Reduced-Rank Linear Interference Suppression for DS-UWB Systems Based on Switched Approximations of Adaptive Basis Functions

Sheng Li, Rodrigo C. de Lamare, *Senior Member, IEEE*, and Rui Fa

***Abstract*—In this paper, we propose a novel low-complexity reduced-rank scheme and consider its application to linear interference suppression in direct-sequence ultrawideband systems (DS-UWB). First, we investigate a generic reduced-rank scheme that jointly optimizes a projection vector and a reduced-rank filter by using the minimum mean square error (MMSE) criterion. Then, a low-complexity scheme, which are denoted the switched approximation of adaptive basis functions (SAABFs), is proposed. The SAABF scheme is an extension of the generic scheme, in which the complexity reduction is achieved by using a multibranch framework to simplify the structure of the projection vector. Adaptive implementations for the SAABF scheme are developed by using least mean squares (LMS) and recursive least squares (RLS) algorithms. We also develop algorithms for selecting the branch number and the model order of the SAABF scheme. Simulations show that, in the scenarios with severe intersymbol interference (ISI) and multiple-access interference (MAI), the proposed SAABF scheme has fast convergence and remarkable interference suppression performance with low complexity.**

***Index Terms*—Adaptive filters, interference suppression, reduced-rank methods, ultrawideband (UWB) systems.**

I. Introduction

Ultrawideband (UWB) technology [1]–[5] is a promising short-range wireless communication technique with the potential to achieve high data rates. In 2005, direct-sequence ultrawideband (DS-UWB) [6]–[10] was proposed as a possible standard physical-layer technology for wireless personal area networks (WPANs) [10]. For DS-UWB systems, the huge transmission bandwidths introduce a high degree of diversity at the receiver due to a large number of resolvable multipath components (MPCs) [11]. In multiuser scenarios, the receiver is required to effectively mitigate the multiple-access interference (MAI) and the intersymbol interference (ISI) with affordable complexity. Possible solutions of interference suppression include the linear schemes and nonlinear schemes, such as the successive interference cancelation (SIC) [13] and decision feedback (DF) [14] schemes. For DS-UWB communications, the major challenge for the interference suppression schemes is to obtain fast convergence and satisfactory steady-state performance in dense multipath environments. In conventional full-rank adaptive algorithms, a long filter length is required for DS-UWB systems, and hence, these algorithms confront slow convergence and poor tracking performance.

To overcome the drawbacks of the full-rank algorithms in UWB communications, reduced-rank schemes have recently been considered. A reduced-order finger selection linear minimum mean square error (MMSE) receiver with RAKE-based structures have been proposed in [16], which requires the knowledge of the channel and the noise variance. Solutions for reduced-rank channel estimation and synchronization in single-user UWB systems have been proposed in [17]. For multiuser detection in UWB communications, reduced-rank schemes have been developed in [18]–[20], requiring knowledge of the multipath channel. The reduced-rank filtering techniques have faster convergence than the full-rank algorithms [21]–[39], and the well-known reduced-rank techniques include the eigendecomposition methods, such as the principal components (PC) [23] and the cross-spectral metric (CSM) [24], the Krylov subspace methods such as the powers of R (POR) [22], the multistage Wiener filter (MSWF) [25], [27], and auxiliary vector filtering (AVF) [34]. Eigendecomposition methods are based on the eigendecomposition of the estimated covariance matrix of the input signal. These methods have very high computational complexity, and when the performance is compared with the full-rank linear filtering techniques, the MSWF and AVF methods have faster convergence speed, with a much smaller filter size. However, their computational complexity is still very high.

In this paper, we first investigate a generic reduced-rank scheme with joint and iterative optimization of a projection vector and a reduced-rank linear estimator to minimize the mean square error (MSE) cost function. Because information is exchanged between the projection matrix and the reduced-rank filter for each adaptation, this generic scheme outperforms other existing reduced-rank schemes. However, in this generic scheme, a large projection vector is required to be updated for each time instant and, hence, introduces high complexity. To obtain a low-complexity configuration of the generic scheme and maintain the performance, we propose the novel switched approximation of adaptive basis functions (SAABF) scheme. The basic idea of the SAABF scheme is to simplify the design

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S. Li is with Ilmenau University of Technology, 98693 Ilmenau, Germany. (e-mail: sl546@ohm.york.ac.uk)

R. C. de Lamare is with the Communications Research Group, Department of Electronics, University of York, YO10 5DD York, U.K. (e-mail: rcdl500@ohm.york.ac.uk).

R. Fa is with the University of Liverpool, L69 3BX Liverpool, U.K. (e-mail: rf533@ohm.york.ac.u)

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of the projection vector by using a multiple-branch framework such that the number of coefficients to be adapted in the projection vector is reduced and, hence, achieves complexity reduction. The least mean squares (LMS) and recursive least squares (RLS) adaptive algorithms are then developed for the joint adaptation of the shortened projection vector and the reduced-rank filter. We also propose adaptive algorithms for branch number selection and model order adaptation.

The main contributions of this paper are listed as follows.

- A novel low-complexity reduced-rank scheme is proposed for interference suppression in the DS-UWB system.
- The LMS and RLS adaptive algorithms are developed for the proposed scheme.
- Algorithms for selecting the scheme parameters are proposed.
- The relationships between the proposed SAABF scheme, the generic scheme, and the full-rank scheme are established.
- Simulations are performed with the IEEE 802.15.4a channel model, and severe ISI and MAI are assumed for the evaluation of the proposed scheme.

The rest of this paper is structured as follows. Section II presents the DS-UWB system model. In Section III, the design of the generic reduced-rank scheme is detailed. The proposed SAABF scheme is described in Section IV, and the adaptive algorithms and the complexity analysis are presented in Section V. The proposed adaptive algorithms for selecting the key parameters of the SAABF scheme are described in Section VI. Simulations results are shown in Section VII, and conclusions are drawn in Section VIII.

II. Direct-Sequence Ultrawideband System Model

In this paper, we consider the uplink of a binary phase-shift keying (BPSK) DS-UWB system with K users. A random spreading code $\mathbf{s}_k$ is assigned to the kth user. The spreading gain is $N_c = T_s/T_c$, where T_s and T_c denote the symbol duration and chip duration, respectively. The transmit signal of the kth user, i.e., $k = 1, 2, \ldots, K$, can be expressed as

$$x^{(k)}(t) = \sqrt{E_k} \sum_{i=-\infty}^{\infty} \sum_{j=0}^{N_c-1} p_t(t - iT_s - jT_c)s_k(j)b_k(i) \quad (1)$$

where $b_k(i) \in \{\pm 1\}$ denotes the BPSK symbol for the kth user at the ith time instant, and $s_k(j)$ denotes the jth chip of the spreading code $\mathbf{s}_k$. E_k denotes the transmission energy. $p_t(t)$ is the pulse waveform of width T_c. For UWB communications, widely used pulse shapes include the Gaussian waveforms, raised-cosine pulse shaping, and root-raised cosine (RRC) pulse shaping [7], [10]. Throughout this paper, the pulse waveform $p_t(t)$ is modeled as the RRC pulse with a roll-off factor of 0.5 [8], [10], [15].

The channel model considered is the IEEE 802.15.4a standard channel model for the indoor residential non-line-of-sight (NLOS) environment [40]. This standard channel model includes some generalizations of the Saleh–Valenzuela model and takes the frequency dependence of the path gain into account [41]. In addition, the IEEE 802.15.4a channel model is valid for both low- and high-data-rate UWB systems [41]. For the kth user, the channel impulse response (CIR) of the standard channel model is $h_k(t) = \sum_{u=0}^{L_c-1}\sum_{v=0}^{L_r-1} \alpha_{u,v} e^{j\phi_{u,v}} \delta(t - T_u - T_{u,v})$, where L_c denotes the number of clusters, and L_r is the number of MPCs in one cluster. $\alpha_{u,v}$ is the fading gain of the vth MPC in the uth cluster, and $\phi_{u,v}$ is uniformly distributed in $[0, 2\pi)$. T_u is the arrival time of the uth cluster, and $T_{u,v}$ denotes the arrival time of the vth MPC in the uth cluster. For simplicity, we express the CIR as

$$h_k(t) = \sum_{l=0}^{L-1} h_{k,l}\delta(t - lT_\tau) \quad (2)$$

where $h_{k,l}$ and lT_τ present the complex-valued fading factor and the arrival time of the lth MPC ($l = uL_c + v$), respectively. $L = T_{DS}/T_\tau$ denotes the total number of MPCs, where T_{DS} is the channel delay spread. Note that, to achieve high-data-rate communications, the channel delay spread is assumed significantly larger than one symbol duration. Hence, the received signal encounters severe ISI.

Assuming that the timing is acquired, the received signal can be expressed as

$$z(t) = \sum_{k=1}^{K} \sum_{l=0}^{L-1} h_{k,l} x^{(k)}(t - lT_\tau) + n(t)$$

where $n(t)$ is the additive white Gaussian noise (AWGN) with zero mean and a variance of σ_n^2. This signal is first passed through a chip-matched filter (CMF) and then sampled at the chip rate. We select a total number of $M = (T_s + T_{DS})/T_c$ observation samples for the detection of each data bit, where T_s is the symbol duration, T_{DS} is the channel delay spread, and T_c is the chip duration. Assuming that the sampling starts at the zeroth time instant, the mth sample can be expressed as $r_m = \int_{mT_c}^{(m+1)T_c} z(t)p_r(t)dt$, where $m = 1, 2, \ldots, M$, $p_r(t) = p_t^*(-t)$ denotes the CMF, and $(\cdot)^*$ denotes the complex conjugation. After the chip-rate sampling, the discrete-time received signal for the ith data bit can be expressed as $\mathbf{r}(i) = [r_1(i), r_2(i), \ldots, r_M(i)]^T$, where $(\cdot)^T$ is the transposition. We can further express it in a matrix form as

$$\mathbf{r}(i) = \sum_{k=1}^{K} \sqrt{E_k}\mathbf{P}_r\mathbf{H}_k\mathbf{P}_t\mathbf{s}_k b_k(i) + \boldsymbol{\eta}(i) + \mathbf{n}(i) \quad (3)$$

where $\mathbf{H}_k$ is the Toeplitz channel matrix for the kth user, with the first column being the CIR of $\mathbf{h}_k = [h_k(0), h_k(1), \ldots, h_k(L-1)]^T$ zero-padded to length $M_H = (T_s/T_\tau) + L - 1$. Matrix $\mathbf{P}_r$ represents the CMF and chip-rate sampling with the size $M \times M_H$. $\mathbf{P}_t$ denotes the $(T_s/T_\tau) \times N_c$ pulse-shaping matrix. The vector $\boldsymbol{\eta}(i)$ denotes the ISI from $2G$ adjacent symbols, where G denotes the minimum integer that is larger than or equal to the scalar term T_{DS}/T_s. Here, we express the ISI vector in a general form that is given by

$$\boldsymbol{\eta}(i) = \sum_{k=1}^{K}\sum_{g=1}^{G} \sqrt{E_k}\mathbf{P}_r\mathbf{H}_k^{(-g)}\mathbf{P}_t\mathbf{s}_k b_k(i-g) + \sum_{k=1}^{K}\sum_{g=1}^{G} \sqrt{E_k}\mathbf{P}_r\mathbf{H}_k^{(+g)}\mathbf{P}_t\mathbf{s}_k b_k(i+g) \quad (4)$$

where the channel matrices for the ISI are given by

$$\mathbf{H}_k^{(-g)} = \begin{bmatrix} \mathbf{0} & \mathbf{H}_k^{(u,g)} \\ \mathbf{0} & \mathbf{0} \end{bmatrix}; \mathbf{H}_k^{(+g)} = \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{H}_k^{(l,g)} & \mathbf{0} \end{bmatrix}. \quad (5)$$

Note that the matrices $\mathbf{H}_k^{(u,g)}$ and $\mathbf{H}_k^{(l,g)}$ have the same size as $\mathbf{H}_k$, which is $M_H \times (T_s/T_\tau)$, and can be considered the partitions of an upper triangular matrix $\mathbf{H}_{\rm up}$ and a lower triangular matrix $\mathbf{H}_{\rm low}$, respectively, where

$$\mathbf{H}_{\rm up} = \begin{bmatrix} h_k(L-1) & \ldots & h_k\left(L - \frac{T_{DS}-(g-1)T_s}{T_\tau}\right) \\ & \ddots & \vdots \\ & & h_k(L-1) \end{bmatrix}$$

$$\mathbf{H}_{\rm low} = \begin{bmatrix} h_k(0) & & \\ \vdots & \ddots & \\ h_k\left(\frac{T_{DS}-(g-1)T_s}{T_\tau} - 2\right) & \ldots & h_k(0) \end{bmatrix}.$$

These triangular matrices have a row dimension of $[T_{DS} - (g-1)T_s]/T_\tau - 1 = L - (g-1)T_s/T_\tau - 1$. Note that, when the channel delay spread is large, the row dimension of these triangular matrices could surpass the column dimension of the matrix $\mathbf{H}_k$, which is T_s/T_τ. Hence, in the case of

$$L - (g-1)T_s/T_\tau - 1 > T_s/T_\tau, \quad L > gT_s/T_\tau + 1 \quad (6)$$

the matrix $\mathbf{H}_k^{(u,g)}$ is the last T_s/T_τ columns of the upper triangular matrix $\mathbf{H}_{\rm up}$, and $\mathbf{H}_k^{(l,g)}$ is the first T_s/T_τ columns of the lower triangular matrix $\mathbf{H}_{\rm low}$. When $L < gT_s/T_\tau + 1$, $\mathbf{H}_k^{(u,g)} = \mathbf{H}_{\rm up}$ and $\mathbf{H}_k^{(l,g)} = \mathbf{H}_{\rm low}$. It is interesting to review the expression of the ISI vector through its physical meaning, because the row dimension of the matrices $\mathbf{H}_k^{(u,g)}$ and $\mathbf{H}_k^{(l,g)}$, which is $L - (g-1)T_s/T_\tau - 1$, reflects the time-domain overlap between the data symbol $b(i)$ and the adjacent symbols of $b(i-g)$ and $b(i+g)$.

To estimate the data bit, an M-dimensional full-rank filter $\mathbf{w}(i)$ can be employed to minimize the MSE cost function, i.e.,

$$\mathbf{J}_{\rm MSE}(\mathbf{w}(i)) = E\left[\left|d(i) - \mathbf{w}^H(i)\mathbf{r}(i)\right|^2\right] \quad (7)$$

where $d(i)$ is the desired signal, $(\cdot)^H$ denotes the Hermitian transpose, and $E[\cdot]$ represents the expected value. Without loss of generality, we consider user 1 as the desired user and omit the subscript of this user for simplicity. The optimal solution that minimizes (7) is given by

$$\mathbf{w}_{\rm o} = \mathbf{R}^{-1}\mathbf{p} \quad (8)$$

where $\mathbf{R} = E[\mathbf{r}(i)\mathbf{r}^H(i)]$ is the correlation matrix of the discrete-time received signal $\mathbf{r}(i)$, and $\mathbf{p} = E[d^*(i)\mathbf{r}(i)]$ is the cross-correlation vector between $\mathbf{r}(i)$ and $d(i)$. The corresponding MMSE can be expressed as

$$\mathbf{MMSE}_{\rm f} = \sigma_d^2 - \mathbf{p}^H\mathbf{R}^{-1}\mathbf{p} \quad (9)$$

where σ_d^2 is the variance of the desired signal. Full-rank adaptive algorithms can update $\mathbf{w}(i)$ to approach the optimal solution in (8). The final decision is made by $\hat{b}(i) = {\rm sign}(\Re[\mathbf{w}^{\rm H}(i)\mathbf{r}(i)])$, where ${\rm sign}(\cdot)$ is the algebraic sign function, and $\Re(\cdot)$ represents the real part of a complex number. The full-rank adaptive filters experience slow convergence rate in DS-UWB systems because of the long channel delay spread. To accelerate the convergence and increase the robustness against interference, we propose a generic reduced-rank scheme in the following section.

III. Generic Reduced-Rank Scheme and Problem Statement

Reduced-rank signal processing can be divided into two parts: 1) an $M \times D$ projection matrix that projects the M-dimensional received signal onto a D-dimensional subspace (where $D \ll M$) and 2) a D-dimensional reduced-rank linear filter that produces the output. The projection stage of the reduced-rank schemes is given by

$$\bar{\mathbf{r}}(i) = \mathbf{T}^H(i)\mathbf{r}(i) \quad (10)$$

where $\bar{\mathbf{r}}(i)$ is the reduced-rank signal, and $\mathbf{T}(i)$ is the projection matrix, which can be expressed as

$$\mathbf{T}(i) = [\boldsymbol{\phi}_1(i), \ldots, \boldsymbol{\phi}_d(i), \ldots \boldsymbol{\phi}_D(i)] \quad (11)$$

where $\{\boldsymbol{\phi}_d(i) | d = 1, \ldots, D\}$ are the M-dimensional basis vectors. The vector $\bar{\mathbf{r}}(i)$ is then passed through a D-dimensional linear filter. The MMSE solution of such a filter is

$$\bar{\mathbf{w}}_{\rm o} = \bar{\mathbf{R}}^{-1}\bar{\mathbf{p}} \quad (12)$$

where $\bar{\mathbf{R}} = E[\bar{\mathbf{r}}(i)\bar{\mathbf{r}}^H(i)]$, and $\bar{\mathbf{p}} = E[d^*(i)\bar{\mathbf{r}}(i)]$.

In reduced-rank schemes, the main challenge is how the projection matrix $\mathbf{T}(i)$ can effectively be designed. To simplify the expression of the proposed SAABF scheme in later sections, the reduced-rank signal is expressed as

$$\begin{aligned}\bar{\mathbf{r}}(i) &= \mathbf{T}^H(i)\mathbf{r}(i) \\ &= \begin{bmatrix} \mathbf{r}^T(i) & & & \\ & \mathbf{r}^T(i) & & \\ & & \ddots & \\ & & & \mathbf{r}^T(i) \end{bmatrix}_{D\times MD} \begin{bmatrix} \boldsymbol{\phi}_1(i) \\ \boldsymbol{\phi}_2(i) \\ \vdots \\ \boldsymbol{\phi}_D(i) \end{bmatrix}^*_{MD\times 1} \\ &= \mathbf{R}_{\rm in}(i)\mathbf{t}(i) \end{aligned} \quad (13)$$

where the projection matrix is transformed into a vector form, and $\mathbf{t}(i)$ is called projection vector in the following discussion. It is shown that the dth element in the reduced-rank signal is $\bar{r}_d(i) = \mathbf{r}^T(i)\boldsymbol{\phi}_d^*(i)$, where $d = 1, \ldots, D$. The generic reduced-rank scheme is proposed to jointly and iteratively adapt the projection vector and the reduced-rank linear estimator to minimize the MSE cost function, i.e.,

$$\mathbf{J}_{\rm MSE}(\bar{\mathbf{w}}(i), \mathbf{t}(i)) = E\left[\left|d(i) - \bar{\mathbf{w}}^H(i)\mathbf{R}_{\rm in}(i)\mathbf{t}(i)\right|^2\right]. \quad (14)$$

The MMSE solution of the reduced-rank filter in the generic scheme has the same form as (12). By setting the gradient

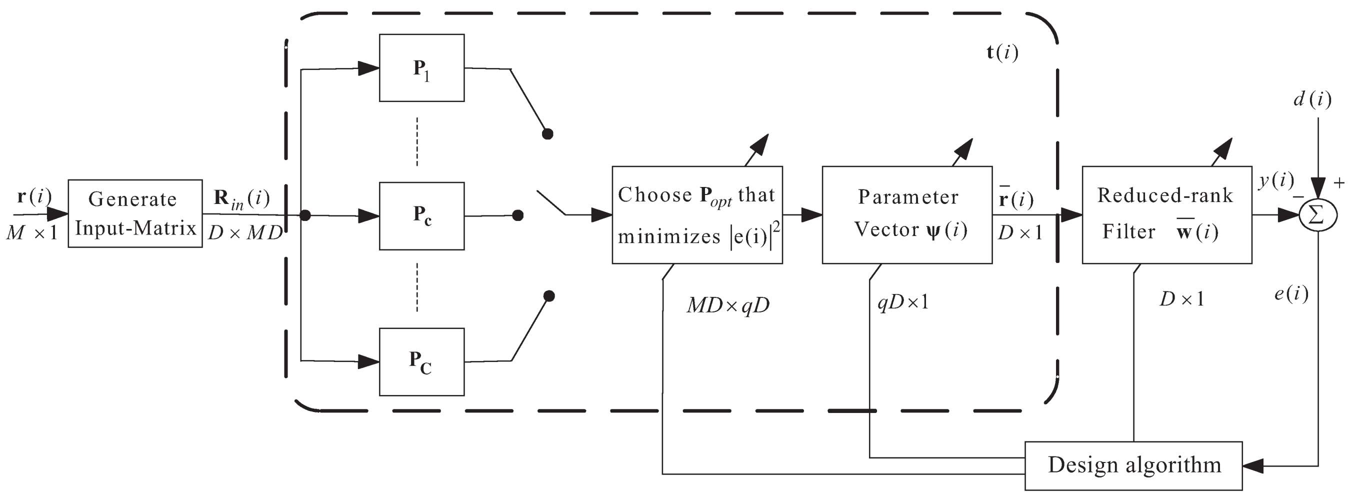

Fig. 1. Block diagram of the proposed reduced-rank linear receiver using the SAABF scheme.

vector of (14) with respect to $\mathbf{t}(i)$ to a null vector, the optimum projection vector is given by

$$\mathbf{t}_{\rm opt} = \mathbf{R}_w^{-1}\mathbf{p}_w \tag{15}$$

where $\mathbf{R}_w = E[\mathbf{R}_{\rm in}^H(i)\bar{\mathbf{w}}(i)\bar{\mathbf{w}}^H(i)\mathbf{R}_{\rm in}(i)]$, and $\mathbf{p}_w = E[d(i)\mathbf{R}_{\rm in}^H(i)\bar{\mathbf{w}}(i)]$. The MMSE of the generic scheme can be expressed as

$$\mathbf{MMSE}_{\rm g} = \sigma_d^2 - \bar{\mathbf{p}}^H\bar{\mathbf{R}}^{-1}\bar{\mathbf{p}}. \tag{16}$$

Note that, when adaptive algorithms are implemented to estimate $\bar{\mathbf{w}}_{\rm o}$ and $\mathbf{t}_{\rm opt}$, $\bar{\mathbf{w}}(i)$ is a function of $\mathbf{t}(i)$, and $\mathbf{t}(i)$ is a function of $\bar{\mathbf{w}}(i)$. Thus, the joint MMSE design is not in a closed form, and one possible solution for such an optimization problem is to jointly and iteratively adapt these two parts with an initial guess. The joint adaptation is operated as follows. For the ith time instant, $\bar{\mathbf{w}}(i)$ is obtained with the knowledge of $\mathbf{t}(i-1)$ and $\bar{\mathbf{w}}(i-1)$, and then, $\mathbf{t}(i)$ is updated with $\mathbf{t}(i-1)$ and $\bar{\mathbf{w}}(i)$. The iterative adaptation repeats the joint adaptation until the satisfactory estimates are obtained. Hence, the number of iterations is environment dependent. Compared with existing reduced-rank schemes such as MSWF [28] and AVF [35], this generic scheme enables the projection vector and the reduced-rank filter to exchange information at each iteration. This feature leads to a more effective operation of the adaptive algorithms. However, the drawback of such a feature is that we cannot obtain a closed-form design. It will be illustrated by the simulation results that this generic scheme outperforms the MSWF [28] and AVF [35] with a few iterations.

Note that, in DS-UWB systems where the length of the full-rank received signal M is large, the complexity of updating the MD-dimensional projection vector is very high. To reduce the complexity of this generic scheme, we propose the following SAABF scheme.

IV. Proposed Switched Approximation Of Adaptive Basis Functions Scheme and Filter Design

In this section, we detail the proposed SAABF scheme, whose primary idea is to constrain the structure of the MD-dimensional projection vector $\mathbf{t}(i)$ using a multiple-branch framework such that the number of coefficients to be computed is substantially reduced. The block diagram of the proposed SAABF scheme is shown in Fig. 1. There are C branches in the SAABF scheme. For each branch, a projection vector is equivalent to a projection matrix $\mathbf{T}_c(i) = [\boldsymbol{\phi}_{c,1}(i),\ldots,\boldsymbol{\phi}_{c,d}(i),\ldots,\boldsymbol{\phi}_{c,D}(i)]$, where $c = [1,2,\ldots,C]$, $d = [1,2,\ldots,D]$, and the M-dimensional adaptive basis function is given by

$$\boldsymbol{\phi}_{c,d}(i) = \begin{bmatrix} \mathbf{0}_{z_{c,d}\times q} \\ \mathbf{I}_q \\ \mathbf{0}_{(M-q-z_{c,d})\times q} \end{bmatrix}_{M\times q} \boldsymbol{\varphi}_d(i) = \mathbf{Z}_{c,d}\boldsymbol{\varphi}_d(i) \tag{17}$$

where $z_{c,d}$ is the number of zeros before the $q\times 1$ function $\boldsymbol{\varphi}_d(i)$ (where $q \ll M$), which is called the inner function in the following discussion. The matrix $\mathbf{Z}_{c,d}$ consists of zeros and ones. With a $q\times q$ identity matrix $\mathbf{I}_q$ in the middle, the zero matrices have a size of $z_{c,d}\times q$ and $(M-q-z_{c,d})\times q$, respectively. Hence, we can express the projection vector as

$$\begin{aligned}\mathbf{t}_c(i) &= \left[\boldsymbol{\phi}_{c,1}^T(i),\boldsymbol{\phi}_{c,2}^T(i),\cdots,\boldsymbol{\phi}_{c,D}^T(i)\right]^H \\ &= \begin{bmatrix}\mathbf{Z}_{c,1} & & & \\ & \mathbf{Z}_{c,2} & & \\ & & \ddots & \\ & & & \mathbf{Z}_{c,D}\end{bmatrix}\begin{bmatrix}\boldsymbol{\varphi}_1(i)\\ \boldsymbol{\varphi}_2(i)\\ \vdots \\ \boldsymbol{\varphi}_D(i)\end{bmatrix}^* \\ &= \mathbf{P}_c\boldsymbol{\psi}(i)\end{aligned} \tag{18}$$

where the $MD\times qD$ block diagonal matrix $\mathbf{P}_c$ is called the position matrix, which determines the positions of the q-dimensional inner functions, and $\boldsymbol{\psi}(i)$ denotes the qD-dimensional projection vector, which is constructed by the inner functions. For each time instant, rank reduction in the SAABF scheme is achieved by instantaneously selecting the position matrix $\mathbf{P}(i)$ from a set of prestored position matrices $\mathbf{P}_c$, where $c = 1,\ldots,C$, and updating the $\boldsymbol{\psi}(i)$. Compared with (13), (18) shows the constraint that we use in the SAABF scheme. With the multibranch structure, the dimension of the projection vector is shortened from MD to qD.

For simplicity, we denote the proposed scheme with its main parameters as "SAABF(C, D, q), where C is the number of branches, D is the length of the reduced-rank filter, and q is the length of the inner function. Note that, in the case of the SAABF$(1, D, M)$, where $C = 1$, and $q = M$, the proposed scheme is equivalent to the generic scheme described in Section III. For SAABF$(1, 1, M)$, where $C = 1$, $D = 1$, and $q = M$, the proposed scheme can be considered a full-rank scheme. All these equivalences are proved in the Appendix B, which shows that the optimal solutions in these scenarios will lead to the same MMSE.

It is interesting to note that the adaptation in the proposed SAABF scheme can be considered to be a hybrid adaptive technique, which includes a discrete parameter optimization for choosing the instantaneous position matrix and a continuous filter design for adapting the projection vector and the reduced-rank filter. In the following discussion, we detail the discrete parameter optimization and the filter design.

A. Discrete Parameter Optimization

In this section, the selection rule for choosing $\mathbf{P}(i)$ is introduced, and the designs of the prestored position matrices $\mathbf{P}_c$ are detailed. The problem of computing the optimal $\mathbf{P}(i)$ is a discrete optimization problem, because $\mathbf{P}(i)$ can be considered a time-independent parameter, which is selected from a set of prestored matrices at each time instant for minimizing the instantaneous square error. The output signal of each branch is given by

$$y_c(i) = \bar{\mathbf{w}}^H(i)\mathbf{R}_{\text{in}}(i)\mathbf{t}_c(i) = \bar{\mathbf{w}}^H(i)\mathbf{R}_{\text{in}}(i)\mathbf{P}_c\boldsymbol{\psi}(i)$$

where the corresponding error signal is $e_c(i) = d(i) - y_c(i)$. Hence, the selection rule can be expressed as

$$c_{\text{opt}} = \arg\min_{c\in\{1,\ldots,C\}} |e_c(i)|^2, \quad e(i) = e_{c_{\text{opt}}}(i) \quad \mathbf{P}(i) = \mathbf{P}_{c_{\text{opt}}}. \tag{19}$$

As shown in (17) and (18), the position matrices are distinguished by the values of $z_{c,d}$. The optimal way for selecting $z_{c,d}$ is to test all the possibilities of the position matrices and choose a structure that corresponds to the minimum square error. However, in the DS-UWB system, the number of possible positions is $(M - q)^D$, where M is much larger than q and D, e.g., $M = 112$, and $q = D = 3$. Therefore, it is very expensive to find the optimal position matrix from such a huge number of possibilities. Hence, we design a small number of C prestored position matrices that enables us to find a suboptimum instantaneous position matrix that provides an attractive tradeoff between performance and complexity. Note that the number C can be considered a system parameter for the designer and increasing the number of position matrices will benefit the performance but also increase the complexity. In Section IV-A, we propose a branch number selection algorithm to determine C within a given range to decrease the averaged required number of branches while maintaining the performance.

To design the prestored matrices, we propose a simple deterministic way of setting the values of $z_{c,d}$ as follows:

$$z_{c,d} = \left\lfloor \frac{M}{D} \right\rfloor \times (d-1) + (c-1)q \tag{20}$$

where $c = 1, \ldots, C$, and $d = 1, \ldots, D$. Bearing in mind the matrix form shown in (17) and (18), the first $MD \times qD$ position matrix $\mathbf{P}_1$ can be expressed as

$$\mathbf{P}_1 = \begin{bmatrix} \mathbf{I}_q & & & \\ \mathbf{0}_{M-q} & & & \\ & \mathbf{0}_{\lfloor\frac{M}{D}\rfloor} & & \\ & \mathbf{I}_q & & \\ & \mathbf{0}_{M-q-\lfloor\frac{M}{D}\rfloor} & & \\ & & \ddots & \\ & & & \mathbf{0}_{\lfloor\frac{M}{D}\rfloor(D-1)} \\ & & & \mathbf{I}_q \\ & & & \mathbf{0}_{M-q-\lfloor\frac{M}{D}\rfloor(D-1)} \end{bmatrix} \tag{21}$$

where all the zero and identity matrices have q columns, and the subscripts denote the number of rows of these matrices. We remark that the proposed approach arranges the $q \times q$ identity matrices in a simple fixed sliding pattern. This approach then allows an efficient generation of the remaining position matrices. For example, the second projection matrix $\mathbf{P}_2$ can be considered a shifted version of $\mathbf{P}_1$, in which each column has been shifted down by q elements. Note that the prestored position matrices can also be randomly generated, in which approach the values of $z_{c,d}$ are randomly set. However, the random method will require extra storage space for all the prestored matrices, and the performance of this method is inferior to the proposed deterministic method.

B. Filter Design

After determining the position matrix $\mathbf{P}(i)$, the LS design of the reduced-rank filter and the projection vector can be developed to minimize the following cost function:

$$\mathbf{J}_{\text{LS}}(\bar{\mathbf{w}}(i), \boldsymbol{\psi}(i)) = \sum_{j=1}^{i} \lambda^{i-j} \left| d(j) - \bar{\mathbf{w}}^H(i)\mathbf{R}_{\text{in}}(j)\mathbf{P}(i)\boldsymbol{\psi}(i) \right|^2 \tag{22}$$

where λ is a forgetting factor. First, we calculate the gradient of (22) with respect to $\bar{\mathbf{w}}(i)$, which is

$$\mathbf{g}_{\text{LS}_{\bar{w}^*(i)}} = -\bar{\mathbf{p}}_{w_{\text{LS}}}(i) + \bar{\mathbf{R}}_{w_{\text{LS}}}(i)\bar{\mathbf{w}}(i) \tag{23}$$

where $\bar{\mathbf{p}}_{w_{\text{LS}}}(i) = \sum_{j=1}^{i} \lambda^{i-j} d^*(j)\bar{\mathbf{r}}(j)$, and $\bar{\mathbf{R}}_{w_{\text{LS}}}(i) = \sum_{j=1}^{i} \lambda^{i-j}\bar{\mathbf{r}}(j)\bar{\mathbf{r}}^H(j)$. Assuming that $\boldsymbol{\psi}(i)$ is fixed, the LS solution of the reduced-rank filter is

$$\bar{\mathbf{w}}_{\text{LS}}(i) = \bar{\mathbf{R}}_{w_{\text{LS}}}^{-1}(i)\bar{\mathbf{p}}_{w_{\text{LS}}}(i). \tag{24}$$

Second, we examine the gradient of (22) with respect to $\boldsymbol{\psi}(i)$, which is

$$\mathbf{g}_{\text{LS}_{\psi^*(i)}} = -\mathbf{p}_{\psi_{LS}}(i) + \mathbf{R}_{\psi_{\text{LS}}}(i)\boldsymbol{\psi}(i) \tag{25}$$

where $\mathbf{p}_{\psi_{\rm LS}}(i) = \sum_{j=1}^{i} \lambda^{i-j} d(j)\mathbf{r}_{\psi}(j)$, $\mathbf{R}_{\psi_{\rm LS}}(i) = \sum_{j=1}^{i} \lambda^{i-j} \mathbf{r}_{\psi}(j)\mathbf{r}_{\psi}^{H}(j)\boldsymbol{\psi}(i)$, and $\mathbf{r}_{\psi}(j) = \mathbf{P}^{H}(j)\mathbf{R}_{\rm in}^{H}(j)\bar{\mathbf{w}}(j)$. With the assumption that $\bar{\mathbf{w}}(i)$ is fixed, the LS solution of the projection vector is

$$\boldsymbol{\psi}_{\rm LS}(i) = \mathbf{R}_{\psi_{\rm LS}}^{-1}(i)\mathbf{p}_{\psi_{\rm LS}}(i). \tag{26}$$

Finally, (24) and (26) summarize the LS design of the reduced-rank filter and the projection vector in the SAABF scheme. A discussion on the optimization of the SAABF scheme is presented in Appendix A.

V. Adaptive Algorithms

In this section, the joint LMS and RLS algorithms are developed for estimating the reduced-rank filter and the projection vector. The complexity analysis is also given to compare the computational load of existing and the proposed algorithms. We remark that, in the SAABF scheme, when a number of branches are implemented, the joint adaptation only requires one iteration for each time instant.

A. LMS Version

The joint LMS version of the SAABF scheme is developed to minimize the MSE cost function as

$$\mathbf{J}_{\rm MSE}\left(\bar{\mathbf{w}}(i), \boldsymbol{\psi}(i)\right) = E\left[\left|d(i) - \bar{\mathbf{w}}^{H}(i)\mathbf{R}_{\rm in}(i)\mathbf{P}(i)\boldsymbol{\psi}(i)\right|^{2}\right] \tag{27}$$

where $\mathbf{P}(i)$ is the instantaneous position matrix. The MMSE solution of the SAABF scheme is shown in Appendix B.

At the ith time instant, we first determine the instantaneous position matrix with the selection rule (19). Then, the reduced-rank filter weight vector $\bar{\mathbf{w}}(i)$ can be updated with the LMS algorithm [42]. Taking the gradient vector of (27) with respect to $\bar{\mathbf{w}}(i)$ and using the instantaneous values of the gradient vector, the adaptation equation for the reduced-rank filter is given by

$$\bar{\mathbf{w}}(i+1) = \bar{\mathbf{w}}(i) + \mu_{w}\mathbf{R}_{\rm in}(i)\mathbf{P}(i)\boldsymbol{\psi}(i)e^{*}(i) \tag{28}$$

where μ_w is the step size. With the knowledge of the updated reduced-rank filter, the projection vector can be adapted to minimize the cost function (27). Taking the gradient vector of (27) with respect to $\boldsymbol{\psi}(i)$ and using the instantaneous estimate of the gradient vector, the adaptation equation for the projection vector is obtained as

$$\boldsymbol{\psi}(i+1) = \boldsymbol{\psi}(i) + \mu_{\psi}\mathbf{P}^{H}(i)\mathbf{R}_{\rm in}^{H}(i)\bar{\mathbf{w}}(i+1)e(i) \tag{29}$$

where μ_ψ is the step size. We summarize the LMS version of the SAABF scheme in Table I.

B. RLS Version

Let us consider the RLS design of the SAABF scheme, which can be developed to minimize the cost function shown in (22). The instantaneous position matrix is determined with the selection rule (19). The reduced-rank filter will first be updated.

TABLE I
Proposed Adaptive Algorithms

LMS :	
Step 1:	Initialization:
	$\boldsymbol{\psi}(0)$=ones(qD, 1) and $\bar{\mathbf{w}}(0)$=zeros(D, 1)
	Set values for μ_w and μ_ψ
	Generate the position matrices $\mathbf{P}_1, \ldots, \mathbf{P}_C$
Step 2:	For i=0, 1, 2, ...
	(1) Compute the error signals $e_c(i)$ for each branch,
	(2) Select the branch $c_{\rm opt} = \arg\min_{c\in\{1,\ldots,C\}} \lvert e_c(i)\rvert^2$,
	(3) Set the instantaneous position matrix $\mathbf{P}(i)$=$\mathbf{P}_{c_{\rm opt}}$,
	(4) Update $\bar{\mathbf{w}}(i+1)$ using (28)
	(5) Update $\boldsymbol{\psi}(i+1)$ using (29).
RLS :	
Step 1:	Initialization:
	$\boldsymbol{\psi}(0)$=ones(qD, 1) and $\bar{\mathbf{w}}(0)$=zeros(D, 1)
	$\bar{\mathbf{R}}_{w_{\rm LS}}^{-1}(0)$=$\mathbf{I}_D/\delta_w$ and $\mathbf{R}_{\psi_{\rm LS}}^{-1}(0)$=$\mathbf{I}_{qD}/\delta_\psi$
	Set values for λ, δ_w and δ_ψ
	Generate the position matrices $\mathbf{P}_1, \ldots, \mathbf{P}_C$
Step 2:	For i=1, 2, ...
	(1) Compute the error signals $e_c(i)$ for each branch,
	(2) Select the branch $c_{\rm opt} = \arg\min_{c\in\{1,\ldots,C\}} \lvert e_c(i)\rvert^2$,
	(3) Set the instantaneous position matrix $\mathbf{P}(i)$=$\mathbf{P}_{c_{\rm opt}}$,
	(4) Update $\bar{\mathbf{w}}(i) = \bar{\mathbf{w}}(i-1) + \mathbf{K}_w(i)e^*(i)$,
	(5) Update $\bar{\mathbf{R}}_{w_{\rm LS}}^{-1}(i)$ using (30),
	(6) Update $\boldsymbol{\psi}(i) = \boldsymbol{\psi}(i-1) + \mathbf{K}_\psi(i)e(i)$,
	(7) Update $\mathbf{R}_{\psi_{\rm LS}}^{-1}(i)$ using (34).

The gradient of (22) with respect to $\bar{\mathbf{w}}(i)$ is shown in (23). By applying the matrix inversion lemma to $\bar{\mathbf{R}}_{w_{\rm LS}}(i)$, we obtain its inverse matrix in a recursive way as

$$\bar{\mathbf{R}}_{w_{\rm LS}}^{-1}(i) = \lambda^{-1}\bar{\mathbf{R}}_{w_{\rm LS}}^{-1}(i-1) - \lambda^{-1}\mathbf{K}_{w}(i)\bar{\mathbf{r}}^{H}(i)\bar{\mathbf{R}}_{w_{\rm LS}}^{-1}(i-1) \tag{30}$$

where $\mathbf{K}_w(i) = (\bar{\mathbf{R}}_{w_{\rm LS}}^{-1}(i-1)\bar{\mathbf{r}}(i))/(\lambda + \bar{\mathbf{r}}^{H}(i)\bar{\mathbf{R}}_{w_{\rm LS}}^{-1}(i-1)\bar{\mathbf{r}}(i))$. To obtain a recursive update equation, we express the vector $\bar{\mathbf{p}}_{w_{\rm LS}}(i)$ as

$$\bar{\mathbf{p}}_{w_{\rm LS}}(i) = \lambda\bar{\mathbf{p}}_{w_{\rm LS}}(i-1) + d^{*}(i)\bar{\mathbf{r}}(i). \tag{31}$$

By substituting (30) and (31) into (23) and setting the gradient to zero, we obtain the RLS adaptation equation for the reduced-rank filter as

$$\bar{\mathbf{w}}(i) = \bar{\mathbf{w}}(i-1) + \mathbf{K}_{w}(i)e^{*}(i). \tag{32}$$

With the knowledge of the updated reduced-rank filter, we can adapt the projection vector to minimize the cost function (22). The gradient of (22) with respect to $\boldsymbol{\psi}(i)$ is shown in (25).

To obtain the recursive update equation for the projection vector, we express $\mathbf{p}_{\psi_{\rm LS}}(i)$ in a recursive form as

$$\mathbf{p}_{\psi_{\rm LS}}(i) = \lambda\mathbf{p}_{\psi_{\rm LS}}(i-1) + d(i)\mathbf{r}_{\psi}(i) \tag{33}$$

where $\mathbf{r}_{\psi}(j) = \mathbf{P}^{H}(j)\mathbf{R}_{\rm in}^{H}(j)\bar{\mathbf{w}}(j)$.

Applying the matrix inversion lemma to $\mathbf{R}_{\psi_{\rm LS}}(i)$, we recursively obtain its inverse as

$$\mathbf{R}_{\psi_{\rm LS}}^{-1}(i) = \lambda^{-1}\mathbf{R}_{\psi_{\rm LS}}^{-1}(i-1) - \lambda^{-1}\mathbf{K}_{\psi}(i)\mathbf{r}_{\psi}^{H}(i)\mathbf{R}_{\psi_{\rm LS}}^{-1}(i-1) \tag{34}$$

where $\mathbf{K}_{\psi}(i) = (\mathbf{R}_{\psi_{\rm LS}}^{-1}(i-1)\mathbf{r}_{\psi}(i))/(\lambda + \mathbf{r}_{\psi}^{H}(i)\mathbf{R}_{\psi_{\rm LS}}^{-1}(i-1)\mathbf{r}_{\psi}(i))$. By substituting (33) and (34) into (25) and setting the

TABLE II
COMPLEXITY ANALYSIS

Algorithm	Complex Additions	Complex Multiplications
Full-Rank LMS	$2M$	$2M+1$
Full-Rank RLS	$3M^2+M$	$4(M^2+M)$
MSWF-LMS	$DM^2+(D+2)M$	$(D+1)M^2+(3D+2)M+2D+1$
MSWF-RLS	$DM^2+(D+2)M+3D^2-D$	$(D+1)M^2+(3D+2)M+4(D^2+D)$
AVF	$(3D+1)M^2+M-2D-1$	$(5D+2)M^2+(D+1)M$
SAABF(C,D,q)-LMS	$qD(C+1)-CD+C+D$	$DM+2Dq(C+1)+D+2$
SAABF(C,D,q)-RLS	$4(qD)^2+CD(q-1)+3D^2+C+D$	$DM+5(qD)^2+2CDq+4D^2+3Dq+3D$

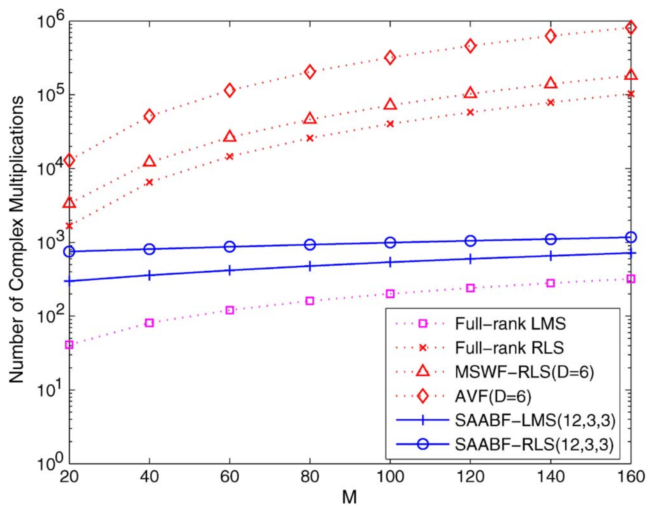

Fig. 2. Computational complexity of the linear adaptive algorithms.

gradient to zero, we obtain the RLS adaptation equation for the projection vector as

$$\boldsymbol{\psi}(i)=\boldsymbol{\psi}(i-1)+\mathbf{K}_{\psi}(i)e(i). \qquad (35)$$

The RLS version of the SAABF scheme is summarized in Table I.

C. Complexity Analysis

The computational complexity for different adaptive algorithms with respect to the number of complex additions and complex multiplications for each processed data bit is shown in Table II. We compare the complexity of the full-rank LMS and RLS, the LMS and RLS versions of MSWF, AVF, and the proposed SAABF scheme. The quantity M is the length of the full-rank filter, D is the dimension of the subspace, C is the number of branches in the SAABF scheme, and q is the length of the inner function. In Fig. 2, the number of complex multiplications of the linear adaptive algorithms is shown as a function of M. We remark that the complexity of the receiver with the proposed SAABF scheme is linearly proportional to the length of the received signal and is much lower than the existing reduced-rank schemes in the large-signal-length scenarios. Note that, for each time instant, the SAABF scheme requires one simple search procedure, which will select the minimum square error from a C-dimensional error vector.

There is an extremely simple configuration of the proposed scheme that can be expressed as SAABF$(C,D,1)$, in which the length of the inner function is only 1, and the projection vector $\boldsymbol{\psi}(i)$ is fixed to its initial value of $\boldsymbol{\psi}(i)=\text{ones}(D,1)$. This feature significantly reduces the complexity of the SAABF scheme, and the performance of this configuration will be illustrated with simulation results.

VI. MODEL ORDER AND PARAMETER ADAPTATION

In the SAABF(C,D,q) scheme, the computational complexity and the performance are highly dependent on the values of the parameter C and the model order D and q. Although we can set suitable values for these parameters in a specific operation environment with some performance requirements, the best tradeoffs between the complexity and performance usually cannot be obtained. To automatically and effectively choose these parameters in different environments, we propose adaptive algorithms as follows.

A. Branch Number Selection

The algorithm for selecting the suboptimum branch number is developed with the following observations: All the branches will be used at least once, but some branches are more likely to be selected. For a target square error, with a given number of branches, it is unnecessary to test all of them at each time instant, and we can choose the first branch that assures the target. With these observations and assuming that D and q are fixed, we propose an algorithm to select the number of branches. First, we set a minimum and a maximum number of branches, denoted as $C_{\min}$ and $C_{\max}$, respectively. Then, we define a threshold γ that is related to the MMSE. For each time instant, we test the first $C_{\min}$ branches. If the MSE target is not assured, we test the $(C_{\min}+1)$th branch, and so on. We stop the search when the target is achieved or when the maximum allowed number of branches $C_{\max}$ is reached. The proposed algorithm can be expressed as

$$C_{\rm r}(i)=\arg\min_{c\in\{C_{\min},\ldots,C_{\max}\}}\left[\left|e_c^2(i)-e_{\rm MMSE}^2\right|<\gamma\right] \qquad (36)$$

where $e_c(i)=d(i)-\bar{\mathbf{w}}^H(i)\mathbf{R}_{\rm in}(i)\mathbf{P}_c\psi(i)$ is the error signal that corresponds to the cth branch, and $C_{\rm r}(i)$ represents the required number of branches at the ith time instant. Note that the $e_{\rm MMSE}$ is the ideal minimum error signal, and we can replace it with a given value for the target environment. The aim of this selection algorithm is to reduce the average number of used branches while maintaining the BER (or MSE) performance.

B. Rank Adaptation

The computational complexity and the performance of the novel SAABF reduced-rank scheme is sensitive to the determined rank D. Unlike prior work that used the approach proposed in [25], we develop a rank adaptation algorithm based on the *a posteriori* LS cost function to estimate the MSE, which is a function of the parameters $\bar{\mathbf{w}}_D^H(i)$, $\mathbf{R}_{\text{in},D}(i)$, $\mathbf{P}_D(i)$, and $\boldsymbol{\psi}_D(i)$. We have

$$\mathcal{C}_D(i) = \sum_{n=0}^{i} \lambda_D^{i-n} \left| d(i) - \bar{\mathbf{w}}_D^H(i)\mathbf{R}_{\text{in},D}(i)\mathbf{P}_D(i)\boldsymbol{\psi}_D(i) \right|^2 \tag{37}$$

where λ_D is a forgetting factor. Because the optimal rank can be considered a function of the time index i [25], the forgetting factor is required and allows us to track the optimal rank. We assume that the number of branches C and the length of the inner function q are fixed. For each time instant, we update a reduced-rank filter $\bar{\mathbf{w}}_{\text{M}}(i)$ and a projection vector $\boldsymbol{\psi}_M(i)$ with the maximum rank $D_{\max}$, which can be expressed as

$$\begin{aligned} \bar{\mathbf{w}}_{\text{M}}(i) &= [\bar{w}_{\text{M},1}(i), \ldots, \bar{w}_{\text{M},D}(i), \ldots, \bar{w}_{\text{M},D_{\max}}(i)]^T \\ \boldsymbol{\psi}_{\text{M}}(i) &= [\psi_{\text{M},1}(i), \ldots, \psi_{\text{M},qD}(i), \ldots, \psi_{\text{M},qD_{\max}}(i)]^T. \end{aligned} \tag{38}$$

After the adaptation, we test values of D within the range $D_{\min}$–$D_{\max}$. For each tested rank, we use the following estimators:

$$\begin{aligned} \bar{\mathbf{w}}_D(i) &= [\bar{w}_{\text{M},1}(i), \ldots, \bar{w}_{\text{M},D}(i)]^T \\ \boldsymbol{\psi}_D(i) &= [\psi_{\text{M},1}(i), \ldots, \psi_{\text{M},qD}(i)]^T. \end{aligned} \tag{39}$$

The position matrices for different model orders can be prestored, and the instantaneous position matrix $\mathbf{P}_D(i)$ can be determined by the decision rule as shown in (19). After selecting the position matrix and given the input data matrix, we substitute (39) into (37) to obtain the value of $\mathcal{C}_D(i)$, where $D \in \{D_{\min}, \ldots, D_{\max}\}$. The proposed algorithm can be expressed as

$$D_{\text{opt}}(i) = \arg \min_{D \in \{D_{\min}, \ldots, D_{\max}\}} \mathcal{C}_D(i). \tag{40}$$

We remark that the complexity of updating the reduced-rank filter and the projection vector in the proposed rank adaptation algorithm is the same as the SAABF $(C, D_{\max}, q)$, because we only adapt $\bar{\mathbf{w}}_{\text{M}}(i)$ and $\boldsymbol{\psi}_{\text{M}}(i)$ for each time instant. However, additional computations are required to calculate the values of $\mathcal{C}_D(i)$ and select the minimum value of a $(D_{\max} - D_{\min} + 1)$-dimensional vector that corresponds to a simple search and comparison.

C. Inner Function Length Selection

In the SAABF scheme, the length of the inner function is also a sensitive parameter that affects the complexity and the overall performance. In this paper, we apply the similar idea used for the rank adaptation to select the optimal value of q. The criterion for choosing q_{opt} is that it minimizes the following cost function:

$$\mathcal{C}_q(i) = \sum_{n=0}^{i} \lambda_q^{i-n} \left| d(i) - \bar{\mathbf{w}}^H(i)\mathbf{R}_{\text{in}}(i)\mathbf{P}_q(i)\boldsymbol{\psi}_q(i) \right|^2 \tag{41}$$

where the forgetting factor λ_q is applied, because we observe that, in the SAABF scheme, the length of q plays a similar role as the rank D, and the optimal q can change as a function of the time index i.

When the model order D and the branch number C are fixed, for each time instant, we adapt a $D \times 1$ reduced-rank filter $\bar{\mathbf{w}}(i)$ jointly with a $Dq_{\max} \times 1$ projection vector, $\boldsymbol{\psi}_{\text{Q}}(i) = [\psi_{\text{Q},1}(i), \ldots, \psi_{\text{Q},Dq}(i), \ldots, \psi_{\text{Q},Dq_{\max}}(i)]^T$. For different values of q, we use the estimate

$$\boldsymbol{\psi}_q(i) = \left[\boldsymbol{\psi}_{q,1}^T(i), \ldots, \boldsymbol{\psi}_{q,D}^T(i)\right]^T \tag{42}$$

where the vectors of $\boldsymbol{\psi}_{q,d}(i)$, $d = 1, \ldots, D$ can be expressed as

$$\boldsymbol{\psi}_{\text{q,d}}(i) = \left[\psi_{\text{Q},(d-1)q_{\max}+1}(i), \ldots, \psi_{\text{Q},(d-1)q_{\max}+q}(i)\right]^T. \tag{43}$$

At the ith moment, we search from $q_{\min}$ to $q_{\max}$ and determine the q_{opt} using the following algorithm:

$$q_{\text{opt}}(i) = \arg \min_{q \in \{q_{\min}, \ldots, q_{\max}\}} \mathcal{C}_q(i). \tag{44}$$

The computational complexity of updating the reduced-rank filter and the projection vector in this algorithm is the same as the SAABF $(C, D, q_{\max})$. Because we only adapt a $D \times 1$ reduced-rank filter and a $Dq_{\max} \times 1$ projection vector for all tested values of q, additional computations are needed to compute the values of $\mathcal{C}_q(i)$ and search the minimum value in a $(q_{\max} - q_{\min} + 1)$-dimensional vector.

VII. Simulations

In this section, we apply the proposed generic and SAABF schemes to the uplink of a multiuser BPSK DS-UWB system and evaluate their performance against existing reduced-rank and full-rank methods. In all numerical simulations, all the users are assumed to continuously transmit at the same power level. The pulse shape adopted is the RRC pulse with a pulsewidth of 0.375 ns. The spreading codes are randomly generated for each user in each independent simulation with a spreading gain of 32, and the data rate of the communication is approximately 83 Mb/s. The standard IEEE 802.15.4a channel model for the NLOS indoor environment is employed [40], and we assume that the channel is constant during the whole transmission. The channel delay spread is $T_{DS} = 30$ ns, which is much larger than the symbol duration, which is $T_s = 12$ ns. Hence, the severe ISI from $2G = 6$ neighbor symbols are taken into the account for the simulations. The sampling rate at the receiver is assumed to be 2.67 GHz, and the length of the discrete time received signal is $M = 112$. For all the simulations, the adaptive filters are initialized as null vectors. This approach allows a fair comparison between the analyzed techniques for

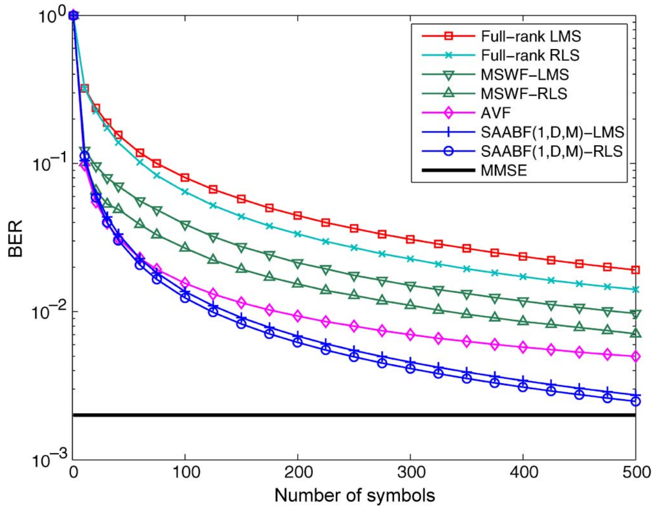

Fig. 3. BER performance of different algorithms for a SNR $= 20$ dB and eight users. The following parameters were used: full-rank LMS ($\mu = 0.075$), full-rank RLS ($\lambda = 0.998, \delta = 10$), MSWF–LMS ($D = 6, \mu = 0.075$), MSWF–RLS ($D = 6, \lambda = 0.998$), AVF ($D = 6$), SAABF$(1, 3, M)$–LMS ($\mu_w = 0.15$, $\mu_\psi = 0.15$, three iterations), and SAABF$(1, 3, M)$–RLS ($\lambda = 0.998$, $\delta = 10$, three iterations).

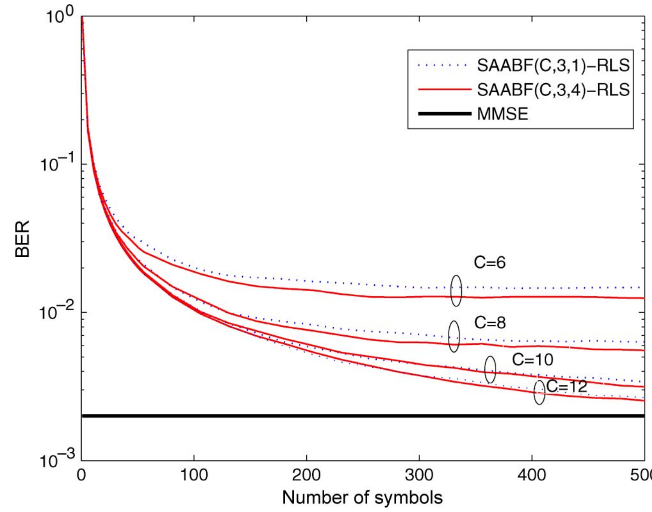

Fig. 4. BER performance of the proposed SAABF scheme versus the number of training symbols for a SNR $= 20$ dB. The number of users is eight, and the following parameters were used: SAABF–RLS ($\lambda = 0.998, \delta = 10$).

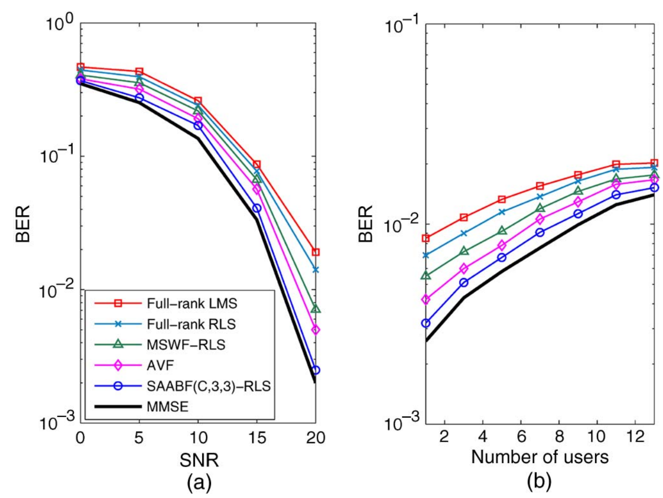

Fig. 5. BER performance of the proposed scheme with different SNRs and numbers of users.

their convergence performance. In practice, the filters can be initialized with prior knowledge about the spreading code or the channel to accelerate the convergence. In this paper, we present the uncoded bit error rate (BER) for all the comparisons. All the curves are obtained by averaging 200 independent simulations.

The first experiment that we perform compares the uncoded BER performance of the generic reduced-rank scheme, which is denoted as SAABF$(1, D, M)$, with the full-rank LMS and RLS algorithms, the LMS and RLS versions of the MSWF, and the AVF method. We consider the scenario with a signal-to-noise ratio (SNR) of 20 dB with eight users. Fig. 3 shows the BER performance of different schemes as a function of the training symbols transmitted. The proposed generic scheme outperforms all the other methods with three iterations. In the generic scheme, the joint RLS algorithm could converge faster than the joint LMS algorithm with the same number of iterations.

Fig. 4 shows the uncoded BER performance of the RLS version of the novel SAABF scheme with different numbers of branches in the same scenario as in the first experiment. In this experiment, the performance of the simple configuration SAABF$(C, D, 1)$ is compared with SAABF(C, D, q), where $q = 4$. Note that, in SAABF$(C, D, 1)$, the projection vector $\boldsymbol{\psi}(i)$ is no longer updated; therefore, we use its initial value for the whole transmission. In the SAABF(C, D, q) scheme, when a sufficient number of branches are employed, both versions of the joint adaptive algorithm can achieve excellent performance with only one iteration for each input data. Increasing the number of branches, the performance approaches that of the full-rank MMSE filter. The SAABF$(C, D, 1)$ scheme can achieve a similar convergence speed to SAABF(C, D, q), but SAABF(C, D, q) has better steady-state performance.

Fig. 5(a) and (b) shows the uncoded BER performances of algorithms with different SNRs in an eight-user communication and with different numbers of users in an 18-dB scenario, respectively. Note that, if the number of training symbols is sufficient, the performance of the full-rank algorithms and the reduced-rank algorithms will approach the performance of the full-rank MMSE filter. However, for short data support, the reduced-rank algorithms outperform the full-rank algorithms due to their faster training. In these experiments, 500 symbols are transmitted for each tested environment in each independent simulation. SAABF$(C, 3, 3)$–RLS is employed with C in the range of 2–12. For different scenarios, the minimum number of branches that enables the proposed scheme to approach the linear MMSE performance is chosen. The novel SAABF scheme outperforms all other schemes in all the simulated scenarios.

The uncoded BER performance of the proposed RLS version of the SAABF scheme with the implementation of the branch number selection algorithm is shown in Fig. 6. The proposed algorithm instantaneously chooses the number of branches C_r using (36) from the range $C_{\min} = 6$ to $C_{\max} = 12$. As the threshold γ increases, the average required number of branches

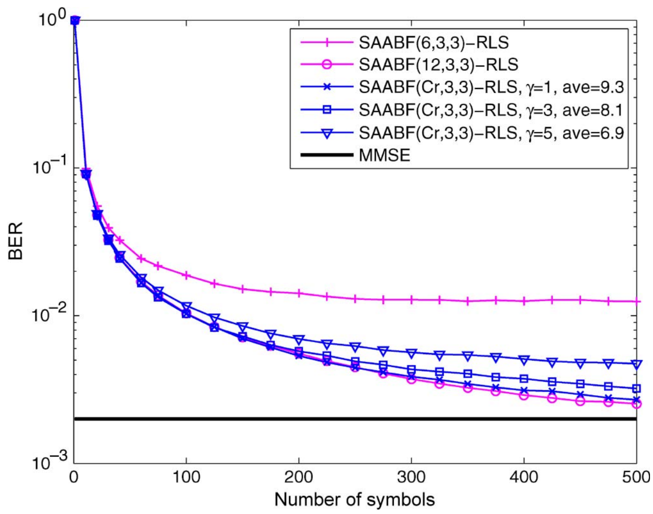

Fig. 6. BER performance of the SAABF scheme with branch number selection. The scenario of 20 dB and eight users is considered. The following parameters used: SAABF–RLS ($\lambda = 0.998, \delta = 10$). For the branch number selection algorithm, $C_{\min} = 6$, $C_{\max} = 12$, and threshold γ is given in decibels.

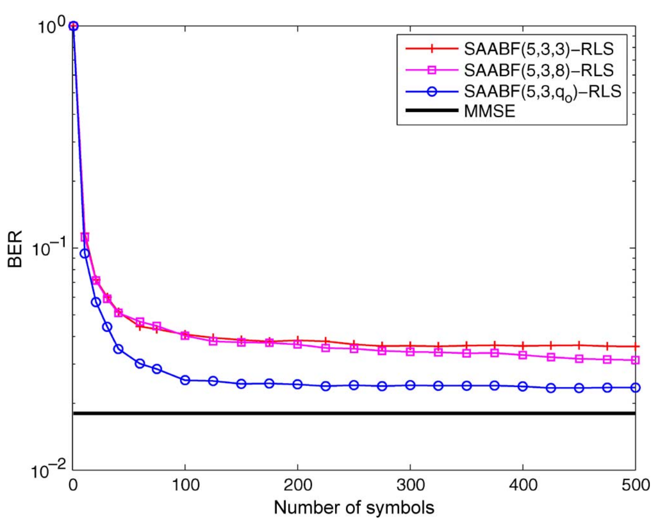

Fig. 7. BER performance of the SAABF scheme with rank adaptation. The scenario of 16 dB and eight users is considered. The following parameters are used: SAABF–LMS ($\mu_w = 0.15, \mu_\psi = 0.15$). For the rank adaptation algorithm, $D_{\min} = 3$, $D_{\max} = 8$, and $\lambda_D = 0.998$.

C_r and the overall complexity are reduced, but the performance degrades. For a 1-dB threshold, the performance of the branch number selection SAABF (C_r, D, q) is very close to the SAABF $(C_{\max}, D, q)$, whereas the average branch number C_r is only 9.3, which is considerably lower than $C_{\max} = 12$. Hence, with the branch number selection algorithm, we obtain a solution with lower complexity and similar performance to when the $C_{\max}$ is used.

Fig. 7 compares the BER performance of the SAABF–LMS using the rank-adaptation algorithm, with $C = 5$ and $q = 3$. The results using a fixed rank of 3 and 8 are also shown in Fig. 7 for comparison purposes and illustration of the sensitivity of the SAABF scheme to the rank D. The rank-adaptation solution selects the optimal rank $D_o(i)$ using (40) for each time instant from the range $D_{\min} = 3$ to $D_{\max} = 8$. The BER

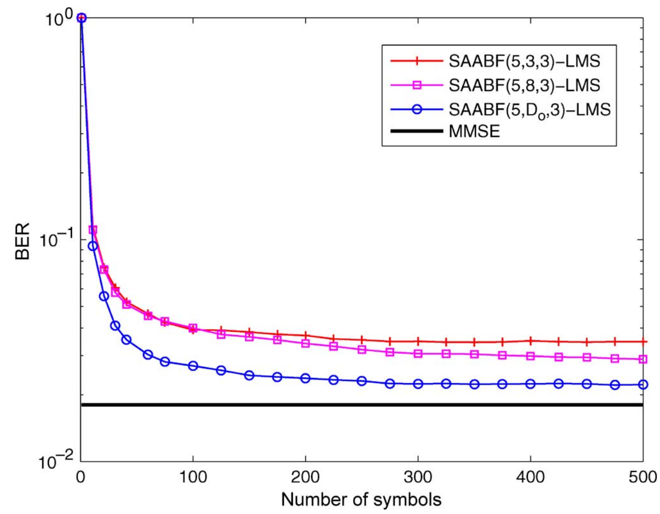

Fig. 8. BER performance of the SAABF scheme with adaptive short-function length. The scenario of 16 dB and eight users is considered. The following parameters are used: SAABF–RLS ($\lambda = 0.998, \delta = 10$). $q_{\min} = 3$, $q_{\max} = 8$, and $\lambda_q = 0.998$.

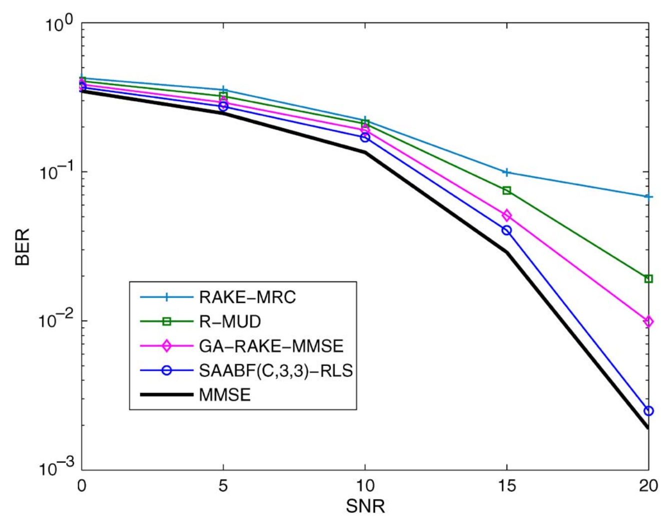

Fig. 9. BER performance against the SNR of different receiver structures in a system with eight users.

performance of the SAABF scheme with the rank-adaptation algorithm outperforms the fixed-rank SAABF scheme with $D_{\min}$ or $D_{\max}$. In this environment, $D = 8$ has better steady-state performance than $D = 3$, with both cases showing the same convergence speed.

Fig. 8 shows the BER behavior of the SAABF–RLS scheme equipped the adaptive algorithm, which determines the length of the inner function, with $C = 5$ and $D = 3$. The value of $q_o(i)$ for each time instant is determined by (44), with $q_{\min} = 3$ and $q_{\max} = 8$. A clear improvement is shown when the algorithm that selects q is used.

In the last experiment, we conduct a comparison of the proposed and existing linear receiver structures as shown in Fig. 9. In a system with eight users, we examine the performance of the traditional RAKE receiver with the maximal-ratio combining (MRC), reduced-order multiuser detection (RMUD) [20] with 15 taps, the generic algorithm (GA)-based RAKE–MMSE receiver [16] with 25 fingers and 20 iterations, and the proposed

SAABF-RLS scheme (the parameters are the same as in Fig. 5). For each independent run, 500 symbols are transmitted. The receiver with the SAABF–RLS scheme outperforms other receiver structures, particularly in high-SNR scenarios. Compared with the GA–RAKE–MMSE scheme, a 2-dB gain is obtained for a BER around 10^{-2}. The proposed SAABF scheme can efficiently suppress the interference without the knowledge of the channel, the noise variance, and the spreading codes.

VIII. Conclusion

In this paper, we have introduced a generic reduced-rank scheme for interference suppression, which jointly updates the projection vector and the reduced-rank filter. Then, by constraining the design of the projection vector in the generic scheme, we investigated a novel reduced-rank interference suppression scheme based on SAABF for DS-UWB systems. The LMS and RLS algorithms were developed for adaptive estimation of the parameters of the SAABF scheme. The uncoded BER performance of the novel receiver structure was then evaluated in various scenarios with severe MAI and ISI. With low complexity, the SAABF scheme outperforms other reduced-rank schemes and full-rank schemes. A discussion of the global optimality of the reduced-rank filter was presented, and the relationships between the SAABF and the generic schemes and the full-rank scheme were established.

Appendix A
Analysis of the Optimization Problem

In this Appendix, we discuss the optimization problem of the proposed SAABF scheme. In particular, we consider the convergence of the SAABF scheme through the computation of the Hessian matrix of the MSE cost function, which can be expressed as

$$\mathbf{J}_{\mathrm{MSE}}\left(\bar{\mathbf{w}}(i), \boldsymbol{\psi}(i)\right) = E\left[\left|d(i) - \bar{\mathbf{w}}^H(i)\mathbf{R}_{\mathrm{in}}(i)\mathbf{P}(i)\boldsymbol{\psi}(i)\right|^2\right]. \tag{45}$$

It is known that the convexity of the function can be verified if its Hessian matrix is positive semidefinite. However, the SAABF scheme includes a discrete optimization of the position matrix and a continuous adaptation of the reduced-rank filter and the projection vector. For the position matrix selection problem, we constrain the design of the position matrix to a small number of prestored matrices and switch between these matrices to choose the instantaneous suboptimum position matrix. This feature of the SAABF scheme suggests that the optimum values of the three variables of the MSE cost function may be difficult to obtain together and that there are multiple solutions of the cost function. The convexity is only verified when we consider one of the continuously adapted variables, whereas the others are kept fixed. First, let us compute the $D \times D$ Hessian matrix for (45) with respect to the reduced-rank filter as

$$\begin{aligned}\mathbf{H}_{J,\bar{\mathbf{w}}} &= \frac{\partial^2 \mathbf{J}_{\mathrm{MSE}}}{\partial \bar{\mathbf{w}}^H(i)\partial \bar{\mathbf{w}}(i)} \\ &= E\left[\mathbf{R}_{\mathrm{in}}(i)\mathbf{P}(i)\boldsymbol{\psi}(i)\boldsymbol{\psi}^H(i)\mathbf{P}^H(i)\mathbf{R}_{\mathrm{in}}^H(i)\right].\end{aligned} \tag{46}$$

For any D-dimensional nonzero vector $\mathbf{a}$, we discuss the following scale term:

$$\begin{aligned}\mathbf{a}^H\mathbf{H}_{J,\bar{\mathbf{w}}}\mathbf{a} &= E\left[\mathbf{a}^H\mathbf{R}_{\mathrm{in}}(i)\mathbf{P}(i)\boldsymbol{\psi}(i)\boldsymbol{\psi}^H(i)\mathbf{P}^H(i)\mathbf{R}_{\mathrm{in}}^H(i)\mathbf{a}\right] \\ &= E\left[\hat{a}(i)\hat{a}^*(i)\right] = E\left[\left|\hat{a}(i)\right|^2\right]\end{aligned} \tag{47}$$

where $\hat{a}(i) = \mathbf{a}^H\mathbf{R}_{\mathrm{in}}(i)\mathbf{P}(i)\boldsymbol{\psi}(i)$. Assume that the position matrix $\mathbf{P}(i)$ and the projection vector $\boldsymbol{\psi}(i)$ are fixed. The scale term in (47) is always nonnegative. Hence, the Hessian matrix $\mathbf{H}_{J,\bar{\mathbf{w}}}$ is a positive semidefinite matrix. Similarly, the $qD \times qD$ Hessian matrix for (45) with respect to the projection vector is

$$\mathbf{H}_{J,\boldsymbol{\psi}} = E\left[\mathbf{P}^H(i)\mathbf{R}_{\mathrm{in}}^H(i)\bar{\mathbf{w}}(i)\bar{\mathbf{w}}^H(i)\mathbf{R}_{\mathrm{in}}(i)\mathbf{P}(i)\right] \tag{48}$$

which is also a positive semidefinite matrix if the position matrix and the reduced-rank filter are fixed.

In the SAABF scheme, after determining the position matrix, the optimization problems for the projection vector and the reduced-rank filter can be consider a biconvex problem [43]: by fixing one of the parameters, the other design problem is convex. To test the convergence of the SAABF scheme in the case of jointly updating $\bar{\mathbf{w}}(i)$ and $\boldsymbol{\psi}(i)$, we checked the impact of different initializations, which confirmed that the performance of the algorithms are not subject to degradation due to the initialization. However, the proof of the global optimum and no local minima with the joint adaptive algorithm remains an interesting open problem to be researched.

Appendix B
Proof of the Equivalence of the Schemes

In this section, we prove that SAABF$(1, D, M)$ is equivalent to the generic scheme and that SAABF$(1, 1, M)$ is equivalent to the full-rank scheme.

First, we express the MMSE solutions for the SAABF scheme as

$$\bar{\mathbf{w}}_{\mathrm{MMSE}} = \bar{\mathbf{R}}^{-1}\bar{\mathbf{p}} \quad \boldsymbol{\psi}_{\mathrm{MMSE}} = \mathbf{R}_{\psi}^{-1}\mathbf{p}_{\psi} \tag{49}$$

where $\bar{\mathbf{R}}=E[\mathbf{R}_{\mathrm{in}}(i)\mathbf{P}(i)\boldsymbol{\psi}(i)\boldsymbol{\psi}^H(i)\mathbf{P}^H(i)\mathbf{R}_{\mathrm{in}}^H(i)]$, $\bar{\mathbf{p}}=E[d^*(i)\mathbf{R}_{\mathrm{in}}(i)\mathbf{P}(i)\boldsymbol{\psi}(i)]$, $\mathbf{R}_{\psi} = E[\mathbf{P}^H(i)\mathbf{R}_{\mathrm{in}}^H(i)\bar{\mathbf{w}}(i+1)\bar{\mathbf{w}}^H(i+1)\mathbf{R}_{\mathrm{in}}(i)\mathbf{P}(i)]$, and $\mathbf{p}_{\psi} = E[d(i)\mathbf{P}^H(i)\mathbf{R}_{\mathrm{in}}^H(i)\bar{\mathbf{w}}(i+1)]$. Revisit the expression of the basis functions in the SAABF scheme in (17). In SAABF$(1, D, M)$, the length of the inner function is equal to the length of the basis function, and the position matrix in (18) becomes an $MD \times MD$ identity matrix. Hence, the MMSE solutions of the generic scheme shown in (15) are the same as (49) when $\mathbf{P}(i)$ is an identity matrix, which means that SAABF$(1, D, M)$ is equivalent to the generic scheme.

Second, we prove that SAABF$(1, 1, M)$, or the generic scheme with $D = 1$, is equivalent to the full-rank scheme in the sense that it has the same MMSE that corresponds to the optimum solutions. Here, we expand the cost function of the generic scheme that is shown in (14) as

$$\begin{aligned}\mathbf{J}_{\mathrm{G}} = \sigma_d^2 &- E\left[d(i)\mathbf{t}^H(i)\mathbf{R}_{\mathrm{in}}^H(i)\bar{\mathbf{w}}(i)\right] \\ &- E\left[d^*(i)\bar{\mathbf{w}}^H(i)\mathbf{R}_{\mathrm{in}}(i)\mathbf{t}(i)\right] \\ &+ E\left[\bar{\mathbf{w}}^H(i)\mathbf{R}_{\mathrm{in}}(i)\mathbf{t}(i)\mathbf{t}^H(i)\mathbf{R}_{\mathrm{in}}^H(i)\bar{\mathbf{w}}(i)\right].\end{aligned} \tag{50}$$

In the case of $D = 1$, the input data matrix $\mathbf{R}_{\text{in}}(i) = \mathbf{r}^T(i)$ becomes a $1 \times M$ vector, and the reduced-rank filter has only one tap. Hence, the $\bar{w}_{\text{opt}}$ is a scalar term, and we can find the relationship between $\mathbf{t}_{\text{opt}}$ and $\bar{w}_{\text{opt}}$ as

$$\begin{aligned}\mathbf{t}_{\text{opt}} &= \left(E\left[\mathbf{r}^*(i)\mathbf{r}^T(i)\right]\bar{w}_{\text{opt}}\bar{w}^*_{\text{opt}}\right)^{-1} E\left[d(i)\mathbf{r}^*(i)\right]\bar{w}_{\text{opt}} \\ &= (\mathbf{R}^T)^{-1}\mathbf{p}^*\left(\bar{w}^*_{\text{opt}}\right)^{-1}.\end{aligned}$$

Hence, the second term in (50) becomes

$$\begin{aligned}&E\left[d(i)\mathbf{t}^H(i)\mathbf{R}^H_{\text{in}}(i)\bar{\mathbf{w}}(i)\right] \\ &= \mathbf{t}^H_{\text{opt}}E\left[d(i)\mathbf{r}^*(i)\right]\bar{w}_{\text{opt}} \\ &= \left[(\mathbf{R}^T)^{-1}\mathbf{p}^*\left(\bar{w}^*_{\text{opt}}\right)^{-1}\right]^H \mathbf{p}^*\bar{w}_{\text{opt}} = \mathbf{p}^T(\mathbf{R}^T)^{-1}\mathbf{p}^* \\ &= (\mathbf{p}^H\mathbf{R}^{-1}\mathbf{p})^T = \mathbf{p}^H\mathbf{R}^{-1}\mathbf{p}. \qquad (51)\end{aligned}$$

Note that, here, we use the fact that the transpose of the scale term $\mathbf{p}^H\mathbf{R}^{-1}\mathbf{p}$ is itself and $(\mathbf{R}^T)^H = \mathbf{R}^T$. Because the third scalar term in (50) is the conjugate of the second term, we have $E[d^*(i)\bar{\mathbf{w}}^H(i)\mathbf{R}_{\text{in}}(i)\mathbf{t}(i)] = (\mathbf{p}^H\mathbf{R}^{-1}\mathbf{p})^H = \mathbf{p}^H\mathbf{R}^{-1}\mathbf{p}$. The fourth term of (50) can be expanded as

$$\begin{aligned}&E\left[\bar{\mathbf{w}}^H(i)\mathbf{R}_{\text{in}}(i)\mathbf{t}(i)\mathbf{t}^H(i)\mathbf{R}^H_{\text{in}}(i)\bar{\mathbf{w}}(i)\right] \\ &= \bar{w}^*_{\text{opt}}E\left[\mathbf{r}^T(i)\mathbf{t}_{\text{opt}}\mathbf{t}^H_{\text{opt}}\mathbf{r}^*(i)\right]\bar{w}_{\text{opt}} \\ &= \bar{w}^*_{\text{opt}}E\left[\mathbf{t}^H_{\text{opt}}\mathbf{r}^*(i)\mathbf{r}^T(i)\mathbf{t}_{\text{opt}}\right]\bar{w}_{\text{opt}} \\ &= \mathbf{p}^T(\mathbf{R}^T)^{-1}\mathbf{p}^* = \mathbf{p}^H\mathbf{R}^{-1}\mathbf{p}. \qquad (52)\end{aligned}$$

Hence, the MMSE of the generic scheme for $D = 1$ is $\mathbf{J}_{\text{GMMSE}} = \sigma_d^2 - \mathbf{p}^H\mathbf{R}^{-1}\mathbf{p}$, which is the same as the MMSE obtained through the full-rank Wiener filter as shown in (9). This condition completes the proof. ■

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Sheng Li received the B.Eng. degree from Zhejiang University of Technology, Hangzhou, China, in 2006 and the M.Sc. (with distinction) degree in communications engineering and the Ph.D. degree from the University of York, York, U.K., in 2007 and 2010, respectively.

In November 2010, he started a postdoctoral research with the Ilmenau University of Technology, Ilmenau, Germany. His research interests include wireless communications and adaptive signal processing

Dr. Li received the K. M. Stott Prize for his excellence in scientific research in 2010.

Rodrigo C. de Lamare (M’05–SM’10) received the B.S. degree in electronics engineering from the Federal University of Rio de Janeiro, Rio de Janeiro, Brazil, in 1998 and the M.Sc. and Ph.D. degrees in electrical engineering from the Pontifical Catholic University of Rio de Janeiro, in 2001 and 2004, respectively.

Since January 2006, he has been with the Communications Research Group, Department of Electronics, University of York, York, U.K., where he is currently a Lecturer in communications engineering. His research interests include communications and signal processing, areas in which he has published about 180 papers in refereed journals and conference proceedings. He serves as an Associate Editor for the *EURASIP Journal on Wireless Communications and Networking*.

Dr. de Lamare served as the General Chair of the Seventh IEEE International Symposium on Wireless Communications Systems, held in York, U.K., in September 2010.

Rui Fa received the B.Eng. and M.Eng. degrees in electronic and electrical engineering from Nanjing University of Science and Technology, Nanjing, China, in 2000 and 2003, respectively, and the Ph.D. degree in electrical engineering from the University of Newcastle, Tyne, U.K., in 2007.

From January 2008 to February 2010, he was with the University of York, York, U.K., where he was a Postdoctoral Research Associate. From March 2010 to October 2010, he was a Research Associate with the University of Leeds, Leeds, U.K. Since November 2010, he has been with the University of Liverpool, Liverpool, U.K. His research interests include radar signal processing, signal processing and information theory for wireless communications, and data and signal processing for biotechnology.