Structured Compressive Sensing-Based Channel Estimation for Time Frequency Training OFDM Systems Over Doubly Selective Channel

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***Abstract*—This letter proposes a novel doubly selective channel estimation scheme based on structured compressive sensing (SCS) for time-frequency training orthogonal frequency division multiplexing systems. By exploiting the proposed pilot pattern, an SCS model is built by utilizing the jointly sparse property of the coefficient vectors corresponding to the channel expansion bases. The doubly selective channel can be recovered through the proposed adaptive support-aware block orthogonal matching pursuit algorithm. Simulation results demonstrate that the proposed scheme has superior performance than conventional counterparts over doubly selective channel with lower computational complexity.**

***Index Terms*—Channel estimation, doubly selective channel, structured compressive sensing (SCS), TFT-OFDM.**

I. Introduction

ORTHOGONAL frequency division multiplexing (OFDM) is widely applied in modern communications systems. The well-known cyclic prefixed OFDM (CP-OFDM) uses the cyclic prefix (CP) as the guard interval. Time-frequency training OFDM (TFT-OFDM) adopts the pseudo-random noise (PN) sequence instead to facilitate the implementation of synchronization and coarse channel estimation, while frequency-domain pilots are exploited to perform more accurate channel estimation [1].

For OFDM systems, accurate synchronization and channel estimation is the prerequisite of the system stability and superior performance [2]–[5]. The channel frequency selectivity caused by multipath propagation has drawn plenty of research attention. However, in high-speed mobile environment, in addition to frequency selectivity, the channel also suffers from time selectivity resulting from the Doppler effect. Over this complicated channel, which is often referred to as doubly selective channel, the channel estimation becomes challenging.

The channel impulse responses (CIRs) for different samples within a single OFDM frame vary over doubly selective channel, which means a large number of coefficients should be estimated. Therefore, much more pilots are required to recover the doubly selective channel than the solely frequency selective channel, which results in inevitable great loss of spectral efficiency. To reduce the amount of coefficients, the channel variation was addressed as a linear model [6]. The channel sparsity was widely considered for channel estimation [7], [8] and the structured CS (SCS) model was utilized. However, only time-invariant channel was considered in [7], and the symbol structure and pilot pattern were not fully investigated in [8] which could be optimized.

In this letter, a time-frequency training (TFT) based doubly selective channel estimation scheme is proposed for TFT-OFDM systems. Assuming the supports of the CIRs for different samples are the same during the OFDM symbol, the CIR of the doubly selective channel is modeled as block sparse vectors in delay dimension, and can be meanwhile represented by the expansion of some complex exponential bases in sample dimension. The partial support is acquired from the PN sequence, while a novel frequency-domain pilot pattern is proposed to formulate an SCS model. After cyclic reconstruction of the OFDM symbol, the doubly selective channel can be recovered utilizing the proposed adaptive support-aware block orthogonal matching pursuit (ASA-BOMP) algorithm. Simulation results show that the proposed scheme outperforms the conventional counterparts and can achieve higher spectral efficiency and accuracy.

Notation: Uppercase and lowercase boldface letters denote matrices and column vectors, respectively; $\otimes$, $(\cdot)^T$, $(\cdot)^H$, and $\text{diag}(\cdot)$ denote the circular convolution, transpose, conjugate transpose, and changing a vector into a diagonal matrix, respectively. $[\cdot]_{i,j}$ and $[\cdot]_{\mathbf{p},\mathbf{q}}$ denote (i, j)-th entry of a matrix, and a submatrix with row indices $\mathbf{p}$ and column indices $\mathbf{q}$, respectively.

II. System Model

A. TFT-OFDM Signal Structure and Proposed Pilot Pattern

The TFT-OFDM has both time-domain training sequence (TS) and frequency-domain pilots for every frame, which is illustrated in Fig. 1. The M-length TS $\mathbf{c}$ is a PN sequence identical for all frames, which is of good auto-correlation property and can be used to acquire partial support. Meanwhile, some sub-carriers in the OFDM frame are filled with pilots to perform accurate channel estimation.

The proposed scheme aims to utilize a small amount of frequency-domain pilots to perform accurate channel estimation. As shown in Fig. 1, the pilots are combined and classified into G pilot sets. For one pilot set, $2Q - 1$ sub-carriers are employed, in which Q sub-carriers in the center are filled with non-zero pilots, while the other $Q - 1$ sub-carriers are padded with zeros, preventing the interference from the data sub-carriers caused by the time selective channel. Q is assumed to be an odd number for convenience. The location of the pilot sets are randomly configured for high performance of

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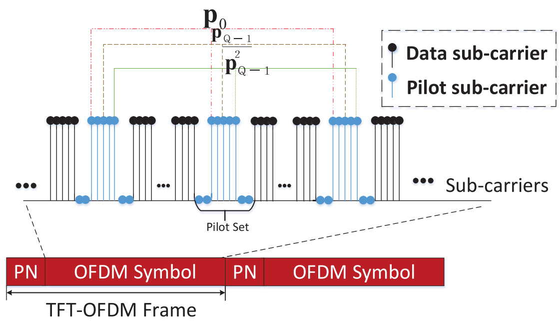

Fig. 1. TFT-OFDM signal structure with the proposed pilot pattern.

CS recovery. The non-zero pilots with the same index in different pilot sets are denoted as $\mathbf{p}_q \in \mathbb{C}^G$, $0 \le q < Q$, which have been marked in Fig. 1.

B. Channel Model

A discrete and sparse CIR model for doubly selective channel is considered in this letter, which can be described in the dimensions of sample and delay.

The l-th discrete channel delay at sample m is denoted by $h[m, l]$, where $0 \le l < L$ and L is the channel length. It has been widely investigated that the number of resolvable paths is always much less than the channel length [1]. Therefore, the sample-based CIR for sample m, which is denoted as $\mathbf{h}_\mathrm{d}^{(m)} = [h[m, 1], h[m, 2], \ldots, h[m, L]]^T$, is a sparse vector with sparsity level S. The supports of $\mathbf{h}_\mathrm{d}^{(m)}$ for adjacent samples are considered identical in this letter since the variation of the CIR can be assumed to be slow compared with the duration of the OFDM symbol [9]. Therefore, The N sample-based CIR vector $\mathbf{h}_\mathrm{d}^{(m)} (0 \le m < N)$ are jointly sparse.

The tap-based CIR vector consisting of all the l-th discrete channel delay taps from all the N sample-based CIRs over the OFDM symbol is denoted by $\mathbf{h}_\mathrm{t}^{(l)} = [h[1, l], h[2, l], \ldots, h[N, l]]^T$, where N is the length of OFDM symbol. To reduce the number of the estimated coefficients, $\mathbf{h}_\mathrm{t}^{(l)} (0 \le l < L)$ can often be represented as the expansion of $Q_0 (Q_0 \ll L)$ bases, which are called BEM [8] and given by

$$\mathbf{h}_\mathrm{t}^{(l)} = \sum_{q=0}^{Q_0-1} c[q, l]\mathbf{b}_q + \mathbf{n}_l, \tag{1}$$

where $\mathbf{b}_q \in \mathbb{C}^N$ and $c[q, l]$ represent the q-th basis and corresponding BEM coefficients for l-th discrete channel delay, respectively, while $\mathbf{n}_l \in \mathbb{C}^N$ denotes the modeling error. The number of non-zero sub-carriers in a pilot set is set equal to the number of bases, i.e., $Q = Q_0$.

The BEM coefficients vector can be represented as

$$\mathbf{c}_q = [c[q, 0], c[q, 1], \ldots, c[q, L-1]]^T, \tag{2}$$

where $0 \le q < Q$. Given a jointly sparse sample-based CIR vector $\mathbf{h}_\mathrm{d}^{(m)}$ for $0 \le m < N$, $\mathbf{c}_q$ are also jointly sparse according to the definition in (2) and (1), whose supports are identical with that of $\mathbf{h}_\mathrm{d}^{(m)}$.

The complex exponential BEM (CE-BEM), which is employed as CIR bases in this letter, has been introduced in [8], whose q-th basis can be represented as

$$\mathbf{b}_q^{\mathrm{CE}} = (1, \ldots, e^{j\frac{2\pi}{N}n(q-\frac{Q-1}{2})}, \ldots, e^{j\frac{2\pi}{N}(N-1)(q-\frac{Q-1}{2})})^T. \tag{3}$$

III. The Proposed Channel Estimation Scheme

A. Step 1: Partial Common Support Estimation

The proposed channel estimation scheme uses PN sequence to acquire the partial common support of $\mathbf{h}_\mathrm{d}^{(m)}$. Even though the CIR can be time-variant over a long period, the supports among different samples are identical, which are estimated in the first place.

At the receiver, the partial common support is acquired by correlating the received PN sequence $\mathbf{c}_r$ with the local PN sequence $\mathbf{c}$. The correlation result can be denoted as

$$\mathbf{z} = \frac{1}{M}\mathbf{c}_r \otimes \mathbf{c}, \tag{4}$$

where $\mathbf{z} \in \mathbb{C}^M$. According to the good auto-correlation property of PN sequence, $\mathbf{z}$ is a rough estimation of CIR, even over a time-selective channel due to the common support among different samples.

The partial common support T_0 can be obtained by selecting the elements greater than a threshold a, e.g., $T_0 = \{l : \|z[l] \ge a\|\}_{l=0}^{L-1}$. The threshold a can be approximately selected by $a = 3(\sum_{l=0}^{L-1} |z[l]|^2)^{1/2}/L$ [1]. T_0 will be further used in *Step 3* to reduce the complexity and improve the recover accuracy.

B. Step 2: Symbol Cyclic Reconstruction and Its Structure

The TFT-OFDM system sacrifices the cyclic property, which causes inter-symbol interference. Therefore, before performing accurate channel estimation using frequency pilots, the cyclic reconstruction is an essential process, which is based on the overlapping and adding operation (OLA) [10]. The difference lies in that the time-invariant channel should be considered in the reconstruction process.

After cyclic reconstruction, the OFDM symbol in time domain can be given by [6]

$$\mathbf{r} = \mathbf{H}_T\mathbf{s} + \mathbf{w}_t, \tag{5}$$

where $\mathbf{r}, \mathbf{s} \in \mathbb{C}^N$ are transmitted and received OFDM symbols in the time domain, respectively. $\mathbf{w}_t \in \mathbb{C}^N$ describes the i.i.d. additive white Gaussian noise (AWGN). The elements of $\mathbf{H}_T \in \mathbb{C}^{N\times N}$ are $[\mathbf{H}_T]_{i,j} = h[i, \mathrm{mod}(i-j, N)]$.

In the frequency domain, equation (5) can be rewritten as

$$\widetilde{\mathbf{r}} = \mathbf{F}_N(\mathbf{H}_T(\mathbf{F}_N^H\widetilde{\mathbf{s}}) + \mathbf{w}_t) = \mathbf{F}_N\mathbf{H}_T\mathbf{F}_N^H\widetilde{\mathbf{s}} + \mathbf{F}_N\mathbf{w}_t = \mathbf{H}_F\widetilde{\mathbf{s}} + \mathbf{w}_f, \tag{6}$$

where $\widetilde{\mathbf{r}}$ and $\widetilde{\mathbf{s}}$ are the received and transmitted frequency symbols, respectively. $\mathbf{F}_N \in \mathbb{C}^{N\times N}$ is the fast Fourier transform matrix, while $\mathbf{H}_F = \mathbf{F}_N\mathbf{H}_T\mathbf{F}_N^H$ is not a diagonal matrix due to time-selective channel condition.

Considering the BEM expansion of the channel, $\mathbf{H}_F$ can be represented as [8]

$$\mathbf{H}_F = \sum_{i=0}^{Q-1} \mathbf{B}_i^{\mathrm{CE}}\mathbf{C}_i, \tag{7}$$

where $\mathbf{B}_i^{\mathrm{CE}} = \sqrt{N}\mathbf{F}_N\mathrm{diag}(\mathbf{b}_i^{\mathrm{CE}})\mathbf{F}_N^H$ and $\mathbf{C}_i = \mathrm{diag}(\mathbf{F}_N(\mathbf{c}_i^T, \mathbf{0}_{1\times(N-L)})^T)$. Therefore, equation (6) can be transformed to

$$\widetilde{\mathbf{r}} = \sum_{i=0}^{Q-1} \mathbf{B}_i^{\mathrm{CE}}\mathbf{C}_i\widetilde{\mathbf{s}} + \mathbf{w}_f. \tag{8}$$

Algorithm 1 Proposed ASA-BOMP for Doubly Selective Channel Estimation

Input:
1) Initial channel partial common support T_0;
2) Noisy measurements $\widetilde{\mathbf{r}}_p \in \mathbb{C}^{QG}$;
3) Sensing matrix $\hat{\mathbf{\Phi}} \in \mathbb{C}^{QG \times QL}$;
4) Channel sparsity $S = 0$;

Initialization:
$T \leftarrow T_0$

Iterations:
repeat
$S \leftarrow S + 1$
for $s = 0{:}S - \|T_0\|_0 - 1$ **do**
  $\mathbf{c}^{(s)} \leftarrow \mathbf{0}$; $\mathbf{c}_T^{(s)} \leftarrow \hat{\mathbf{\Phi}}_T^{\dagger} \widetilde{\mathbf{r}}_p$
  $\mathbf{r}^{(s)} \leftarrow \widetilde{\mathbf{r}}_p - \hat{\mathbf{\Phi}} \mathbf{c}^{(s)}$
  $\mathbf{g} \leftarrow \hat{\mathbf{\Phi}}^H \mathbf{r}^{(s)}$
  $T \leftarrow T \cup \arg\max_j \sum_{i=0}^{Q-1} |\mathbf{g}_{iL+j}|$
end for
$\mathbf{c}^{(S-\|T_0\|_0)} \leftarrow \mathbf{0}$; $\mathbf{c}_T^{(S-\|T_0\|_0)} \leftarrow \hat{\mathbf{\Phi}}_T^{\dagger} \widetilde{\mathbf{r}}_p$
$\mathbf{r}^{(S-\|T_0\|_0)} \leftarrow \widetilde{\mathbf{r}}_p - \hat{\mathbf{\Phi}} \mathbf{c}^{(S-\|T_0\|_0)}$
until $\|\mathbf{r}^{(S-\|T_0\|_0)}\|_2 < \epsilon^2$

Output: $\hat{\mathbf{c}} = \mathbf{c}^{(S-\|T_0\|_0)}$

C. Step 3: Accurate Doubly Selective Channel Estimation

In order to employ the jointly sparse property of $\mathbf{c}_i$ as previously described in Section II-B, CS models should be decoupled from (8). According to the property of CE-BEM, $\mathbf{B}_i^{\mathrm{CE}}$ can be simplified as

$$\mathbf{B}_i^{\mathrm{CE}} = \sqrt{N}\mathbf{F}_N \mathrm{diag}(\mathbf{b}_i^{\mathrm{CE}})\mathbf{F}_N^H = \sqrt{N}\mathbf{I}_N^{\langle i - \frac{Q-1}{2} \rangle}, \tag{9}$$

where $\mathbf{I}_N^{\langle i - \frac{Q-1}{2} \rangle}$ is a permutation matrix obtained from a unit matrix. On the other hand, $\mathbf{C}_i \widetilde{\mathbf{s}}$ can be formulated as

$$\mathbf{C}_i \widetilde{\mathbf{s}} = \mathrm{diag}(\mathbf{F}_N(\mathbf{c}_i^T, \mathbf{0}_{(N-L)\times 1})^T)\widetilde{\mathbf{s}} = \frac{1}{\sqrt{N}} \mathrm{diag}(\widetilde{\mathbf{s}})\mathbf{F}'_N \mathbf{c}_i, \tag{10}$$

where $\mathbf{F}'_N = [\mathbf{F}_N]_{0:N-1,0:L-1}$. Therefore, $\widetilde{\mathbf{r}}$ now can be derived as

$$\widetilde{\mathbf{r}} = \sum_{i=0}^{Q-1} \mathbf{I}_N^{\langle i - \frac{Q-1}{2} \rangle} \mathrm{diag}(\widetilde{\mathbf{s}})\mathbf{F}'_N \mathbf{c}_i + \mathbf{w}_f. \tag{11}$$

We select the pilots $\mathbf{p}_q (0 \le q < Q)$ through $\widetilde{\mathbf{r}}$ by using a selector matrix $\mathbf{\Psi}_q = [\mathbf{I}_N]_{\mathbf{p}_q, 0:N-1} \in \mathbb{C}^{G \times N}$. Then, the received pilots in the frequency domain can be represented as

$$\widetilde{\mathbf{r}}_{\mathbf{p}_q} = \mathbf{\Psi}_q \widetilde{\mathbf{r}} = \sum_{i=0}^{Q-1} \mathbf{\Psi}_q \mathbf{I}_N^{\langle i - \frac{Q-1}{2} \rangle} \mathrm{diag}(\widetilde{\mathbf{s}})\mathbf{F}'_N \mathbf{c}_i + \mathbf{w}', \tag{12}$$

where $\mathbf{w}' = \mathbf{\Psi}_q \mathbf{w}_f$. According to the pilot pattern in Fig. 1, $\mathbf{\Psi}_q \mathbf{I}_N^{\langle i - \frac{Q-1}{2} \rangle} \mathrm{diag}(\widetilde{\mathbf{s}}) = \mathbf{0}$ for $i + q < 1$ and $i + q > Q$. Then, the received pilots in the frequency domain are simplified as

$$\widetilde{\mathbf{r}}_{\mathbf{p}_q} = \sum_{i=0}^{Q-1} \mathbf{\Phi}_{i-q+\frac{Q-1}{2}} \mathbf{c}_i + \mathbf{w}', \qquad 0 \le q < Q, \tag{13}$$

where $\mathbf{\Phi}_k = \mathbf{\Psi}_k \mathrm{diag}(\widetilde{\mathbf{s}})\mathbf{F}'_N$ for $0 \le k < Q$, and $\mathbf{\Phi}_k = \mathbf{0}^{G \times L}$ for other k. Furthermore, equation (13) can be represented as the matrix format as

$$\widetilde{\mathbf{r}}_{\mathbf{p}_q} = \mathbf{\Phi}\widetilde{\mathbf{c}}_q + \mathbf{w}', \qquad 0 \le q < Q, \tag{14}$$

where $\mathbf{\Phi} = [\mathbf{\Phi}_0, \mathbf{\Phi}_1, \dots, \mathbf{\Phi}_{Q-1}]$ and $\widetilde{\mathbf{c}}_q = [\mathbf{c}^T_{-\frac{Q-1}{2}+q}, \mathbf{c}^T_{-\frac{Q-1}{2}+q+1}, \dots, \mathbf{c}^T_{\frac{Q+1}{2}+q}]^T$ are sensing matrix and sparse vector, where $\mathbf{c}_i^T = \mathbf{0}^{L \times 1}$ for $i < 0$ and $i \ge Q$.

Without loss of generality, the following derivation will take $Q = 3$ and noise-free condition as an example. The same conclusion also holds for the general value of Q with noise, which can be derived similarly.

Combining the equations in (14) for $0 \le q < 3$, we have

$$\widetilde{\mathbf{r}}_p = \mathbf{\Phi}_\Lambda \widetilde{\mathbf{c}}, \tag{15}$$

where $\widetilde{\mathbf{r}}_p = [\widetilde{\mathbf{r}}_{\mathbf{p}_0}^T, \widetilde{\mathbf{r}}_{\mathbf{p}_1}^T, \widetilde{\mathbf{r}}_{\mathbf{p}_2}^T]^T$, $\mathbf{\Phi}_\Lambda = \mathrm{diag}(\mathbf{\Phi}, \mathbf{\Phi}, \mathbf{\Phi}) \in \mathbb{C}^{3G \times 9L}$ is a block diagonal matrix. $\widetilde{\mathbf{c}} = [\widetilde{\mathbf{c}}_0^T, \widetilde{\mathbf{c}}_1^T, \widetilde{\mathbf{c}}_2^T]^T = [\mathbf{0}^T, \mathbf{c}_0^T, \mathbf{c}_1^T, \mathbf{c}_0^T, \mathbf{c}_1^T, \mathbf{c}_2^T, \mathbf{c}_1^T, \mathbf{c}_2^T, \mathbf{0}^T]^T$ has $\mathbf{0}^T \in \mathbb{C}^{L \times 1}$ elements and identical parts of $\mathbf{c}_1^T$, $\mathbf{c}_2^T$, and $\mathbf{c}_3^T$. The $\mathbf{0}^T$ components can be eliminated by removing the relevant columns of $\mathbf{\Phi}_\Lambda$, while identical parts can be gathered by replacing the relevant columns of $\mathbf{\Phi}_\Lambda$, and then (15) can be readily rewritten as

$$\widetilde{\mathbf{r}}_p = \hat{\mathbf{\Phi}}_\Lambda \check{\mathbf{c}}, \tag{16}$$

where $\check{\mathbf{c}} = [\mathbf{c}_0^T, \mathbf{c}_0^T, \mathbf{c}_1^T, \mathbf{c}_1^T, \mathbf{c}_1^T, \mathbf{c}_2^T, \mathbf{c}_2^T]^T$, and $\hat{\mathbf{\Phi}}_\Lambda \in \mathbb{C}^{3G \times 7L}$ is a matrix after columns removed and replaced for $\mathbf{\Phi}_\Lambda$. Dividing $\hat{\mathbf{\Phi}}_\Lambda$ into 7 parts, which can be denoted as $\hat{\mathbf{\Phi}}_\Lambda = [\hat{\mathbf{\Phi}}_{\Lambda 0}, \hat{\mathbf{\Phi}}_{\Lambda 1}, \dots, \hat{\mathbf{\Phi}}_{\Lambda 6}]$, where $\hat{\mathbf{\Phi}}_{\Lambda i} \in \mathbb{C}^{3G \times L}$ for $0 \le i < 7$, then, we have the final CS equation as

$$\widetilde{\mathbf{r}}_p = [\hat{\mathbf{\Phi}}_{\Lambda 0} + \hat{\mathbf{\Phi}}_{\Lambda 1}, \hat{\mathbf{\Phi}}_{\Lambda 2} + \hat{\mathbf{\Phi}}_{\Lambda 3} + \hat{\mathbf{\Phi}}_{\Lambda 4}, \hat{\mathbf{\Phi}}_{\Lambda 5} + \hat{\mathbf{\Phi}}_{\Lambda 6}]\hat{\mathbf{c}}, \tag{17}$$

where $\hat{\mathbf{c}} = [\mathbf{c}_0^T, \mathbf{c}_1^T, \mathbf{c}_2^T]^T$.

As $\mathbf{c}_q$ are jointly sparse for $0 \le q < Q$, equation (17) is a typical block sparse model, with L blocks in total, where the i-th block in $\hat{\mathbf{c}}_{\mathrm{est}}$ implies the elements $[\widehat{\mathbf{c}}]_{i:L:(Q-1)L+i}$ are either all zeros or all non-zeros.

Therefore, $\mathbf{c}_q$ can be recovered through SCS algorithms. The conventional greedy algorithm like block orthogonal matching pursuit (BOMP) [11] does not consider the partial common support in *Step 1*. In order to improve the recovery performance, an ASA-BOMP algorithm is proposed in Algorithm 1 to make use of the prior information.

In the algorithm, $\mathbf{c}_T^{(s)}$ denotes the blocks of $\mathbf{c}^{(s)}$ whose indices are in the set T, while $\hat{\mathbf{\Phi}}_T$ is a sub-matrix of $\hat{\mathbf{\Phi}}$ whose column indices are based on T. The proposed ASA-BOMP exploits the obtained partial common support as input, which offers more accurate initial configuration and reduces the computational complexity, since on average only $S - \|T_0\|_0$ iterations are needed to maintain the recovery performance instead of S iterations in conventional BOMP. The algorithm will perform more accurately due to the utilization of the auxiliary information of the partial common support. Moreover, by testing the sparsity level S adaptively, the sparsity level is assumed to be unknown, which is more practical in real applications.

After $\mathbf{c}_q (0 \le q < Q)$ are recovered, the doubly selective channel can be estimated by utilizing (1).

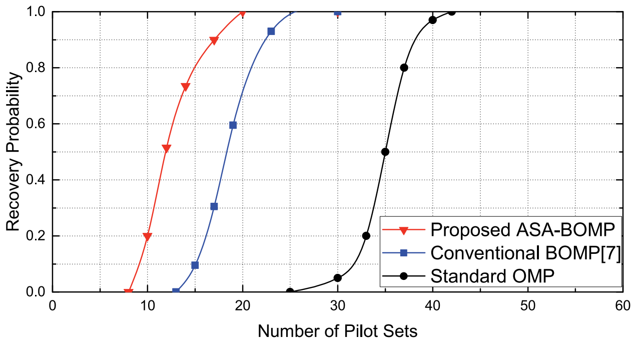

Fig. 2. Doubly selective channel recovery probabilities comparison.

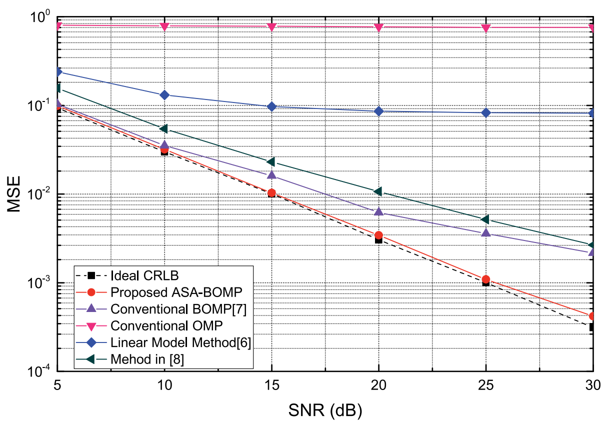

Fig. 3. MSE performance comparison among different schemes.

IV. Simulation Results

In this section, the performance of the proposed doubly selective channel estimation scheme is investigated through simulations. The simulation setup is in a typical wireless mobile transmission environment, where the simulation parameters are summarized as follows: the length of OFDM symbol and the PN sequence are $N = 4096$ and $M = 256$, respectively. The system bandwidth is $W = 7.56$ MHz located at the central frequency of 634 MHz. The 6-tap ITU vehicular-B channel model [12] is adopted to simulate the channel frequency selectivity and the normalized Doppler frequencies $f_{\max} = 0.080$ is considered to represent time selectivity [6], while $Q = 3$ for BEM function.

Fig. 2 compares the probability of correct recovery with the proposed ASA-BOMP and the conventional BOMP [7], while the standard OMP is also illustrated as a comparison. The correct recovery here is defined as the estimation mean square error (MSE) is lower than 10^{-2}. The signal-to-noise ratio (SNR) is configured as 20 dB. It can be seen from Fig. 2 that by utilizing the obtained partial common support information and the block sparse property, 20 pilot sets can ensure the correct CIR recovery probability for the ASA-BOMP algorithm, which saves 6 sets and 22 sets compared with the conventional BOMP and standard OMP, respectively.

The MSE performance of CIR estimation versus SNR is shown in Fig. 3, where $G = 20$ pilot sets are applied. The linear model method [6], the conventional scheme [8], and the schemes using BOMP [7] and OMP are evaluated for comparison, while the ideal Cramer-Rao lower bound (CRLB) ($CRLB = S\sigma^2/G$) is also illustrated as the benchmark. The proposed channel estimation method outperforms the conventional BOMP scheme and scheme in [8] because the auxiliary information of non-zero support is utilized and larger power measurements of the non-zero pilots are adopted. The linear model scheme [6] has poor performance due to not considering the channel sparsity and inaccurate channel modeling, while the OMP scheme also fails to recover the coefficients due to the insufficient pilots. When 10^{-2} of MSE is considered, the proposed algorithm for TFT-OFDM system has a 2.5 dB and 5 dB gain compared to the BOMP method and scheme in [8] and is only 0.1 dB away from the ideal CRLB.

V. Conclusion

In this letter, a novel doubly selective channel estimation scheme is proposed for TFT-OFDM systems using time-frequency training. The time-domain PN sequence is exploited to perform partial common support acquisition, while the frequency-domain pilots achieve the accurate channel estimation under the framework of SCS which is formulated by exploiting the proposed pilot pattern. A novel SCS greedy algorithm ASA-BOMP is proposed for doubly selective channel estimation. Simulation results show that the proposed scheme and algorithm outperform the conventional ones with low computational complexity and small amount of pilot overhead.

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