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# Compressive Sensing-Based Channel Estimation for FBMC-OQAM System Under Doubly Selective Channels

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**ABSTRACT** Filter-bank multicarrier with offset quadrature amplitude modulation (FBMC-OQAM) has been considered as an alternative scheme to orthogonal frequency division multiplexing (OFDM). However, the traditional channel estimation techniques of the OFDM cannot be directly applied to the FBMC-OQAM system because of the real-field orthogonality of the FBMC-OQAM signals. Although traditional channel estimation techniques, such as least square (LS) and minimum mean square error (MMSE), are widely applied to the FBMC-OQAM system via canceling the intrinsic imaginary interference from adjacent data symbols, the LS algorithm is subject to noise enhancement and it results in large mean square error (MSE), while the mmse algorithm needs to know the statistical information of channel in advance. Due to sparsity of the wireless channel, channel estimation is investigated as a compressive sensing (CS) problem. In this paper, we first introduce the coding method to cancel intrinsic imaginary interference for the FBMC-OQAM system. Then, a novel sparse adaptive subspace pursuit (SASP) method is proposed to improve the accuracy of LS channel estimation. Finally, we develop two distinctive algorithms, namely, auxiliary pilot (AP) SASP and coding-SASP, to estimate channel frequency response (CFR) in the FBMC-OQAM system. The simulation results show that the AP-SASP and coding-SASP algorithms can offer a low complexity and fewer measurements compared with conventional orthogonal matching pursuit (OMP) and regularized OMP (ROMP) methods. Moreover, the proposed AP-SASP and coding-SASP algorithms have a better bit error ratio (BER) performance than the conventional OMP and ROMP methods for FBMC system in the doubly selective channels.

**INDEX TERMS** FBMC-OQAM, channel estimation, compressive sensing (CS), coding-SASP, doubly selective channels.

## I. INTRODUCTION

Orthogonal frequency division multiplexing (OFDM) system has been widely applied to long term evolution (LTE) and digital video broadcasting-terrestrial (DVB-T), which is robust against multipath channels by inserting a cyclic prefix (CP). However, the OFDM system adopts rectangular shaping filter on each sub-channel, which leads to large out-of-band emission [1]. To address the problem of spectrum scarcity, filter-bank multicarrier with offset quadrature amplitude modulation (FBMC-OQAM) was proposed and it may be an alternative to OFDM system, because it does

not use any cyclic prefix, and can achieve high spectral efficiency and low out-of-band emission [2]. Unlike OFDM system, the sub-carriers of the FBMC-OQAM system are only orthogonal in the real field. Therefore, traditional channel estimation techniques, such as least square (LS) channel estimation and minimum mean square error (MMSE) channel estimation, for OFDM system cannot be directly applied to FBMC-OQAM system due to the intrinsic imaginary interference [3] among sub-carriers and symbols of FBMC-OQAM system. Therefore, the channel estimation is a challenge for FBMC-OQAM system.

Up to now, cancelling the intrinsic imaginary interference based on pilots mainly has two categories: auxiliary pilot

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method (AP) [4] and coding pilot method [5]. The AP scheme is simple and effective. However, the shortcoming of the AP method has power offset, which leads to a high peak to average power ratio (PAPR) value. Thus, reference [6] uses a new non-linear scattered pilot design to address the problem of increased power of the AP scheme, while reference [7] proposes a very effective linear precoding method, which completely cancels the power offset at the expense of increased computational complexity. Reference [8] proposes an intermediate complexity and small power offset scheme combining the methods of [6] and [7]. Through eliminating the intrinsic interference above these algorithms, the well-known MMSE method has very good channel estimation performance and it has been applied to FBMC-OQAM system [9]. However, it has high complexity and needs to know the statistical information of channel in advance. While LS channel estimation is also widely applied to FBMC-OQAM system [10] because it does not need prior information of channel and is easy to implement. However, only using AP or coding method, the performance of LS channel estimation is unsatisfactory because it is difficult to entirely cancel the intrinsic imaginary interference. Moreover, it has large mean square error (MSE) and is easily affected by the noise.

To further improve the performance of channel estimation, a more attractive method, namely compressive sensing (CS) method [11], is researched in wireless communications recently because the wireless channel exhibits sparsity in practice. The channel estimation based on CS theory has been widely researched for OFDM system in the past few years. Such as, by skillfully designing pilot and utilizing the sparsity of the channel impulse response (CIR), references [12]–[14] realize high-accuracy channel estimation for OFDM system. Moreover, reference [15] proposes a simple sparse channel estimation and tracking scheme for time-varying OFDM system. However, the literatures of CS-based channel estimation methods are few for FBMC-OQAM system. An adaptive regularized compressive sampling matching pursuit (ARCoSaMP) algorithm is proposed to improve the accuracy of reconstruction in [16]. However, the ARCoSaMP algorithm has high computational complexity.

In this paper, compared with the existing CS-based work of FBMC-OQAM system, our main contributions of this paper are as follows:

- 1) A novel sparse adaptive subspace pursuit (SASP) method is proposed for channel estimation in FBMC-OQAM system. The advantage of the proposed SASP method is that it does not need priori channel sparsity utilizing conventional sparse adaptive matching pursuit (SAMP) algorithm [17]. The proposed SASP method is based on the thought of backtracking of subspace pursuit (SP) algorithm [18]. Moreover, the SP algorithm is more efficient than compressive sampling matching pursuit (CoSaMP) algorithm [19] in terms of computational complexity. Thus, the SASP algorithm is based on the advantages of both SAMP and SP algorithms.

**TABLE 1. The neighbor interference coefficients of the normalized PHYDYAS prototype filter.**

	Time →						
Frequency ↓	0.0005	-0.0001	0	0	0	-0.0001	0.0005
	-0.0428i	-0.1249	0.2057i	0.2392	-0.2057i	-0.1249	0.0428i
	-0.0667	0.0002	0.5644	1	0.5644	0.0002	-0.0667
	0.0428i	-0.1249	-0.2057i	0.2392	0.2057i	-0.1249	-0.0428i
	0.0005	-0.0001	0	0	0	-0.0001	0.0005

- 2) The conventional CS-based channel estimation methods generally estimate channel impulse response (CIR) utilizing sparse characteristic of wireless multipath channels in time domain. However, The proposed CS-based channel estimation method firstly uses LS algorithm based on conventional pilot for FBMC-OQAM system. Then, the proposed SASP algorithm estimates channel frequency respond (CFR) utilizing sparsity of scattered pilot spacing in frequency domain.
- 3) The existing CS-based channel estimation methods of FBMC-OQAM system consider only interference approximation method (IAM) or interference cancellation method (ICM) utilizing AP symbols to eliminate the intrinsic imaginary interference. This method easily leads to a high peak-to-average ratio (PAPR) in the transmitter, which degrades the efficiency of the high power amplifier (HPA) [20]. To address this problem, we develop a new coding-SASP algorithms to estimate channel frequency respond (CFR) in FBMC-OQAM system. Meanwhile, we analyze the complexity of both AP-SASP and coding- SASP algorithms

For brevity, we remove the suffix OQAM from FBMC system in the rest of this paper. Thus, any mention of FBMC system should be understood as being FBMC-OQAM system. The remainder of this paper is organized as follows. A description of FBMC system model is presented in section II. Then, we present scattered pilot schemes in section III. Moreover, the proposed CS based on channel estimation method is analyzed in section IV, where we mainly analyze CS theory for channel estimation and the proposed SASP algorithm. Numerical results and discussions are given by section V. Finally, conclusions are drawn in section VI.

## II. FBMC SYSTEM MODEL

The transmitted data of discrete FBMC system can be expressed as [21]

$$x[i] = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} a_{m,n} g[i - nN/2] e^{j\frac{2\pi}{M} m(i - \frac{D}{2})} e^{j\phi_{m,n}}, \quad (1)$$

where  $N$  denotes the total number of sub-carriers,  $D = UN$  denotes the delay term,  $U$  denotes the overlapping factor. The transmitted symbol  $a_{m,n}$  denotes a real-valued symbol which is the real or imaginary part of QAM symbol for the  $m$ th sub-carrier and the  $n$ th symbol, and  $\phi_{m,n} = \frac{\pi}{2} (m + n) - \pi mn$  denotes an additional phase term.  $g[i]$  denotes prototype filter.

We can rewrite equation (1) in a simple manner

$$x[i] = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} a_{m,n} g_{m,n}[i], \quad (2)$$

where  $g_{m,n}[i]$  denotes the shifted versions of prototype filter  $g[i]$  in time and frequency domain. In this paper, we consider the prototype filter of the PHYDYAS project in [22]. The impulse response coefficients of the PHYDYAS prototype filter can be expressed using the following closed-form representation:

$$g[i] = 1 + 2 \sum_{u=1}^{U-1} (-1)^u G[u] \cos\left(\frac{2\pi u}{UN}(N+1)\right) \quad (3)$$

where  $U = 4$ ,  $G_1 = 0.971960$ ,  $G_2 = 1/\sqrt{2}$  and  $G_3 = 0.235147$ . The reader can refer to [23] computing  $G_u$  for any  $U$  value in detail. We use  $H_{m,n}$  to denote CFR coefficients at the receiver for the  $m$ th sub-carrier and the  $n$ th symbol. Moreover, a complex AWGN channel is considered. Thus, the  $m$ th sub-carrier and the  $n$ th symbol at the receiver can be expressed as

$$Y_{m,n} = H_{m,n} \left( \underbrace{a_{m,n} + ja_{m,n}^{(*)}}_{x_{m,n}} \right) + \eta_{m,n}, \quad (4)$$

where  $\eta_{m,n}$  and  $a_{m,n}^{(*)}$  denote the channel noise and intrinsic imaginary interference, respectively. The intrinsic imaginary interference  $a_{m,n}^{(*)}$  can be written as

$$a_{m,n}^{(*)} = \sum_{(p,q) \neq (0,0)} a_{m+p,n+q} \langle g \rangle_{m+p,n+q}^{m,n} \quad (5)$$

where

$$\langle g \rangle_{m+p,n+q}^{m,n} = \sum_{i=-\infty}^{\infty} g_{m+p,n+q}[i] g_{m,n}^*[i]. \quad (6)$$

It is worthwhile to note that, for the PHYDYAS prototype filter  $g[i]$ ,  $\langle g \rangle_{m+p,n+q}^{m,n} = 1$  when  $(p, q) = (0, 0)$  and is a pure imaginary value when  $(p, q) \neq (0, 0)$ . According to equation (6), the neighbor interference coefficients of the PHYDYAS prototype filter can be obtained as following Table 1. It can be observed from Table 1 that the interference of the PHYDYAS prototype filter is staggered in time and frequency domain for FBMC system. The demodulated data symbols will not be affected because the FBMC system adopts OQAM modulation and the transmitted data symbols are real values. However, the CFR is often a complex value at a time-frequency point for channel estimation of the FBMC system. Due to the intrinsic imaginary interference, it is very difficult to accurately estimate the CFR value for FBMC system. Thus, the term  $x_{m,n}$  of equation (4) must be known at the receiver. Then,  $a_{m,n}$  must be a pilot. From equation (5), we will seek out a method in order to make  $a_{m,n}^{(*)} = 0$  at pilot position. Finally, our channel estimation can be expressed as

$$\hat{H}_{m,n} = H_{m,n} + \frac{\eta_{m,n}}{a_{m,n}} \quad (7)$$

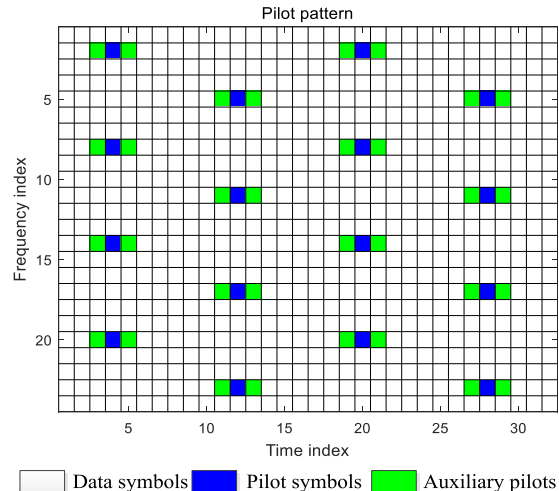


FIGURE 1. Auxiliary pilots method in FBMC-OQAM systems.

### III. SCATTERED PILOT SCHEMES

In order to utilize scattered pilot symbols aided channel estimation for FBMC system under doubly selective channels, thus, we have to eliminate the intrinsic imaginary interference.

#### A. AUXILIARY PILOT METHOD

In order to eliminate intrinsic imaginary interference, the AP method is used as shown in Fig.1 in this paper. If we sacrifice one additional data symbol as auxiliary pilot symbol, it leads to a high PAPR because of large power offset. The AP method generally uses two auxiliary pilot symbols adjacent pilot symbol  $a_{m,n}$  [7].

The AP method can make  $a_{m,n}^{(*)}$  to zero. In [24], we use the matrix representation to express this canceling condition in a general way.

Let  $\mathbf{D}$  denotes transmission matrix, defined as  $\mathbf{D} = \mathbf{G}^H \mathbf{G}$ , where  $\mathbf{G}$  is the sampled PHYDYAS prototype filter  $g_{m,n}[i]$ . Let  $\mathbf{x}_P \in R^{|P| \times 1}$  denotes pilot symbols,  $\mathbf{x}_D \in R^{|D| \times 1}$  denotes data symbols, and  $\mathbf{x}_A \in R^{|A| \times 1}$  denotes auxiliary pilot symbols. Let  $\mathbf{D}_{P,P} \in C^{|P| \times |P|}$  denotes interference of arbitrary pilot position to current pilot position,  $\mathbf{D}_{P,D} \in C^{|P| \times |D|}$  denotes interference of arbitrary data position to current pilot position, and  $\mathbf{D}_{P,A} \in C^{|P| \times |A|}$  denotes the interference of arbitrary auxiliary pilot position to the current pilot position. Thus, the condition of interference cancellation can be expressed as

$$\mathbf{x}_P = [\mathbf{D}_{P,P}, \mathbf{D}_{P,D}, \mathbf{D}_{P,A}] \begin{bmatrix} \mathbf{x}_P \\ \mathbf{x}_D \\ \mathbf{x}_A \end{bmatrix}. \quad (8)$$

If the number of auxiliary pilot symbols  $|A|$  is larger than that of pilot symbol  $|P|$ , equation (8) has infinite solutions. However, the solution of the equation (8) can be obtained by the method of generalized pseudoinverse [25] as follows:

$$\mathbf{x}_A = \mathbf{D}_{P,A}^\# (\mathbf{I}_P - \mathbf{D}_{P,P}) \mathbf{x}_P - \mathbf{D}_{P,A}^\# \mathbf{D}_{P,D} \mathbf{x}_D \quad (9)$$

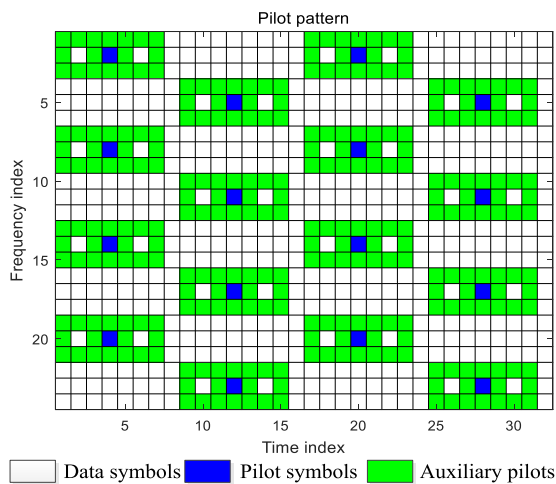


FIGURE 2. Coding pilots method in FBMC-OQAM systems.

with

$$D_{P,A}^\# = D_{P,A}^H (D_{P,A} D_{P,A}^H)^{-1} \tag{10}$$

where  $I_P$  and  $(\cdot)^H$  denotes identity matrix and conjugate transpose, respectively.

**B. CODING PILOT METHOD**

Instead of using auxiliary pilot symbols, we can code the data to cancel the intrinsic imaginary interference at the pilot positions in a way. Let  $\mathbf{x}$  denotes transmitted symbols vector, and  $\mathbf{y}$  denotes received symbols vector. The data symbols  $\hat{\mathbf{x}}$  are pre-coded by a coding or spreading matrix  $\mathbf{C}$ . Thus, the data symbols  $\mathbf{x}$  can be expressed as

$$\hat{\mathbf{x}} = \mathbf{C}\mathbf{x}. \tag{11}$$

By decoding  $\mathbf{C}^H$  of the received symbols, the received data symbols  $\mathbf{y}$  can be expressed as

$$\hat{\mathbf{y}} = \mathbf{C}^H \mathbf{y}. \tag{12}$$

In order to eliminate the intrinsic imaginary interference, the coding matrix must satisfy the following condition:

$$\mathbf{C}^H \mathbf{D} \mathbf{C} = \mathbf{I}, \tag{13}$$

where  $\mathbf{I}$  denotes an identity matrix. The matrix  $\mathbf{D}$  is easy to perform singular value decomposition,  $\mathbf{D} = \mathbf{U}\mathbf{\Lambda}\mathbf{U}^H$ , so that it satisfies equation (13). The  $\mathbf{U}$  denotes an unitary matrix and it is selected by the first  $MN/2$  column vectors as our  $MN \times MN/2$  coding matrix  $\mathbf{C}$ . The disadvantage of this method has the high complexity. However, a method with low complexity was researched in [5] and was based on Hadamard matrices. The greatest advantage of Hadamard matrices is that only additions but no multiplications are required, so that the additional complexity becomes very low. Thus, the coding pilot method is used as shown in Fig.2 in this paper.

**IV. PROPOSED COMPRESSIVE SENSING BASED ON CHANNEL ESTIMATION**

In this section, we propose a novel SASP channel estimation algorithm based on CS theory for FBMC system. We briefly introduce CS theory for channel estimation. Then we detailedly analyze the proposed SASP algorithm for channel estimation in FBMC system.

**A. CS THEORY FOR CONVENTIONAL CHANNEL ESTIMATION**

The CS theories [26], [27] explain that sparse signal can be reconstructed accurately from non-adaptive measurements. In order to write simply, we only express a FBMC system with one symbol and  $N$  subcarriers, among which  $N_p$  are used as pilot sub-carriers. The receiver signal  $\mathbf{Y}$  in equation (4) can be expressed in matrix form as

$$\mathbf{Y} = \mathbf{X}\mathbf{H} + \boldsymbol{\eta}, \tag{14}$$

where  $\mathbf{Y} = [y(0), y(1), \dots, y(N-1)]$ ,  $\mathbf{X} = \text{diag}[x(0), x(1), \dots, x(N-1)]$ ,  $\boldsymbol{\eta}$  denotes the vector of noise and  $\mathbf{H}$  denotes the multipath CFR sampling values.  $\mathbf{H} = \mathbf{F}\mathbf{h}$ , where  $\mathbf{F}$  is a  $L$  row discrete Fourier transform matrix (DFT),  $L$  denotes the channel length and  $\mathbf{h} = [h(0), h(1), \dots, h(L-1)]$  is the CIR of length  $L \leq N$ . We denote the set of pilot subcarriers by  $\mathbf{p} = \{p_0, p_1, \dots, p_{N_p-1}\}$ , where  $N_p \subset \{0, 1, \dots, N-1\}$ . The equation (14) can be rewritten at pilot positions as

$$\mathbf{Y}_p = \mathbf{X}_p \underbrace{\mathbf{F}_p \mathbf{h}}_{\mathbf{H}_p} + \boldsymbol{\eta}_p. \tag{15}$$

By defining  $\mathbf{A}_p = \mathbf{X}_p \mathbf{F}_p$ , the equation (15) can be expressed as

$$\mathbf{Y}_p = \mathbf{A}_p \mathbf{h} + \boldsymbol{\eta}_p, \tag{16}$$

where  $\mathbf{A}_p$  is the sensing matrix. Thus, in order to estimate CIR, we need to solve the linear inverse problem (16) for  $\mathbf{h}$ . It seems an undetermined problem, as  $N_p \leq N$ . However, it was proved in [28] that accurate reconstruction can be guaranteed if the  $\mathbf{A}_p$  satisfies the following condition of the restricted isometry property (RIP) for  $K$ -sparse signal  $\mathbf{h}$ ,

$$(1 - \delta_K) \|\mathbf{h}\|_2^2 \leq \|\mathbf{A}_p \mathbf{h}\|_2^2 \leq (1 + \delta_K) \|\mathbf{h}\|_2^2 \tag{17}$$

where  $\delta_K \in (0, 1)$  is the isometry constant. We can utilize minimizing the  $\ell_1$ -norm of  $\mathbf{h}$  to recover signal  $\mathbf{h}$ .

**B. PROPOSED SPARSE ADAPTIVE SUBSPACE PURSUIT ALGORITHM**

In this paper, the values of  $N_p$  pilot points are taken as measurement vector in frequency domain. Channel estimation value of the  $\mathbf{H}_p$  is obtained by LS algorithm at the pilot positions, and then the accuracy of channel estimation will be improved by CS algorithm in frequency domain. The SP algorithm is more efficient than CoSaMP algorithm in terms of computational complexity. However, the SP algorithm requires the priori sparse information. The SAMP algorithm can reconstruct signal when the sparsity is unknown.

Inspired by the advantages of the two algorithms, we propose a novel iterative greedy SASP algorithm.

The proposed SASP algorithm can adaptively adjust the selected candidates to recover the unknown sparse signal in each iteration. The basic idea of the proposed SASP algorithm is to re-estimate the reliability of all candidates during each iteration using the theory of backtracking. Each iterative process is divided into many stages, the proposed SASP algorithm adaptively estimates the sparsity by moving forward stage by stage, and obtains the accurate target signal. The processing flowsheet of SASP algorithm is as follows:

**Input:** the measurement matrix  $\mathbf{X}_p$ , the measurement vector  $\mathbf{Y}_p$ , the step size  $S$ .

**Output:** a  $K$ -sparse approximation  $\hat{\mathbf{H}}_p$  of the CFR value  $\mathbf{H}_p$ .

*Notations:* The  $\mathbf{r}_t$  denotes residue and  $t$  denotes iterative times. The  $\Lambda_t$  represents a set of indexes for  $t$  iterations, and the number of its elements is  $K$  and the  $K$  equals integer multiples of step  $S$ .  $\mathbf{X}_t = \{\mathbf{x}_j\}$  (for all  $j \in \mathbf{C}_k$ ) denotes that a column set of the matrix  $\mathbf{X}_p$  is selected by index set  $\mathbf{C}_k$ .  $\mathbf{H}_t$  is a column vector with  $Kt \times 1$ . The  $\cup$ ,  $\langle \cdot \rangle$  and  $\text{abs}|\cdot|$  denote union operation of set, quadrature operation of vector and modular operation.

- 1) Initialization: residual  $\mathbf{r}_0 = \mathbf{Y}_p$ , index value set  $\Lambda_0 = \emptyset$ ,  $K = S$ , iterative  $t = 1$ ;
- 2) Calculate  $\mathbf{u} = \text{abs}|\mathbf{X}_p^T \mathbf{r}_{t-1}| = \text{abs}|\langle \mathbf{r}_{t-1}, \mathbf{x}_j \rangle|$ , select the  $K$  maximum values in the  $\mathbf{u}$ , and these values correspond to the column number  $j$  of the  $\mathbf{X}_p$  to form the set  $\mathbf{S}_k$ ;
- 3) Let  $\mathbf{C}_k = \Lambda_{t-1} \cup \mathbf{S}_k$ , and  $\mathbf{X}_t = \{\mathbf{x}_j\}$  (for all  $j \in \mathbf{C}_k$ );
- 4) Use equation (18) to obtain the least square solution of  $\mathbf{Y}_p = \mathbf{X}_t \mathbf{H}_t$ :

$$\hat{\mathbf{H}}_t = \arg \min_{\mathbf{H}_t} \|\mathbf{Y}_p - \mathbf{X}_t \mathbf{H}_t\|_2 = (\mathbf{X}_t^T \mathbf{X}_t)^{-1} \mathbf{X}_t^T \mathbf{Y}_p; \quad (18)$$

- 5) Select the largest absolute values with  $K$  term from  $\hat{\mathbf{H}}_t$  to constitute  $\hat{\mathbf{H}}_{tK}$ , the  $K$  term of the corresponding  $\mathbf{X}_t$  to constitute  $\mathbf{X}_{tK}$ , and the column number of the corresponding  $\mathbf{X}_p$  to constitute  $\Lambda_{tK}$ ;
- 6) Update the residual  $\mathbf{r}_{new} = \mathbf{Y}_p - (\mathbf{X}_{tK}^T \mathbf{X}_{tK})^{-1} \mathbf{X}_{tK}^T \mathbf{Y}_p$ ;
- 7) If  $\mathbf{r}_{new} = 0$ , then stop the iteration and move to step 8; if  $\|\mathbf{r}_{new}\|_2 \geq \|\mathbf{r}_{t-1}\|_2$ , then update  $K = K + S$  and return to step 2; if the two previous conditions are not satisfied in turn, then  $\Lambda_t = \Lambda_{tK}$ ,  $\mathbf{r}_t = \mathbf{r}_{new}$ ,  $t = t + 1$ ; if  $t \leq N_p$ , then stop the iteration and move to step 8, otherwise return to step 2;
- 8) Reconstruct signal  $\hat{\mathbf{H}}_p$ .

The proposed SASP algorithm only require  $S \leq K$ , and if the initial step size  $S$  is very large, it can lead to overestimation. Thus, the safest choice is  $S = 1$  if  $K$  is unknown. However, there is a trade-off between recovery speed and the proposed SASP algorithm requires more iterations if  $S$  is smaller. The derivation of the optimal  $S$  remains as an open question.

### C. COMPUTATIONAL COMPLEXITY OF PROPOSED ALGORITHM

In this section, the complexity of CS-based channel estimation is analyzed for FBMC-OQAM System. Compared with other conventional compressive sensing algorithms-based channel estimation, the proposed SASP algorithm is only different in the signal reconstruction part. Therefore, we will only analyze the complexity of the conventional orthogonal matching pursuit (OMP) and regularized orthogonal matching pursuit (ROMP) algorithms and the proposed SASP algorithm in the signal reconstruction part. The reconstruction complexity of the conventional OMP and ROMP algorithms is roughly  $O(KN_p N)$  [29], [30], where  $N_p$  must satisfy  $N_p = O(K \log N)$  [27]. The proposed SASP algorithm utilizes the advantages of both SAMP and SP algorithms. The complexity of SAMP and SP algorithms are firstly analyzed before analyzing the complexity of the SASP algorithm. The total computational complexity of the SP algorithm is  $O(N_p(N + K^2) \log K)$  for compressible sparse signals. When the signal is too sparse, the total complexity of SP algorithm is given by  $O(N_p N \log K)$  for compressible sparse signals [18], while the SAMP algorithm becomes exactly SP if the RIP condition is satisfied when  $S = K$ , and it can be roughly regarded as the OMP associated with refinement feature that can remove bad coordinates during each iteration when  $S = 1$  [17]. Thus, each stage in SASP algorithm still uses a similar principle of the SP when  $S < K$ . Based on above analysis and discussion, the total complexity of the proposed SASP algorithm is given by  $O((N_p N \log K) K/S)$  for most practical sparse signals. For example, we have  $C_{SASP}/C_{COMP} = 89.59\%$  or  $C_{SASP}/C_{ROMP} = 89.59\%$  in the doubly selective channels (pedestrian-B and vehicular-B channels) [31], where  $K = 6$ ,  $N_p = 24$ , and  $N = 64$ .

### V. NUMERICAL RESULTS

In this section, the performance of the proposed sparse channel estimation-based SASP algorithm is presented in the pedestrian-B and vehicular-B channels compared with the OMP, ROMP, CoSaMP and SP algorithms. The parameters for pedestrian B and vehicular B channels are as follows:

Pedestrian-B channel

- o Relative delays = [0 200 800 1200 2300 3700]ns,
- o Average powers = [0 -0.9 -4.9 -8.0 -7.8 -23.9]dB;

Vehicular-B channel

- o Relative delays = [0 300 8900 12900 17100 20000]ns,
- o Average powers = [-2.5 0 -12.8 -10.0 -25.2 -16.0]dB;

respectively. The system parameters are set as follows: the system bandwidth is set to 9.6MHz; the number of subcarriers is set to 64; the subcarrier spacing is 1.5KHz; maximum Doppler frequency is set to 10 Hz; the number of FBMC-OQAM symbols is 32; the pilot spacing in the frequency and time domain is set to 6 and 8, respectively. The un-coded offset 16QAM (16OQAM) modulation is adopted

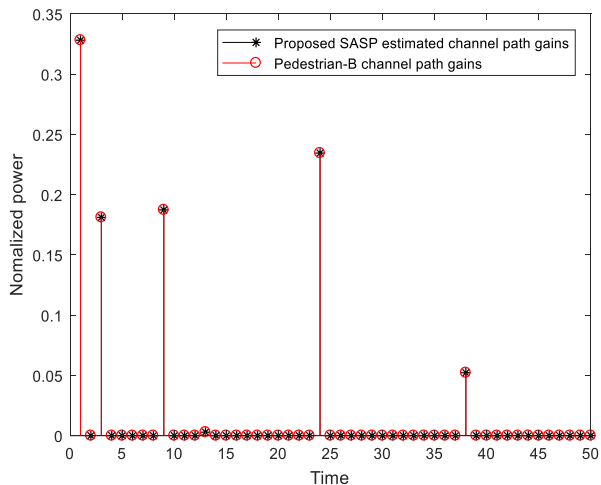


FIGURE 3. Pedestrian-B channel path gains and estimated channel path gains.

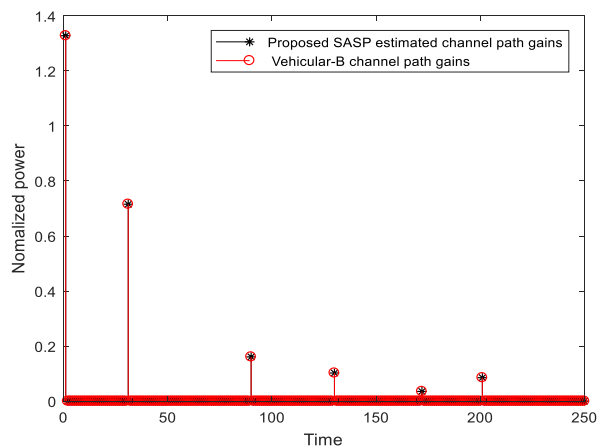


FIGURE 4. Vehicular-B channel path gains and estimated channel path gains.

for FBMC-OQAM system. The interpolation method is linear and the equalization method is zero forcing (ZF) equalizer.

Fig. 3 and Fig. 4 show reconstructed performance of the pedestrian-B and vehicular-B channels. It is observed from Fig. 3 and Fig. 4 that the proposed SASP algorithm successfully recovers path gains of six-path channels. It also shows that the proposed SASP algorithm is very effective for simple sparse signals.

We also analyze the probability of reconstruction for a fixed sparsity  $K = 6$  using conventional OMP, ROMP, CoSaMP and SP algorithms and proposed SASP algorithm. Fig. 5 shows these probability curves of Gaussian sparse signals. For successful probability of reconstruction exceeding 95%, the conventional OMP and ROMP algorithms require 60 and 35 measurements, while the proposed SASP algorithm requires only around 25 measurements. Compare with conventional OMP and ROMP algorithms, the measurements of the proposed SASP algorithm only needs 71.42% of the conventional OMP algorithm and 41.66% of the conventional ROMP algorithm. It is observed from Fig. 5 that the probability of reconstruction of the proposed SASP algorithm

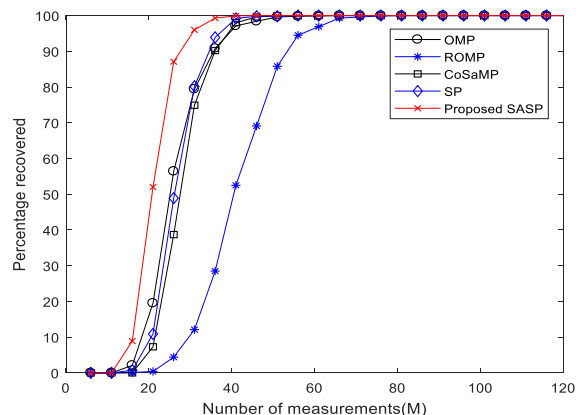


FIGURE 5. Probability of accurate reconstruction for different measurements.

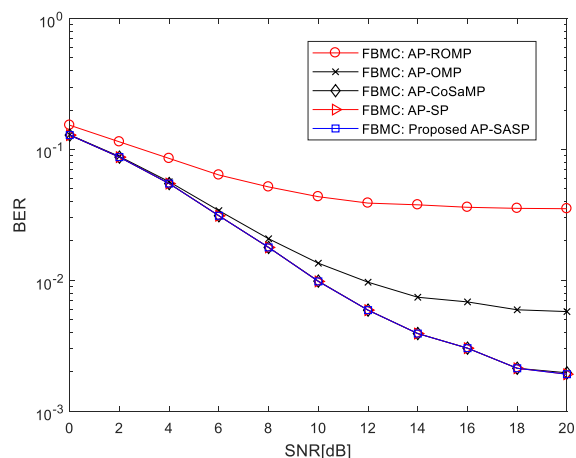


FIGURE 6. Comparison of BER performances for AP method in pedestrian-B channel.

outperforms the conventional OMP and ROMP algorithms in the region of  $M = 10$  to  $M = 60$ . When  $M > 35$ , with the measurements increasing, the conventional OMP and ROMP algorithms have the same probability of reconstruction. When  $M > 65$ , with the measurements increasing, the proposed SASP algorithm and conventional OMP and ROMP algorithms have the same probability of reconstruction.

Fig. 6 and Fig. 7 compare the BER performance of the proposed AP-SASP and coding-SASP schemes as well as the conventional AP-OMP and coding-ROMP algorithms when AP and coding methods are adopted to cancel intrinsic imaginary interference for FBMC systems in the pedestrian-B channel. It is observed from Fig. 6 that the proposed AP-SASP algorithm can obtain significantly BER improvement compared with conventional AP-OMP and AP-ROMP algorithms. Careful observation shows that the proposed AP-SASP algorithm outperforms other conventional algorithms in the whole SNR region considered. The error floors happen in the AP-OMP, AP-ROMP and proposed AP-SASP algorithms for FBMC systems in the pedestrian-B channel since the symbol interval is much longer than the maximum channel delay spread in the high SNR region. In Fig. 7, the BER performance of the coding-SASP algorithm is

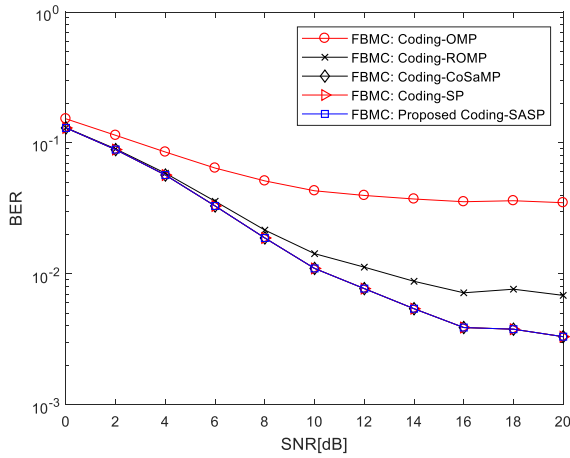


FIGURE 7. Comparison of BER performances for coding method in pedestrian-B channel.

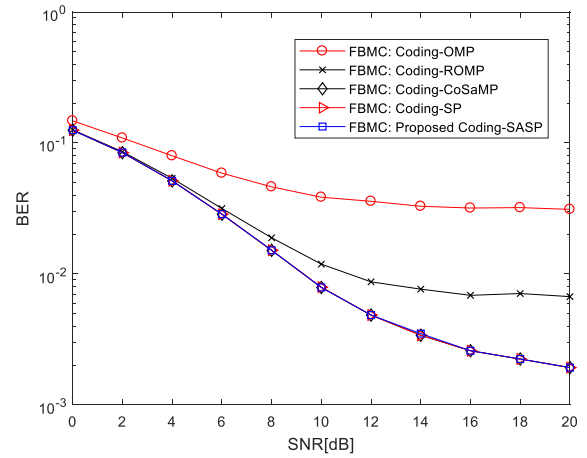


FIGURE 9. Comparison of BER performances for coding method in Vehicular-B channel.

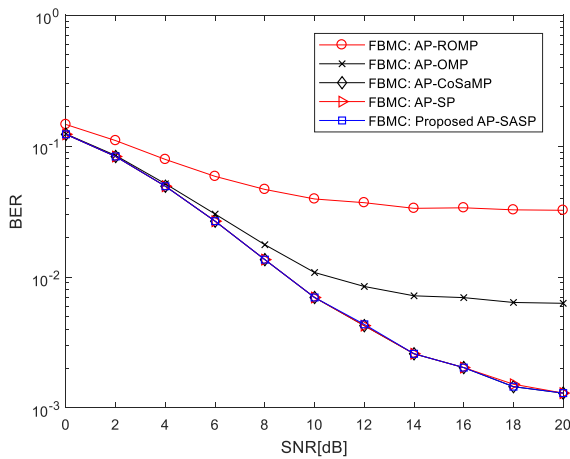


FIGURE 8. Comparison of BER performances for AP method in Vehicular-B channel.

similar to those of the Fig. 6. It is observed from Fig. 7 that the proposed coding-SASP algorithm can obtain significantly BER improvement compare with conventional coding-OMP and coding-ROMP algorithms. Careful observation shows that the proposed Coding-SASP algorithm outperforms conventional coding-OMP and coding-ROMP algorithms in the whole SNR region since they can be roughly regarded as the ROMP associated with refinement feature that can remove bad coordinates during each iteration.

Fig. 8 and Fig. 9 depict the BER performance of the proposed AP-SASP and coding-SASP schemes as well as the conventional AP-OMP and coding-ROMP algorithms when AP and coding methods are adopted to cancel intrinsic imaginary interference for FBMC systems in the vehicular-B channel. We can see that the BER curves of Fig. 8 and Fig. 9 are similar as that in Fig. 6 and Fig. 7, respectively. It is observed from Fig. 8 that the proposed AP-SASP algorithm outperforms conventional AP-OMP and AP-ROMP algorithms in the whole SNR region. The error floors also happen in the AP-OMP, AP-ROMP and proposed AP-SASP algorithms for FBMC systems in the vehicular-B channel.

In Fig. 9, the BER performance of the coding-SASP algorithm is similar to those of the Fig. 8. It is observed from Fig. 8 that the proposed coding-SASP algorithm outperform conventional coding-OMP and coding-ROMP algorithms in the whole SNR region.

The simulation times of the propose AP-SASP and coding-SASP algorithms are less than the conventional AP-OMP and AP-ROMP algorithms for FBMC systems in pedestrian-B and vehicular-B channels. Moreover, The simulation times of the propose AP-SASP algorithm is less than the propose coding-SASP algorithm for FBMC systems in pedestrian-B and vehicular-B channels.

## VI. CONCLUSION

In this paper, we research CS-based channel estimation for FBMC system in pedestrian-B and vehicular-B channels. A novel SASP-based channel estimation method is proposed for FBMC system. Moreover, we develop two new AP-SASP and coding-SASP algorithms to estimate CFR values in FBMC systems. The proposed algorithm can accurately estimate CFR value in doubly-selective channels and it reduces computational complexity utilizing low complexity of the SP algorithm. Compared with conventional AP-OMP, AP-ROMP, coding-OMP and coding-ROMP channel estimation methods, simulation results show that the proposed AP-SASP and coding-SASP methods can obtain significantly better BER performance than convention AP-OMP, AP-ROMP, coding-OMP and coding-ROMP methods, respectively. The complexity of the proposed SASP algorithm is only 89.59% of that of the convention OMP and ROMP algorithms without priori sparse information of the channel. The measurements of proposed SASP algorithm only need 71.42% of the conventional OMP algorithm and 41.66% of the conventional ROMP algorithm. It has been verified that the proposed SASP based on channel estimation algorithm is an efficient method for FBMC systems in doubly selective channels.

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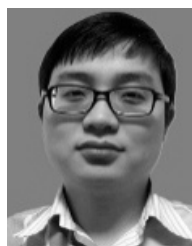


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