

Structured Distributed Sparse Channel Estimation for High Mobility OFDM Systems

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Abstract—In high mobility environments, the significant Doppler shift introduces severe inter-carrier interference (ICI) to an orthogonal frequency-division multiplexing (OFDM) system, which makes channel estimation very challenging. In this paper, we propose an efficient structured distributed compressive sensing (SDCS) based joint channel estimation scheme within multiple OFDM symbols. By utilizing the complex exponential basis expansion model (CE-BEM) in the time domain and exploiting the channel sparsity in the delay domain, we obtain a joint-block-sparse model. Then a novel block-based simultaneous orthogonal matching pursuit (BSOMP) is proposed to make joint estimation of channel parameters accurately. Simulation results demonstrate that the proposed SDCS scheme achieves better channel estimation performance than the conventional CS and DCS scheme over high mobility channels.

Index Terms—Channel estimation; high mobility; OFDM; structured distributed compressive sensing; multiple OFDM symbols

I. INTRODUCTION

ORTHOGONAL frequency division multiplexing (OFDM) has been widely used due to its robustness against frequency-selective (FS) fading [1]. However, in high mobility environments, time-selective (TS) fading caused by Doppler effect destroys the orthogonality among subcarriers and introduce inter-carrier interference (ICI) [2]. Channel estimation for high mobility channels is very challenging due to the channel parameters needed to be estimated are numerous, which forces us to allocate lots of pilot subcarriers to estimate channel accurately [3].

Recently, various experimental studies demonstrate that many wireless broadband channels can be modeled as sparse channels [4], [5]. Further, the recently introduced compressive sensing (CS) is able to reconstruct a sparse signal from fewer samples than what is required by Nyquist rate [6]. As such, applying CS theory to the sparse channel estimation can significantly improve spectral efficiency through a reduction of the number of pilot subcarriers. In contrast to conventional CS theory that reconstructs each single sparse signal individually, the distributed CS (DCS) proposed in [7] jointly recovers a collection of sparse signals. It is shown in [8], [9] that DCS-based methods achieve better performance than CS-based methods in terms of recovery probability.

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In this paper, we propose an efficient structured DCS (SDCS) based joint channel estimation scheme within multiple OFDM symbols. In specific, to avoid the reduction of the sparsity in Doppler domain [10], we utilize complex exponential basis expansion model (CE-BEM) to model the channel impulse responses (CIR) in the time domain, and exploit the sparsity in the delay domain. Then, by designing special sparse pilot pattern, we are able to decouple CE-BEM coefficient vectors into a jointly sparse block structure. In order to design a channel estimation method consistent with this joint-block-sparse model, a block-based simultaneous orthogonal matching pursuit (BSOMP) algorithm is proposed to compute the channel parameters. Numerical results demonstrate that the proposed SDCS-based scheme achieves a better channel estimation performance than the conventional CS-based and DCS-based scheme over high mobility channels.

The rest of the paper is organized as follows. Section II introduces an OFDM system model over high mobility channels and the CE-BEM. Section III describes formulation of SDCS-based channel estimation model and the proposed BSOMP algorithm. In section IV, simulation results are provided to demonstrate the superior performance of our proposed scheme. Finally, Section V concludes the paper.

II. SYSTEM MODEL

Here, we first review background knowledge of OFDM systems over high mobility channels. Then, we introduce the CE-BEM channel model within multiple OFDM symbols.

A. OFDM System Model over High Mobility Channels

We consider an OFDM transmission system with N subcarriers. Let us denote the transmit signal at the n -th ($0 \leq n \leq N-1$) subcarrier of the j -th ($0 \leq j \leq J-1$) OFDM symbol as $X^{(j)}(n)$. The data symbols $\mathbf{X}^{(j)} = [X^{(j)}(0), \dots, X^{(j)}(N-1)]$ are first modulated by N point inverse discrete Fourier transform (DFT) matrix \mathbf{F}_N^H , then concatenated by a cyclic prefix (CP) of length L_{CP} and finally transmitted serially through a channel [11].

At the receiver side, once the CP is removed, the samples are demodulated by N point DFT matrix \mathbf{F}_N . We can express the received signal of the j -th OFDM symbol as

$$\mathbf{Y}^{(j)} = \mathbf{F}_N \mathbf{H}_T^{(j)} \mathbf{F}_N^H \mathbf{X}^{(j)} + \mathbf{W}^{(j)} = \mathbf{H}_F^{(j)} \mathbf{X}^{(j)} + \mathbf{W}^{(j)}, \quad (1)$$

where $\mathbf{W}^{(j)}$ denotes the additive noise, $\mathbf{H}_T^{(j)}$ represents the time-domain channel matrix including the effects of CP insertion and removal, and $\mathbf{H}_F^{(j)}$ denotes the corresponding frequency-domain channel matrix. With $h_{n,l}$ ($0 \leq l \leq L-1$) denoting the time-domain channel gain of the l -th path at time n , the (p,q) -th entry of $\mathbf{H}_T^{(j)}$ can be written as

$$[\mathbf{H}_T^{(j)}]_{p,q} = h_{j(N+L_{CP})+L_{CP}+p, \text{mod}(p-q, N)}, \quad (2)$$

where $p, q \in [0, N-1]$, $\text{mod}(a, b)$ represents the remainder of a divided by b . Note that L is the maximum number of resolvable channel paths, subject to $L \leq L_{CP}$.

Obviously, if the channel is assumed to be time-invariant during the j -th OFDM symbol, $\mathbf{H}_T^{(j)}$ will be truly circular and $\mathbf{H}_F^{(j)}$ turns out to be a diagonal matrix. While in a high mobility channel, $\mathbf{H}_T^{(j)}$ exhibits pseudo-circular, which results in a full matrix $\mathbf{H}_T^{(j)}$ and introduces ICI.

B. CE-BEM Channel Model

In this section, we will utilize a CE-BEM to model the time-domain channel $h_{n,l}$. After CP removal, the l -th channel tap of the j -th OFDM symbol $\mathbf{h}_l^{(j)} \triangleq (h_{j(N+L_{CP})+L_{CP},l}, \dots, h_{j(N+L_{CP})-1,l})^T$ can be expressed as

$$\mathbf{h}_l^{(j)} = (\mathbf{b}_0, \dots, \mathbf{b}_{Q-1}) \begin{pmatrix} c^{(j)}[0, l] \\ \vdots \\ c^{(j)}[Q-1, l] \end{pmatrix} + \boldsymbol{\xi}_l^{(j)}, \quad (3)$$

where Q ($Q \ll N$) is the BEM order, $(\mathbf{b}_0, \dots, \mathbf{b}_Q) \in \mathbb{C}^{N \times Q}$ consists of Q orthonormal basis function as columns, $c^{(j)}[q, l]$ represents the corresponding BEM coefficient of the j -th OFDM symbol, and $\boldsymbol{\xi}_l^{(j)}$ stands for the BEM modeling error. In specific, CE-BEM basis function \mathbf{b}_q is complex exponential with a period of N , expressed as

$$\mathbf{b}_q = \left(1, \dots, e^{j \frac{2\pi}{N} n (q - \frac{Q-1}{2})}, \dots, e^{j \frac{2\pi}{N} (N-1) (q - \frac{Q-1}{2})} \right)^T. \quad (4)$$

Let us define the q -th CE-BEM coefficient vector of the j -th OFDM symbol as $\mathbf{c}_q^{(j)} \triangleq (c^{(j)}[q, 0], \dots, c^{(j)}[q, L-1])^T \in \mathbb{C}^L$. Then the frequency-domain channel matrix $\mathbf{H}_F^{(j)}$ of the j -th OFDM symbol can be denoted as

$$\mathbf{H}_F^{(j)} = \mathbf{F}_N \mathbf{H}_T^{(j)} \mathbf{F}_N^H = \sum_{q=0}^{Q-1} \mathbf{F}_N \mathcal{D}\{\mathbf{b}_q\} \mathbf{F}_N^H \mathcal{D}\{\mathbf{V}_L \mathbf{c}_q^{(j)}\}, \quad (5)$$

where $\mathcal{D}\{\mathbf{b}_q\}$ denotes a diagonal matrix with \mathbf{b}_q on its diagonal, \mathbf{V}_L denotes the matrix that consists of the first L columns of $\sqrt{N} \mathbf{F}_N$ [11]. Substituting (5) into (1), we can rewrite the received subcarriers in terms of the CE-BEM as

$$\mathbf{Y}^{(j)} = \sum_{q=0}^{Q-1} \mathbf{F}_N \mathcal{D}\{\mathbf{b}_q\} \mathbf{F}_N^H \mathcal{D}\{\mathbf{V}_L \mathbf{c}_q^{(j)}\} \mathbf{X}^{(j)} + \mathbf{W}^{(j)}. \quad (6)$$

According to (6), we express the received J consecutive OFDM samples as

$$\mathbf{Y} = \mathcal{D}\{\mathbf{H}_F^{(0)}, \dots, \mathbf{H}_F^{(J-1)}\} \mathbf{X} + \mathbf{W}, \quad (7)$$

where $\mathcal{D}\{\mathbf{H}_F^{(0)}, \dots, \mathbf{H}_F^{(J-1)}\}$ denotes a block-wise diagonal matrix with the matrices $\mathbf{H}_F^{(0)}, \dots, \mathbf{H}_F^{(J-1)}$ on the diagonal, $\mathbf{Y} = (\mathbf{Y}^{(0)T}, \dots, \mathbf{Y}^{(J-1)T})^T$ and $\mathbf{X} = (\mathbf{X}^{(0)T}, \dots, \mathbf{X}^{(J-1)T})^T$ denote the received and transmitted samples during J consecutive OFDM symbols, respectively. Note that each OFDM symbol is associated with same CE-BEM basis functions, but with different CE-BEM coefficients.

Therefore, rather than estimate numerous channel coefficients $h_{n,l}$, we turn to identify the CE-BEM coefficients $\{\mathbf{c}_q^{(j)}\}_{q=0}^{Q-1}$. It is clear that CE-BEM is able to notably reduce the total number of unknown channel coefficients within J consecutive OFDM symbols from JNL to JQL .

III. PROPOSED CHANNEL ESTIMATION SCHEME

In this section, by designing a special sparse pilot pattern within multiple OFDM symbols, we obtain a decoupling form and transform original problem into a SDCS form. Then a novel BSOMP algorithm is proposed to compute the channel parameters.

A. The Sparse CE-BEM Coefficient Vectors within Multiple OFDM Symbols

In a broadband system with a small number of propagation paths, the delay domain turns out to be sparse due to the fast decay of the sinc function [3]. Let \mathcal{L} denotes the aggregate dominant paths with the cardinality $|\mathcal{L}| = K$. For a high mobility channel, the path delays usually vary much more slowly than the path gains [12]. During several adjacent OFDM symbols, although the path gains will be quite different, the path delays remain relatively unchanged [13]. As a result, we can assume $h_{n,l} = 0$ for $l \notin \mathcal{L}$ during J consecutive OFDM symbols. Then we have $\mathbf{h}_l^{(j)} = 0$ ($0 \leq j \leq J-1$) for $l \notin \mathcal{L}$. Further, based on (3), we have

$$c^{(j)}[0, l] = \dots = c^{(j)}[Q-1, l] = 0 \quad (l \notin \mathcal{L}) \quad (8)$$

due to $(c^{(j)}[0, l], \dots, c^{(j)}[Q-1, l])^T = (\mathbf{b}_0, \dots, \mathbf{b}_{Q-1})^\dagger \mathbf{h}_l^{(j)}$ regardless of the modeling error. Consequently, the aggregate vectors $\{\mathbf{c}_0^{(0)}, \dots, \mathbf{c}_{Q-1}^{(0)}, \dots, \mathbf{c}_0^{(J-1)}, \dots, \mathbf{c}_{Q-1}^{(J-1)}\}$ are jointly sparse, i.e., not only does each vector $\mathbf{c}_q^{(j)}$ have the sparsity of K , but also the nonzero elements of all vectors occur in common positions.

B. The SDCS Formulation

We have shown the joint sparsity among the CE-BEM coefficient vectors within J consecutive OFDM symbols. Here, we will design sparse pilot pattern within J consecutive OFDM symbols, leading to an ICI free structure and finally formulate the channel estimation problem into SDCS framework.

Let us assume that the total number of pilot subcarriers within J OFDM symbols is P , and the corresponding pilot indices is denoted by \mathcal{P} . The set of pilot subcarriers is categorized into two subsets:

- 1) The value pilot index set \mathcal{P}_{val} (with cardinality $|\mathcal{P}_{val}| = G$).

$$\mathcal{P}_{val} = \{p_0, \dots, p_{G-1}\}, \quad (9)$$

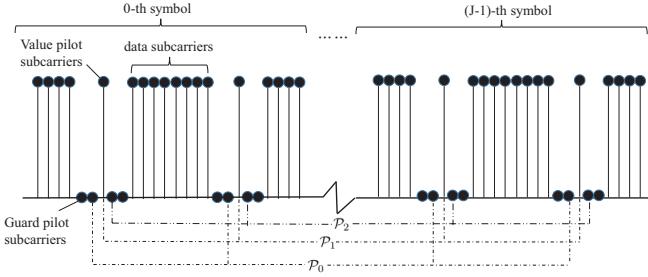


Fig. 1: The pilot pattern within J consecutive OFDM symbols ($Q = 3$)

where $K < G \ll JL$, $0 \leq p_0 < \dots < p_{G-1} \leq JN - 1$ and the corresponding pilot subcarriers \mathbf{P}_{val} are given by

$$[\mathbf{X}]_{\mathcal{P}_{val}} = \mathbf{P}_{val} = ([\mathbf{X}]_{p_0}, \dots, [\mathbf{X}]_{p_{G-1}})^T. \quad (10)$$

- 2) The guard pilot index \mathcal{P}_{guard} (with cardinality $|\mathcal{P}_{guard}| = (2Q - 2)G$).

$$\mathcal{P}_{guard} = \cup\{k - Q + 1, \dots, k - 1, k + 1, \dots, k + Q - 1\}, \quad (11)$$

where $k \in \mathcal{P}_{val}$ and the corresponding guard pilot subcarriers $\mathbf{P}_{guard} \in \mathbb{C}^{(2Q-2)G}$ are given by

$$[\mathbf{X}]_{\mathcal{P}_{guard}} = \mathbf{P}_{guard} = \mathbf{0}. \quad (12)$$

Next, we re-divide \mathcal{P} into Q subsets, denoted as

$$\begin{aligned} \mathcal{P}_0 &= \mathcal{P}_{val} - \frac{Q-1}{2} \\ &\vdots \\ \mathcal{P}_{\frac{Q-1}{2}} &= \mathcal{P}_{val} \\ &\vdots \\ \mathcal{P}_{Q-1} &= \mathcal{P}_{val} + \frac{Q-1}{2}, \end{aligned} \quad (13)$$

where $\mathcal{P}_{val} - \frac{Q-1}{2}$ describes a new set with all elements in \mathcal{P}_{val} subtract $\frac{Q-1}{2}$. Fig. 1 shows such an arrangement \mathcal{P} with $Q = 3$.

Based on the sparse pilot pattern and CE-BEM, the estimation of CE-BEM coefficients $\{\mathbf{c}_q^{(j)}\}_{q=0}^{Q-1}$ could be decoupled from (6) by Q separated equations without ICI as

$$\left\{ \begin{aligned} [\mathbf{Y}^{(j)}]_{\mathcal{P}_0^{(j)}} &= \Psi^{(j)}[\mathbf{V}_L]_{\mathcal{P}_{\frac{Q-1}{2}}^{(j)}} (\Lambda_0 \mathbf{c}_0^{(j)}) + \mathbf{W}_0^{(j)} \\ &\vdots \\ [\mathbf{Y}^{(j)}]_{\mathcal{P}_{\frac{Q-1}{2}}^{(j)}} &= \Psi^{(j)}[\mathbf{V}_L]_{\mathcal{P}_{\frac{Q-1}{2}}^{(j)}} (\Lambda_{\frac{Q-1}{2}} \mathbf{c}_{\frac{Q-1}{2}}^{(j)}) + \mathbf{W}_{\frac{Q-1}{2}}^{(j)} \\ &\vdots \\ [\mathbf{Y}^{(j)}]_{\mathcal{P}_{Q-1}^{(j)}} &= \Psi^{(j)}[\mathbf{V}_L]_{\mathcal{P}_{\frac{Q-1}{2}}^{(j)}} (\Lambda_{Q-1} \mathbf{c}_{Q-1}^{(j)}) + \mathbf{W}_{Q-1}^{(j)}, \end{aligned} \right. \quad (14)$$

where $\Psi^{(j)} = \mathcal{D}(\mathbf{P}_{val}^{(j)})$ denotes a diagonal matrix with the value pilot subcarriers of the j -th OFDM symbol on its diagonal, $\mathcal{P}_q^{(j)}$ ($0 \leq q \leq Q - 1$) represents a subset of \mathcal{P}_q corresponding to the j -th OFDM symbol, $\{\mathbf{W}_q^{(j)}\}_{q=0}^{Q-1}$

includes the noise and the modeling errors, and Λ_q is a diagonal matrix, denoted as

$$\Lambda_q = \mathcal{D}(1, w^{q-\frac{Q-1}{2}}, \dots, w^{(q-\frac{Q-1}{2})(L-1)}), \quad (15)$$

where $w \triangleq e^{-i\frac{2\pi}{N}}$. (Please refer to [3] for the proof.)

Based on (14), we could decouple JQ CE-BEM coefficient vectors within J consecutive OFDM symbols from (7) by Q separated equations without ICI as

$$\left\{ \begin{aligned} [\mathbf{Y}]_{\mathcal{P}_0} &= \Psi[\mathbf{I}_J \otimes \mathbf{V}_L]_{\mathcal{P}_{\frac{Q-1}{2}}} \begin{pmatrix} \Lambda_0 \mathbf{c}_0^{(0)} \\ \vdots \\ \Lambda_0 \mathbf{c}_0^{(J-1)} \end{pmatrix} + \mathbf{W}_0 \\ &\vdots \\ [\mathbf{Y}]_{\mathcal{P}_{\frac{Q-1}{2}}} &= \Psi[\mathbf{I}_J \otimes \mathbf{V}_L]_{\mathcal{P}_{\frac{Q-1}{2}}} \begin{pmatrix} \Lambda_{\frac{Q-1}{2}} \mathbf{c}_{\frac{Q-1}{2}}^{(0)} \\ \vdots \\ \Lambda_{\frac{Q-1}{2}} \mathbf{c}_{\frac{Q-1}{2}}^{(J-1)} \end{pmatrix} + \mathbf{W}_{\frac{Q-1}{2}} \\ &\vdots \\ [\mathbf{Y}]_{\mathcal{P}_{Q-1}} &= \Psi[\mathbf{I}_J \otimes \mathbf{V}_L]_{\mathcal{P}_{\frac{Q-1}{2}}} \begin{pmatrix} \Lambda_{Q-1} \mathbf{c}_{Q-1}^{(0)} \\ \vdots \\ \Lambda_{Q-1} \mathbf{c}_{Q-1}^{(J-1)} \end{pmatrix} + \mathbf{W}_{Q-1}. \end{aligned} \right. \quad (16)$$

Here, $\Psi = \mathcal{D}(\mathbf{P}_{val})$, \otimes represents the Kronecker product, and \mathbf{I}_J stands for an $J \times J$ identity matrix. Clearly, we know that for a channel with sparsity K , QG ($K < G \ll JL$) pilot subcarriers are sufficient to estimate the channel within J consecutive OFDM symbols.

Since we have verified in section A that the aggregate vectors $\{\mathbf{c}_0^{(0)}, \dots, \mathbf{c}_{Q-1}^{(0)}, \dots, \mathbf{c}_0^{(J-1)}, \dots, \mathbf{c}_{Q-1}^{(J-1)}\}$ are jointly sparse, it is easy to show that all vectors in $\{\Lambda_0 \mathbf{c}_0^{(0)}, \dots, \Lambda_{Q-1} \mathbf{c}_{Q-1}^{(0)}, \dots, \Lambda_0 \mathbf{c}_0^{(J-1)}, \dots, \Lambda_{Q-1} \mathbf{c}_{Q-1}^{(J-1)}\}$ are also jointly sparse. Let us define $\mathbf{c}'_q \triangleq ((\Lambda_q \mathbf{c}_q^{(0)})^T, \dots, (\Lambda_q \mathbf{c}_q^{(J-1)})^T)^T \in \mathbb{C}^{JL \times 1}$. Clearly, we have $\{\mathbf{c}'_q\}_{q=0}^{Q-1}$ exhibiting jointly sparse. In addition, each equation in (16) shares the same measurement matrix $\Psi(\mathbf{I}_J \otimes \mathbf{V}_L)_{\mathcal{P}_{\frac{Q-1}{2}}}$. Then we are able to estimate $\{\mathbf{c}'_q\}_{q=0}^{Q-1}$ based on DCS theory.

However, considering the fact that $\{\mathbf{c}'_q\}_{q=0}^{Q-1}$ has the inherent structured sparsity, we are motivated to exploit the theory of SDCS developed from the DCS theory to estimate channel coefficients. By rearranging the elements of the vector \mathbf{c}'_q as

$$\mathbf{s}_q = \left((\mathbf{s}_q^0)^T, \dots, (\mathbf{s}_q^{L-1})^T \right)^T, \quad (17)$$

in which

$$\mathbf{s}_q^l = (\mathbf{c}'_q(l), \dots, \mathbf{c}'_q((J-1)L+l))^T \in \mathbb{C}^{J \times 1}. \quad (18)$$

Then the system model of (16) can be rewritten as

$$\left\{ \begin{array}{l} [\mathbf{Y}]_{\mathcal{P}_0} = \Phi \mathbf{s}_0 + \mathbf{W}'_0 \\ \vdots \\ [\mathbf{Y}]_{\mathcal{P}_{\frac{Q-1}{2}}} = \Phi \mathbf{s}_{\frac{Q-1}{2}} + \mathbf{W}'_{\frac{Q-1}{2}} \\ \vdots \\ [\mathbf{Y}]_{\mathcal{P}_{Q-1}} = \Phi \mathbf{s}_{Q-1} + \mathbf{W}'_{Q-1}, \end{array} \right. \quad (19)$$

where $\Phi = (\Phi_0, \dots, \Phi_{L-1})$ and Φ_l is denoted as

$$\Phi_l = \left[\Psi(\mathbf{I}_J \otimes \mathbf{V}_L)_{\mathcal{P}_{\frac{Q-1}{2}}} \right]_{l:L:(J-1)L+l}. \quad (20)$$

Here, $[\mathbf{A}]_{l:L:(J-1)L+l}$ denotes a submatrix of \mathbf{A} with the column indices $\{l, L+l, \dots, (J-1)L+l\}$.

Thanks to the inherent structured sparsity of $\{\mathbf{c}'_q\}_{q=0}^{Q-1}$, the rearranged aggregate coefficient vectors $\{\mathbf{s}_q\}_{q=0}^{Q-1}$ exhibit not only joint sparsity but also block sparsity, leading to an special block structural constraint on the system model. In addition, each equation in (19) shares the same measurement matrix Φ . Let us write (19) in a more compact form, and we obtain an novel SDCS model as

$$([\mathbf{Y}]_{\mathcal{P}_0}, \dots, [\mathbf{Y}]_{\mathcal{P}_{Q-1}}) = \Phi(\mathbf{s}_0, \dots, \mathbf{s}_{Q-1}) + \mathbf{W}'. \quad (21)$$

In order to recover $\{\mathbf{s}_q\}_{q=0}^{Q-1}$ with high probability, we need to seek optimal pilot placement to make $\mu(\Phi)$ as small as possible. Here, $\mu(\Phi)$ denotes the coherence of matrix Φ [9]. We formulate the optimization problem as

$$\begin{aligned} & \min_{\mathcal{P}_{\frac{Q-1}{2}}} \mu(\Phi) \\ & \text{s.t. } |p_i - p_j| \geq 2Q - 1, \forall i, j, i \neq j, \end{aligned} \quad (22)$$

where $|p_i - p_j| \geq 2Q - 1, \forall i, j, i \neq j$ must be met to the establishment of (21). Utilizing the discrete stochastic optimization (DSO) based effective pilot pattern design algorithm proposed in [3], the optimal value pilot allocation \mathcal{P}_{val} is obtained. Next we will propose a novel algorithm based on the SDCS model in (21) to compute the coefficient vectors.

C. The Proposed BSOMP Algorithm

Based on the simultaneous orthogonal matching pursuit (SOMP) algorithm, we propose an efficient block-based SOMP (BSOMP) algorithm exploiting the joint-block-sparse structure in $\{\mathbf{s}_q\}_{q=0}^{Q-1}$, presented in **Algorithm 1**.

In **Algorithm 1**, $\mathbf{1}_J$ and $\mathbf{0}_J$ denote the $J \times 1$ column vector of all ones and zeros, respectively. In each iteration, the proposed algorithm first searches the optimal index to make the residual error minimal, and then adds the corresponding index block to the current support set. Note that we update J entries of the support vector simultaneously, and update the measure matrix Φ at the resolution of submatrixs with J column vectors, which is different from the SOMP algorithm that only updates one vector in each iteration.

Clearly, Q sparse coefficients $\{\mathbf{s}_q\}_{q=0}^{Q-1}$ could also be recovered individually based on the CS theory or recovered based on DCS theory. However, SDCS-BSOMP could notably

Algorithm 1 Block-based Simultaneous Orthogonal Matching Pursuit for Channel estimation

Input:

$\mathbf{Y} = ([\mathbf{Y}]_{\mathcal{P}_0}, \dots, [\mathbf{Y}]_{\mathcal{P}_{Q-1}})$ and $\Phi = (\Phi_0, \dots, \Phi_{L-1})$.

Output:

$\mathbf{S} = (\mathbf{s}_0, \dots, \mathbf{s}_{Q-1})$.

- 1: Initialize the iteration index $i = 0$, the sparse vector $\mathbf{S}^0 = \mathbf{0}_{JL \times Q}$, the residual $\mathbf{r}^0 = \mathbf{Y} - \Phi \mathbf{S}^0 = \mathbf{Y}$, the support vector $\Omega = [\Omega_0^T, \dots, \Omega_{L-1}^T]^T = [\mathbf{0}_J^T, \dots, \mathbf{0}_J^T]^T$ with length JL .
 - 2: Calculate the residual errors for all $l \in \{0, \dots, L-1\}$ as $\epsilon_l^i = \|\mathbf{r}^i - \Phi_l(\Phi_l^H \Phi_l)^{-1} \Phi_l^H \mathbf{r}^i\|_2^2$.
 - 3: Among $\{\epsilon_l^i\}_{l=0}^{L-1}$ calculated above, find the index m with the minimal residual error ϵ_m^i . Then update the support vector Ω by $\Omega_m = \mathbf{1}_J$.
 - 4: Update Φ_Ω by extracting the columns of Φ according to the updated support vector Ω . And update the residual as $\mathbf{r}^i = \mathbf{Y} - \Phi_\Omega(\Phi_\Omega^H \Phi_\Omega)^{-1} \Phi_\Omega^H \mathbf{Y}$.
 - 5: $i \leftarrow i + 1$.
 - 6: Repeat Steps 2 to 5 until meeting a certain stop criterion.
 - 7: Based on the optimal least square (LS) estimate, we obtain $\mathbf{S}_\Omega = (\Phi_\Omega^H \Phi_\Omega)^{-1} \Phi_\Omega^H \mathbf{Y}$. Then \mathbf{S} is calculated as $\mathbf{S}(\Omega) = \mathbf{S}_\Omega$, while the coefficient vectors out of the support are denoted as $\mathbf{S}(\tilde{\Omega}) = 0$.
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improve the recovery accuracy compared to DCS-SOMP and CS-OMP due to the fact that the joint block processing in SDCS-BSOMP improves the success rate in searching the location of nonzero values.

To this end, once we recover $\{\mathbf{s}_q\}_{q=0}^{Q-1}$ based on BSOMP, $\{\mathbf{c}_q^{(j)}\}_{q=0}^{Q-1}$ can be calculated based on (17), (18). Then we can obtain channel coefficients $h_{n,l}$ according to (3).

IV. SIMULATION RESULTS AND DISCUSSION

In this section, simulation studies were carried out to compare the performance of the proposed SDCS based channel estimation scheme with conventional DCS/CS based methods. The used parameters of OFDM symbols are listed in Table I.

TABLE I: PARAMETERS OF THE SIMULATION

| Parameters | Values |
|-----------------------|-----------------------------|
| Number of subcarriers | $N = 512$ |
| Length of CP | $L_{CP} = 64$ |
| Length of CIR | $L = 64$ |
| Nonzero taps | $K = 6$ |
| Subcarrier spacing | $\Delta f = 15 \text{ KHz}$ |
| Bandwidth | $B = 7.68 \text{ MHz}$ |
| CE-BEM order | $Q = 3$ |
| Carrier frequency | $f_c = 3 \text{ GHz}$ |
| Modulation | QPSK |

The sparse multiple channel $h_{n,l}$ is modeled with $L = 64$ taps, where $K = 6$ dominant nonzero channel taps are randomly placed among L taps. The channel gain of each path is assumed to be complex Gaussian distributed according to $\mathcal{CN}(0, \frac{1}{K})$. We assume the number of multiple OFDM

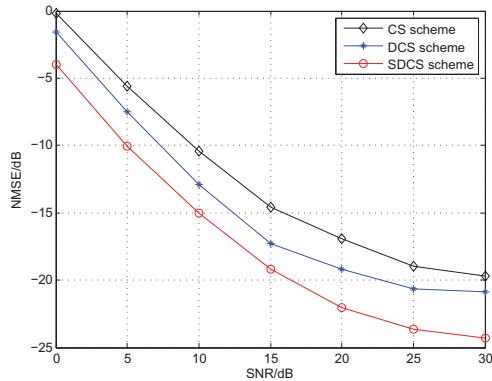


Fig. 2: Comparison of the NMSE performance between the proposed SDCS scheme and the conventional DCS/CS scheme with 350 km/h

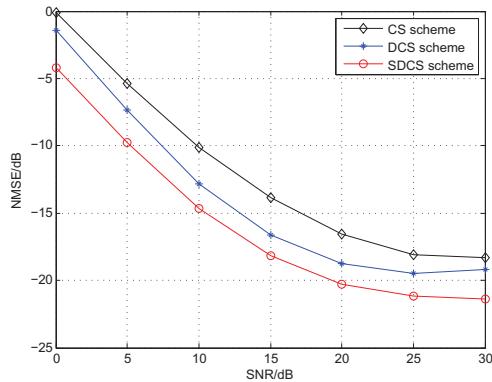


Fig. 3: Comparison of the NMSE performance between the proposed SDCS scheme and the conventional DCS/CS scheme with 500 km/h

symbols that are jointly estimated to be $J = 3$. The average number of pilot subcarriers within a OFDM symbol is fixed to be $P = (2Q - 1)G/J = 5 \times 20 = 100$, in which $G = 60$.

In Fig. 2, we carry out the NMSE comparison between the proposed SDCS scheme and the conventional DCS/CS scheme within multiple OFDM symbols with the speed of $v = 350 \text{ km/h}$. Here we could compute the maximum normalized Doppler frequency as $v_{Dmax} = \frac{f_c v}{\Delta f} = 0.065$, where c is the speed of light. It can be observed in Fig. 2 that the SDCS scheme significantly outperforms the DCS and CS scheme in terms of the channel estimation accuracy. For example, at $\text{NMSE} = -15 \text{ dB}$, the SDCS scheme achieves an signal to noise ratio (SNR) gain of around 2.5 dB compared with DCS scheme and 6 dB compared with CS scheme.

To further illustrate the better performance of our proposed scheme over higher normalized Doppler shift, we carry out the similar comparison in Fig. 3 with the speed of $v = 500 \text{ km/h}$ ($v_{Dmax} = 0.093$). Similarly, we can observe the superiority of our proposed SDCS scheme. However, the performances of all the curves are degraded compared with the corresponding curves in Fig. 2, which is mainly caused by CE-BEM modeling errors getting larger when Doppler shift increases.

V. CONCLUSION

In this paper, we presented a novel SDCS-based joint channel estimation scheme within multiple OFDM symbols over a high mobility channel. By utilizing the CE-BEM and designing special sparse pilot pattern, we transformed the original sparse time-varying channel into a joint-block-sparse channel model, and proposed a novel BSOMP algorithm to exploit the joint block sparsity property of the coefficient vectors. The proposed SDCS-based scheme achieves a better performance than the conventional CS-based and DCS-based scheme in terms of channel estimation accuracy.

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