Estimation and Equalization of Doubly Selective Channels Using Known Symbol Padding

Olivier Rousseaux, Geert Leus, and Marc Moonen

***Abstract*—This paper considers the situation where users that experience high-mobility transmit data over frequency-selective channels, resulting in a doubly selective channel model (i.e., time- and frequency-selective channels) and this within the framework of Known Symbol Padding (KSP) transmission. KSP is a recently proposed block transmission technique where short sequences of known symbols acting as guard bands are inserted between successive blocks of data symbols. This paper proposes three novel *channel estimation methods* that allow for an accurate estimation of the time-varying transmission channel solely relying on the knowledge of the redundant symbols introduced by the KSP transmission scheme. The first method is a direct adaptive one while the others rely on a recently proposed model, the Basis Expansion Model (BEM), where the doubly selective channel is approximated with high accuracy using a limited number of complex exponentials. An important characteristic of the proposed methods is that they exploit all the received symbols that contain contributions from the training sequences and blindly filter out the contribution of the unknown surrounding data symbols. Besides these channel identification methods, the classical *KSP equalizers* are adapted to the context of doubly selective channels, which allows evaluation of the bit-error-rate (BER) performance of a KSP transmission system relying on the proposed channel estimation methods in the context of doubly selective channels. Simulation results show that KSP transmission is indeed a suitable transmission technique toward the delivery of high data rates to users experiencing a high mobility, when adapted KSP equalizers are used in combination with the proposed channel estimation methods.**

***Index Terms*—Basis Expansion Model (BEM), channel estimation, channel equalization, doubly selective channels, Known Symbol Padding (KSP).**

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I. Introduction

Wireless networks of the next generation will aim at delivering high data rates to users experiencing possibly high mobility. The delivery of the required data rates will rely on broad-band communication channels. When the bandwidth gets large, the sampling period can become smaller than the delay spread of the channel, especially in multipath scenarios, which gives rise to frequency-selective channels. High user mobility causes the transmission channel to change rapidly in time, which is referred to as the time selectivity of the channel. *Doubly selective channels* as encountered in high mobility broad-band communications then exhibit both time and frequency selectivity.

Block transmission techniques (see, e.g., [1]–[4]) offer efficient and computationally affordable schemes that are able to cope with the frequency selectivity of stationary transmission channels. Amongst these block transmission techniques, *Known Symbol Padding (KSP) transmission*, where short sequences of known symbols acting as guard bands are inserted between blocks of data symbols, has attracted significant attention (see, e.g., [2], [5], [6]) for it guarantees channel-irrespective symbol recovery (i.e., perfect symbol recovery in the absence of noise irrespective of the channel), and equivalently, it fully exploits the delay diversity of the channel, as opposed to other block transmission techniques such as orthogonal frequency-division multiplexing (OFDM) (see [7]). Moreover, the padded sequences can be exploited to accurately estimate the transmission channel (see, e.g., [5] or [8]–[10].)

When the channel changes in time, it has been proved in [11] and [12] that the optimal placement of the training symbols in order to track the channel variations consists of equispaced sequences of constant length. This placement of training symbols matches the KSP transmission scheme which therefore seems to be a natural candidate for data transmission over doubly selective channels. In this paper, we briefly describe the KSP transmission scheme in the context of doubly selective channels and present *KSP equalizers* suited to equalize such channels. Furthermore, we investigate how the knowledge of the padded sequences can be optimally exploited in order to accurately estimate doubly selective transmission channels. We propose three new methods toward that goal.

The *first channel estimation technique* is directly inspired by [9] and [10], where we have presented a Gaussian maximum-likelihood (ML) channel estimation technique in the context of KSP transmission over stationary frequency-selective channels. We propose here an adaptive version [exponentially weighted recursive least-squares (RLS) scheme] of that method, which is able to track the time variations of the channel.

The two other techniques rely on a recently proposed approach for modeling doubly selective channels, namely the Basis Expansion Model (BEM) [13]–[15]. This new model has attracted a lot of attention recently for it allows for an accurate representation of doubly selective channels with a limited number of complex exponentials and allows for cheap and efficient channel equalization schemes [14], [16], [17]. The problem of identifying the BEM parameters of the transmission channel through training has already been discussed in [12] and [18]. These methods only exploit the channel output samples that solely contain contributions from the training symbols, neglecting the channel output samples containing mixed contributions from the training symbols and the unknown surrounding data symbols. It has been proved in [12] that, when these estimation methods are used, the optimal training sequences for a fixed power of the training sequences consist of $2Q+1$ equispaced bursts of $2L+1$ pilot symbols with a single nonzero element placed in the middle ($2Q+1$ represents the number of complex exponentials in the BEM and $L+1$ represents the channel length). However, it is not clear whether or not these training sequences are optimal if all the channel output samples containing contributions from the training symbols are considered for channel estimation. Note as well that when the channel order increases, inserting training sequences of length $2L+1$ significantly reduces the effective throughput if these sequences need to be repeated on a regular basis. Moreover, concentrating the whole training energy in one single symbol results in large peaks in the transmitted signal, which is an important issue for the power amplifiers of the radio-frequency (RF) stage. It might therefore be interesting to develop channel identification methods that are able to optimally exploit training sequences that differ from the optimal ones. Another problem of existing methods is that they assume that the period of the BEM is equal to the interval over which the channel is identified, which generally leads to large modeling errors at the edges of the interval. In this paper, we develop a new BEM channel estimation technique that also takes into account the channel output samples containing contributions from both the training symbols and the unknown surrounding data symbols. The proposed methods are able to cope with arbitrary periods for the BEM model, leading to reduced modeling errors. Moreover, they work for any structure and composition of the available training sequences and show better performance than the existing BEM methods. The *first BEM method* relies on the channel estimates produced by the proposed adaptive method and finds the set of BEM coefficients that fit best [in a least-squares (LS) sense] the adaptive solution. The *second BEM method* directly identifies the BEM coefficients and outperforms the other methods.

Notation: We use upper (lower) case bold face letters to denote matrices (column vectors). $\mathbf{I}_N$ is the identity matrix of size $N \times N$ and $\mathbf{0}_{M\times N}$ is the all-zero matrix of size $M\times N$; the subscripts are omitted when the dimension of the matrices is clear from the context. The operator $(\cdot)^*$ denotes the complex conjugate, $(\cdot)^T$ the transpose of a matrix, $(\cdot)^H$ its complex conjugate transpose, $(\cdot)^{1/2}$ represents its square root, and $\mathrm{tr}(\cdot)$ its trace. Finally, $\mathrm{diag}(\mathbf{v})$ is a diagonal matrix with the elements of the vector $\mathbf{v}$ placed on its main diagonal, $\mathbf{A}(i,j)$ is the jth element of the ith row of the matrix $\mathbf{A}$, and $\mathbf{A}(i:j,:)$ is the matrix constructed with the rows i to j of the matrix $\mathbf{A}$.

II. Models for Time-Varying Channels

In this section, we focus on the mathematical description of data communication over doubly selective channels. We present a general data model for data communications over such channels and, relying on the physical description of the transmission channel, we then show how realistic channels can be simulated within the presented transmission model. Subsequently, we introduce the BEM that is used to model such doubly selective channels with a limited number of parameters.

A. Physical Channel Model

Let $\mathbf{x} = [x[1],\ldots,x[N]]^T$ be the sequence of transmitted data symbols, where N is the length of the burst. The relative motion between the transmitter and the receiver causes the communication channel to change during the transmission of that burst. Several models have been developed to model the evolution of the time-varying channel. A general model for the description of such channels is introduced in [19], which we will also use in this paper. Sampling the output of the receive antenna at the symbol rate, this model describes the sequence of received samples $\mathbf{y} = [y[1],\ldots,y[N+L]]$ as

$$y[n] = \sum_{\nu=0}^{L} h[n;\nu]x[n-\nu] + \eta[n] \tag{1}$$

where $h[n;\nu]$ accounts for the effects of the transmission channel and the transmit and receive filters, and $\eta[n]$ is the additive noise, which we will consider to be white and Gaussian distributed. More specifically, the channel coefficients are described as

$$h[n;\nu] = \sum_{c=1}^{C} \psi(\nu T_s - \tau_c) \sum_{r=1}^{R} G_{c,r} e^{j2\pi f_{c,r} n T_s} \tag{2}$$

where T_s is the symbol period and $\psi(t)$ is the total impulse response of the transmit and receive filters, τ_c is the delay of the cth cluster, $G_{c,r}$ and $f_{c,r}$ are, respectively, the complex gain and the frequency offset of the rth ray of the cth cluster. The frequency offset is caused by the relative motion between the transmitter, the receiver, and the scatterer and is the source of the time variation of the channel coefficients.

The physical channel model presented here, though very handy for simulating realistic time-varying transmission channels, still contains many parameters that makes it impractical to use for channel estimation/equalization applications. In the rest of the text, we define the $(N+L)\times(L+1)$ matrix $\mathbf{H}$ as $\mathbf{H}(i,j) = h[i;j-1]$, where the channel coefficients $h[i;j-1]$ are derived from (2) to characterize the evolution of the channel during the transmission of $\mathbf{x}$.

B. Basis Expansion Model

Exploiting the limited Doppler spread of physical channels, the BEM, which has been proposed recently, models each tap of the time-varying channel with a limited number of complex exponentials. This approach allows us to represent the channel with a reduced number of parameters, namely the multiplicative coefficients of the complex exponentials, referred to as the BEM parameters. The true channel $h[n;\nu]$ is approximated over the burst interval by the BEM as

$$h[n;\nu] \approx \sum_{l=1}^{L} \delta[\nu - l] \sum_{q=-Q}^{Q} h_{q,l} e^{j2\pi qn/N_{\text{mod}}}. \quad (3)$$

Each channel tap is modeled as the sum of $2Q+1$ complex exponentials, and the whole channel is described with a limited number of $(2Q+1)(L+1)$ parameters, namely the $h_{q,l}$ coefficients. The parameters Q and N_{mod} should be selected carefully in order to allow for an accurate approximation of the true channel over the burst interval. The Doppler spread of the channel's BEM (which is equal to its highest frequency component) is equal to $Q/(N_{\text{mod}}T_s)$. Hence, Q and N_{mod} should be chosen such that the Doppler spread of the BEM is approximately equal to the Doppler spread of the true channel. Furthermore, the BEM is periodic with a period N_{mod}. Therefore, as the true channel is generally not periodic, N_{mod} should at least be as large as N; the match of the BEM to the true channel over the burst interval gets tighter as N_{mod} increases. However, increasing N_{mod} forces us to increase Q in order to fulfill the Doppler spread requirement. A good empirical rule for most practical cases is to choose $N_{\text{mod}} = 3N$ and then choose Q according to the Doppler spread rule: $Q = \lceil f_{\max} N_{\text{mod}} T_s \rceil$, which generally yields a very tight match of the BEM with a limited number of parameters. When the channel varies slowly and $1/(3NT_s) \gg f_{\max}$, the above procedure yields $Q=1$, but the Doppler Spread of the BEM will be significantly larger than the true Doppler spread, yielding a poor match of the BEM. In this case, increasing N_{mod} in order to make the true Doppler spread equal to the BEM Doppler spread largely improves the accuracy of the BEM: $N_{\text{mod}} = \lceil 1/(T_s f_{\max}) \rceil$. Existing methods [12], [18] do not follow this rule and simply take $N_{\text{mod}} = N$ as the period of the BEM, resulting in large modeling errors at the edges of the considered interval.

Defining the $(2Q+1) \times (L+1)$ matrix $\mathbf{H}_{\text{BEM}}$ of the BEM coefficients as $\mathbf{H}_{\text{BEM}}(i,j) = h_{i-(Q+1),j-1}$ and the $(N+L) \times (2Q+1)$ matrix $\mathbf{C}$ of complex exponentials as $\mathbf{C}(m,n) = e^{j2\pi(n-(Q+1))m/N_{\text{mod}}}$, the channel matrix $\mathbf{H}$ is modeled as

$$\mathbf{H} \approx \mathbf{C}\mathbf{H}_{\text{BEM}}. \quad (4)$$

The optimal (in the LS sense) matrix of BEM coefficients is obtained as

$$\mathbf{H}_{\text{BEM}} = \mathbf{C}^{\dagger}\mathbf{H}. \quad (5)$$

This optimal set of BEM coefficients is simply called the set of BEM parameters of the channel in the rest of the text. When the design parameters Q and N_{mod} are chosen following the procedure described above, the difference between the true channel and its BEM representation is negligible (experimental results show that the relative modeling error varies between 10^{-5} and 10^{-10} for the experimental setups considered in this paper). Hence, the modeling error of the BEM can be neglected and the channel is equivalently described by its $(2Q+1)(L+1)$ BEM parameters $\mathbf{H}_{\text{BEM}}$ or by the $(N+L)(L+1)$ parameters of the channel matrix $\mathbf{H}$.

Using the BEM, the input–output relationship (1) of the transmission channel over the burst interval can be written as

$$y[n] = \sum_{l=0}^{L} \sum_{q=-Q}^{Q} h_{q,l} e^{j2\pi qn/N_{\text{mod}}} x[n-l] + \eta[n]. \quad (6)$$

III. Known Symbol Padding

In this section, we introduce the data model of a KSP transmission scheme when doubly selective channels are considered. We then show how classical KSP equalizers can be adapted to cope with such doubly selective channels.

A. Data Model

In KSP transmission, the transmitted data symbols are organized in blocks of length N_s and a sequence of length N_t of known symbols is appended at the end of every transmitted block. When the length of the padded sequence is larger than the channel order ($N_t \geqslant L$), there is no interblock interference [(IBI) interference between two successive blocks of data symbols]. In this section, we adapt the classical data model for KSP transmission over frequency-selective channels (see, e.g., [1], [2], [6]) to the context of doubly selective channels.

Denoting the block index with $k = 1 \ldots K$, a block $\mathbf{s}_k (N_s \times 1)$ of data symbols is defined as a column vector of size N_s:

$$\mathbf{s}_k = [s_k[1], \ldots, s_k[N_s]]^T. \quad (7)$$

A block $\mathbf{t}_k (N_t \times 1)$ of training symbols is defined similarly, as follows:

$$\mathbf{t}_k = [t_k[1], \ldots, t_k[N_t]]^T. \quad (8)$$

The kth block of transmitted symbols, $\mathbf{x}_k$ of length $N_x = N_s + N_t$, is then defined as

$$\mathbf{x}_k = \left[\mathbf{s}_k^T, \mathbf{t}_k^T\right]^T. \quad (9)$$

The transmitted sequence is the concatenation of all these blocks: $\mathbf{x} = [\mathbf{x}_1^T, \mathbf{x}_2^T, \ldots, \mathbf{x}_K^T]^T$ and the total length of the transmitted burst is $N = KN_x$. The received sequence $\mathbf{y}$, which is derived from (1), can be organized in blocks $\mathbf{y}_k (N_x \times 1)$ of received symbols corresponding to the blocks of transmitted symbols:

$$\mathbf{y}_k = [y[(k-1)N_x + 1], \ldots, y[kN_x]]^T. \quad (10)$$

Using these definitions and assuming $N_t \geqslant L$, the transmission scheme can be expressed on a block level: the kth received block contains contributions from the kth transmitted block of data symbols $\mathbf{s}_k$, the known sequences $\mathbf{t}_k$ and $\mathbf{t}_{k-1}$ plus some noise

$$\mathbf{y}_k = \mathbf{H}_{\text{KSP},k}\mathbf{s}_k + \mathbf{H}_{0,k}\mathbf{t}_k + \mathbf{H}_{1,k}\mathbf{t}_{k-1} + \boldsymbol{\eta}_k \quad (11)$$

where $\boldsymbol{\eta}_k$ is the additive white Gaussian noise (AWGN) vector and, using $n_{k,j}$ as a shorthand notation for the time index of the jth element of the kth received block $\mathbf{y}_k$, i.e., $n_{k,j} = (k-1)N_x + j$, we can write

$$\mathbf{H}_{\mathrm{KSP},k} = \begin{bmatrix} h[n_{k,1};0] & 0 & \cdots & 0 \\ \vdots & \ddots & & \vdots \\ h[n_{k,L};L] & \ddots & \ddots & 0 \\ 0 & \ddots & \ddots & h[n_{k,N_x-N_t};0] \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & h[n_{k,N_x-N_t+L};L] \\ \hline & \mathbf{0}_{(N_t-L)\times N_s} & & \end{bmatrix} \tag{12}$$

$$\mathbf{H}_{1,k} = \begin{bmatrix} 0 & \cdots & 0 & h[n_{k,1};L] & \cdots & h[n_{k,1};1] \\ \vdots & & & \ddots & \ddots & \vdots \\ 0 & \cdots & & \cdots & 0 & h[n_{k,L};L] \\ \vdots & & & & \vdots & 0 \\ \vdots & & & & \vdots & \vdots \\ 0 & \cdots & & \cdots & 0 & 0 \end{bmatrix} \tag{13}$$

and

$$\mathbf{H}_{0,k} = \left[\mathbf{H}_{0,k}^{L} \middle| \mathbf{H}_{0,k}^{R}\right] \tag{14}$$

with

$$\mathbf{H}_{0,k}^{L} = \begin{bmatrix} 0 & \cdots & \cdots & 0 \\ \vdots & & & \vdots \\ 0 & & & \vdots \\ h[n_{k,N_x-N_t+1};0] & \ddots & & \vdots \\ \vdots & \ddots & \ddots & \vdots \\ h[n_{k,N_x-N_t+L+1};L] & & \ddots & 0 \\ 0 & \ddots & & h[n_{k,N_x-L};0] \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & h[n_{N_x};L] \end{bmatrix} \tag{15}$$

and

$$\mathbf{H}_{0,k}^{R} = \begin{bmatrix} 0 & \cdots & 0 \\ \vdots & & \vdots \\ 0 & & \vdots \\ h[n_{N_x-L+1};0] & \ddots & \vdots \\ \vdots & \ddots & 0 \\ h[n_{N_x};L-1] & \cdots & h[n_{N_x};0] \end{bmatrix}. \tag{16}$$

Note that $\mathbf{H}_{0,k}^{L}$ consists of $N_t - L$ columns and only exists when $N_t > L$.

B. KSP Equalizers

Based on the above data model, the conventional KSP equalizers can be adapted to the doubly selective channel situation. We focus on minimum mean-squared error (MMSE) equalization and assume that the receiver has perfect channel knowledge. Note that, since the channel is time varying, the equalizers will differ from block to block.

1) Optimal KSP Equalizers: The contribution of the known padded sequences is subtracted from the received blocks before the equalization step, as follows:

$$\tilde{\mathbf{y}}_k = \mathbf{y}_k - \mathbf{H}_{0,k}\mathbf{t}_k - \mathbf{H}_{1,k}\mathbf{t}_{k-1}. \tag{17}$$

The data model then reduces to $\tilde{\mathbf{y}}_k = \mathbf{H}_{\mathrm{KSP},k}\mathbf{s}_k + \boldsymbol{\eta}_k$ and the MMSE equalizer is expressed as

$$\mathbf{W}_k = \left(\mathbf{H}_{\mathrm{KSP},k}^{H}\mathbf{H}_{\mathrm{KSP},k} + \sigma^2\mathbf{I}_{N_x}\right)^{-1}\mathbf{H}_{\mathrm{KSP},k}^{H} \tag{18}$$

where σ^2 is the noise variance. The kth block of data symbols is then estimated as $\hat{\mathbf{s}}_k = \mathbf{W}_k\tilde{\mathbf{y}}_k$.

This MMSE equalizer is optimal in the mean-squared error (MSE) sense. In addition, when the channel can be considered constant over one block, channel-irrespective symbol recovery is guaranteed as $\mathbf{H}_{\mathrm{KSP},k}$ then always has full column rank, and equivalently, the delay diversity of the channel is fully exploited [7] (as long as $\nexists n : h[n,\nu] = 0\ \forall\nu$). Its drawback, however, is its computational complexity. The equalization step requires $\mathcal{O}(N_x)$ operations per estimated data symbol and a specific equalizer must be computed for each received block, which requires the inversion of an $N_x \times N_x$ matrix.

2) Low-Complexity Frequency-Domain KSP Equalizers: When the coherence time of the channel is larger than the duration of a KSP block ($1/f_{\max} \gg N_xT_s$), the channel coefficients can be considered as constant during the transmission of such a KSP block: $\|h[n;\nu]-h[n';\nu]\| \ll \|h[n;\nu]\|, \forall|n-n'| < N_x$. In this case, if constant training sequences are used ($\mathbf{t}_k = \mathbf{t}, \forall k$), the data model can be expressed with a circulant channel matrix

$$\mathbf{y}_k = \left[\mathbf{H}_{\mathrm{KSP},k} \,|\, \mathbf{H}_{0,k} + \mathbf{H}_{1,k}\right]\begin{bmatrix} s_k \\ \mathbf{t} \end{bmatrix} = \mathbf{H}_{\mathrm{circ},k}\mathbf{x}_k \tag{19}$$

where $\mathbf{H}_{\mathrm{circ},k}$ is an $N_x \times N_x$ circulant matrix with $[h[kN_x;0],\ldots,h[kN_x;L],0,\ldots,0]^T$ on the first column and $[h[kN_x;0],0,\ldots,0,h[kN_x;L],\ldots,h[kN_x;1]]$ on the first row. Such a circulant matrix is diagonalized by means of discrete Fourier transform (DFT) and inverse DFT (IDFT) operations: $\mathbf{H}_{\mathrm{circ},k} = \mathcal{I}_{N_x}\mathbf{H}_{\mathrm{diag},k}\mathcal{F}_{N_x}$, where $\mathcal{I}_{N_x}$ is the IDFT matrix of size N_x and $\mathcal{F}_{N_x}$ is the DFT matrix of same size. The matrix $\mathbf{H}_{\mathrm{diag},k}$ is diagonal and contains the DFT of the channel impulse response for the kth block on the main diagonal

$$\mathbf{H}_{\mathrm{diag},k} = \mathrm{diag}(\mathcal{F}_{N_x}[h[kN_x;0],\ldots,h[kN_x;L],0,\ldots,0]^T).$$

The data symbols are thus actually transmitted over orthogonal virtual carriers. The orthogonality between these carriers is maintained as long as the training sequences are constant and the channel coefficients do not change significantly within one block of symbols. In this case, the frequency-domain equalizer (FD) for KSP transmission (FD KSP equalizer) can be expressed as

$$\mathbf{W}_k = \mathcal{I}_{N_x}\left(\mathbf{H}_{\mathrm{diag},k}\mathbf{H}_{\mathrm{diag},k} + \sigma^2\mathbf{I}_{N_x}\right)^{-1} \times\mathbf{H}_{diag,k}^{H}\mathcal{F}_{N_x}(1:N_s,:). \tag{20}$$

This equalizer is equivalent to the scalar frequency-domain equalizer used in OFDM systems, followed by an IDFT. The main advantage of this equalizer is its low computational complexity. The DFT and IDFT operations can respectively be implemented as fast Fourier transform (FFT) and inverse FFT (IFFT) operations, thereby requiring only $\mathcal{O}(\log(N_x))$ operations per equalized data symbol and the computation of the equalizers requires only $\mathcal{O}(N_x \log(N_x))$ operations in total.

However, even if the channel can be considered constant over a block, this equalizer is suboptimal as it does not guarantee channel-irrespective symbol recovery (see [1]), and equivalently, it does not fully exploit the delay diversity of the channel (see [7]). Moreover, although one can expect the hypothesis of constant channel coefficients to hold in moderate velocity scenarios, the channel coefficients can vary significantly within a KSP block as the speed increases. In that case, the channel matrix is not circulant anymore and the orthogonality between the carriers is lost. This causes intercarrier interference (ICI) and significantly reduces the performance of the proposed equalizer. Note that the more complex optimal equalizers do not suffer from increased mobility as they take the channel variations inside a KSP block into account.

IV. Estimation of Doubly Selective Channels for KSP

In this section, we analyze how doubly selective channels can be estimated relying on the known symbols inserted by the KSP transmission scheme. As opposed to most channel estimation methods that only rely on the channel output samples containing contributions only from the known symbols (and thus do not consider the channel output samples containing mixed contributions from the training symbols and the unknown surrounding data symbols), we aim at estimating the channel relying on all the channel output samples containing contributions from the known symbols.

The $(N_t + L) \times 1$ vector of received symbols containing contributions from $\mathbf{t}_k$ is defined as

$$\mathbf{u}_k = [y[kN_x - N_t + 1], \ldots, y[kN_x + L]]^T. \tag{21}$$

We propose below two new methods that aim at estimating the doubly selective transmission channel relying on the set of vectors $\mathbf{u}_k$. Note that these methods are presented in the framework of KSP transmission considered in this paper, but it is straightforward to adapt them to other training schemes.

A. Adaptive Method

In [10], we presented a Gaussian ML method for channel identification that can be used in the context of KSP transmission. This method was originally developed for stationary channels. We propose here an adaptive version that is suited for time-varying frequency-selective channels.

1) Data Model: Assuming that the coherence time of the channel is significantly larger than $N_t + L$, the channel can be considered constant during the reception of $\mathbf{u}_k$. We define the vector $\mathbf{h}_k$ of the approximately constant channel coefficients during this time interval as

$$\mathbf{h}_k \triangleq [h[kN_x; 0], \ldots, h[kN_x, L]]^T \triangleq [h_k[0], \ldots, h_k[L]].$$

Relying on this definition, the received vector $\mathbf{u}_k$ can be expressed as

$$\mathbf{u}_k = \mathbf{T}_k \mathbf{h}_k + \boldsymbol{\epsilon}_k. \tag{22}$$

- The first term $\mathbf{T}_k \mathbf{h}_k$ is a deterministic term where $\mathbf{T}_k$ is an $(n_t + L) \times (L+1)$ Toeplitz matrix with $[\mathbf{t}_k^T, 0, \ldots, 0]^T$ as its first column and $[t_k[1]], 0, \ldots, 0]$ as its first row.
- The second term $\boldsymbol{\epsilon}_k$ is stochastic and represents the contributions from the unknown surrounding data symbols and the AWGN

$$\boldsymbol{\epsilon}_k = \underbrace{\left[\mathbf{H}_{s,k}^L \middle| \mathbf{H}_{s,k}^R\right]}_{\mathbf{H}_{s,k}} \mathbf{s}'_k + \boldsymbol{\eta}_k \tag{23}$$

where $\boldsymbol{\eta}_k$ is the AWGN vector and $\mathbf{s}'_k = [s_k - 1[n_s - L + 1], \ldots, s_{k-1}[n_s], s_k[1], \ldots, s_k[L]]^T$ is the vector of the unknown data symbols contributing to $\mathbf{u}_k$ (assuming $n_s \geq L$). $\mathbf{H}_{s,k}$ is an $(n_t + L) \times 2L$ matrix gathering the channel coefficients that multiply these data symbols. It is the concatenation of two matrices

$$\mathbf{H}_{s,k}^L = \left[\begin{array}{ccc} h_k[L] & \cdots & h_k[1] \\ & \ddots & \vdots \\ \mathbf{0} & & h_k[L] \\ \hline & \mathbf{0}_{(N_t \times L)} & \end{array}\right]$$
$$\mathbf{H}_{s,k}^R = \left[\begin{array}{ccc} & \mathbf{0}_{(N_t \times L)} & \\ \hline h_k[0] & & \mathbf{0} \\ \vdots & \ddots & \\ h_k[L-1] & \cdots & h_k[0] \end{array}\right]. \tag{24}$$

Assuming that the noise and the data are white and zero-mean with variance σ^2 for the noise samples and λ^2 for the data symbols (i.e., $\mathrm{E}\{\mathbf{s}_k\} = \mathbf{0}$ and $\mathrm{E}\{\boldsymbol{\eta}_k\} = \mathbf{0}, \mathrm{E}\{\mathbf{s}_k \mathbf{s}_l^H\} = \delta_{kl}\lambda^2\mathbf{I}, \mathrm{E}\{\boldsymbol{\eta}_k \boldsymbol{\eta}_l^H\} = \delta_{kl}\sigma^2\mathbf{I}, \forall k, l$), it is straightforward to derive the first- and second-order statistics of $\boldsymbol{\epsilon}_k$ (assuming also $n_s \geq 2L$)

$$\begin{aligned} &\mathbf{E}\{\boldsymbol{\epsilon}_k\} = \mathbf{0} \\ &\mathbf{E}\left\{\boldsymbol{\epsilon}_k \boldsymbol{\epsilon}_l^H\right\} = \delta_{k,l}\mathbf{Q}_k, \quad \forall k, l \\ &\mathbf{Q}_k = \lambda^2 \mathbf{H}_{s,k} \mathbf{H}_{s,k}^H + \sigma^2 \mathbf{I}. \end{aligned} \tag{25}$$

2) Proposed Algorithm: In [10], we show that when the channel is constant ($\mathbf{h}_k = \mathbf{h}$ and $\mathbf{Q}_k = \mathbf{Q}, \forall k$), the Gaussian ML channel estimate of $\mathbf{h}$ is obtained as

$$\hat{\mathbf{h}} = \left(\sum_{k=1}^{K} \mathbf{T}_k^H \hat{\mathbf{Q}}^{-1} \mathbf{T}_k\right)^{-1} \sum_{k=1}^{K} \mathbf{T}_k^H \hat{\mathbf{Q}}^{-1} \mathbf{u}_k \tag{26}$$

where $\hat{\mathbf{Q}}$ is an estimate of the noise correlation matrix $\mathbf{Q}$ based on the received data.

We propose here an exponentially weighted RLS adaptation of this technique to track the time variations of the channel between successive blocks

$$\hat{\mathbf{h}}_k = \left(\sum_{n=1}^{k} \lambda^{2(k-n)} \mathbf{T}_n^H \hat{\mathbf{Q}}_n^{-1} \mathbf{T}_n\right)^{-1} \sum_{n=1}^{k} \lambda^{2(k-n)} \mathbf{T}_n^H \hat{\mathbf{Q}}_n^{-1} \mathbf{u}_n \tag{27}$$

where λ is the forgetting factor whose value is adapted depending on the variation speed of the channel and the noise conditions. Adopting the notations $\mathbf{S}_1(k)$ and $\mathbf{S}_2(k)$ for the summations present in (27), the following equalities are readily derived:

$$\begin{aligned}\mathbf{S}_1(k+1) &= \lambda^2\mathbf{S}_1(k) + \mathbf{T}_{k+1}^H\hat{\mathbf{Q}}_{k+1}^{-1}\mathbf{T}_{k+1}\\ \mathbf{S}_2(k+1) &= \lambda^2\mathbf{S}_2(k) + \mathbf{T}_{k+1}^H\hat{\mathbf{Q}}_{k+1}^{-1}\mathbf{u}_k\\ \hat{\mathbf{h}}_{k+1} &= (\mathbf{S}_1(k+1))^{-1}\mathbf{S}_2(k+1).\end{aligned} \tag{28}$$

A recursive expression for the channel estimate is then obtained as

$$\hat{\mathbf{h}}_{k+1} = \hat{\mathbf{h}}_k + (\mathbf{S}_1(k+1))^{-1}\,\mathbf{T}_{k+1}^H\hat{\mathbf{Q}}_{k+1}^{-1}(\mathbf{u}_{k+1} - \mathbf{T}_{k+1}\hat{\mathbf{h}}_k) \tag{29}$$

where the explicit computation of $\mathbf{S}_2(k+1)$ is not needed anymore, and the inverse of $\mathbf{S}_1(k+1)$ can be recursively computed using the matrix inversion lemma. Note that an estimate of the noise correlation matrix $\hat{\mathbf{Q}}_{k+1}$ is needed for this method to work. In the stationary channel case [10], an optimal estimate of $\mathbf{Q}$ yielding the Gaussian ML channel estimate was directly derived from the received symbols. This approach is not possible here and we simply propose to derive $\hat{\mathbf{Q}}_{k+1}$ from its definition, assuming that $\hat{\mathbf{h}}_k$ is an acceptable approximation of $\mathbf{h}_{k+1}$. We thus use $\hat{\mathbf{h}}_k$ to construct the matrices $\hat{\mathbf{H}}_{s,k+1}$ and $\hat{\mathbf{Q}}_{k+1}$ from (24) and (25), which we then use in (29).

This method has the advantage of a low computational complexity and a low latency as the channel is estimated "on the fly," allowing us to directly equalize the received samples without keeping them in a receive buffer. Its performance is very sensitive to the value of the parameter λ. Low values of λ allow to track fast channel variations but make the channel estimates more noisy. Higher values of λ allow to filter out the noise, but fast channel variations are harder to follow and the channel estimate becomes biased. The optimal choice of λ results from a tradeoff between channel tracking and noise filtering. The method can be initialized with $\hat{\mathbf{h}}_0 = \mathbf{0}$ and $\hat{\mathbf{Q}}_1 = \mathbf{I}$ but will yield more reliable estimates for the first KSP blocks if a reliable initial channel estimate $\hat{\mathbf{h}}_0$ resulting from a long training sequence is provided.

Using this method, channel values are available for K time instants only (we assume that $\hat{\mathbf{h}}_k$ approximates the channel for the last sample of $\mathbf{y}_k$, i.e., $\hat{\mathbf{h}}_k \approx [h[kN_x;0],\ldots,h[kN_x;L]]^T$). When the full channel is needed (for the computation of the optimal KSP equalizers, for instance), we use a simple linear interpolation between these points.

3) Adaptive BEM Method: Alternatively to the above proposed linear interpolation, it is possible to fit the channel estimates produced by the adaptive method into a BEM as soon as $K \geqslant 2Q+1$ (which is generally the case). In this case, as the BEM has only $2Q+1$ degrees of freedom, it is generally not possible to interpolate between the identified channel points and we have to seek the BEM that best fits them in the LS sense.

Define the $K \times N$ selection matrix $\tilde{\mathbf{S}}$ as

$$\begin{aligned}&\tilde{\mathbf{S}}[i, N_x i] = 1, \quad \forall i = 1\ldots K\\ &\tilde{\mathbf{S}}[i,j] = 0 \quad \text{elsewhere}\end{aligned}$$

and the matrix $\mathbf{H}_{\text{adap}}$ of the channel coefficients identified by the adaptive method as

$$\mathbf{H}_{\text{adap}} = \left[\mathbf{h}_1^H,\ldots,\mathbf{h}_K^H\right]^H.$$

We are seeking the set of BEM coefficients $\hat{\mathbf{H}}_{\text{BEM}}$ that yield the best match (in a LS sense) to the adaptively identified channel coefficients for the K considered time instants. Using the selection matrix and the previously defined matrix $\mathbf{C}$ of complex exponentials, this translates into

$$\tilde{\mathbf{S}}\mathbf{C}\hat{\mathbf{H}}_{\text{BEM}} \approx \mathbf{H}_{\text{adap}}$$

which is solved in a LS sense as

$$\hat{\mathbf{H}}_{\text{BEM}} = (\tilde{\mathbf{S}}\mathbf{C})^{\dagger}\mathbf{H}_{\text{adap}}. \tag{30}$$

The parameters Q and N_{mod} of the BEM are designed as outlined earlier, assuming that the Doppler spread is known. By doing so, the dynamics of the BEM are in line with those of the true channel and the noise-induced variations of the adaptively identified channel coefficients cannot be modeled. The BEM modeling step actually filters out a part of the noise that is present in the adaptively identified channel coefficients. Therefore, the optimal choice of λ is different when the BEM approach is used. Lower values of λ should yield better results as it allows an improved tracking of the channel variations, the increased noise in the channel estimates being filtered out by the BEM modeling step.

B. Direct Estimation of the BEM Parameters

In this section, we propose a new approach in order to directly identify the BEM parameters of the channel, rather than the indirect approach of the previous section where the channel was partly identified before to seek the BEM coefficients that best suit the partly identified channel. The proposed approach directly relies on the knowledge of the training symbols appended by the KSP transmission scheme. Existing methods for training-based BEM estimation of doubly selective channels [12], [18] only exploit the channel output samples that solely contain contributions from the training sequence $\mathbf{t}_k$, discarding all the channel output samples containing mixed contributions from $\mathbf{t}_k$ and the unknown data symbols $\mathbf{s}_k$. The method we present here exploits all the channel output samples that contain contributions from $\mathbf{t}_k$, including those that contain contributions from both unknown data symbols and training symbols, i.e., we rely on the set of vectors $\mathbf{u}_k$ defined in (21).

1) Data Model: Reviewing the BEM expression of the transmission scheme (6) and rearranging the resulting expression, we obtain the following data model that is well suited for the identification of the channel's BEM parameters:

$$\mathbf{u}_k = \mathcal{T}_k\mathbf{h}_{\text{BEM}} + \boldsymbol{\epsilon}_k. \tag{31}$$

- The first term $\mathcal{T}_k\mathbf{h}_{\text{BEM}}$ is a deterministic term where $\mathbf{h}_{\text{BEM}}$ is the $(2Q+1)(L+1) \times 1$ vector of the channel's BEM coefficients $\mathbf{h}_{\text{BEM}} = [h_{-Q,0},\ldots,h_{-Q,L},\ldots,h_{Q,L}]^T$, and $\mathcal{T}_k$ is an $(n_t+L) \times ((2Q+1)(L+1))$ matrix accounting for the contributions of the complex exponentials of the BEM and the training sequences, which has the following structure:

$$\mathcal{T} = \begin{bmatrix} \boxed{\mathbf{T}_{k,0}} & & & \\ & \boxed{\mathbf{T}_{k,1}} & & \\ & & \ddots & \\ & & & \boxed{\mathbf{T}_{k,L}} \end{bmatrix}$$

with $\mathbf{T}_{k,l} = \text{diag}(\mathbf{t}_k)\mathbf{C}'_{k,l}$, where $\mathbf{C}'_{k,l}$ accounts for the BEM's complex exponentials multiplying the $h_{q,l}$ coefficients $\mathbf{C}'_{k,l}(x,y) = e^{j2\pi(y-(Q+1))(kN_x-N_t+l+x-1)/(N_{\text{mod}})}$.

- The second term $\boldsymbol{\epsilon}_k$ can be expressed as in (23), but the time variations of the channel during the reception of $\mathbf{u}_k$ are taken into account and so the left and right parts of $\mathbf{H}_{s,k}$ are redefined as

$$\mathbf{H}_{S,K}^{L} = \left[\begin{array}{ccc} h[n_{k,1;L}] & \cdots & h[n_{k,1;1}] \\ & \ddots & \vdots \\ \mathbf{0} & & h[n_{k,L};L] \\ \hline & \mathbf{0}_{(n_t\times L)} & \end{array}\right]$$

$$\mathbf{H}_{s,k}^{R} = \left[\begin{array}{ccc} & \mathbf{0}_{(n_t\times L)} & \\ \hline h[n_{k,n_t};0] & & \mathbf{0} \\ \vdots & \ddots & \\ h[n_{k,n_t+L};L-1] & \cdots & h[n_{k,n_t+L};0] \end{array}\right]$$

where $n_{k,l}$ is a shorthand notation for the index of the lth element of $\mathbf{u}_k : n_{k,l} = kN_x - N_t + l$.

2) Proposed Algorithms: The statistics of $\boldsymbol{\epsilon}_k$ defined in (25) remain valid in this situation under the same assumptions that were needed to derive them. We directly rely on these statistics to propose the following methods.

LS Channel Estimate: Relying on the first-order statistics of $\boldsymbol{\epsilon}_k$, a simple LS approach provides us with an unbiased estimator of $\mathbf{h}_{\text{BEM}}$

$$\hat{\mathbf{h}}_{\text{LS}} = \left(\sum_{k=1}^{K}\mathcal{T}_k^H\mathcal{T}_k\right)^{-1}\sum_{k=1}^{K}\mathcal{T}_k^H\mathbf{u}_k. \tag{32}$$

Because of the presence of the complex exponentials, the inverse of the sum generally exists as soon as $K(n_t+L) \geq (2Q+1)(L+1)$.

Weighted Least-Squares Channel Estimate: Since $\boldsymbol{\epsilon}_k$ is not white, the LS approach is not optimal. A weighted least-squares (WLS) approach taking into account the color of $\boldsymbol{\epsilon}_k$ would yield an improved estimate of the channel parameters. *Assuming that all the* $\mathbf{Q}_k$*'s are known* (see also next paragraph), the WLS estimate of $\mathbf{h}_{\text{BEM}}$ can be computed as

$$\hat{\mathbf{h}}_{\text{WLS}} = \left(\sum_{k=1}^{K}\mathcal{T}_k^H\mathbf{Q}_k^{-1}\mathcal{T}_k\right)^{-1}\sum_{k=1}^{K}\mathcal{T}_k^H\mathbf{Q}_k^{-1}\mathbf{u}_k. \tag{33}$$

The presence of the AWGN term in $\mathbf{Q}_k$ ensures the existence of its inverse and the inverse of the sum generally exists under the same conditions as for the LS estimate.

3) Iterative WLS Channel Estimate: Unfortunately, $\mathbf{Q}_k$ is not known at the receiver for it depends on the sought channel. The WLS approach can thus not be straightforwardly adopted. We propose below an iterative approach that allows to cope with the dependence of $\mathbf{Q}_k$ on the channel.

Assume a channel estimate $\hat{\mathbf{h}}_{\text{BEM}}^{(i)}$ is available at the receiver (ith iteration). Exploiting (3) and the definition of $\mathbf{H}_{s,k}$, it is possible to construct its estimate $\hat{\mathbf{H}}_{s,k}^{(i)}$, from $\hat{\mathbf{h}}_{\text{BEM}}^{(i)}$, for $k = 1\ldots K$. Relying on the parametric definition of $\mathbf{Q}_k$ and assuming that σ^2 is known, we construct the K estimates $\hat{\mathbf{Q}}_k^{(i)}$ of the color of the different $\boldsymbol{\epsilon}_k$'s. This estimate is used to produce a refined estimate $\hat{\mathbf{h}}_{\text{BEM}}^{(i+1)}$ of the channel model with a WLS approach, as follows:

$$\hat{\mathbf{h}}_{\text{BEM}}^{(i+1)} = \left(\sum_{k=1}^{K}\mathcal{T}_k^H\hat{\mathbf{Q}}_k^{(i)-1}\mathcal{T}_k\right)^{-1}\sum_{k=1}^{K}\mathcal{T}_k^H\hat{\mathbf{Q}}_k^{(i)-1}\mathbf{u}_k.$$

The iterative procedure is stopped when there is no significant difference between two consecutive channel estimates. If the starting point is sufficiently accurate, this iterative procedure converges to a solution which is close to the true WLS estimate.

The iterative procedure can be initialized with the LS channel estimate of (32): $\hat{\mathbf{h}}_{\text{BEM}}^{(0)} = \hat{\mathbf{h}}_{\text{LS}}$, which is equivalent to choosing $\hat{\mathbf{Q}}_k^{(0)} = \mathbf{I}, \forall k$. Experimental results show that this choice allows the iterative procedure to converge in two or three steps. The experimental results presented below are obtained with two iterations of the iterative procedure.

V. Experimental Results

In this section, we assess the performance of the proposed channel estimation methods and the achievable bit-error-rate (BER) performance when the proposed KSP equalizers are used with the resulting channel models. The considered system setup is similar to the OFDM-based Hiperlan2 and IEEE 802.11 standards for WLAN applications that have a similar physical layer, except that KSP transmission is considered rather than OFDM transmission. We also modify the sampling time which is increased by a factor 2: $T_s = 0.1\ \mu$s instead of the proposed 0.05 μs, which increases the effects of mobility. The other parameters of the transmission scheme are as prescribed by the standards: $f_c = 5.5$ GHz, guard band duration (N_t in our scheme) of 16 samples, and useful symbol duration (N_s) of 64 samples. The padded sequences of the KSP scheme are randomly picked quadrature-phase-shift-keying (QPSK) symbols. The constellations used for the mapping of the binary data are Gray-mapping binary-phase-shift keying (BPSK), QPSK, 16-QAM, and 64-QAM. When coded transmissions are considered, the convolutional mother code of rate $r = 1/2$ of the standard is used. No preambles for synchronization or channel estimation are inserted before data transmission and we assume perfect timing and carrier frequency synchronization. The number of KSP blocks transmitted (K in the previously adopted notation) is set to 100. The transmission channels used for the simulations are random realizations of a physical channel model with ten clusters of 100 rays each with a channel order set to $L = 8$ for most experiments (we explicitly state so when the considered channel order differs

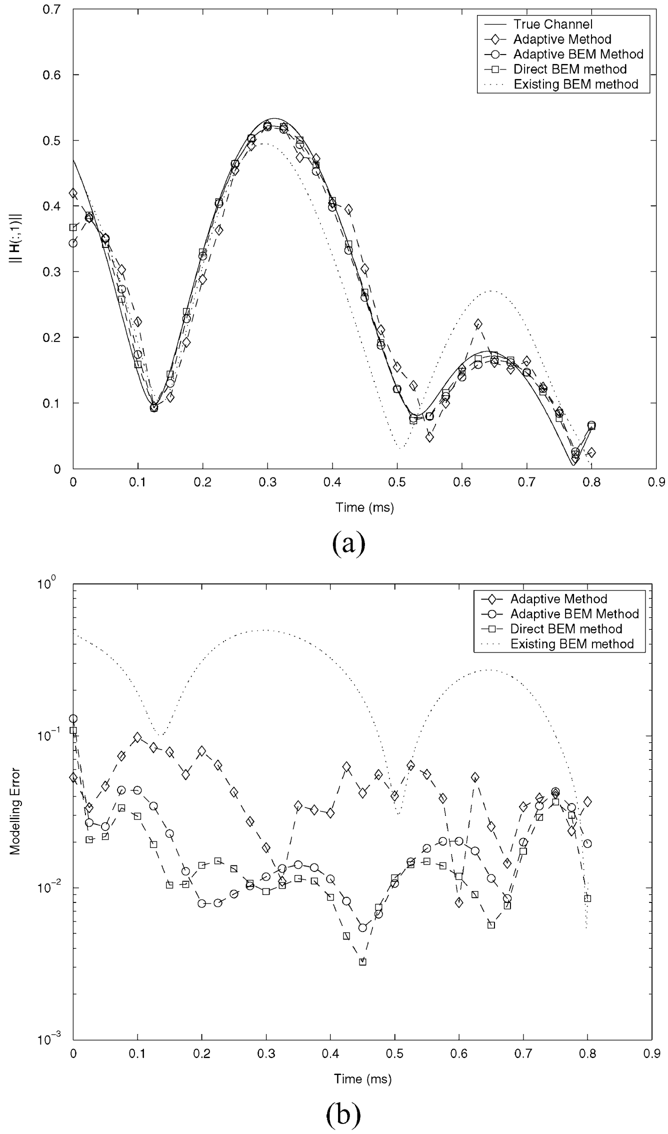

Fig. 1. Norm of the first tap of the (a) channel estimate and of the (b) modeling error versus time for the different channel estimation methods at a speed of 400 km/h and an SNR of 20 dB.

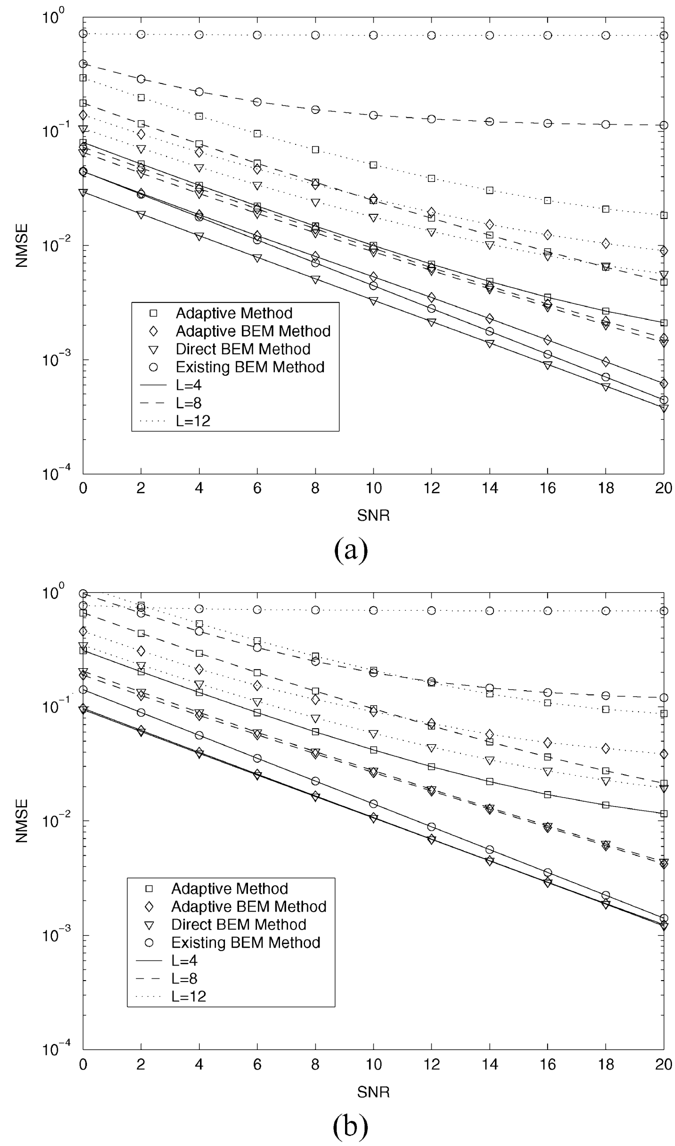

Fig. 2. NMSE of the different channel estimates for varying channel orders when a preamble of length $N_t = 16$ is used. The considered user terminals speeds are (a) 25 km/h and (b) 400 km/h.

from 8). The considered speed of the mobile terminal ranges from 25 km/h (low mobility in an urban environment) to 400 km/h (high speed train), yielding Doppler spreads in the interval 127 Hz $\leqslant f_{\max} \leqslant$ 2 kHz. The number of complex exponentials $(2Q+1)$ required to accurately track the channel variations in this scenario ranges from $3(Q=1)$ at 25 km/h to $9(Q=4)$ at 400 km/h. The period $N_{\rm mod}$ of the BEM is derived from the procedure described in Section II-B, yielding $N_{\rm mod} = 3N$ at 25 km/h and $N_{\rm mod} = 12.27N$ at 400 km/h. The forget factor of the adaptive method ranges from $\lambda = 0.95$ at 25 km/h to $\lambda = 0.75$ at 400 km/h. For the proposed adaptive BEM method, we pick $\lambda = 0.1$ as experimental results indicate that it yields the best accuracy.

A. First Experiment: Channel Estimation

In a first experiment, we compare the proposed channel estimation methods (BEM and adaptive) with the method proposed in [12] and [18] (note that we generalize the method to handle arbitrary BEM periods). In Fig. 1, we show how the different methods track the evolution of a given channel tap with a mobile terminal speed of 400 km/h under a signal-to-noise ratio (SNR) of 20 dB. The proposed BEM methods seem to match the true channel better than the others with a slight advantage for the direct BEM method over the adaptive BEM method. The channel estimates of the purely adaptive method (initialized with $\hat{\mathbf{h}}_0 = \mathbf{0}$) vary less smoothly in time than those of the existing BEM method [12] and [18] but are closer to the true channel.

The performance of the different channel estimation schemes is further assessed in Fig. 2, where the normalized mean-squared error ($\text{NMSE} = ||\mathbf{H} - \hat{\mathbf{H}}||^2/||\mathbf{H}||^2$) of the different channel estimation methods is presented as a function of the SNR for different channel orders ($L = 4, 8$, and 12) for the extremes of the considered user terminal speeds. The proposed BEM methods clearly outperform the purely adaptive scheme as well as the existing BEM method. The performance of the proposed BEM methods are relatively close to each other with some advantage for the direct BEM method. For low channel orders only, the existing BEM method outperforms the purely adaptive one, but for higher channel orders, the existing BEM method shows poor performance and is outperformed by the two proposed schemes. The experiment further shows that the accuracy of all channel estimates is reduced as the speed of the mobile terminal increases. A drawback of the purely adaptive method is that the choice of the forget factor λ results from a tradeoff: when λ approaches 1, the noise is filtered out and its impact on the channel estimates is limited, but the channel variations cannot be tracked accurately. When λ is smaller, the channel variations can be tracked accurately, but the noise has an increased impact on the modeling error, and the final channel estimate becomes noisy. In contrast, the direct BEM method averages out the noise over the duration of the considered burst and models the channel variations with its complex exponentials. No tradeoff between channel tracking and noise reduction has to be made as both are done optimally, resulting in improved channel estimates.

B. Second Experiment: Channel Equalization With Perfect Channel Knowledge

In a second experiment of which the results are presented in Fig. 3, we analyze the BER performance of the presented KSP equalizers (both the optimal equalizer and the less complex FD equalizer are considered) for QPSK transmission when two of the proposed channel estimation methods are used[1]. The considered channel identification methods are the direct BEM approach that yields the most accurate channel model and the purely adaptive method that has the smallest computational complexity. The performance of the optimal KSP equalizer with perfect channel knowledge appears to be speed-independent. When QPSK constellations are used, it has been shown in [6] that the optimal and FD KSP equalizer yield similar performance at the considered SNRs when the channel is stationary. In the presented experiments, it appears that there is a performance degradation of approximately 0.75 dB at 25 km/h and 2 dB at 400 km/h for the FD equalizer. This performance degradation is caused by the time variations of the channel inside a KSP block, resulting in the loss of orthogonality between the carriers and uncompensated ICI. The BER performance when the channel model resulting from the direct BEM method is used matches quite closely the perfect channel knowledge situation. A relatively good match is observed for the adaptive method at low speeds but, as the speed increases and the channel model becomes less accurate, we observe the appearance of a floor in the BER performance of the system. This experiment shows that the higher accuracy of the direct BEM method results in significantly improved BER performance. Channel variations during the transmission of a KSP block have a smaller impact on the system performance than the channel modeling error.

[1]When BEM channel identification is used, the FD equalizer for the kth received block is computed using the BEM-derived channel model for the middle sample of the considered block.

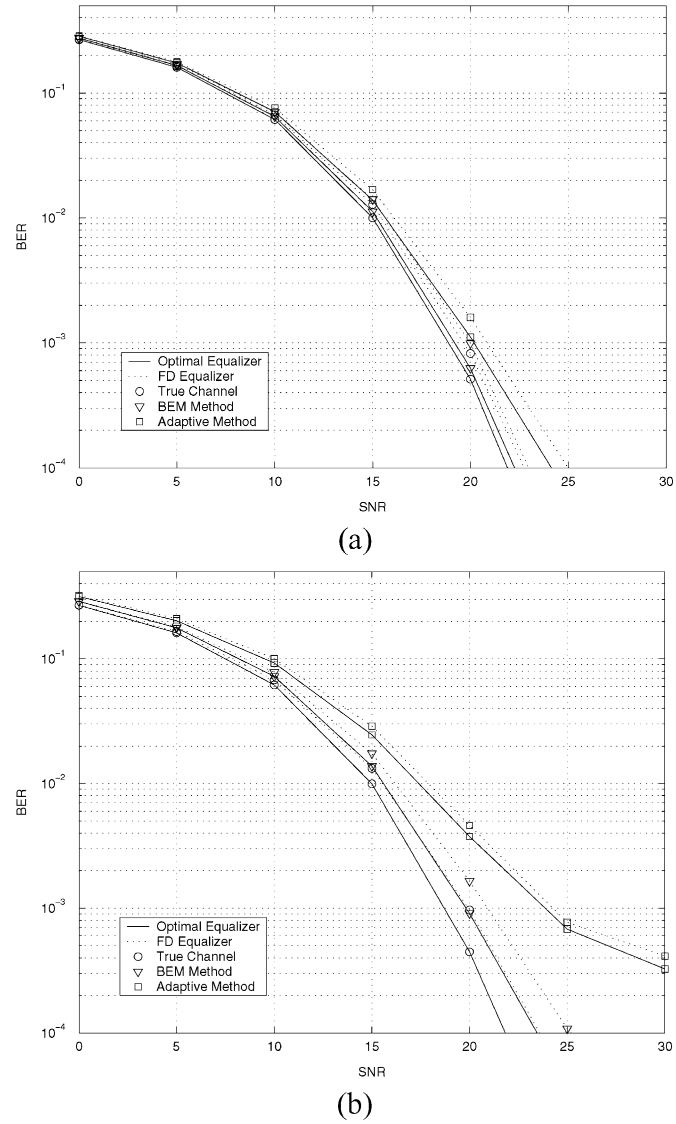

Fig. 3. BER performance of the optimal and FD KSP equalizer when the channel estimates of the purely adaptive and the direct BEM methods are used with QPSK mapping. The considered user terminals speeds are (a) 25 km/h and (b) 400 km/h.

C. Third Experiment: Channel Equalization With Estimated Channel Model

In a third experiment, we further investigate the BER performance of the system when the direct BEM identification method is used and the optimal and FD KSP equalizers are used. As proposed in the Hiperlan2 Standard, the effective data rates are varied through the use of different constellations and coding schemes. We assess the system performance for BPSK, QPSK, 16-QAM and 64-QAM constellations for coded and uncoded transmission. The coded scheme uses a rate $r = 1/2$ binary convolutional encoder as described in the Hiperlan2/IEEE 802.11 standard. The coded scheme is used in combination with an interleaver that differs from the block-interleaver of the standard. In order to exploit the diversity offered by the time variation of the channel, we use an interleaver operating on a burst level. The interleaver is designed such that two consecutive data bits are always encoded in different KSP blocks with a minimum

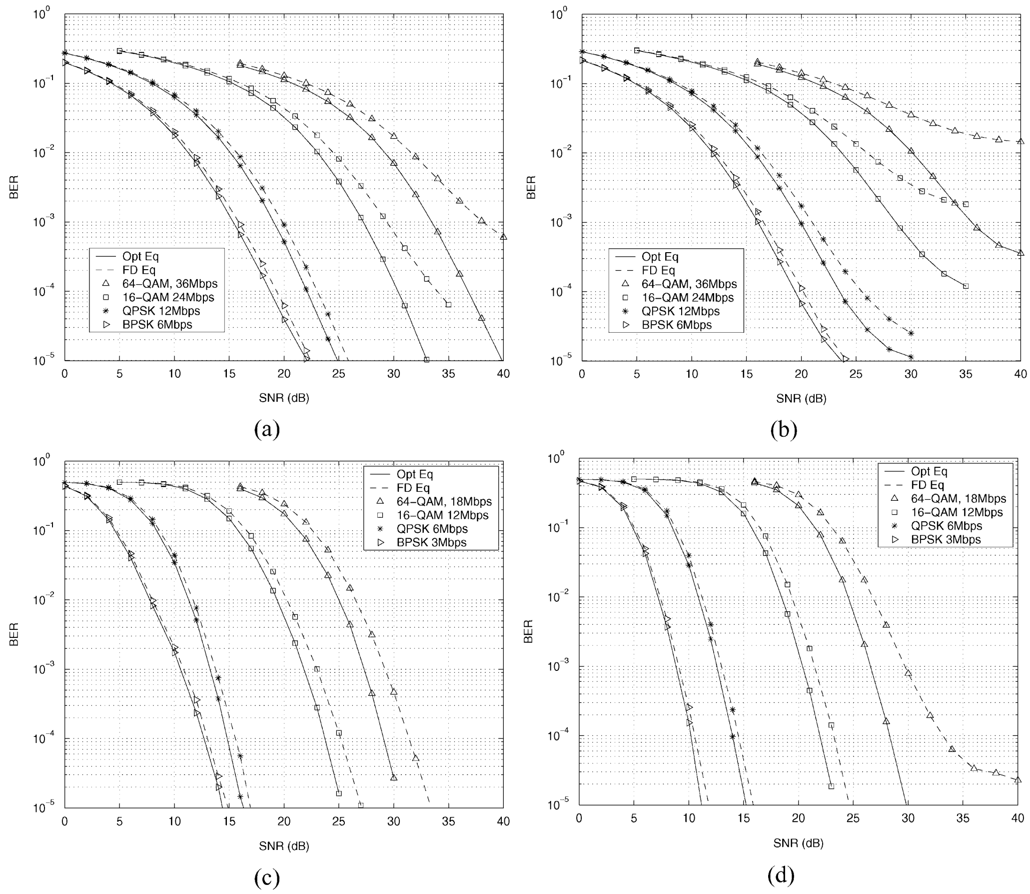

Fig. 4. BER performance of the optimal and FD KSP equalizers relying on the channel estimates of the proposed BEM method when different constellations and coding schemes are used. The considered user terminals speeds are: (a), (c)—25 km/h and (b), (d)—400 km/h. Uncoded transmission is considered in (a) and (b), while coded transmission ($r = 1/2$) is considered in (c) and (d).

distance of 15 blocks between these two blocks. Furthermore, when higher order constellations are used, the interleaver alternates the significance of consecutive bits [a least significant bit (LSB) followed by a most significant bit (MSB) in 16-QAM; LSB, center bit, MSB in 64-QAM]. The combination of these parameters (constellation and coding rate) allows six different data rates ranging from 3 to 36 Mb/s.

The BER performance of the system is presented in Fig. 4 for speeds of 25 and 400 km/h. The uncoded performance of optimal and FD KSP equalizers is similar for BPSK and QPSK constellations, but as the constellation size increases, using the more complex optimal KSP equalizer yields a significant performance gain, especially as the speed increases. The effect of increased speeds results in a performance degradation for both equalization schemes and an error floor appears at high speeds when higher order constellations are used resulting from the increased modeling errors at high speeds (plus the loss of carrier orthogonality for the FD equalization scheme). In contrast to this, coded transmissions show stable or (slightly) improved performance as the speed increases even though the uncoded performance undergoes a significant degradation. This results from the increased diversity offered by higher terminal speeds that is exploited by the coded schemes. The performance gap between optimal and FD equalization is largely reduced as coded schemes are used; both schemes offer similar performance for BPSK and QPSK constellations whilst the optimal KSP equalizer offers a performance gain generally ranging from 1 to 3.5 dB depending on the constellation and the speed of the mobile terminal when higher order constellations are considered. The only exception arises for high speeds, low-target BERs and 64-QAM constellations where the coded FD equalization scheme shows an error floor above 10^{-5}.

Finally, the achievable data rates of the different schemes (coded or uncoded transmission, FD or optimal equalizers) for target bit error rates of respectively 10^{-4} and 10^{-5} as a function of the SNR are presented in Fig. 5 and Fig. 6 for speeds of 25 and 400 km/h respectively. The coded scheme generally dominates the uncoded scheme. The uncoded scheme is suitable only at low speeds and when the optimal equalizer is used, in which case the achievable data rates are increased and the coded scheme are slightly outperformed for intermediate data rates. The coded scheme significantly outperforms the uncoded scheme when lower data rates are considered, independently of the speed. At high speeds, the coded scheme always dominates and the uncoded scheme can be used only with BPSK or QPSK constellation, if the optimal equalizer is used at the receiver. The presented results also highlight the fact that the coded schemes show very stable performance. The achievable data rates remain approximately the same or are slightly improved as the speed increases, except in the specific case where the speed is high, the FD equalizer is used together with 64-QAM constellation.

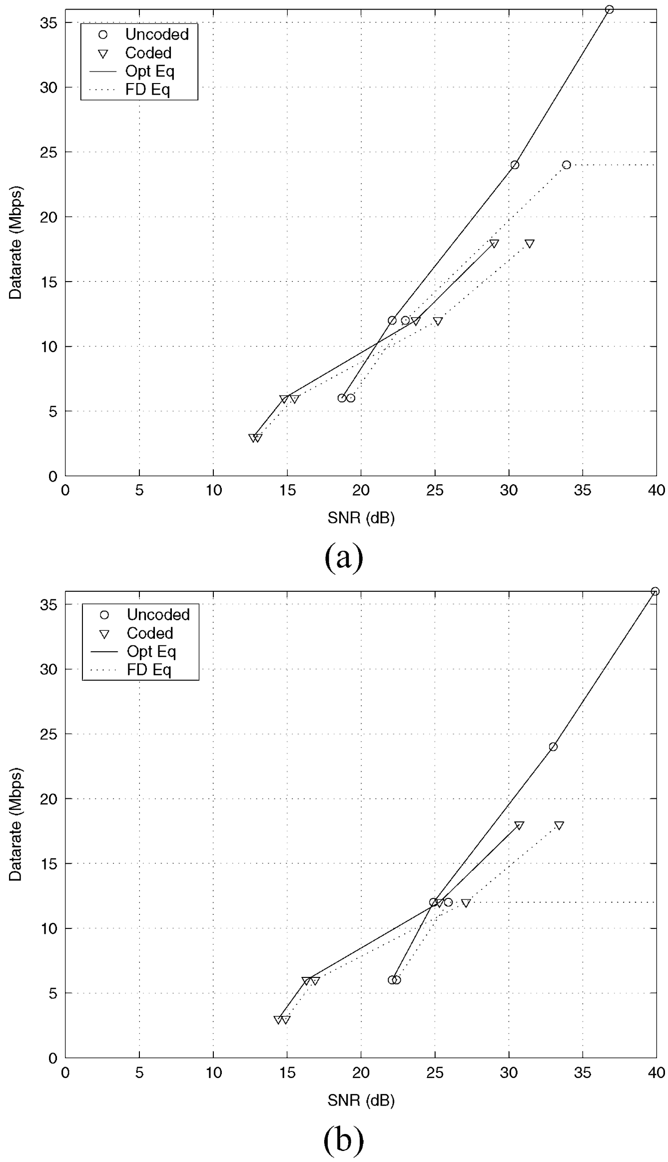

Fig. 5. Achievable data rates with the optimal and FD KSP equalizers relying on the channel estimates of the proposed BEM method when different constellations and coding schemes are used for a target BER of (a) 10^{-4} and (b) 10^{-5} at a speed of 25 km/h.

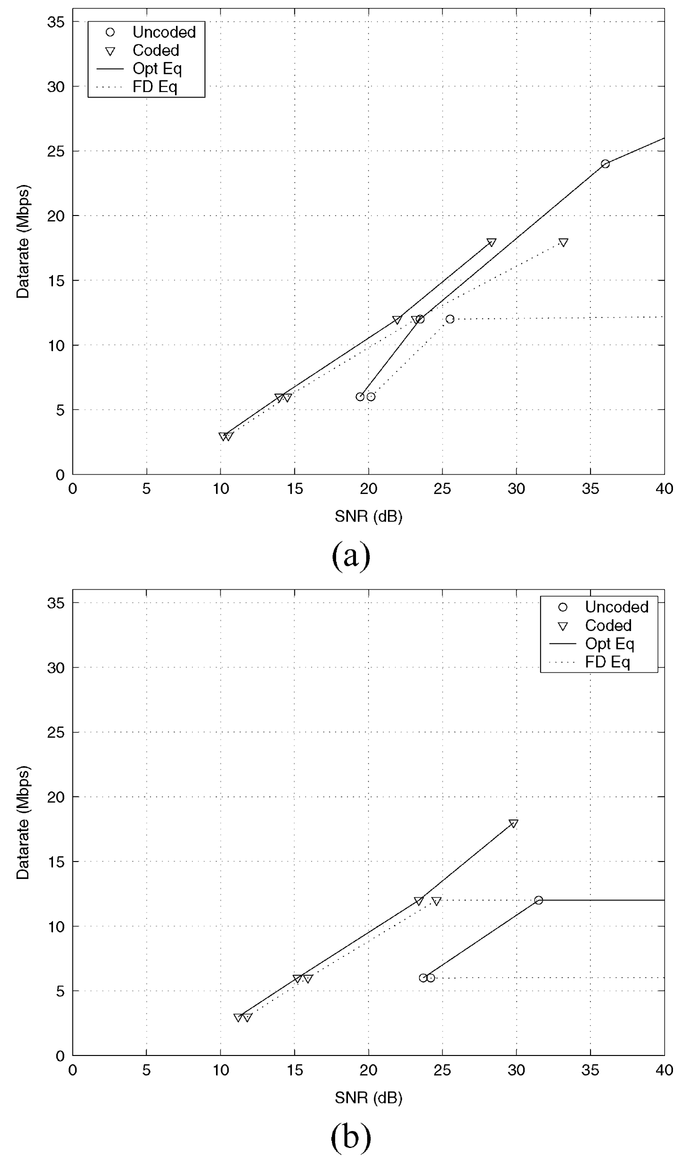

Fig. 6. Achievable data rates with the optimal and FD KSP equalizers relying on the channel estimates of the proposed BEM method when different constellations and coding schemes are used for a target BER of (a) 10^{-4} and (b) 10^{-5} at a speed of 400 km/h.

The coded scheme always dominates in the low SNR region. At low speeds and for low-target BERs, the uncoded scheme performs best in the medium- and high-SNR regions. The difference between coded and uncoded schemes reduces as the speed or BER performance requirement increases. For low-target BERs and high speeds, the coded schemes always perform better. The presented results also highlight the more stable performance of the coded scheme for different speeds and target BERs.

VI. Conclusion

In this paper, we have introduced two new methods that allow to identify doubly selective channels relying on the knowledge of the guard bands introduced by a KSP transmission scheme. The first method copes with the time-variations of the transmission channel using an adaptive scheme whilst the second directly identifies the BEM parameters of the channel. Both methods are able to cope with training sequences of various lengths and compositions. Taking into account the channel output samples that contain contributions from both the training symbols and the unknown surrounding data symbols allows the proposed methods to clearly outperform existing ones, especially for large channel orders. The proposed BEM method performs significantly better than the adaptive one but has a higher latency and requires to buffer the channel output samples before the channel is identified and equalizers can be designed whilst the adaptive method estimates the channel on the fly. Block equalizers for KSP transmission were also described in this paper and experimental results show their efficiency.

Finally, experiments where these equalizers are designed relying on the channel estimates provided by the proposed BEM method show that KSP transmission is a suitable candidate in order to deliver high data rates ranging from 3 Mb/s to 36 Mb/s to users experiencing high mobility. When these equalizers are used in combination with a coding scheme allowing to exploit the diversity offered by the time variation of the channel, it is possible to deliver a speed-independent quality of service to the mobile users.

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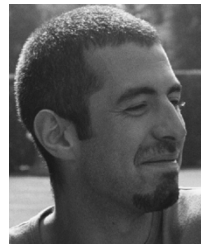

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