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## RESEARCH ARTICLE

# Comparison of multiple-input single-output single-user ultra-wideband systems with pre-distortion

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## ABSTRACT

This paper presents a performance analysis of a baseband multiple-input single-output ultra-wideband system over scenarios CM1 and CM3 of the IEEE 802.15.3a channel model, incorporating four different schemes of pre-distortion: time reversal, zero-forcing pre-equaliser, constrained least squares pre-equaliser, and minimum mean square error pre-equaliser. For the third case, a simple solution based on the steepest-descent (gradient) algorithm is adopted and compared with theoretical results. The channel estimations at the transmitter are assumed to be truncated and noisy. Results show that the constrained least squares algorithm has a good trade-off between intersymbol interference reduction and signal-to-noise ratio preservation, providing a performance comparable to the minimum mean square error method but with lower computational complexity. Copyright © 2011 John Wiley & Sons, Ltd.

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## 1. INTRODUCTION

Ultra-wideband (UWB) is an emerging technology that employs ultra-short pulses to transmit information, resulting in a very large bandwidth. Because of its attractive characteristics, such as very high data rates, low probability of interception and good time domain resolution allowing location and tracking applications at centimetre level, UWB has been considered as a promising solution for short-distance high-data-rate communications, such as wireless personal area networks.

Ultra-wideband channel is characterised by a dense multipath environment. For the energy spread over the multipath components to be effectively captured, the transmit-based time reversal (TR) technique (sometimes called pre-Rake) has been investigated [1–6]. In baseband TR, the channel impulse response (CIR) is estimated from a probe signal, and the data are convolved with the complex conjugate time-reversed version of the estimated CIR (namely, TR coefficients) prior to transmission. This technique is based on the channel reciprocity, which was

experimentally verified in [1] for a particular UWB environment. TR-based UWB transmission can provide intersymbol interference (ISI) mitigation by reducing the delay spread of the channel and also co-channel interference rejection by focusing the signal on the point of interest.

However, for high transmission rates, the residual ISI will still degrade the system performance because the equivalent CIR after TR\* is not a delta function. In order to handle such impairments, we can employ a receiver-based channel equalisation scheme with fewer taps than that used without TR [7–9].

In wireless communications, it is sometimes desired to keep portable devices as simple and as power efficient as possible. From this standpoint, a receiver-based equaliser may aggregate an undesired complexity to the

\*The term equivalent CIR refers to the convolution between the TR coefficients and the original CIR. In a multiple-input single-output (MISO) system, it is the summation of the resultant convolutions from each transmit antenna element.

receiver in a downlink scenario. Hence, some transmitter-based equalisation can be applied to mitigate ISI, without adding complexity to the receiver. In [10], the authors compared the performance of pure TR with a zero-forcing (ZF) pre-equalised system, for fixed wireless access channels, and also proposed a new joint ZF and TR scheme. In [11], the authors proposed additional spatial and frequency filters to the ZF and TR pre-filters over an IEEE 802.11n channel model. In [12], two novel minimum mean square error (MMSE)-based symbol-level pre-equalisation for MISO direct-sequence UWB (DS-UWB) systems in cascade with pre-Rake combining are proposed and shown to achieve a good bit error rate (BER) performance.

In this work, a performance comparison of a downlink MISO UWB system with four different schemes of pre-distortion is presented. An objective function modeled as a constrained least squares (CLS) problem is considered. Imperfect channel estimation, no coding and perfect data synchronisation are considered. The transmission is assumed to be from an access point with relatively good computational capacity to a lower complexity device with hardware constraints. When the number of transmit antennas is  $N_t > 1$ , it is assumed that the small-scale fading components across antennas are independent, but the shadowing factors are correlated, according to the method in [13].

Overall, despite many papers in the field of impulse UWB considering a carrier-free pulse, the IEEE 802.15.3a DS-UWB [14] standard, as well as the IEEE 802.15.4a UWB standard [15], assumes a square-root raised-cosine (RRC) pulse that requires a carrier. All the schemes presented in this paper are performed in baseband considering an RRC pulse shape.

The rest of the paper has the following organisation. Section 2 describes the UWB channel and system model. Section 3 considers the derivation of pre-filter coefficients, whereas Section 4 presents a complexity analysis, and Section 5 considers the signal-to-interference-plus-noise rate (SINR) analysis. Section 6 shows the simulation parameters and results, whereas Section 7 points out the main conclusions.

## 2. CHANNEL AND SYSTEM MODEL

### 2.1. Channel model

A discrete-time complex baseband version of the IEEE 802.15.3a model is used [16, 17], where multipath components arrive in clusters. Cluster and ray arrivals within each cluster are Poisson distributed with rate  $\Lambda$  and  $\lambda > \Lambda$ , respectively. The arrival times of the  $\ell_1$ th cluster and the  $\ell_2$ th ray within the  $\ell_1$ th cluster are denoted by  $\tau_{\ell_1}$  and  $\tau_{\ell_1, \ell_2}$ . The multipath gain  $\beta_{\ell_1, \ell_2}$  is described by a log-normal distribution, and its phase assumes only 0 or  $\pi$  with equal probability. A channel realisation at  $k$ th antenna

**Table I.** Channel parameters for CM1 and CM3 of IEEE 802.15.3a model.

Parameters	CM1	CM3
$\Lambda$ (1/ns)	0.0233	0.0667
$\lambda$ (1/ns)	2.5	2.1
$\sigma_1$ (dB)	3.39	3.39
$\sigma_2$ (dB)	3.39	3.39
$\sigma_x$ (dB)	3	3

consists of

$$h'_k(t) = \chi_k \sum_{\ell_1=0}^{L_1-1} \sum_{\ell_2=0}^{L_2-1} \beta_{\ell_1, \ell_2}^k \delta(t - \tau_{\ell_1}^k - \tau_{\ell_1, \ell_2}^k) \quad (1)$$

where  $\delta(\cdot)$  is the Dirac delta function and  $\chi_k = 10^{(\sigma_x/20)} w_k$  is the log-normal shadowing associated with the Gaussian random variable (r.v.)  $w_k$ , with  $\sigma_x = 3$  dB being the standard deviation of  $\chi_k$  [16]. Two scenarios are considered: CM1 and CM3. Table I summarises the channel parameters [16].

The terms  $\sigma_1$  and  $\sigma_2$  are respectively the standard deviation of cluster log-normal fading ( $\beta_{\ell_1, \ell_2}^k$  for a fixed  $\ell_2$ ) and ray log-normal fading ( $\beta_{\ell_1, \ell_2}^k$  for a fixed  $\ell_1$ ).

The  $k$ th discrete-time complex baseband CIR with sampling interval  $T$  and length  $L$  is obtained by [12]

$$h_k[m] = g_T(t) * h''_k(t) * g_R(t) \Big|_{mT} \quad (2)$$

where  $T$  is the reciprocal of the symbol rate,  $*$  denotes convolution,  $g_R(t)$  is matched to the pulse  $g_T(t)$ , which has an RRC shape, and  $h''_k(t)$  is a baseband version of  $h'_k(t)$ . Here, parameter  $T$  is used for the pulse generation, but the effective symbol rate is controlled by the interval between consecutive symbols,  $T_s = \kappa T$ , where  $\kappa$  is an integer.<sup>†</sup> According to [13], the multipath components are independent across antennas, but the shadowing terms  $\chi_k$  are correlated. Therefore, the CIRs are normalised before inserting the shadowing effect, which for the three antenna cases has the following correlation matrix [13]

$$\mathbf{R}_\chi = \begin{bmatrix} 1 & 0.86 & 0.54 \\ 0.86 & 1 & 0.86 \\ 0.54 & 0.86 & 1 \end{bmatrix} \quad (3)$$

For two transmitter antennas,  $\mathbf{R}_\chi$  is a  $2 \times 2$  matrix with 0.86 in the secondary diagonal. Considering  $\rho_{\chi_k, \chi_j}$ , the correlation coefficient between the log-normal variables  $\chi_k, \chi_j$ , and  $\rho_{w_k, w_j}$ , the correlation coefficient between

<sup>†</sup>In fact, if there was no time interval (multiple of  $T$ ) between consecutive symbols,  $1/T$  would be the effective symbol rate.

the Gaussian variables  $w_k, w_j$ , related to  $\chi_k, \chi_j$ , it was shown in [13] that

$$\rho_{w_k, w_j} = \frac{1}{\xi^2 \sigma_\chi^2} \ln \left\{ \left( e^{\xi^2 \sigma_\chi^2} - 1 \right) \rho_{\chi_k, \chi_j} + 1 \right\} \quad (4)$$

with  $\xi = \ln(10)/2$ .

Hence, from  $\rho_{w_k, w_j}$ , a Gaussian correlated vector of size  $N_t$  is obtained. Finally, a log-normal correlated vector of size  $N_t$  is obtained according to  $\chi_k = 10(\sigma_\chi/20)w_k$ .

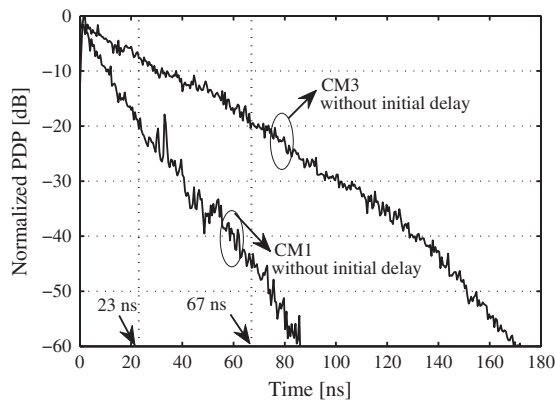
The discrete-time CIR with resolution  $T$ , length  $L$  and correlated shadowing is given by

$$h_k[m] = \sum_{\ell=0}^{L-1} \alpha_\ell^k \delta[m-\ell] \quad (5)$$

### 2.2. Channel estimation

Because of the large number of resolvable paths, the CIR on each antenna is truncated to obtain the TR coefficients. The criterion for this truncation is illustrated in Figure 1. The normalised power delay profile does not take into account the interval (zero samples) before the first significant path. Mainly in the scenario CM3, there might exist a relative delay between the first significant path on each antenna element. However, such a delay must be reinserted in the estimated channels in order to properly combine the components from each antenna. As the original channel model does not consider multiple antennas, the maximum relative delay among CIRs was fixed at 2.505 ns, which corresponds to five times the channel resolution.

Moreover, the TR coefficients are obtained, considering estimate errors. The method for generating CIR estimation errors is based on [4]. Assuming a time duplex division system, a sequence of  $N_p$  probe pulses with a repetition period longer than the maximum effective delay spread of the channel,  $\tau_{ef}$ , is transmitted from the receiver to the



**Figure 1.** Normalised power delay profile (PDP) for CM1 and CM3, not considering the zero samples before the first significant path. A  $-20$ -dB criterion is chosen for the CIR truncation on each antenna.

transmitter side. Assuming perfect synchronisation, the  $N_p$  CIR realisations estimated on each antenna are coherently averaged. If the additive white Gaussian noise (AWGN) double-sided power spectral density per antenna is given by  $N_0/2$ , the signal-to-noise ratio (SNR) per antenna is defined as

$$SNR = \frac{E_b^k}{N_0} \quad (6)$$

where  $E_b^k = E_b/N_t$  is the mean bit energy per antenna, considering  $N_t$  antennas. Assuming a static channel during the frame period, the estimated coefficients on the  $k$ th antenna,  $\{\tilde{\alpha}_\ell^k\}_{\ell=0}^{L-1}$ , are represented as

$$\tilde{\alpha}_\ell^k = \frac{1}{N_p} \sum_{n=1}^{N_p} \tilde{\alpha}_\ell^k(n) = \alpha_\ell^k + e_\ell^k, \quad (7)$$

with  $e_\ell^k$  being a complex Gaussian r.v. that represents the noise of the imperfect channel estimation on the  $\ell$ th resolvable path, with variance of the in-phase and quadrature components given by  $N_0/2 N_p$  [4]. The estimated discrete-time CIR after truncation is defined as  $\tilde{h}_k[m]$ , with length  $L_C$ . It is important to note that channel estimation errors are not explicitly shown in the results. However, in all cases, the pre-filter coefficients are obtained, taking into account the estimated CIR, which is noisy and truncated.

### 2.3. System model

The discrete-time model considered is shown in Figure 2.  $\gamma_k$  represents the sequence of pre-filter coefficients on the  $k$ th antenna, and  $z[m]$  is the sampled AWGN. Signals and systems are represented by their complex baseband equivalents. For antipodal binary signalling with symbols  $b_i \in \{\pm 1\}$  and  $N_t$  antennas, the signal to be transmitted on the  $k$ th antenna element is represented as

$$s_k[m] = \sqrt{E_b^k} \sum_{i=-\infty}^{\infty} b_i \gamma_k[m-i\kappa] \quad (8)$$

with  $\gamma_k[m]$  representing the pre-filter on the  $k$ th antenna. Considering perfect synchronisation, the output of the receive matched filter (MF), resampled at the rate  $1/T_s$ , is

$$y[n] = \sum_{i=-\infty}^{\infty} b_i x[n-i] + z[n] \quad (9)$$

where  $z[n]$  is the discrete-time AWGN at the output of the MF and  $x[n]$  denotes the equivalent CIR, which is obtained from

$$x[m] = \sqrt{E_b^k} \sum_{k=1}^{N_t} (\gamma_k * h_k)[m] \quad (10)$$

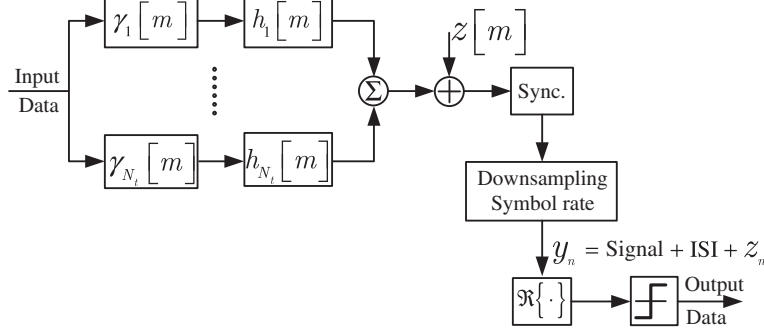


Figure 2. Equivalent discrete-time model. ISI represents the intersymbol interference,  $y_n = y(nT_s)$  and  $z_n = z(nT_s)$ .

downsampling it by a factor of  $\kappa = T_s/T$ . Assuming  $E_b^k = 1$ , the variance of the AWGN per antenna,  $z_k[m]$ ,  $k = 1, \dots, N_t$ , is given by  $\sigma_k^2 = 1/SNR$  (the same for each antenna).

### 3. PRE-FILTER COEFFICIENTS

In all the schemes considered, the length of the pre-filter on each antenna is set as  $L_{PF} \leq L_C$ . An estimate of  $x[m]$  from Equation (10) in a matrix-vector notation can be obtained as

$$\tilde{\mathbf{x}} = \tilde{\mathbf{H}}\boldsymbol{\gamma} \quad (11)$$

where  $\boldsymbol{\gamma} = [(\boldsymbol{\gamma}^0)^\top \dots (\boldsymbol{\gamma}^{L_{PF}-1})^\top]^\top$  is a  $(N_t L_{PF}) \times 1$  vector with  $\boldsymbol{\gamma}^\ell = [\gamma_1[\ell] \dots \gamma_{N_t}[\ell]]^\top$ , with  $\{\cdot\}^\top$  meaning transposition;  $\tilde{\mathbf{H}}$  is a  $p \times q$  block Toeplitz matrix, where  $p = L_C + L_{PF} - 1$  and  $q = N_t L_{PF}$ , given by

$$\tilde{\mathbf{H}} = \begin{bmatrix} (\tilde{\mathbf{h}}^0)^\top & \mathbf{0}^\top & \dots & \mathbf{0}^\top \\ (\tilde{\mathbf{h}}^1)^\top & (\tilde{\mathbf{h}}^0)^\top & \ddots & \vdots \\ \vdots & (\tilde{\mathbf{h}}^1)^\top & \ddots & \mathbf{0}^\top \\ (\tilde{\mathbf{h}}^{L_C-1})^\top & \vdots & \ddots & (\tilde{\mathbf{h}}^0)^\top \\ \mathbf{0}^\top & (\tilde{\mathbf{h}}^{L_C-1})^\top & & (\tilde{\mathbf{h}}^1)^\top \\ \vdots & \ddots & \ddots & \vdots \\ \mathbf{0}^\top & \dots & \mathbf{0}^\top & (\tilde{\mathbf{h}}^{L_C-1})^\top \end{bmatrix} \quad (12)$$

whose first  $N_t$  columns are padded with  $L_{PF} - 1$  null vectors,  $\mathbf{0}^\top$ , with length  $N_t$  and  $\tilde{\mathbf{h}}^\ell = [\tilde{h}_1[\ell] \dots \tilde{h}_{N_t}[\ell]]^\top$ . After obtaining  $\boldsymbol{\gamma}$ , we reshaped it into a matrix of  $N_t$  rows and  $L_{PF}$  columns, whose  $k$ th row represents the pre-filter coefficients on the  $k$ th antenna element,  $\boldsymbol{\gamma}_k = [\gamma_k[0], \dots, \gamma_k[L_{PF} - 1]]$ .

### 3.1. Time reversal pre-filter

Time reversal coefficients on the  $k$ th antenna,  $\boldsymbol{\gamma}_k = \boldsymbol{\gamma}_k^{TR} = [\gamma_k^{TR}[0] \dots \gamma_k^{TR}[L_{PF} - 1]]$ , are obtained as

$$\gamma_k^{TR}[m] = C_k (\tilde{h}_k[-m])^* \quad (13)$$

where the constant  $C_k$  depends on the power allocation scheme.<sup>‡</sup> In this paper,  $C_k$  is set to be equal for all the antenna elements, that is,

$$C_k = C = \frac{N_t}{\sqrt{\sum_{k=1}^{N_t} \|\tilde{\mathbf{h}}_k\|_2^2}} \quad (14)$$

with  $\tilde{\mathbf{h}}_k = [\tilde{h}_k[0] \dots \tilde{h}_k[L_{PF} - 1]]$  being the vector of estimated taps for each antenna element. Note that the total energy of the normalised coefficients from all  $N_t$  antennas is equal to  $N_t$ . It is possible to see that the vector of TR coefficients for all  $N_t$  antennas,  $\boldsymbol{\gamma} = \boldsymbol{\gamma}^{TR}$ , is given by the  $(L_{PF})$ th line of the matrix  $\tilde{\mathbf{H}}$  in Equation (12), multiplied by the normalisation factor  $C_k$ .

### 3.2. Zero-forcing pre-equaliser

The ZF pre-equaliser attempts to cancel the ISI. Here, the ZF coefficients for all  $N_t$  antennas,  $\boldsymbol{\gamma} = \boldsymbol{\gamma}^{ZF}$ , are obtained, considering that

$$\tilde{\mathbf{H}}\boldsymbol{\gamma}^{ZF} = \psi \mathbf{d}_v \quad (15)$$

where  $\mathbf{d}_v = [0, \dots, 0, 1, 0, \dots, 0]^\top$  has length  $p$ , with 1 at the  $v$ th position.  $v$  and  $\psi$  are specified below. The ZF solution is given by

$$\boldsymbol{\gamma} = \boldsymbol{\gamma}^{ZF} = \psi \tilde{\mathbf{H}}^\dagger \mathbf{d}_v \quad (16)$$

<sup>‡</sup>For a causal representation,  $h_k^{TR}[m] = C_k (\tilde{h}_k[L_{PF} - m - 1])^*$  should have been assumed, but it does not change the theoretical results because we are further considering that the index 0th represents the information timing.

with  $\tilde{\mathbf{H}}^\dagger$  being the pseudo-inverse of  $\tilde{\mathbf{H}}$ . If  $q > p$  and  $\text{rank}(\tilde{\mathbf{H}}) = p$ , there are many solutions. One particular solution is  $\tilde{\mathbf{H}}^\dagger = \tilde{\mathbf{H}}^H (\tilde{\mathbf{H}}\tilde{\mathbf{H}}^H)^{-1}$ , which minimises  $\|\tilde{\mathbf{H}}\mathbf{y}^{\text{ZF}} - \psi\mathbf{d}_v\|_2^2$ . In this case,  $v$  is selected in order to maximise  $\psi$  because it determines the power of the received signal [10]. Assuming  $\|\mathbf{y}^{\text{ZF}}\|_2^2 = N_t$ , it follows that

$$\begin{aligned} \|\mathbf{y}^{\text{ZF}}\|_2^2 &= N_t \\ \Rightarrow |\psi|^2 \mathbf{d}_v (\tilde{\mathbf{H}}\tilde{\mathbf{H}}^H)^{-1} \tilde{\mathbf{H}}\tilde{\mathbf{H}}^H (\tilde{\mathbf{H}}\tilde{\mathbf{H}}^H)^{-1} \mathbf{d}_v &= N_t \\ \Rightarrow |\psi|^2 \left[ (\tilde{\mathbf{H}}\tilde{\mathbf{H}}^H)^{-1} \right]_{v,v} &= N_t \end{aligned} \quad (17)$$

Hence,  $v$  is chosen so that  $\left[ (\tilde{\mathbf{H}}\tilde{\mathbf{H}}^H)^{-1} \right]_{v,v}$  is minimum. Note that the condition  $N_t \geq 2$  must be satisfied for a ZF solution. If  $N_t = 2$ ,  $L_{\text{PF}}$  cannot be smaller than  $L_{\text{C}}$ .

On the other hand, if  $p > q$  and  $\text{rank}(\tilde{\mathbf{H}}) = q$ , a ZF solution cannot be guaranteed. However,  $v$  can be fixed as  $v = L_{\text{PF}}$ , for example, and an approximated solution (denoted by ZF') that minimises  $\|\tilde{\mathbf{H}}\mathbf{y} - \mathbf{d}_v\|_2^2$  can be obtained as  $\mathbf{y} = \tilde{\mathbf{H}}^\dagger \mathbf{d}_v$ , where  $\tilde{\mathbf{H}}^\dagger = (\tilde{\mathbf{H}}^H \tilde{\mathbf{H}})^{-1} \tilde{\mathbf{H}}^H$ . This solution has to be normalised in order to generate a power-constrained solution given by  $\mathbf{y}^{\text{ZF}'} = \sqrt{N_t / \|\mathbf{y}\|_2^2} \mathbf{y}$ .

### 3.3. Constrained least squares pre-equaliser

Because  $\tilde{\mathbf{h}}_k$  is available at the transmitter, let  $\tilde{\mathbf{h}}_k = C \mathbf{h}_k$  be a normalised version of  $\mathbf{h}_k$ . Thus, a normalised estimation of  $x[m]$  in a matrix-vector can be obtained as

$$\tilde{\mathbf{x}} = \tilde{\mathbf{H}}\mathbf{y} \quad (18)$$

where  $\tilde{\mathbf{H}}$  is given by Equation (12), substituting  $\tilde{\mathbf{h}}^\ell = C_k [h_1[\ell] \dots h_{N_t}[\ell]]^\top$  for  $\mathbf{h}^\ell = [h_1[\ell] \dots h_{N_t}[\ell]]^\top$ .

Considering a power constraint  $\|\mathbf{y}\|_2^2 \leq N_t$ , the idea of the CLS equaliser is to make  $\tilde{\mathbf{x}}$  be as close as possible to the vector  $\mathbf{d} = [0 \dots N_t \dots 0]^\top$  with length  $p$  and  $N_t$  at position  $L_{\text{PF}}$ . Defining  $J_{\text{CLS}} = \|\tilde{\mathbf{x}} - \mathbf{d}\|_2^2$ , we can obtain  $\mathbf{y} = \mathbf{y}^{\text{CLS}}$  as

$$\begin{aligned} \min_{\mathbf{y}} J_{\text{CLS}} \\ \text{s.t. } \|\mathbf{y}\|_2^2 \leq N_t \end{aligned} \quad (19)$$

In [18], a solution for the CLS problem using the singular-value decomposition (SVD) of  $\tilde{\mathbf{H}}$  and Lagrange multipliers is presented and named least squares minimisation over a sphere. The matrix  $\tilde{\mathbf{H}}$  is decomposed, such that  $\mathbf{U}^H \tilde{\mathbf{H}} \mathbf{V} = \Sigma_{\tilde{\mathbf{H}}}$ , where  $\mathbf{V} = [\mathbf{v}_1 \mathbf{v}_2 \dots \mathbf{v}_q]$  ( $q \times q$ ) and  $\mathbf{U} = [\mathbf{u}_1 \mathbf{u}_2 \dots \mathbf{u}_p]$  ( $p \times p$ ) are unitary matrices,

whereas  $\Sigma_{\tilde{\mathbf{H}}}$  is the matrix (not necessarily square) whose diagonal elements are the singular values of  $\tilde{\mathbf{H}}$ . With this transformation,

$$\begin{aligned} \|\mathbf{U}^H (\tilde{\mathbf{H}}\mathbf{y} - \mathbf{d})\|_2^2 &= \|\mathbf{U}^H (\tilde{\mathbf{H}}\mathbf{V}\mathbf{V}^H\mathbf{y} - \mathbf{d})\|_2^2 \\ &= \|\mathbf{U}^H \tilde{\mathbf{H}}\mathbf{V}\mathbf{V}^H\mathbf{y} - \mathbf{U}^H \mathbf{d}\|_2^2 \\ &= \|\Sigma_{\tilde{\mathbf{H}}}\tilde{\mathbf{y}} - \tilde{\mathbf{d}}\|_2^2 \end{aligned} \quad (20)$$

where  $\tilde{\mathbf{d}} = \mathbf{U}^H \mathbf{d}$ ,  $\tilde{\mathbf{y}} = \mathbf{V}^H \mathbf{y}$  and  $\{\cdot\}^H$  the Hermitian operator. Note that  $\|\tilde{\mathbf{y}}\|_2^2 = \|\mathbf{V}^H \mathbf{y}\|_2^2 = \|\mathbf{y}\|_2^2$ . Therefore, the following Lagrange problem is obtained

$$\mathcal{L}(\tilde{\mathbf{y}}, \lambda) = (\Sigma_{\tilde{\mathbf{H}}}\tilde{\mathbf{y}} - \tilde{\mathbf{d}})^H (\Sigma_{\tilde{\mathbf{H}}}\tilde{\mathbf{y}} - \tilde{\mathbf{d}}) + \lambda (\tilde{\mathbf{y}}^H \tilde{\mathbf{y}} - N_t) \quad (21)$$

with  $\lambda$  being the Lagrange multiplier. With  $\mathcal{L}(\tilde{\mathbf{y}}, \lambda)$  being differentiated with respect to  $\tilde{\mathbf{y}}^*$  and the resulting gradient being set to zero, it follows that

$$\begin{aligned} \frac{\partial \mathcal{L}(\tilde{\mathbf{y}}, \lambda)}{\partial \tilde{\mathbf{y}}^*} = 0 &\Rightarrow \Sigma_{\tilde{\mathbf{H}}}^\top (\Sigma_{\tilde{\mathbf{H}}}\tilde{\mathbf{y}} - \tilde{\mathbf{d}}) + \lambda \tilde{\mathbf{y}} = 0 \\ &\Rightarrow (\lambda I + \Sigma_{\tilde{\mathbf{H}}}^\top \Sigma_{\tilde{\mathbf{H}}}) \tilde{\mathbf{y}} = \Sigma_{\tilde{\mathbf{H}}}^\top \tilde{\mathbf{d}} \end{aligned} \quad (22)$$

Hence, the CLS filter coefficients are given by

$$\tilde{\mathbf{y}} = \left[ \frac{\sigma_1}{\lambda + \sigma_1^2} \tilde{d}_1 \quad \frac{\sigma_2}{\lambda + \sigma_2^2} \tilde{d}_2 \quad \dots \quad \frac{\sigma_r}{\lambda + \sigma_r^2} \tilde{d}_r \right]^\top \quad (23)$$

with the following constraint

$$\sum_{i=1}^r \left( \frac{\sigma_i}{\lambda + \sigma_i^2} \right)^2 |\tilde{d}_i|^2 = N_t \quad (24)$$

where  $r$  is the rank of the matrix  $\tilde{\mathbf{H}}$ . Consequently, if  $\sum_{i=1}^r |\tilde{d}_i|^2 / \sigma_i^2 > N_t$ , then

$$\begin{aligned} \mathbf{y} = \mathbf{y}^{\text{CLS}} &= \sum_{i=1}^r \left( \frac{\sigma_i \tilde{d}_i}{\lambda^* + \sigma_i^2} \right) \mathbf{v}_i \\ \lambda^* &\leftarrow \sum_{i=1}^r \left( \frac{\sigma_i}{\lambda^* + \sigma_i^2} \right)^2 |\tilde{d}_i|^2 = N_t \end{aligned} \quad (25)$$

else,

$$\mathbf{y} = \mathbf{y}^{\text{CLS}} = \sum_{i=1}^r \left( \frac{\tilde{d}_i}{\sigma_i} \right) \mathbf{v}_i \quad (26)$$

The term  $\lambda^*$  can be found using, for instance, the bisection method. In order to find an iterative solution for the CLS problem, we firstly considered the unconstrained

problem. The gradient of  $J$  is  $\nabla J = -2\tilde{\mathbf{H}}^H \mathbf{e}$ , where  $\mathbf{e} = (\mathbf{d} - \tilde{\mathbf{H}}\boldsymbol{\gamma}^{\text{CLS}})$  is the error vector. In the steepest-descent algorithm, the coefficients on the  $(i + 1)$ th iteration are updated as  $\boldsymbol{\gamma}^{\text{CLS}}(i + 1) = \boldsymbol{\gamma}^{\text{CLS}}(i) + \mu (\tilde{\mathbf{H}}^H \mathbf{e}(i))$ , where  $\mu$  is the convergence factor. This algorithm comes out with a solution that is unconstrained. Therefore, Algorithm 3.3 is proposed to generate an energy-constrained vector  $\boldsymbol{\gamma}^{\text{CLS}}$ .

**Algorithm 1** Modified Steepest Descent

Initialisation:  
 $\boldsymbol{\gamma}^{\text{CLS}}(0) = \boldsymbol{\gamma}^{\text{TR}} = \left[ (\boldsymbol{\gamma}_0^{\text{TR}})^\top \cdots (\boldsymbol{\gamma}_{L_{\text{PF}}-1}^{\text{TR}})^\top \right]^\top$ ;  
 $\boldsymbol{\gamma}_\ell^{\text{TR}} = [\gamma_{\ell,1}^{\text{TR}} \cdots \gamma_{\ell,N_t}^{\text{TR}}]^\top$   
**for**  $i = 1, 2, \dots, \text{ITER}$  (Number of iterations)  
 $\mathbf{e}(i-1) = \mathbf{d} - \tilde{\mathbf{H}}\boldsymbol{\gamma}^{\text{CLS}}(i-1)$ ; (Error)  
 $\boldsymbol{\gamma}_{\text{tmp}}^{\text{CLS}} = \boldsymbol{\gamma}^{\text{CLS}}(i-1) + \mu \tilde{\mathbf{H}}^H \mathbf{e}(i-1)$  (Temp. coeff. update)  
 $\boldsymbol{\gamma}^{\text{CLS}}(i) = \sqrt{\frac{N_t}{\|\boldsymbol{\gamma}_{\text{tmp}}^{\text{CLS}}\|_2^2}} \boldsymbol{\gamma}_{\text{tmp}}^{\text{CLS}}$  (Normalisation)  
**end**

The coefficients are normalised right after the updating process within each iteration, and the error and gradient computations are performed with respect to those normalised coefficients. Figure 3 presents the convergence of the proposed CLS algorithm. The convergence factor  $\mu$  is chosen as in the unconstrained gradient algorithm, that is,  $0 < \mu < 2/\lambda_{\text{max}}^{\mathbf{R}}$ , where  $\lambda_{\text{max}}^{\mathbf{R}}$  represents the maximum eigenvalue of the matrix  $\mathbf{R} = \tilde{\mathbf{H}}^H \tilde{\mathbf{H}}$ . Note that 15 to 30 iterations are enough for achieving convergence.

**3.4. Minimum mean square error pre-equaliser**

Another possible power-constrained pre-equalisation is based on [12], where the filter coefficients are obtained by considering the MMSE criterion applied previously to a TR filter. In this paper, the MMSE filter will not be used in cascade with a TR filter but directly, like in the CLS scheme. Considering  $\mathbf{b} = [b_{n+L_{\text{PF}}-1} \cdots b_n \cdots b_{n-L_C+1}]$ , a vector of information bits with  $L_C + L_{\text{PF}} - 1$  components and

$b_n$  at the  $(L_{\text{PF}})$ th position, the estimated received signal after MF can be written as

$$\tilde{y}_n = \mathbf{b}^H \tilde{\mathbf{x}} + z_n = \mathbf{b}^H \tilde{\mathbf{H}}\boldsymbol{\gamma} + z_n \quad (27)$$

Equation (27) is a non-causal representation, but this does not change the results. As considered in [12], the received signal is multiplied by a constant  $\zeta$  in order to help the minimisation procedure. The design goal of the MMSE criterion is to minimise  $J_{\text{MMSE}} = \mathbb{E} [ |b_n - \zeta \tilde{y}_n|^2 ]$ , subjected to  $\|\boldsymbol{\gamma}\|_2^2 = N_t$ .  $J_{\text{MMSE}}$  is given by

$$\begin{aligned} J_{\text{MMSE}} &= \mathbb{E} [ |b_n - \zeta \tilde{y}_n|^2 ] = \mathbb{E} [ (b_n - \zeta \tilde{y}_n)^* (b_n - \zeta \tilde{y}_n) ] \\ &= \mathbb{E} [ 1 - b_n \zeta \tilde{y}_n - \zeta^* \tilde{y}_n^* b_n + |\zeta|^2 |\tilde{y}_n|^2 ] \\ &= \mathbb{E} [ 1 - b_n \zeta (\mathbf{b}^H \tilde{\mathbf{H}}\boldsymbol{\gamma} + z_n) \\ &\quad - \zeta^* (\boldsymbol{\gamma}^H \tilde{\mathbf{H}}^H \mathbf{b} + z_n^*) b_n + |\zeta|^2 |\tilde{y}_n|^2 ] \end{aligned} \quad (28)$$

The term  $\mathbb{E} [ |\tilde{y}_n|^2 ]$  in Equation (28) is given by

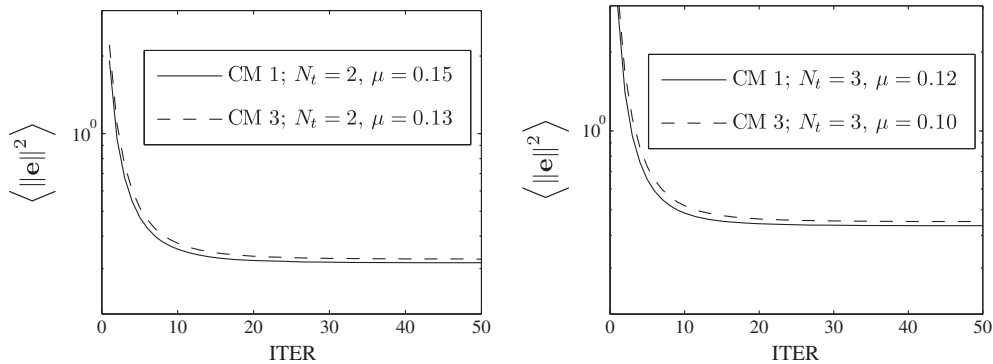
$$\begin{aligned} \mathbb{E} [ |\tilde{y}_n|^2 ] &= \mathbb{E} [ (\boldsymbol{\gamma}^H \tilde{\mathbf{H}}^H \mathbf{b} + z_n^*) (\mathbf{b}^\top \tilde{\mathbf{H}}\boldsymbol{\gamma} + z_n) ] \\ &= \boldsymbol{\gamma}^H \tilde{\mathbf{H}}^H \tilde{\mathbf{H}}\boldsymbol{\gamma} + \sigma_z^2 \end{aligned} \quad (29)$$

Hence,

$$\begin{aligned} J_{\text{MMSE}} &= 1 + |\zeta|^2 \sigma_z^2 - \zeta^* \boldsymbol{\gamma}^H \mathbf{h}_n - \zeta \mathbf{h}_n^H \boldsymbol{\gamma} \\ &\quad + |\zeta|^2 \boldsymbol{\gamma}^H \tilde{\mathbf{H}}^H \tilde{\mathbf{H}}\boldsymbol{\gamma} \end{aligned} \quad (30)$$

where  $\mathbf{h}_n = \tilde{\mathbf{H}}^H \mathbb{E} [ b_n \mathbf{b} ] = \tilde{\mathbf{H}}^H \mathbf{d}_n$  and  $\mathbf{d}_n$  is the vector whose elements are zero, except for the  $(L_{\text{PF}})$ th element, which is equal to 1. Defining  $\tilde{\boldsymbol{\gamma}} = \zeta \boldsymbol{\gamma}$  and noting that  $|\zeta|^2 = (1/N_t) \tilde{\boldsymbol{\gamma}}^H \tilde{\boldsymbol{\gamma}}$ , we automatically insert the power constraint in  $J_{\text{MMSE}}$  [12], resulting in

$$J_{\text{MMSE}} = 1 + \frac{\sigma_z^2}{N_t} \tilde{\boldsymbol{\gamma}}^H \tilde{\boldsymbol{\gamma}} - \tilde{\boldsymbol{\gamma}}^H \mathbf{h}_n - \mathbf{h}_n^H \tilde{\boldsymbol{\gamma}} + \tilde{\boldsymbol{\gamma}}^H \tilde{\mathbf{H}}^H \tilde{\mathbf{H}}\tilde{\boldsymbol{\gamma}} \quad (31)$$



**Figure 3.** Convergence of the constrained least squares algorithm.



With  $J_{\text{MMSE}}$  being differentiated with respect to  $\tilde{\mathbf{y}}^*$  and being set to zero,

$$\begin{aligned} \frac{\partial J_{\text{MMSE}}}{\partial \tilde{\mathbf{y}}^*} &= \frac{1}{\text{SNR}} \tilde{\mathbf{y}} - \mathbf{h}_n + \tilde{\mathbf{H}}^H \tilde{\mathbf{H}} \tilde{\mathbf{y}} = 0 \quad (32) \\ \Rightarrow \left[ \tilde{\mathbf{H}}^H \tilde{\mathbf{H}} + \mathbf{I} \frac{1}{\text{SNR}} \right] \tilde{\mathbf{y}} &= \mathbf{h}_n \end{aligned}$$

Therefore,

$$\tilde{\mathbf{y}}_{\text{opt}} = \left[ \tilde{\mathbf{H}}^H \tilde{\mathbf{H}} + \mathbf{I} \frac{1}{\text{SNR}} \right]^{-1} \mathbf{h}_n \quad (33)$$

where  $\mathbf{I}$  is an identity matrix. Finally,

$$\boldsymbol{\gamma} = \boldsymbol{\gamma}^{\text{MMSE}} = \frac{\tilde{\mathbf{y}}_{\text{opt}}}{\zeta_{\text{opt}}} \Rightarrow \boldsymbol{\gamma}^{\text{MMSE}} = \sqrt{N_t} \frac{\tilde{\mathbf{y}}_{\text{opt}}}{\|\tilde{\mathbf{y}}_{\text{opt}}\|_2} \quad (34)$$

The term  $\zeta$  is just a constant that does not need to be implemented at the receiver side.

Observing Equation (34), one can conclude that if  $\text{SNR} \rightarrow \infty$ ,  $\tilde{\mathbf{y}}_{\text{opt}} \rightarrow (\tilde{\mathbf{H}}^H \tilde{\mathbf{H}})^{-1} \mathbf{h}_n = (\tilde{\mathbf{H}}^H \tilde{\mathbf{H}})^{-1} \tilde{\mathbf{H}}^H \mathbf{d}_n$ , and, consequently, after normalising the power,  $\boldsymbol{\gamma}^{\text{MMSE}} \rightarrow \boldsymbol{\gamma}^{\text{ZF}}$ . On the other hand, if  $\text{SNR} \rightarrow 0$ ,  $\tilde{\mathbf{y}}_{\text{opt}} \rightarrow C \mathbf{I} \mathbf{h}_n = C \tilde{\mathbf{H}}^H \mathbf{d}_n$ , which represents the ( $L_{\text{PF}}$ )th line of  $\tilde{\mathbf{H}}$  in Equation (12) multiplied by a constant  $C$ , and, therefore, after normalising the power,  $\boldsymbol{\gamma}^{\text{MMSE}} \rightarrow \boldsymbol{\gamma}^{\text{TR}}$ .

### 3.5. Channel impulse response comparison

Figure 4 shows examples of equivalent CIRs, considering the schemes TR, ZF, MMSE and CLS, with  $L_{\text{PF}} = L_C$ , but here  $L_C$  is obtained by considering a truncation criterion of  $-30$  dB (Figure 1);  $N_{\text{P}}$  is set to  $N_{\text{P}} = 100$ . The higher SNR is obtained with TR (it represents an MF), but the residual ISI is also higher than the other schemes. The ZF pre-equaliser eliminates the ISI but results in a relatively low power at the receiver, which can be interpreted as the dual problem of noise amplification when ZF is used at the receiver side. For the SNR conditions considered, the peak of the equivalent CIR with MMSE is a little lower than the case with CLS, but the MMSE scheme results in a somewhat better ISI mitigation.

## 4. COMPLEXITY ANALYSIS

Table II presents a comparative analysis of the computational complexity for ZF, CLS and MMSE schemes, where  $p = (L_C + L_{\text{PF}} - 1)$  and  $q = (N_t L_{\text{PF}})$ . Complex multiplication (or division), complex addition (or subtraction), square root extraction and comparison are considered as single operations. All multiplications and additions are assumed to be complex operations. For the CLS solution based on SVD, only the operations needed for the computation of SVD are taken into account, which is the most costly part. For a matrix inversion of dimension  $N \times N$ , the Gaussian elimination method is considered, which requires a total of approximately  $2N^3/3$  operations.

## 5. SIGNAL-TO-INTERFERENCE-PLUS-NOISE RATIO ANALYSIS

Equation (9) can be rewritten as

$$y_n = \sum_{i=-\infty}^{\infty} b_{n-i} x_i + z_n = \underbrace{b_n x_0}_{\text{Signal}} + \underbrace{\sum_{\substack{i=-\infty \\ i \neq 0}}^{\infty} b_{n-i} x_i}_{\text{ISI}} + \underbrace{z_n}_{\text{Noise}} \quad (35)$$

where  $y_n = y(nT_s)$ ,  $z_n = z(nT_s)$  and  $x_i = x(iT_s)$ . Note that the discrete-time sequence that represents the sampled noise after MF,  $z_n$ , is still AWGN and with variance (or power)  $\sigma_z^2 = N_t \sigma_k^2 = N_t / \text{SNR}$ . The decision variable is  $\mathcal{V} = \Re\{y_n\}$ , where  $\Re\{\cdot\}$  represents the real-part operator. If the information symbols are independent and identically distributed with  $b_n = \pm 1$ , the instantaneous SNR conditioned on the  $j$ th set of channel realisations can be obtained as [9]

$$\text{SNR}^j = \frac{\Re\{x_0^j\}^2}{\sum_{\substack{i=-\infty \\ i \neq 0}}^{\infty} \Re\{x_i^j\}^2 + \sigma^2} \quad (36)$$

where  $\sigma^2 = \sigma_z^2/2 = N_t/2 \text{SNR}$  represents the variance of the in-phase and quadrature components of  $z_n$ .

If the residual ISI in Equation (36) is assumed to be Gaussian distributed, the BER conditioned to the  $j$ th set of channel realisations can be written as

$$\text{BER}^j = Q\left(\sqrt{\text{SNR}^j}\right) \quad (37)$$

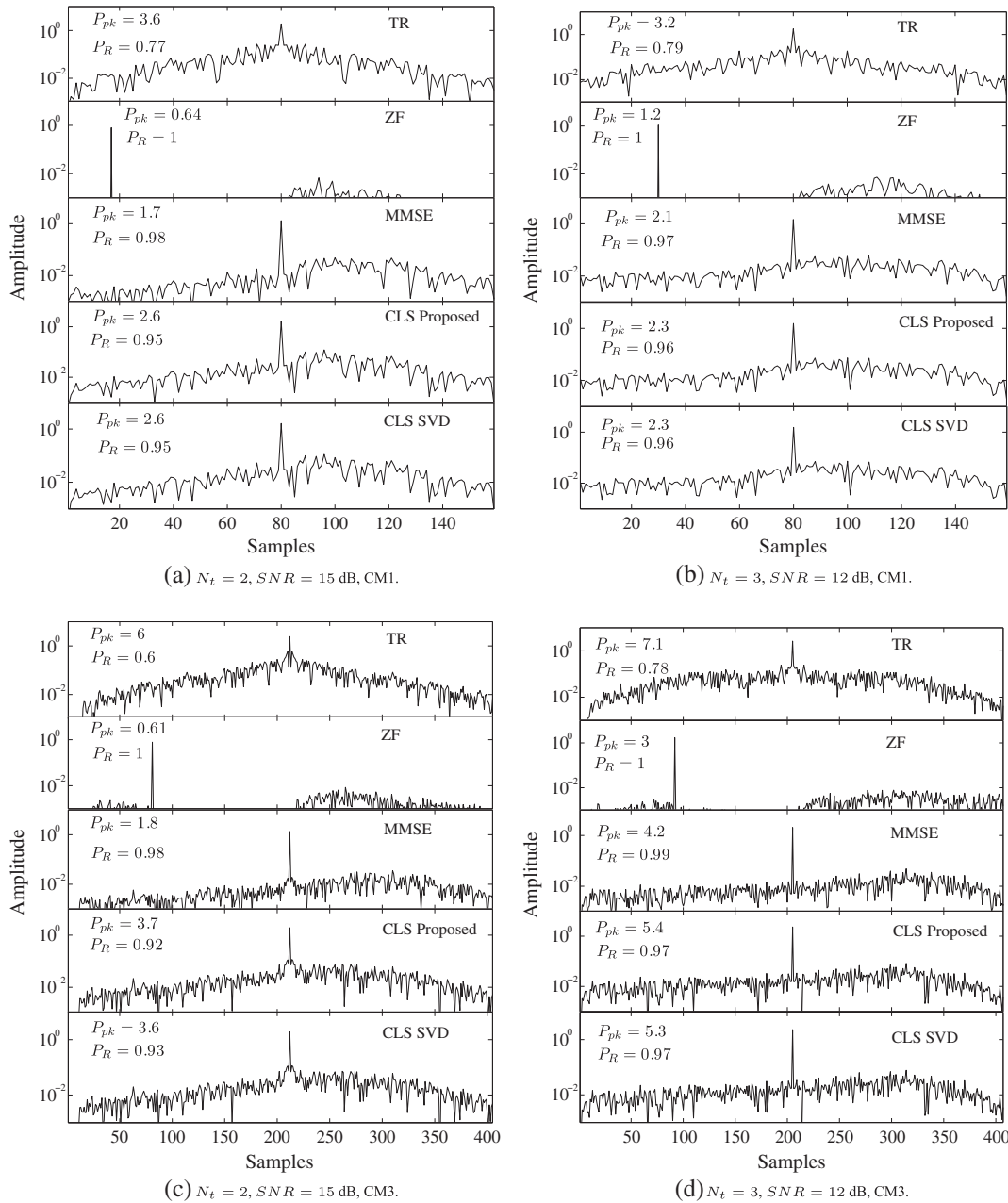
where  $Q(x) = 1/\sqrt{2\pi} \cdot \int_x^{\infty} e^{-y^2/2} dy$ . Considering  $\mathcal{J}$  sets of channel realisations, the average BER can be computed as

$$\text{BER} = \frac{1}{\mathcal{J}} \sum_{j=0}^{\mathcal{J}-1} \text{BER}^j \quad (38)$$

## 6. SIMULATION CONFIGURATION AND RESULTS

Performance results are obtained by considering Monte Carlo simulation and the semi-analytical approach (THEO) shown in Section 5. Two and three antenna elements are adopted. The transmission rate is set to  $R_b = 499$  Mbps ( $\kappa = 4$ ) and  $R_b = 665.3$  Mbps ( $\kappa = 3$ ), and the RRC pulse is generated by considering  $\alpha = 0.3$  and  $T = 501$  ps. Pre-filter coefficients, as well as the CIR, are assumed to be static during the frame duration  $T_f$ , which is considered sufficiently long. The CIRs are randomly chosen among the 100 realisations proposed in [16].  $N_{\text{P}} = 100$  probe





**Figure 4.** Comparison among equivalent channel impulse responses considering time reversal (TR), zero forcing (ZF), minimum mean square error (MMSE) and constrained least squares (CLS), for CM1 and CM3 and  $N_p = 100$ .  $P_{pk}$  represents the peak of the equivalent channel impulse response, whereas  $P_R$  is the ratio between  $P_{pk}$  and the total power. SVD, singular-value decomposition; SNR, signal-to-noise ratio.

**Table II.** Computational complexity analysis.

Scheme	Operations needed
ZF	$2p^3/3 + (2q-1)p^2 + (2p-1)(pq+q) + 2q+1$
MMSE	$2q^3/3 + (2p-1)(q^2+q) + (2q-1)(1+q) + 3q+3$
CLS (SVD)	$9 \cdot q^3 + 4 \cdot p^2q + 8 \cdot pq^2$
CLS (Algorithm 3.3)	ITER · $(4 \cdot pq + 4 \cdot q - p + 2)$

Note that  $p = L_C + L_{PF} - 1$  and  $q = N_t L_{PF}$ .

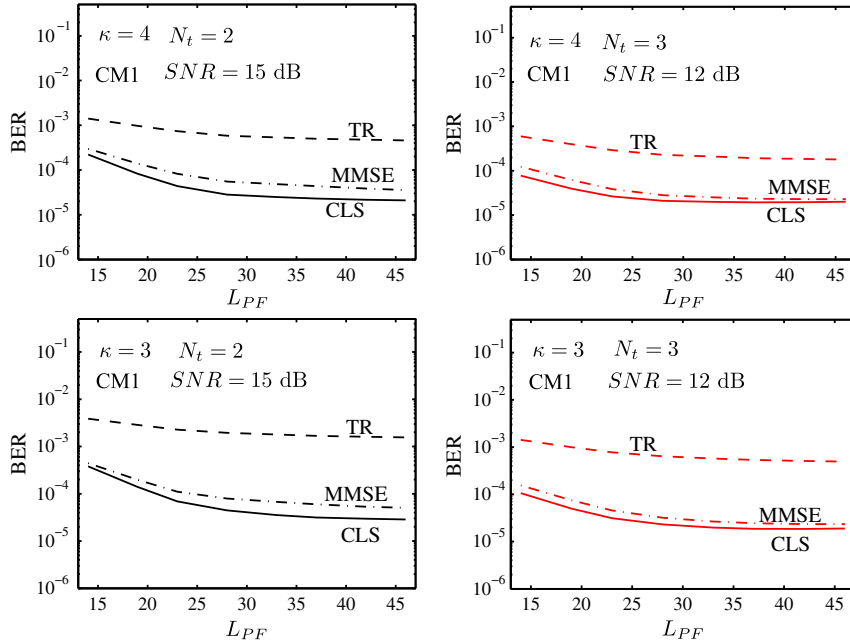
ZF, zero forcing; MMSE, minimum mean square error; CLS, constrained least squares; SVD, singular-value decomposition.

transmissions are considered for testing the channel in order to obtain the CIR estimations at the transmitter.

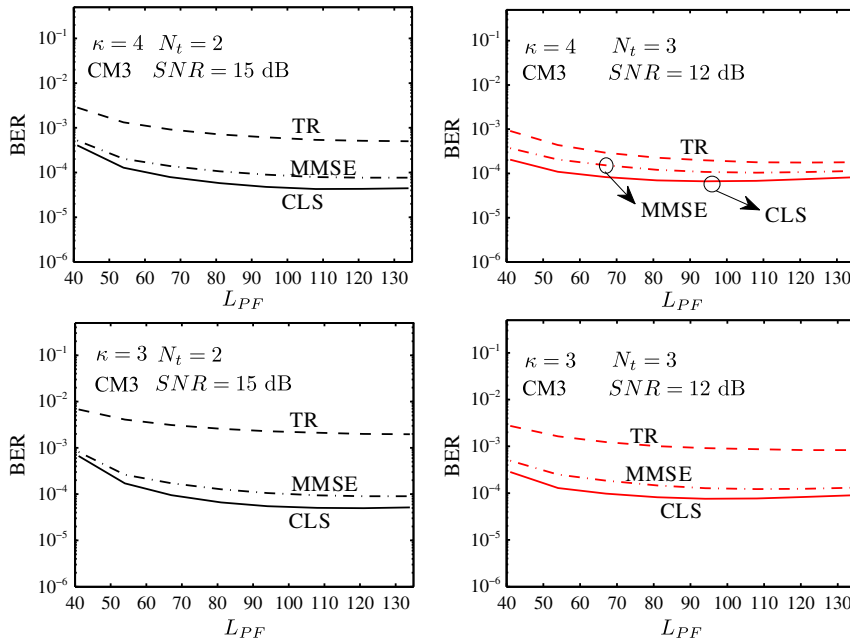
Figures 5 and 6 show the TR, CLS and MMSE analytical BER performances regarding the number of pre-filter coefficients. The CLS scheme is implemented with the modified steepest-descent algorithm considering  $ITER =$

15. For  $N_t = 2$ ,  $SNR = 15$  dB is set, whereas for  $N_t = 3$ ,  $SNR = 12$  dB is set. It is possible to see that in all curves the performances become flat for  $L_{PF} \approx 0.7 L_C$  with  $N_t = 3$  and  $L_{PF} \approx 0.8 L_C$  with  $N_t = 2$ .

Bit error rate results as a function of  $SNR$  in decibels are presented in Figures 7 and 8 for rates  $R_b = 665.3$  Mbps



**Figure 5.** Bit error rate (BER) as a function of  $L_{PF}$  considering CM1. TR, time reversal; MMSE, minimum mean square error; CLS, constrained least squares; SNR, signal-to-noise ratio.



**Figure 6.** Bit error rate (BER) as a function of  $L_{PF}$  considering CM3. TR, time reversal; MMSE, minimum mean square error; CLS, constrained least squares; SNR, signal-to-noise ratio.

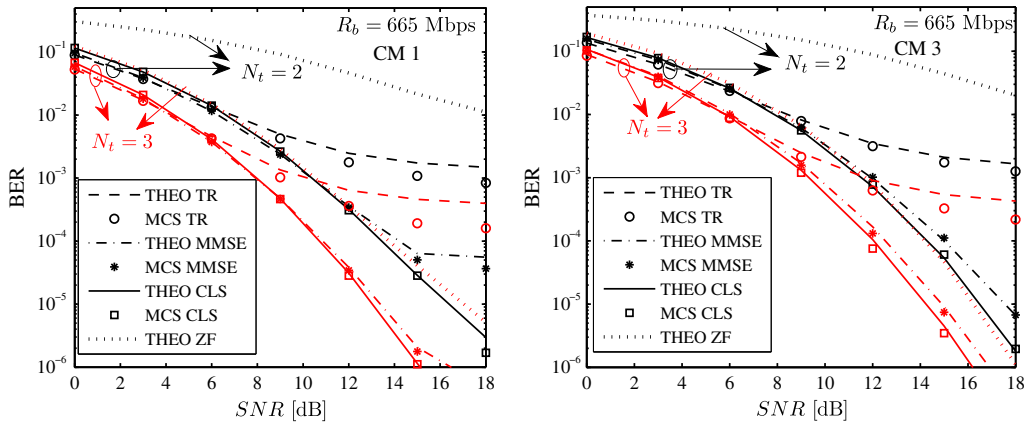
and  $R_b = 499$  Mbps, respectively. In both figures, it was considered that  $L_{PF} \approx 0.7 L_C$  with  $N_t = 3$  and  $L_{PF} \approx 0.8 L_C$  with  $N_t = 2$  for TR, CLS and MMSE, whereas for ZF,  $L_{PF} = L_C$  (ZF' is not considered). Considering the criterion of  $-20$  dB for the CIR truncation,  $L_C = 46$  in CM1 and  $L_C = 134$  (+0 to 5) in CM3. Note that the CLS performance with  $ITER = 15$  is superior to the other techniques for  $SNR > 9$  dB. For the low- $SNR$  region, TR and MMSE perform better than CLS. The ZF scheme, even for  $L_{PF} = L_C$ , has not a satisfactory performance with  $N_t = 2$  antennas, but with  $N_t = 3$ , it is better than TR for high  $SNR$ s. Moreover, ZF, MMSE and CLS are less sensitive than TR regarding an increase in the transmission rate from 499 to 665 Mbps.

Table III shows a numerical analysis of the computational complexity considering the configurations presented in Figures 7 and 8. For the ZF scheme,  $L_{PF} = L_C$ , and

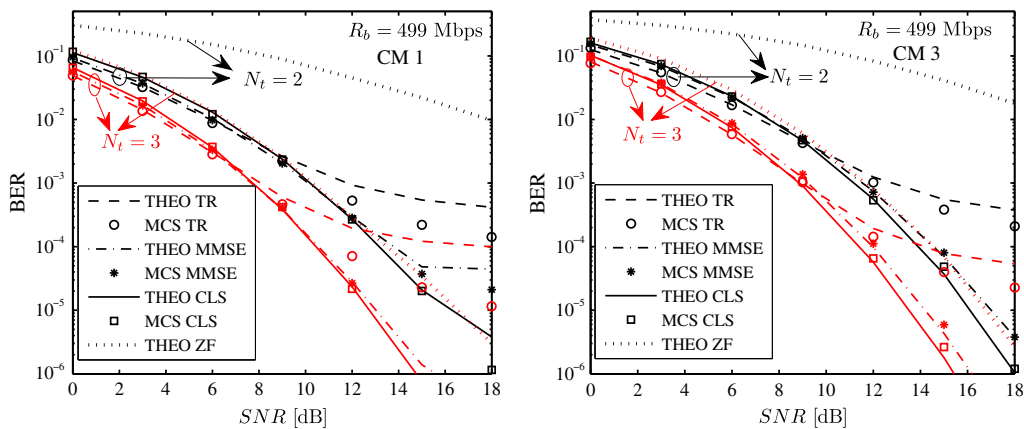
for the CLS with SVD, only the SVD complexity was taken into account. Observe that the method CLS (SVD) is more complex than the other techniques, and ZF has a complexity of the same order as that of MMSE. It is also worth noticing that the CLS method based on the modified steepest-descent algorithm results in a complexity substantially lower than that of the other schemes.

Considering a higher CIR estimation error condition, Figure 9 shows the BER performance for  $R_b = 499$  Mbps,  $N_t = 2$  antennas and  $N_p = 20$ . It can be seen that CLS keeps performing better than MMSE. It is possible to see the superiority of CLS in relation to MMSE, as observed in the previous lower CIR estimation error case ( $N_p = 100$ ), specially for higher  $SNR$ s.

In order to help us understand why CLS performs better than MMSE under the conditions considered, Figure 10 presents BER versus  $SNR$  results considering CM1,  $L_{PF} =$



**Figure 7.** Performance of bit error rate (BER) versus signal-to-noise ratio ( $SNR$ ) for  $R_b = 665.3$  Mbps and  $N_p = 100$  probe pulses for channel impulse response estimation. MCS, Monte Carlo simulation; TR, time reversal; MMSE, minimum mean square error; CLS, constrained least squares; ZF, zero forcing.

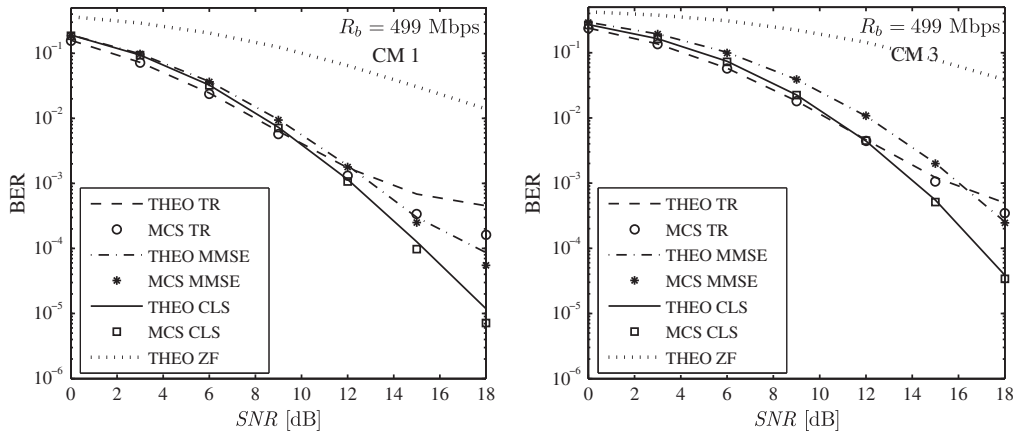


**Figure 8.** Performance of bit error rate (BER) versus signal-to-noise ratio ( $SNR$ ) for  $R_b = 499$  Mbps and  $N_p = 100$  probe pulses for channel impulse response estimation. MCS, Monte Carlo simulation; TR, time reversal; MMSE, minimum mean square error; CLS, constrained least squares; ZF, zero forcing.

**Table III.** Numerical computational complexity analysis.

Configuration	Number of operations			
	ZF	MMSE	CLS (SVD)	CLS (mod. grad.)
CM1, $N_t = 2$	$2.3342 \times 10^6$	$1.1697 \times 10^6$	$9.1030 \times 10^6$	$3.6565 \times 10^5$
CM1, $N_t = 3$	$2.6112 \times 10^6$	$2.0663 \times 10^6$	$1.6179 \times 10^7$	$4.5326 \times 10^5$
CM3, $N_t = 2$	$6.1390 \times 10^7$	$3.0111 \times 10^7$	$2.3682 \times 10^8$	$3.1961 \times 10^6$
CM3, $N_t = 3$	$6.8684 \times 10^7$	$5.3298 \times 10^7$	$4.2041 \times 10^8$	$3.9619 \times 10^6$

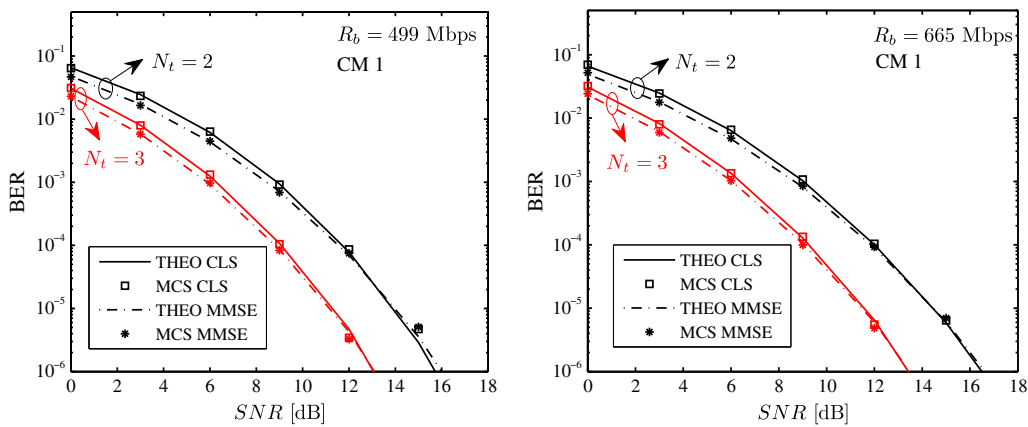
ZF, zero forcing; MMSE, minimum mean square error; CLS, constrained least squares; SVD, singular-value decomposition.



**Figure 9.** Performance of bit error rate (BER) versus signal-to-noise ratio (SNR) for  $R_b = 499$  Mbps,  $N_t = 2$  antennas and  $N_p = .20$  probe pulses for channel impulse response estimation. MCS, Monte Carlo simulation; TR, time reversal; MMSE, minimum mean square error; CLS, constrained least squares; ZF, zero forcing.

$L_C$ , noiseless CIR estimation at the transmitter and a CIR truncation criterion of  $-30$  dB (Figure 1), which corresponds to 40 ns, approximately, rather than 23 ns ( $-20$ -dB criterion). Under these conditions, the performance of MMSE is similar to CLS for  $12 < SNR < 16$  dB

and slightly better than CLS for  $0 < SNR < 12$  dB. Therefore, it is possible to conclude that the CLS scheme is more robust than the MMSE one regarding errors on the CIR estimation (noise and truncation). This observation suggests that the robustness of CLS and MMSE in relation to



**Figure 10.** Bit error rate (BER) as a function of signal-to-noise ratio (SNR) in CM1, with noiseless estimation and truncation of the channel impulse response in 40 ns. MCS, Monte Carlo simulation; MMSE, minimum mean square error; CLS, constrained least squares.

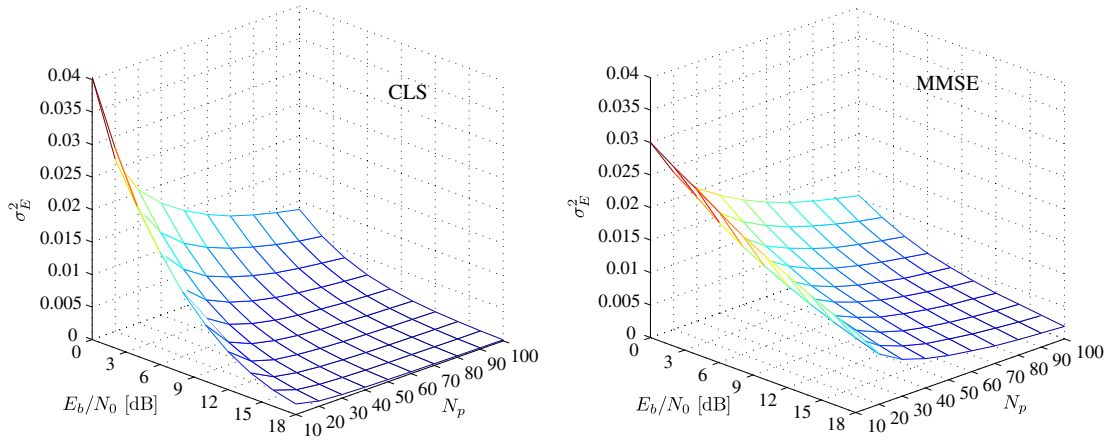
CIR estimation errors depends on how the respective pre-filter coefficients  $\gamma_{\text{CLS}}$  and  $\gamma_{\text{MMSE}}$  deviate from their ideal noiseless values  $\gamma'_{\text{CLS}}$  and  $\gamma'_{\text{MMSE}}$ , respectively, obtained considering perfect knowledge of the CIR at the transmitter side. In their turn, these deviations can be measured in each case by  $\sigma_E^2 = \mathbb{E} \left[ \|\gamma - \gamma'\|^2 \right] / L_{\text{PF}}$ .

In order to test this dependency, we estimated  $\sigma_E^2$  for CLS and MMSE, considering different values of SNR ( $E_b/N_0$ ) and the number of probe transmissions  $N_p$ . A thousand noisy CIR generations were considered for each simulated point. The results are presented in Figures 11 and 12. It can be seen that CLS performs better than MMSE for higher  $E_b/N_0$  and/or higher  $N_p$ . Moreover, for higher  $E_b/N_0$  and lower values of  $N_p$ , CLS is quite better than MMSE. These results are consistent with the BER performance in Figures 7 to 9 and therefore corroborate the dependency of the BER on  $\sigma_E^2$ .

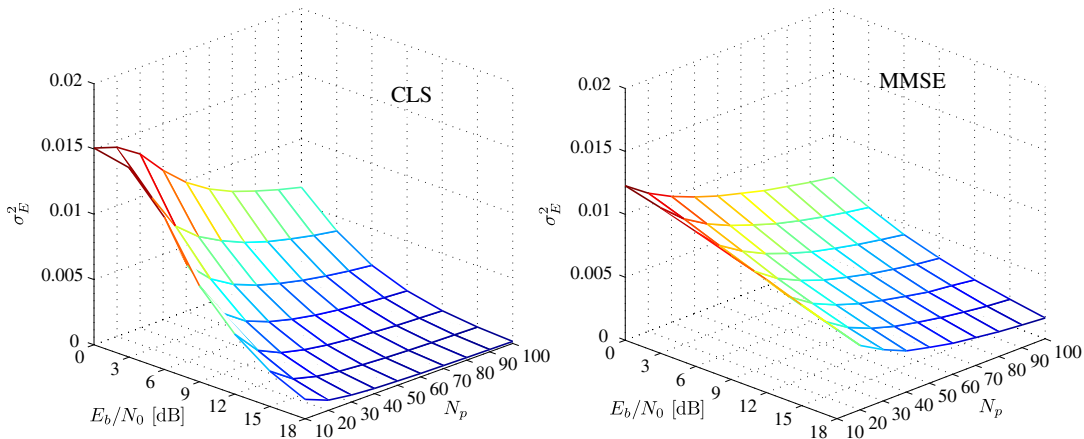
## 7. CONCLUSIONS

This paper presented a performance analysis for a single-user MISO UWB system incorporating four different pre-distortion schemes: TR, ZF, MMSE and CLS. Results showed that CLS has a BER performance comparable to that of the MMSE and better than that of TR and ZF. For instance, when  $N_t = 2$  antennas, the performance of ZF is not satisfactory because of its power inefficiency, and its performance for  $N_t = 3$  antennas is better than that of TR, considering high SNRs. Furthermore, when TR is considered for high transmission rates, there is a residual ISI degrading the system's performance, which suggests some post-equalisation scheme at the receiver side.

Under the conditions considered in this paper, it is possible to conclude that the CLS scheme is more robust than the MMSE one regarding errors on the CIR estimation. Besides, the CLS method using the modified gradi-



**Figure 11.** Constrained least squares (CLS) and minimum mean square error (MMSE) sensitivity to channel impulse response errors in CM1,  $N_t = 2$  and  $R_b = 499$  Mbps.



**Figure 12.** Constrained least squares (CLS) and minimum mean square error (MMSE) sensitivity to channel impulse response errors in CM3,  $N_t = 2$  and  $R_b = 499$  Mbps.

ent algorithm has a lower complexity compared with ZF and MMSE. Such a scheme could be a good solution for the downlink of high-data-rate applications having good computational capacities at the access point and requiring low-complexity receivers, in no fast varying channels.

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## REFERENCES

1. Qiu RC, Zhou C, Guo N, Zhang JQ. Time reversal with MISO for ultrawideband communications: experimental results. *IEEE Antennas and Wireless Propagation Letters* 2006; **5**(1): 269–273.
2. Nguyen HT, Kovács IZ, Eggers PCF. A time reversal transmission approach for multiuser UWB communications. *IEEE Transactions on Antennas and Propagation* 2006; **54**(11): 3216–3224.
3. Guo N, Sadler BM, Qiu RC. Reduced-complexity UWB time-reversal techniques and experimental results. *IEEE Transactions on Wireless Communications* 2007; **6**(12): 4221–4226.
4. Cao W, Nallanathan A, Chai CC. Performance analysis of pre-rake DS UWB multiple access system under imperfect channel estimation. *IEEE Transactions on Wireless Communications* 2007; **6**(11): 3892–3896.
5. Zhou C, Guo N, Sadler BM, Qiu RC. Performance study on time reversed impulse MIMO for UWB communications based on measured spatial UWB channels. In *IEEE Military Communications Conference (MILCOM 2007)*, 2007; 1–6.
6. Kaiser T, Zheng F. *Ultra Wideband Systems with MIMO*. John Wiley and Sons: Chichester, UK, 2010.
7. Strohmer T, Emami M, Hansen J, Papanicolaou G, Paulraj AJ. Application of time-reversal with MMSE equalizer to UWB communications, In *IEEE Global Telecommunications Conference (GLOBECOM '04)*, Vol. 5, 2004; 3123–3127.
8. Song HC, Hodgkiss WS, Kuperman WA, Stevenson M, Akal T. Improvement of time-reversal communications using adaptive channel equalizers. *IEEE Journal of Oceanic Engineering* 2006; **31**(2): 487–496.
9. Angélico BA, Burt PMS, Jeszensky PJE, Hodgkiss WS, Abrão T. Improvement of MISO single-user time reversal ultra-wideband using a DFE channel equalizer, In *10th IEEE International Symposium on Spread Spectrum Techniques and Applications (ISSSTA'08)*, 2008; 582–586.
10. Kyritsi P, Stoica P, Papanicolaou G, Eggers P, Oprea A. Time reversal and zero-forcing equalization for fixed wireless access channels. In *Thirty-Ninth Asilomar Conference on Signals, Systems and Computers*, 2005; 1297–1301.
11. Kyritsi P, Papanicolaou G, Tsogka C. Optimally Designed Time Reversal and Zero Forcing Schemes, In *Proc. Int. Symp. Wireless Personal Multimedia Communication 2005 (WPMC2005)*, September 18-22, 2005; 105–109.
12. Torabi E, Mietzner J, Schober R. Pre-equalization for MISO DS-UWB systems with pre-rake combining. *IEEE Transactions on Wireless Communications* 2009; **8**(3): 1295–1307.
13. Zhiwei L, Xiaoming P, Png KB, Chin F. Kronecker modeling for correlated shadowing in UWB MIMO channels. In *IEEE Wireless Communications and Networking Conference (WCNC 2007)*, 2007; 1583–1587.
14. Fisher R, Kohno R, McLaughlin M, Welbourn M. DS-UWB physical layer submission to IEEE 802.15 Task Group 3a, Jan. 2005. Doc. number P802.15-04/0137r4, April IEEE P802.15.
15. IEEE. IEEE 802.15.4a-2007. Part 15.4: wireless Medium Access Control (MAC) and physical layer (PHY) specifications for low-rate wireless personal area networks (WPANs). Amendment 1: add alternate PHYs, April 2007.
16. Foerster JR. Channel Modeling Sub-committee report final. IEEE P802.15-02/368r5-SG3a, IEEE P802.15 Working Group for Wireless Personal Area Networks (WPAN), Dec. 2002.
17. Molisch AF, Foerster JR, Pendergrass M. Channel models for ultrawideband personal area networks. *IEEE Wireless Communications* 2003; **10**(6): 14–21.
18. Golub GH, Van Loan CF. *Matrix Computations*, 3rd edn. Johns Hopkins University Press: Baltimore, MD, USA, 1996.

## AUTHORS' BIOGRAPHIES

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