.22 and duration \( T_g = 8T_s = 1 \) µs while \( \tau_\ell \) are the path delays. The latter are kept fixed over a frame but varies from frame to frame with uniform distribution over the interval \([0, 1] \) µs. This corresponds to a maximum CIR length of 2 µs (i.e., \( L = 16 \)). The path gains \( \alpha_\ell(m) \) have powers \( \sigma_\ell^2 = \sigma_h^2 \cdot \exp(-\ell) \) for \( \ell = 0, 1, \ldots, 7 \), where \( \sigma_h^2 \) is chosen such that the average energy of the channel is normalized to unity. Each gain varies independently of the others within a frame and is generated by filtering a white Gaussian process in a third-order low-pass Butterworth filter. The 3-dB bandwidth of the filter is taken as a measure of the Doppler rate \( f_D = f_0v/c \), where \( f_0 = 2 \) GHz is the carrier frequency, \( v \) denotes the speed of the mobile terminal and \( c = 3 \times 10^8 \) m/s is the speed of light. The channel frequency response \( H(m, i_n) \) is computed as the DFT of \( h(m) \).

A simulation run begins with the generation of the distances \( d_k \), which are kept fixed over a frame. The amplitudes \( \gamma_k \) are generated from (2) and, unless otherwise specified, they are estimated using the MLE in conjunction with WH training sequences of length \( N_T = 8 \). Pilot blocks are periodically inserted within the frame with period \( M = 8 \). Estimates of the channel response and noise power are computed based on the observation of a pilot block and are kept fixed over the next data blocks [13]. The system is fully-loaded \((K = 8)\) and the mobile speed is \( v = 60 \) km/h (corresponding to \( f_D = 110 \) Hz). Without loss of generality, we present simulation results only for MT#1.

5.2. Performance assessment

We begin by assessing the accuracy achieved in the estimation of the signals’ amplitudes. Figure 2 illustrates the MSEE of \( \hat{\Gamma}_{ML} \) and \( \hat{\Gamma}_{AH} \) vs. \( 1/\sigma^2 \) with either \( N_T = 4 \) or 8. The dotted lines indicate theoretical results as given by (14) and (19)-(20). We see that the MSEE of \( \hat{\Gamma}_{ML} \) and \( \hat{\Gamma}_{AH} \) are 1.5 dB worse than the predicted value. The reason is that theoretical results have been derived assuming perfect knowledge of \( H(m) \) while in practice \( \hat{\Gamma}_{ML} \) and \( \hat{\Gamma}_{AH} \) are computed from (11) and (18) after replacing \( H(m) \) with its estimate \( \hat{H}(m) \). As expected, MLE performs remarkably better than AHE and achieves a gain of approximately 10 dB in terms of estimation accuracy. As shown later, however, using AHE instead of MLE does not produce large degradations in the error rate performance.

At this stage an obvious question is how to design the threshold in (3). Intuitively, increasing \( \lambda \) reduces the complexity of RBIC since the number of interfering signals that are canceled from the DFT output becomes smaller. In this way, however, the amount of residual interference increases and the system performance approaches that of SU-MMSE. Simulation results (not shown for space limitations) indicate that a reasonable trade-off between these two conflicting
requirements can be achieved by setting $\lambda = 1.2$. This value is adopted for RBIC in all subsequent simulations.

Figures 2-3 compare the BER performance of the SU-MMSE, PIC, OID and RBIC detectors vs. $E_b/N_0$. The PIC employs a single stage of cancellation for a fair comparison with OID and RBIC. The distance $d_1$ is $0.4R$ in Figure 2 and $0.8R$ in Figure 3. The single user bound (SUB) is also shown as a benchmark. We see that RBIC gives the best results irrespective of $d_1$, even though at an error probability of $10^{-3}$ the gain with respect to OID is limited to 1 dB. Still, it should be noted that this gain comes for free since RBIC and OID have comparable complexity. It is worth noting that SU-MMSE performs poorly when $d_1 = 0.4R$. The reason is that the user of interest is relatively near the BS and strong interfering signals are likely. While they degrade the performance of SU-MMSE, they are reliably canceled by the other
detectors. Increasing $d_1$ reduces the near-far effect, thereby improving the error probability of SU-MMSE. When $d_1 = 0.8R$, SU-MMSE outperforms the PIC. This can be explained by observing that the user of interest is now located near the cell boundaries and $\lambda_k \ll \lambda_1$ with high probability. In these circumstances, the tentative decisions employed by PIC to remove the MAI are not reliable. If they are wrong, MAI is enhanced and PIC performs poorly.

In Figure 4 we show the BER of RBIC when the users’ amplitudes are estimated using either the MLE or AHE. The distance $d_1$ is fixed to 0.6R and the number of training blocks is $N_T = 2$ or 4. The SUB and the BER with perfect knowledge of the channel parameters (PKCP) (i.e., ideal channel state information and $\hat{\Gamma} = \Gamma$) are also indicated for comparison. As expected, the best results are obtained with MLE due to its better estimation accuracy as compared to AHE. We see that the BER is quite insensitive to $N_T$ when the estimates of the
signals’ amplitudes are provided by MLE while it is significantly degraded when AHE operates with $N_T = 2$. Good results are achieved using AHE with $N_T = 4$.

6. Conclusions

We have discussed a single-stage non-linear receiver (RBIC) which performs interference cancellation provided that the power of the interfering signal exceeds a given threshold. To this end, we have proposed two schemes for estimating the users’ amplitudes in power-controlled MC-CDMA downlink transmissions. The first is based on ML reasoning and exploits orthogonal training sequences with length equal to the spreading gain. The second is derived with heuristic arguments and can be used with training sequences of arbitrary length.

Computer simulations indicate that the proposed scheme is superior to other existing techniques in that it achieves a better trade-off between error rate performance and computational complexity.

REFERENCES