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Enhanced Channel Estimation Performance-Based Intelligent Reflecting Surface Massive MIMO Systems

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ABSTRACT

Intelligent reflecting surfaces (IRS) are an innovative technique that dramatically increases system efficiency. The integration of massive multiple-input multiple-output (massive MIMO) and IRS has been considered the most efficient route to 6G networks. An important challenge in IRS-aided massive MIMO wireless systems is channel estimation. With a rise in the number of IRS-reflecting elements and IRS-assisted users, channel training overhead becomes too large, resulting in large transmission delays and poor data transfer rates. To overcome this problem, an enhanced compressive sensing (CS) method to determine reliable channel state information (CSI) in IRS-aided massive MIMO systems is proposed, which combines enhanced compressive sensing with a deep denoising convolution neural network (CsiNet-DeCNN). By using deep learning methods to denoise channel data, our proposed model is validated numerically, indicating that it is accurate with low NMSE. Further, the results indicate that CsiNet-DeCNN performs better than traditional CS methods in estimating channel parameters.

1. Introduction

Massive multiple-input multiple-output (massive MIMO) is emerging as an effective technique for coping with the exponential growth of mobile terminals and data traffic [1]. The advantages of massive MIMO systems include both reducing antenna transmission power and improving spectral efficiency [2]. Channel state information (CSI) is a vital component of massive MIMO systems in terms of allocating radio resources and controlling interference. Therefore, these advantages can be achieved through the utilization of CSI in base stations (BS) [3]. Due to the absence of mutuality of uplink and downlink channels in frequency division duplex (FDD) systems, obtaining CSI requires two phases, which are the estimation of the downlink channel and the feedback of the CSI on the uplink. User equipment (UE) receives a CSI pilot signal from the BS, which it uses to estimate the channel.

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The estimated CSI is then communicated through feedback links to the BS. Massive MIMO systems that have more antennas at the BS have higher CSI feedback overheads, which makes it more difficult to implement massive MIMO in FDD systems [4].

Researchers have investigated compressed sensing (CS) to estimate channels [5]. Spatial and temporally correlated CSI collected by CS reduces feedback overhead significantly while collecting CSI with sufficient accuracy [6]. The channel characteristics were estimated using a least absolute shrinkage and selection operator (LASSO) L1 solver introduced by Daubechies *et al.,* [7] and an approximate message-passing (AMP) algorithm introduced by Donoho *et al.,* [8]. Gamal *et al.,* [9] added the Adaptive Boosting (AdaBoost) algorithm to channel estimation techniques such as the Least Squares (LS) and was used to improve the bit error rate (BER) performance of various estimation techniques in a Rayleigh fading environment. The CSI model developed by Dong *et al.,* [10] combines deep learning (DL) techniques with massive MIMO using CS as a basis. To reduce CSI feedback and achieve high-accuracy recovery, Wen *et al.,* [11] introduced an auto-encoder channel state information network (CsiNet) arrangement with a few neural network (NN) layers in the FDD system. A channel estimation method was proposed by Helmy *et al.,* [12] based on DL that improves massive MIMO performance that utilized CsiNet combined with a gated recurrent unit.

Beyond fifth generation (B5G) and higher wireless networks, a recent innovation called intelligent reflecting surfaces (IRS) can boost massive MIMO system performance without raising hardware costs or energy usage. This technology can potentially revolutionize wireless communication systems design [13]. The IRS typically consists of a lot of passive elements that are energy-efficient, such as phase shifters, which can dynamically alter the incident signal's phase or amplitude without adding any additional hardware [14]. The IRS advantage has attracted researchers to develop applications for a wide range of communication scenarios, including coverage enhancements, data transmission rate optimizations, accurate channel estimation, and protected communication [15-18]. In IRS-aided massive MIMO systems, obtaining accurate CSI is crucial to achieving effective control over the radio frequency propagation environment [19].

Because there are several IRS reflecting elements and there aren't any signal processing capabilities there, it is, however, practically challenging to realize [20]. A cascaded channel is estimated for the user/IRS/BS channel as both channels are not individually available [21]. In this regard, cascaded channels pose two major challenges to channel parameter estimation: limited accuracy and significant training overhead. To improve channel estimation accuracy, CS and DL methodologies were proposed by Sur *et al.,* [22]. An IRS-aided wireless communication system with negligible training overhead and an IRS architecture was demonstrated by Teha *et al.,* [23]. Chen *et al.,* [24] proposed a compressive channel estimation technique for IRS-based millimeter wave (mm-wave) MIMO systems to reduce training overhead, with the IRS reflection matrix designed through CS and DL algorithms. A convolution neural network (CNN) based denoising module for the estimation of channels in IRS-multiuser communication systems (MUCs) to reduce noise in the channel data was introduced by Liu *et al.,* [25].

A Deep Learning technique is presented as a contribution to this paper to enhance the efficiency of IRS-aided massive MIMO systems by improving channel estimation accuracy. Based on the technique presented in the previous study by Wen *et al.,* [11], DL-based CSI feedback networks (CsiNet) are modified for FDD IRS-aided massive MIMO. The system's CSI accuracy is enhanced by reducing channel noise using a denoising CNN (DECNN) module. A comparison is made between the proposed model (CsiNet-DeCNN) and other similar models available in the literature. In the remainder of the paper, the following structure is used: - Sections 2 and 3 outline the system model and the proposed channel state information network-denoising convolution neural network (CsiNet-

DeCNN), respectively. Section 4. presents a numerical analysis, following that Section 5. Conclusions of the paper are provided.

2. The System Model

Consider an FDD IRS-aided massive MIMO system with the BS equipped with $\mathrm{N_t}$ transmit antennas that are arranged in a uniform linear array (ULA), One antenna is included with the UE. and $\mathrm{N_I}$ passive reflecting elements at the IRS. A wireless communication system based on IRS-aided massive MIMO operates using orthogonal frequency division multiplexing (OFDM) with $\mathrm{\acute{N}_S}$ subcarriers. The signal that UE received on the $\mathrm{n^{th}}$subcarrier can be represented as follows from the previous study conducted by Liu *et al.,* [25].

$$\mathrm{y_n} = \hat{\mathbf{h}}_\mathrm{n}^\mathrm{H} \mathrm{v_n}\, \mathrm{x_n} + \mathrm{s_n} \tag{1}$$

Where $\hat{\mathbf{h}}_\mathrm{n} \in \mathbb{C}^{\mathrm{N_t}\times 1}$ is the cascaded channel vector BS-IRS-UE, $\mathrm{v_n}$ is the precoding vector, $\mathrm{x_n}$ represents the image of transmitted data, $\mathrm{s_n}$is the Noise of additive white Gaussian distribution with unit variance and zero mean, and $(\cdot)^\mathrm{H}$ is the conjugate transpose. The $\hat{\mathbf{h}}_\mathrm{n}$ for IRS-aided massive MIMO is presented in Eq. (2).

$$\hat{\mathbf{h}}_\mathrm{n}^\mathrm{H} = \mathbf{h}_\mathrm{nIU}^\mathrm{H} \mathbf{\Phi} \mathbf{H}_\mathrm{nBI} \tag{2}$$

Where $\mathbf{H}_\mathrm{nBI} \in \mathbb{C}^{\mathrm{N_I}\times\mathrm{N_t}}$, $\mathbf{h}_\mathrm{nIU} \in \mathbb{C}^{\mathrm{N_I}\times 1}$, is the channel between BS-IRS and the channel between IRS-UE respectively. The reflection coefficient matrix $\mathbf{\Phi} = \beta\, \mathrm{diag}[\mathrm{e}^{\mathrm{j}\theta_1}, \mathrm{e}^{\mathrm{j}\theta_2}, \ldots \ldots \ldots, \mathrm{e}^{\mathrm{j}\theta_\mathrm{N}}]^\mathrm{T} \in \mathbb{C}^{\mathrm{N_I}\times\mathrm{N_I}}$ is a diagonal matrix with $0 \leq \beta \leq 1$ and $0 \leq \theta_i \leq 2\pi$ where $i \in \{1,2, \ldots \ldots \ldots, \mathrm{N_I}\}$ for IRS element. Let $\widehat{\mathbf{H}} = [\hat{\mathbf{h}}_1, \hat{\mathbf{h}}_2, \ldots, \hat{\mathbf{h}}_{\mathrm{\acute{N}_S}}]^\mathrm{H} \in \mathbb{C}^{\mathrm{\acute{N}_S}\times\mathrm{N_t}}$ is the CSI matrix in the space-frequency domain as defined in Figure 1, Where $\mathrm{\acute{N}_S}$ is the number of subcarriers. A large number of parameters will be sent in an IRS-aided massive MIMO system, creating a considerable overhead in feedback. By transmitting the matrix of channels $\widehat{\mathbf{H}}$ to the angle delay domain, feedback overhead can be reduced, resulting in a sparse matrix $\widehat{\mathbf{H}'}$, Eq. (3) can be used to define the 2D discrete Fourier transform (2D-DFT).

$$\widehat{\mathbf{H}'} = \mathbf{K}_\mathrm{d} \widehat{\mathbf{H}} \mathbf{K}_a^\mathrm{T} \tag{3}$$

Where $\mathbf{K}_\mathrm{d}$ and $\mathbf{K}_a$ are $\mathrm{\acute{N}_s} \times \mathrm{\acute{N}_s}$ and $\mathrm{N_t} \times \mathrm{N_t}$ DFT matrices respectively.

In $\widehat{\mathbf{H}'}$, large components comprise only a few elements, and all other components have a very small value due to the limited time delay between arrivals of the multipath. As a result, we can keep the first $\mathrm{N_s}$ rows of $\widehat{\mathbf{H}'}$and get rid of the remaining rows. Thus, the new channel coefficient matrix will be called **H** is the truncated channel matrix with size $\mathrm{N_s} \times \mathrm{N_t}$. Utilizing a channel estimation module based on CsiNet introduced in the previous study by Wen *et al.,* [11], Calculating $\widehat{\mathbf{H}}$ and utilizing 2D-DFT in Eq. (3). To obtain a truncated channel matrix **H**, the user generates the code word using an auto-encoding algorithm that utilizes compression techniques. Through a feedback link, the IRS sends this codeword to BS. BS performs auto-decoding to calculate the reconstructed channel matrix $\widetilde{\boldsymbol{H}}$. By performing an inverse DFT, a final channel matrix can be determined.

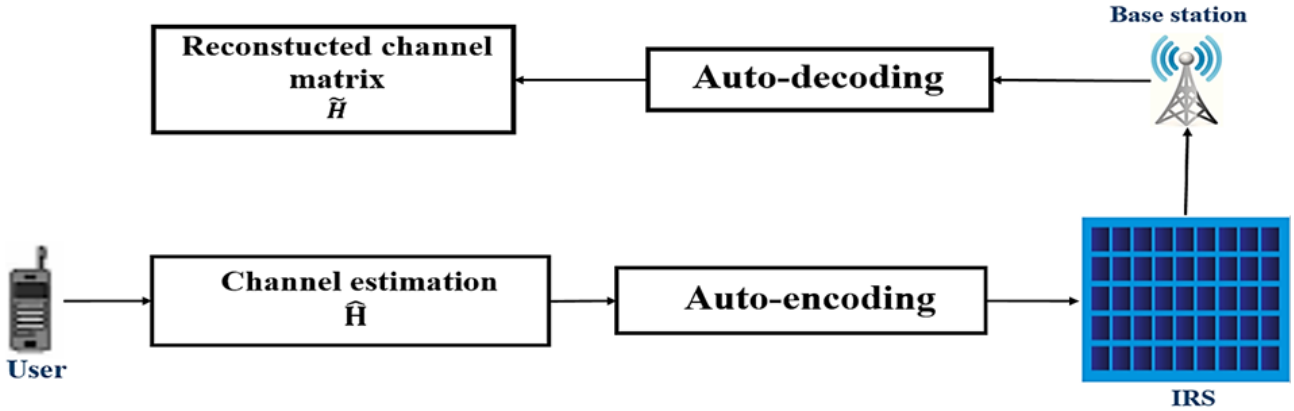

Fig. 1. IRS-aided massive-MIMO-based CsiNet [11]

3. Proposed CsiNet-DeCNN Model

This section presents a detailed explanation of our proposal CSI reconstruction method CsiNet-DeCNN. The CsiNet-DeCNN system consists of an auto-encoder on the UE side is presented in Figure 2, and an auto-decoder on the BS side after reflected from IRS elements is presented in Figure 3. In UE, **H** is divided into real and imaginary sections for deep NN processing, and its values are normalized within a range between [0,1]. Figure 2 shows the auto-encoder module has two steps. In the feature extraction module, a 3x3 kernel convolution (Conv.) layer filter is employed as well as a leaky rectified linear unit (LeakyRELU) as a nonlinear activation function, and batch normalization (BN) is applied to each layer. A 3x3 kernel layer model has been used throughout this paper according to previously published work from Wen *et al.,* [11]. The 3x3 kernel layer model has demonstrated superior performance simultaneously with achievable and acceptable computational complexity. After reshaping the feature maps into vectors, the data is split into two separate flows: a fully connected network (FCN) that accelerating convergence and solving vanishing gradient problems [26], while the DeCNN network is the second flow that can reduce the noise from the channel matrix by using the denoising module.

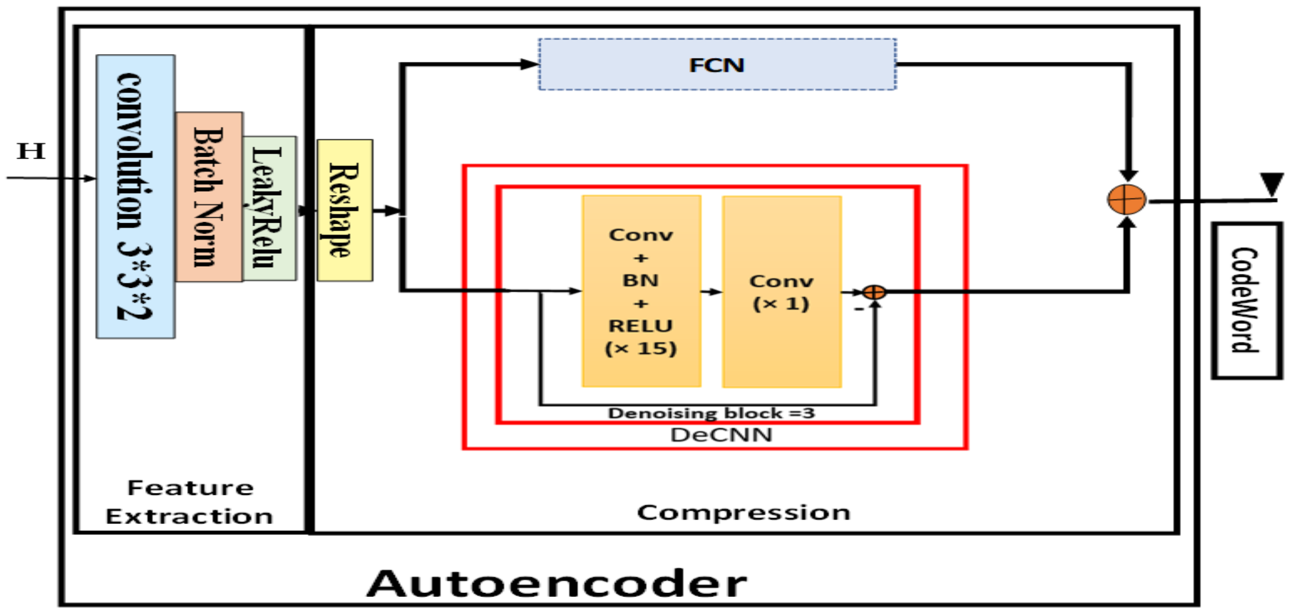

Fig. 2. The proposed model CsiNet-DeCNN auto-encoder

Compression is performed by reshaping a vector as the input layer. To progressively improve denoising performance, identically structured three denoising blocks are used. The denoising blocks consist of 15 layers of Conv+BN+rectified linear units (ReLU). A combination of Conv. and ReLU operations was implemented with consideration of the spatial properties of the channel matrix. By introducing BN between Conv. and RELU, network stability and training speed were enhanced. This model employs 15 layers consistent with previous work by Liu *et al.,* [25]. These 15 layers have demonstrated higher performance in removing noise and achieving higher accuracy. Due to the additive nature of the noise in the received signals, element-wise subtraction of the inputs and outputs is performed to determine the denoised channel matrix. Upon integrating the FCN and DeCNN modules, the output of the encoder is produced by combining the feature information between the two modules, and then adding it to the encoder output.

By using the feedback channel, the compressed vector is then transmitted to IRS and reflected to BS for CSI recovery as depicted in Figure 3. A reliable feedback channel is considered to be adequate to relay a decompressed codeword efficiently during feedback transmission. By utilizing a decoder that is comprised of feature decompression and channel recovery, the codeword is utilized at the BS for the recovery of the truncated matrix **H**. The feature decompression module is composed of DeCNN and FCN. simultaneously, identical to the compression module in the encoder as shown in Figure 3. To enhance the efficiency of information recovery, the output codeword passes through RefineNet units, which overcomes the vanishing gradient problem. RefineNet units consist of four layers. Layer one is the input layer; subsequent layers use 3x3 kernels. Layers two and three produce 8 and 16 feature maps, respectively, while layer four produces the reconstructed version of $\widetilde{\boldsymbol{H}}$. With zero padding, we set the feature maps generated by the three convolutional layers equivalent to the size of the input channel matrix using leakyRELU as the activation function. We apply BN to each layer individually.

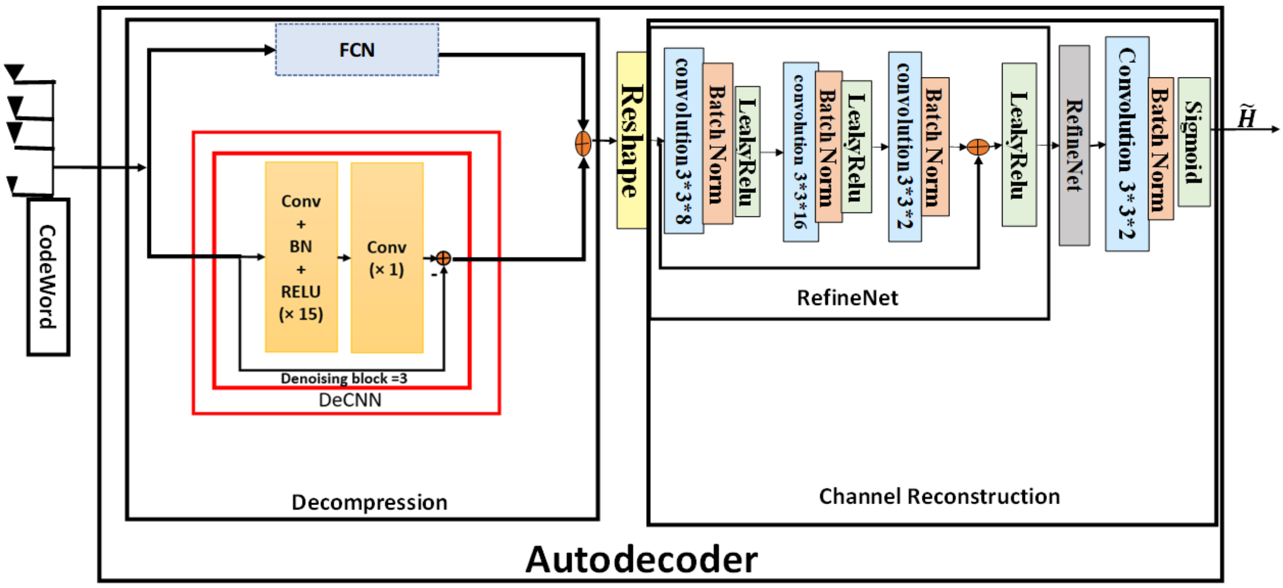

Fig. 3. The proposed model CsiNet-DeCNN auto-decoder

Several RefineNet units were used to refine the channel matrix before input to Conv. Layer where the sigmoid function was applied to scale the values to [0, 1]. Two RefineNet units produce good performance, according to experiments by Wen *et al.,* [11]. While increasing computational complexity, more RefineNet units do not significantly improve reconstruction quality. As a final step, the reconstructed channel matrix $\widetilde{\boldsymbol{H}}$ is incorporated into the original channel matrix **H** through inverse 2D-DFT operations and non-zero connections.

4. Numerical Result

The proposed technique CsiNet-DeCNN is implemented in Collaboratory (Python) without requiring any configuration. The COST 2100 MIMO channel model is used to obtain channel matrix datasets, which include training, validation, and testing sets [27]. An algorithm of the proposed CsiNet-DeCNN, which includes offline training and online recovery is shown below. Training will provide feedback directly to the trained neural network and in Table 1, a summary of the total parameters of the IRS-aided massive MIMO channel system is provided.

Input: Generated channel matrix H.

Training data:

Step 1: Create the initial channel matrix $\widehat{\mathbf{H}}$ according to the MIMO module of Cost 2100 [27]. Transform the channel matrix using 2D-DFT $\widehat{\mathbf{H}'}$ and truncation. Identify the real and imagined components, then aggregate both to produce the original channel **H**.

Step 2: **H** is provided to the encoder. Convolution and reshaping operations are used to extract feature vectors. FCN and DeCNN are used to compress the vector and encode it.

Step 3: In the UE, the encoder will transmit the codeword to the IRS and the IRS will reflect that codeword to BS.

Step 4: The BS decompresses the codeword using FCN and DeCNN to a vector, which is then recovered into CSI via the RefineNet units.

Step 5: To mitigate the inaccuracy compared to the initial matrix **H** and the calculated $\widehat{\mathbf{H}'}$, determine the loss function using MSE, and then enhance the model's parameters through the Adaptive Moment Estimation algorithm (ADAM) optimization.

Iterate Steps 2 - 4 until optimal CSI feedback NN is obtained.

Testing data: The UE imports the estimated CSI into the encoder and transmits it to the BS via the IRS reflecting element. By transmitting vectors to the decoder and using them to provide feedback to the CSI system without many iterations at BS, the complexity of channel feedback systems is effectively reduced.

Output: Reconstructed channel matrix $\widetilde{\boldsymbol{H}}$**.**

Table 1
Simulation parameters

Parameters	Settings
COST 2100 channel model [27]	Indoor: Pico cellular - 5.3 GHz Outdoor: rural - 300MHz
N_t	32 antennas
$\acute{N}_s$	1024 subcarrier
N_I	32
H	32 ×32
Training Samples	100 000
Validation Samples	30 000
Testing Samples	20 000
Epochs	1000
Learning Rate	0.001
Batch size	200
Compress ratio (CR)	1/4, 1/16, 1/32, 1/64

The proposed models were compared to previous similar modeling approaches, including LASSO [7], CsiNet [11], and TVAL3 [28], as part of our analysis. We examine the comparisons considering the Normalized Mean Square Error (NMSE), correlation coefficient, and accuracy in both indoor and outdoor channels. The NMSE is a measurement of the variation between the reconstructed channel $\widetilde{\boldsymbol{H}}$ with the original channel **H,** can be calculated as follows for the time T_s [11].

$$\mathrm{NMSE} = \mathrm{E}\left\{\frac{1}{T_s}\sum_{t_s=1}^{T_s}\left\|\mathbf{H}_{t_s} - \widetilde{\boldsymbol{H}}_{t_s}\right\|_2^2 / \left\|\mathbf{H}_{t_s}\right\|_2^2\right\} \tag{4}$$

Where $\|.\|_2$ is the Euclidean norm. The correlation coefficient measures the correlation between the original channel $\hat{\mathbf{h}}_{n,t_s}$ and the reconstructed channel value $\tilde{\mathbf{h}}_{n,t_s}$ of the n^{th} subcarrier at time T_s. It can be expressed as follows.

$$correlation\ coefficient\ = E\left\{\frac{1}{T_s}\frac{1}{\acute{N}_s}\sum_{t_s=1}^{T_s}\sum_{n=1}^{\acute{N}_s}\frac{|\tilde{\mathbf{h}}_{n,t_s}^{H}\,\hat{\mathbf{h}}_{n,t_s}|}{\|\tilde{\mathbf{h}}_{n,t_s}\|_2\|\hat{\mathbf{h}}_{n,t_s}\|_2}\right\} \tag{5}$$

To measure accuracy, the estimated channel vector is compared with the original channel vector as follows based on the previous study conducted by Helmy *et al.,* [12].

$$Accuracy = E\left\{\frac{1}{T_s}\frac{1}{\acute{N}_s}\sum_{t_s=1}^{T_s}\sum_{n=1}^{\acute{N}_s}\frac{|\tilde{\mathbf{h}}_{n,t_s}^{H}|}{\|\hat{\mathbf{h}}_{n,t_s}\|_2}\right\} \tag{6}$$

The relationship between compression ratio (CR) and NMSE is examined in all types of models, as shown in Figure 4 and Figure 5. The analysis considers both indoor and outdoor situations. For each CR, the proposed model consistently achieves superior results than other published works, where CsiNet has reduced the error by -0.36 dB as depicted in Figure 4, but by increasing the CR, our model outperforms the other models and CsiNet. In general, our model performs significantly better than other published models. As illustrated in Figure 5, CsiNet procedures outperformed the other CR-based methods (LASSO and TVAL3) for outdoor situation. Our model, however, outperformed the CsiNet model in all test conditions. This indicates that our model is more effective than existing models for both situations. Furthermore, our results reveal that the proposed model can achieve higher accuracy for outdoor CR.

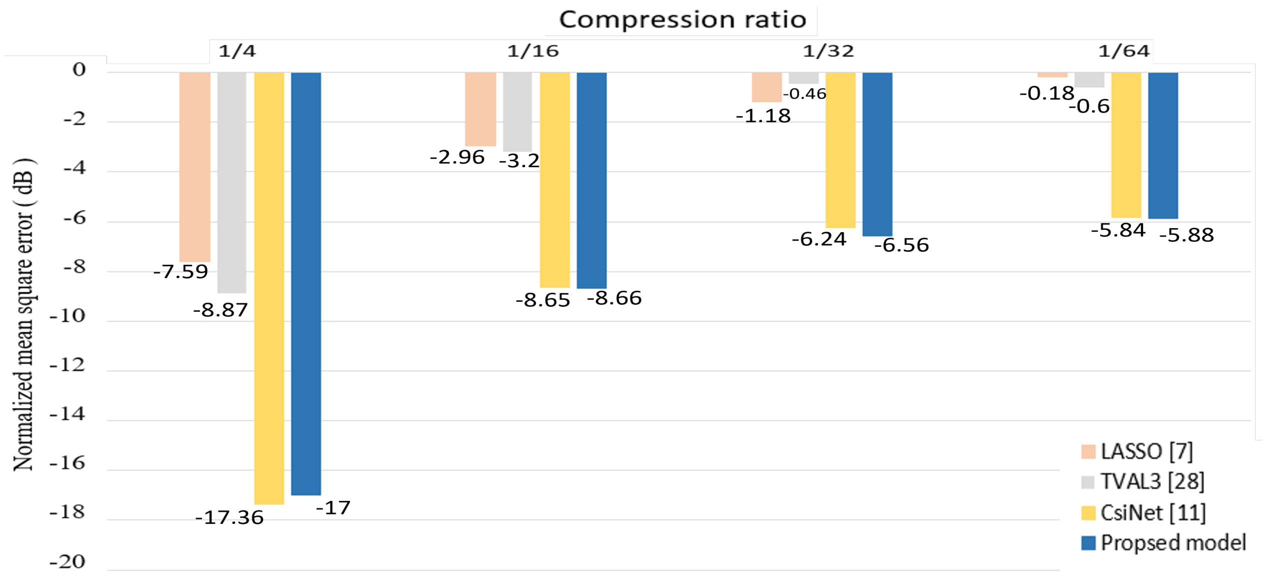

Fig. 4. NMSE versus compression ratio in indoor situations

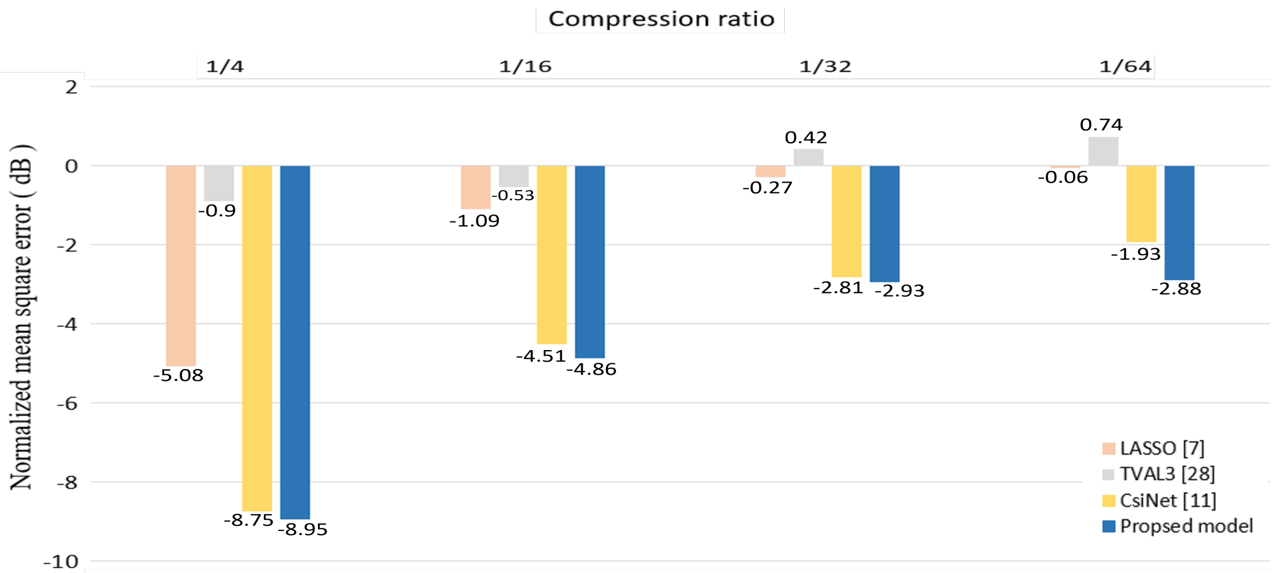

Fig. 5. NMSE versus compression ratio in outdoor situations

For all structures in both indoor and outdoor situations, Figure 6 and Figure 7 illustrate the relationship between correlation coefficients and CR. As compared to other models, the proposed model has a higher correlation coefficient of 0.99 for indoor situations and 0.88 for outdoor situations with lower CR. The outcomes show that the suggested model is capable of achieving superior-quality compression with high correlation coefficients. Moreover, the proposed model exhibits robustness to different types of situations. The results indicate that it is an effective and reliable model for compression applications.

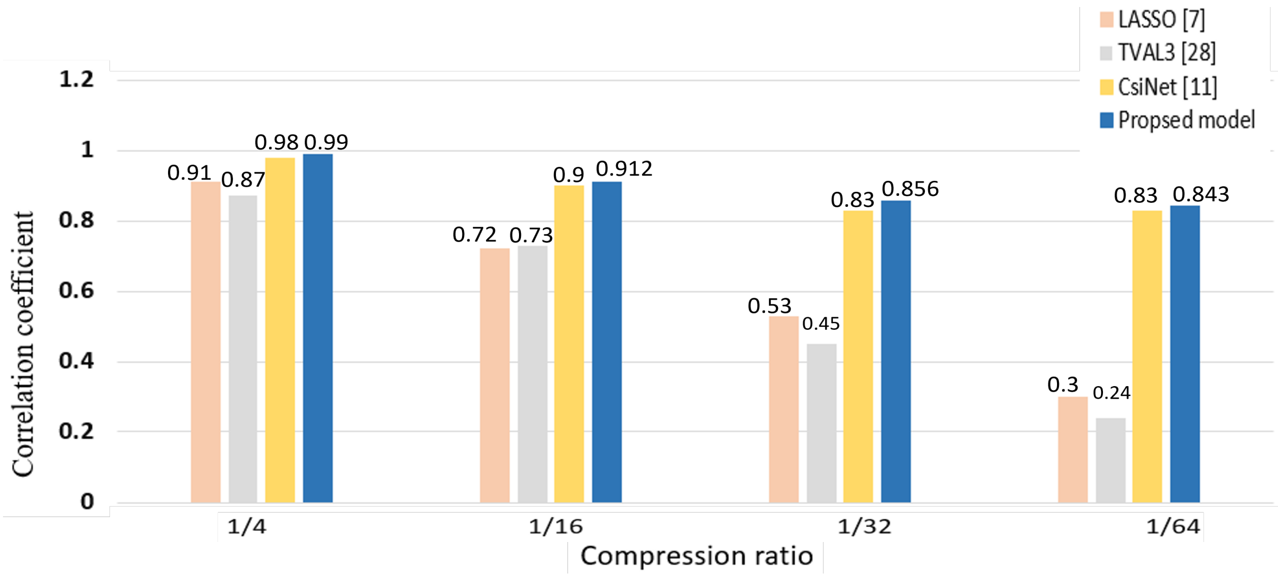

Fig. 6. Correlation coefficient versus compression ratio in indoor situations

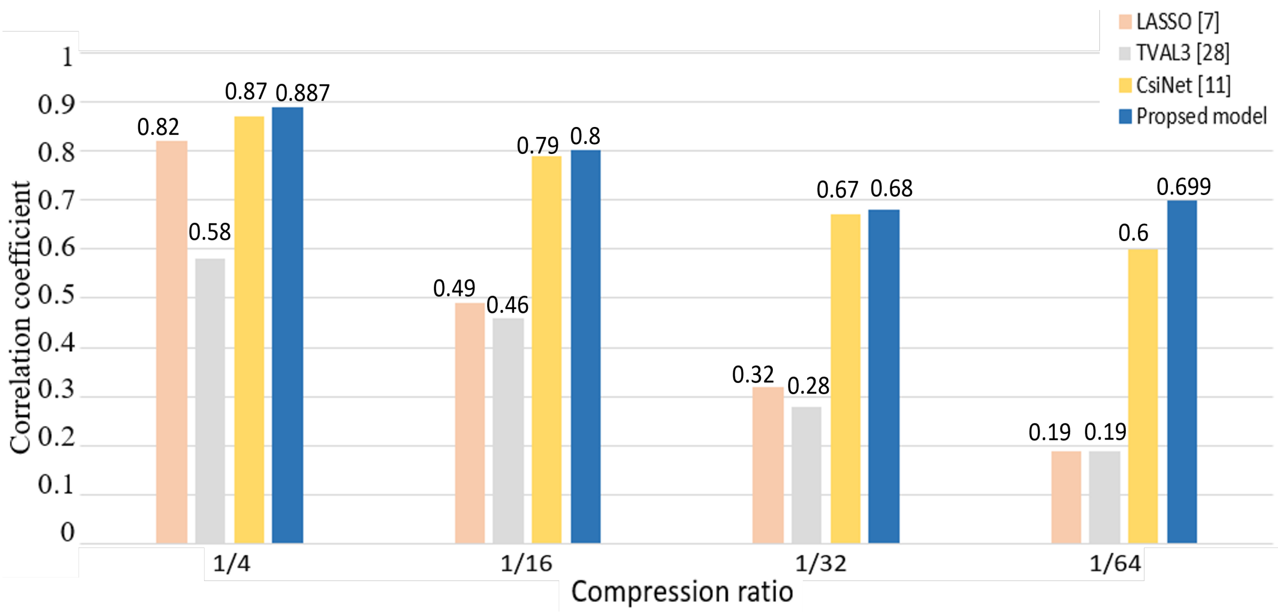

Fig. 7. Correlation coefficient versus compression ratio in outdoor situations

In Figure 8 and Figure 9, the relationship between CR and accuracy is shown for indoor and outdoor situations. Figure 8 and Figure 9 demonstrate that the proposed model outperforms previously published models in both situations. Compared to other models, the proposed model yields 0.82 indoor and 0.7 outdoor at low CR, showing better accuracy.

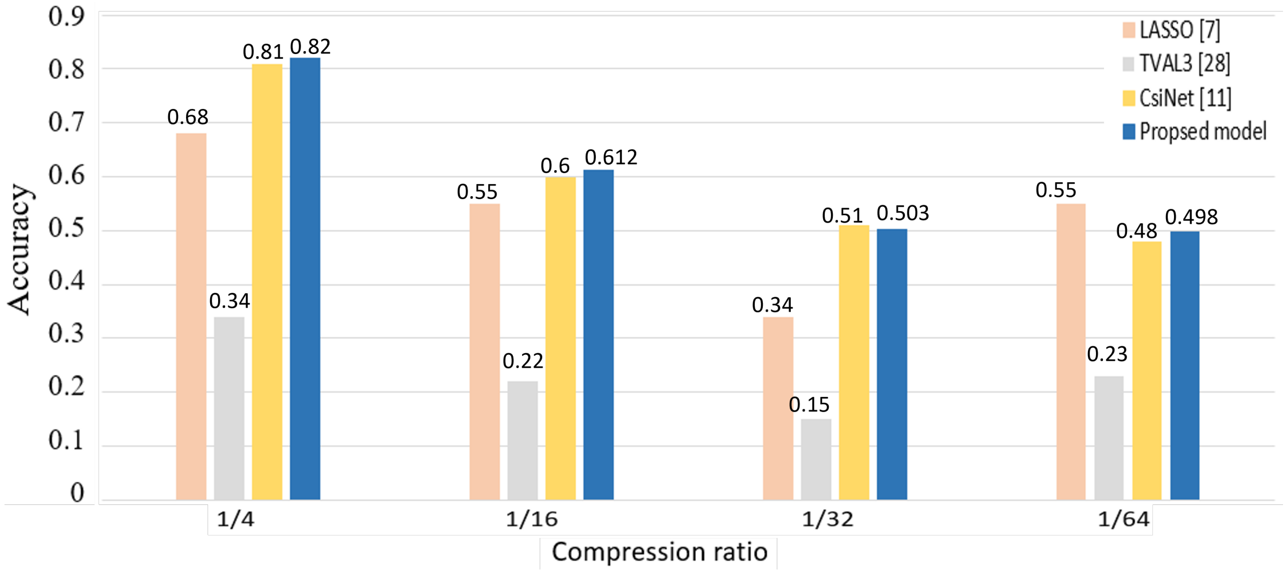

Fig. 8. Accuracy versus compression ratio in indoor situations

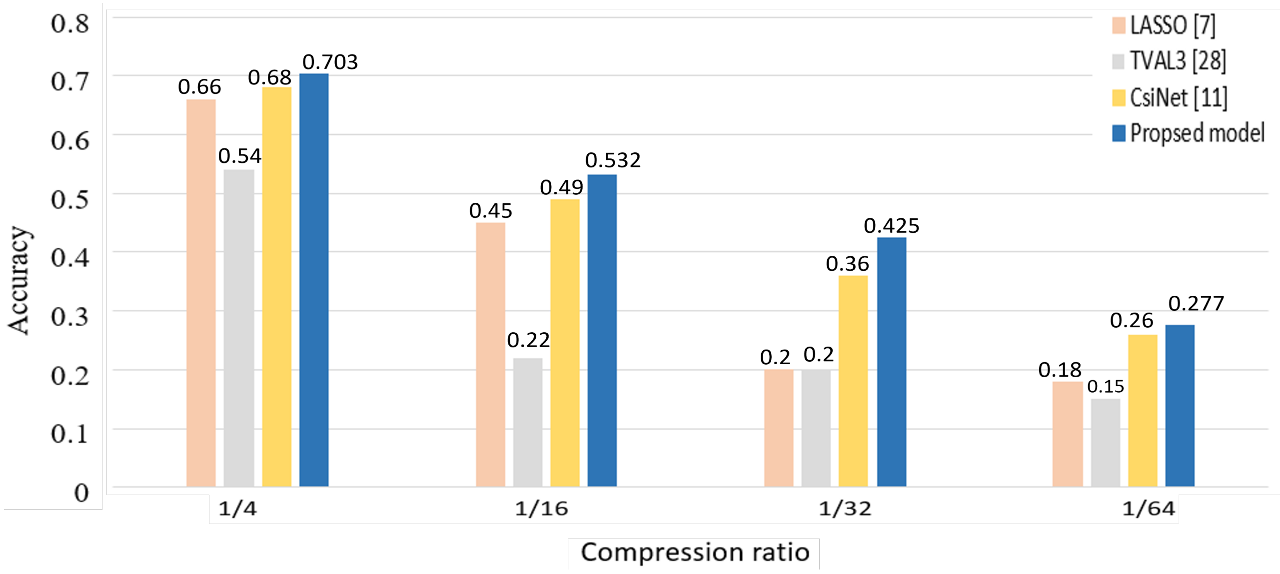

Fig. 9. Accuracy versus compression ratio in outdoor situations

5. Conclusions

In this paper, we focus on the development of a CsiNet-based denoising module, referred to as CsiNet-DeCNN, which addresses the feedback compression problem in IRS-aided massive MIMO wireless communication systems. Based on the system mean square error (NMSE), correlation coefficient, and accuracy performance, the proposed model has been evaluated, analyzed, and compared with existing techniques such as LASSO, TVAL3, and CsiNet. As a result of the introduction of a denoising module for channel recovery to reduce the noisy channel matrix, the proposed CsiNet-DeCNN model achieves a low NMSE, which is significantly different from traditional convolutional auto-encoding schemes. The proposed model achieves higher accuracy performance at higher CR than other models and a higher correlation coefficient of 0.99 compared to the LASSO, TVAL3, and CsiNet models. As a direction for future work, we will explore ways to reduce model complexity and increase system accuracy performance.

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