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Robust FDD M-MIMO Channel Estimation with Structured Orthogonal Matching Pursuit Algorithm

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Abstract: - Massive MIMO(M-MIMO) is recognized as one of the promising technologies to meet the demands of the fifth generation of wireless telecommunications. The channel matrix of OFDM Massive MIMO systems is sparse in delay domain. In the compressed sensing-based channel estimation, the channel matrix sparsity is used to improve the channel estimation accuracy and decrease the pilot overhead. This study presents a structured compressed sensing channel estimation plan to reduce the required pilot. As a result, it is possible to enhance the inherent spatial sparsity of the M-MIMO delay domain channels. We propose an algorithm that estimates the channel based on the greedy orthogonal matching pursuit (OMP) algorithm. This algorithm uses the common spatial sparsity of M-MIMO channels for accurate channel estimation. We also present simulations that show the capacity of the proposed approach for reducing the required pilot. The simulation results indicate that the presented channel estimation method has a low bit error rate. In addition, it reliably obtains the sparsity of the channel, suggesting its suitability for channel estimation in OFDM M-MIMO systems.

Keywords: *compressed sensing, sparsity, required pilots, spatial correlation, massive MIMO*.

I. INTRODUCTION

New solutions for meeting the needs of wireless telecommunications have led to the ideation of the fifth generation of cellular telecommunications with its new technologies. In 5G networks, five new technologies and orientations have emerged, including massive MIMO systems [1].

Recently, great attention has been paid to massive MIMO systems because of their prominent characteristics, including better communication gains and greater capacity. It is a promising technology for the future 5G communications for spectral efficiency and high energy efficiency. A precise channel estimation is necessary to realize its potential performance. One of the primary parts of M-MIMO systems is channel estimation, which is among the limitations of using this technology. Taking advantage of massive MIMO requires having appropriate knowledge of CIR between receiver-transmitter links. The CIR estimation challenges massive MIMO systems because the BS has several antennas.

Various methods have been introduced for extracting channel coefficients. The most appropriate method selection for M-MIMO systems depends on the pilots' location and meeting the design requirements, e.g., delay and error rate.

It is possible to classify channel estimation methods into non-blind and blind methods [2]. In the latter, the channel is estimated using the statistical behavior of the data and the assumptions. In the blind channel estimation approaches, the transmitter does not insert any pilot signal into the transmitted signal. Therefore, the receiver estimates the telecommunication channel using the structural and statistical features of the received signals, i.e., the statistical properties of the data or the statistical properties of the channel or both of them. This method requires a large amount of data to estimate the communications channel [3,4].

In this research, non-blind methods are considered. Pilot refers to specific amounts of data known to the receiver that can be used to estimate the number of channels. Although blind-channel estimation methods work better than non-blind methods concerning spectral efficiency for the lack of pilot signals, channel estimation using these methods involves using complex signal processing techniques.

In a general category, the methods of pilot assistance or data assistance are divided into two categories 1) transfer to other domains and 2) compute in the primary domain. In the transfer technique to other domains, orthogonal

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transformations such as Fourier transform are performed in another domain. Thus, in addition to reducing the computational complexity, noise cancellation is much easier and more efficient. For example, in [5, 6], discrete Fourier transform is applied to the orthogonal frequency division multiplexing system (OFDM), in which the data are analyzed in the frequency domain. By transferring to the time domain, channel values are found more effectively, neutralizing their impact. Primary domain calculation methods are different estimation methods that try to find the channel value using pilots. Two popular methods in this field are the linear minimum mean square error (LMMSE) algorithm and the least squares (LS) method. In this work, we use these two methods as the criterion of comparison with the presented channel estimation algorithm of the article. Pilot-based channel estimation methods employ simple algorithms to process in receivers. In these methods, the problem of channel estimation and data detection is usually separated from each other, simplifying the receiver structure. Most of the studies done in the channel estimation field have presumed that a telecommunication channel between a sender and receiver consists of many paths. As a result, the signal sent from the transmitter is received at the receiver with different delays after passing through these paths. Under this assumption, the proposed pilot-based algorithms are often linear and optimized for rich multipath channels. However, many experiments and studies have shown that telecommunication channels have sparse structures in many environments. In other words, in these environments, most of the received signals are received from very attenuated paths so that their power is lower than the noise power [7, 8]. In such sparse environments, very few communication paths are useful for use on the receiver. In sparse telecommunication channels, algorithms with a linear reconstruction structure that are developed based on the channel richness from various paths do not perform well. In fact, as these algorithms are designed to estimate many different paths, they use many pilot signals, resulting in excessive energy consumption, decreased spectral efficiency, and a decrease in the quality of the telecommunication system [7].

Once the sparse channel matrix representation is obtained, channel estimation is possible with fewer pilots using compressive sensing methods. In this regard, sparse signal retrieval methods in compressive sensing are divided into three general categories: greedy, convex optimization, and repetitive methods. In studies conducted in this field, one of these methods has been used proportional to the function. However, in addition to special compressive sensing algorithms, some papers have proposed control methods for adaptively adjusting the required pilot to find the best number of pilots adaptively and to improve channel estimation [9],[10],[11].

Advances in compressed sensing theory, which allows the reconstruction of a sparse signal by a very small number of samples, have motivated many researchers to use this theory to estimate sparse telecommunication channels. Because this theory shows that sparse telecommunication channels can be estimated with very good accuracy with only a small number of pilots. In [12, 13] and [14], it was proved that the channel parameters could be recovered by CS with less training, leading to enhanced system performance and improved bandwidth efficiency. Since the methods of estimating channels based on compressed sensing theory can adapt to the structures of sparse channels and estimate sparse telecommunication channels more accurately than classical methods. However, it should be noted that channel estimation using compressed sensing theory has more computational complexity than the classical methods [15, 16].

Therefore, the use of compressed sensing theory in estimating sparse telecommunication channels increases the channel estimation accuracy and enhances the telecommunication system’s spectral efficiency. High spectrum efficiency is one of the basic needs for future generations of telecommunication systems. Increasing the use of telecommunication networks, systems must be designed to serve a large number of users simultaneously. M-MIMO systems are one of the emerging technologies designed for this purpose. In [14, 17] and [18], channel estimation was considered based on CS techniques. They proved that increasing the number of BS antennas, will increase the CIR sparsity for the local scatters at the BS.

Many applications consider a time division duplexing (TDD) scenario. In this case, the reciprocity property is established so, the CSI in the downlink is obtained from the uplink CSI. The channel reciprocity property is not established in FDD systems. The reason is that the downlink and uplink utilize different frequency bands in FDD mode so, the CSIs are different according to uplink and downlink. FDD performs well in symmetric traffic, latency-sensitive systems, and many cellular systems. Therefore, FDD cannot be ignored as there is a great interest in discovering effective approaches for obtaining channel state information at the transmitter (CSIT) in M-MIMO systems in FDD.

Therefore, it is difficult to achieve precise channel estimation with low pilot requirements, particularly for FDD-based M-MIMO systems. FDD systems can provide more efficient communication with less latency than TDD systems [19], leading to more use of FDD. Many authors have considered the FDD massive MIMO systems [3, 20][5][21, 22]. Also, some other efforts have proposed uplink CSI feedback and downlink pilot design[12,23]-[24]. In the present research, the issue of channel estimation of FDD M-MIMO systems is addressed using compressive sensing techniques and the inherent sparsity of channels in different modes.

In [25], an iterative thresholding method was proposed for approximating the channel matrix, which has been effective in the channel estimation because of high amount of BS antennas and channel paths. Also, in line with applying channel estimation in M-MIMO systems, channel estimation based on FDD, [26] and [27] using spatial correlation of channels have shown that the required pilot to evaluate the channel can be reduced by Rice distribution. In channel estimation the sparsity level of the channel at the user is assumed to be known such as in [26] and [28,29] that is not the case in real situations.

The spatial correlation of sparse channels and the common location sparsity of MIMO channels in the delay domain and structured sparsity of M-MIMO channels are modeled and described in this work. The remainder of this research is organized as follows. The second section illustrates the proposed structured orthogonal matching pursuit channel estimation algorithm. The third section shows the simulation results. Finally, the conclusions and future work suggestions are presented in the fourth section.

structured orthogonal matching pursuit channel estimation algorithm

This section models spatial sparsity and reviews the proposed channel estimation strategy and algorithm.

Spatial sparsity modeling

Experimental studies show that broadband wireless channels are sparse in the delay domain. This sparsity is attributed to the low number of multiple paths dominating the channel energy due to the low number of considerable scatterers in wireless signal propagation settings. However, there could be a large channel delay spread due to the great difference between the arrival times of the first and the last received paths. Specifically, the delay-domain channel impulse response (CIR) in the downlink between the m^{th} transmit antenna at the BS and a user, $\boldsymbol{h}_m$, is expressed as follows:

$$\boldsymbol{h}_{m=} [h_m[1], h_m[2], \dots, h_m[L]^T], 1 \le m \le M \quad (1)$$

where L is equal to the channel length. We define the support set, V_m, as follows.

$$V_m = Supp\{\boldsymbol{h}_m\} = \{l: |h_m[l]| > \eta, 1 \le l \le L\} \quad (2)$$

Here, the channel noise threshold level (η) corresponds to the effective semi-blind solution for detecting the most significant taps in sparse channel estimation of OFDM MIMO systems. The sparsity level of wireless channels, i.e., the number of the sparsity of the mth transmit antenna, is defined as $NS_m = |V_m|_c$.

The delay domain channels have a sparse nature, $NS_m \ll L$ [26]. In addition, measurements show very similar path delays in the channel impulse response (CIR) between different transmit antennas and a user. Because in typical M-MIMO geometry, the compressed antenna array in BS has a negligible and quite small scale compared to the large signal transmission distance. Also, there are common scatters between each transmitter and receiver antenna pairs. Therefore, there is a high overlap between the sparsity pattern of different CIRs of different transmit-receive antenna pairs. Moreover, for MIMO systems that do not have an excessively high M, a common sparse pattern can be shared by these CIRs [30][31] that is,

$$V_1 = V_2 = \cdots = V_M \quad (3)$$

V_M is called the spatial common sparsity of wireless MIMO channels. Channels between transmitter and receiver can have temporal, spatial, or frequency correlations. Spatial correlation occurs when the channel matrices of different users have common support, meaning that some non-zero locations in their matrices are the same. Having several common scatterers in signaling to all users will create such a feature.

Channel estimation scheme

Here, we present a structured compressive sensing and channel estimation plan for FDD massive MIMO systems with a structured algorithm based on the greedy OMP algorithm, using the spatial domain correlation at the user-side. The discrete Fourier transform and cyclic prefix are removed at the user side. Thus, the pilot sequence $\boldsymbol{y} \in \mathbb{C}^{N_p \times 1}$ can be expressed for an OFDM symbol as follows

$$\boldsymbol{y} = \sum_{m=1}^{M} diag\{\boldsymbol{p}_m\} \boldsymbol{F}|_\gamma \begin{bmatrix} \boldsymbol{h}_m \\ 0_{(N-L)\times 1} \end{bmatrix} + \boldsymbol{w} = \sum_{m=1}^{M} \boldsymbol{P}_m \boldsymbol{F}_L|_\gamma \boldsymbol{h}_m + \boldsymbol{w} = \sum_{m=1}^{M} \boldsymbol{\Phi}_m \boldsymbol{h}_m + \boldsymbol{w} \quad (4)$$

N denotes the number of subcarriers in an OFDM system. γ represents a set of sub-carriers assigned to pilots that are uniquely selected from the sets $\{1,2, \dots, N\}$ and thus it is the location of the pilots. $N_p = |\gamma|_c$ is the number of pilots and

$\boldsymbol{p}_m \in \mathbb{C}^{N_P\times 1}$ is the training sequence of the mth antenna on the transmitter $\{\boldsymbol{p}_m\}_{m=1}^{M}$. $\boldsymbol{P}_m = diag\{\boldsymbol{p}_m\}$ with elements $\boldsymbol{p}_m$. $\mathbf{F}$ represents a DFT matrix with $N \times N$ size. $\boldsymbol{F}_L \epsilon \mathbb{C}^{N\times L}$ includes the L first column of the $\mathbf{F}$ matrix. $\boldsymbol{F}_{|\gamma} \in \mathbb{C}^{N_P\times N}$ and $\boldsymbol{F}_{L|\gamma} \in \mathbb{C}^{N_P\times L}$ are submatrices obtained by selecting rows F and $\boldsymbol{F}_L$, respectively, with respect to γ. $\boldsymbol{w} \in \mathbb{C}^{N_P\times 1}$ is defined by the additive white Gaussian noise vector (AWGN) and $\boldsymbol{\Phi}_m = \boldsymbol{P}_m\boldsymbol{F}_{L|\gamma}$.

Accordingly, Eq. (4) can be rewritten more concisely below,

$$\boldsymbol{Y} = \boldsymbol{\Phi}\boldsymbol{h} + \boldsymbol{W} \qquad (5)$$

where $\boldsymbol{\Phi} = \left[\boldsymbol{P}_1\boldsymbol{F}_{L|\gamma}, \boldsymbol{P}_2\boldsymbol{F}_{L|\gamma}, \cdots, P_M\boldsymbol{F}_{L|\gamma}\right] = [\boldsymbol{\Phi}_1, \boldsymbol{\Phi}_2, \dots, \boldsymbol{\Phi}_M] \epsilon \mathbb{C}^{N_p\times ML}$ $\boldsymbol{h} = [\boldsymbol{h}_1^T, \boldsymbol{h}_2^T, \dots, \boldsymbol{h}_M^T]^T \epsilon \mathbb{C}^{ML\times 1}$, $\boldsymbol{h}$ can be considered the equivalent CIR.

For M-MIMO systems, since the number of M transmit antennas is large and the number of pilots N_p is limited, we usually have $N_p \ll ML$. This problem gives an under-determinate system of equations whose equations are fewer than the unknowns. Also, we know that this system of equations has an infinite answer. These interpretations, show that we cannot trust channel estimation from pilot sequence by using channel estimation mathods that require a high number of samples for channel estimation because (5) is an indeterminate equation.

Given that the sparse solution of an under-determined system of equations is unique, to retrieve a channel from a measurement vector uniquely, the channel vector itself must be sparse or sparse in other domains. However, it was found that $\boldsymbol{h}$ is a sparse signal because of the $\{\boldsymbol{h}_m\}_{m=1}^{M}$ sparsity. Therefore, it was inspired to estimate the high-dimensional sparse signal of $\boldsymbol{h}$ from the received low-dimensional pilot $\boldsymbol{Y}$ sequence within the CS theory framework [32]. In addition, wireless MIMO channels inherent spatial sparsity, helps improve system quality and performance, which we will be deal with in the following.

$\boldsymbol{\Phi}$ can be arranged as follows.

$$\boldsymbol{\Psi} = [\boldsymbol{\Psi}_1, \boldsymbol{\Psi}_2, \dots, \boldsymbol{\Psi}_L] \epsilon \mathbb{C}^{N_p\times ML} \qquad (6)$$

where $\boldsymbol{\Psi}$ elements are in the following order $\boldsymbol{\Psi}_l = \left[\boldsymbol{\Phi}_1^{(l)}, \boldsymbol{\Phi}_2^{(l)}, \dots, \boldsymbol{\Phi}_M^{(l)}\right] = \left[\boldsymbol{\psi}_{1,l}, \boldsymbol{\psi}_{2,l}, \dots, \boldsymbol{\psi}_{M,l}\right] \epsilon \mathbb{C}^{N_p\times M}$. Similarly, (5) can be rewritten as follows.

$$\boldsymbol{Y} = \boldsymbol{\Psi}\boldsymbol{V} + \boldsymbol{W} \qquad (7)$$

Specifically, we arrange the channel impulse response vector $\boldsymbol{h}$ so that the correspondent CIR vector, $\boldsymbol{V}$, is obtained as follows: $\boldsymbol{V} = [\boldsymbol{V}_1^T, \boldsymbol{V}_2^T, \dots, \boldsymbol{V}_L^T]^T \in \mathbb{C}^{ML\times 1}$. Here, for the $\mathbf{V}$ elements, $\boldsymbol{V}_l$ is aexpressed as $\boldsymbol{V}_l = [\boldsymbol{h}_1[l], \boldsymbol{h}_2[l], \dots, \boldsymbol{h}_M[l]]^T\ for\ 1 \le l \le L$. The matrix $\boldsymbol{V}$, corresponding to CIR in (7), shows a structured sparsity because of the spatial sparsity of the wireless MIMO channels. Also, the channel estimation performance can be enhanced by the inherent sparsity in $\boldsymbol{V}$. Hence, the channels related to the M transmitter antennas can be estimated jointly.

TABLE 1. THE IMPLEMENTATION FLOW OF THE SOMP ALGORITHM

algorithm proposed SOMP channel estimation algorithm
1- Input: measurement matrix $\boldsymbol{Y}$ Sensing matrix $\boldsymbol{\Psi}$ 2- Sparsity level of the channel s=1 3- Iterative variable n=1 4- Support set $\boldsymbol{\Omega}^{n-1} = \boldsymbol{\phi}$ 5- Residual matrix $\boldsymbol{R}^{n-1} = Y, \|\|\boldsymbol{R}_{s-1}\|\|_F = +inf$ "iteration loop to find the sparse $\mathbf{V}$ matrix according to Eq. (7)" 6- Correlation $\boldsymbol{X} = \boldsymbol{\Psi}^H\boldsymbol{R}^{n-1}$ 7- Estimating support set $\widetilde{\boldsymbol{\Omega}}^n = \text{MAXINDX}^s(\{\|\|\boldsymbol{X}_l\|\|_F\}_{l=1}^{L})$ 8- Estimating matrix $\breve{\boldsymbol{V}}_{\widetilde{\Omega}^n} = \Psi_{\widetilde{\Omega}^n}^{\dagger}\boldsymbol{Y}, \breve{\boldsymbol{V}}_{(\widetilde{\Omega}^n)^c} = 0$ 9- Residual update $\boldsymbol{Y}^n = \boldsymbol{\Psi}\breve{\boldsymbol{V}}$; $\boldsymbol{R}^n = \boldsymbol{Y} - Y^n$ 10- Matrix update $\breve{\boldsymbol{V}}^n = \breve{\boldsymbol{V}}$ If $(\|\boldsymbol{R}^{n-1}\|_F > \|\boldsymbol{R}^n\|_F)$

11- Iteration with fixed sparsity level $\mathbf{\Omega}^n = \widetilde{\mathbf{\Omega}}^n$, $n = n + 1$
else
12- Updating sparsity level $\breve{\boldsymbol{V}}_s = \breve{\boldsymbol{V}}^{n-1}$, $\boldsymbol{R}_s = \boldsymbol{R}^{n-1}$
$\mathbf{\Omega}_s = \mathbf{\Omega}^{n-1}$, $s = s + 1$
end if
13- Stopping criteria $\|\boldsymbol{R}^n\|_F > \|\boldsymbol{R}_{s-1}\|_F$ or $\left\| \breve{\boldsymbol{V}}_{\tilde{l}} \right\|_F \leq \sqrt{M}\eta$
End loop
14- Output $\widehat{\boldsymbol{V}} = \breve{\boldsymbol{V}}_{s-1}$
15- Obtain channel estimates according to Eqs. (4) to (7) $\{\boldsymbol{h}_m\}_{m=1}^{m=M}$

Using the structured sparsity of $\boldsymbol{V}$ in (7), the SOMP algorithm is proposed for estimating the channels of the M-MIMO system as described in the steps above in table 1. With the development of the OMP algorithm, this algorithm uses structured sparsity of $\boldsymbol{V}$ to improve the sparse signal retrieval performance further. The proposed algorithm also obtains sparsity adaptively. The following are some of the features of the proposed algorithm.

The two vectors $\boldsymbol{X}$ and $\breve{\boldsymbol{V}}$ are as follows, $\boldsymbol{X} \epsilon\ \mathbb{C}^{ML\times 1}$ *and* $\breve{\boldsymbol{V}} \in \mathbb{C}^{ML\times 1}$, which include L sub-matrix of equal size $M \times 1$, i.e., $\boldsymbol{X} \epsilon\ [\boldsymbol{X}_1^T, \boldsymbol{X}_2^T, \ldots, \boldsymbol{X}_L^T]^T$ *and* $\breve{\boldsymbol{V}} = [\breve{\boldsymbol{V}}_1^T, \breve{\boldsymbol{V}}_2^T, \ldots, \breve{\boldsymbol{V}}_L^T]^T$.

We also have $\breve{\boldsymbol{V}}_{\widetilde{\Omega}} = [\breve{\boldsymbol{V}}^T_{\widetilde{\Omega}(1)}, \breve{\boldsymbol{V}}^T_{\widetilde{\Omega}(2)}, \ldots, \breve{\boldsymbol{V}}^T_{\widetilde{\Omega}(|\widetilde{\Omega}|_c)}]^T$ and $\mathbf{\Psi}_{\widetilde{\Omega}} = [\mathbf{\Psi}_{\widetilde{\Omega}(1)}, \mathbf{\Psi}_{\widetilde{\Omega}(2)}, \ldots, \mathbf{\Psi}_{\widetilde{\Omega}(|\widetilde{\Omega}|_c)}]$, where $\widetilde{\mathbf{\Omega}}(1) < \widetilde{\mathbf{\Omega}}(2) < \cdots < \widetilde{\mathbf{\Omega}}(|\widetilde{\mathbf{\Omega}}|_c)$ are the elements of the $\widetilde{\mathbf{\Omega}}$ set. MAXINDX$^s(\cdot)$ represents a set with its elements denoting the indexes of the s largest elements of its argument. Ultimately, to obtain sparsity level reliably, we will stop the iteration if $\|\boldsymbol{R}^n\|_F > \|\boldsymbol{R}_{s-1}\|_F$or $\|\breve{\boldsymbol{V}}_{\tilde{l}}\|_F \leq \sqrt{M}\eta$ is established. In the above relation, $\|\breve{\mathbf{V}}_{\tilde{l}}\|_F$ is the smallest $\|\breve{\mathbf{V}}_l\|_F$ for $l \in \widetilde{\Omega}$ and η is the threshold level. The stop iteration $\|\boldsymbol{R}^n\|_F > \|\boldsymbol{R}_{s-1}\|_F$ shows the larger residual of the current sparsity level compared to the previous sparsity level. Iteration pause can help the algorithm achieve good MSE performance. On the other hand, the stop criterion $\left\| \breve{\boldsymbol{V}}_{\tilde{l}} \right\|_F \leq \sqrt{M}\eta$ indicates that the $\tilde{l}$th path is dominated by AWGN. It can be stated that the channel sparsity level is over-satisfied, although the MSE with the current sparsity level outperforms MSE with the last sparsity level. In fact, MSE performance improvements are because of noise reconstruction.

In this part, the main steps of the SOMP algorithm are explained. In Steps 6 to 11, the proposed algorithm intends to obtain the solution of $\boldsymbol{V}$ by Eq. (6) to the fixed sparsity level s, using the OMP algorithm as a greedy method. Also, $\|\boldsymbol{R}^{n-1}\|_F \leq \|\boldsymbol{R}^n\|_F$ shows that solution $\boldsymbol{V}$ is obtained with the sparsity of s for Eq. (7). The sparsity level is then updated for finding solution $\boldsymbol{V}$ with the sparsity of $(s + 1)$. Finally, there is no iteration if the stop criterion is met.

In the following, the distinguishing features of the presented SOMP algorithm compared to the OMP algorithm are discussed.

A high-dimensional sparse vector is reconstructed with the OMP algorithm from a low-dimensional measurement vector without using a structured sparsity of sparse vector. On the contrary, the presented algorithm retrieves $\boldsymbol{h}$ using an inherently structured sparsity. In this case, matrix reconstruction performance is improved using the SOMP algorithm.

The OMP algorithm at low SNR needs the primary information in the form of the sparsity level to reliably reconstruct the sparse signal. However, the presented algorithm can adaptively obtain the sparsity level of the structured matrix.

It is worth noting that most CS-based channel estimation plans usually require a sparsity channel level as the primary information to make the channel estimation reliable.

II. RESULTS OF SIMULATION

Simulations are performed here for evaluating the performance of the channel estimation plan proposed for M-MIMO systems based on FDD. For providing a performance comparison benchmark, an LS algorithm is considered, presuming a well-known channel support sequence at the user side. An algorithm similar to the proposed algorithm, called the modified algorithm, assumes knowing the sparsity level of the channel at the user side. This algorithm presents a particular case of our proposed algorithm in which we set the channel's initial sparsity level, s, to the channel sparsity level. We do not perform Step 12 of the proposed algorithm, the stop criterion is $\|\boldsymbol{R}^n\|_F \geq \|\boldsymbol{R}^{n-1}\|_F$ and in step 14, $\widehat{\boldsymbol{V}} = \breve{\boldsymbol{V}}_{n-1}$. Table 2 presents the simulation parameters.

TABLE 2. SETTINGS of SIMULATION SYSTEM PARAMETERS

Simulation Parameters	Value
OFDM symbol DFT size	$N = 4096$
System bandwidth	$10MHz\ f_s =$
System carrier frequency	$f_c = 2$ GHz
Cyclic Prefix	CP=64
Planar antenna array	$(M = 64) 16 \times 4$
Channel model	EPA[a]
Number of multipath	$P = 6$
Delay spread	6.4 μs
Number of pilots	N_p
Overhead ratio	$\beta = N_p/N$
$\eta = 0.1, 0.06, 0.04$	SNR=10, 20, 30 dB

In Fig. 1, the presented MSE algorithm, the proposed modified algorithm, and the LS algorithm on the EPA channel at SNR = 20 dB are compared in terms of their performance.

As shown in Fig .1, for $\beta \geq 18.82\%$, similar MSE performance is observed in the proposed modified algorithm and the proposed algorithm, which is close to

the LS algorithm's performance. As can be seen, the sparsity level of the channel and the support set for $\beta \geq 18.82\%$

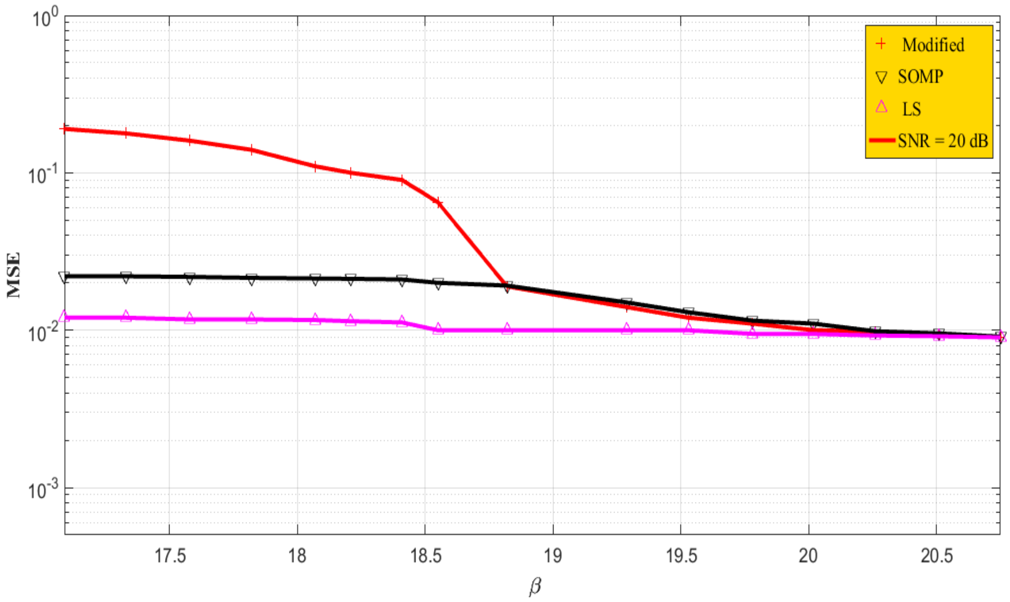

Fig. 1. Comparison of MSE performance of proposed algorithms and LS versus pilot ratio and SNR = 20.

can be reliably obtained by the presented algorithm.

Fig. 1 shows the better SOMP algorithm performance than the modified SOMP algorithm at $\beta < 18.82\%$. This outperformance suggests that the presented algorithm adaptively can obtain the channel's sparsity level.

For a better comparison in Fig. 2, we compared the performance of the proposed MSE algorithm, the proposed modified algorithm, and the LS algorithm at 10-dB and 30-dB SNRs. The SOMP algorithm can obtain the sparsity of the channel with a high probability when the SNR and β increase. In addition, even in cases where the number of pilots is insufficient, and the reliable recovery of sparse channels is not guaranteed,

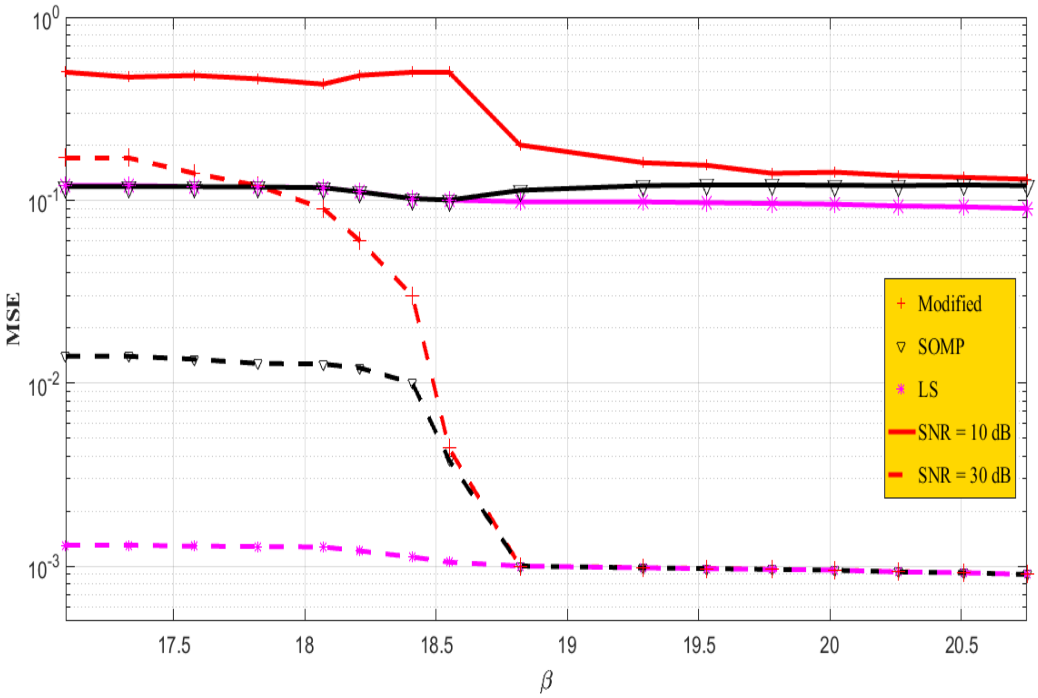

Fig. 2. Comparison of the performance of MSE and LS algorithms versus the pilot ratio and SNR = 10, 30.

the presented algorithm can still measure the sparsity level of the channel with a slight deviation from the sparsity level of the channel.

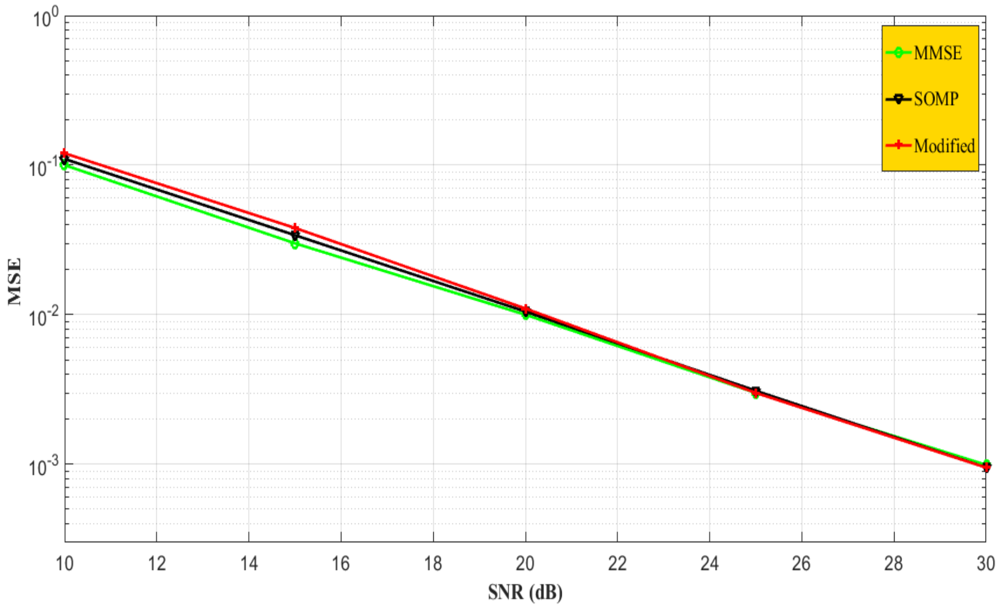

Fig. 3. Comparison of MSE and MMSE performance with the proposed channel estimation schemes of FDD M-MIMO systems.

Fig. 3 compares the SOMP, the Modified channels estimation algorithms and the MMSE algorithm in terms of MSE [33]. It is notablethat the presented scheme considerably reduces the training sequence because the MMSE algorithm shows good performance when (5) is specified well.

In Fig. 4, we compare the downlink bit error rate (BER), assuming BS recognizes the estimated downlink channels using ZF precoding. In this simulation, BS with M=64 antennas concurrently serves K =8 users using QAM-16. A relative improvement of our proposed channel estimation scheme is seen compared to its counterparts.

IV. CONCLUSIONS

The present work proposed a channel estimation scheme based on structured sparsity and OMP algorithm, we called it, SOMP. This algorithm utilizes the intrinsic sparsity of OFDM M-MIMO channels for reducing the required pilots. On the user side, the proposed algorithm can make a reliable estimation for reducing the pilot overhead and low bit error rate. As shown by the simulation results, the presented channel estimation scheme can obtain a high channel estimation performance concerning the comparative channel sparsity acquisition.

The reason for the spatial common sparsity of MIMO channels is the array of antennas with a common location in the BS. However, for M-MIMO, such a common sparsity could not be guaranteed for separate antennas with a large antenna array. Examining and simulating a way to ensure this can also be a solution for the future. For M-MIMO systems with many transmit antennas, orthogonal pilots have a higher required pilot inhibition. As another future work, we can pilot design for reducing the pilot overhead. Also, studying the mentioned spatial sparsity in other compressed sensing formats (e.g., Bayesian and group Bayesian) and its comparison with the mentioned plan will be among the future works. Investigating temporal correlation and combining it with spatial sparsity using this algorithm is another research subject in this area. In addition to the mentioned solutions, optimizing the proposed algorithm in terms of complexity or examining other methods are tasks that can be updated in this field.

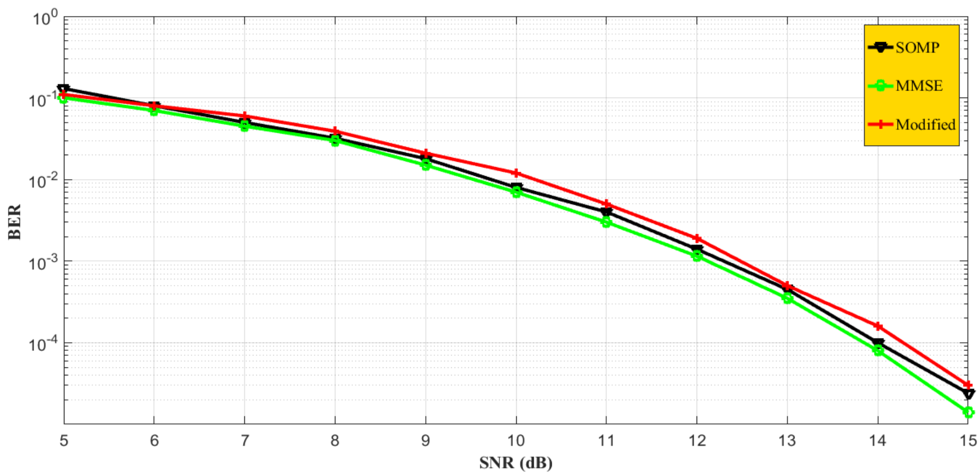

Fig. 4. Comparison of BER performance of the SOMP, the Modified and the MMSE of MIMO M-FDD systems.

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