RMIMO–OFDM COMMUNICATION SYSTEMS FOR TRAFFIC DATA TRANSMISSION IN 5G DRONE SMALL CELLS

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***Abstract**: A compressed sensing-based channel estimation (CE) method is proposed for doubly selective channels whilst multiple-input multiple-output (MIMO)–orthogonal frequency-division multiplexing (OFDM) system is employed. According to the simulation results, the proposed CE method, which is dubbed as the MIMO-linearising scheme performs better than the basic expansion model (BEM), which is a state-of-the-art CE method and applies frequency domain scattered pilots. Furthermore, MIMO-linearising can be utilised as an accurate procedure for estimating only the positions of non-zero channel taps in the scenarios where those positions change with a slower rate than amplitudes and phases of the channel taps. Based on that priori estimated positions (PEPs), modified versions of the linearising scheme and the BEM methods, called MIMO-linearising-PEP and BEM-PEP, respectively, are described, showing improvement on performance and spectral efficiency. In addition, by considering the physical characteristic of the vehicular channels, an alternative version of the MIMO-linearising-PEP, called MIMO-linearising-efficient, is described to reduce the computational complexity and increase the spectral efficiency further. Simulation results indicate that the proposed CE methods can measure the channel more accurately and enhance the car detection accuracy in the frames which have been used as the inputs of the communication systems.*

INTRODUCTION

Multiple-input multiple-output (MIMO) technology has become very important for high-speed wireless communications and is considered an essential part of the next fifth generation (5G) communication systems [1]. The combination of MIMO and orthogonal frequency division multiplexing (OFDM) makes the required large bandwidth of the future communication systems feasible; however, high Doppler shifts of the transportation systems create inter carrier interference (ICI) among the subcarriers of the OFDM signal. In order to obtain accurate data demodulation, ICI should be mitigated. High Doppler shifts can be created even at the regular speeds when the carrier frequency of the communication system is high. Such scenarios can occur in future 5G systems where the expected centre frequency is between 27 and 71 GHz [1]. One of the conditions that high Doppler shift occurs is the utilisation of the drone small cells (DSCs) for both communication systems and traffic surveillance simultaneously as we discussed in [2]. This is the scenario that we considered in the current paper too; however, by considering a very higher Doppler shift of the 5G communication systems and MIMO condition in contrast to the single-input single-output condition of [2]. Owing to the timevarying nature of channels in the presence of the Doppler shift, channel estimation (CE), which is essential for the data demodulation of any communication systems that uses OFDM signals, is challenging and usually requires a lot of pilot data to be transmitted. The number of required pilots is even higher in massive MIMO systems, making bandwidth efficiency of the CE method even more important. While vehicular channels can have very long delay spreads, the experimental results indicate that they are generally sparse [3, 4]. As a result, the emerging compressed sensing (CS) approaches can be utilised for CE using lower number of pilot data. In the case of MIMO systems, it is shown that the positions of non-zero channel taps in all the pairs of transmitter and receiver antennas are the same [5]. As a result, group-CS (GCS) methods that exploit common sparsity between the channels can be utilised for CE.

There are several papers that proposed CS-based MIMO– OFDM CE methods [5]. Some of these papers study zero Doppler shift conditions and therefore, they proposed CE for frequency selective channels [6–17]. The previous CS-based CE methods for doubly selective (DS) channels, time and frequency selective, in MIMO–OFDM systems utilise scattered pilots in the frequency domain and can be categorised into three major groups. The first group only exploits delay sparsity of the channel and applies least square (LS) or linear minimum mean square estimation to estimate the diagonal elements of the frequency domain channel matrix [5, 18–20]. Since these CE methods cannot construct the whole frequency domain channel matrix for ICI cancellation, they are not suitable for high Doppler shift scenarios. However, they have high spectral efficiency since they can utilise GCS methods. The methods of the second group consider the sparsity of both delay domain and Doppler domain [21–25]. In these papers, a sparse matrix is expressed, which its elements should be found. Any nonzero element of that matrix represents the delay and Doppler shift of a path. The disadvantage of these methods is that the size of the sparse matrix increases in high Doppler shift conditions which results in the performance degradation of any CS methods. On the other hand, these methods cannot use GCS methods since due to the different Doppler shifts of the different paths, they cannot put the non-zero complex amplitudes of the different transmit receiver pairs in one group. The third category of CE schemes consider the sparsity in the time domain directly and the sparsity in the Doppler domain indirectly by defining the bases that are created in the frequency domain [26–28]. Those bases are defined by the basic expansion models (BEMs) and are exploited to estimate the sparse vectors, which are expressed in the delay domain. These methods can apply GCS methods as it is indicated in the next section and therefore, they are superior to the first two groups. However, they also have some disadvantageous. They require large guard intervals between pilots and data which results in the degradation of spectral efficiency, and they also require a refining step that increases the computational complexity of the CE [26].

The employment of time domain training sequences for massive MIMO conditions is challenging since in contrast to the BEM methods that a few subcarriers can be considered as a guard interval between data and pilots, the guard interval for the employment of long as the training sequence itself, making the CE very spectral inefficient. This is the main reason that the papers have not considered time domain training sequences for MIMO–OFDM systems up to now. In this study, however, by employing a specific time domain training sequence structure for the transmitter antennas and analysing the received data by a new method, we propose time domain pilot-assisted CE methods that can be used in MIMO systems. Specifically, at each transmitter antenna, two identical pseudo noise (PN) sequences are used as training signals and two sets of linear equations are constructed to estimate the complex amplitudes and Doppler shifts of the channel taps. The method is called MIMO-linearising. The performance of the MIMOlinearising method is then compared to that of the MIMO–BEM method in [26] using Monte–Carlo simulation in the same environment, showing considerable enhancement.

The performance of both the MIMO-linearising and the MIMO–BEM schemes can be even improved further if we consider the condition presented in [29] about the position of the non-zero taps. According to Telatar and Tse [29], the fluctuating rate of the complex amplitudes of the channel taps is proportional to the carrier frequency while the changing rate of the positions of the non-zero channel taps is proportional to the channel bandwidth and can be considered to be fixed during the transmission of several OFDM symbols. As a result, the CS-based CE procedure can be performed in two steps. First, a time domain training sequence is used to calculate the positions of non-zero elements by using methods such as the MIMO-linearising scheme. Then, these priori estimated positions (PEPs) are used for several OFDM symbols to calculate the complex amplitudes and Doppler shifts of the channel taps using much lower number of equations. Using PEP, the modified version of the MIMO–BEM and MIMO-linearising methods are proposed and are called MIMO–BEM–PEP and MIMO-linearizing-PEP, respectively. Simulation results indicate that the MIMO–BEM–PEP scheme performs better than the MIMO–BEM scheme, while the performance of the MIMOlinearizing-PEP is even better than the MIMO–BEM–PEP.

On the other hand, in the high Doppler shift condition of the 5G communication systems that the coherence time of the channel is low, the estimated channel would only be valid for limited data. As a result, the number of OFDM subcarriers cannot be high in high Doppler shift scenarios and that results in low-spectral efficiency for the communication systems. In addition, it is essential to have a low-computational complexity CE method to track the fast channel variations in fast time varying channels. The most important contribution of the current paper is to propose an efficient version of the MIMO-linearising-PEP method, called MIMO-linearising efficient, to enhance the spectral efficiency and reduce the computational complexity of the CE procedure for the majority of the vehicular channels whose power distribution characteristics follow some limitations. In addition, a new data demodulation procedure is proposed to employ the estimated channel by the MIMO-linearising-efficient method for detecting the transmitted data.

Finally, in order to assess the performance of the proposed CE and data demodulation methods, a traffic surveillance scenario is considered. Frames of an actual video that has been taken by a drone [30] are employed as inputs to the simulation system. Those frames are converted to the binary codes and transmitted using the MIMO–OFDM scheme through a DS vehicular communication channel. At the receiver, after the CE procedure and data demodulation, the transmitted frames are reconstructed. Afterwards, the faster region-based convolutional network (Faster R-CNN) method [31] is utilised to detect the vehicles in those frames. The results indicate the considerable effect of the different CE and data demodulation schemes on the accuracy of the car detection procedure.

The remainder of this paper is organised as follows. Section 2 studies the transmission of MIMO–OFDM signal through DS channels and explains how the received OFDM symbols should be demodulated by using channel state information. In addition, the previous CE method of [26] is summarised in Section 2. The MIMO-linearising method is elaborated in Section 3 while the approach of the estimation and the employment of the non-zero channel tap positions are discussed in Section 4. Section 5 elaborates the MIMO-linearising-efficient scheme. The computational complexity of the CE methods is calculated in Section 6. Section 7 presents the simulation results and finally, Section 8 concludes the paper.

Notations: Boldface small and capital letters denote vectors and matrices, respectively; (.)T, (.)H, (.)*, and (.)† denote the transpose, Hermitian, conjugate, and Moore–Penrose pseudo-inverse of a matrix, respectively, I, 1, and 0 are the identity, ones, and zeros matrixes, respectively, J = −1, [.] defines the floor function, O(.) expresses the order of computational complexity and ⊗ denotes the Kronecker product.

LITERATURE SURVEY

In this method, which is elaborated in [26], the complex amplitudes and the phase variation of Doppler shifts are combined with each other and are expressed as one variable. The lth channel tap between the ith transmitter and the jth receiver is defined

$$h_{ij_l} = [b_0, b_1, \ldots, b_{D-1}] \begin{bmatrix} c(0,l)_{i,j} \\ c(1,l)_{i,j} \\ \vdots \\ c(D-1,l)_{i,j} \end{bmatrix} + e_l, \quad (7)$$

The received symbols in terms of the BEM are expressed as

$$y_{f_j} = \sum_{i=1}^{N_T} \sum_{d=0}^{D-1} B_d C_{d_{i,j}} x_{f_i} + W_j, \quad (9)$$

$$y_{f_{j_d}} = \left[\hat{P}_1 F_{N(D-1)/2}, \hat{P}_2 F_{N(D-1)/2}, \ldots, \hat{P}_{N_T} F_{N(D-1)/2}\right] \propto_d \left[\hat{c}_{d_1}^T, \hat{c}_{d_2}^T, \ldots, \hat{c}_{d_{N_T}}^T\right]^T + W_d, \quad (10)$$

By this formulation, all the coefficients for pairs of antennas and different bases (ds) obtain the same non-zero locations. As a result, GCS methods can be applied for sparse signal estimation. At the last step, the linear smoothing procedure was proposed in [26] in order to reduce the BEM modelling error and Doppler effect on the estimation of complex amplitudes. For data demodulation, the estimated coefficients are inserted in (9).

PROPOSED MODEL

MIMO–OFDM system model

Consider a MIMO–OFDM system with N_T transmitters and N_R receivers. The tap delay line channel model between the ith transmitter and the jth receiver at time n is expressed as

$$h_{ij}(n) = \sum_{l=1}^{L} \alpha_{l_{ij}} e^{J2\pi f_{D_{l_{ij}}} nT_s} \delta((n-l)T_s), \quad (1)$$

where hij, αlij and f Dl ij determine the discrete equivalent of the channel, the lth tap complex amplitude and the lth tap Doppler shift between the ith transmitter and the jth receiver, respectively, and Tsis the sampling time of the system. The total number of taps is indicated by L which is obtained by dividing the maximum delay spread of the channel by Ts .

At the transmitter, inverse fast Fourier transform of the transmitted symbols is obtained and transmitted through the channel while at the receiver, the fast Fourier transform of the received time domain samples is calculated to obtain the frequency domain received symbols. Considering an N subcarriers OFDM from each transmitter antenna, the output at the jth receiver in the frequency domain is obtained as

$$y_{f_j} = \sum_{i=1}^{N_T} H_{ij} x_{f_i} + z_{f_j}, \quad j = 1, 2, \ldots, N_R \quad (2)$$

where xfi , i = 1, 2, …, NT is the N × 1 vector of the frequency domain transmitted symbols from the ith transmitter and Hij is a N × N frequency domain channel matrix between the ith transmitter and the jth receiver. Vector zf j is a N × 1 vector and indicates the additive noise in the frequency domain.

In order to obtain the transmitted signals from the received signals, the received symbols can be put in a single vector of size N · NR × 1 as $y_f = \left[y_{f_1}^T, y_{f_2}^T, \ldots, y_{f_{N_R}}^T\right]^T$ and its relationship to the transmitted signals $x_f = \left[x_{f_1}^T, x_{f_2}^T, \ldots, x_{f_{N_T}}^T\right]^T$,is defined as

$$y_f = Hx_f + z_f \quad (3)$$

where H is a N · N_R × N · N_T matrix which is expressed as

$$H = \begin{bmatrix} H_{11} & H_{12} & \cdots & H_{1N_T} \\ H_{21} & \ddots & \cdots & H_{2N_T} \\ \vdots & \cdots & \ddots & \vdots \\ H_{N_R1} & \cdots & \cdots & H_{N_RN_T} \end{bmatrix}, \quad (4)$$

And $z_f = \left[z_{f_1}^T, z_{f_2}^T, \ldots, z_{f_{N_R}}^T\right]^T$ is the N.N_Rx1 additive noise vector. The k, m th element of Hij is obtained as

$$(H_{k,m})_{i,j} = \frac{1}{N} \sum_{l=1}^{L} \alpha_{l_{ij}} e^{J2\pi f_{D_{l_{ij}}} LT_s} e^{-j2\pi lk/N} \times \frac{1 - e^{JN\left(2\pi f_{D_{l_{ij}}} T_s + (2\pi/N)(m-k)\right)}}{1 - e^{J\left(2\pi f_{D_{l_{ij}}} T_s + (2\pi/N)(m-k)\right)}}. \quad (5)$$

When there is no Doppler shift, $(H_{k,m})_{i,j}$ = 0 for k ≠ m and each H_{ij} becomes a diagonal matrix. However, in the presence of Doppler shift, H_{ij} is not diagonal and y_{f_j} depends on all the transmitted subcarriers. When all the Hijs are estimated, the transmitted data can be extracted by the employment of minimum mean square error estimate

$$\hat{X} = \hat{H}^* \times \left[\hat{H} \times \hat{H}^* + \sigma^2 I_{NN_R}\right]^{-1} Y, \quad (6)$$

where H ^ and X ^ define the estimated channel matrix and the transmitted symbols, respectively, and σ 2 is the noise variance.

MIMO–BEM CE scheme

In this method, which is elaborated in, the complex amplitudes and the phase variation of Doppler shifts are combined with each other and are expressed as one variable. The lth channel tap between the ith transmitter and the jth receiver is defined as

$$h_{ij_l} = [b_0, b_1, \ldots, b_{D-1}] \begin{bmatrix} c(0,l)_{i,j} \\ c(1,l)_{i,j} \\ \vdots \\ c(D-1,l)_{i,j} \end{bmatrix} + e_l, \quad (7)$$

Where $h_{ij_l} = [h_{ij_l}(G), h_{ij_l}(G+1), \ldots, h_{ij_l}(G+N)]^T$ (G is a cyclic prefix (CP) of the OFDM symbol), D is the BEM order, el is the BEM modelling error and $c(d,l)_{ij}$,is the coefficient of the dth BEM base (b_d) which is defined as

$$b_d = \left[1, \ldots, e^{(J2\pi/N)n(d-((D-1)/2))}, \ldots, e^{(J2\pi/N)(N-1)(d-((D-1)/2))}\right]^T. \quad (8)$$

The received symbols in terms of the BEM are expressed as

$$y_{f_j} = \sum_{i=1}^{N_T} \sum_{d=0}^{D-1} B_d C_{d_{i,j}} x_{f_i} + W_j, \quad (9)$$

As a result, GCS methods can be applied for sparse signal estimation. At the last step, the linear smoothing procedure was proposed in [26] in order to reduce the BEM modelling error and Doppler effect on the estimation of complex amplitudes. For data demodulation, the estimated coefficients are inserted in (9).

MIMO-linearising scheme

If the duration of a single OFDM block is less than the coherence time of the channel, one can assume that the complex amplitudes and Doppler shifts do not change during the transmission of one OFDM block. However, the phases of the exponential terms are changed proportionally to the Doppler shifts and time according to (1). By applying the truncated Taylor expansion, $\alpha_{l_{ij}} e^{J2\pi f_{D_{l_{ij}}} n T_{\text{sample}}}$ term in (1) can be approximated by

$\alpha_{l_{ij}}(1 + j2\pi f D_{ij}\, T_{sample})$.

For estimating the channel, we proposed the utilisation of two identical PN sequences in time domain where different PN sequences are employed at different transmitters in order to reduce the mutual coherence of the measurement matrix as it is discussed later in this section. The length of each PN sequence is Q, where Q ≥ G > L and G is the CP. Those PN sequences are transmitted before the CP and the OFDM data block. As a result, the first Q received time domain samples are obtained as

$$y_{t_j}(n) = \sum_{n_c=1}^{\max\{L,n\}} \sum_{i=1}^{N_T} p_{n-n_c+1_i} \alpha_{n_{c_{ij}}} \left(1 + J2\pi n f_{D_{n_{c_{ij}}}} T_s\right) + \mathrm{BI}_D(n) + w_j(n), \quad n = 1, 2, \ldots, Q \quad (11)$$

where ytj n is the received time domain sample at the jth receiver and time n, pn − nc + 1i is the transmitted pilot from the ith transmitter at the time n − nc + 1, wj n is the additive noise to the nth received sample at the jth receiver. The block interference (BI) of the previous OFDM data block is indicated by BID n where BID n = 0 for L < n. As the similar PN sequence is transmitted after the first one, the corresponding second Q received samples are obtained as

$$y_{t_j}(n) = \sum_{n_c=1}^{\max\{L,n\}} \sum_{i=1}^{N_T} p_{n-n_c+1_i} \alpha_{n_{c_{ij}}} \left(1 + J2\pi(n+Q) f_{D_{n_{c_{ij}}}} T_s\right) + \mathrm{BI}_{\mathrm{PN}}(n) + w_j(n), \quad n = 1, 2, \ldots, Q \quad (12)$$

where BIPN n is the BI of the first PN sequence and BIPN n = 0 for L < n. By considering the last Q - L equations of (11) and (12) which are free of BI, a (Q − L) × 1 vector of the scaled difference of (11) and (12) is obtained where each element is expressed as

$$\begin{aligned} y_{t_{\mathrm{da}_1} j}(n) &= \left(\frac{Q+n}{Q}\right) \cdot y_{t_j}(n) - \frac{n}{Q} \cdot y_{t_j}(n+Q) \\ &= \sum_{l=1}^{L} \sum_{i=1}^{N_t} p_{n-l+1_i} \alpha_{l_{ij}} + \left(\frac{Q+n}{Q}\right) \cdot w_j(n) - \frac{n}{Q} \cdot w_j(n+Q), \end{aligned} \quad (13)$$

and all the elements are written in a matrix form as

$$\boldsymbol{y}_{t_{\mathrm{da}}j} = \boldsymbol{\varphi} \times \boldsymbol{a} + \boldsymbol{w}_{j_{\mathrm{diff}_1}}, \qquad (14)$$

nd its elements are obtained according to (11).

Since the number of columns of φ is larger than its rows, (14) cannot be solved linearly; however, considering a sparse tapped delay line channel model, awould be a sparse vector. As a result, a CS method can be applied for solving (12).

It is indicated in [33] that any CS method such as orthogonal matching pursuit (OMP) performs more accurately when the maximum mutual coherence of the columns of the measurement matrix, which is defined by the following equation, is as small as possible

$$\mu\{\boldsymbol{\varphi}\} = \max \frac{\left|cl_{\alpha}^{\mathrm{H}} \cdot cl_{\beta}\right|}{\| cl_{\alpha} \| \cdot \| cl_{\beta} \|}, \quad \text{for } \alpha \neq \beta \qquad (15)$$

$$\begin{aligned} y_{t_{\mathrm{df}_1}j}(n) &= y_{t_j}(n+Q) - y_{t_j}(n) \\ &= \sum_{\tau=1}^{K} \sum_{i=1}^{N_T} p_{n-\Gamma_{\tau_i}} \hat{\alpha}_{\Gamma_{\tau_{ij}}} \left(J2\pi Q f_{D_{\Gamma_{\tau_{ij}}}} T_{\mathrm{s}}\right) + w_j(n+Q) - w_j(n). \end{aligned} \qquad (16)$$

The upper equation can be written in matrix form as

$$\boldsymbol{y}_{t_{\mathrm{df}_1}j} = \Omega \times (\boldsymbol{d} \cdot J2\pi Q T_{\mathrm{s}}) + \boldsymbol{w}_{j_{\mathrm{diff}_2}}, \qquad (17)$$

By considering that the number of rows of Ω is larger than the number of its columns, LS is applied for solving (17) as

$$\hat{\boldsymbol{d}} = \mathrm{Real}\left\{\frac{1}{\mathrm{j}2\pi Q T_{\mathrm{s}}} (\Omega)^{\dagger} \boldsymbol{Y}_{\mathrm{df}}\right\}. \qquad (18)$$

RESULTS

CE schemes are compared based on several criteria. Normalised mean square error (NMSE) of the CE procedure and bit error rate (BER) of data demodulation are plotted versus signal-to-noise ratio (SNR). In order to evaluate the car detection performance, the precision-recall curves are considered. The precision tp /(tp + f p) and recall tp /(tp + f n) are obtained from tp, fp, and fn, which are the number of true positive, false positive, and false negative detections, respectively. By reducing the score threshold, the detector finds more vehicles and f n is increased and the recall is enhanced. However, f p increases which results in the reduction of precision. As a result, higher precision and higher recall indicate better detection performance.

Normalised mean square error (NMSE):

The NMSE curves based on the communication system parameters that are defined in Table 1 are presented for vehicular type B and random vehicular B channels in Figs. 2 and 3, respectively.

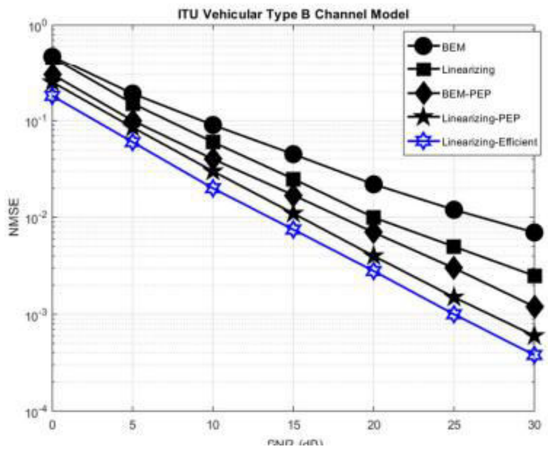

Fig. 2 NMSE of CE versus SNR for ITU vehicular type B channel model

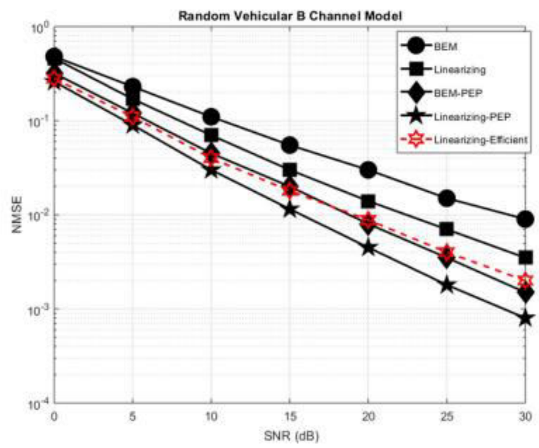

Fig. 3 NMSE of CE versus SNR for the random vehicular B channel model

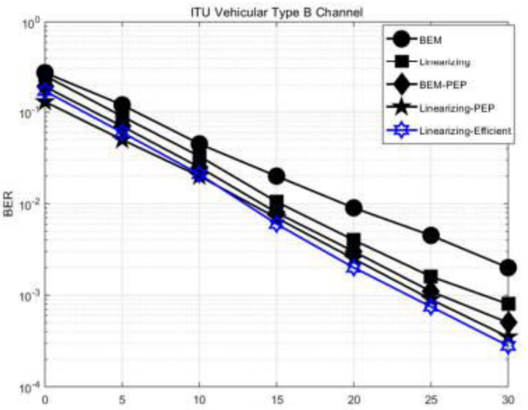

Fig. 4 BER versus SNR for ITU vehicular type B channel model

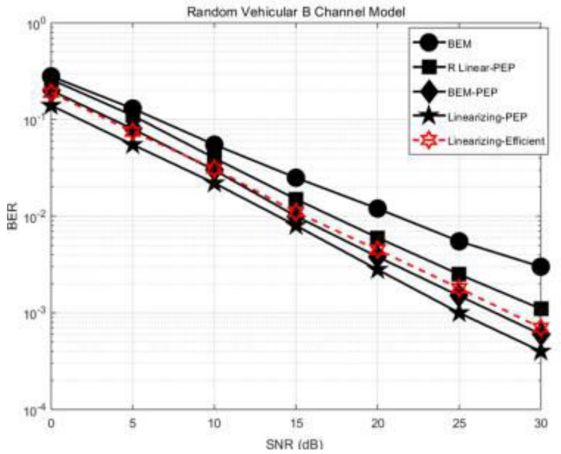

Fig. 5 BER versus SNR for random vehicular B channel model

As shown in Fig. 2, the linearising method measures the channel more accurately than the BEM method. Besides that, the employment of PEP enhances the performance of the CE procedure considerably. The simulation results also depict that the performance of the linearising-efficient is even better than the linearising-PEP since it performs averaging among the received samples which reduce the noise effect. On the other hand, the simulation results in Fig. 3 indicate that the performance of the linearising-efficient method is better than the BEM and linearising methods and almost the same as the BEM–PEP even when the places of non-zero channel taps are chosen randomly which results in the conditions that only two taps of the channel could be estimated. However, please be noted that for all the vehicular channel models that we mentioned in Section 5, the $\Gamma\tau + 1 - \Gamma\tau \geq 2NT$ condition is true for Na = 1, 2, …, 15. As a result, Fig. 2 should be considered as the performance of the CE schemes in the real environment.

Bit error rate (BER):

The BER curves based on the communication system parameters that are defined in Table 1 are presented for vehicular type B and random vehicular B channels in Figs. 4 and 5, respectively.

As is presented in Figs. 4 and 5, the BER curves follow the same pattern as the NMSE curves except for the linearisingefficient at low SNR, which indicates worse performance than the linearising-PEP which is because of the error propagation of CE on BI cancellation and CP construction.

Car detection:

The visual performance of the car detection by the Faster R-CNN method for one of the frames is presented in Fig. 6. In this figure, by considering the ITU vehicular type B channel model and SNR = 10 dB, the results of the car detection are indicated in yellow boxes. Since the linearising-PEP and linearising-efficient methods perform almost the same at SNR = 10 dB, only the results for the linearising-PEP is indicated in Fig. 6. It is observed in that figure that the reconstructed figure based on the linearising-PEP method, Fig. 6d has less noise compared to the other methods which result in the decrement in fn and fp. The precision-recall value for this frame is indicated in Table 3.

The complete quantitative performance evaluation is executed over 100 frames. The precision-recall curves for SNR = 10 (solid lines) and 30 dB (dashed lines) for ITU vehicular type B channel model are presented in Fig. 7. As it is indicated in this figure, the performance of the linearising is better that the BEM. In addition, the employment of PEP significantly enhances performance.

In order to summarise the performance of the CE methods, the area under the curves (AUCs) for the precision-recall curves are indicated in Table 4.

CONCLUSION

In this study, the performance of the MIMO–OFDM communication systems for applying DSC for the communication data transmission and traffic surveillance was appraised. A CSbased CE scheme, called MIMO-linearising, for sparse DS channels of MIMO–OFDM systems, was proposed that utilises time-domain training sequences. Simulation results indicated that

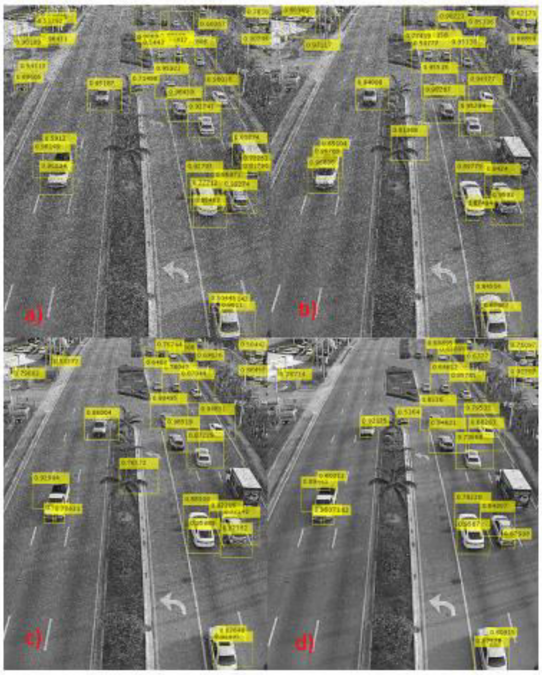

Fig. 6 *Car detection in a typical frame at SNR = 10 dB and ITU vehicular type B channel model for*

Table 3 Precision-recall values for the frame of Fig. 6

Method	Precision	Recall
BEM	0.69	0.72
linearising	0.72	0.78
BEM–PEP	0.76	0.80
linearising-PEP	0.82	0.81

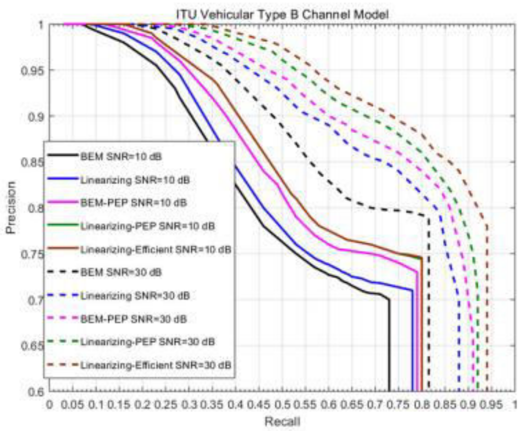

Fig. 7 *Precision-recall curves for CE methods*

the MIMO-linearising scheme, compared to the M

IMO–BEM method that uses frequency domain scattered pilots, can estimate the channel more accurately with lower computational complexity. In addition, other variations of the linearising method are described by considering some assumptions about the channel. Assuming that the positions of the non-zero channel taps change with much slower rate than amplitudes and Doppler frequencies, the MIMOlinearising-PEP scheme improves spectral efficiency and performance of CE. With further assumption that the first two nonzero taps of vehicular channel contain most of the channel energy, the MIMO-linearising-efficient method was proposed which reduces the computational complexity and enhances spectral efficiency even further. In addition, the proposed CE approaches perform better than the MIMO–BEM procedure for traffic surveillance and car detection even when the state-of-the-art Faster R-CNN method is utilised. In conclusion, the proposed CE methods can be applied for high Doppler shift scenarios of vehicular technologies including 5G mobile communication systems and high-speed vehicles such as high-speed trains.

Table 4 AUC for precision-recall curves

Method	SNR = 10 dB	SNR = 30 dB
BEM	0.6212	0.7489
linearising	0.6681	0.7813
BEM–PEP	0.6821	0.8003
linearizing-PEP	0.6981	0.8254
linearizing-efficient	0.6982	0.8307

REFERENCES

[1] 5G Americas: '5G spectrum recommendations' (5G Americas, 2017), pp. 1– 29

[2] Vahidi, V., Saberinia, E., Morris, B.T.: 'OFDM performance assessment for traffic surveillance in drone small cells', IEEE Trans. Intell. Transp. Syst., 2019, 20, (8), pp. 2869–2878

[3] Masood, M., Afify, L., Al-Naffouri, T.: 'Efficient coordinated recovery of sparse

channels in massive MIMO', IEEE Trans. Signal Process., 2015, 63, (1), pp. 104–118

[4] Berger, C., Wang, Z., Huang, J., et al.: 'Application of compressive sensing to sparse channel estimation', IEEE Commun. Mag., 2010, 48, (11), pp. 164–174

[5] Choi, J.W., Shim, B., Chang, S.H.: 'Downlink pilot reduction for massive MIMO systems via compressed sensing', IEEE Commun. Lett., 2015, 19, (11), pp. 1889–1892

[6] Ma, X., Yang, F., Liu, S., et al.: 'Design and optimization on training sequence for mmWave communications: a new approach for sparse channel estimation in massive MIMO', IEEE J. Sel. Areas Commun., 2017, 35, (7), pp. 1486–1497

[7] De, P.: 'Semi-blind sparse channel estimation using reduced rank filtering', IEEE Trans. Wirel. Commun., 2018, 17, (3), pp. 1418–1431

[8] Mishra, A., Jagannatham, A.K.: 'SBL-based joint sparse channel estimation and maximum likelihood symbol detection in OSTBC MIMO–OFDM systems', IEEE Trans. Veh. Technol., 2018, 67, (5), pp. 4220–4232

[9] Sure, P., Bhuma, C.M.: 'Large random matrix-based channel estimation for massive MIMO–OFDM uplink', IET Commun., 2018, 12, (9), pp. 1035–1041

[10] Huang, Y., He, Y., Luo, Q., et al.: 'Channel estimation in MIMO–OFDM systems based on a new adaptive greedy algorithm', IEEE Wirel. Commun. Lett., 2019, 8, (1), pp. 29–32

[11] Talaei, F., Dong, X.: 'Hybrid mmWave MIMO–OFDM channel estimation based on the multi-band sparse structure of channel', IEEE Trans. Commun., 2019, 67, (2), pp. 1018–1030

[12] Wang, H.: 'Sparse channel estimation for MIMO–FBMC/OQAM wireless communications in smart city applications', IEEE Access, 2018, 6, pp. 60666–60672.