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Karine Zidane*, Jérôme Lacan*, Marie-Laure Boucheret‡, Charly Poulliat‡,
Mathieu Gineste§, Damien Roques§, Caroline Bes¶ and Arnaud Deramecourt¶
*University of Toulouse, ISAE/DMIA & TéSA
Email: {karine.zidane, jerome.lacan}@isae.fr
‡University of Toulouse, IRIT/ENSEEIHT
Email: {marie-laure.boucheret, charly.poulliat}@enseeiht.fr
§Thales Alenia Space, Toulouse
Email: {mathieu.gineste, damien.roques}@thalesaleniaspace.com
¶CNES, Toulouse
Email: {caroline.bes, arnaud.deramecourt}@cnes.fr

***Abstract*—In recent random access methods used for satellite communications, collisions between packets are not considered as destructive. In fact, to deal with the collision problem, successive interference cancellation is performed at the receiver. Generally, it is assumed that the receiver has perfect knowledge of the interference. In practice, the interference term is affected by the transmission channel parameters, i.e., channel attenuation, timing offsets, frequency offsets and phase shifts, and needs to be accurately estimated and canceled to avoid performance degradation. In this paper, we study the performance of an enhanced channel estimation technique combining estimation using an autocorrelation based method and the Expectation-Maximization algorithm integrated in a joint estimation and decoding scheme. We evaluate the effect of residual estimation errors after successive interference cancellation. To validate our experimental results, we compare them to the Cramer-Rao lower bounds for the estimation of channel parameters in case of superimposed signals.**

Keywords—Satellite communication, Network coding, Channel estimation, Expectation-maximization algorithms, Cramer Rao Bounds

I. Introduction

In the context of satellite communications the main weakness of traditional random access (RA) methods like Aloha [1] and Slotted Aloha [2] is destructive packet collisions and retransmission delays, which might be incompatible with some application requirements. To deal with this problem, recent TDMA (Time Division Multiple Access) based RA methods like CRDSA (Contention Resolution Diversity Slotted Aloha [3]) and MuSCA (Multi-Slot Coded Aloha [4]) allow the receiver to perform iterative interference cancellation in order to achieve a better throughput and support a higher load. However, in a real system, the receiver has not perfect knowledge of the interference channel, and estimation errors are added to the frame when the packets are removed.

The problem to be addressed in this paper is the impact of residual channel estimation errors on recent TDMA based RA methods. The main issue is to be able to estimate the channel parameters in the case of multiple superimposed signals and to achieve performance close to the perfect knowledge case. This challenge has already been addressed in part in the existing literature. In [5] a method based on the Expectation-Maximization (EM) algorithm is presented to estimate channel parameters simultaneously. In [6], another approach uses the autocorrelation to derive channel amplitude and frequency offsets from packets that did not experience collision. In [7], channel estimation using EM is evaluated for a network coded diversity protocol (NDCP). We have also presented a first contribution of our work in [8], where we have used an EM based channel estimation method and evaluated experimentally the effect of imperfect interference cancellation on the decoding of the remaining packet.

The main contributions of this paper are the following:

- Introduction of a joint EM estimation and decoding scheme with autocorrelation initialization;
- Consideration of symbol level misalignment between signals in collision, and integration of estimated timing offsets inside the EM algorithm;
- Comparison of mean square errors with respect to the Cramer-Rao lower bounds for joint estimation of multiple channel parameters;
- Application of the proposed estimation technique in case of more than two superimposed signals.

The rest of this paper is organized as follows. Section II presents the system overview. Section III presents the proposed channel estimation method. In Section IV we derive the Cramer-Rao lower bounds (CRLB) as well as the mean square errors (MSE) for the joint estimation of channel parameters. Section V presents experimental results. We conclude and discuss future work in Section VI.

II. System Overview

We consider the transmission scenario in Fig.1. Each user sends two replicas of the same packet on different time

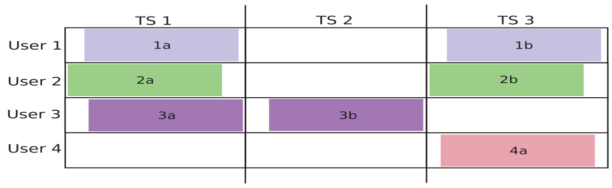

Fig. 1: A part of a frame (three time slots) with four users transmitting their packets to a destination D

slots (TS). The packets of different users are not synchronized at the symbol level. We consider the case where the receiver has previously decoded packets $1b$ and $3b$ successfully and needs to remove the signals corresponding to their replicas ($1a$ and $3a$) leaving the signal of user 2 on $TS1$ collision free. Therefore, the receiver has to accurately estimate the channel parameters of the signals on $TS1$, i.e., channel attenuation, timing offsets, frequency offsets and phase shifts. Otherwise, significant residual estimation errors are added to packet $2a$, and it may not be decoded successfully.

In the rest of the paper, we consider a one-way system where K users share the same time slot ($TS1$) to transmit their signals to a destination node D. We suppose that phase noise is neglected. Pilot symbol assisted modulation (PSAM) [9] is used to refine the estimation of the channel frequency offset. PSAM relies on the insertion of orthogonal data blocks called pilots inside the payload sequence. A preamble and a postamble are added to the beginning and the end of each packet. The training symbols (i.e. the preamble, the postamble and the pilots) are unique orthogonal sequences modulated with binary phase shift keying (BPSK) known at the destination node and used for the purpose of channel estimation.

The received signal, y, at the destination node D during TS1, after pulse shaping, and oversampling by a factor Q, is given by

$$y(i) = \sum_{k=1}^{K} h_k(i) \sum_{n=0}^{L-1} x_k(n) g(iT_e - nT_s - \tau_k T_s) + w(i) \quad (1)$$

where:

- T_s and $T_e = T_s/Q$ are respectively the symbol period and the oversampling period;
- $i = 0, 1, ..., LQ-1$ and $n = 0, 1, ..., L$ refer to T_e-spaced and T_s-spaced samples respectively, with L being the length of the entire packet in symbols.
- $x_k(n)$ refers to the n^{th} symbol sent by user k.
- g stands for the root raised cosine pulse function.
- w is a complex additive white Gaussian noise process of variance σ_w^2.
- τ_k is the timing offset relative to the signal sent by user k, supposed to take a random value uniformly distributed in $\left[0, \frac{1}{Q}, \frac{2}{Q}, ..., \frac{Q-1}{Q}\right]$.

Like in [5], we assume a block fading channel model with unknown channel parameters, as given below

$$h_k(i) = A_k e^{j(2\pi \Delta f_k i T_e + \varphi_k)} \quad (2)$$

where A_k is a lognormally distributed random variable modeling the channel amplitude, Δf_k is the frequency offset supposed to take a random value uniformly distributed in $[0, \Delta f_{max}]$ with Δf_{max} equal to 1% of the symbol rate $1/T_s$. A_k and Δf_k are assumed to remain constant during the frame duration. φ_k represents the phase shift of the signal, it is a random variable drawn independantly from one slot to another from a uniform distribution in $[0, 2\pi]$.

We suppose that, D has successfully decoded the replicas of all the packets in collision on TS1 except the ones corresponding to user 2, either because they have been received without collision on other slots (like in CRDSA), or because their combination has allowed successful decoding (like in CSA or MuSCA). Thus, D knows the number of the interference packets on TS1, as well as the interference symbols $x_1(n), x_3(n), ..., x_K(n)$. The goal is to demodulate and decode the signal of user 2. Therefore, D needs to compute the channel estimates $\widehat{h_1}, \widehat{h_2}, \widehat{h_3}, ..., \widehat{h_K}$ and the timing offsets $\widehat{\tau_1}, \widehat{\tau_2}, \widehat{\tau_3}, ..., \widehat{\tau_K}$ then suppress the interference signals from y in order to obtain the discrete signal s_2 as follows

$$\begin{aligned} s_2(i) &= h_2(i) \sum_{n=0}^{L-1} x_2(n) g(iT_e - nT_s - \tau_2 T_s) \\ &+ \sum_{k=1, k\neq 2}^{k=K} h_k(i) \sum_{n=0}^{L-1} x_k(n) g(iT_e - nT_s - \tau_k T_s) \\ &- \widehat{h_k}(i) \sum_{n=0}^{L-1} x_k(n) g(iT_e - nT_s - \widehat{\tau_k} T_s) + w(i) \quad (3) \end{aligned}$$

The signal s_2 is matched filtered and sampled at the sampling times $T_{2,n,\widehat{\tau_2}} = nQ + Q\widehat{\tau_2}$, with $T_{2,n,\widehat{\tau_2}}$ being an integer time index, and $\widehat{\tau_2}$ being the estimated timing offset of user 2. The resulting estimated symbols $s_2(T_{2,n,\widehat{\tau_2}})$ are

$$\begin{aligned} s_2(T_{2,n,\widehat{\tau_2}}) &= \sum_{n=0}^{L-1} h_2(T_{2,n,\widehat{\tau_2}}) q((\widehat{\tau_2} - \tau_2)T_s) x_2(n) \\ &+ \sum_{k=1, k\neq 2}^{k=K} \sum_{n=0}^{L-1} h_k(T_{2,n,\widehat{\tau_2}}) q((\widehat{\tau_2} - \tau_k)T_s) x_k(n) \\ &- \widehat{h_k}(T_{2,n,\widehat{\tau_2}}) q((\widehat{\tau_2} - \widehat{\tau_k})T_s) x_k(n) + w(T_{2,n,\widehat{\tau_2}}) \end{aligned} \quad (4)$$

with q being the raised cosine function. For ease of simplicity, we suppose that the timing offset of user 2 is the reference time, $\tau_2 = 0$, and the timing offsets of the other users are relative to τ_2.

III. Proposed Channel Estimation Method

A. Timing Offset Estimation

Our approach is to apply a delayed matched filter ($delay = Q\tau'$) on the received signal y and then sample at times $T_{k,n,\tau'} = nQ + Q\tau'$ for each user k, with τ' being the timing offset to estimate. The resulting sequence r is then correlated with the training symbols corresponding to each user. The correlation peak position determines the apropriate timing offset. For each iteration m of the E step of the EM algorithm, the estimates $\widehat{\tau_k}$ for each user k are computed as follows

- For $m = 0$:

$$\widehat{\tau_k}^{(0)} = \underset{\tau'}{argmax} \left| \sum_{n=0}^{L_{pre}-1} r(n) \times pre_k(n) \right| \quad (5)$$

where pre_k is the preamble of user k of length L_{pre} symbols.

- For $m > 0$, we derive the signal y_k by compensating the effect of prior estimated frequency offset $\widehat{\Delta f_k}^{(m-1)}$. Then we re-compute $\widehat{\tau_k}$ as shown below

$$y_k(i) = y(i) \times e^{-j2\pi \widehat{\Delta f_k}^{(m-1)} iT_e} \quad (6)$$

$$\widehat{\tau_k}^{(m)} = \underset{\tau'}{argmax} \left| \sum_{n \in \Upsilon} r_k(n) \times z_k(n) \right| \quad (7)$$

where $r_k(n)$ is the result of matched filtering and sampling of y_k at $T_{k,n,\tau'}$, z_k is the vector of training symbols of user k and Υ is the set of training symbols indexes in a packet.

B. Channel Parameters Estimation

EM is an iterative estimation algorithm. At each iteration m we go through the following steps:

For each user k,

1) We filter and sample the received signal y at different sampling times $T_{k,n,\widehat{\tau_k}^{(m)}}$, to obtain samples $s_k^{(m)}$.
2) At $m = 0$, to avoid inaccurate random initialization, we use autocorrelation to initialize the parameters

$$\widehat{A_k}^{(0)} = \sum_{n=0}^{Lpre-1} \frac{s_k(n) \times z_k(n)}{L_{pre}} \quad (8)$$

$$\widehat{\varphi_k}^{(0)} = arg \left(\sum_{n=0}^{Lpre-1} s_k(n) \times z_k(n) \right) \quad (9)$$

$$\widehat{\Delta f_k}^{(0)} = \frac{f_{2,k} - f_{1,k}}{2\pi(L_{pre} + L_{data})}; \quad (10)$$

with

$$f_{1,k} = arg \left(\sum_{n=0}^{L_{pre}-1} s_k(n) \times z_k(n) \right) \quad (11)$$

$$f_{2,k} = arg \left(\sum_{n=L_{pre}+L_{data}}^{L_{pilot}+L_{pre}+L_{data}-1} s_k(n) \times z_k(n) \right) \quad (12)$$

where L_{pre}, L_{pilot} and L_{data} are symbol lengths of the preamble, postamble and data blocks respectively.
3) **Expectation - E Step:**

$$\widehat{p_k}^{(m)}(n) = z_k(n) \widehat{A_k}^{(m-1)} e^{j(2\pi \widehat{\Delta f_k}^{(m-1)} T_s n + \widehat{\varphi_k}^{(m-1)})} + \beta_k \left[s_k(n) - \sum_{l=1}^{K} \widehat{h_l}(n)^{(m-1)} z_l(n) q((\tau_k - \tau_l)T_s) \right] \quad (13)$$

where $\widehat{p_k}$ are the estimated training symbols of user k, n here refers to the index of a training symbol, β_k is a coefficient arbitrarily set to 0.8 for all users and $\widehat{h_l}(n)^{(m-1)}$ is expressed as follows

$$\widehat{h_l}(n)^{(m-1)} = \widehat{A_l}^{(m-1)} e^{j(2\pi \widehat{\Delta f_k}^{(m-1)} nT_s + \widehat{\varphi_k}^{(m-1)})} \quad (14)$$

4) **Maximization - M Step:**

$$\min_{A', \Delta f', \varphi'} \sum_{n=1}^{\Upsilon} \left| z_k(n) \widehat{p_k}^{(m)}(n) - A' e^{j(2\pi \Delta f' T_s n + \varphi')} \right|^2 \quad (15)$$

where A', $\Delta f'$ and φ' are tentative values of the channel parameters to be estimated.

C. Joint Estimation and Decoding Approach

Joint estimation and decoding [10] allows to feedback decoded bits to the channel estimator. In [11], a similar scheme is used in the context of physical-layer network coding [12]. In our work we implement joint estimation and decoding with hard-decision feedback for the purpose of accurate interference cancellation in RA methods.

In fact, to approach the interference free case, it is better to use the data symbols constituting the packets and not just the training symbols in the estimation process. This can be done with joint iterative estimation and decoding. In a first step, channel parameters are estimated using training symbols as done in Section III-B. Then the interference is removed from the considered slot. Practically the first estimation is not perfect and residual estimation errors are added to the signal of interest. However, we demodulate and decode the desired signal even in presence of residual estimation errors. The resulting decoded bits, although not all correct, are fed back to the estimator. Thus, the estimation process relies not only on the training symbols but also on the payload data, making the channel parameters estimation more accurate.

IV. Derivation of CRLBs and MSEs

The Cramer-Rao lower bounds (CRLB) express lower bounds on the variance of estimation errors of deterministic parameters [13]. In [14] the CRLBs for joint estimation of multiple channel impairments are derived for an amplify and forward (AF) two-way relaying network. We use the same approach to compare our results to the CRLBs. For sake of simplicity, we consider a system with two users. The vector y_t corresponding to the training parts of the received signal y (Eq. (1)), can be written as

$$y_t = \Omega\alpha + W \quad (16)$$

where $\Omega = [\Lambda_1 G z_1 \Lambda_2 G z_2]$ is an $MQ \times 2$ matrix, with M the length of the training vector z, Λ is an $LQ \times LQ$ matrix equal to $diag\left([e^{j(2\pi\Delta f(0)T_e)}, ..., e^{j(2\pi\Delta f(LQ-1)T_e)}]\right)$, G is the $MQ \times L$ matrix of the samples of the shaping filter g, α is equal to the transpose of $[\alpha_1, \alpha_2]$ with $\alpha_k = A_k e^{j\varphi_k}$ and W is the complex noise vector of length MQ.

Following [14], the vector y_t of the received signal is a circularly symmetric complex Gaussian random vector with mean μ given by

$$\mu = \Omega\alpha = \alpha_1 \Lambda_1 G z_1 + \alpha_2 \Lambda_2 G z_2 \quad (17)$$

We suppose that timing offsets are estimated separately at an earlier stage than the rest of the channel impairments. Therefore, the parameter vector of interest λ (i.e. the channel parameters to estimate jointly) is

$$\lambda = [\Re(\alpha_1), \Re(\alpha_2), \Im(\alpha_1), \Im(\alpha_2), \Delta f_1, \Delta f_2]^T \qquad (18)$$

We derive the 6×6 Fisher's information matrix (FIM), denoted by F, using the following equation

$$F(\theta)_{l,q} = \frac{2}{\sigma_w^2} \Re \left\{ \frac{\partial \mu^H}{\partial \theta_l} \frac{\partial \mu}{\partial \theta_q} \right\} \qquad (19)$$

where θ represents each element of λ, the indexes l and $q \in \{1, 6\}$ and the superscript $(.)^H$ denotes the conjugate transpose operator. The CRLB for the estimation of λ is the vector containing the diagonal elements of the inverse of F. Note that the CRLB for the estimation of α is the sum of the CRLBs for the estimation of real and imaginary parts of α.

To compare the performance of the actual estimator with the calculated CRLBs, we dervie the MSEs for the estimated parameters of each user based on experimental simulations. The equations used to plot the MSEs in Fig. 2 and Fig. 3 are

$$MSE(\alpha_k) = E\left[\left|e_{\alpha_k}\right|^2\right] = E\left[\left|A_k e^{j\phi_k} - \widehat{A_k} e^{j\widehat{\phi_k}}\right|^2\right] \qquad (20)$$

$$MSE(\Delta f_k) = E\left[\left|e_{\Delta f_k}\right|^2\right] = E\left[\left|\Delta f_k - \widehat{\Delta f_k}\right|^2\right] \qquad (21)$$

Fig. 2 and Fig. 3 plot results for user 1 with confidence intervals equal to $[mse - \sigma_e^2, mse + \sigma_e^2]$ where σ_e^2 is the variance of the estimation error. Similar results are obtained for user 2 on the E_s/N_0 range considered. The figures show that the loss with respect to the CRLB is constantly around 3 dB and 6 dB for the estimation of α_1 and Δf_1 respectively.

To further show how meaningful is the estimation error, we derive the mean signal to noise plus residual estimation errors ratio for the remaining user to decode (user 2)

$$E\left[\frac{C}{N_0 + P_{e_1}}\right] = \frac{E\left[\left|\widehat{h_2}\right|^2\right]}{N_0 + E\left[P_{e_1}\right]} \qquad (22)$$

where N_0 is the noise power spectral density and P_{e_1} is the power of the residual estimation errors of user 1, detailed as follows

$$\begin{aligned} P_{e_1} =& E\left[\left|\widehat{h_1} - h_1\right|^2\right] \\ =& E\left[\left|\widehat{\alpha_1} e^{j2\pi\widehat{\Delta f_1} n T_s} - \alpha_1 e^{j2\pi \Delta f_1 n T_s}\right|^2\right] \\ =& A_1^2 E\left[\left|\frac{\widehat{A_1}}{A_1} e^{j2\pi(\widehat{\Delta f_1} - \Delta f_1) n T_s + (\widehat{\phi_1} - \phi_1)} - 1\right|^2\right] \end{aligned} \qquad (23)$$

According to Fig. 3, we can neglect the effect of $(\widehat{\Delta f_1} - \Delta f_1)$ over a limited packet length (620 symbols in our case). Then, we can suppose that after several simulations, the mean power of estimation errors $E\left[P_{e_1}\right]$ is equal to $MSE(\alpha_1)$. If we compute the ration in Eq. (23) for $E_s/N_0 = 2$ dB, we obtain a degradation around 0.2 dB.

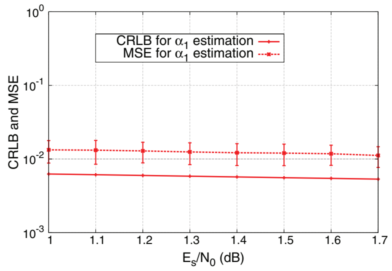

Fig. 2: CRLB and MSE for estimation of α_1 at destination node D.

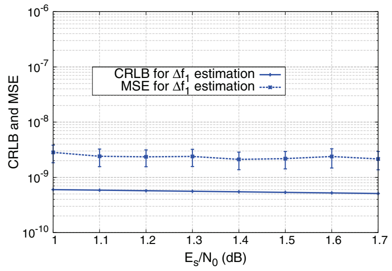

Fig. 3: CRLB and MSE for the estimation of Δf_1 at destination node D.

V. Experimental Results

In this section we compute the packet error rate (PER) after demodulating and decoding the sampled signal $s2$ in presence of residual estimation errors. We compare the results to the case of perfect channel state information (CSI). We use as training sequences, Walsh-Hadamard words of lengths 40 symbols for preambles and 12 symbols for pilots and postambles. We uniformly distribute 9 pilot blocks inside each packet. The payload data is encoded with a CCSDS (Consultative Committee for Space Data Systems [15]) turbo code of rate $1/2$, provided by the CML (Coded Modulation Library [16]). The resulting codeword has a length of 460 symbols modulated with quadrature phase-shift keying (QPSK). The pilot symbols result in an overhead of 23.4%. The oversampling rate of the shaping filter is set to $Q = 5$, and the noise variance $\sigma_n^2 = 1/(E_s/N_0)$. Note that the execution time of our method increases linearly with the number of iterations. To achieve convergence, The EM algorithm is iterated 4 times, and joint estimation and decoding is repeated up to 3 times. For each run, the MSEs and the PER are calculated over 10000 packets.

A. One Interference

We consider two users colliding on the same time slot. We suppose the channel amplitudes A_2 and A_1 normalized to 1 (worst case scenario). The timing offsets τ_1 and τ_2 are uniformly distributed over the range $\left[0, \frac{Q-1}{Q}\right]$. Fig.4 illustrates the PER obtained with application of the proposed channel estimation (CE) technique and joint estimation and decoding (JED) on misaligned packets. It shows that with JED, the PER performance degradation in comparison to perfect CSI is around 0.1 dB for $E_s/N_0 < 2$ dB, and around 0.3 dB for $E_s/N_0 > 2$ dB. The results correlate with the signal to

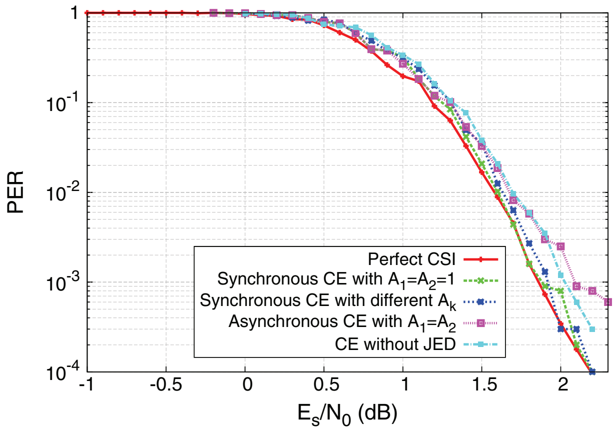

Fig. 4: PER vs E_s/N_0 after channel estimation and interference cancellation in case of one interference

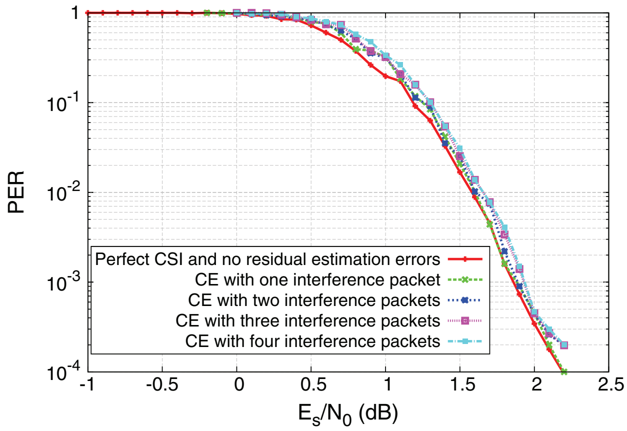

Fig. 5: PER vs E_s/N_0 after cumulative interference cancellation and channel estimation in case of more than one interference packet

noise plus residual estimation errors ratio calulated in Section IV. Fig.4 also shows that in the case of two synchronous packets with different channel attenuations ($A_1 \in [0.7, 1]$ and $A_2 = 1$), the estimation is good enough to induce negligeable degradation on the PER after interference cancellation.

B. More than One Interference

Now we consider the case where several packets collide on the same time slot, and we decode the packet of interest after iterative interference cancellation in the presence of cumulative residual estimation errors. Fig. 5 illustrates the PER after cancellation of up to four interferents all having equal power. We notice that the degradation of PER does not exceed 0.1 dB.

VI. Discussion, conclusion and future work

The summary of our work is the use of the iterative EM algorithm and the integration of accurate timing offset estimation inside EM, as well as applying a joint estimation and decoding approach on the whole system. We have been able to jointly estimate different channel impairments while keeping a relatively low performance loss that does not exceed 0.3 dB, with the experimental assumptions considered. We have also showed that the MSEs obtained are close to the CRLBs. We have not compared the gains of this EM-based solution for RA methods with respect to existing implementation in [7] because the use case is different. In [7], the channel estimation has been done in presence of superimposed packets, but its effect has been evaluated on the simultaneous decoding of multiple users (NDCP). While in our paper, we have investigated the impact of cumulative residual estimation errors after interference cancellation.

Furthermore, we have noticed that timing offset estimation with autocorrelation causes an additional loss in the PER, so we can consider to use more accurate timing estimators in the future studies. Also, the evaluation has been performed for a certain range of E_s/N_0 corresponding to a high performance forward error correction (FEC) code, and it may be useful to evaluate the performance degradation at higher values of E_s/N_0 for different FEC codes.

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