Distributed Compressed Sensing Based Channel Parameter Estimation for MIMO-FBMC Communications

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Abstract—For the sparse correlation between channels in multiple input multiple output filter bank multicarrier with offset quadrature amplitude modulation (MIMO-FBMC/OQAM) systems, the distributed compressed sensing (DCS)-based channel estimation approach is studied. A sparse adaptive distributed sparse channel estimation method based on weak selection threshold is proposed. Firstly, the correlation between MIMO channels is utilized to represent a joint sparse model, and channel estimation is transformed into a joint sparse signal reconstruction problem. Then, the number of correlation atoms for inner product operation is optimized by weak selection threshold, and sparse signal reconstruction is realized by sparse adaptation. The experiment results show that proposed DCS-based method not only estimates the multipath channel components accurately but also achieves higher channel estimation performance than classical orthogonal matching pursuit (OMP) method and other traditional DCS methods in the time-frequency dual selective channels.

Keywords: Distributed compressed sensing, MIMO-FBMC, Channel estimation, Sparsity.

I. INTRODUCTION

Multiple input multiple output (MIMO) systems can double the capacity of wireless channel by using multi-antenna technology, and greatly improve the spectrum efficiency without increasing the bandwidth and antenna transmission power. Orthogonal frequency division multiplexing (OFDM) technology realizes the parallel transmission of high speed serial data through frequency division multiplexing, and it has better ability to resist multipath fading. Due to its technical characteristics and advantages, MIMO technology has been widely used in fourth generation (4G) and fifth generation (5G) networks after combining with OFDM technology, and has become one of the key technologies for the next generation mobile communications [1-3]. Although the traditional OFDM technology can achieve low complexity and high bandwidth efficiency, it is difficult to achieve strict synchronization and discontinuous band transmission when it is applied to more complex dynamic or multi-user networks in future mobile communication scenarios. Filter bank multicarrier with offset quadrature amplitude modulation (FBMC/OQAM) technology [4, 5] can solve the above problems by using well time-frequency (TF) property filter banks. FBMC/OQAM, abbreviated as FBMC, provides a way to overcome the known limitations of OFDM. Firstly, FBMC is not strictly orthogonal, when the channel is not highly selective, it does not need cyclic prefix, and so it has higher spectrum efficiency [6]. Secondly, FBMC system can flexibly control the interference between adjacent subcarriers and make good use of the scattered spectrum resources. Finally, each subcarrier of the FBMC system processes channel estimation and synchronization separately, which makes it more suitable for uplink communication [4]. Although, the latest 3rd Generation Partnership Project (3GPP) organization has pointed out that 5G mobile communication system will adopt filtered OFDM (F-OFDM) technology as the multi carrier transmission scheme. In view of the advantages of FBMC technology, scholars still maintain the research enthusiasm for FBMC, and hope to apply it to future mobile communications [7, 8].

The development of mobile communication technology is focused on how to improve the transmission rate and quality in limited bandwidth. By combining FBMC/OQAM technology with MIMO technology, the communication system has the advantages of both technologies, so as to meet the demands of the development of next generation mobile communication technology [9]. However, FBMC/OQAM systems will also be
affected by inherent imaginary interference and inter antenna interference when combined with spatial multiplexing MIMO technology. In channel estimation (CE) of MIMO-FBMC/OQAM (abbreviated as MIMO-FBMC) system, the existence of these interference terms will lead to the deterioration of the performance of traditional CE methods, which seriously affects the CE performance.

Currently, research on CE for MIMO-FBMC systems has mainly focused on preamble-based methods. There are mainly two traditional preamble-based CE methods, they are interference approximation method (IAM) [10] and interference cancellation method (ICM) [11]. Compared with the SISO-FBMC system [12], more imaginary interference between the preamble symbols is existed in the MIMO-FBMC system, which leads to the low accuracy of the preamble-based CE [13].

In recent studies [14-18], compressed sensing (CS) based CE approach has been proposed for FBMC systems. In Ref. [14], a CE method based on orthogonal matching pursuit (OMP) was proposed. Compared with the least square (LS) estimation method, the CS method in FBMC/OQAM can significantly improve the CE performance. In Ref. [15], the authors proposed a weak selection regularized OMP CE method based on Tanimoto sparsity, which has better bit rate ratio (BER) performance than the classical CS methods. For MIMO-FBMC systems, the authors in [16] proposed an approximate information transfer CS-based CE method. Ref. [17] proposed an effective sparse adaptive MIMO-FBMC system CE method. The above two CS methods have better CE performance than classical methods. Traditional greedy CS-based CE approach has high computational complexity. Ref. [18] adopted an inner product operation optimization strategy to reduce the algorithm complexity, and proposed a low complexity sparse CE method for MIMO-FBMC.

Distributed compressed sensing (DCS) theory [19] pointed out that the inter-correlation of multiple signal sparse structures can be used to achieve joint reconstruction, which greatly improves the reconstruction efficiency. In Ref. [20], the authors proposed a CE scheme based on DCS theory, the proposed scheme can achieve higher estimation accuracy than traditional methods. It is found in literature [20-22] that the existing research on DCS-based CE methods are mainly concentrated in OFDM systems, while the CE based on DCS in FBMC systems is still in exploratory research stage.

This paper utilizes the sparse correlation between MIMO channels and characterizes it as a joint sparse model to study the CE of MIMO-FBMC systems based on DCS approach. To the best of our knowledge, it is the first time to study DCS-based CE algorithm for FMBC systems. In our work, the weak selection threshold is used to optimize the number of related atoms for the inner product operation, so as to reduce the amount of calculation of the inner product. Simulation results showed that proposed DCS-based method can achieve accurate CE estimation values than traditional methods.

The rest of this paper is organized as follows. Section 2 gives the system model, including MIMO-FBMC system and preamble-based channel estimation. In Section 3, compressed sensing channel estimation theory is analyzed, and the proposed distributed compressed sensing approach is given. Channel estimation performance comparisons of traditional algorithms are given in Section 4. In Section 5, it gives the conclusions.

II. SYSTEM MODEL

A. MIMO-FBMC System

Consider a $N_r \times N_t$ MIMO-FBMC/OQAM system, as shown in Fig.1. The baseband transmitted signal over the $n$th branch in general form can be written as

$$s^n(t) = \sum_{m=0}^{N_r-1} \sum_{n=0}^{N_t-1} d^n_{m,n} g_{m,n}(t)$$

where $d^n_{m,n}$ are real valued QAM symbols, $N_r$ is the total number of subcarriers. $g_{m,n}(t)$ expresses the synthesis basis which is obtained by the time-frequency translated version of the prototype function $g(t)$, shown as below

$$g_{m,n}(t) = g(t-n\tau_0)e^{2\pi i mf_0}e^{i\phi_{m,n}}$$

where $F_0$ being the subcarrier spacing, with $F_0 = 1/T_0 = 1/2\tau_0$, and $\phi_{m,n}$ an additional phase term. $T_0$ denotes the OFDM symbol duration, and $\tau_0$ denotes the time offset between the real and imaginary parts of the QAM symbols. The double subscript $(.)_{m,n}$ denotes the $(m,n)$ -th frequency-time (FT) point, the subcarrier index is $m$ and the QAM symbol time index is $n$.

In the real domain, the relevant subcarrier functions $g_{m,n}$ are orthogonal, with

$$\text{Re}\{g_{m,n}^* g_{m',n}\} = \text{Re}\{\sum_{n=0}^{N_t-1} g_{m,n}(t)g_{m',n}(t)\} = \delta_{m,m'} \delta_{n,n}$$

where $\text{Re}(\cdot)$ denotes the real-part of a complex number. $\delta$ is the Kronecker delta, $\delta_{m,m} = 1$ if $m = m'$, and $\delta_{m,m} = 0$ if $m \neq m'$. It should be noted that even in the distortion-free channel and with perfect time and frequency synchronization, the purely imaginary inter-carrier interference at the output of analysis
filter bank is still exist. Therefore, we give the expression formula of the weights of interference as

\[ \langle g \rangle_{m,a} = -j \langle g, g_{m,a} \rangle \]

where \( \langle g, g_{m,a} \rangle \) being a pure imaginary term for \( (m, n) \neq (m_0, n_0) \).

The received signal on the \( n_{th} \) receive antenna with an additive noise can be written as

\[ r^n(t) = \sum_{n=1}^{N_t} \sum_{m=0}^{M-1} H_{m,a}^{n,k} \sum_{n=1}^{N_t} d_{m,n} g_{m,n}(t) + \eta^n(t) \]

with

\[ H_{m,a}^{n,k}(t) = \int_{0}^{T} h_{m,a}^{n,k}(t, \tau) e^{-j2\pi f_{r} \tau} d\tau \]

where \( h_{m,a}^{n,k}(t, \tau) \) represents the channel impulse response (CIR) at \( (m, n) \) between \( m_{th} \) transmit antenna and \( n_{th} \) receive antenna. \( H_{m,a}^{n,k}(t) \) denotes the complex response of the channel at instant \( t \). Sub-channels are often assumed to be constant for the duration of the prototype length. Hence, \( H_{m,a}^{n,k}(t) = H_{m,a}^{n,k} \).

**B. Conventional Preamble-Based CE**

When the output is on the \( n_{th} \) receive antenna at the \( m_{th} \) subcarrier and \( n_{th} \) OQAM symbol, and noise is eliminated, the single is given as

\[ y_{m,n}^{n,k} = \sum_{n=1}^{N_t} H_{m,a}^{n,k} d_{m,n}^{k} + \sum_{n=1}^{N_t} H_{m,a}^{n,k} d_{m,n}^{k} \langle g \rangle_{m,a} \]

where \( H_{m,a}^{n,k} \) is channel frequency response at \( (m, n) \) between \( n_{th} \) transmit antenna and \( n_{th} \) receive antenna.

A common definition is that only the first-order neighborhood \( \Omega_{0,1} \) of a given FT point \( (m_0, n_0) \) causes the interference. \( \Omega_{0,1} = \{(m_0, n_0), (m_0+1, n_0), (m_0, n_0+1)\} \).

We can rewrite (7) as

\[ y_{m,n}^{n,k} = \sum_{n=1}^{N_t} H_{m,a}^{n,k} d_{m,n}^{k} + j \sum_{n=1}^{N_t} H_{m,a}^{n,k} d_{m,n}^{k} \langle g \rangle_{m,a} \]

With the increasing of \( m_0 \) and \( n_0 \), and \( \langle g \rangle_{m,a} \) becomes very close to zero. Then, with noise taken into consideration, (8) can be rewritten as

\[ y_{m,n}^{n,k} \approx H_{m,a}^{n,k} c_{m,n}^{k} + \eta_{m,n}^{n,k} \]

where \( c_{m,n}^{k} = d_{m,n}^{k} + j \sum_{n=1}^{N_t} H_{m,a}^{n,k} d_{m,n}^{k} \langle g \rangle_{m,a} \) is the virtual transmitted symbol at \( (m, n, k) \). \( d_{m,n}^{k} \) and \( \langle g \rangle_{m,a} \) being the imaginary interference from the neighboring FT point. \( d_{m,n}^{k} \) being the real valued OQAM symbol, \( H_{m,a}^{n,k} \) is the channel response.

Therefore, the MIMO-FBMC/OQAM signal model can be expressed in the form of the matrix

\[ y_{m,n} \approx H_{m,a} c_{m,n} + \eta_{m,n} \]

where

\[ y_{m,n} = \begin{bmatrix} y_{m,n}^{1} \\ y_{m,n}^{2} \\ \vdots \\ y_{m,n}^{N_t} \end{bmatrix}, \]

\[ c_{m,n} = \begin{bmatrix} c_{m,n}^{1} \\ c_{m,n}^{2} \\ \vdots \\ c_{m,n}^{N_t} \end{bmatrix}, \]

\[ \eta_{m,n} = \begin{bmatrix} \eta_{m,n}^{1} \\ \eta_{m,n}^{2} \\ \vdots \\ \eta_{m,n}^{N_t} \end{bmatrix}, \]

and

\[ H_{m,a} = \begin{bmatrix} H_{1,1}^{1} & H_{1,1}^{2} & \cdots & H_{1,1}^{N_t} \\ H_{2,1}^{1} & H_{2,1}^{2} & \cdots & H_{2,1}^{N_t} \\ \vdots & \vdots & \ddots & \vdots \\ H_{N_t,1}^{1} & H_{N_t,1}^{2} & \cdots & H_{N_t,1}^{N_t} \end{bmatrix} \]

is the MIMO channel frequency response (CFR) matrix.

\[ c_{m,n} = d_{m,n} + j \mathbf{u}_{m,n} \] is the equivalent transmission symbol vector form of the MIMO-FBMC/OQAM system, with
It can be found clearly from (10) that, for a $N_t \times N_r$ spatial multiplexing MIMO system, at least $N_f$ number of nonzero pilot symbols is needed to estimate the channel frequency response matrix. Fig. 2 gives a classical preamble structure for a 2x2 MIMO-FBMC system.

\[
\begin{bmatrix}
0 & 1 & 0 & -1 & 0 \\
0 & -1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 1 \\
\end{bmatrix}
\]

which is the matrix with zero mean and variance of $\sigma^2$.

We set $P$ as the number of pilots, $\phi = (e_1, e_2, \ldots, e_P)$ is a $P \times N$ pilot selection matrix. $s_i (i = 1, 2, \ldots, P)$ is the $i$th pilot’s position. It should be noted that, the preamble pilots exist in all sub-carriers in the FBMC system, and the preamble sequence is superimposed on the data. Therefore, formula (17) can be rewritten as

\[
Y_p^N = X_p^N F_p h_p^{N,\phi} + \eta_p
\]

where $Y_p^N = \phi Y^N$ is received pilot signal. In this paper, $R_p^N$ is the LS estimation channel values, $\eta_p = \phi \eta^N$. $X_p^N = \phi X^N \phi^T$ is a diagonal matrix, the diagonal elements are pilot values, $F_p = \phi F_{NL}$.

Assuming that $F = X_p^N F_p$, converting (18) to

\[
Y_p^N = X^N_h + \eta^N
\]

where $X^N_h$ is multipath CIR, $Y_p^N$ and $F$ are available during the transmission process, then $h_p^{N,\phi}$ can be re-established by the CS recovery algorithm.

Consider all the receiving antennas in MIMO system, formula (19) can be written as

\[
Y^N = X^N h + \eta^N
\]

where $X$ is the observation matrix with $M \times N$, here, $M = N$, and $\eta$ is the noise. For all $K$-sparse signal $h$, the channel values $X_p^N$ should satisfy the Restricted Isometry Property (RIP), with

\[
1 - \delta_K \leq \frac{\|\phi h_p^{N,\phi}\|_2}{\|h_p^{N,\phi}\|_2} \leq 1 + \delta_K
\]

where the RIP parameter $\delta_K$, with $0 < \delta_K < 1$.

On the $n$th receive antenna, the received signal in (5) in section 2 can be given as

\[
\hat{Y}_n = X_n^N H_n^{n,\phi} + \eta_n
\]

where

\[
\begin{align*}
Y^N &= \left[ r^1(0), r^2(1), \ldots, r^N(N-1) \right]^T, \\
X^N &= diag(x^1(0), x^2(1), \ldots, x^N(N-1)), \\
H_n^{n,\phi} &= F_{NL} h_n^{n,\phi}. L \text{ is the channel length, and } F_{NL} \text{ is the } N \times L \text{ discrete Fourier Transform matrix.}
\end{align*}
\]

\[
\eta_n = \text{a } N \times N \text{ matrix with zero mean and variance of } \sigma^2.
\]

where the RIP parameter $\delta_K$, with $0 < \delta_K < 1$.

On the $n$th receive antenna, the received signal in (5) in section 2 can be given as

\[
\hat{Y}_n = X_n^N H_n^{n,\phi} + \eta_n
\]

where

\[
\begin{align*}
Y^N &= \left[ r^1(0), r^2(1), \ldots, r^N(N-1) \right]^T, \\
X^N &= diag(x^1(0), x^2(1), \ldots, x^N(N-1)), \\
H_n^{n,\phi} &= F_{NL} h_n^{n,\phi}. L \text{ is the channel length, and } F_{NL} \text{ is the } N \times L \text{ discrete Fourier Transform matrix.}
\end{align*}
\]

A. MIMO Sparse CE

CS theory [23, 24] indicated that a $K$-sparse signal $h$ can be steadily re-established from linear measurement

\[
y = Xh + \eta
\]
B. Proposed DCS-Based Method

Consider the following reconstruction of multiple signals
\[ Y^j = \Phi^j h^j + \eta^j \]  
(21)
where \( Y^j \) is measurement signal, \( \Phi^j \) is observation matrix, and \( \eta^j \) is noise matrix. \( j = 1, 2, \ldots, J \), and \( h^j \) is multiple \( K \)-sparse signal with the same sparse index set.

The traditional CS method is mainly used to construct a single sparse signal. There may also be some problems involving multiple sparse vectors that are related to each other, such as MIMO channels and array signals. To solve this kind of problem, DCS was proposed. By using the characteristics of the joint sparse signal, \( \Phi^j \) should also satisfy the RIP constraint, for all \( K \)-sparse signal
\[ 1 - \delta_K \leq \frac{\|\Phi^j h^j\|^2}{\|h^j\|^2} \leq 1 + \delta_K, \quad j = 1, \ldots, J \]  
(22)

Define the set \( \Theta \) which contains the antennas, \( \Theta = \{ \beta=(n_j, n_i) | n_j = 1, \ldots, N, n_i = 1, \ldots, N \} \). Let \( Y^\beta = Y^{N_j} \), \( h^\beta = h_j \), \( \eta^\beta = \eta_j \), MIMO CS-based CE problem can be transformed into the following equation
\[ Y^\beta = \Phi^\beta h^\beta + \eta^\beta, \quad \beta \in \Theta \]  
(23)
where \( \Phi^\beta \) is observation matrix, \( h^\beta \) can be recovered by DCS approach.

Based on the above sparse MIMO-FBMC model, a distributed sparse adaptive CE algorithm based on weak selection threshold is proposed. The algorithm flow is as follows:

Input: \( y^j, \Phi^j, s \)

Output: a \( K \)-sparse \( h^j \)

1. Initialization: \( r_{j,0} = y^j, \quad it = 1, \quad s = 1, \quad stage = 1, \) index set \( \Lambda_0 = \phi \).
2. Set a threshold value \( \varepsilon \), and \( \varepsilon = 10^{-7} \), if \( h^j \) satisfies
\[ \|h^{it-1} - h^j\|^2 \leq \varepsilon \], stop the iteration, otherwise continue with step (3).
3. Use \( u_j = \sum_{j=1}^{J} \frac{\|r_{j,tt-1} - \Phi^j h^j\|^2}{\|\Phi^j h^j\|^2} \) to calculate the inner product of all \( J \) residual vectors and the column vectors of the observation matrix, where \( \Phi^{j,l} \) is the \( l \)-th column of the observation matrix.
4. Select the \( 2K \) maximum values in \( u_j \), then set a threshold \( Th = 0.5 \times \text{max}(\text{abs}(u_j)) \), select values in \( u_j \) that are greater than the threshold \( Th \), and record the column vector positions in \( \Phi^j \) corresponding to these values into the index set \( \Lambda_j \).
5. Update \( \Lambda_j = \Lambda_{j-1} \cup \Lambda_j \).
6. Update \( r_{j,tt} = \arg \min_h \|y^j - \Phi^j h\|_2 \), with \( h \subset \Lambda_j \).
7. If \( \|r_{j,tt}\|_2 > \|r_{j,tt-1}\|_2 \), stage = stage + 1, \( s = s \cdot stage \), return to step (3); otherwise \( r_j = r_{j,tt} \), it = it + 1 return to step (2).

IV. RESULTS AND DISCUSSION

Performance of mean square error (MSE) and bit error rate (BER) of different CE methods of MIMO-FBMC system in time-frequency channel are compared in this Section. We select the least square (LS) method, OMP, distributed OMP (DOMP) and distributed sparse adaptive matching pursuit (DSAMP) for comparative analysis. Simulation parameters are summarized in Table 1. The following three channels are 3GPP extended pedestrian A (EPA), pedestrian A (PA) channel and Vehicular A (VA) channel models, which are used to evaluate CE performance of different algorithms.

| Modulation   | Number of antennas | Filter bank | Number of Subcarriers | Preamble structure |
|-------------|---------------------|-------------|-----------------------|--------------------|
| 4OQAM       | 2 x 2               | IOTA        | 256                   | IOTA               |

Firstly, the estimation accuracy of the proposed algorithm in PA channel is analyzed. Fig. 3 shows the original and estimated channel power time delay. Obviously, the proposed algorithm can accurately estimate the number of multi-paths and the relative power of each path.

Then, the CE performance of the proposed algorithm is analyzed and discussed in PA, EPA and VA multipath fading channels. Figs. 4 and 5 show the MSE and BER performance curves of different algorithms in PA channel. It is important to note that the initial CE of all methods is based on IAM structure, and we can find that the proposed DCS algorithm has better CE...
performance than other four methods. The proposed method maintains robustness in practical channel scenario without the prior knowledge of sparse degree.

In Fig. 4, the proposed algorithm has the best MSE performance. Compared with OMP and DOMP, it is found that the MSE performance of DCS approach is better than that of traditional CS approach. The Proposed DCS method can provide slightly better MSE values than DOMP method. The simulation results verify the conclusion, which was given in Introduction.

In Fig. 5, the proposed algorithm also has the best BER performance. Compared with the traditional distributed sparse adaptive algorithm, the BER performance of the proposed method is significantly improved. Compared with OMP, DOMP and DSAMP, the proposed algorithm improves the BER performance by 4 dB, 1 dB, 3.9 dB when the BER = 10^-2 is considered. Compared with the classical DSAMP algorithm, the proposed DCS method has significant BER performance improvement. This is due to the fact that the proposed algorithm improves the reconstruction probability through the week selection strategy of atoms.

Figs. 6 and 7 give the MSE and BER performance curves of different algorithms in 7-th path EPA channel environment. The results show that the performance curve trend of all algorithms under EPA channel is consistent with that of PA channel. The proposed algorithm still has the best CE performance in EPA channel model.

Compared with Fig. 6 and Fig. 4, it is found that the performance curves of the five methods have more obvious floor effect due to the increase of multipath number.

In Fig. 7, the BER performance curves of different algorithms under the EPA channel are also towards the floor effect. The result indicates that increasing the number of channel multipath will affect the accuracy of CE. With the increase of SNR, the BER performance of OMP algorithms is getting better, while other algorithms tend to be more flat. The performance of OMP algorithm under high SNR is close to that of the proposed algorithm. This is due to the reason that
traditional CS method processes each channel separately, while the DCS method is joint processing, and the performance of joint processing will be affected by the number of joint processing operations.

Fig. 7. Comparison of BER performance in EPA channel.

Fig. 8. Comparison of BER performance in VA channel.

Fig. 8 shows comparison of BER performance of different algorithms in VA channel. Compared with Figs. 5 and 7, the performance of the five algorithms in Fig. 8 deteriorates with the increase of terminal speed. The increase of multipath delay will further deteriorate the performance of CE. However, the curve trends of the algorithms are consistent with those of the PA channel model. The proposed algorithm still has the best BER performance.

Finally, we also study the computational complexity of the CS-based algorithms. Fig. 9 shows the simulation running time of four different CS algorithms under different SNR values, where PA channel is adopted. Obviously, the traditional OMP method has the lowest computational complexity. The simulation running time of the proposed algorithm is between DOMP and DSAMP, the proposed algorithm can provide better adaptive CE performance under certain computational complexity.

Fig. 9. Running time of CS methods under different SNR.

V. CONCLUSIONS

This paper explored the CE problem of MIMO-FBMC systems based on DCS, and proposed a sparse adaptive CE method based on weak selection threshold. The proposed method utilized backtracking ideas and weak selection thresholds to optimize the number of relevant atoms for inner product operations, and combined sparse adaptive to achieve sparse signal reconstruction. The CE performance of the proposed method was simulated and compared in three multipath fading channel models. The simulation results showed that the proposed DCS algorithm achieved better CE performance than traditional OMP method and other classical DCS methods. Under certain computational complexity, the proposed method maintains robustness in practical channel scenario without the prior knowledge of sparse degree.

Abbreviations

MIMO: Multiple input multiple output; FBMC/OQAM: Filter bank multicarrier with offset quadrature amplitude modulation; DCS: Distributed compressed sensing; OMP: Orthogonal matching pursuit; OFDM: Orthogonal frequency division multiplexing; 4G: Fourth generation; 5G: Fifth generation; 3GPP: 3rd Generation Partnership Project; F-OFDM: Filtered OFDM; CE: Channel estimation; IAM: interference approximation method; ICM: interference cancellation method; CS: Compressed sensing; BER: Bit rate ratio; MSE: Mean square error; EPA: Extended pedestrian A; PA: Pedestrian A; VA: Vehicular A; DOMP: Distributed OMP; DSAMP: Distributed sparsity adaptive matching pursuit

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Authors’ Contributions
Dr. Han Wang proposed the method. Dr. Xianpeng Wang contributed towards the performance results and analytic evaluations.

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Availability of data and materials
Unfortunately not available online. Kindly, contact the author for data requests.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable

Competing Interests
The author declares that there is no conflict of interests regarding the publication of this paper.

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Figures

**Figure 1**

MIMO-FBMC system model.

\[
\begin{array}{cccccccc}
0 & 1 & 0 & -1 & 0 \\
0 & -j & 0 & j & 0 \\
0 & -1 & 0 & 1 & 0 \\
0 & j & 0 & -j & 0 \\
0 & 1 & 0 & -1 & 0 \\
0 & -j & 0 & j & 0 \\
0 & -1 & 0 & 1 & 0 \\
0 & j & 0 & -j & 0 \\
\end{array}
\]

antenna 1

\[
\begin{array}{cccccccc}
0 & 1 & 0 & 1 & 0 \\
0 & -j & 0 & -j & 0 \\
0 & -1 & 0 & -1 & 0 \\
0 & j & 0 & j & 0 \\
0 & 1 & 0 & 1 & 0 \\
0 & -j & 0 & -j & 0 \\
0 & -1 & 0 & -1 & 0 \\
0 & j & 0 & j & 0 \\
\end{array}
\]

antenna 2

**Figure 2**

IAM-C preamble structure, with N=8
Figure 3

Channel parameter estimation
Figure 4

Comparison of MSE performance in PA channel
Figure 5

Comparison of BER performance in PA channel.
**Figure 6**

Comparison of MSE performance in EPA channel.
Figure 7

Comparison of BER performance in EPA channel.
Figure 8

Comparison of BER performance in VA channel.
Figure 9

Running time of CS methods under different SNR.