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On channel estimation for spatial modulated systems over time-varying channels

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A B S T R A C T

Spatial Modulation (SM) has been proposed recently for multiple-input multiple-output (MIMO) systems to cope with the interchannel interference and to reduce the detection complexity as compared to the conventional MIMO systems. In SM system, the data symbols are transmitted by a randomly selected active antenna of a MIMO transmitter to the receiver through a wireless channel. The information is carried both by the data symbol from any signal constellation such as M-ary phase shift keying (M-PSK) or M-ary quadrature amplitude modulation (M-QAM), by the index of the selected antenna. The channel estimation is a critical process at the receiver during the coherent detection of the transmitted symbol and the antenna index, randomly selected. Recently, the channel estimation of channel for SM systems has been investigated by the recursive least square (RLS) algorithm for only quasi-static fading channels. In this paper, a novel channel estimation is proposed for SM systems in the presence of rapidly time-varying channels. The Bayesian mean square error (MSE) bound has been derived as a benchmark and the performance of the proposed approaches is studied in terms of MSE and bit-error rate (BER). Computer simulation results have confirmed that the proposed iterative channel estimation technique has significant BER/MSE performance advantages compared with existing channel estimation algorithm proposed earlier in the literature.

1. Introduction

Conventional multiple-input multiple-output (MIMO) systems use all transmit antennas to transmit multiple data streams. Therefore, its performance depends on some important parameters such as the distance between receiver and transmitter antennas [1,2], inter-channel interference (ICI) at the receiver and inter-antenna synchronization (IAS) at the transmitter [3,4]. For example, it was shown that uncorrect IAS causes performance degradation for MIMO systems [3,4].

Spatial modulation (SM) is a promising MIMO transmission technique that has been recently proposed [5–7]. The basic principle of the SM is to use the indices of multiple antennas to convey information in addition to the conventional two-dimensional signal constellations such as M-ary phase shift keying (M-PSK) and M-ary quadrature amplitude modulation (M-QAM), where M is the constellation size. Optimal SM decoder at the receiver searches jointly for all M-ary constellation points and transmit antennas to decide on both the transmitted symbol and the index of the transmitted antenna over which the symbol is transmitted. Consequently, it is an effective way to remove the intercarrier interference (ICI) completely between the transmitter antennas of a MIMO link. Furthermore, SM does not require IAS of the MIMO link and only one radio frequency chain (RF) is needed at the transmitter.

The SM technique is different from the transmit antenna selection (TAS) since TAS is a closed-loop mechanism and provides spatial-multiplexing while the SM is open-loop with transmit-diversity [8]. SM technique adds a third dimension to the two-dimensional signal space which is the spatial dimension and it maps multiple information bits into one symbol and the corresponding antenna index. Therefore, the number of total transmitted information bits depends on the constellation diagram and the total number of transmitter antennas [9]. Consequently, the spatial modulation has a very flexible mechanism that provides high spectral efficiency with low complexity [10].

The receiver has to detect both the transmitted symbol and the active antenna index since the desired information carried by the modulated signal and the transmit antenna index, chosen at random. In the literature, the antenna index and symbol detection are realized by means of optimal and non-optimal detection

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methods [5,11]. It has been shown in [11] and [9] that SM can achieve better error performance than V-BLAST (Vertical-Bell Lab Layered Space–Time) in some cases under the assumption that perfect channel information (CSI) is available at the receiver. However, in practice, we hardly have a perfect CSI at the receiver and thus a channel estimator is employed to provide unknown channel parameters. Recently, the effect of imperfect channel estimation on the SM-MIMO systems has been investigated [12,13]. In [12], the least square (LS) estimation technique is employed for MIMO systems operating over quasi-static Rayleigh flat fading channels and its mean-square error (MSE) performance is investigated. In [13], a joint channel estimation with data detection is proposed while assuming the channel correlation matrix is available at the receiver.

Pilot symbol assisted modulation (PSAM) has been generally employed to achieve coherent detection performance in wireless environments [14]. Based on this approach, in [15] the channel estimation for SM systems has been investigated by means of a pilot-based recursive least square (RLS) method while assuming the wireless channel is quasi-static for a duration of at least one frame length. The RLS algorithm is known to possess fast convergence, but also to yield high channel estimation errors on fast fading channels mainly because it solely depends on the pilot symbols and does not take the mobility into account [16]. In communication systems, pilot symbols, known to the receiver, can be inserted periodically, usually in the beginning of each frame consisting of several transmitted symbols. However, when the channel varies rapidly, pilot symbol sequence cannot be effective to implement the channel estimation efficiently.

In this work, the pilots are sent out through only one transmit antenna at each time instant. Hence, using pilot-based channel estimation, only the CSI of the active transmit antenna can be obtained at the receiver. This leads to a challenging task for the channel estimation in SM systems over fast time-varying channels. In [17], performance bounds for training and superimposed training-based channel estimation for time-varying flat-fading channels have been discussed. It was shown that the regular periodic placements (RPPs) perform better at high SNR and for slowly varying channels, whereas the superimposed scheme is superior for relatively fast time-varying channels. However, in MIMO systems it is required that the pilot sequences transmitted from each transmit antenna should be orthogonal to each other to prevent inter-antenna interference. This a challenging design problem in general. On the other hand, this problem can be easily handled in spatial modulated MIMO systems since the pilot sequences transmitted from each transmit antenna are surely orthogonal each other due to the fact that they are mutually disjoint at all the time.

Channel coefficients in a real mobile environment change smoothly in time. This smoothness helps us to employ well designed curve fitting methods in order to further improve the channel estimation accuracy [18]. In [19], the rectangular-windowed recursive least squares algorithm where each tap of the frequency selective fading channel modeled as a polynomial in time is proposed. On the other hand, all channels could not be observed within the duration of a symbol transmission since only one antenna is active at the given signaling interval. This also motivates us to use curve fitting methods to interpolate unknown channel durations [20]. It is clear that to track the channel coefficients for data duration we need to employ a decision directed channel estimation scheme. Different methods based on decision directed are also proposed to enhance the tracking capability of the RLS algorithm in [21] for MIMO systems. In [21], optimizing the involved window size and forgetting factor and the initialization of the autocorrelation matrix of RLS are also investigated.

To the best of our knowledge, there is not any efficient and computationally feasible channel estimation algorithm, in the presence of a rapidly varying channel, exists for the SM-MIMO systems in the literature. Motivated by the existing correspondences between the RLS, the decision directed channel estimation and the polynomial fitting, in this paper a novel channel estimation technique and an iterative receiver design are proposed based on the curve fitting and the detected symbols employed in a decision-directed mode that ensure excellent tracking for SM-MIMO systems. We insert periodic pilot blocks to cope with the errors, introduced in decision-directed channel estimation mode, due to the accumulate over bits. The data block length between adjacent pilot blocks can be adjusted based on the channel mobility in our proposed scheme. This results in minimum overhead for pilot symbols. It is known that the iterative receivers provide significant advantages [22–24] over conventional receivers and shown that the SM receiver employing the proposed channel estimator has superior performance as compared to the conventional RLS channel estimation-based receivers. Moreover, we derived analytically an overall Bayesian MSE lower bound for the channel estimator proposed in this work to serve as a benchmark. We performed new computer simulations to determine how the MSE performance of our channel estimation algorithm can approach this lower bound.

Notation: Throughout the paper, the following notations and assumptions are used. Bold and capital letters '**A**' denote matrices. Bold and small letters '**a**' denote vectors. diag{**a**} is a diagonal matrix with **a** on its main diagonal. $E_{x,y}[.]$ is the expectation over x and y. The notations, $(.)^*$, $(.)^T$, $(.)^\dagger$, $(.)^+$, $(.)^{-1}$ and $\|.\|_F$ denote conjugate, transpose, Hermitian, pseudoinverse, inverse and Frobenius norm, of a matrix or a vector respectively.

2. System model

An SM-MIMO system with N_t transmit antennas and N_r receive antennas is considered. In general, the total number of bits that is transmitted by a M-ary SM-MIMO system is

$$k = \log_2(N_t) + \log_2(M) \tag{1}$$

where M represents the total number of bits per transmitted symbol. At the nth symbol interval the SM mapper takes a random sequence of k bits and maps them into an N_t-dimensional signal vector as

$$\mathbf{x}(n) = \left[x_1(n), x_2(n), \cdots, x_{N_t}(n)\right]^T. \tag{2}$$

Only one of $x_j(n)$ that is active in $\mathbf{x}(n)$ is nonzero. Then, at the nth symbol interval, the output of the SM-MIMO system at the transmitter can be expressed as

$$\mathbf{x}_j(n) \triangleq \Big[0\cdots \underbrace{\qquad x_q(n) \qquad}_{j.\ \text{transmitted antenna}} \cdots 0\Big]^T \tag{3}$$

where j is the active antenna index and $x_q(n)$ is the qth symbol from the M-ary constellation diagram. The other antennas remain silent over this symbol duration. The symbol $x_q(n)$ is transmitted from antenna j over an $N_r \times N_t$ MIMO channel. The observation model at receiver can be expressed as

$$\begin{bmatrix} y_1(n) \\ \vdots \\ y_r(n) \\ \vdots \\ y_{N_r}(n) \end{bmatrix} = \begin{bmatrix} h_{1,1}(n) & h_{1,2}(n) & \cdots & \cdots & h_{1,N_t}(n) \\ h_{2,1}(n) & h_{2,2}(n) & \cdots & \cdots & h_{2,N_t}(n) \\ \vdots & \vdots & \ddots & & \vdots \\ \vdots & \vdots & & \ddots & \vdots \\ h_{N_r,1}(n) & h_{N_r,2}(n) & \cdots & \cdots & h_{N_r,N_t}(n) \end{bmatrix}$$

$$\times\begin{bmatrix}0\\ \vdots\\ x_q(n)\\ \vdots\\ 0\end{bmatrix}+\begin{bmatrix}w_1(n)\\ \vdots\\ w_r(n)\\ \vdots\\ w_{N_r}(n)\end{bmatrix}\tag{4}$$

where $h_{r,j}(n)$ is the channel coefficient between jth transmitter antenna and rth receiver antenna, $w_r(n)$ is complex-valued, zero-mean white Gaussian noise (AWGN) with variance σ_w^2.

In the SM-MIMO system, the time-varying, frequency non-selective fading channel coefficients, $h_{r,j}(n)$, introduce a random amplitude and phase shift to the transmitted signal. We assume they are modeled as wide-sense stationary (WSS) process narrow-band complex Gaussian random variables with means $\mu_{h_{r,j}}$ and variances $\sigma^2_{h_{r,j}}$ (Rician channel model), having Jakes' model with the autocorrelation function of the channel [25] given by

$$R_{\mathbf{h}}(m,n)\triangleq E\left\{h_{r,j}(m)h^*_{r,j}(n)\right\}=\sigma^2_{h_{r,j}}J_0\big(2\pi f_d(m-n)T_s\big),\tag{5}$$

where T_s stands for the symbol period, f_d is the Doppler frequency in Hertz and $J_0(\cdot)$ is the zeroth order Bessel function of the first kind. There is a dominant component in the Rician fading, distinct from the Rayleigh fading channels. The Rician factor, R, is defined as the ratio of the power in the Line-of-sight (LOS) component to the power of the non-line-of-sight (non-LOS) multipath components. Rayleigh fading is a special case of the Rician fading when $R=0$. Also $R=\propto$ describes a channel having only a LOS component.

Observation model (4) can be written in matrix form as follows:

$$\mathbf{y}(n)=\mathbf{H}(n)\mathbf{x}_j(n)+\mathbf{w}(n),\quad n=1,2,\cdots,N.\tag{6}$$

3. Optimal detection

Antenna index detection is a crucial step of the SM scheme since only one transmit antenna is active among the set of transmit antennas and both the data symbol, transmitted by this antenna, and the antenna index should be decided at the receiver. Optimal detector based on the maximum likelihood (ML) principle can be stated as follows, [11]:

$$\big[\widehat{j}_{ML}(n),\widehat{q}_{ML}(n)\big]=\arg\max_{j,q} p_Y\big(\mathbf{y}(n)\mid\mathbf{x}_j(n),\mathbf{H}(n)\big)\tag{7}$$

where $\mathbf{x}_j(n)$ varies for different q and j as indicated in (3). From (6), the probability density function (pdf) of $\mathbf{y}(n)$, conditioned on $\mathbf{x}_j(n)$ and $\mathbf{H}(n)$, can be written as:

$$p_Y\big(\mathbf{y}(n)\mid\mathbf{x}_j(n),\mathbf{H}(n)\big)=\pi^{-N_r}\exp\big(\big\|-\mathbf{y}(n)-\mathbf{h}_j(n)x_q(n)\big\|_F^2\big)\tag{8}$$

where $\mathbf{h}_j(n)=[h_{1,j}(n),h_{2,j}(n),\cdots,h_{N_t,j}(n)]^T$ is jth column vector of the matrix $\mathbf{H}(n)$. Using (8), optimal detector in (7) can be expressed as

$$\big[\widehat{j}_{ML}(n),\widehat{q}_{ML}(n)\big]=\arg\max_{j,q}\big\|\mathbf{g}_{jq}(n)\big\|_F^2-2\Re e\big\{\mathbf{y}^\dagger(n)\mathbf{g}_{jq}(n)\big\}\tag{9}$$

where $\mathbf{g}_{jq}(n)$ is:

$$\mathbf{g}_{jq}(n)=\mathbf{h}_j(n)x_q(n),\quad 1\le j\le N_t,\ 1\le q\le M.\tag{10}$$

If the receiver detects both $\widehat{j}_{ML}(n)$ and $\widehat{q}_{ML}(n)$ correctly, they can be easily de-mapped and combined to get back to the transmitted bits. However, it is clear that the receiver needs to know the full CSI, $\mathbf{H}$ where

$$\mathbf{H}=\big[\mathbf{H}(1),\mathbf{H}(2),\cdots,\mathbf{H}(n),\cdots\mathbf{H}(N)\big].\tag{11}$$

4. Channel estimation

In the SM-MIMO system, the CSI is needed at the receiver in order to detect the modulated signal transmitted for the selected transmit antenna as well as the index of the antenna selected. In this work we propose a new iterative channel estimation technique which yields a superior error performance for the SM-based receivers. The RLS algorithm is employed only for the initialization of the proposed iterative algorithm.

4.1. Initialization

We now summarize the RLS algorithm which will be employed to initialize our iterative channel estimation algorithm by means of the pilot symbols denoted by $x^{(p)}(n)$. The RLS algorithm works for $j=1,\cdots,N_t$, $r=1,\cdots,N_r$. The pilot symbols are first transmitted sequentially from transmit antennas and the channel coefficients between the selected transmit antenna and the receive antennas are individually estimated by the RLS algorithm within each pilot symbol duration as shown in Fig. 1. Let $y_r^{(p)}(n)$, $r=1,2,\cdots,N_r$, be the received signal corresponding to the pilot symbols. At the receiver, the received signal samples are processed sequentially and the channel estimates are updated as the new samples arrive. This section explains briefly how the least squares estimates of the channel are computed recursively. Given the set of pilot symbols, $\mathbf{x}^{(p)}=[x^{(p)}(1),x^{(p)}(2),\cdots,x^{(p)}(N_p)]^T$ where N_p is the total number pilot symbols for each active antenna, and the corresponding desired responses $\mathbf{y}_r^{(p)}(n)=[y_r^{(p)}(1),y_r^{(p)}(2),\cdots,y_r^{(p)}(N_p)]^T$, the outputs of the set of linear filters are determined according to

$$\Omega_{r,j}(n)=\widehat{h}^{RLS}_{r,j}(n)x^{(p)}(n),\quad n=1,\cdots,N_p\tag{12}$$

The channel coefficients $\hat{h}^{RLS}_{r,j}(n)$ between jth transmit and rth receive antennas are estimated recursively in the time-domain to minimize the sum of the squared errors as

$$\varepsilon(n)=\sum_{i=1}^{n}\lambda^{(n-i)}\big(y_r^{(p)}(i)-\widehat{h}^{RLS}_{r,j}(i)x^{(p)}(i)\big)^2,\quad n=1,\cdots,N_p\tag{13}$$

where the forgetting or weighting factor, λ, $0<\lambda\le 1$ reduces the influence of the old data. The basic steps of the RLS parameter estimation algorithm can be found easily in the open literature and thus will not be given here, [15,26].

4.2. The iterative receiver

Receivers with iterative decision-directed channel estimation (DD-CE) are very attractive since they yield superior error performance [27], especially when operating in the presence of fast time-varying channels and they need less pilot symbols as compared to the non-iterative channel estimators [28]. Moreover, it was also shown that the computational complexity of the receiver [29] can be reduced substantially.

As mentioned in Section 4.1, a pilot-aided RLS algorithm is employed to find the initial channel estimates. Unlike multi-stream MIMO schemes, the SM requires a longer time to transmit pilots as shown in Fig. 1 and the channels for different transmit antennas are individually estimated by the corresponding pilot symbols. The main problem is that we have only one active antenna during transmission so that the other channels could not be known at that time. Therefore, the data symbols transmitted from randomly selected antennas are detected first by means of the initial channel estimates using pilot symbols. As shown in Fig. 2, the channel coefficients, associated with the detected symbols, are then updated. The unknown channel coefficients that cannot be estimated by the

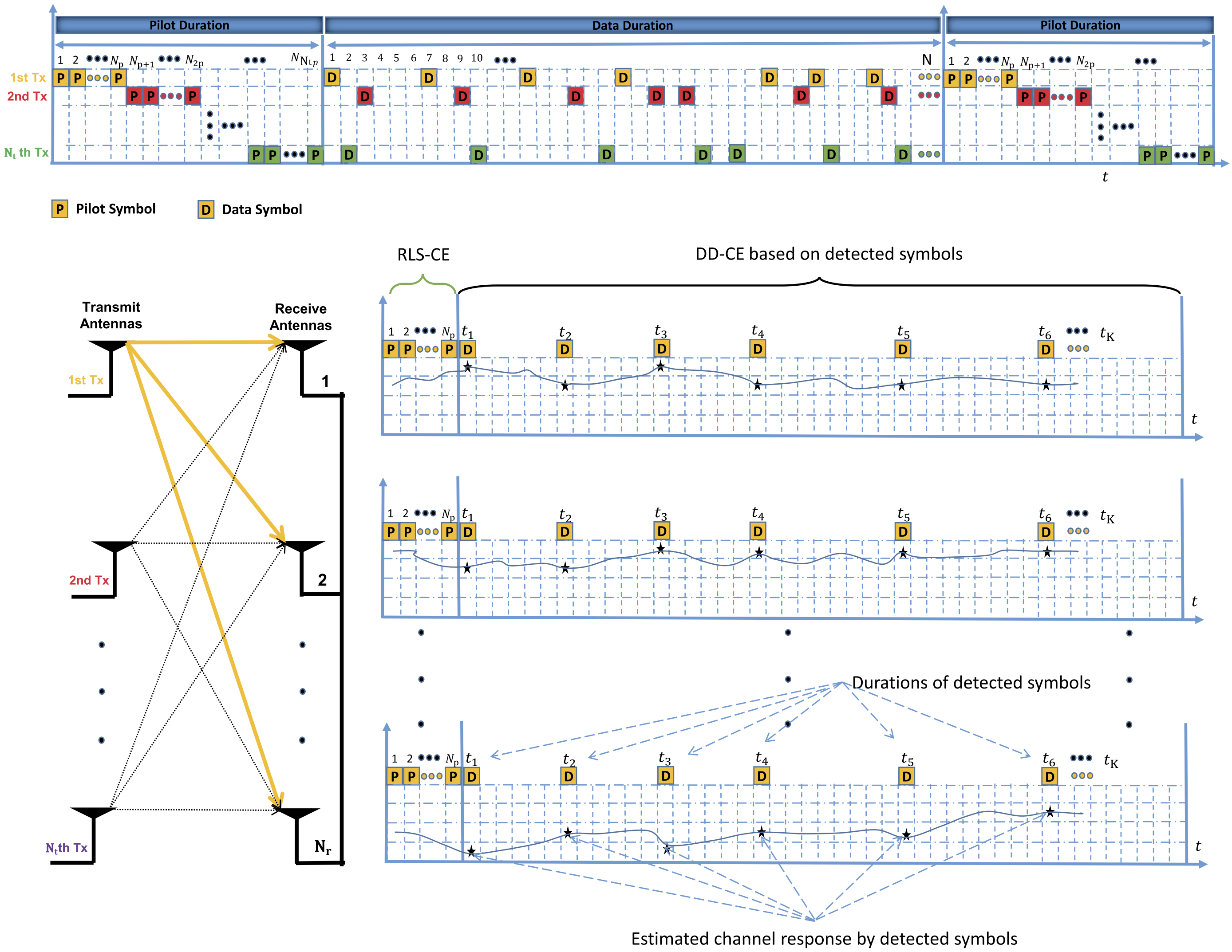

Fig. 1. Channel estimation based on pilot and data durations.

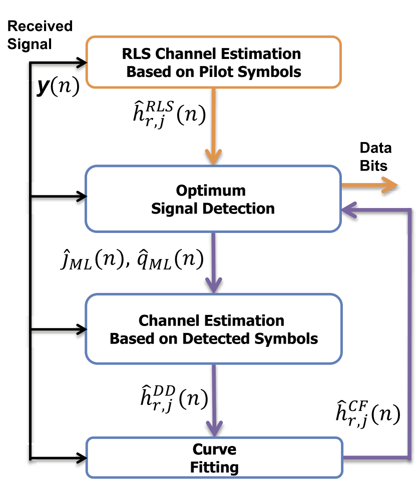

Fig. 2. Proposed iterative receiver structure.

detected symbols are determined by a curve fitting technique. Consequently, the channel estimation algorithm has also the capability of tracking the time-varying channel at the receiver.

If jth transmitter antenna is assumed to be active ($\tau = j$) and transmits the data symbol $x_q(t_k)$ at discrete times t_k, $k = 1, 2, \cdots, K$ within an observation frame of length N ($N \gg K$), the received signal at the rth receiver antenna can be written as:

$$y_r(t_k) = h_{r,j}(t_k) x_q(t_k) + w_r(t_k) \tag{14}$$

In this case, the DD channel estimates at discrete times $t_1, t_2, \cdots, t_K$ can be determined as:

$$\hat{h}^{DD}_{r,\tau=j}(t_k) = y_r(t_k)/\widehat{x}_q(t_k), \quad t_k \in \{1, 2, \cdots N\} \tag{15}$$

where $\widehat{x}_q(t_k)$ represents the detected symbol at the t_kth symbol duration. Note that there are approximately $K = N/N_t$ symbols detected for each channel if we assume that the transmitted antennas are selected with equal probabilities. The detected symbols are then updated iteratively, employing the last updated channel estimates for the next iteration, as shown in Fig. 2.

4.3. Curve fitting

By means of a polynomial curve fitting at discrete times $t_1, t_2, \cdots, t_K$, the estimated channel coefficients, $\hat{h}^{DD}_{r,\tau}(t_k)$, $\tau = j$ between τth transmit and jth receive antennas can be modeled as a $(L-1)$th degree polynomial

$$\hat{h}^{DD}_{r,\tau}(t_k) = \theta_{r,\tau}(1) + \theta_{r,\tau}(2) t_k + \cdots + \theta_{r,\tau}(L) t_k^{L-1} + u_{r,\tau}(t_k) \tag{16}$$

where $u_{r,\tau}(t_k)$ is a random modeling error assumed to be zero-mean Gaussian with variance σ_u^2, conditioned on the scalar variable t_k. Then we have the following usual linear model:

$$\widehat{\mathbf{h}}_{r,\tau}^{DD} = \mathbf{T}\boldsymbol{\theta}_{r,\tau} + \mathbf{u}_{r,\tau} \tag{17}$$

where,

$$\widehat{\mathbf{h}}_{r,\tau}^{DD} = \left[\widehat{h}_{r,\tau}^{DD}(t_1), \widehat{h}_{r,\tau}^{DD}(t_2), \cdots, \widehat{h}_{r,\tau}^{DD}(t_K)\right]^T$$
$$\mathbf{u}_{r,\tau} = \left[u_{r,\tau}(t_1), u_{r,\tau}(t_2), \cdots, u_{r,\tau}(t_K)\right]^T$$
$$\boldsymbol{\theta}_{r,\tau} = \left[\theta_{r,\tau}(1), \theta_{r,\tau}(2), \cdots, \theta_{r,\tau}(L)\right]^T$$
$$\mathbf{T} = \begin{bmatrix} 1 & t_1 & \cdots & t_1^{L-1} \\ 1 & t_2 & \cdots & t_2^{L-1} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & t_K & \cdots & t_K^{L-1} \end{bmatrix}$$

where K is the total number of samples for curve fitting and the observation matrix $\mathbf{T}$ has the form of a Vandermonde matrix. The minimum variance unbias (MVU) estimator for $\boldsymbol{\theta}_{r,\tau}$ is [30]

$$\widehat{\boldsymbol{\theta}}_{r,\tau} = \left(\mathbf{T}^T\mathbf{T}\right)^{-1}\mathbf{T}^T\widehat{\mathbf{h}}_{r,\tau}^{DD}. \tag{18}$$

Then the resulting curve fitting for all discrete times $n = 1, 2, \cdots, N$ is

$$\widehat{h}_{r,\tau}^{CF}(n) = \sum_{i=1}^{L}\widehat{\theta}_{r,\tau}(i)t_n^{i-1}. \tag{19}$$

The time-varying channel can be estimated using (19) over the duration of one frame. After the channel estimation step, the data symbols are detected as shown in Fig. 2. Note that the wrong/poor symbol and antenna index detections made by the SM-MIMO receiver may cause some error accumulation that could affect the mean-square error performance of the channel estimation algorithm. However, our extensive computer simulations as well as the work in [12] show that wrongly detected antenna indices rarely occur and the polynomial fitting, employed in the channel estimation algorithm, reduces this effect by means of the other correct detected antenna indexes. Periodic pilot blocks are also inserted in the decision-directed estimation mode to reduce further the error propagation effect.

5. Performance limits of the channel estimation algorithm

To serve as a benchmark, we now derive an overall Bayesian MSE bound for the channel estimator proposed in this paper [31]. The overall MSE for the channel impulse response vector can be expressed as the sum of the truncation MSE and estimation MSE:

$$\mathrm{MSE_{all}} = \mathrm{MSE_{trun}} + \mathrm{MSE_{est}}. \tag{20}$$

We assume that all the channel coefficients of the spatial modulated MIMO system, between transmit and receive antennas, $\{h_{r,\tau}(n)\}$, $r = 1, 2, \cdots, N_r$, $\tau = 1, 2, \cdots, N_t$, are fast-time varying, frequency non-selective Rayleigh fading and independent of each other. Consequently, the performance bounds obtained below are independent of the label of the transmit antenna, τ, selected from the set of the transmit antennas randomly with equal probability. Therefore, we will drop the subscript τ for notational simplicity. The truncation MSE, $\mathrm{MSE_{trun}}$, can be evaluated as follow:

$$\mathrm{MSE_{trun}} = \frac{1}{N_r N}\sum_{r=1}^{N_r} E_{\mathbf{h}'_r,\mathbf{h}_r^{opt}}\left\{\left(\mathbf{h}'_r - \mathbf{h}_r^{opt}\right)^{\dagger}\left(\mathbf{h}'_r - \mathbf{h}_r^{opt}\right)\right\} \tag{21}$$

where, $\mathbf{h}'_r = [h_r(1), h_r(2), \cdots, h_r(N)]^T$ and $\mathbf{h}_r^{opt}$ is the optimal polynomial in (19) which is the least-squares fitted to $\mathbf{h}'_r$ and its optimal coefficient vector $\widehat{\boldsymbol{\theta}}_r = [\widehat{\theta}_r(1), \widehat{\theta}_r(2), \cdots, \widehat{\theta}_r(L)]^T$ is given by [32]

$$\mathbf{h}_r^{opt} = \tilde{\mathbf{T}}\widehat{\boldsymbol{\theta}_r} \quad \text{and} \quad \widehat{\boldsymbol{\theta}_r} = \left(\tilde{\mathbf{T}}^T\tilde{\mathbf{T}}\right)^{-1}\tilde{\mathbf{T}}^T\mathbf{h}'_r, \tag{22}$$

where $\tilde{\mathbf{T}}$ is $N \times L$ matrix. From (22) it follows that

$$\mathbf{h}_r^{opt} = \boldsymbol{\Upsilon}\mathbf{h}'_r \tag{23}$$

where $\boldsymbol{\Upsilon} \triangleq \tilde{\mathbf{T}}(\tilde{\mathbf{T}}^T\tilde{\mathbf{T}})^{-1}\tilde{\mathbf{T}}^T$. Than it can be easily show from (21) that

$$\mathrm{MSE_{trun}} = \frac{1}{N}\operatorname{tr}\left\{\left(\mathbf{I}_N - \boldsymbol{\Upsilon}^{\dagger}\right)\mathbf{C}_{\mathbf{h}_r}\left(\mathbf{I}_N - \boldsymbol{\Upsilon}\right)\right\}, \tag{24}$$

where $\mathbf{C}_{\mathbf{h}_r}$ represents the covariance matrix of the channels between any transmit and receive antennas whose (m, n)th element is given by (5).

We now evaluate the Bayesian mean-square estimation error, $\mathrm{MSE_{est}}$ in (20) as follows. Received signal given in (6) model, can be expressed at discrete times $t_1, t_2, \cdots, t_K$, between any transmit antenna and the rth receive antenna as

$$\mathbf{y}_r = \mathbf{X}_q\mathbf{h}_r + \mathbf{w}_r, \quad r = 1, 2, \cdots, N_r \tag{25}$$

where

$$\mathbf{y}_r = \left[y_r(t_1), y_r(t_2), \cdots, y_r(t_K)\right]^T,$$
$$\mathbf{h}_r = \left[h_r(t_1), h_r(t_2), \cdots, h_r(t_K)\right]^T,$$
$$\mathbf{X}_q = \operatorname{diag}\left[x_q(t_1), x_q(t_2), \cdots, x_q(t_K)\right],$$
$$\mathbf{w}_r = \left[w_r(t_1), w_r(t_2), \cdots, w_r(t_K)\right]^T.$$

Note that $h_r(t_k)$ is independent of $h_{r'}(t_k)$ for $r \neq r'$. Using the relation $\mathbf{h}_r = \mathbf{T}\boldsymbol{\theta}_r + \mathbf{u}_r$ in (19), we have

$$\mathbf{y}_r = \boldsymbol{\Psi}_q\boldsymbol{\theta}_r + \mathbf{v}_r, \quad r = 1, 2, \cdots, N_r \tag{26}$$

where $\boldsymbol{\theta}_r = [\theta_1, \theta_2, \cdots, \theta_L]^T$, $\boldsymbol{\Psi}_q \triangleq \mathbf{X}_q\mathbf{T}$ and $\mathbf{v}_r = \mathbf{w}_r + \mathbf{u}_r$. Since we assume that the polynomial fitting error vector $\mathbf{u}_r$ is zero-mean Gaussian with covariance matrix $\sigma_u^2\mathbf{I}_K$, it is clear that the overall additive noise vector $\mathbf{v}_r$ is also Gaussian having the covariance matrix $\sigma^2\mathbf{I}_K$ with $\sigma^2 \triangleq \sigma_w^2 + \sigma_u^2$. Then the Bayesian MSE error for the estimator of $\boldsymbol{\theta}_r$ is defined as

$$\mathrm{MSE}_{\widehat{\boldsymbol{\theta}}_r} = \frac{1}{LN_r}\sum_{r=1}^{N_r} E_{\boldsymbol{\theta}_r,\widehat{\boldsymbol{\theta}}_r}\left\{(\boldsymbol{\theta}_r - \widehat{\boldsymbol{\theta}}_r)^{\dagger}(\boldsymbol{\theta}_r - \widehat{\boldsymbol{\theta}}_r)\right\}, \tag{27}$$

where $\widehat{\boldsymbol{\theta}}_r = [\widehat{\theta}_r(1), \widehat{\theta}_r(2), \cdots, \widehat{\theta}_r(L)]^T$ is given by (18). The left hand side of (27) can be lower bounded as

$$E_{\boldsymbol{\theta}_r,\widehat{\boldsymbol{\theta}}_r}\left\{(\boldsymbol{\theta}_r - \widehat{\boldsymbol{\theta}}_r)^{\dagger}(\boldsymbol{\theta}_r - \widehat{\boldsymbol{\theta}}_r)\right\} = \operatorname{tr}\left\{E_{\boldsymbol{\theta}_r,\widehat{\boldsymbol{\theta}}_r}\left\{(\boldsymbol{\theta}_r - \widehat{\boldsymbol{\theta}}_r)(\boldsymbol{\theta}_r - \widehat{\boldsymbol{\theta}}_r)^{\dagger}\right\}\right\}$$
$$\geq (\mathbf{J}_{\theta_r} + \mathbf{C}_{\theta_r})^{-1} \tag{28}$$

where $\mathbf{J}_{\theta_r}$ is the Fisher information matrix (FIM) and $\mathbf{C}_{\theta_r}$ is the covariance matrix of the prior probability distribution of $\boldsymbol{\theta}_r$ and it can be determined from (22) as

$$\mathbf{C}_{\theta_r} = \left(\mathbf{T}\mathbf{T}^T\right)^{-1}\mathbf{T}^T\mathbf{C}_{\mathbf{h}_r}\mathbf{T}\left(\mathbf{T}\mathbf{T}^T\right)^{-1} \tag{29}$$

where $\mathbf{C}_{\mathbf{h}_r}$ is the autocorrelation matrix of $\mathbf{h}_r$ with elements given by (5). On the other hand, for the linear observation model in (26), the FIM of $\boldsymbol{\theta}_r$ is given by [30]

$$\mathbf{J}_{\theta_r} = \frac{E_{\mathbf{X}_q}\{(\boldsymbol{\Psi}_q^{\dagger}\boldsymbol{\Psi}_q)^{-1}\}}{\sigma^2} \tag{30}$$

The expectation in (30) can be taken easily in the case of constant envelope data symbols. Otherwise, it can be evaluated by using a tight lower bound $E\{X\} \geq 1/E\{X\}$ resulting

Table 1
Complexity analysis.

Equation number	RLS-CE		Iterative-CE	
	$\times$	$+$	$\times$	$+$
	$12N_p$	$4N_p$	$12N_p$	$4N_p$
(15)	–	–	K	–
(18)	–	–	$L^2K+LK+O(L^2)+L^2$	$L^2K+LK-2L$
(19)	–	–	$(L-1)N$	$(L-1)N$
Total	$12N_p$	$4N_p$	$K(L^2+L+1)+N(L-1)+12N_p+O(L^2)+L^2$	$K(L^2+L)+N(L-1)+4N_p-2L$

$$\mathbf{J}_{\theta_r} \geq \frac{E_s}{\sigma^2}\left(\mathbf{T}^\dagger \mathbf{T}\right)^{-1} \tag{31}$$

where $E_s \triangleq E\{|x_q(t_k)|^2\}$ and $\mathbf{J}_{\theta_r}$ achieves the lower bound when constant envelope symbols are employed.

Consequently, the mean-square estimation error $\mathrm{MSE_{est}}$ for the channel vector from any transmit antenna to the rth receive antenna for $r = 1, 2, \cdots, N_r$ is defined as

$$\mathrm{MSE_{est}} = \frac{1}{KN_r}\sum_{r=1}^{N_r} E_{\mathbf{h}_r,\widehat{\mathbf{h}}_r}\left\{(\mathbf{h}_r - \widehat{\mathbf{h}}_r)^\dagger(\mathbf{h}_r - \widehat{\mathbf{h}}_r)\right\} \tag{32}$$

where ignoring the truncation error, $\widehat{\mathbf{h}}_r = \mathbf{T}\widehat{\boldsymbol{\theta}}_r$ and $\mathbf{h}_r = \mathbf{T}\boldsymbol{\theta}_r$. Using (28) in (32) and after some algebra we have

$$\mathrm{MSE_{est}} \geq \frac{1}{K}\,\mathrm{tr}\left\{\mathbf{T}\left(\mathbf{J}_{\theta_r} + \mathbf{C}_{\theta_r}^{-1}\right)^{-1}\mathbf{T}^T\right\}. \tag{33}$$

Finally, the overall Bayesian MSE lower bound of the proposed channel estimator can be expressed from (20), (24), (31) and (32) as follows:

$$\mathrm{MSE_{all}} \geq \frac{1}{N}\,\mathrm{tr}\left\{\left(\mathbf{I}_N - \boldsymbol{\Upsilon}^\dagger\right)\mathbf{C}_{\mathbf{h}_r}(\mathbf{I}_N - \boldsymbol{\Upsilon})\right\} + \frac{E_s}{K\sigma^2}\,\mathrm{tr}\left\{\mathbf{T}\left(\left(\mathbf{T}^T\mathbf{T}\right)^{-1} + \mathbf{C}_{\theta_r}\right)^{-1}\mathbf{T}^T\right\}. \tag{34}$$

6. Computational complexity

Computational complexity of the iterative receiver proposed in this work is determined by the parameters N_p, K, N and L. Computational load to implement the RLS and the iterative channel estimation algorithms are summarized in Table 1.

The RLS-based initial channel estimates (RLS-CE) are determined by the associated pilot symbols transmitted through the active antennas. Therefore, the whole algorithm requires $12N_p$ complex multiplications (CMs) and $4N_p$ complex additions (CAs) per channel [15].

On the other hand, the computational load to implement the iterative-CE scheme is based on Eqs. (15), (18) and (19) as well as on the RLS-CE algorithm for initialization. We need K CMs to calculate the channel by the detected symbols in (15). According to (18), computation of $\mathbf{T}^T\mathbf{T}$ requires[1] L^2K real multiplications (RMs) and $L^2(K-1)$ real additions (RAs) where $\mathbf{T}$ is $K \times L$ matrix. The computational complexity to evaluate $(\mathbf{T}^T\mathbf{T})^{-1}$ is[2] $O(L^2)$ [33]. The product of $\mathbf{T}^T$ with $\widehat{\mathbf{h}}_{r,\tau}^{DD}$ requires LK CMs and $L(K-1)$ CAs. Then to evaluate the term $(\mathbf{T}^T\mathbf{T})^{-1}\mathbf{T}^T\widehat{h}_{r,\tau}^{DD}$, on the right hand side of (18) requires L^2 CMs and $L^2 - L$ CAs. Consequently, to compute Eq. (18) overall $L^2K + LK + O(L^2) + L^2$ multiplications and $L^2K + LK - 2L$ additions are required. According to (19), we need $(L-1)N$ CMs and $(L-1)N$ CAs.

Finally, total complexity of the curve fitting is equal to $K(L^2 + L + 1) + N(L-1) + 12N_p + O(L^2) + L^2$ multiplications and $K(L^2 + L) + N(L-1) + 4N_p - 2L$ additions for per channel. Note that iterations will require recalculations of (15), (18), (19). In [19], the channel estimation with a polynomial time-varying channel model was investigated and a polynomial order (L) selection probability was given. Similarly, in this work, it is concluded that the degree of polynomial takes small values within the acceptable range of Doppler frequencies in practice to track the channel variations. Therefore, the computational complexity of the iterative-CE is quite feasible for real applications.

7. Simulation results

In this section, performance of an $N_t \times N_r$ SM-MIMO system is investigated based on the proposed channel estimation for various velocities of mobile users in the presence of Rician channels having different Rician factors.

Two benchmarks are considered in our computer simulations for comparison: i) the conventional RLS channel estimation, which is denoted as “RLS-CE” in the sequel; ii) perfect channel state information (P-CSI). Main parameters chosen for the simulations are as follows:

- RLS parameters are selected as $\mu = 0.0005$ and $\lambda = 1$.
- Four receiver antennas are considered in all cases. SM mappings are shown for 2×4 and 4×4 in Fig. 3 and Fig. 4 respectively.
- The symbol duration and the carrier frequency are selected as 1μ sn and 1.8 GHz respectively.
- We have the same signal-to-noise ratio (SNR) value at each receiver antenna.
- The SNR is defined as $\frac{E_s}{\sigma^2}$ where E_s is energy per symbol and σ^2 is noise power.
- In all simulations except Figs. 7, 9 and 10, one iteration is employed for the proposed receiver.
- The channel between transmitter and receiver is modeled as rapidly time-varying Rician fading channel where Doppler effect is taken into consideration.

7.1. Application scenario-1: 2×4 SM-MIMO system

Bit error rate (BER) performance of the SM-MIMO system with two transmit antennas and four receiver antennas are investigated using 4-QAM signaling. Total number of pilot and data symbols are selected as $N_p = 12$ and $N = 216$ respectively. In Fig. 5, the BER performance of the proposed iterative-CE is compared with the RLS-CE scheme assuming P-CSI and $V = 150$ km/h ($f_d = 250$ Hz) over Rician fading channel having $R = 7$. The initial channel coefficients are determined first by the RLS-CE technique using the pilot symbols [15]. The iterative-CE is then implemented to obtain the enhanced channel estimates as described in Fig. 2.

Computer simulation results in Fig. 5 show that the BER performance of the iterative-CE is better than that of the RLS-CE while

[1] The total real multiplications (RMs) and real additions (RAs) to evaluate the multiplication of $L \times K$ matrix with $K \times N$ matrix are LKN and $L(K-1)N$ respectively.

[2] The computational complexity of an $L \times L$ Vandermonde matrix inversion is $O(L^2)$.

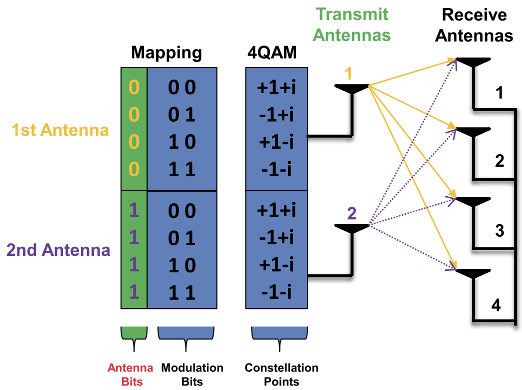

Fig. 3. Spatial modulation mapping: 3-bits transmission using 4-QAM, two transmit antennas and four receiver antennas.

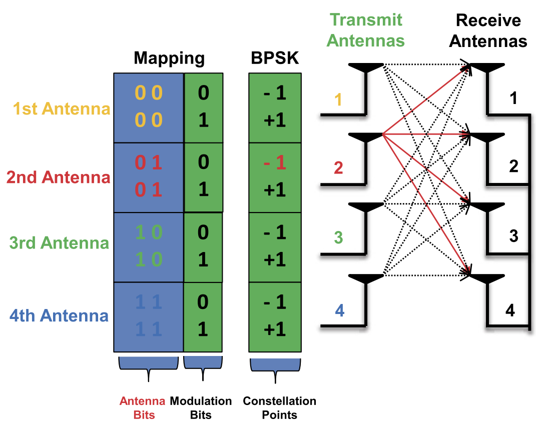

Fig. 4. Spatial modulation mapping: 3-bits transmission using BPSK, four transmit antennas and four receiver antennas.

it achieves the BER performance of that of the P-CSI. In particular, it is observed that about 2 dB gain is achieved at $BER = 10^{-6}$, as compared with the RLS-based receiver.

The effect of the Rician channel factor, R, on the BER performance is investigated in Fig. 6. It is shown that as R increases from 0 to 10, the BER increases and difference in BER performance between the RLS-CE and the iterative-CE increases for small values of R. In other words, the RLS-CE with $R = 0$ and the iterative-CE with $R = 2$ have the same performances at $SNR = 16$ dB. Therefore, the iterative-CE has about 2 dB Rician factor gain at $BER = 10^{-5}$, as compared with the RLS-CE.

7.2. Application scenario-2: 4 × 4 SM-MIMO system

In order to show the potential advantages of iterative-CE, $V =$ 150 km/h with Rayleigh fading channel is considered in Fig. 7. It is shown that the RLS-CE exhibits an error floor at high velocity and high SNRs while iterative-CE has similar BER performance to the P-CSI case. In Fig. 7, it shown that additional iterations may help to improve the performance of the iterative-CE, and that increasing the number of iterations enable the algorithm to approach the performance of the P-CSI case. As indicated in Fig. 7 that four iterations would be sufficient for the proposed iterative-CE scheme to converge.

The main objective of this paper is to propose a robust and efficient channel estimation to support permanent accessibility and high data rates for users employing the SM-MIMO systems in a highly mobile environment. Therefore, finally, the effect of velocity on the BER performance is also investigated and the computer simulation results are presented in Fig. 8. As can be seen, mobility

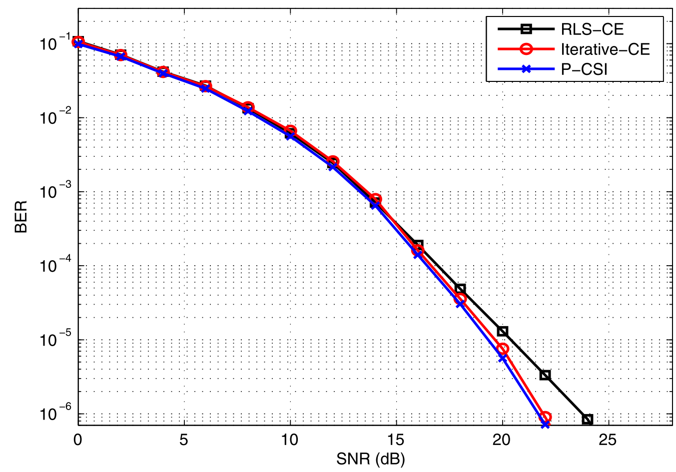

Fig. 5. BER comparison of the RLS estimator and proposed iterative based channel estimator for $V = 150$ km/s, $R = 7$, $N_t = 2$.

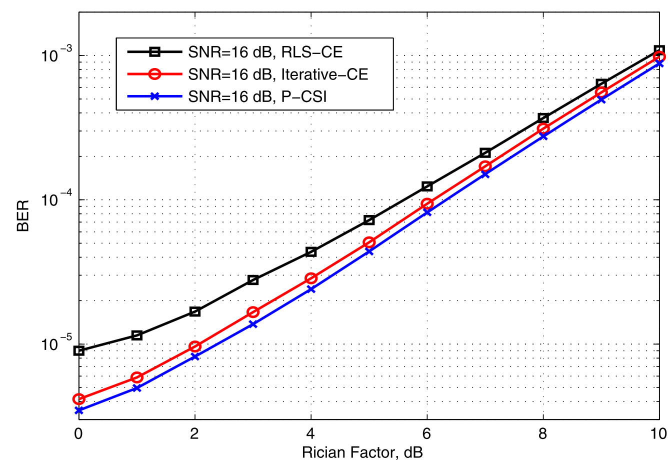

Fig. 6. Behavior of the BER with respect to the Rician factors for $V = 150$ km/s, $SNR = 16$ dB, $N_t = 2$.

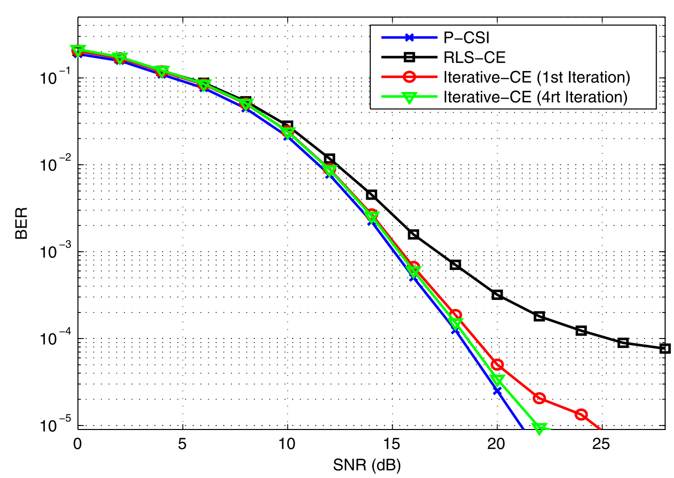

Fig. 7. BER comparison of 4 × 4 SM-MIMO system for Rayleigh fading channel with $V = 150$ km/h, $R = 7$, $N_t = 4$.

has a substantial impact on the performance of the RLS-CE technique while the proposed iterative-CE is more robust.

In mobile wireless channels the bandwidth efficiency is at absolute premium, therefore higher modulations such as 16-QAM and 64-QAM are also considered for 4 × 4 SM-MIMO system in Fig. 9. The severe amplitude and phase fluctuations caused by wireless

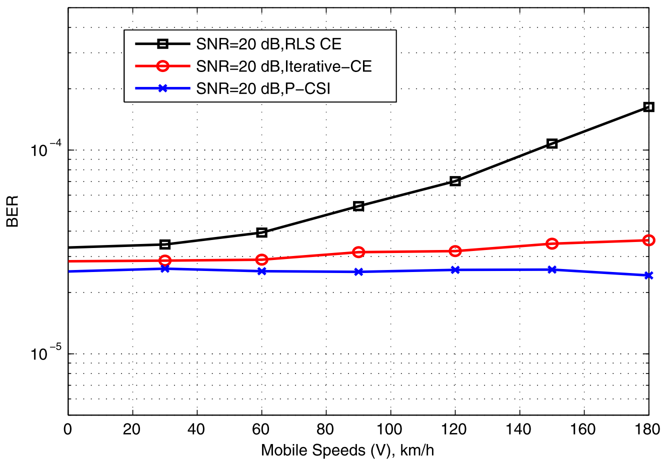

Fig. 8. BER comparison of channel estimators for different mobile speeds with 4 × 4 SM-MIMO system, $R = 7$, $SNR = 20$ dB.

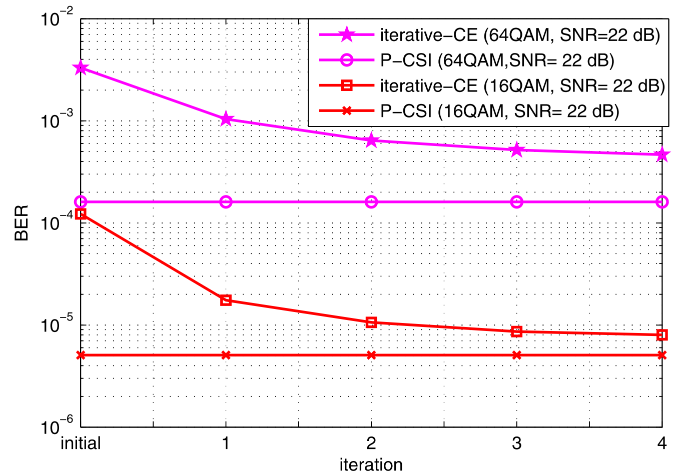

Fig. 10. Iterations 4 × 4 SM-MIMO system, $V = 150$ km/h, $R = 0$.

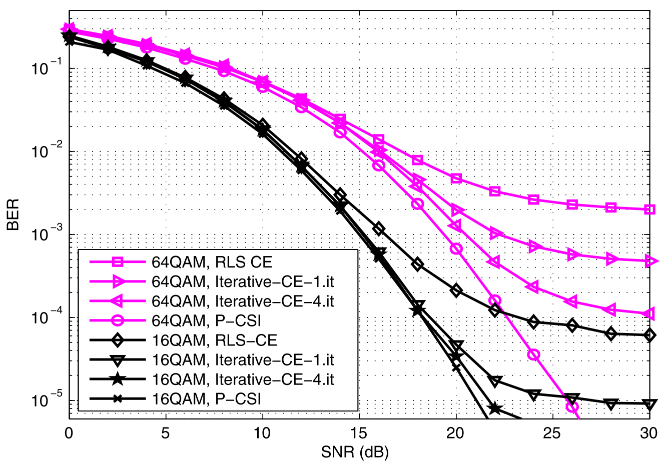

Fig. 9. BER comparison of channel estimators for higher modulations with 4 × 4 SM-MIMO system, $V = 150$ km/h, $R = 0$.

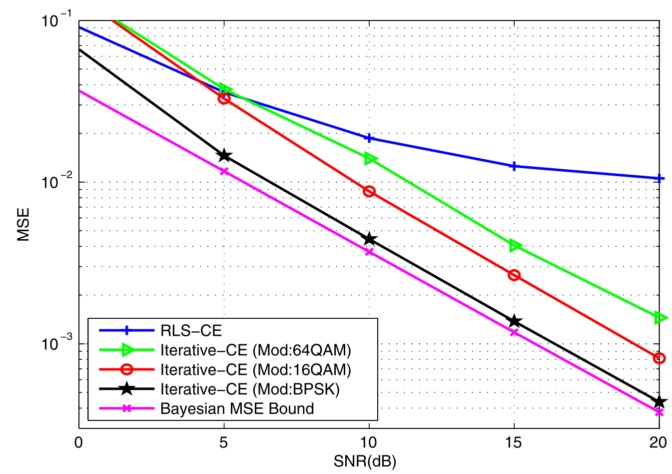

Fig. 11. MSE comparison of channel estimators for time-varying channel with 4 × 4 SM-MIMO systems, $V = 150$ km/h, $R = 0$.

channels significantly degrade the BER performance of M-QAM. In [34], it was shown that the QAM is very sensitive to channel estimation errors and the performance degradation of higher order QAM is more serious than that of lower order QAM for $V = 150$ km/h and $R = 0$. This figure indicates that an error floor occurs for higher order modulations because the iterative channel estimation depends on detected symbols. However, it is concluded that proposed algorithm is robust up to $BER = 10^{-5}$ for 16-QAM modulation. Moreover, it is shown that the proposed channel estimation significantly outperforms the RLS channel estimation for higher modulations. We conclude from Fig. 10 that much more iterations are needed for 16-QAM and 64-QAM to achieve performance close to the perfect CSI case.

7.3. Mean square error (MSE) performance

The SM-MIMO system with four transmit antennas with a BPSK, 16-QAM and 64-QAM modulations are considered for $V = 150$ km/h and $R = 0$. Total number of pilot and data symbols are selected as $N_p = 12$ and $N = 216$ respectively. The proposed iterative channel estimator is compared with previously reported RLS channel estimator, in terms of average MSE for a wide range of signal to noise ratio (E_s/N_0) levels. A MSE lower bound is of particular interest to serve as a bench mark when we compare the channel estimation algorithms. The overall Bayesian MSE lower bound for the channel estimator, obtained analytically in Section 5, is evaluated as a function of SNR in Fig. 11. It can be observed that the MSE performance of the iterative-CE channel estimator is fairly close to the BMSE lower bound depending on the signaling format employed. However, the MSE performance of the RLS-based channel estimation algorithm has substantially lower than that of the iterative-CE algorithm and experiences a large error floor at higher SNRs mainly due to the effect of the rapidly varying channel.

8. Conclusions

In this paper, it was shown that proposed iterative CE algorithm technique employed in SM-MIMO systems has superior BER and MSE performances in the presence of rapidly varying Rician fading channel over the conventional RLS based methods. It was demonstrated by computer simulations that the RLS-based channel estimator has yielded irreducible error floors at higher mobilities and the mobility effect was more devastating effect for channels with lower Rician factor. Based on the extensive computer simulations as well as on the analytical MSE analysis, we concluded that the proposed decision-feedback SM-MIMO receiver structure in which a curve fitting technique is employed to track the channel variations in the case of high mobility provided excellent performance with manageable computational complexity for different SM-MIMO systems such as 2 × 4 4-QAM, 4 × 4 BPSK. A comparison with other previously known RLS-CE algorithm was also made and it was demonstrated that the iterative-CE provides performance that is close to that of the perfect CSI for realistic fading conditions and that the BER performance is more robust against channel variations than that of the RLS-CE technique.

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