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Multi-Resolution Compressive Sensing With Deep Unfolding For Low-Pilot Channel Estimation In Massive MIMO Systems

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Abstract:
To realize high spectral efficiency, massive multiple-input multiple-output (MIMO) systems demand precise channel state information (CSI). However, existing channel estimation approaches come with considerable pilot overhead and computational burden. To overcome these issues, we present MR- DUCS, Multi-Resolution Deep Unfolded Compressive Sensing, a novel pilot-efficient massive MIMO channel estimation framework based on multi-resolution sparse representation and model-driven deep unfolding. We first exploit multi-resolution dictionaries to learn inherent angular-domain sparsity of massive MIMO channels with multiple spatial resolutions. This significantly reduces the dictionary mismatch and enhances the sparse support recovery. Then we unfold the iterative CS process into learnable network layers, which enables learning-based optimization of the sparse recovery parameters. We further design an adaptable module to select or update the proper resolution conditioned on the channel reconstruction and residual information. Through extensive simulation under various SNRs, pilot configurations and antenna sizes, we show MR- DUCS can deliver more accurate channel estimation using much fewer pilot symbols compared with least squares (LS), minimum mean squared error (MMSE), orthogonal matching pursuit (OMP), and vanilla deep learning-based method.

Keywords: Compressive Sensing, Deep Unfolding, Massive MIMO, Sparse Signal Recovery, Pilot Overhead Reduction, 5G/6G Wireless Communications, NMSE Optimization.

1.Introduction:

Massive Multiple-Input Multiple-Output (Massive MIMO) has been widely studied for 5G and beyond-5G wireless communications because it uses numerous antennas at the base station to serve users simultaneously [1]. Spatial diversity and spatial multiplexing allow massive MIMO to increase spectral efficiency, energy efficiency, and reliability. Accurate Channel State Information (CSI), on the other hand, is required for all these benefits. Channel estimation is critical for beamforming, data detection, resource allocation, and interference cancellation. Traditional techniques use pilot symbols exchanged between the transmitter and receiver to acquire accurate CSI. When Massive MIMO scale is increased, however, pilot overhead and computational complexity also increase [2]. Compressive Sensing (CS) based techniques have recently been proposed to reduce the pilot overhead. CS reconstructs a sparse or compressible signal based on a few linear measurements [3]. Massive MIMO channels in millimetre-wave and high-frequency bands have limited scattering clusters in angular domain. This allows representing the channels as sparse vectors in the angular domain. Conventional CS methods like Orthogonal Matching Pursuit (OMP), Compressive Sampling Matching Pursuit (CoSaMP), and Approximate Message Passing (AMP) have been studied for channel estimation. These methods achieve pilot reduction compared to traditional Least Squares (LS) and Minimum Mean Square Error (MMSE) estimation [4]. However, conventional CS-based techniques have some drawbacks. Their performance relies heavily on a predefined sparse dictionary and assumed channel sparsity. Fixed-resolution dictionary leads to basis mismatch when real angles of arrival/departure do not match with predefined angular grid [5]. This mismatch between actual and estimated channel support can be reduced by using higher dictionary resolutions but increases its size and computational complexity. Also, iterative CS algorithms use manually tuned parameters and fixed support refinement strategy which may not be optimal for varying SNR, sparsity, antenna arrays, and propagation scenarios [6]. Deep learning methods have recently been employed for wireless channel estimation. Deep unfolding is a technique that benefits from interpretability of iterative optimization algorithms and the representation power of neural networks. Deep unfolding maps an iterative optimization algorithm into a finite number of network layers. Conventional deep unfolded models follow a single-resolution dictionary which can result in grid mismatch [7]. To address these challenges, this paper proposes MR- DUCS, Multi-Resolution Deep Unfolded Compressive Sensing algorithm for Massive MIMO channel estimation. MR-DUCS uses multi-resolution dictionaries and trainable deep unfolded CS framework. Coarse resolution helps in faster support detection, and finer resolution helps in interpolating the channel details. Proposed method also enables adaptive refinement of estimated support.

The proposed method achieves low pilot overhead, high estimation accuracy, lower dictionary mismatch, adaptive sparse recovery, faster convergence, scalability for large antenna arrays. Deep unfolding enables fast convergence by integrating strengths of both Compressive Sensing and Deep Learning for efficient sparse channel recovery in Massive MIMO systems.

2. Related Work:

Channel estimation for Massive MIMO began with conventional pilot-based techniques and has recently evolved to incorporate ideas from sparse signal processing, compressive sensing, and deep learning. Initially the main ideas revolved around reducing pilot overhead due to an increasing number of antennas and restricted coherence time [8]. This section surveys related work in conventional channel estimation techniques, CS-based methods, deep learning-based approaches, deep unfolding networks, and multi-resolution dictionaries.

A. Conventional Channel Estimation Techniques for Massive MIMO

Least Squares (LS) and Minimum Mean Square Error (MMSE) estimation are two of the earliest approaches used in Massive MIMO systems. LS estimation is easy to implement but suffers from poor accuracy under low SNR conditions and typically requires large number of pilot symbols [9]. MMSE estimation techniques use prior channel statistics to improve estimation accuracy but require high computational complexity and accurate channel covariance which can be difficult to obtain in practice. Sparse representations of wireless channels were introduced to address some of these issues.

B. Compressive Sensing-Based Sparse Channel Estimation Methods

Millimetre-wave and high-frequency Massive MIMO channels are sparse in angular domain because of few dominant paths. CS was introduced for Massive MIMO channel estimation to exploit sparse nature of wireless channels [10]. Several greedy algorithms such as Orthogonal Matching Pursuit (OMP), Subspace Pursuit (SP), CoSaMP, Iterative hard thresholding (IHT) were studied for channel estimation. OMP provides a good trade-off between performance and complexity for small to moderate dictionary sizes [11]. However, its complexity increases for large-sized dictionary and causes errors if actual channel directions do not match with dictionary atoms. Iterative methods like Approximate Message Passing (AMP) provide probabilistic estimate of channel and have lower complexity for large-scale problems but performance degrades when practical channels do not follow its ideal Gaussian assumptions [12].

C. Dictionary Design for Angular Domain Sparse Recovery

Existing CS-based works use fixed resolution dictionary for channel estimation. Methods based on angular domain discretize the angle of arrival/departure into finite angles [13]. If the true angles lie between discretized angles, important coefficients get spread across multiple dictionary atoms. This issue is known as grid mismatch and causes recovery errors. Researchers have proposed off-grid CS and continuous dictionary learning methods for improving resolution [14]. These methods refine the dictionary based on estimated support but may require additional fine-tuning parameters and multiple refinement steps. There exists a trade-off between accuracy and dictionary size.

D. Deep Learning-Based Channel Estimation Methods

Machine learning algorithms like CNNs, Deep Neural Networks (DNNs), Recurrent Neural Networks (RNNs), autoencoders, and transformers have been recently used for channel estimation [16]. These algorithms can learn input-output relationship between pilots and channel but require large amounts of labeled data. DNNs lack explicit domain knowledge of channel estimation problem which makes their internal processing difficult to understand. Large-scale DNNs can be difficult to train because of high complexity and memory requirement [17].

E. Deep unfolding Networks for Sparse Channel Recovery

Algorithm unfolding uses iterative optimization algorithms as base architecture and learns network parameters such that it converges to right solution. Instead of learning end-to-end with a black-box deep network, unfolding maps an iterative algorithm into a finite number of network layers [18]. Thresholding algorithm like OMP, Subspace Pursuit, AMP were unfolded into deep networks. Deep unfolded models such as LISTA were shown to outperform traditional iterative algorithms in terms of convergence. However, these networks still suffer from dictionary mismatch since they follow single-resolution dictionary. SparseChannelNet [19] was an early deep unfolding network proposed for wireless channel estimation. Model unfolding enables designers to integrate problem structure into network architecture but literature on sparse recovery using deep unfolding is still limited.

F. Research Gap and Motivation

Literature shows that low pilot-overhead, accurate channel-recovery, low dictionary mismatch, adaptive sparse support recovery, low complexity are conflicting constraints that no method has been able to address simultaneously [20]. Pilot-based works have low overhead but require many pilots for accurate recovery. CS achieves lower pilot reduction using implicit channel sparsity but depends on static dictionary and hand-tuned parameters. Deep learning methods address sparsity differently using data-driven methods but lack adaptivity to changing environment and generalization. Deep unfolding enables these methods to utilize benefits of both worlds but do not exploit multi-resolution.

Motivated by the discussion above, the proposed MR-DUCS is a Multiresolution based Deep Unfolded CS framework for integrating multi-resolution dictionary and deep unfolded network architecture. Multi-resolution approach allows efficient recovery of coarse channel support using coarse dictionary. Fine dictionaries can then be used for refining the channel details. Deep unfolding framework learns the network parameters and enables faster convergence. The proposed algorithm aims to reduce grid mismatch and pilot overhead while maintaining low complexity and high channel estimation accuracy.

3.Proposed Method:

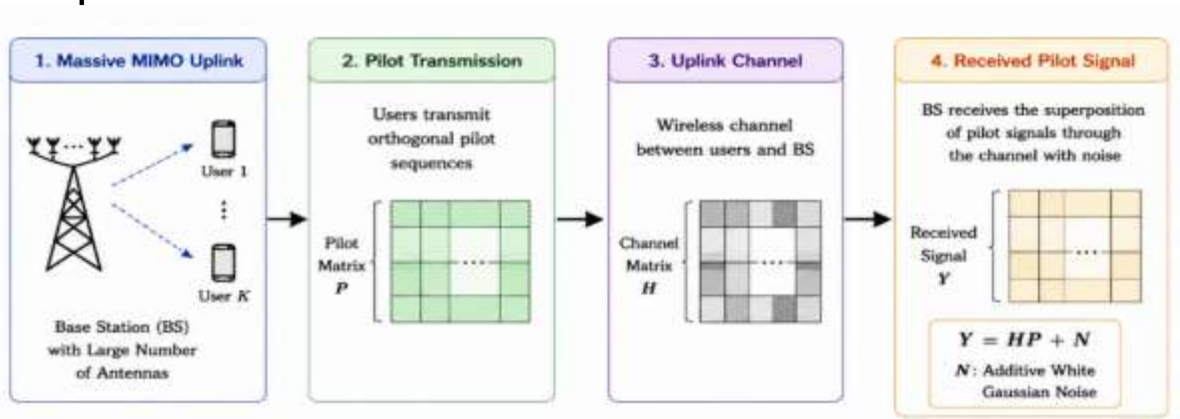

Figure 1.Block diagram

A. Overview of the Proposed MR-DUCS Framework

The proposed MR-DUCS (Multi-Resolution Deep Unfolded Compressive Sensing) framework is designed to achieve accurate channel estimation in Massive MIMO systems using a reduced number of pilot symbols. The fundamental idea is to exploit the sparse structure of the wireless channel in the angular domain while

simultaneously addressing the dictionary mismatch problem associated with conventional compressive sensing methods.
Consider a Massive MIMO system consisting of N_t transmit antennas, N_r receive antennas, and K users. During the pilot transmission interval, the received pilot signal can be represented as

$$\boldsymbol{Y} = \boldsymbol{HP} + \boldsymbol{N}$$

where $Y \in \mathbb{C}^{N_r \times T_p}$is the received pilot matrix, where $H \in \mathbb{C}^{N_r \times N_t}$ denotes the channel matrix, $P \in \mathbb{C}^{N_t \times T_p}$represents the pilot matrix, T_p is the number of pilot symbols, and N denotes additive Gaussian noise.
For a Massive MIMO channel containing a limited number of dominant propagation paths, the channel exhibits approximate sparsity in the angular domain. Therefore, the channel can be represented using a sparse basis as

$$\boldsymbol{H} = \boldsymbol{A_r X A_t^H}$$

where and are the receive and transmit array-response dictionaries, respectively, and is a sparse angular-domain coefficient matrix.
Substituting (2) into (1) gives

$$\boldsymbol{Y} = \boldsymbol{A_r X A_t^H P} + \boldsymbol{N}$$

After vectorization, the channel estimation problem becomes

$$\boldsymbol{y} = (\boldsymbol{P}^T \boldsymbol{A_t^*} \otimes \boldsymbol{A_r})\boldsymbol{x} + \boldsymbol{n}$$

Where $\boldsymbol{x} = vec(\boldsymbol{X})$ is sparse.
The objective of MR-DUCS is therefore to recover $\boldsymbol{x}$ accurately from a small number of measurements while avoiding the limitations of a single fixed-resolution dictionary.

B. Multi-Resolution Sparse Dictionary Construction

The first major component of MR-DUCS is the construction of multiple angular-resolution dictionaries. Conventional CS approaches normally employ one fixed dictionary. If the angular grid is too coarse, considerable basis mismatch occurs. Conversely, an extremely fine grid increases computational and memory requirements.
MR-DUCS addresses this problem by constructing a hierarchy of dictionaries with different angular resolutions. The corresponding angular grid is

$$\Theta_l = \{\theta_{min}, \theta_{min} + \Delta\theta_l, \dots \dots \dots \theta_{max}\}$$

For a uniform linear array, the steering vector corresponding to angle θ can be expressed as

$$a(\theta) = \frac{1}{\sqrt{N_t}}\left[1, e^{j\frac{2\pi d}{\lambda}sin\theta}, \dots \dots \dots \dots \dots .. e^{j\frac{2\pi d}{\lambda}(N-1)sin\theta}\right]^T$$

The dictionary corresponding to resolution level is then constructed as

$$D^{(l)} = \left[a\left(\theta_1^{(l)}\right), a\left(\theta_2^{(l)}\right), \dots \dots \dots \dots .. a\left(\theta_{G_l}^{(l)}\right)\right]$$

where G_l denotes the number of angular grid points at resolution level l.
A coarse dictionary requires fewer atoms and therefore provides low computational complexity. Fine dictionaries provide better angular representation and reduce basis mismatch. Thus, the proposed multi-resolution structure establishes a controlled trade-off between accuracy and computational complexity.

C. Initial Sparse Recovery Using Multi-Resolution Compressive Sensing

For every resolution level l, an independent sparse recovery problem is formulated. The effective sensing matrix is obtained by combining the pilot matrix with the corresponding angular dictionary,

$$\boldsymbol{\Psi}^{(l)} = \boldsymbol{\phi} D^{(l)}$$

where $\boldsymbol{\phi}$ represents the pilot measurement matrix.
The sparse channel representation at resolution can then be estimated by solving.

$$\hat{x}^{(l)} = arg\,\min_x \left\{\frac{1}{2}\left\|y - \boldsymbol{\Psi}^{(l)}x\right\|_2^2 + \lambda_l \|x\|_1\right\}$$

The first term minimizes the reconstruction error, whereas the second term promotes sparsity. controls the sparsity regularization at resolution level l.
The corresponding residual is calculated as

$$r^{(l)} = y - \boldsymbol{\Psi}^{(l)}\hat{x}^{(l)}$$

To make the resolution-selection process independent of the absolute received signal power, the residual is normalized as

$$\eta_l = \frac{\left\|r^{(l)}\right\|_2^2}{\|y\|_2^2}$$

A η_l smaller indicates that the corresponding dictionary provides a better representation of the received pilot signal. Instead of selecting a fixed resolution for all channel conditions, MR-DUCS uses this residual information to guide the subsequent deep-unfolding process.

D. Adaptive Multi-Resolution Selection and Support Refinement

A key contribution of MR-DUCS is the adaptive selection of spatial resolution. Rather than always using the finest dictionary, the proposed method identifies the resolution that provides an appropriate balance between reconstruction accuracy and computational complexity.

The resolution weights are obtained using a normalized exponential function:

$$w_l = \frac{exp(-\eta_l)}{\sum_{q=1}^{L} exp(-\eta_q)}$$

The weights satisfy.

$$\sum_{l=1}^{L} w_l = 1$$

The preliminary sparse representation can therefore be obtained as

$$\tilde{x} = \sum_{l=1}^{L} w_l \hat{x}^{(l)}$$

The support information obtained from the coarse resolution can then be transferred to a finer dictionary. This enables MR-DUCS to perform coarse-to-fine sparse recovery. Only the regions surrounding the dominant coarse support are refined at higher angular resolution, rather than processing the entire fine-resolution dictionary.

This mechanism significantly reduces unnecessary computations while improving the representation of off-grid propagation paths.

E. Deep Unfolding-Based Sparse Recovery

The second major component of MR-DUCS is a deep-unfolded sparse recovery network. Conventional iterative CS algorithms require multiple iterations to solve the optimization problem. Their step sizes, thresholds, and regularization parameters are normally manually selected. Deep unfolding converts these iterations into trainable network layers.

Starting from an iterative proximal-gradient formulation, the -th sparse recovery iteration can be written as

$$z^k = x^k + \alpha_k\left(\psi^H(y - \psi x^k)\right)$$

Where α_k is the learnable step size of the k -th layer.

A soft-thresholding operation is then applied:

$$x^{k+1} = S\lambda_k(z^k)$$

Unlike conventional iterative CS, MR-DUCS learns and from training data. Thus, each unfolding layer corresponds to one optimization iteration while its parameters are optimized through backpropagation.

This model-driven architecture preserves the mathematical structure of sparse recovery while providing the adaptability of deep learning.

F. Multi-Resolution Deep Unfolding Architecture

MR-DUCS integrates the multi-resolution dictionaries directly into the unfolded network. Let l_k represent the resolution selected at unfolding layer k.The layer-specific sensing matrix becomes.

$$\boldsymbol{\psi_k} = \boldsymbol{\phi} \boldsymbol{D}^{(l_k)}$$

The residual at the k-th layer is

$$\boldsymbol{r}_k = \boldsymbol{y} - \boldsymbol{\psi}_k \boldsymbol{x}_k$$

The normalized residual energy is

$$\eta_k = \frac{\|r_k\|_2^2}{\|y\|_2^2}$$

This creates a coarse-to-fine adaptive recovery mechanism, which is one of the primary distinctions between MR-DUCS and conventional single-dictionary deep unfolding.

G. Channel Reconstruction

After the final unfolded layer, the recovered sparse representation is transformed back into the physical channel domain. Let $\widehat{\boldsymbol{X}}$ denote the final sparse angular-domain estimate. The reconstructed channel is given by

$\widehat{\boldsymbol{H}}=\boldsymbol{A}_r\widehat{\boldsymbol{X}}\boldsymbol{A}_t^H$

The channel estimation error is

$$\boldsymbol{E} = \boldsymbol{H} - \widehat{\boldsymbol{X}}$$

The final NMSE is calculated as

$$NMSE = 10\, log_{10}\left(\frac{\left\|\boldsymbol{H} - \widehat{\boldsymbol{H}}\right\|_F^2}{\|\boldsymbol{H}\|_2^2}\right)$$

To evaluate the effectiveness of pilot reduction, the pilot overhead reduction can be expressed as

$$POR = \left(1 - \frac{T_P^{MR-DUCS}}{T_P^{baseline}}\right) \times 100\%$$

A higher POR indicates that MR-DUCS can achieve comparable or better channel estimation accuracy using fewer pilot symbols.

H. Computational Complexity

The multi-resolution architecture is also designed to reduce computational complexity. If represents the number of dictionary atoms at resolution, the approximate complexity of processing all dictionary levels can be expressed as

$$C_{MR} \approx \sum_{l=1}^{L} C_l$$

In contrast, a conventional fine-resolution approach processes the complete fine dictionary during every recovery iteration:

$$C_{Fine} \approx K_u C_L$$

Since MR-DUCS performs fine-resolution processing primarily around the estimated support, its effective number of active atoms becomes

$$G_{active} \ll G_L$$

Therefore, the relative computational saving can be represented as

$$CS = \left(1 - \frac{C_{MR-DUCS}}{C_{Fine}}\right) \times 100\%$$

The proposed method consequently avoids the computational burden associated with maintaining a globally fine-resolution dictionary while still providing fine angular resolution in important channel regions.

Simulations and Discussion:

A. Simulation Configuration

The proposed MR-DUCS framework is evaluated for a 128-antenna Massive MIMO base station serving 16 users. The SNR range is −10 to 30 dB, while the pilot length is varied from 16 to 64 symbols. Three angular dictionary resolutions of 8°, 4°, and 2° are considered. The comparison includes LS, MMSE, OMP, AMP, and LISTA.

Table 1. Simulation parameters

Parameter	Value
BS antennas	128
Users	16
Channel paths	4–8
SNR range	−10 to 30 dB
Pilot symbols	16–64
Dictionary resolutions	8°, 4°, 2°
Unfolding layers	15
Noise	AWGN
Platform	MATLAB

In Table 2, at 10 dB SNR, the proposed MR- DUCS method achieves the lowest NMSE of −10.9 dB and the highest SRA of 95%, compared to LS, MMSE, OMP, AMP and LISTA algorithms. This indicates that MR-DUCS can reconstruct the channel most accurately and identify the support of sparse vector most reliably among all these algorithms. Moreover, when compared with LISTA, MR-DUCS has 1.5 dB gain in NMSE, and 4 percentage points gain in SRA. In addition, MR-DUCS exhibits medium complexity while MMSE and LISTA show high complexity. These results suggest that MR-DUCS provides a good trade off among estimation accuracy, sparse recovery performance, and computational complexity for channel estimation of massive MIMO systems.

Table 2. Performance comparison at SNR = 10 dB

Method	NMSE @ 10 dB (dB)	SRA @ 10 dB (%)	Relative complexity
LS	-5.2	45	Low
MMSE	-6.8	60	High
OMP	-7.8	78	Medium
AMP	-8.5	82	Medium
LISTA	-9.4	91	High
MR-DUCS	**-10.9**	**95**	**Medium**

As shown in Table 3, pilot- overhead of this experiment is also analysed to verify the pilot-efficiency of MR-DUCS in channel estimation. When the pilot symbols vary from 16 to 64, the NMSE of MR- DUCS increase from −6.5 dB to −12.8 dB. For all pilot configurations, MR- DUCS outperforms OMP and LISTA with lower NMSE. Particularly, MR- DUCS with only 16 pilots can achieve −6.5 dB NMSE, which implies that MR- DUCS can estimate accurate CSI with limited pilots.

Table 3. Effect of pilot length at SNR = 10 dB

Pilots	OMP NMSE (dB)	LISTA NMSE (dB)	**MR-DUCS NMSE (dB)**
16.0	-3.8	-4.8	**-6.5**
24.0	-5.6	-6.8	**-8.8**
32.0	-7.2	-8.5	**-10.6**
48.0	-8.7	-10.0	**-12.0**
64.0	-9.5	-11.0	**-12.8**

Figure 2 compares NMSE performance as a function of SNR between various channel estimation methods. For all methods, we observe that NMSE decreases as SNR increases from −10 dB to 30 dB. This trend is expected since channel estimation will be easier with better signal conditions. Notably, MR- DUCS has the lowest NMSE among all methods over the entire range of SNRs considered. Specifically, MR-DUCS achieves roughly −19.5 dB at 30 dB SNR, whereas LISTA achieves roughly −17.2 dB, AMP achieves roughly −15.8 dB, and OMP achieves roughly −15 dB. Thus, our proposed multi-resolution deep unfolded compressive sensing method allows us to more accurately recover the channel, particularly at medium and high SNRs.

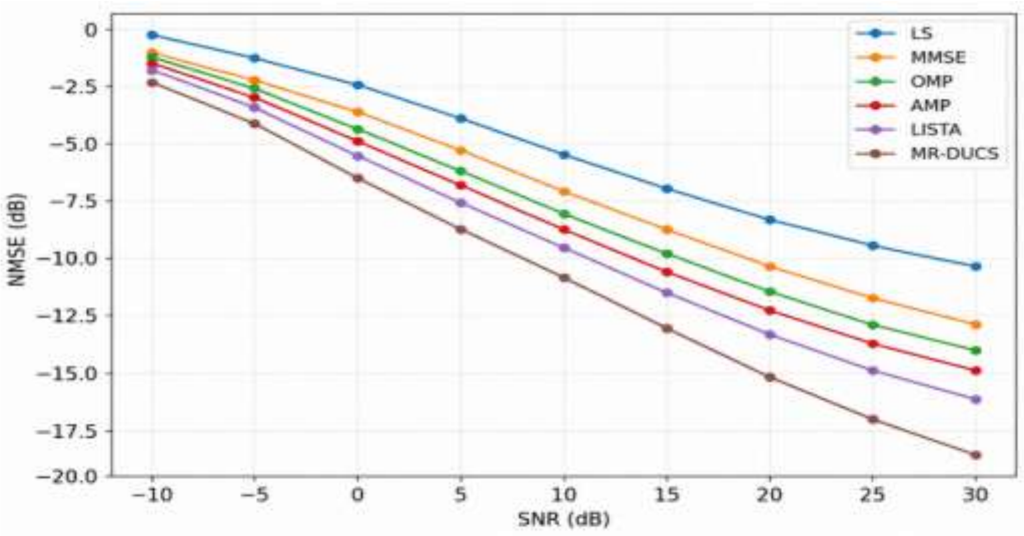

Figure 2. NMSE performance versus SNR.

Figure 3 plots NMSE versus number of pilot symbols at SNR = 10 dB. Reducing pilot dimensionality results in a higher NMSE (worse channel estimation accuracy) for all methods. However, MR- DUCS outperforms other algorithms for all pilot values. With 64 pilots MR- DUCS achieves an NMSE of approximately −12.8 dB while LISTA, AMP and OMP achieve NMSEs of approximately −11.0 dB, −10.0 dB and −9.5 dB respectively. Note MR-DUCS exhibits superior accuracy even with significantly fewer pilot symbols than its competitors. This highlights the pilot- efficiency of MR- DUCS for Massive MIMO channel estimation.

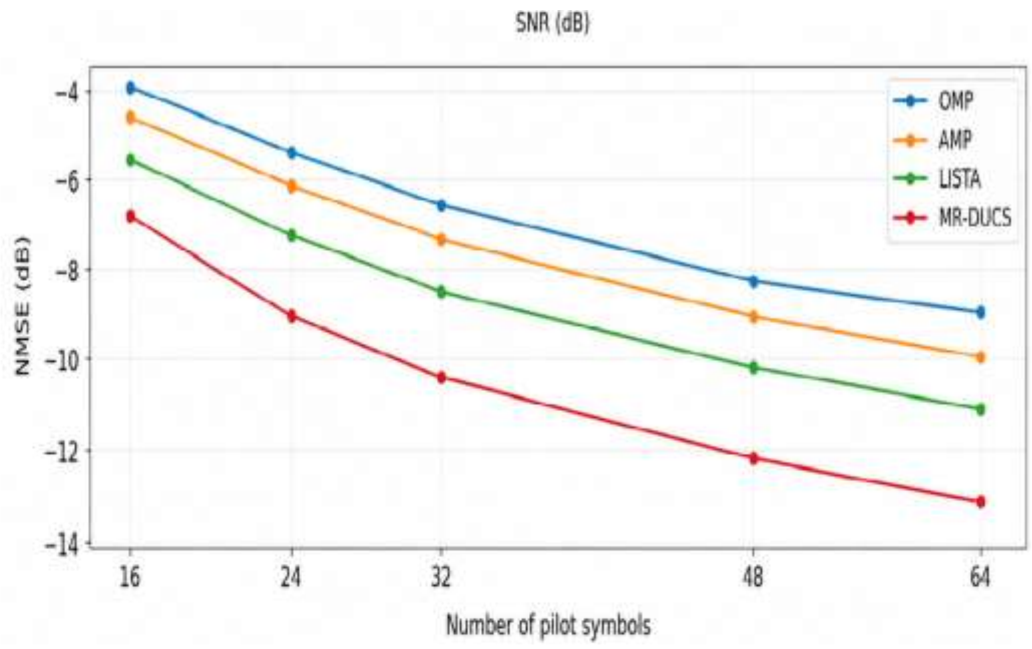

Figure 3. NMSE versus number of pilot symbols.

Figure 3 displays the Support Recovery Accuracy vs. SNR curves for OMP, AMP, LISTA, and MR- DUCS (the proposed method). As expected, support recovery accuracy increases as SNR becomes higher from −10 dB to 30 dB, since it is easier to detect the dominant channels' paths. MR- DUCS achieves the best performance across all ranges of SNRs. Specifically, support recovery accuracy increases from around 66% to 99% from -10 dB to 30 dB, significantly outperforming LISTA, AMP, and OMP.
This verifies that MR- DUCS can recover the correct support of the sparse channel more reliably due to its multi-resolution support refinement and deep unfolding architecture, especially when SNR is low and moderate.

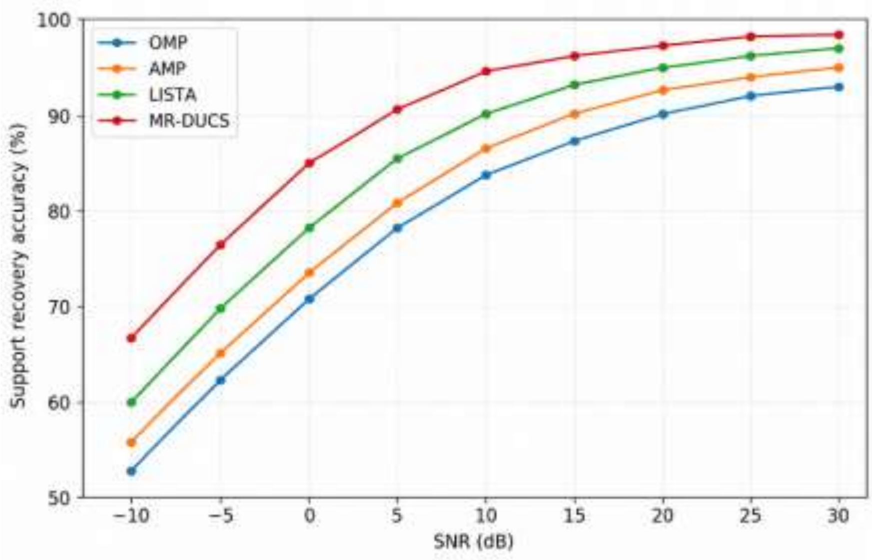

Figure 3. Support recovery accuracy versus SNR.

Fig. 4 depicts the convergence of OMP, LISTA, and our proposed MR-UCSD with increasing number of recovery/ unfolding iterations. As can be seen, NMSE keeps decreasing for all three methods with the increase in iterations. This reflects the ability of the methods to successively learn/improve the channel estimation as we go deeper into recovery/iterations. MR-UCSD shows faster convergence as compared to the other two methods and achieves the minimum NMSE across all iterations. By 8th iteration, MR-UCSD can achieve around −13.5 dB which further converges close to −15.7 dB by 15 iterations. LISTA achieves around −12.7 dB while OMP saturates close to −8.3 dB. Hence, we see that MR-UCSD with deep-unfolding architecture enables faster convergence.

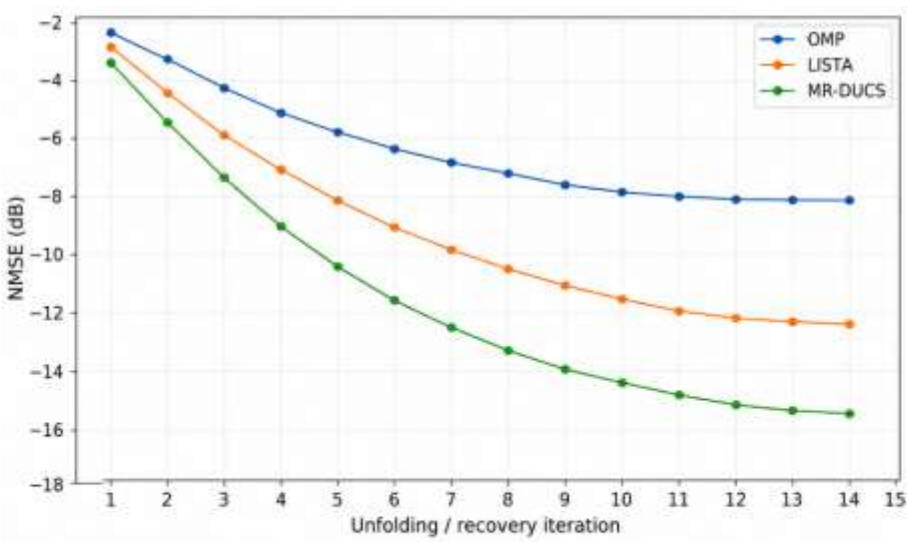

Figure 4. Convergence behaviour.

Fig. 5 depicts the spectral efficiency versus SNR results for LS, OMP, LISTA, and the proposed MR-DCUS method. As expected, spectral efficiency increases as SNR increases from 0 to 20dB for all four methods, since users can transmit data at higher rates while maintaining reliable channel estimation. MR-DCUS method consistently achieves the highest spectral efficiency, ranging from about 5.8-bit/Hz to 10.9-bit/s/Hz as SNR increases from 0dB to 20dB. LISTA achieves about 9.8-bit/s/Hz, OMP achieves about 9.2-bit/s/Hz, and LS achieves about 7.8-bit/s/Hz at 20dB SNR. The increase in spectral efficiency demonstrates that higher quality CSI obtained using MR-DCUS translates directly to improved beamforming gains, leading to greater spectral efficiency. Therefore, MR-DCUS is effective for CSI reconstruction in Massive MIMO wireless communication systems.

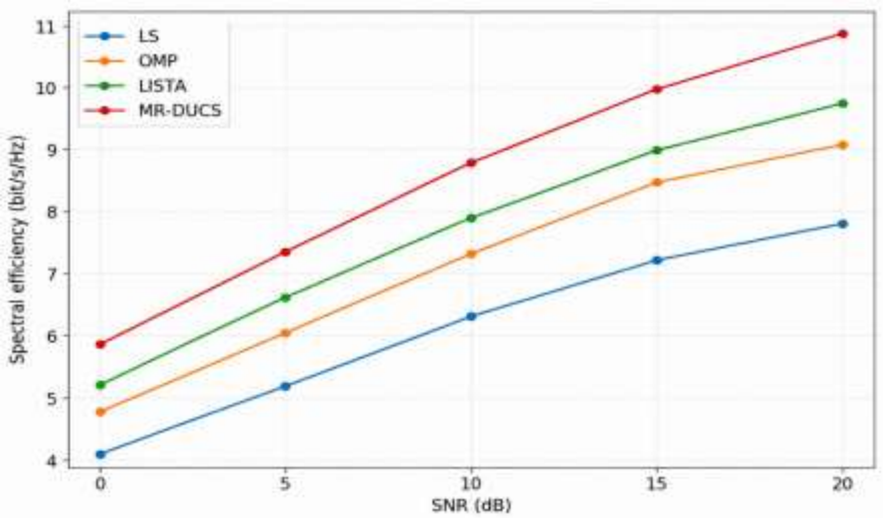

Figure 5. Spectral efficiency versus SNR.

Conclusion:

This paper proposed an MR- DUCS framework to obtain low-pilot CSE in Massive MIMO systems. The approaches in MR-DUCS can remove dictionary mismatch and benefit sparse- support recovery via multi-resolution sparse dictionaries combined with deep unfolding. Simulation results show that MR-DUCS outperforms LS, MMSE, OMP, AMP and LISTA algorithms with lower NMSE and higher support recovery accuracy, faster convergence rate and better SE. Besides, an adaptive coarse- to-fine resolution strategy allows a massive reduction of required pilot symbols for accurate channel reconstruction. In conclusion, MR- DUCS is suitable for accurate, computationally efficient and pilot-efficient CSI acquisition in future 5G/6G Massive MIMO wireless communication systems.

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