Wireless Pers Commun (2017) 94:1387–1404
DOI 10.1007/s11277-016-3687-9

Pilot Symbol Aided Channel Estimation for Spatial Modulation-OFDM Systems and its Performance Analysis with Different Types of Interpolations

Yusuf Acar[1] · Hakan Doğan[2] · Erdal Panayirci[3]

Published online: 10 September 2016

Abstract Spatial modulation orthogonal frequency division multiplexing (SM-OFDM) system has been recently proposed as an alternative for multiple-input multiple-output (MIMO)-OFDM systems to increase spectral efficiency by keeping a low-complexity implementation. In the literature, SM-OFDM systems assume a perfect channel state information (P-CSI) available at the receiver for coherent detection and the channel estimation problem is not considered. It is clear that the channel estimation is a critical issue on the performance of SM-OFDM systems. In this paper, a frame structure where pilot symbols are typically interspersed with data symbols among the sub-carriers to aid the channel estimation is considered. Then the pilot symbol aided channel estimation (PSA-CE) technique with different interpolations is proposed for the SM-OFDM systems. It is shown that in the proposed PSA-CE, equidistantly spaced pilot symbols allow to reconstruct the channel response by means of interpolation if the spacing of the pilots is sufficiently close to satisfy the sampling theorem. Linear, nearest neighbor, piecewise cubic Hermite and the low-pass interpolations are investigated to explore trade-off between complexity and performances. We show that the low pass interpolator yields better

This work is supported in part by the Turkish Scientific and Technical Research Institute(TUBITAK) under Grant 114E011.

✉ Yusuf Acar
y.acar@iku.edu.tr

Hakan Doğan
hdogan@istanbul.edu.tr

Erdal Panayirci
eepanay@khas.edu.tr

[1] Department of Electronics Engineering, Istanbul Kültür University, 34156 Bakirkoy, Istanbul, Turkey

[2] Department of Electrical and Electronics Engineering, Istanbul University, 34320 Avcilar, Istanbul, Turkey

[3] Department of Electrical and Electronics Engineering, Kadir Has University, 34083 Cibali, Istanbul, Turkey

performance than the other interpolation techniques for selected cases such as higher order modulations. The results validate the potential of the proposed PSA-CE estimation applying to SM-OFDM systems.

Keywords Multiple-input multiple-output (MIMO) · Orthogonal frequency division multiplexing (OFDM) · Spatial modulation (SM) · Channel estimation · Interpolation

1 Introduction

The combination of multiple-input multiple-output (MIMO) technology with orthogonal frequency division multiplexing (OFDM) is a promising solution for next-generation fixed and mobile wireless systems [1]. However, some practical problems such as inter antenna synchronization (IAS), interchannel interference (ICI) and antenna spacing substantially limit the performance and capacity of MIMO-OFDM systems [2], [3]. To mitigate MIMO-OFDM problems, the spatial modulation (SM)-OFDM technique employing the indices of transmit antennas to convey information, in addition to the two-dimensional signal constellations has been proposed as a low-complexity implementation of the MIMO systems by Mesleh et al. [4]. As a result, the spatial modulation for OFDM systems is a very attractive technique that provides high spectral efficiency with a low-complexity for systems [5–7].

In SM-OFDM systems, transmitter maps the incoming information bits per subchannel on to a combination of transmit symbol and a indices of transmit antenna. Hence, the transmission is only performed at the selected transmit antenna and other antennas are not active for that particular subchannel and time instant. At the receiver, the transmit antenna number and the received symbol estimated for each subcarrier and transmitted information symbol could be resolved without ICI.

The pioneering works on the coherent SM-OFDM systems have assumed the perfect channel state information (P-CSI) were available at the receiver [4]. As an alternative, a differential scheme for the SM-OFDM based ML detection is proposed with a loss of approximately 4-dB (SNR) for the non-coherent detection [8]. It is clear that differential modulation based SM-OFDM system does not need a channel estimate but its performance is inferior to the coherent SM-OFDM system. Therefore, the channel estimation is crucial for the power efficient SM-OFDM systems. In [9], channel imperfections such as Rician fading, spatial correlation and mutual antenna coupling are investigated and it is shown that the SM-OFDM exhibits a better performance as compared to the V-BLAST in the presence of those channel imperfections. However, channel estimation is not also considered in [9].

Recently, channel estimation has been considered only for a single carrier SM systems [10, 11]. In [10], the iterative channel estimation based detection systems is proposed and compared with the conventional recursive least square (RLS) based channel estimation for SM systems in the presence of rapidly time-varying channels. In [11], differently, the entire channel is estimated by sending the pilot signal through only one antenna to decrease the total number of pilot symbols. It is shown that the performance depends on channel statistics and yields error floors for higher signal to noise ratio (SNR) values [11]. It is clear that the nonselectivity assumption for channel estimation is not reasonable for SM-OFDM systems over frequency selective channels. The pilot symbols based channel estimators

(PSA-CE) is one of the promising techniques for frequency selective channels [12]. The PSA-CE with interpolation techniques is widely used for new wireless communication systems, such as IEEE 802.16 m worldwide interoperability for microwave access (WiMAX) [13], the third generation partnership project (3GPP) and long-term evolution (LTE) Advanced [14]. The PSA-CE with several interpolation techniques based channel estimation for OFDM systems were proposed in [15–17]. It is shown that the piecewise linear interpolation is the frequently used interpolation techniques mainly due to its easy implementation and inherent simplicity.

The classical comp-type based frame structure for MIMO systems is not applicable for SM-OFDM systems because only one transmit antenna is activated while the other antennas do not transmit for each subcarrier. Therefore, we proposed new frame structure for the $N_t \times N_r$ SM-OFDM system. In this work, pilot symbols are inserted systematically in the frequency domain to track the frequency selectivity of the channel. After that, some interpolation techniques are employed to determine the channel frequency responses at data symbols. Note that, designing a PSA-CE with interpolation is quite different and challenging than the conventional PSA-CE techniques due to the special structure of the SM-OFDM systems since in SM system there is only one active antenna during transmission and other channels could not be known at that time.

The rest of our paper is organized as follows. In Sect. 2, we introduce the signal model for the SM-OFDM systems. This is followed by the detection of SM-OFDM systems in Sect. 3. In Sect. 4, the proposed pilot assisted and interpolation based channel estimation is investigated. Computational complexity is given in Sect. 5. Finally, computer simulation results are provided in Sect. 5, while our conclusions are given in Sect. 6.

Notation: Throughout the paper, bold and capital letters '$\mathbf{A}$' denote matrices and bold and small letters '$\mathbf{a}$' denote vectors. The notations, $(.)^*$, $(.)^T$, $(.)^\dagger$ and $\|.\|_F$ denote conjugate, transpose, Hermitian and Frobenius norm, of a matrix or a vector respectively.

2 Spatial Modulation-Orthogonal Frequency Division Multiplexing (SM-OFDM) Systems

Let $\mathbf{B}(k)$ be an $b \times N$ binary matrix, where b is the total number bits per symbol per subcarrier (bits/symbol/subcarrier) and N is the total number of OFDM subcarriers. The data to be transmitted in one subcarrier is shown by the column vectors of $\mathbf{B}(k)$. By using the SM mapping table shown in Fig. 1, the SM maps $\mathbf{B}(k)$ data bits into matrix $\mathbf{X}(k)$ of size $N_t \times N$, where N_t is the total number of transmit antennas. All elements of $\mathbf{X}(k)$ are zero except at the position of the mapped transmit antenna indices. Thus, it has one nonzero value only in each column. For example, three bits can be transmitted by BPSK and four transmit antennas on each subcarrier. Alternatively, quadrature phase shift keying (QPSK) modulation and two transmit antennas can be used to transmit the same number of information bits, as shown in Fig. 1. The number of bits that can be transmitted on each OFDM subchannel can be written as follows:

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

where M is the modulation degree. Then, each row vector of $\mathbf{X}(k)$ is processed by an N-sample inverse fast Fourier transform (IFFT) operation. The N output samples of the IFFT is extended by a guard interval containing G sample cyclic extension whose length is selected to be longer than the expected channel delay spread to avoid the inter symbol

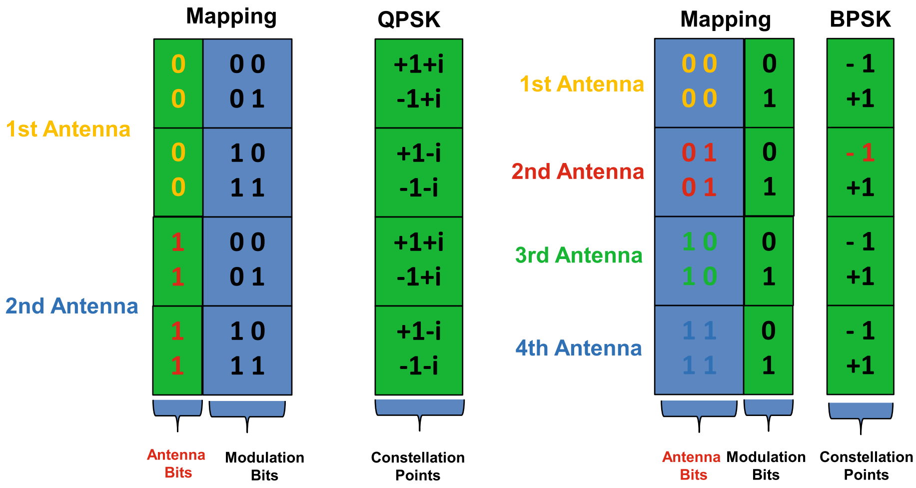

Fig. 1 SM-OFDM mapping table structure

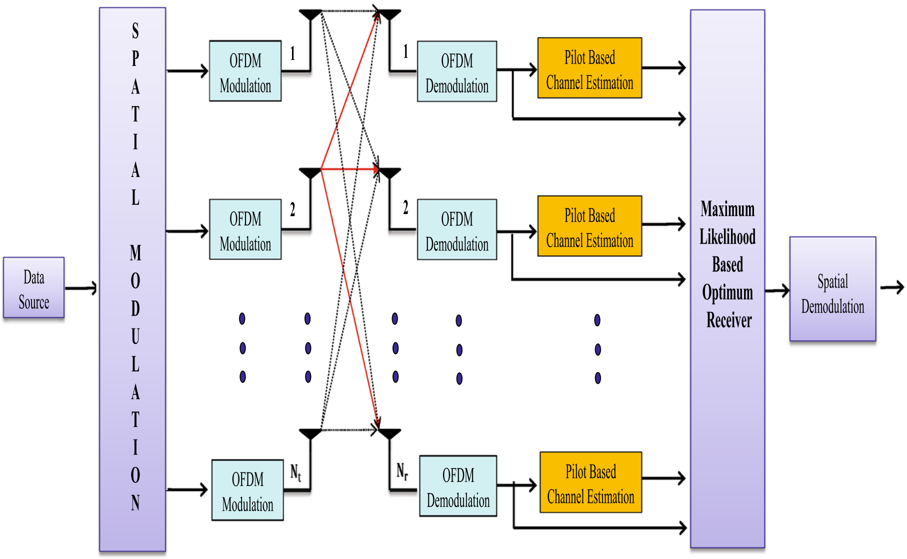

Fig. 2 SM-OFDM block diagram with channel estimation

interference (ISI). The resulting signal is converted into an analog signal by a digital-to-analog (D/A) converter. After pulse shaping with a raised-cosine filter, it is transmitted with the total symbol duration of $T = N_g T_s$ where T_s is the sampling period and $N_g = N + G$. Finally, OFDM symbols at each transmit antennas are simultaneously transmitted from the N_t transmit antennas over the MIMO channel as shown in Fig. 2. At the receiver, after using the analog-to-digital converter (A/D) and deleting the cyclic prefix (CP), a fast Fourier transform (FFT) is applied to each N_r received antennas. The output the OFDM demodulators can be written for kth subcarrier as follows:

$$\begin{bmatrix} y_1(k) \\ \vdots \\ y_r(k) \\ \vdots \\ y_{N_r}(k) \end{bmatrix} = \begin{bmatrix} h_{1,1}(k) & h_{1,2}(k) & \cdots & \cdots & h_{1,N_t}(k) \\ h_{2,1}(k) & h_{2,2}(k) & \cdots & \cdots & h_{2,N_t}(k) \\ \vdots & \vdots & \ddots & & \vdots \\ \vdots & \vdots & & \ddots & \vdots \\ h_{N_r,1}(k) & h_{N_r,2}(k) & \cdots & \cdots & h_{N_r,N_t}(k) \end{bmatrix} \begin{bmatrix} 0 \\ \vdots \\ x_q(k) \\ \vdots \\ 0 \end{bmatrix} + \begin{bmatrix} w_1(k) \\ \vdots \\ w_r(k) \\ \vdots \\ w_{N_r}(k) \end{bmatrix} \tag{2}$$

where $h_{r,j}(k)$ is the channel coefficient between jth transmitter antenna and rth receiver antenna, $x_q(k)$ is the qth active antenna symbol from the M-ary constellation diagram, $w_r(k)$ is complex-valued, zero-mean white Gaussian noise (AWGN) with variance σ_w^2.

The signal model (2) can be expressed in matrix form as follows:

$$\mathbf{y}(k) = \mathbf{H}(k)\mathbf{x}_j(k) + \mathbf{w}(k), \quad k = 1, 2, \ldots, N. \tag{3}$$

where

$$\mathbf{x}_j(k) \triangleq [0 \cdots \underbrace{x_q(k)}_{j.\text{ transmitted antenna}} \cdots 0]^T \tag{4}$$

3 Detection in SM-OFDM Systems

To detect the transmitted symbol and the transmit antenna label the maximum lieklihood (ML) based optimum receiver is used in the frequency domain for each OFDM subchannel as follows:

$$\left[\hat{j}_{ML}, \hat{q}_{ML}\right]_k = \arg\max_{j,q} p_Y(\mathbf{y}(k) \mid x_q(k), \mathbf{h}_j(k)) \tag{5}$$

where $x_q(k)$ is qth symbols from M-QAM constellation and $\mathbf{h}_j(k)$ is jth column of $\mathbf{H}(k)$. The probability density function (PDF) of $\mathbf{y}(k)$ conditioned on $x_q(k)$ and $\mathbf{h}_j(k)$ can be written as:

$$p_Y(\mathbf{y}(k) \mid x_q(k), \mathbf{h}_j(k)) = \pi^{-N_r} \exp\left(\left\|\mathbf{y}(k) - \mathbf{h}_j(k)x_q(k)\right\|_F^2\right) \tag{6}$$

Using (6), the optimal detector given in (5) can be expressed as

$$\left[\hat{j}_{ML}, \hat{q}_{ML}\right]_k = \arg\max_{j,q} \left\|\mathbf{g}_{jq}(k)\right\|_F^2 - 2\Re\text{e}\left\{\mathbf{y}^\dagger(k)\mathbf{g}_{jq}(k)\right\} \tag{7}$$

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

$$\mathbf{g}_{jq}(k) = \mathbf{h}_j(k)x_q(k), \quad 1 \le j \le N_t, \quad 1 \le q \le M. \tag{8}$$

If the receiver detects both $\hat{j}_{ML}$ and $\hat{q}_{ML}$ 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 CSI.

4 Channel Estimation for the OFDM-SM System

The SM-OFDM system needs the CSI to detect modulated symbols and indices of transmit antenna. Therefore, the channel estimation is the essential part of the receiver structure of $N_t \times N_r$ SM-OFDM systems. Wireless communications systems generally operate in the presence of frequency selective fading channel caused by the multipath propagation. Thus, the channel frequency response of a wireless channel may severely change with frequency. We propose a new channel estimation method based on pilot symbols placed properly in each individual data block. The classical comp-type based frame structure for MIMO systems is shown in Fig. 3. However, this frame structure is not applicable for SM-OFDM systems because only one transmit antenna is activated while the other antennas transmit zero for each subcarrier. Therefore, we employ the proposed frame structure of the $N_t \times N_r$ spatial modulated OFDM system as illustrated in Fig. 4.

In Fig. 4, to track the frequency variation of the channel, pilot symbols are inserted periodically over the subcarriers. Consequently, each transmit antenna transmits the pilots for the corresponding OFDM symbol number. For example, as shown in Fig. 4, fourth transmit antenna sends pilot symbols for fourth OFDM symbol.

The received signals at pilot subcarrier (k_p) for each OFDM symbol can be written as follows:

$$\mathbf{y}_b(k_p) = \mathcal{P}\mathbf{h}_b(k_p) + \mathbf{w}_b(k_p), \quad b = 1, 2, \ldots, B \tag{9}$$

where $\mathcal{P}$ is pilot symbol and B equals to the total number of transmit antennas. Then the received blocks are serially operated with the known pilot blocks for estimating the channel frequency response at all pilot positions. From (9), the least square (LS) solution of the observation model with the pilot symbols, can be written as,

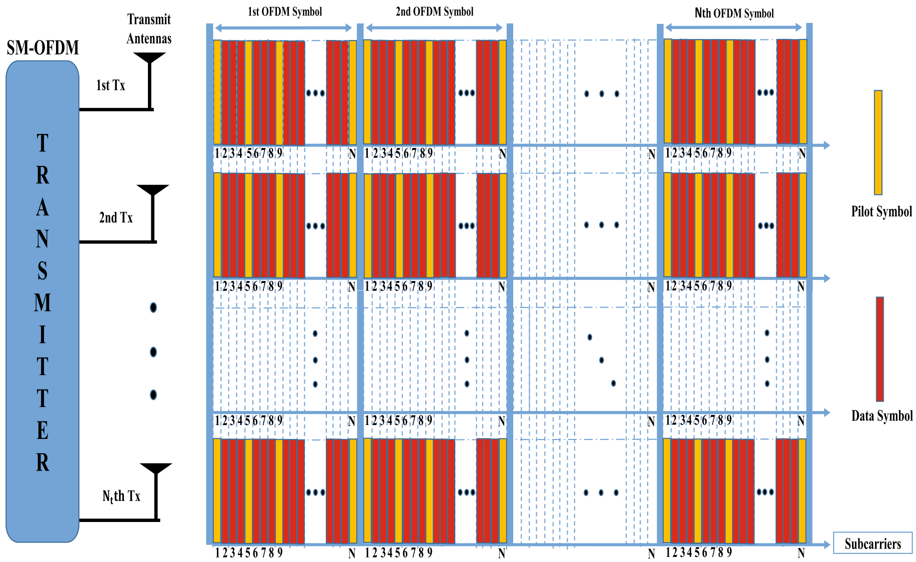

Fig. 3 SM-OFDM frame structure

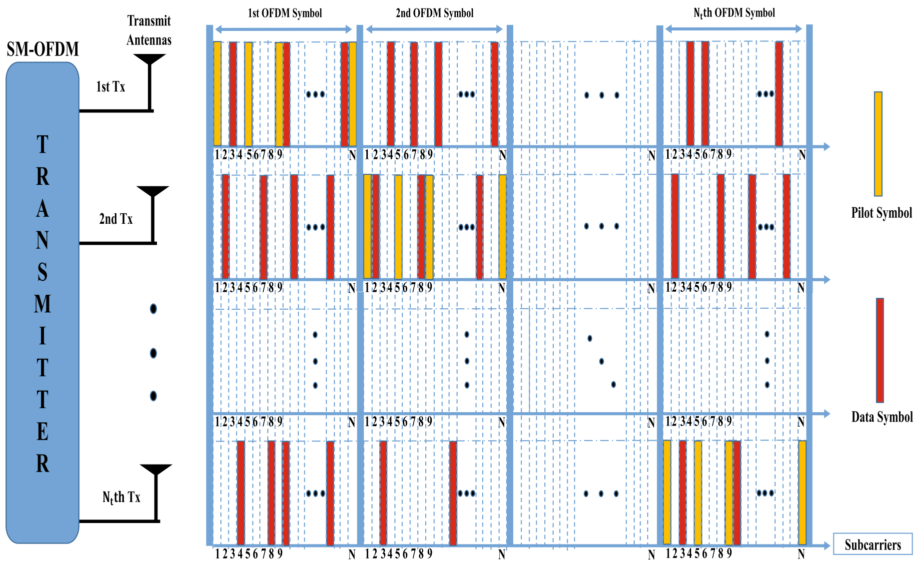

Fig. 4 Comp-type pilot based frame structure for MIMO

$$\widehat{\mathbf{h}}_b(k_p) = \mathbf{y}_b(k)/\mathcal{P}. \tag{10}$$

Channel variations at the data subcarriers should be estimated by an interpolation techniques. In this paper, channel models are considered under quasi-static assumption so that the estimated channel coefficients in the OFDM symbol can be employed as the channel response of the other OFDM symbols in the same frame. We propose a PSA-CE technique for the SM-OFDM systems that efficiently tracks the selectivity of channels. By using the channel frequency response determined at pilot positions, the channel frequency response at data positions is obtained by different interpolation techniques. The channel interpolation algorithms proposed for PSA-CE are discusses in the following subsections.

4.1 Interpolation Techniques

The interpolation methods are used to solve the problems in receiver design caused by pilot overhead. After estimation of the channel frequency responses at pilot positions, whole channel frequency response can be determined by an interpolation technique. Several interpolation techniques have been comparatively considered by Coleri et al. [15], and suggested that the low pass interpolation was preferable among the others mainly due its superior performance .

In the following subsection, we present some potential interpolation techniques for the SM-OFDM systems where $h_{r,j}(k_p), j = 1, 2, \ldots, N_t,\ r = 1, 2, \ldots, N_r$ is estimated channel parameters at the pilot positions $k_p = 0, 1, \ldots, P-1$.

4.1.1 *Piecewise Linear Interpolation*

The piecewise linear interpolation is a very popular and intermittently used with PSA-CE techniques. Thanks to its easy implementation and inherent simplicity [18]. After the channel frequency responses at pilots are estimated by the LS then channel parameters at the positions of data symbols are determined by the piecewise linear interpolation for $r = 1, 2, \ldots, N_r$ and $k_p = 1 : P_l : N$ as follows:

$$h_{r,j}(k) = \hat{h}_{r,j}(k_p) + \left(\hat{h}_{r,j}(k_{p+1}) - \hat{h}_{r,j}(k_p)\right) \times \left(\frac{k - k_p}{P_l}\right) \tag{11}$$

where k_p the is subcarrier position from which pilot symbols are transmitted, P_l is data length between two consecutive pilot positions, $\hat{h}_{r,j}(k_p)$ is the estimated channel frequency responses at pilot positions and $h_{r,j}(k)$ denotes the estimated channel frequency responses at all data positions. $h_{r,j}(k)$ is a linear function of k passing through the points $(k_p, h_{r,j}(k_p))$ and $(k_{p+1}, h_{r,j}(k_{p+1}))$. Note that $h_{r,j}(k)$ is a continuous function of k being decreasing, increasing or constant over the same intervals with the estimated channel coefficients, $\hat{h}_{r,j}(k_p)$, and it is not likely to overshoot $\hat{h}_{r,j}(k_p)$. As a conclusion, the derivative has a constant value on each subinterval and it has jumps at its first derivative. Note that the interval index p must be decided to satisfy $k_p \le k \le k_{p+1}$ at which the pilot symbols located and are usually called "breakpoints" or "breaks".

4.1.2 *Piecewise Cubic Hermite Interpolation*

The piecewise cubic polynomials is the another effective interpolation technique that could be applied for SM-OFDM systems [19]. Consider the following function on the interval $k_p \le n \le k_{p+1}$, expressed in terms of the local variables $m = k - k_p$,

$$\begin{aligned} h_{r,j}(k) = & \frac{3P_l m^2 - 2m^3}{P_l^3} \hat{h}_{r,j}(k_{p+1}) + \frac{P_l^3 - 3P_l m^2 + 2m^3}{P_l^3} \hat{h}_{r,j}(k_p) \\ & + \frac{m^2(m - P_l)}{P_l^2} d_{p+1} + \frac{m(m - P_l)^2}{P_l^2} d_p \end{aligned} \tag{12}$$

where d_p is the slope of the interpolant at k_p and P_l is the length of the subinterval. There are different ways to calculate the values d_p. To obtain the piecewise cubic Hermite interpolation, we describe the *pchip* and *spline* interpolation methods whose slope d_p can be defined properly in some way.

Piecewise Cubic Hermite Interpolating Polynomial (pchip) In this method, the values of the function do not cross out the values at the end of each interval [20]. In other words the pchip guarantees that the interpolated value stays within the limits of the local data points. Let the first-order difference of $\hat{h}_{r,j}(k_p)$ can be defined as

$$\delta_p = \frac{\hat{h}_{r,j}(k_{p+1}) - \hat{h}_{r,j}(k_p)}{P_l}. \tag{13}$$

We assume here that two pilot intervals have the same length. Therefore, we set $d_p = 0$ if δ_p and δ_{p-1} have opposite signs, or if neither of them is zero. In this case, k_p is a discrete local minimum or maximum. For other case, if δ_p and δ_{p-1} have the same sign, then d_p can be evaluated as [21]

$$d_p = \frac{2\delta_{p-1}\delta_p}{\delta_{p-1} + \delta_p}. \tag{14}$$

We can say that, d_p is the harmonic mean of the two discrete slopes and its slopes occur at the interior breakpoints.

Cubic Shape-Preserving Interpolation (Cubic Spline) One of the piecewise cubic Hermite interpolation function is the cubic spline interpolation, that satisfies the same interpolation constraints as the pchip [19]. It has a continuous second derivative and its second derivative is zero at the end breakpoints. All d_p values could be written as follows;

$$\mathbf{Ad} = \mathbf{r} \tag{15}$$

where $\mathbf{d} = [d_0, d_1, \ldots, d_{P-1}]^T$ is a vector of the unknown slopes, d_p and

$$\mathbf{A} = \begin{bmatrix} P_l & 2P_l & & & & \\ P_l & 4P_l & P_l & & & \\ & P_l & 4P_l & P_l & & \\ & & \ddots & \ddots & \ddots & \\ & & & P_l & 4P_l & P_l \\ & & & & P_l & 4P_l \end{bmatrix}$$

is a tridiagonal matrix of P_l. The right-hand side of (15) is $\mathbf{r} = 3\left[\frac{5}{6}P_l\delta_0 + \frac{1}{6}P_l\delta_1, P_l\delta_0 + P_l\delta_1, \ldots, P_l\delta_{P-3} + P_l\delta_{P-2}, \frac{1}{6}P_l\delta_{P-3} + \frac{5}{6}P_l\delta_{P-2}\right]^T$.

As a conclusion, the pchip has only first continuous derivatives. However, the spline has first and second continuous derivatives and is also smoother than the pchip interpolant. Moreover, the pchip is protected to preserve shape, but the spline might not [22].

4.1.3 Low Pass Interpolation

Low-pass interpolation is most effective technique for the channel estimation [18]. In this paper, after estimation channel frequency responses at the pilot position, all frequency responses at the positions of data symbols are initially set to zeros. Then, the low-pass filter is applied to the zero-inserted function to determine the entire channel frequency responses as follows: Firstly, the low pass interpolator inserts $P_l - 1$ zeros between successive samples of the signal $\hat{h}_{r,j}(k_p)$ with a sampling rate f_p, as:

$$\tilde{h}_{r,j}(k) = \begin{cases} \hat{h}_{r,j}(k_p) & \mathrm{k = 0 : P_l : P_l(P-1)} \\ 0 & \text{otherwise.} \end{cases} \tag{16}$$

As a result, the sampling rate of $\tilde{h}_{r,j}(k)$ is increased to $\tilde{f}_p = P_l f_p$. Then, the intermediate signal is convolved with a unit sample response $h(k)$ of the raised-cosine low pass filter, to get the interpolated signal $h_{r,j}(k)$ as follows:

$$h_{r,j}(k) = \sum_{k_p=-\infty}^{\infty} h(k-k_p)\tilde{h}_{r,j}(k_p) \tag{17}$$

where $h(k)$ is designed with a cutoff frequency, specified by $f_c = \frac{\tilde{f}_p}{2P_l} = \frac{f_p}{2}$.

4.1.4 Nearest Interpolation(Zero-Order Hold)

Nearest-neighbor interpolation selects the value of the nearest point until next point. Therefore, it is simplest interpolation among them but it was shown that piecewise-linear interpolation method better than the nearest-neighbor interpolation [23].

To determine the entire channel frequency responses determined by a zero-order hold interpolation which convolves the intermediate signal, $\tilde{h}_{r,j}(k)$, with a $h(k)$ as:

$$h_{r,j}(k) = \sum_{k_p=-\infty}^{\infty} h(k - k_p)\tilde{h}_{r,j}(k_p) \tag{18}$$

where

$$h(k) = \begin{cases} 1, & 0 \leq k \leq D \\ 0, & otherwise. \end{cases} \tag{19}$$

5 Simulation Results

In this section, we provide computer simulation results for the 4×4 SM-OFDM systems to demonstrate the bit error rate (BER) performance of the proposed channel estimation with interpolation under frequency selective channels where the total transmitted power is normalized for the transmit antennas. We also investigate the mean square error (MSE) performances of the proposed channel estimation technique. The data symbols are generated as uncorrelated symbols and the M-level quadrature amplitude modulation (QAM) modulation formats chosen such as 4-QAM, 16-QAM and 64-QAM. The signal to noise ratio (SNR) is defined as E_s/N_0 where E_s is energy per symbol and N_0 is the noise power. The optimum receiver is used for 4×4 SM-OFDM system.

OFDM signal is generated within the 1 MHz bandwidth with $N = 256$ subcarriers and CP is selected as $G = 16$ samples. Each frame consists of 4 OFDM symbols. At the receiver, it is assumed that channel frequency response is estimated with all pilot based channel estimation for a fixed pilot insertion rate (PIR) of one every 8 data symbols. MIMO wireless channels between mobiles antennas and the receiver antennas are modeled based on Typical Urban (TU) and Bad Urban (BU) channel models proposed by the COST-259 project where the channel has the channel length $L = 12$ as shown in Table 1 [24]. We have used LS method to estimate the channel at pilot subcarriers. Then five interpolations were applied with the LS estimation to investigate the interpolations effects.

In Fig. 5, the BER performance of the PSA-CE technique is shown for the 4-QAM signaling under TU channel models. It is not surprising to observe that the performance of the nearest interpolation technique degrades especially for higher SNRs. It is observed that the detection gain between P-CSI case and lowpass interpolation is about 3.2 dB over at $\mathrm{BER} = 10^{-5}$ and the performance of lowpass interpolation is slightly better than the spline interpolation at high SNRs. It is shown that the performance among the comb-type estimation techniques ranges from the best to the worst as follows: the low-pass, the spline, the pchip, the linear and the nearest interpolations. The effect of channel estimation on BER performance of the 4×4 SM-OFDM with BU channel models for 4-QAM signaling is presented in Fig. 6 and similar conclusions are drawn. It is concluded that the lowpass and spline interpolation are also robust for more frequency selective channels.

Table 1 Power delay profile: COST 207 model (TU, BU)

Tab	Typical urban (TU)			Bad urban (BU)		
	Relative delay [us]	Average power	Doppler spectrum	Relative delay [us]	Average power	Doppler spectrum
1	0.0	0.092	Classic	0.0	0.033	Classic
2	0.1	0.115	Classic	0.1	0.089	Classic
3	0.3	0.231	Classic	0.3	0.141	Classic
4	0.5	0.127	Classic	0.7	0.194	GAUS1
5	0.8	0.115	GAUS1	1.6	0.114	GAUS1
6	1.1	0.074	GAUS1	2.2	0.052	GAUS2
7	1.3	0.046	GAUS1	3.1	0.035	GAUS2
8	1.7	0.074	GAUS1	5.0	0.140	GAUS2
9	2.3	0.051	GAUS2	6.0	0.136	GAUS2
10	3.1	0.032	GAUS2	7.2	0.041	GAUS2
11	3.2	0.018	GAUS2	8.1	0.019	GAUS2
12	5.0	0.025	GAUS2	10.0	0.006	GAUS2

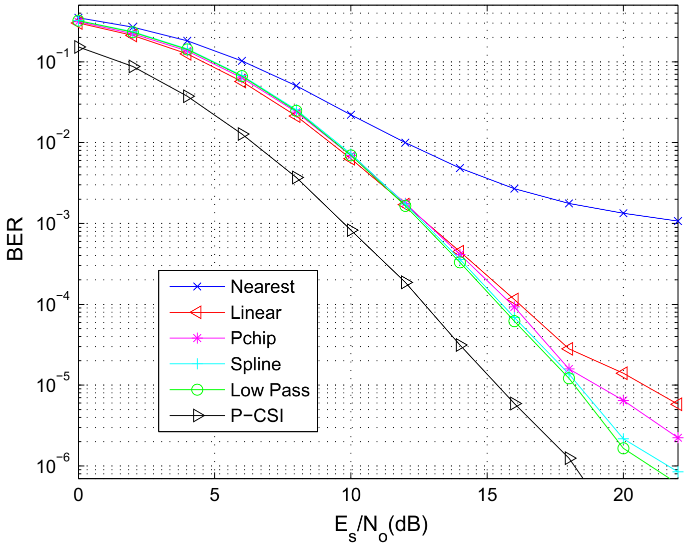

Fig. 5 The BER performance of 4×4 4QAM-SM-OFDM with channel estimation under TU channel models, PIR $= 8$

In Figs. 7 and 8, the effect of channel estimation on BER performance of the 4×4 SM-OFDM with 16-QAM scheme for TU and BU channel models are presented, respectively. It is shown that error floor also observable for the linear and pchip interpolations. The results show that the low pass interpolation schemes outperforms among all interpolation schemes for higher modulation orders. In particular, it is seen that the low pass

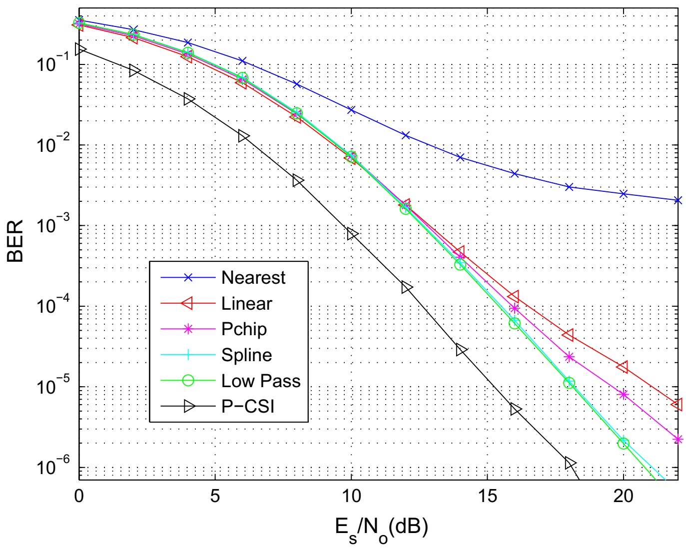

Fig. 6 The BER performance of 4 × 4 4QAM-SM-OFDM with channel estimation under BU channel models, PIR = 8

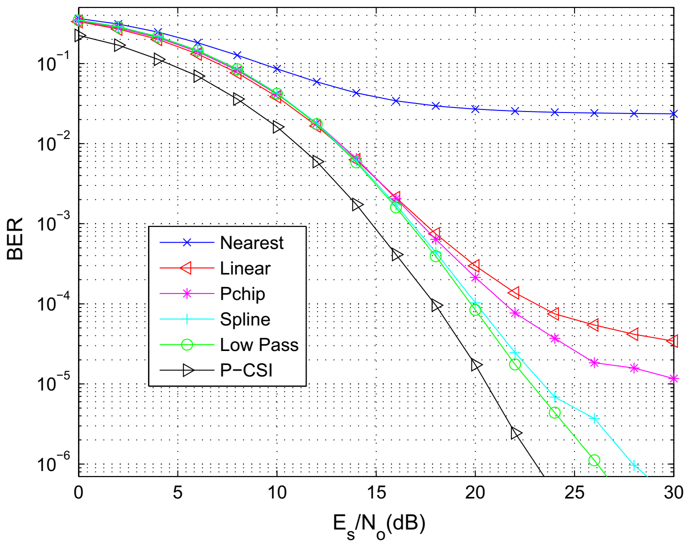

Fig. 7 The BER performance of 4 × 4 16QAM-SM-OFDM with channel estimation under TU channel models, PIR = 8

interpolation exhibits a detection gain of about 0.6 and 7.5 dB over the spline interpolation and the pchip interpolation at a BER value of BER $= 10^{-5}$, respectively.

To achieve higher bandwidth efficiency, the performance of the higher order modulations such as 64-QAM is considered in Figs. 9 and 10 for TU and BU channel models, respectively. The BER performance of the channel estimation algorithm based on the low-

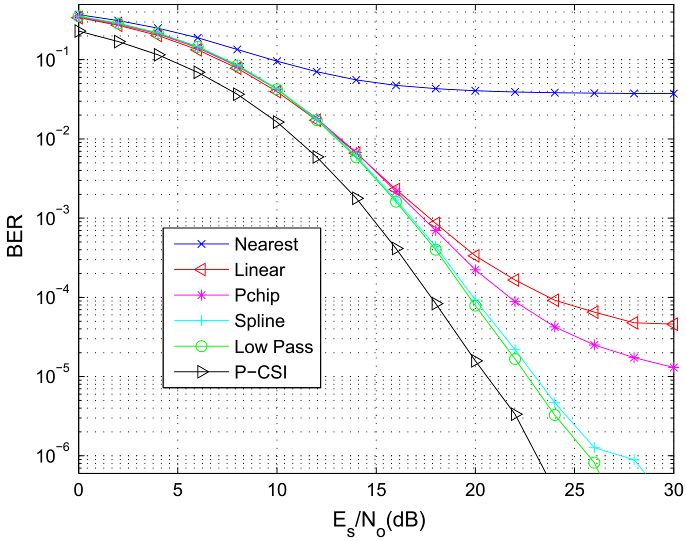

Fig. 8 The BER performance of 4 × 4 16QAM-SM-OFDM with channel estimation under BU channel models, PIR = 8

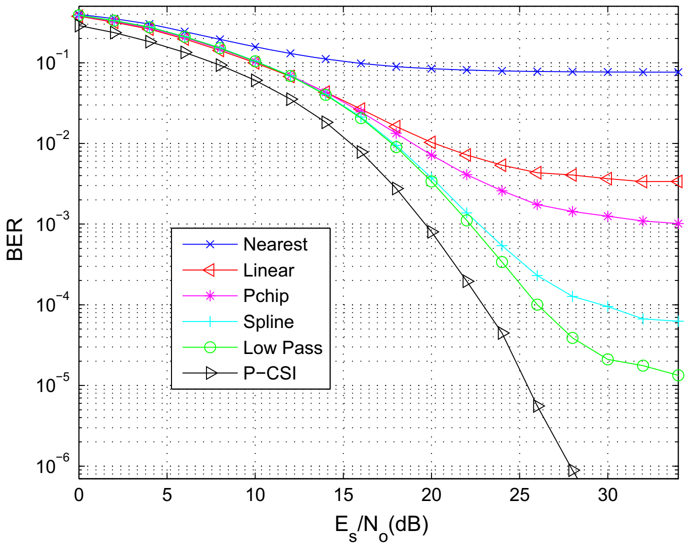

Fig. 9 The BER performance of 4 × 4 64QAM-SM-OFDM with channel estimation under TU channel models, PIR = 8

pass interpolation is substantially better than that of all the proposed interpolation algorithms while it also yields error floor at high SNRs. As can be observed from Fig. 9, due to the resulting severe amplitude and phase fluctuations caused by the wireless channel [25], the BER performance of the spline interpolation, pchip interpolation, linear interpolation and nearest interpolation are degraded due to the higher order modulation type. For

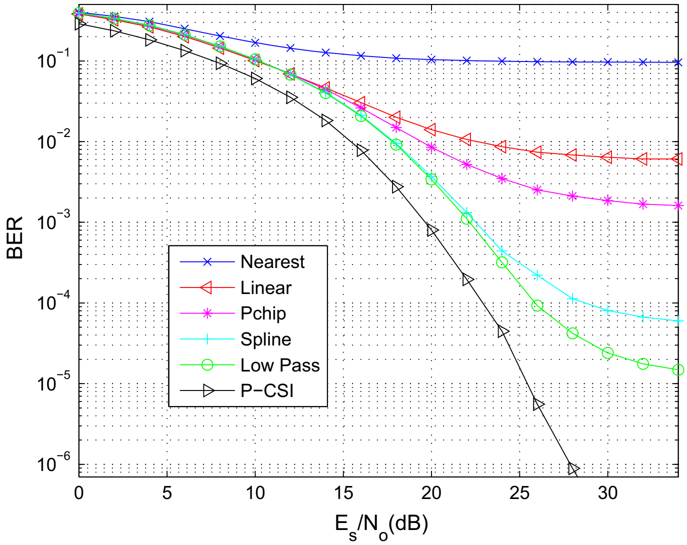

Fig. 10 The BER performance of 4 × 4 64QAM-SM-OFDM with channel estimation under BU channel models, PIR = 8

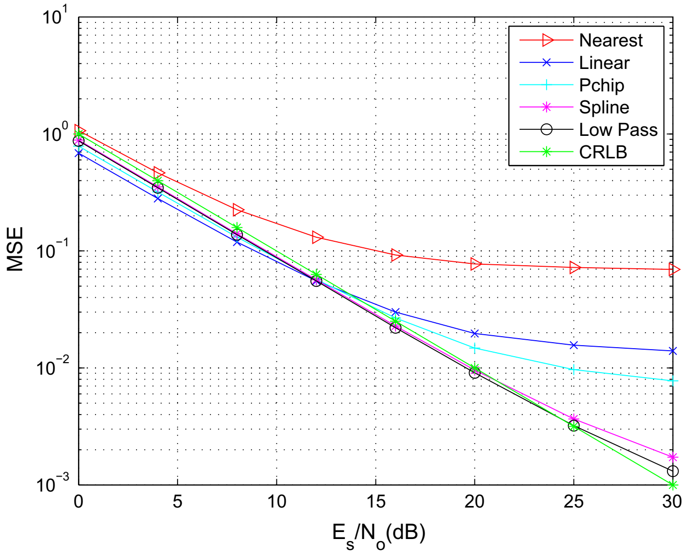

Fig. 11 The MSE performance of 4 × 4 16QAM-SM-OFDM with channel estimation under TU channel models, PIR = 8

instance, in Fig. 10 it is demonstrated that the low pass interpolation exhibits a detection gain of about 2.5 dB over the spline interpolation at a BER value of 10^{-4}. It also is shown that the nearest, linear and pchip interpolation methods has irreducible error floors at high SNRs.

Table 2 Tradeoffs for interpolations

Method	Advantages	Disadvantage
Nearest	Simplest method	Irreducible error floor
	There is no computational complexity at the non-pilot locations	
Linear	Superior BER performance as compared to the nearest method	Higher computational computational complexity than the nearest interpolation
		The BER performance of the linear interpolation degrades significantly in the presence of frequency selective channels for higher order modulations
pchip	Better BER performance than the linear interpolation	Due to its oscillatory response, an additional complexity is introduced as compared with linear interpolation techniques
		The BER performance of pchip is also significantly degraded due to the high order modulation such as 16-QAM and 64-QAM
Spline	Better BER performance than linear interpolation	Due to its oscillatory response, an additional complexity is introduced as compared with linear interpolation techniques
	The slopes are determined by tridiagonal matrix algorithm (TDMA) which is an efficient way of solving tridiagonal matrix systems	The BER performance of spline is significantly degraded for 64-QAM modulation
	Lower computational complexity than pchip algorithm	
Lowpass	Best BER performance in the case of high mobility and high order modulation	Its computational complexity is much lower than that of the piecewise polynomial interpolation algorithms
		Its computational complexity is little more than that of the linear and nearest interpolation algorithms

In Fig. 11, the proposed low pass interpolation based channel estimator is compared with other aforementioned interpolation methods based channel estimator, in terms of average MSE for a wide range of SNRs. A Cramér-Rao lower bound (CRLB) is of particular interest to serve as a bench mark when we compare the channel estimation algorithms. Under the assumption that the channel and noise are independent of each other and noise is a zero-mean Gaussian vector, CRLB can be easily written as follows [26];

$$CRLB = \sigma_w^2 \tag{20}$$

where there is no information about channel correlation over subcarriers is considered. In Fig. 11, it can be observed that the MSE performance of the low pass interpolation is fairly close to the CRLB for all 16QAM signaling format. However, the MSE performance of the pchip, linear and nearest interpolation experience an large error floor at higher SNRs mainly due to the effect of the frequency selectivity. Finally, the low pass channel estimator in terms of MSE clearly is the best among the five interpolation methods studied in that paper.

As a result, the performance improvement of the low pass interpolation, in the case of the frequency selectivity and higher order modulations, indicates that it is a better choice for a SM-OFDM system which is can be considered in the standards and to meet the expectations of the next-generation wireless communications systems [27].

We now summarize the tradeoffs in terms of computational complexity and performance of proposed channel estimations in Table 2. There are two main contributions on the computational complexities of interpolation techniques: namely, the computational complexities incurred at the pilot locations and at the non-pilot locations (data points). Thus, computational complexity depends critically on the relative number of breaks and the number of data points to interpolate.

6 Conclusions

In this paper two key issues regarding the design of a SM-OFDM communications system, namely, frame structure and channel estimation, are addressed. We have also focused on the various aspects of using an interpolation technique in channel estimation for the SM-OFDM system where the antennas are regularly active associated with the selected subcarriers.

The simulation results and the mathematical analysis show that in pilot based channel estimation, the LS estimator with low-pass interpolation performs the best of all 1D interpolation methods, and it has a low computational complexity. It is shown that the proposed algorithm is capable of estimating MIMO channel and there is no ambiguity in either the amplitude or the phase of the estimated channel.

References

1. Blcskei, H. (2006). MIMO-OFDM wireless systems: Basics, perspectives, and challenges. *IEEE Wireless Communications*, *13*(4), 31–37.
2. Chiani, M., Win, M. Z., & Zanella, A. (2003). On the capacity of spatially correlated MIMO Rayleigh-fading channels. *IEEE Transactions on Information Theory*, *49*(10), 2363–2371.
3. Shiu, D. S., Foschini, G. J., Gans, M. J., & Kahn, J. M. (2000). Fading correlation and its effect on the capacity of multielement antenna systems. *IEEE Transactions on Communications*, *48*(3), 502–513.
4. Mesleh, R., Haas, H., Ahn, C. W., & Yun, S. (2006, October). Spatial modulation-a new low complexity spectral efficiency enhancing technique. *In processing of the IEEE First International Conference on Communications and Networking in China* (ChinaCom'06), (pp. 1–5), (Oct 2006).
5. Renzo, M. D., Haas, H., & Grant, P. M. (2011). Spatial modulation for multiple-antenna wireless systems: A survey. *IEEE Communications Magazine*, *49*(12), 182–191.
6. Yang, P., Xiao, Y., Zhou, B., & Li, S. (2011, August). Initial performance evaluation of spatial modulation OFDM in LTE-based systems. *In processing of the IEEE 6th International ICST Conference on Communications and Networking in China (CHINACOM)*, (pp. 102–107), (August 2011).
7. Basar, E., Aygolu, U., Panayirci, E., & Poor, H. V. (2013). Orthogonal frequency division multiplexing with index modulation. *IEEE Transactions on Signal Processing*, *61*(22), 5536–5549.
8. Jeganathan, J., Ghrayeb, A., & Szczecinski, L. (2008). Spatial modulation: Optimal detection and performance analysis. *IEEE Communications Letters*, *12*(8), 545–547.
9. Mesleh, R., Ganesan, S., & Haas, H. (2007). Impact of channel imperfections on spatial modulation OFDM. In Personal, *IEEE 18th International Symposium on Indoor and Mobile Radio Communications (PIMRC 2007)*, (pp. 1–5). (Sept. 2007).
10. Acar, Y., Doğan, H., & Panayirci, E. (2015). On channel estimation for spatial modulated systems over time-varying channels. *Digital Signal Processing*, *37*, 43–52.
11. Wu, X., Claussen, H., Di Renzo, M., & Haas, H. (2014). Channel estimation for spatial modulation. *IEEE Transactions on Communications*, *62*(12), 4362–4372.

12. Yalcin, M., Akan, A., & Doğan, H. (2012). Low-complexity channel estimation for OFDM systems in high-mobility fading channels. *Turkish Journal of Electrical Engineering & Computer Sciences*, *20*(4), 583–592.
13. Andrews, J. G., Ghosh, A., & Muhamed, R. (2007). Fundamentals of WiMAX: understanding broadband wireless networking. Pearson Education.
14. Dahlman, E., Parkvall, S., & Skold, J. (2013). *4G: LTE/LTE-advanced for mobile broadband*. Cambridge: Academic press.
15. Coleri, S., Ergen, M., Puri, A., & Bahai, A. (2002). Channel estimation techniques based on pilot arrangement in OFDM systems. *IEEE Transactions on Broadcasting*, *48*(3), 223–229.
16. Doğan, H. (2016). On detection in MIMO-OFDM systems over highly mobile wireless channels. *Wireless Personal Communications*, *86*(2), 683–704.
17. Wu, Y., Zhao, Y., & Li, D. (2012). Channel estimation for pilot-aided OFDM systems in single frequency network. *Wireless Personal Communications*, *62*(1), 227–245.
18. Colieri, S., Ergen, M., Puri, A., & Bahai, A. (2002). A study of channel estimation in OFDM systems. *Proceedings the IEEE 56th Vehicular Technology Conference (VTC2002-Fall)*, (pp. 894–898), (2011).
19. Dyer, S. A., & He, X. (2001). Cubic-spline interpolation: Part 2. *IEEE Instrumentation & Measurement Magazine*, *4*(2), 34–36.
20. Kahaner, D., Moler, C., & Nash, S. (1989). *Numerical methods and software* (p. 1). Englewood Cliffs: Prentice Hall.
21. Fritsch, F. N., & Carlson, R. E. (1980). Monotone piecewise cubic interpolation. *SIAM Journal on Numerical Analysis*, *17*(2), 238–246.
22. Moler, C. B. (2008). Numerical Computing with MATLAB: Revised Reprint. Siam.
23. Rinne, J., & Renfors, M. (1996). Pilot spacing in orthogonal frequency division multiplexing systems on practical channels. *IEEE Transactions on Consumer Electronics*, *42*(4), 959–962.
24. Patzold, M. (2003). *Mobile fading channels*. Hoboken: Wiley.
25. Xia, B., & Wang, J. (2005). Effect of channel-estimation error on QAM systems with antenna diversity. *IEEE Transactions on Communications*, *53*(3), 481–488.
26. Cirpan, H. A., Panayirci, E., & Doğan, H. (2006). Nondata-aided channel estimation for OFDM systems with space-frequency transmit diversity. *IEEE Transactions on Vehicular Technology*, *55*(2), 449–457.
27. Di Renzo, M., Haas, H., Ghrayeb, A., Sugiura, S., & Hanzo, L. (2014). Spatial modulation for generalized MIMO: Challenges, opportunities, and implementation. *Proceedings of the IEEE*, *102*(1), 56–103.

Yusuf Acar received the B.S.E. degree (with honors), M.S.E. degree and Ph.D. degrees in Electrical and Electronics Engineering from Istanbul University, Istanbul, Turkey, in 2008, 2011 and 2015, respectively. From 2009 to 2015 he was employed as a research and teaching assistant at the faculty of the Department of Electronics Engineering, Istanbul Kültür University. In 2015, he joined the same faculty as an Assistant Professor. He was a visiting scholar at the Purdue University, Fort Wayne, USA, between the June 2012 and September 2012. His general research interests cover communication theory, estimation theory, statistical signal processing, and information theory. His current research activities are focused on wireless communication concepts with specific attention to equalization and channel estimation for spread-spectrum and multicarrier systems.

Hakan Doğan received the B.S.E in Electronics Engineering in 2001, and the M.S.E. and Ph.D. degrees in Electrical Electronics Engineering in 2003 and 2007, respectively, all from the Istanbul University. From 2001 to 2007 he was employed as a research and teaching assistant at the faculty of the Department of Electrical and Electronics Engineering, Istanbul University. In 2007, he joined the same faculty as an Assistant Professor. He has been an adjunct professor in the Turkish Air Force academy since 2008. His interests lie in the areas of estimation theory, statistical signal processing, and their applications in wireless communication systems. His current research areas are focused on wireless communication concepts with specific attention to equalization and channel estimation for spread-spectrum and multicarrier (orthogonal frequency-division multiplexing) systems. He was a visiting scholar at the Purdue University, Fort Wayne, USA from May 15, 2010 to 16 August, 2010. He currently serves as a vice head of the Department of Electrical and Electronics Engineering, Istanbul University.

Erdal Panayirci received the Diploma Engineering degree in Electrical Engineering from Istanbul Technical University, Istanbul, Turkey and the Ph.D. degree in Electrical Engineering and System Science from Michigan State University, USA. Until 1998 he has been with the Faculty of Electrical and Electronics Engineering at the Istanbul Technical University, where he was a Professor and Head of the Telecommunications Chair. Currently, he is Professor of Electrical Engineering and Head of the Electronics Engineering Department at Kadir Has University, Istanbul, Turkey. Dr. Panayirci's recent research interests include communication theory, synchronization, advanced signal processing techniques and their applications to wireless communications, coded modulation and interference cancelation with array processing. He published extensively in leading scientific journals and international conferences. He has co-authored the book "Principles of Integrated Maritime Surveillance Systems" (Boston, Kluwer Academic Publishers, 2000). Dr. Panayirci spent the academic year 2008–2009, in the Department of Electrical Engineering, Princeton University, New Jersey, USA. He has been the principal coordinator of a 6th and 7th Frame European project called NEWCOM (Network of Excellent on Wireless Communications) and WIMAGIC Strep project representing Kadir Has University. Dr. Panayirci was an Editor for IEEE Transactions on Communications in the areas of Synchronization and Equalizations in 1995–1999. He served as a Member of IEEE Fellow Committee in 2005–2008. He was the Technical Program Chair of ICC-2006 and PIMRC-2010 both held in Istanbul, Turkey. Presently he is head of the Turkish Scientific Commission on Signals and Systems of URSI (International Union of Radio Science). He is an IEEE Life Fellow.