# Low-Complexity Reduced-Rank Adaptive Detection in Hybrid Direct-Sequence Time-Hopping Ultrawide Bandwidth Systems

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*Abstract*— **In this contribution reduced-rank adaptive minimum mean-square error multiuser detector (MMSE-MUD) is proposed and investigated for the hybrid direct-sequence time-hopping ultrawide bandwidth (DS-TH UWB) systems. The adaptive MMSE-MUD is operated based on the normalised least mean-square (NLMS) principles associated with using Taylor polynomial approximation (TPA)-assisted reduced-rank technique. It can be shown that the reduced-rank adaptive technique is beneficial to achieving low-complexity, high convergence speed and robust detection in hybrid DS-TH UWB systems. In this contribution bit-error-rate (BER) performance of the hybrid DS-TH UWB systems using proposed reduced-rank adaptive MMSE-MUD is investigated, when communicating over UWB channels modelled by the Saleh-Valenzuela (S-V) channel model. Our simulation results show that the TPA-assisted reduced-rank adaptive MMSE-MUD is capable of achieving a similar BER performance as that of the full-rank adaptive MMSE-MUD but with significantly lower detection complexity.**

## I. Introduction

One of the major challenges in pulse-based ultrawide bandwidth (UWB) communications is to design a low-complexity receiver, which is capable of achieving a reasonable BER performance [1–3]. However, as the multipath delay profile (MDP) in UWB communications environment is generally sparse [2], a large number of resolvable multipaths are usually required to be dealt with at the receiver side in order to achieve good BER performance. Hence, even when the conventional single-user correlation detector is employed, the complexity might still be extreme, because a huge number of multipath channels must be estimated before detection and the detection complexity also increases linearly with the number of resolvable multipaths [4]. Furthermore, the single-user correlation detector conflicts multiuser interference (MUI) and its BER performance deteriorates significantly as the number of users increases [5]. In order to improve the BER performance, multiuser detection (MUD), such as the MMSE-MUD, may be employed by the UWB systems at the expense of higher complexity. It has been illustrated that the MMSE-MUD is capable of combining all the multipath components presented within the time-duration of an observation window, which retains a constant complexity for the MMSE-MUD [6]. Furthermore, the MMSE-MUD can be implemented using low-complexity adaptive techniques [7].

Adaptive MMSE-MUDs may be implemented without requiring channel estimation. They are capable of achieving the approximate MMSE solutions with the aid of training sequences of certain length [8]. The efficiency of an adaptive MMSE-MUD can be well-characterised by its convergence speed, BER performance, robustness and implementation complexity [7]. According to the adaptive filter theory [7], the above-mentioned characteristics are dependent on the length of the traversal filter involved. In general, a longer traversal filter results in a lower convergence speed. This in turn means that a longer sequence is required to train the filter. Consequently, the data-rate and spectral efficiency of the corresponding communications system decrease. The robustness of an adaptive filter degrades as the filter length increases, resulting in that more channel-dependent variables need to be estimated [7, 9]. Furthermore, when a longer adaptive filter is employed, the computational complexity is also higher, since more operations are required for the corresponding detection and estimation, as above-mentioned. Therefore, in this contribution reduced-rank technique is proposed for the adaptive MMSE-MUD, which is operated based on the normalised least mean-square (NLMS) principles, in order to achieve low-complexity detection in hybrid DS-TH UWB systems.

To be more specific, in this contribution the TPA-based reduced-rank scheme is applied for determining a detection subspace, where the adaptive detection is implemented. The TPA-based reduced-rank technique is given preference, because the rank of its resultant detection subspace does not scale with the system size [6, 10–13]. In this contribution the BER performance of the hybrid DS-TH UWB systems using the proposed reduced-rank NLMS adaptive MMSE-MUD is investigated, when communicating over UWB channels modelled by the S-V channel model [14]. Our analysis and simulation results show that the TPA-based reduced-rank technique can be employed for achieving a low-complexity detection, for obtaining a high convergence speed [9] and for improving the robustness of the adaptive MMSE-MUD [7, 9]. Furthermore, given a detection subspace having a rank of about 5, the TPA-based reduced-rank NLMS adaptive MMSE-MUD is capable of achieving the BER performance, that is comparable to that achieved by the full-rank NLMS adaptive MMSE-MUD.

## II. Description of the Hybrid DS-TH UWB System

### A. *Transmitted Signal*

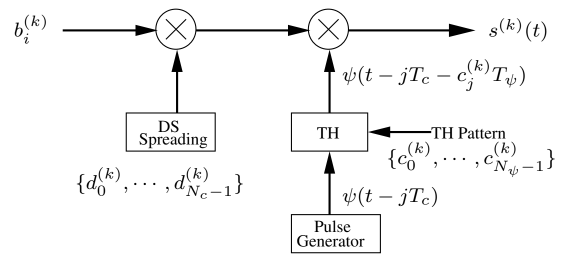


Fig. 1. Transmitter block diagram of the hybrid DS-TH UWB systems.

The transmitter schematic block diagram of the considered hybrid DS-TH UWB system is shown in Fig. 1. In our hybrid DS-TH UWB system binary phase-shift keying (BPSK) baseband modulation is assumed for simplicity. As shown in Fig. 1, a data bit of the $k$th user is first spread by a DS spreading sequence of length $N_c$, yielding $N_c$ chips. Then, the $N_c$ chips are transmitted by invoking $N_c$ time-domain pulses, where the positions of the $N_c$ time-domain pulses are determined by a TH sequence (patterns) assigned to the $k$th user. According to Fig. 1, it can be shown that the hybrid DS-TH UWB

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signal transmitted by the $k$th user can be written as [5]

$$s^{(k)}(t) = \sqrt{\frac{E_b}{N_c T_\psi}} \sum_{j=0}^{\infty} b^{(k)}_{\lfloor \frac{j}{N_c} \rfloor} d_j^{(k)} \psi \left[ t - jT_c - c_j^{(k)} T_\psi \right] \quad (1)$$

where $\lfloor x \rfloor$ returns the largest integer less than or equal to $x$, $\psi(t)$ is a basic time-domain pulse of width $T_\psi$, which satisfies $\int_0^{T_\psi} \psi^2(t)dt = T_\psi$. The bandwidth of the hybrid DS-TH UWB system is inversely proportional to the width $T_\psi$ of the basic time-domain pulse. For brevity, the parameters used in (1) and also in our forthcoming discourse are listed as follows:

- $E_b$: Energy per bit;
- $N_c$: Number of chips per bit and DS spreading factor;
- $N_\psi$: Number of time-slots in a chip and TH spreading factor;
- $T_b$ and $T_c$: Bit-duration and chip-duration, where $T_b = N_c T_c$;
- $T_\psi$: Pulse width or width of a time-slot, where $T_c = N_\psi T_\psi$;
- $b_i^{(k)} \in \{+1, -1\}$: The $i$th data bit transmitted by user $k$;
- $\{d_j^{(k)}\}$: DS spreading sequence assigned to the $k$th user;
- $\{c_j^{(k)} \in \{0, 1, \cdots, N_\psi - 1\}\}$: TH pattern assigned to $k$th user;
- $N_c N_\psi$: Total spreading factor of hybrid DS-TH UWB system.
- $K$: Total number of users supported.

Note that, from the above description we can know that, if $N_\psi = 1$ and $N_c > 1$, we have $T_\psi = T_c$. In this case, the hybrid DS-TH UWB system is reduced to the pure DS-UWB system. By contrast, when $N_\psi > 1$ and $N_c = 1$, then the hybrid DS-TH UWB system is reduced to the pure TH-UWB system.

### B. Channel Model

In this contribution the IEEE 802.15.4a channel model is considered [14]. This channel model is suitable for industrial environments, where the abundance of metallic scatterer causes dense multipath scattering, resulting in Rayleigh distributed small-scale fading [14]. Specifically, in this contribution the Saleh-Valenzuela (S-V) channel model is considered, which represents the channel impulse response (CIR) as [14]

$$h(t) = \sum_{v=0}^{V-1} \sum_{u=0}^{U-1} h_{u,v} \delta(t - T_v - T_{u,v}) \quad (2)$$

where $V$ represents the number of clusters and $U$ denotes the number of resolvable multipaths in a cluster. Hence the total number of resolvable multipath components can be as high as $L = UV$. In (2) $h_{u,v} = |h_{u,v}| e^{j\theta_{u,v}}$ represents the fading gain of the $u$th multipath in the $v$th cluster, $T_v$ denotes the arrival time of the $v$th cluster and $T_{u,v}$ the arrival time of the $u$th multipath in the $v$th cluster. In the considered UWB channel, the average power of a multipath component at a given delay, say at $T_v + T_{u,v}$, is related to the power of the first resolvable multipath of the first cluster by the relation of [14]

$$\Omega_{u,v} = \Omega_{0,0} \exp\left(-\frac{T_v}{\Gamma}\right) \exp\left(-\frac{T_{u,v}}{\gamma}\right) \quad (3)$$

where $\Omega_{u,v} = E\left[|h_{u,v}|^2\right]$ represents the expected power of the $u$ resolvable multipath of the $v$th cluster, $\Gamma$ and $\gamma$ are the respective cluster and ray power decay constants. Note that, in order to make the channel model sufficiently general, in this contribution the delay spread is assumed to span $g \geq 1$ data bits, yielding $(g-1)N_c N_\psi \leq (L-1) < g N_c N_\psi$.

### C. Receiver Structure

When the DS-TH UWB signal shown in (1) is transmitted over the S-V channel with the CIR as shown in (2), the received signal can be expressed as [5]

$$\begin{aligned} r(t) = & \sqrt{\frac{E_b}{N_c T_\psi}} \sum_{k=1}^{K} \sum_{v=0}^{V-1} \sum_{u=0}^{U-1} \sum_{j=0}^{MN_c-1} h_{u,v}^{(k)} b^{(k)}_{\lfloor \frac{j}{N_c} \rfloor} d_j^{(k)} \\ & \times \psi_{rec}\left[ t - jT_c - c_j^{(k)} T_\psi - T_v^{(k)} - T_{u,v}^{(k)} - \tau_k \right] \\ & + n(t) \end{aligned} \quad (4)$$

where $n(t)$ represents an additive white Gaussian noise (AWGN) process, with zero-mean and single-sided power spectrum density of $N_0$ per dimension, $\tau_k$ takes into account the lack of synchronisation among the users as well as the transmission delay, while $\psi_{rec}(t)$ represents the time-domain pulse received, which is usually the second derivative of the transmitted pulse $\psi(t)$ [1].

The receiver schematic block diagram for the hybrid DS-TH UWB using the proposed reduced-rank NLMS adaptive detection is shown in Fig. 2. The received signal is first passed through a matched-filter (MF) having the impulse response of $\psi_{rec}^*(-t)$. The output of the MF is then sampled at a rate of $1/T_\psi$. Finally, the observation samples are projected to a lower dimensional subspace, where adaptive detection is carried out based on the NLMS principles, in order to generate the estimates to the transmitted data bits. Let us assume that a block of $M$ data bits are transmitted. Then, the detector can collect a total of $(MN_c N_\psi + L - 1)$ number of observation samples, where $(L-1)$ is due to the $L$ number of resolvable multipaths. In more detail, the $\lambda$th sample can be obtained by sampling the MF's output at the time instant $t = T_0 + (\lambda + 1)T_\psi$, which can be expressed as

$$y_\lambda = \left( \sqrt{\frac{E_b T_\psi}{N_c}} \right)^{-1} \int_{T_0 + \lambda T_\psi}^{T_0 + (\lambda+1)T_\psi} r(t) \psi_{rec}^*(t) dt \quad (5)$$

where $T_0$ denotes the arrival time of the first path in the first cluster.

In this contribution we consider the bit-by-bit based detection, in order to reduce the detection complexity of the hybrid DS-TH UWB systems. Let the observation vector $\boldsymbol{y}_i$ and the noise vector $\boldsymbol{n}_i$ corresponding to the $i$th data bit of user 1 be represented by

$$\boldsymbol{y}_i = \left[ y_{iN_cN_\psi}, y_{iN_cN_\psi+1}, \cdots, y_{(i+1)N_cN_\psi+L-2} \right]^T \quad (6)$$

$$\boldsymbol{n}_i = \left[ n_{iN_cN_\psi}, n_{iN_cN_\psi+1}, \cdots, n_{(i+1)N_cN_\psi+L-2} \right]^T \quad (7)$$

where the components of $\boldsymbol{n}_i$ are Gaussian random variables distributed associated with mean zero and a common variance of $\sigma^2 = N_0/2E_b$ per dimension. Then, as shown in [5, 15], $\boldsymbol{y}_i$ can be expressed as

$$\begin{aligned} \boldsymbol{y}_i = & \underbrace{\sum_{k=1}^{K} \sum_{\substack{j=\max(0,i-g) \\ i \neq 0}}^{i-1} \underline{\boldsymbol{C}}_j^{(k)} \boldsymbol{h}_k \boldsymbol{b}_j^{(k)}}_{\text{ISI from the previous bits of } K \text{ users}} + \underbrace{\boldsymbol{C}_i^{(1)} \boldsymbol{h}_1 b_i^{(1)}}_{\text{Desired signal}} + \boldsymbol{n}_i \\ & + \underbrace{\sum_{k=2}^{K} \boldsymbol{C}_i^{(k)} \boldsymbol{h}_k b_i^{(k)}}_{\text{Multiuser interference}} + \underbrace{\sum_{k=1}^{K} \sum_{\substack{j=i+1 \\ i \neq M-1}}^{\min(M-1, i+g)} \bar{\boldsymbol{C}}_j^{(k)} \boldsymbol{h}_k \boldsymbol{b}_j^{(k)}}_{\text{ISI from the latter bits of } K \text{ users}} \end{aligned} \quad (8)$$

where the matrices and vectors have been defined in detail in [5, 15]. As shown in (8), the $i$th data bit conflicts both severe inter-symbol interference (ISI) and MUI, in addition to the Gaussian noise.

## III. Detection of Hybrid DS-TH UWB Signals

### A. Full-Rank MMSE Multiuser Detection

In the context of the full-rank MMSE detection, the received observation vector $\boldsymbol{y}_i$ is linearly processed by a complex weight vector $\boldsymbol{w}$,

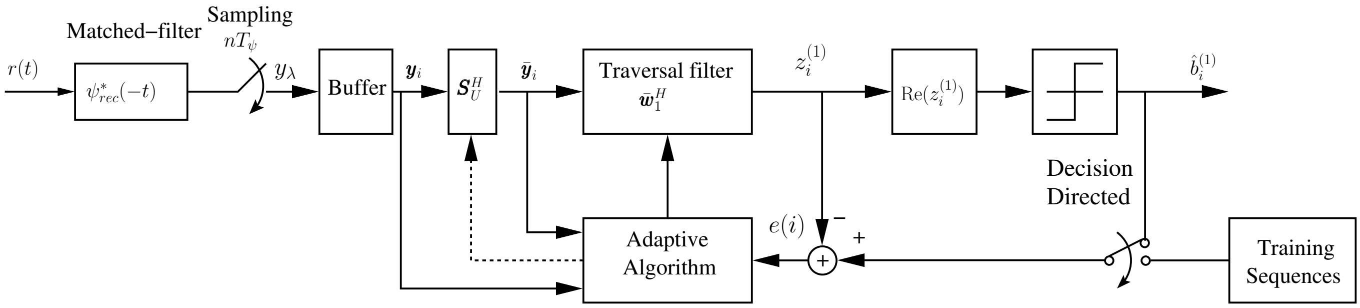


Fig. 2. Receiver schematic block diagram for the hybrid DS-TH UWB systems using reduced-rank adaptive multiuser detection operated in normalised least mean-square principles.

which generates a decision variable for the data bit $b_i^{(1)}$

$$z_i^{(1)} = \boldsymbol{w}_1^H \boldsymbol{y}_i \tag{9}$$

where the optimum weight vector $\boldsymbol{w}_1$ is chosen such that it minimises the mean-square error (MSE) between the transmitted bit $b_i^{(1)}$ and the decision variable $z_i^{(1)}$, yielding

$$\boldsymbol{w}_1 = \boldsymbol{R}_{y_i}^{-1} \boldsymbol{r}_{y_i b_i^{(1)}} \tag{10}$$

In (10) $\boldsymbol{R}_{y_i}$ represents the autocorrelation matrix of $\boldsymbol{y}_i$ and $\boldsymbol{r}_{y_i b_i^{(1)}}$ is the cross-correlation vector between $\boldsymbol{y}_i$ and $b_i^{(1)}$. From (9) and (10) it can be readily observed that the detection complexity of the full-rank MMSE-MUD is mainly determined by the inverse operation of the matrix $\boldsymbol{R}_{y_i}$ which is $((N_cN_\psi+L-1)\times(N_cN_\psi+L-1))$ dimensional. Hence, the complexity of the full-rank MMSE-MUD might be very high, if the spreading factor $N_cN_\psi$ and/or the number of resolvable multipaths are high. Therefore, in this paper the TPA-based reduced-rank scheme is employed for reducing the detection complexity in the hybrid DS-TH UWB systems.

### *B. Reduced-Rank MMSE Multiuser Detection*

In reduced-rank MMSE-MUD the number of coefficients to be estimated are reduced by projecting the observations to a lower dimensional subspace [10]. Specifically, let $\boldsymbol{P}_U$ be a $((N_cN_\psi+L-1)\times U)$ processing matrix with its column vectors forming a $U$-dimensional detection subspace, where $U < (N_cN_\psi + L - 1)$. Then, for a given received observation vector $\boldsymbol{y}_i$, the observations in the detection subspace can be expressed as

$$\bar{\boldsymbol{y}}_i = \underbrace{(\boldsymbol{P}_U^H\boldsymbol{P}_U)^{-1}\boldsymbol{P}_U^H}_{\boldsymbol{S}_U^H}\boldsymbol{y}_i \tag{11}$$

where $(\boldsymbol{P}_U^H\boldsymbol{P}_U)^{-1}$ is for normalisation. Based on $\bar{\boldsymbol{y}}_i$ of (11) the estimate to $b_i^{(1)}$ of the $i$th data bit of the first user can now be expressed as

$$z_i^{(1)} = \bar{\boldsymbol{w}}_1^H \bar{\boldsymbol{y}}_i \tag{12}$$

As shown in (11), in order to implement the reduced-rank detection, the processing matrix $\boldsymbol{P}_U$ must first be determined. In this contribution the TPA-assisted reduced-rank technique is employed for constructing the processing matrix, which, for a given rank of $U$, can be expressed as [12]

$$\boldsymbol{P}_U = [\boldsymbol{C}_i^{(1)}\boldsymbol{h}_1, \boldsymbol{R}_{y_i}\boldsymbol{C}_i^{(1)}\boldsymbol{h}_1, \cdots, \boldsymbol{R}_{y_i}^{U-1}\boldsymbol{C}_i^{(1)}\boldsymbol{h}_1] \tag{13}$$

In comparison with the other reduced-rank techniques, the TPA-based reduced-rank technique has some advantages [6]. It does not depend on the eigen-decomposition of the auto-correlation $\boldsymbol{R}_{y_i}$. The BER performance of the TPA-based reduced-rank MMSE-MUD is capable of converging to the full-rank BER performance with a rank $U$ that is much lower than that of the other types of reduced-rank MMSE-MUDs [6]. Furthermore, in the TPA-based reduced-rank detection, the detection subspace's rank does not scale with the system size.

### *C. Adaptive Reduced-Rank Detection Algorithm*

In comparison with the ideal MMSE-MUD as shown in (10), which requires both the channel state information (CSI) and the knowledge about the user signatures, the adaptive MMSE-MUD requires neither the CSI nor the knowledge about the user signatures. Generally, adaptive MUDs can be characterize by their convergence speed, achievable BER performance, robustness and computational complexity. When applied in the hybrid DS-TH UWB systems, the TPA-based reduced-rank adaptive MUDs may provide us the following advantages, in comparison with the conventional full-rank adaptive MUD.

- **Convergence Speed**: Owing to, possibly, a high spreading factor and/or a huge number of resolvable multipaths of the UWB channels, the length of the traversal filter may be extreme. Consequently, the convergence speed of the adaptive MUDs might be very low, since the convergence speed of an adaptive filter is inversely proportional to its length [16]. By contrast, when the TPA-based reduced-rank adaptive MUD is employed, as shown in (12), the traversal filter is $U$-length, which may be significantly shorter than the length of $(N_cN_\psi+L-1)$ of the traversal filter in the full-rank adaptive MUD. Therefore, the convergence speed of the TPA-based reduced-rank adaptive MUD may be significantly higher than that of the corresponding full-rank adaptive MUD.
- **Achievable BER Performance**: As shown in Section IV, for given system parameters, the hybrid DS-TH UWB system using the TPA-based reduced-rank adaptive MUD is capable of achieving a similar BER performance as that using full-rank adaptive MUD, provided that the rank $U$ of the detection subspace is sufficiently high.
- **Robustness:** According to the adaptive filter theory [7], the robustness of an adaptive algorithm usually becomes worse, when the length of its traversal filter increases. Our TPA-based reduced-rank adaptive MUD only requires to find $U$ estimates for the $U$-length traversal filter, instead of finding $(N_cN_\psi + L - 1)$ estimates in the full-rank adaptive MUD. Furthermore, due to the characteristics of UWB channels, there are many resolvable multipaths conveying only very low power. The low-power resolvable multipaths are hard to acquire by the full-rank adaptive MUD and are sensitive to the background noise. By contrast, the TPA-based reduced-rank technique is capable of identifying automatically the relatively strong multipath signals and projecting them to the reduced-rank detection subspace. Hence, the adaptive filter

operated in this reduced-rank detection subspace becomes less sensitive to the background noise. Therefore, we may argue that the TPA-based reduced-rank adaptive MUD is more robust than the full-rank adaptive MUD.

- **Computational Complexity**: In comparison with the full-rank adaptive MUD, which is operated in a space of rank $(N_cN_\psi+L-1)$, the TPA-based reduced-rank adaptive MUD is operated in the detection subspace having a rank of $U$, which can be significantly lower than $(N_cN_\psi+L-1)$. Furthermore, it can be shown that the complexity of the full-rank MMSE-MUD is on the order of $\mathcal{O}((N_cN_\psi+L-1)^3)$, while the complexity of the proposed TPA-based reduced-rank adaptive MUD is only on the order of $\mathcal{O}(U(N_cN_\psi+L-1))$.

In this contribution the reduced-rank NLMS adaptive MUD is operate in two modes. The first mode is training based, where the weight vector for the traversal filter is adjusted with the aid of a training sequence, which is known to the receiver. As shown in Fig. 2, during the training mode, the observation vector $\boldsymbol{y}_i$ is first projected to the detection subspace, forming $\bar{\boldsymbol{y}}_i$. Then, $\bar{\boldsymbol{y}}_i$ is weighted by a weight vector $\bar{\boldsymbol{w}}_1$, generating an estimate $z_i^{(1)}=\bar{\boldsymbol{w}}_1^H(i)\bar{\boldsymbol{y}}_i$ for the training bit $b_i^{(1)}$. Then, as shown in Fig. 2, the receiver computes the estimation error $e(i)=b_i^{(1)}-z_i^{(1)}$, which is sent to the adaptive algorithm. Finally, according to the NLMS algorithm [7], the weight vector $\bar{\boldsymbol{w}}_1$ is updated according to the update equation

$$\bar{\boldsymbol{w}}_1(i+1)=\bar{\boldsymbol{w}}_1(i)+\frac{\mu}{||\bar{\boldsymbol{y}}_i||^2}e^*(i)\bar{\boldsymbol{y}}_i \qquad (14)$$

for $i=1,2,\ldots$, until the training stage is completed. In (14) $\mu$ is an adaptation step-size, which satisfies $0<\mu<2$.

After the training stage is completed, the reduced-rank NLMS adaptive MUD is then switched to the second operation mode of the decision-directed mode. During the decision-directed mode, the hybrid DS-TH UWB system transmits useful data. The reduced-rank NLMS adaptive MUD is operated in the same way as that under the training mode, except that the weight vector $\bar{\boldsymbol{w}}_1$ is now updated with the aid of the detected data bits. As shown in Fig. 2, the estimation error during the decision-directed mode is given by $\bar{e}(i)=\hat{b}_i^{(1)}-z_i^{(1)}$, where $\hat{b}_i^{(1)}=\text{sgn}(\text{Re}(\hat{z}_i^{(1)}))$ represents the estimate to $b_i^{(1)}$ and $\text{sgn}(\cdot)$ is the sign function. Correspondingly, the update equation for the weight vector is

$$\bar{\boldsymbol{w}}_1(i+1)=\bar{\boldsymbol{w}}_1(i)+\frac{\mu_{DD}}{||\bar{\boldsymbol{y}}_i||^2}\bar{e}^*(i)\bar{\boldsymbol{y}}_i \qquad (15)$$

where $\mu_{DD}$ denotes the adaptation step-size used during the decision-directed mode.

Furthermore, as the channel is time-varying, the detection subspace is also updated with the detected data bits, which updates $\boldsymbol{S}_U$ according to the equation [17]

$$\boldsymbol{S}_U(i+1)=\boldsymbol{S}_U(i)+\frac{\eta_{DD}}{||\bar{\boldsymbol{w}}_1(i)||^2||\boldsymbol{y}_i||^2}\bar{e}^*(i)\boldsymbol{y}_i\bar{\boldsymbol{w}}_1^H(i) \qquad (16)$$

where $\eta_{DD}$ is the adaptation step-size, which also satisfies $0<\eta_{DD}<2$.

## IV. Simulation Results and Discussion

In this section a range of performance results are presented, in order to characterize the achievable BER performance of the hybrid DS-TH UWB systems employing the TPA-based reduced-rank NLMS adaptive MUD. Our simulations were carried out based on the S-V channel model considered in [14], which is characterized by the parameters $1/\Lambda=14.11$ ns, $\Gamma=2.63$ ns and $\gamma=4.58$ ns. Furthermore, we assumed that the UWB channels experienced correlated Rayleigh fading.

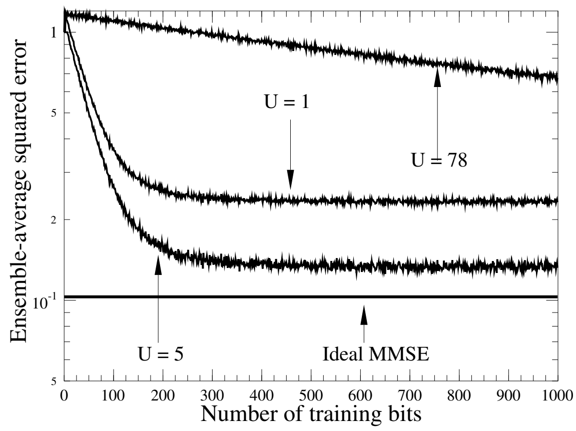


Fig. 3. Learning curves of the reduced-rank NLMS adaptive MUD for the hybrid DS-TH UWB system supporting $K=5$ users and employing the detection subspaces having different ranks, when communicating over the UWB channels experiencing correlated Rayleigh fading. The other parameters were $E_b/N_0=10$dB, Doppler frequency-shift $f_dT_b=0.0001$, $\mu=0.005$, $g=1$, $N_c=16$, $N_\psi=4$ and $L=15$, respectively.

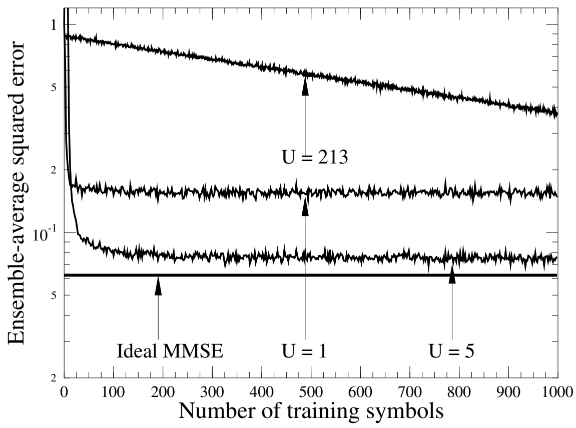


Fig. 4. Learning curves of the reduced-rank NLMS adaptive MUD for the hybrid DS-TH UWB system supporting $K=5$ users and employing the detection subspaces having different ranks, when communicating over the UWB channels experiencing correlated Rayleigh fading. The other parameters were $E_b/N_0=10$dB, Doppler frequency-shift $f_dT_b=0.0001$, $\mu=0.005$, $g=3$, $N_c=16$, $N_\psi=4$ and $L=150$, respectively.

Figs. 3 and 4 show the ensemble average squared-error learning curve of the TPA-based reduced-rank NLMS adaptive MMSE-MUD. In our simulations the ensemble average squared-error was calculated from 2000 independent realizations of the correlated S-V channel, when the hybrid DS-TH UWB system supported $K=5$ users at a given SNR value of $E_b/N_0=10$dB. From Figs. 3 and 4, it can be observed that the TPA-based reduced-rank NLMS adaptive algorithm converges much faster than the full-rank NLMS adaptive MMSE-MUD for the same step-size. Note that, the rank for the full-rank NLMS adaptive MMSE-MUD is given by $(N_cN_\psi+L-1)$. Hence, the full rank for Fig. 3 is 78 and for Fig. 4 is 213. As mentioned previously, higher convergence speed means that shorter training sequences are required, which in turn results in higher transmission data rate or higher spectral-efficiency of the hybrid DS-TH UWB system, when the TPA-based reduced-rank technique is employed. Furthermore, when comparing the results in Fig. 3 corresponding to $L = 15$ with that in Fig. 4 corresponding to $L = 150$, we can observe that, for a given value of $U$, the TPA-based reduced-rank NLMS adaptive MUD in Fig. 4 converges to a lower squared-error than that in Fig. 3, despite the hybrid DS-TH UWB system considered in Fig. 4 conflicts higher ISI than that considered in Fig. 3. However, for both Figs. 3 and 4, if an inappropriate rank $U$ is applied, the adaptive MUD may converge to a very high squared error.

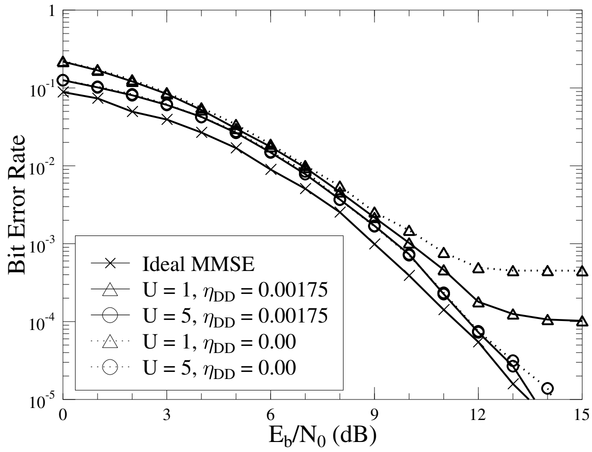


Fig. 5. BER versus SNR per bit performance of the hybrid DS-TH UWB system using TPA-based reduced-rank NLMS adaptive MMSE-MUD, when communicating over the UWB channels experiencing correlated Rayleigh fading. The other parameters were $K = 5$, $f_dT_b = 0.0001$, $\mu = 0.005$, $\mu_{DD} = 0.0015$, $g = 1$, $N_c = 16$, $N_\psi = 4$ and $L = 15$, respectively.

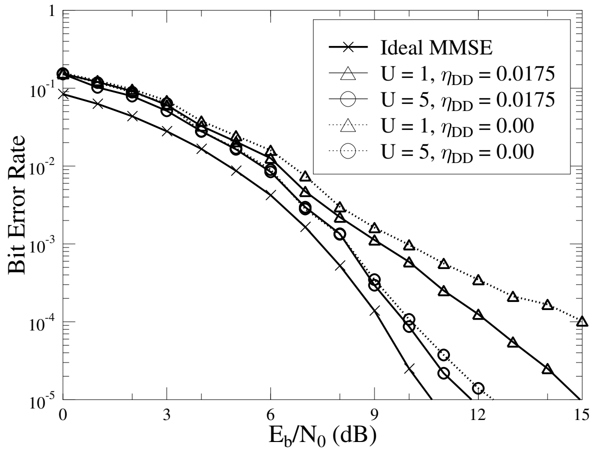


Fig. 6. BER versus SNR per bit performance of the hybrid DS-TH UWB system using TPA-based reduced-rank NLMS adaptive MMSE-MUD, when communicating over the UWB channels experiencing correlated Rayleigh fading. The other parameters were $K = 5$, $f_dT_b = 0.0001$, $\mu = 0.005$, $\mu_{DD} = 0.0015$, $g = 3$, $N_c = 16$, $N_\psi = 4$ and $L = 150$, respectively.

Figs. 5 and 6 demonstrate the BER versus SNR per bit performance of the hybrid DS-TH UWB system using the TPA-based reduced-rank NLMS adaptive MMSE-MUD. It can be observed that the BER performance improves, as the rank $U$ of the detection subspace increases from $U = 1$ to $U = 5$. Note that, when $U = 1$, the TPA-based reduced-rank NLMS adaptive MMSE-MUD is actually reduced to an adaptive correlation detector. From Figs. 5 and 6, it can be observed that the BER performance achieved by the proposed TPA-based reduced-rank NLMS adaptive MUD associated with a detection subspace of rank $U = 5$ is close to that achieved by the ideal MMSE-MUD. Furthermore, when the detection subspace is updated with the aid of the detected data bits, the BER performance may be further improved, especially, at a relatively higher SNR value.

## V. Conclusion

In this paper the TPA-based reduced-rank NLMS adaptive MMSE-MUD is proposed and investigated for the hybrid DS-TH UWB system, when communicating over UWB channels. From our study and simulation results, we can conclude that the TPA-based reduced-rank NLMS adaptive MUD is beneficial to achieving low-complexity and robust detection. It constitutes one of the high-efficiency detection schemes. Furthermore, it is capable of providing good trade-off between the achievable BER performance and the affordable complexity.

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