# Adaptive Sparse Channel Estimation Scheme for Wideband Massive MIMO-OFDM Systems Postprint

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**Date:** 2018-08-13T00:00:00+00:00

## Abstract

In large-scale MIMO-OFDM system downlinks, obtaining channel state information via compressed sensing algorithms requires prior knowledge of signal sparsity as a prerequisite; however, in practical environments, the sparsity of wireless channels is unknown. By exploiting the spatial-temporal joint sparsity characteristics of large-scale MIMO channels and adopting the concept of setting different stopping iteration thresholds under different SNRs, the compressed sensing reconstruction algorithm is improved, aiming to enable the proposed algorithm to not only enhance estimation performance but also accurately obtain the dynamic sparsity of channels. Experimental results demonstrate that, compared with traditional CoSaMP and S-CoSaMP algorithms, the SSA-CoSaMP algorithm exhibits superior channel estimation performance under the same signal-to-noise ratio and can adaptively acquire sparsity, making it more suitable for practical engineering applications.

## Full Text

## Preamble

### Adaptive Sparse Channel Estimation for Broadband Massive MIMO-OFDM Systems

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**Abstract:** In massive MIMO-OFDM systems, most compressed sensing reconstruction algorithms require the sparsity level of the signal as prior knowledge. However, in practical environments, the sparsity of wireless channels is unknown. This paper proposes an improved compressed sensing reconstruction algorithm that leverages the space-time common sparsity characteristics of massive MIMO channels and employs different stopping iteration thresholds under various SNR conditions. The objective is to enhance estimation performance while accurately obtaining the dynamic sparsity of channels. Experimental results demonstrate that compared with traditional CoSaMP and S-CoSaMP algorithms, the proposed SSA-CoSaMP algorithm achieves superior channel estimation performance under the same SNR and can adaptively obtain sparsity, making it more suitable for practical engineering applications.

**Keywords:** massive MIMO; compressive sensing; sparsity adaptive; sparse channel estimation; spatio-temporal common sparsity

## 0 Introduction

Current cellular systems predominantly operate in FDD mode [5], making research on channel estimation for massive MIMO in FDD mode profoundly significant. However, massive MIMO systems achieve simultaneous service to multiple single-antenna users by deploying a large number of transmit antennas at the base station [1]. Consequently, massive MIMO exhibits excellent resistance to noise and narrowband fading, enabling better utilization of increasingly precious spectrum and energy resources, and has become a key technology for future 5G development [2,3]. In massive MIMO systems, accurate channel state information (CSI) is essential for signal detection, beamforming, resource allocation, and channel assignment. Therefore, outstanding channel estimation schemes constitute a supporting technology for massive MIMO.

At present, the vast majority of research on massive MIMO is conducted in time division duplex (TDD) mode, aiming to utilize channel reciprocity between uplink and downlink to obtain downlink CSI through uplink channel estimation [4]. However, frequency division duplex (FDD) mode offers lower latency and higher communication efficiency than TDD mode, and most countries internationally currently operate their cellular systems in FDD mode [5]. Therefore, research on channel estimation for massive MIMO in FDD mode is of far-reaching significance. Nevertheless, in FDD mode, accurate downlink estimation is extremely difficult [6] because the base station is equipped with numerous transmit antennas that simultaneously send data to users, requiring the user side to accurately estimate the CSI for each transmit antenna and the single receive antenna. Simultaneously achieving high accuracy and low pilot overhead is also very challenging.

OFDM systems offer numerous advantages, such as high spectral efficiency, excellent resistance to multipath interference, and robustness against narrowband fading [7]. With the surge in wireless communication users requiring increased system capacity, combining orthogonal frequency division multiplexing with massive MIMO systems enables antenna diversity and spatial multiplexing [7]. In the current communication environment, available wireless bandwidth frequencies are increasingly scarce. Integrating these two systems can substantially improve spectrum utilization while effectively addressing frequency-selective fading environments in wireless channels.

Typical broadband wireless transmission environments exhibit frequency-selective fading. To solve this problem, we jointly employ massive MIMO and OFDM systems to establish a massive MIMO-OFDM system [8]. In massive MIMO-OFDM transmission environments, numerous scatterers create Rayleigh multipath transmission channels. Moreover, the vast majority of wireless channel energy concentrates on very few components of the channel impulse response (CIR) [9], causing the CSI formed between users and base stations to naturally exhibit sparsity [10,11].

Based on this sparsity, compressive sensing (CS) can be utilized for channel estimation [12]. However, in practical environments, the sparsity of wireless channels is unknown, requiring algorithms to estimate channel sparsity without prior knowledge [13]. Therefore, this paper proposes a Sparsity Adaptive Compressive Sampling Matching Pursuit (SSA-CoSaMP) algorithm that leverages spatial common sparsity to not only improve estimation performance and save pilot overhead but also enable the algorithm to achieve sparsity adaptation.

The main contributions of this paper include four aspects:
a) Sparsity adaptive improvement of the CoSaMP algorithm, enabling it to obtain sparsity autonomously when the sparsity level is unknown;
b) Utilizing the spatio-temporal common sparsity characteristics of massive MIMO channels for structured processing on the basis of sparsity adaptation, which not only accelerates sparsity acquisition but also improves estimation performance and accuracy;
c) Determination of algorithm stopping iteration parameters;
d) Verification of the proposed channel estimation algorithm' s accuracy and performance through simulation programs.

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## 1 Massive MIMO-OFDM Spatio-Temporal Common Sparsity

### 1.1 Spatial Common Sparsity

In typical massive MIMO systems, the base station antenna array is dense. The spacing between antennas is negligible compared to the distance traveled by signals from each transmit antenna to the user' s single antenna, and common scatterers exist in the channels between each transmit-receive antenna pair. Consequently, each base station antenna and the user' s single antenna exhibit highly similar path delays [18,19], as shown in [Figure 1: see original paper]. Moreover, the sparse characteristics of CIRs between different transmit antenna pairs largely coincide. This is the spatial common sparsity of massive MIMO channels, where different transmit antennas maintain the same sparsity for the r-th OFDM symbol, expressed as:

$$\Gamma_{1,r} = \Gamma_{2,r} = \cdots = \Gamma_{M,r}$$

where $\Gamma_{m,r}$ represents the support set of $\mathbf{h}_{m,r}$, which can be expressed as:

$$\Gamma_{m,r} = \mathrm{supp}(\mathbf{h}_{m,r}) = \{\ell : |h_{m,r}(\ell)| > \eta_{\min}, 1 \leq \ell \leq L\}$$

where $\eta_{\min}$ represents the minimum noise value in the channel, and the sparsity $\lambda_{m,r} = |\Gamma_{m,r}|$.

### 1.2 Temporal Correlation of Massive MIMO Channels

In practical massive MIMO-OFDM system transmission environments, numerous scatterers create Rayleigh multipath transmission channels, with the vast majority of channel energy concentrated on very few CIR components [14], causing CSI to naturally exhibit sparsity [15]. Meanwhile, signals emitted from each base station transmit antenna travel through very similar scatterers before reaching the user' s receive antenna. In other words, the user' s single antenna and all base station antennas share spatial common sparsity characteristics. Additionally, because path delays change much more slowly than path gains related to temporal channels, this sparsity remains almost unchanged during the coherence time [16], forming temporal correlation characteristics.

In the temporal dimension, path gains of channels change much more slowly [20], thus exhibiting temporal correlation characteristics, even in fast time-varying scenarios. In other words, although path gains may vary significantly from one OFDM symbol to the next, path delays remain almost constant across several consecutive OFDM symbols. This is because in time-varying channels, path delay variation time is inversely proportional to system bandwidth, while path gain coherence time is inversely proportional to carrier frequency [21]. Within the coherence time of path gains, CIRs of G consecutive OFDM symbols maintain unchanged common sparsity, as shown in [Figure 2: see original paper], i.e.:

$$\Gamma_{m,r} = \Gamma_{m,r+1} = \cdots = \Gamma_{m,r+G-1}$$

In summary, spatial common sparsity and temporal correlation are collectively referred to as spatio-temporal common sparsity [22]. Leveraging this spatio-temporal common sparsity can improve the reconstruction performance of CS algorithms.

## 2 Massive MIMO-OFDM System Model

We establish a typical FDD-mode massive MIMO-OFDM system with M base station antennas and K single-antenna users (M   K), as shown in [Figure 3: see original paper]. The total number of subcarriers per OFDM symbol is N, and the signal (including data and pilots) transmitted by the m-th base station antenna is $\mathbf{s}_m$. After removing the guard interval and performing DFT transformation, the user extracts pilot information $\mathbf{y}_r$ from the received information $\mathbf{Y}_r$ for the r-th OFDM symbol according to pilot allocation scheme $\mathcal{P}$. The expression is:

$$\mathbf{y}_r = \sum_{m=1}^{M} \ _{m,r}\mathbf{h}_{m,r} + \mathbf{n}_r$$

where $\ _{m,r} = \mathbf{C}_m \mathbf{F}_L \ _r$ represents the measurement matrix, $\mathbf{C}_m$ denotes the pilot amplitude set for the m-th antenna, $\mathbf{F}_L$ is the DFT matrix of size N×N taking the first L rows, $\ _r$ is the submatrix extracted from $\mathbf{F}_L$ according to $\mathcal{P}$, and $\mathbf{n}_r$ represents the additive white Gaussian noise vector in the r-th OFDM symbol.

Simplifying equation (5) yields:

$$\mathbf{y}_r = \ _r\mathbf{h}_r + \mathbf{n}_r$$

In massive MIMO-OFDM systems, $P \ll ML$. Therefore, equation (6) is an underdetermined system that cannot be reliably estimated using traditional channel estimation methods such as least squares (LS). However, based on the above analysis, $\mathbf{h}_r$ is a high-dimensional sparse signal, so compressive sensing theory can be utilized to reconstruct $\mathbf{h}_r$ from low-dimensional $\mathbf{y}_r$.

Furthermore, leveraging the spatial common sparsity mentioned in Section 1.1, we can rearrange $\mathbf{h}_r$ and express it as:

$$\mathbf{d}_r = [\mathbf{h}_{1,r}^T, \mathbf{h}_{2,r}^T, \dots, \mathbf{h}_{M,r}^T]^T$$

Correspondingly, $\ _r$ can be rearranged as:

$$\ _r = [\ _{1,r}, \ _{2,r}, \cdots, \ _{M,r}]$$

Thus, equation (8) can be reorganized as:

$$\mathbf{y}_r = \ _r\mathbf{d}_r + \mathbf{n}_r$$

Through the above transformation utilizing the common sparsity of wireless massive MIMO systems, the sparsity of $\mathbf{d}_r$ is structurally processed and enhanced.

Using the temporal correlation mentioned in Section 1.2, the spatial common sparsity of massive MIMO systems remains almost unchanged across several consecutive OFDM symbols within the coherence time. Therefore, under pilot allocation scheme $\mathcal{P}$, processing R consecutive OFDM symbols within the coherence time, equation (9) can be reorganized as:

$$\mathbf{Y} = \ \mathbf{H} + \mathbf{N}$$

where:

$$\mathbf{Y} = [\mathbf{y}_r, \mathbf{y}_{r+1}, \dots, \mathbf{y}_{r+R-1}]$$
$$\mathbf{N} = [\mathbf{n}_r, \mathbf{n}_{r+1}, \dots, \mathbf{n}_{r+R-1}]$$
$$\mathbf{H} = [\mathbf{d}_r, \mathbf{d}_{r+1}, \dots, \mathbf{d}_{r+R-1}]$$

By further structuring the channel CIR matrix based on the temporal correlation of wireless massive MIMO channels, equation (10) enhances sparsity and improves CS algorithm estimation performance. The pilot design scheme in this paper is a non-orthogonal pilot allocation scheme (detailed in Section 3).

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## 3 Non-Orthogonal Pilot Design Scheme

Pilots play a crucial role in channel estimation. Excellent pilot design can substantially improve channel estimation performance. Conversely, unreasonable or unsuitable pilot design not only prevents accurate channel estimation but may also increase pilot overhead, wasting broadband resources and energy.

### 3.1 Orthogonal vs. Non-Orthogonal Pilots

Traditional orthogonal pilot design is developed under the Nyquist sampling theorem framework, requiring pilots on different antennas to occupy different subcarriers. Subcarriers already assigned pilots on one antenna must be left empty on corresponding positions of other antennas. Currently, orthogonal pilot design is widely used in existing MIMO systems because the small number of antennas makes pilot overhead less severe, such as in 8-antenna LTE-Advanced systems. However, when developing to massive MIMO with 128 or more base station antennas, this problem can no longer be ignored, as pilot overhead becomes extremely severe, causing substantial energy and spectrum waste.

Based on the above issues, we adopt the non-orthogonal pilot design scheme from reference [23], which is based on CS theory. Unlike traditional orthogonal pilot schemes, it allows pilots on different antennas to completely occupy the same subcarriers. By leveraging the naturally inherent sparsity of massive MIMO, pilot overhead for channel estimation can be substantially reduced.

[Figure 4: see original paper] illustrates the orthogonal and non-orthogonal pilot design schemes.

### 3.2 Theoretical Derivation of Non-Orthogonal Pilot Design

In CS theory, according to reference [23], the design of the sensing matrix   in equation (10) is crucial for efficiently and reliably compressing high-dimensional sparse signals **H**. In massive MIMO channel estimation,   is determined solely by pilot allocation scheme $\mathcal{P}$ and pilot sequence $\{c_m\}_{m=1}^{M}$. Therefore, designing   can be transformed into designing $\mathcal{P}$ and $\{c_m\}_{m=1}^{M}$. CS theory indicates that if   has low mutual coherence between columns, it is very helpful for reliable sparse signal recovery. This inspires the design approach for $\mathcal{P}$ and $\{c_m\}_{m=1}^{M}$.

First, from the perspective of pilot sequence $\{c_m\}_{m=1}^{M}$ design, the goal is to minimize mutual coherence between any two columns in  . This mutual coherence is inherently determined by:

$$\mu(\ _{m_1},\ _{m_2}) = \frac{|\ ^{H}_{m_1}\ _{m_2}|}{\|\ _{m_1}\|_2 \|\ _{m_2}\|_2}$$

where $\ _m$ represents the m-th column of  . To achieve smaller $\mu(\ _{m_1},\ _{m_2})$, we assume $\{c_m\}_{m=1}^{M}$ follows an independent and identically distributed (i.i.d.) uniform distribution $\mathcal{U}[0, 2\pi)$. Each column of   has constant norm, i.e., $\|\ _m\|_2^2 = P$. At this point:

$$\mu(\ _{m_1},\ _{m_2}) = \frac{1}{P}\left|\sum_{k=1}^{P} e^{j(\theta_{k,m_1} - \theta_{k,m_2})}\right|$$

According to random matrix theory (RMT), and considering that $P$ is finite in practical situations, equation (12) shows that non-orthogonal pilot allocation scheme $\mathcal{P}$ and pilot sequence $\{c_m\}_{m=1}^{M}$ can achieve good mutual orthogonality between any two columns in  .

Second, from the perspective of pilot allocation scheme $\mathcal{P}$ design, we further investigate the mutual correlation of  . Under the condition $P \gg L$, the design of $\mathcal{P}$ can also achieve smaller $\mu(\ _{m_1},\ _{m_2})$.

In typical massive MIMO systems, the characteristic $P \gg L$ exists. For example, in a typical massive MIMO system with 128 base station antennas, each antenna must have at least one pilot to ensure channel estimation, so the pilot number must be at least 128. Additionally, the maximum channel delay spread is $L \leq 35\mu s$ [24], and typical LTE-Advanced system bandwidth is 10MHz, therefore $L \leq 128$. In summary, the condition $P \gg L$ holds. If uniformly spaced pilot allocation is used, not only is the application scope broader, but it also makes the inner product expression of $\mu(\ _{m_1},\ _{m_2})$ more tractable.

Let the uniform pilot interval be $I = \lfloor N/P \rfloor$. Then:

$$\mu(\ _{m_1},\ _{m_2}) = \frac{1}{P}\left|\sum_{k=1}^{P} e^{j(\theta_{k,m_1}-\theta_{k,m_2})} e^{j2\pi I(k-1)\Delta\ell/N}\right|$$

where $\Delta\ell = \ell_2 - \ell_1$, and $1 \leq \ell_1, \ell_2 \leq L$, $\ell_1 \neq \ell_2$.

Let $\eta = P/N$ represent the pilot ratio. When $P \gg L$, we can obtain:

$$\lim_{P,N\to\infty,P/N=\eta} \mu(\ _{m_1},\ _{m_2}) = \left|\frac{1-e^{j2\pi\eta\Delta\ell}}{2\pi\eta\Delta\ell}\right|$$

Since $0 < \eta < 1$ and $1 \leq |\Delta\ell| \leq L-1$, we have:

$$\lim_{P,N\to\infty,P/N=\eta} \mu(\ _{m_1},\ _{m_2}) \approx 0$$

This demonstrates the rationality and effectiveness of equation (17).

In summary, the dynamic sparsity adaptation scheme has the following characteristics:
a) Sparsity adaptation: It can control iteration times through equation (20) and obtain sparsity when the sparsity level is unknown, thereby improving practical engineering applicability;
b) Dynamic setting of stopping iteration parameter $\beta$: Under different channel conditions, noise affects observations differently, so $\beta$ cannot be a fixed value but should vary with channel conditions. We use SNR to characterize channel states, meaning $\beta$ differs under different SNR conditions.

Reference [26] also mentions using threshold methods to enable algorithms to adaptively obtain sparsity, but the stopping iteration parameter is set as a fixed value that cannot change according to channel conditions. In contrast, the algorithm proposed in this paper can dynamically obtain the stopping iteration parameter.

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# 4 Sparsity-Adaptive Channel Estimation for Massive MIMO Using Compressive Sensing

## 4.1 Principle of Sparsity Adaptation

In practical communication environments, channel sparsity is unknown and varies with time or space. Therefore, to better enable engineering applications, we propose a dynamic sparsity adaptation improvement scheme based on threshold thinking. Unlike traditional reconstruction algorithms that determine iteration times based on sparsity, this scheme determines iteration times by setting a threshold—when the ratio between residual and observation values meets the requirement specified by the stopping iteration parameter, the algorithm stops iterating. Moreover, the stopping iteration parameter is not fixed but varies under different channel states, which we characterize using SNR. This can be expressed as:

$$\|\mathbf{V}_k\|_2^2 \leq \beta\|\mathbf{Y}\|_2^2$$

where $\mathbf{V}_k$ represents the residual, $\mathbf{Y}$ represents the observation value, and $\beta$ represents the stopping iteration parameter, which is not fixed but differs under different SNR conditions.

From the improved SSA-CoSaMP algorithm flow, we can see it consists of two main parts: The first part determines sparsity $S$. The algorithm initializes sparsity $S = 1$ and uses iterative cycling to finally obtain sparsity satisfying the stopping condition (see steps a) and h) in the algorithm). The second part utilizes the spatio-temporal common sparsity characteristics of wireless massive MIMO channels. During the reconstruction process with preset sparsity $S$, multiple sparse vectors can be updated simultaneously in each iteration, corresponding to steps b)~g) in the SSA-CoSaMP algorithm, ultimately obtaining accurate sparsity and channel CIR.

If we apply only the spatio-temporal common sparsity to CoSaMP without considering sparsity adaptation, we call it Structured CoSaMP (S-CoSaMP). The S-CoSaMP algorithm can only perform loop iterations based on given sparsity rather than judging whether to end the algorithm based on actual channel states. This leads to two consequences: a) The algorithm has already reconstructed the result but continues iterating to satisfy the given sparsity, causing waste of time and energy; b) The reconstructed result is not accurate enough, but the given sparsity has met the loop iteration count, causing premature termination and insufficient estimation accuracy. Section 6 provides performance comparisons between S-CoSaMP and SSA-CoSaMP algorithms.

In the SSA-CoSaMP algorithm, $\beta$ differs under different SNR conditions. If $\beta$ is fixed rather than dynamically changing according to channel states, it will severely impact reconstruction results. If $\beta$ is set too small, the algorithm' s iteration count increases, leading to excessive computation time that is unfavorable for engineering applications. Conversely, if $\beta$ is set too large, the algorithm terminates prematurely, resulting in excessive reconstruction error and reduced accuracy. Therefore, $\beta$ setting critically impacts both reconstruction accuracy and iteration time. In Section 6, we determine parameter $\beta$ through simulation experiments to minimize computation time while satisfying reconstruction accuracy.

## 5 Simulation Results and Analysis

Massive MIMO wireless channel estimation technology is primarily evaluated using mean square error (MSE). Experiments can demonstrate performance from three aspects: a) Estimation accuracy comparison experiments, where estimated multipath components are compared with actual modeling to characterize estimation performance intuitively; b) Performance simulation experiments varying with pilot numbers, where reduced pilot numbers inevitably affect estimation performance, and using pilot number variation better reflects whether estimation algorithms can reduce pilot overhead without significantly affecting performance; c) Performance simulation experiments varying with SNR, where SNR well reflects channel conditions, and using SNR variation effectively demonstrates algorithm performance under different channel states. This scheme primarily uses these three experimental aspects to illustrate its superiority.

This section uses MATLAB simulation software to verify the performance of the proposed SSA-CoSaMP algorithm in massive MIMO-OFDM wireless communication systems. System parameters are set as: 128 transmit antennas at the base station, 1024 system subcarriers, 256 channel multipath components, R=5 consecutive OFDM symbols, each channel being i.i.d. Rayleigh fading, non-orthogonal pilot allocation scheme, and noise composed of zero-mean unit-variance complex Gaussian random variables. The system model follows the International Telecommunication Union Vehicular B (ITU-B) channel model. The proposed SSA-CoSaMP algorithm is compared with S-CoSaMP and CoSaMP algorithms. Performance is measured using normalized mean square error (NMSE), where smaller NMSE indicates smaller estimation error and better performance.

In this chapter, NMSE is defined as:

$$\text{NMSE} = \frac{\mathbb{E}\{\|\hat{\mathbf{h}} - \mathbf{h}\|_F^2\}}{\mathbb{E}\{\|\mathbf{h}\|_F^2\}}$$

For comparison algorithms, CoSaMP refers to reference [27], and S-CoSaMP refers to reference [28].

### 5.1 Determination of Stopping Iteration Parameter $\beta$

As SNR decreases, noise impact on signal observation $\mathbf{Y}$ increases, so $\beta$ changes accordingly under different SNR conditions. This section uses Exact LS algorithm to obtain sparsity under different SNR values for $\beta$ determination.

Channel estimation algorithms generally have two phases: first, estimating the positions of taps; second, estimating tap values at those positions. Exact LS algorithm directly provides accurate tap positions, only requiring estimation of tap values. Therefore, Exact LS represents the performance benchmark for CS-based estimation algorithms. In this experiment, we compare the NMSE of

SSA-CoSaMP algorithm with gradually changing $\beta$ against Exact LS algorithm. The $\beta$ value that makes their NMSE equal is the appropriate value for that SNR.

[Figure 5: see original paper] shows the stopping iteration parameter under different SNR conditions. In [FIGURE:5(a)], when $\beta = 0.058$, the NMSE values are exactly equal. When greater than this value, the NMSE values are equal but not at the critical point.

Similarly, based on simulation results in [FIGURE:5(b)] and [FIGURE:5(c)], we can summarize the $\beta$ value ranges, as shown in .

**TABLE:2** Corresponding algorithm stopping parameters for different SNR ranges

| SNR Range | $\beta$ Value |
|---|---|
| $<$ 10 dB | 0.058 (Fig. 5(a)) |
| 10 dB–25 dB | 0.054 (Fig. 5(b)) |
| $>$ 25 dB | 0.052 (Fig. 5(c)) |

### 5.2 Channel Estimation Algorithm Accuracy Comparison

Algorithm performance can be evaluated from two aspects: estimated tap positions and amplitudes. This section compares algorithm estimation results with the constructed channel model to verify performance.

[FIGURE:6(a)] shows simulation results at SNR = 20 dB with 700 pilots. The results indicate that CoSaMP estimates neither tap positions nor amplitudes accurately; S-CoSaMP only accurately estimates some tap positions, with other tap positions and amplitudes being inaccurate. In contrast, SSA-CoSaMP is much more accurate, with correctly estimated tap positions and amplitudes.

When SNR = 20 dB and pilot number = 900, [FIGURE:6(b)] shows the comparison. CoSaMP still cannot estimate accurately, while SSA-CoSaMP and S-CoSaMP perform consistently well and very accurately.

### 5.3 Performance Simulation with Varying Pilot Numbers

Pilots are special data arranged on specific subcarriers of OFDM symbols at the base station, which the receiver uses for channel estimation. Pilot data occupies transmission resources. To improve spectral efficiency, the proportion of pilot data in each OFDM symbol frame must be reduced, but reducing pilot numbers inevitably affects estimation performance. Therefore, simulation experiments on pilot number variation are essential.

[Figure 7: see original paper] shows NMSE performance versus pilot numbers for SSA-CoSaMP, S-CoSaMP, and CoSaMP algorithms at SNR = 10 dB and 20 dB. The results demonstrate that as pilot numbers increase, all three algorithms' performance improves. When pilot numbers are below 750, SSA-CoSaMP performs best, followed by S-CoSaMP, with CoSaMP performing worst. When pilot numbers exceed 750, SSA-CoSaMP and S-CoSaMP perform similarly.

### 5.4 Performance Simulation with Varying SNR

Besides pilot numbers, SNR also significantly impacts algorithm performance. To further verify the relationship between algorithm performance and SNR variation, this section conducts performance simulation experiments. [Figure 8: see original paper] shows NMSE versus SNR for channel estimation algorithms, with pilot numbers of 650, 750, and 850 selected for clearer results.

From [FIGURE:8(a)], when pilot number = 650, SSA-CoSaMP significantly outperforms S-CoSaMP. CoSaMP shows no obvious improvement with increasing SNR, remaining ineffective. This demonstrates that the improved algorithm can still estimate channel states well under low pilot overhead conditions—only SSA-CoSaMP can effectively estimate channel states when low pilot overhead is required.

[FIGURE:8(b)] shows that when pilot number increases to 750, SSA-CoSaMP slightly outperforms S-CoSaMP, while CoSaMP remains ineffective even at 750 pilots.

[FIGURE:8(c)] shows results with pilot number = 850. When SNR $<$ 15 dB, SSA-CoSaMP still outperforms S-CoSaMP; when SNR $>$ 15 dB, SSA-CoSaMP and S-CoSaMP perform similarly.

Comprehensive simulation data shows that CoSaMP performance is far inferior to S-CoSaMP and SSA-CoSaMP in all cases. When pilot numbers are below 750, SSA-CoSaMP outperforms S-CoSaMP, and SSA-CoSaMP has sparsity adaptation capability, making it more suitable for practical environments with unknown sparsity. The results demonstrate that SSA-CoSaMP enhances sparsity, reduces pilot overhead while maintaining equivalent estimation performance, saves spectrum resources, and offers advantages particularly under low pilot overhead conditions.

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## 6 Conclusion

This chapter proposes the SSA-CoSaMP algorithm based on the important characteristic of spatio-temporal common sparsity inherent in massive MIMO channels, improving the CoSaMP algorithm from both dynamic sparsity adaptation and structural perspectives. The algorithm not only optimizes estimation performance but also reduces pilot overhead, saving energy consumption and spectrum resources, aligning with China' s green communication development trend. Simulation results show that the proposed method achieves significant performance gains over traditional pilot-based channel estimation methods under both low pilot and low SNR conditions.

In wireless communication environments, structural characteristics exist not only in the actual delay multipath domain but also in the virtual angular-delay domain. Therefore, future research will focus on the structured sparsity problem in the virtual angular domain generated by massive MIMO antenna arrays, enabling structured improvement schemes to be applied in the virtual angular domain, deeply exploring the application scope of structured approaches to enhance the scheme' s applicability.

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*Note: Figure translations are in progress. See original paper for figures.*