Indonesian Journal of Electrical Engineering and Computer Science
Vol. 38, No. 3, June 2025, pp. 1862~1869
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v38.i3.pp1862-1869

A novel deep learning based spatial delay feature aware encoder decoder module for enhanced CSI feedback in massive MIMO

Parinitha Jayashankar[1], Chigalakkappa Rangaswamy[1], Byrappa N. Shobha[2]
[1]Department of Electronics and Communication Engineering, S J C Institute of Technology, Chickballapur, India
[2]Department of ECE, B G S Institue of Technology, Adichunchanagiri University, Mandya, India

Article Info

Article history:

Received Mar 18, 2024
Revised Nov 30, 2024
Accepted Feb 27, 2025

Keywords:

Channel state information
Multiple input multiple output
Normalized mean square error
Spatial delay feature aware encoder-decoder
Spatial delay feature extraction

ABSTRACT

The algorithm presented in this study addresses the challenge of reconstructing downlink channel state information (CSI) in massive multiple input multiple output (MIMO) systems with a focus on enhancing efficiency and accuracy. It begins by acquiring both downlink and uplink CSI data alongside other critical parameters such as the number of iterations and convolutional filter specifications. The process initiates with the vectorization of downlink CSI data followed by compression through a fully connected layer, effectively reducing dimensionality to manage computational complexity. The iterative reconstruction phase then unfolds, where each iteration updates an intermediary variable using a refined formula that incorporates the compressed CSI representation and correction factors. This iterative refinement aims to progressively enhance the accuracy of the reconstructed CSI. A pivotal aspect of the algorithm involves an optimized Encoder-Decoder framework designed to handle spatial-delay features inherent in MIMO systems. This framework employs thresholding operations to eliminate insignificant features, ensuring that the reconstructed CSI accurately reflects the crucial aspects of the channel. Simultaneously, an information module utilizes uplink CSI data to adjust weights during reconstruction, thereby further refining the accuracy of the downlink CSI estimation.

Corresponding Author:

Parinitha Jayashankar
Department of Electronics and Communication Engineering, S J C Institute of Technology
Chickballapur, India
Email: parinithaj_12@rediffmail.com

1. INTRODUCTION

In recent years, there has been significant interest in massive multiple-input multiple-output (MIMO) systems due to their potential to greatly enhance the spectral efficiency (SE) of wireless communication networks [1]. This technology is crucial in enabling the realization of fifth-generation (5G) wireless communication networks. To achieve the best system SE and throughput in a real massive MIMO system, the base station (BS) relies on having accurate channel state information (CSI) for efficient design [2]. Precise acquisition of the CSI matrix is crucial for the BS in large MIMO systems, especially in multiuser communications that are affected by interference. In TDD systems, the BS can directly estimate the uplink CSI by utilizing a pilot sequence transmitted by a user equipment (UE). By leveraging channel reciprocity, the estimate can be utilized to predict the corresponding downlink CSI [3]. Nevertheless, FDD methods are widely utilized in modern cellular networks. Comprehending the CSI in FDD can pose a challenge when the channel reciprocity is disrupted by transmitting the (CSI) from a UE back to the BS is crucial in frequency division duplex (FDD) systems [4]-[7] have demonstrated that the feedback signaling overhead of CSI for massive MIMO increases as the number of BSs antennas and active UEs grows, both at the link and network levels. It is important to develop an effective CSI feedback or re-evaluate the feedback channel. In various computer vision domains, deep learning (DL) has proven to be highly effective due to its impressive ability to extract features and transfer knowledge across different domains [8], [9]. The growing interest in DL in wireless communication has been driven by its accomplishments in interdisciplinary research [10]. Advanced physical-layer technologies, such as precoding designs utilizing DL, channel estimation methods enhanced by DL, MIMO detection approaches based on DL, and security technologies empowered by DL, need to be redesigned to fully leverage the capabilities of DL [11]. DL has been utilized to develop efficient CSI reconstruction and compression for systems that require large-scale MIMO CSI feedback, enabling optimal utilization of its capabilities. Research conducted in [12] has demonstrated the significant potential of CSI feedback methods that utilize DL. These methods have proven to be more effective than traditional restricted feedback techniques in revealing the underlying structures of the CSI and improving overall performance. This is due to the sparsity of massive MIMO channels. A cutting-edge network called CsiNet was developed to tackle the difficulties of CSI compression and reconstruction. This model combines a residual convolutional neural network (CNN) with a fully-connected neural network (FNN). This approach was inspired by the impressive accomplishments of the residual network (ResNet) in the field of computer vision. The CsiNet showcased exceptional performance when compared to various conventional techniques, such as [13]-[15], in terms of both algorithms running time and CSI reconstruction accuracy. Various methods are investigated to improve the effectiveness of large-scale MIMO CSI feedback with the help of CsiNet. The primary objective was to develop various neural networks that enhance the precision of CSI reconstruction and cater to practical requirements. In previous times, DL techniques commonly regarded the channel matrix as a two-channel image. Compression can be viewed as introducing noise to the image [16], [17]. Decompression can be seen as a method of eliminating unwanted noise in order to improve clarity. Deep convolutional networks have demonstrated impressive effectiveness in denoising, as indicated by their ability to extract complex patterns from data. If the primary objective of CSI feedback is to improve reconstruction speed, employing a deep decoder network may offer a viable solution. The process of reducing CSI feedback overhead involves a compression and decompression process, similar to the addition and subsequent elimination of noise [18]-[20].

The motivation for the research into advanced CSI estimation methodologies stems from the critical role that CSI plays in the optimization of massive MIMO systems, which are foundational to the current and future generations of wireless communication networks, particularly 5G and beyond. Accurate CSI is pivotal for effective beamforming and throughput maximization in such systems. The challenges in acquiring reliable CSI in frequency division duplexing (FDD) systems, due to the lack of channel reciprocity, necessitate innovative approaches to reduce feedback signaling overhead without compromising the quality of information. DL presents a promising frontier in this regard, proven in other fields such as computer vision for its superior pattern recognition and feature extraction capabilities. By applying DL to the design of efficient CSI compression and reconstruction, there is potential to significantly enhance SE and system performance. The motivation is further amplified by the limitations of traditional feedback methods and the demonstrated superiority of DL-based models in exploiting the inherent sparsity of massive MIMO channels for improved CSI reconstruction. This research aims to build upon these advancements, proposing a methodology that not only contributes to the theoretical understanding of CSI management but also provides practical solutions to meet the demands of rapidly evolving wireless networks.

- Development of a deep learning-based spatial delay feature aware encoder decoder module (SDFEFD) for improved CSI feedback in Massive MIMO systems.
- Integration of spatial delay feature extraction with parameter tuning optimization, enhancing CSI processing efficiency.
- Comprehensive performance evaluation using the COST 2100 dataset, demonstrating SDFEFD's superiority in reducing Normalized Mean Squared Error compared to existing methods.
- Illustration of SDFEFD's potential in optimizing wireless network performance, particularly in massive MIMO scenarios.

The research in this paper is organized in 4 sections: the section 1 introduces investigates CSI eedback mechanisms in massive MIMO systems, focusing on enhancing downlink CSI compression and feedback for 5G and beyond. The section 2 introduces a proposed methodology as a novel deep learning-based approach. The section 3 evaluates the results in the form of graphs and tables, the proposed method is compared with state-of-art techniques validated using the COST 2100 channel dataset and 3GPP specifications.

2. METHOD

2.1. Preliminary analysis

The preliminary including downlink CSI (J^f), uplink CSI (J_w), the number of algorithm iterations (V), and the number of filters in convolutional layers (h_p), suggests a comprehensive approach to address the intricacies of CSI management in wireless communication systems. By specifying the spatial-delay domain for both downlink and uplink CSI, the methodology emphasizes the significance of capturing spatiotemporal characteristics for more accurate transmission. The inclusion of the number of iterations (V) and filters (h_p) underscores the iterative and DL aspects of the algorithm, indicating a commitment to enhancing the quality of CSI recovery. Overall, this preliminary analysis suggests that the methodology is poised to leverage advanced techniques to optimize CSI handling in complex communication environments.

2.2. System model and problem formulation

In this section, the methodology begins by introducing a single-cell downlink massive MIMO system, featuring $\widetilde{P}_h$ transmit antennas at the BS and one antenna at the UE, operating over P_v subcarriers. The received signals, including channel vectors, precoding vectors, data-bearing symbols, and additive noise, are described. The use of the proposed model to transform channel matrices into the delay domain is highlighted, leading to truncated matrices for efficient processing. The methodology also emphasizes the need for dimensionality reduction due to massive MIMO systems, which is achieved through linear sensing. The ultimate goal is to recover downlink CSI while considering the sparsity in the delay domain and exploiting auxiliary uplink CSI to enhance accuracy.

2.3. Proposed spatial delay optimized encoder decoder-based network

This section presents the core of the proposed methodology, a Shrinkage Algorithm for CSI recovery. The network architecture comprises a compression module and a reconstruction module, with the latter consisting of multiple iterations (V). Each iteration involves Auto-encoders, and spatial delay constraints for uplink and downlink CSI. A pivotal component is the spatial delay optimized Encoder Decoder, designed to learn spatial delay and inverse transforms for both uplink and downlink CSI. The Info module complements this by mapping spatial delay representations of uplink CSI to minimization, further improving recovery accuracy. Convolutional layers and rectified linear units (ReLU) are deployed within the integrated spatial delay optimized Encoder Decoder to extract essential values from transformed CSIs. The methodology of this research provides a comprehensive approach to compressing and recovering CSI in massive MIMO systems, emphasizing spatial delay features, and leveraging advanced neural network components for enhanced accuracy. Figure 1 shows the proposed spatial delay optimized encoder decoder-based network. Algorithm 1 shows the proposed architecture.

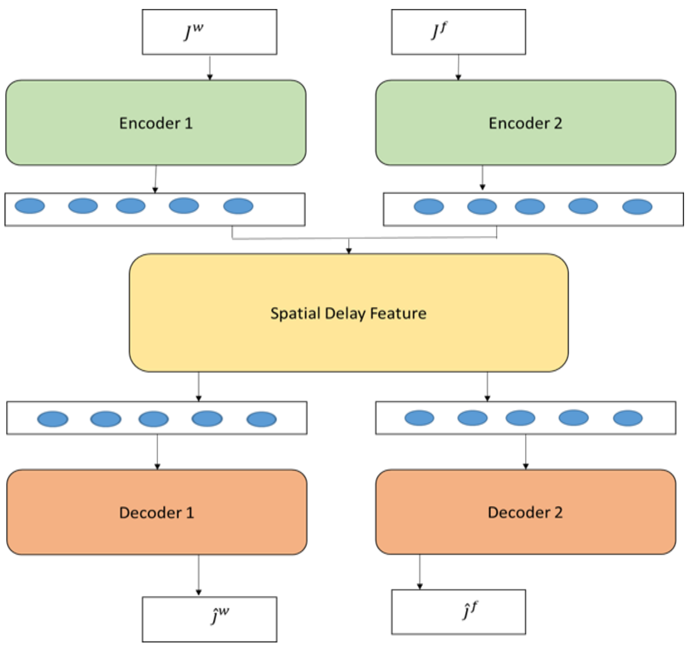

Figure 1. Proposed spatial delay optimized encoder decoder based network

2.4. Algorithm

The algorithm is an advanced procedure for reconstructing downlink CSI in the spatial-delay domain for massive MIMO systems. Initially, it takes in the CSI for both downlink and uplink, and other parameters like the number of iterations and convolutional filters. The process begins with the vectorization of downlink CSI, followed by its compression using a fully connected layer to reduce dimensionality. It then embarks on an iterative reconstruction phase, where in each iteration, the algorithm updates an intermediary variable through a formula that refines the previous CSI estimate by incorporating the compressed version and applying a correction factor. This is followed by a integrated spatial delay feature optimized Encoder Decoder that learns the spatial delay feature features and inverses them for recovery. A thresholding operation is applied to eliminate insignificant features, and the inverse transform reconstructs the downlink CSI. This cycle repeats for a set number of iterations. Concurrently, an information module uses uplink CSI to adjust the weights in the reconstruction, enhancing accuracy. The final output is the meticulously reconstructed downlink CSI, expected to significantly improve the performance of wireless communication networks. Algorithm 1 shows the proposed architecture.

Algorithm 1. Proposed architecture

Input: Downlink CSI in spatial-delay domain J^f
Uplink CSI in spatial-delay domain J^w
Number of iterations for the algorithm, V
Number of filters in convolutional layers, h_p

Step 1: Vectorize Downlink CSI:
- Convert J^f into vectorized form j^f

Step 2: Compression Module:
- Compress j_f to u using a fully connected (FC) layer, denoted as $i(.)$

Step 3: Initialization:
- Initialize iterative variables j^f_{v-1} and t_v

Step 4: Iterative Reconstruction (v Iterations):
- For t from 1 to v do:
  - Update t_v using the formula:
$$t_v = j^f_{v-1} + \vartheta_v Y(u - i(j^f_{v-1}))$$
  - Apply the integrated spatial delay optimized Encoder Decoder to learn the spatial delay feature/inverse transform for t_v, yielding h_2 (t_v)

Apply the soft thresholding function:
$$h_2(j^f_v) = \mathrm{soft}(h_2(t_v), \theta y)$$
  - Apply the inverse transform to $h_2(j^f_v)$ to obtain j^f_v

Step 5: Info Module for Support Information:
- For each iteration, obtain the support information of the transformed uplink CSI (uinvec)
- Map uinvec to weights y using two convolutional layers and a ReLU

Step 7: Final Output:
The output after the v-th iteration, j^f_v, is the reconstructed downlink CSI J^w

Output: Reconstructed downlink CSI J^w

The output of the proposed methodology, based on the provided elements of downlink CSI (J^f), uplink CSI, the number of iterations for the algorithm (V), and the number of filters in convolutional layers (h_p), is expected to be a highly refined and reconstructed CSI dataset. Through the algorithm's iterative and DL processes, it aims to compress and recover the spatial-delay domain CSI with improved accuracy. The final output, represented by the reconstructed CSI, holds the potential to enhance the performance and efficiency of massive MIMO systems in wireless communication, ultimately contributing to more reliable and resource-efficient data transmission.

3. RESULTS AND DISCUSSION

The evaluation of various models for CSI estimation, as presented in the tables, reveals a consistent trend of improvement in performance across different environments. Starting with CsiNet, which consistently shows the least effectiveness in both indoor and outdoor settings across the tables, there is a notable progression in the performance of subsequent models. CRNet and CLNet demonstrate slight improvements over CsiNet, with marginally better scores in both environments. DCRNet, TransNet, and STNet each present further enhancements, particularly in indoor settings, indicating their improved capability in more controlled environments.

3.1. Dataset details

This section provides comprehensive details about the Cost 2100 [21] database. The COST (European Cooperation in Science and Technology) 2100 channel model is a geometric stochastic channel model (GSCM) designed to replicate the stochastic characteristics of MIMO channels across time, frequency, and space dimensions. It characterizes a multipath component (MPC) in terms of delay and both departure and arrival angles (specifically, azimuth of departure (AoD), elevation of departure (EoD), azimuth of arrival (AoA), and elevation of arrival (EoA)). The MATLAB implementation of the cost 2100 channel model (C2CM) accommodates both single and multiple MIMO channel links. It is applicable in various channel scenarios, including indoor environments at 285 MHz and semi-urban environments at 5.3 GHz. The dataset encompasses information from two distinct environments: an indoor cellular environment and an outdoor cellular environment. The indoor environment data is collected at a frequency of 5.3 GHz, while the outdoor environment data is gathered at a higher frequency of 300 GHz.

3.2. Results

In Figure 2 and Table 1 the compression ratio for 1/4 is evaluated for various models for CSI estimation, the performance is quantified by values in both indoor and outdoor settings. CsiNet, with -17.36 indoor and -8.75 outdoor, is the least effective. In the evaluation of various models for CSI estimation, the performance is quantified by values in both indoor and outdoor settings. CsiNet, with -17.36 indoor and -8.75 outdoor, is the least effective. The performance progressively improves with CRNet (-26.99 indoor, -12.7 outdoor), CLNet (-29.16 indoor, -12.09 outdoor), DCRNet (-30.61 indoor, -13.72 outdoor), and further with TransNet (-32.38 indoor, -14.86 outdoor) and STNet (-31.81 indoor, -12.91 outdoor). ES shows a significant improvement in outdoor settings (-16.35) compared to its indoor performance (-32.61). The Proposed Model outshines all with the most effective performance, scoring -35.94 indoor and -19.87 outdoor, indicating its superior methodology in CSI estimation under both environmental conditions.

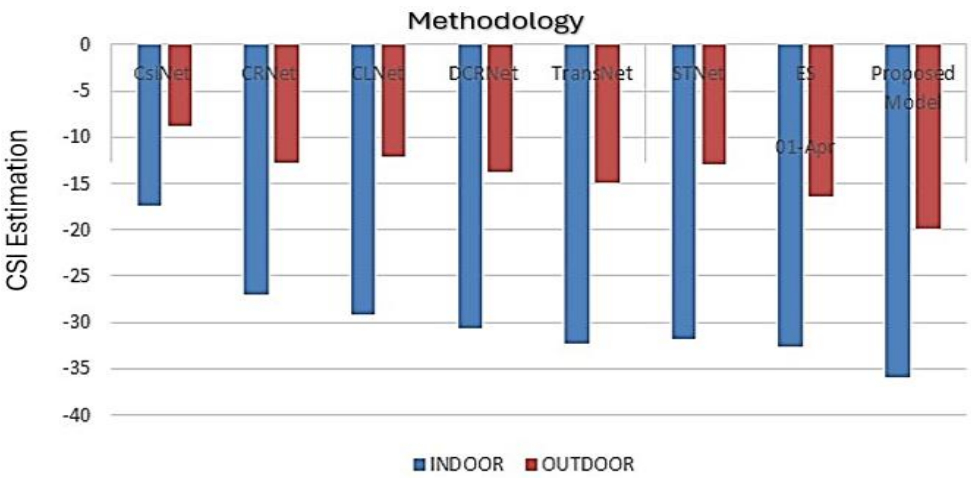

Figure 2. CSI Reconstruction results for compression ratio ¼ from 0 to -40

Table 1. CR results for ¼

CR	Classical CSI methods	Indoor	Outdoor
	CsiNet [19]	-17.36	-8.75
	CRNet [20]	-26.99	-12.7
	CLNet [21]	-29.16	-12.09
	DCRNet [22]	-30.61	-13.72
1/4	TransNet [23]	-32.38	-14.86
	STNet [24]	-31.81	-12.91
	ES [25]	-32.61	-16.35
	Proposed Model	**-35.94**	**-19.87**

In Figure 3 and Table 2 the compression ratio for 1/8 is evaluated for various models for CSI estimation, the performance is quantified by values in both indoor and outdoor settings. CsiNet, with -17.36 indoor and -8.75 outdoor, is the least effective. The provided table compares the performance of various models in CSI estimation for indoor and outdoor environments. The models are CRNet, CLNet, DCRNet, TransNet, STNet, ES, and a Proposed Model. CRNet and CLNet show moderate performance with CRNet scoring -16.01 indoor and -8.04 outdoor, and CLNet with -15.6 indoor and -8.29 outdoor. DCRNet marks an improvement, especially indoors, with -19.92 indoor and -10.17 outdoor. TransNet and STNet show further enhancements, with TransNet at -22.91 indoor and -9.99 outdoor, and STNet scoring -21.28 indoor and -8.53 outdoor. ES performs comparably, especially well outdoors (-11.04), with -22.13 indoor. The Proposed Model outperforms all others, scoring -25.36 indoor and -14.78 outdoor, indicating its superior capability in CSI estimation in both environments. This progression from CRNet to the Proposed Model reflects continuous advancements in the field.

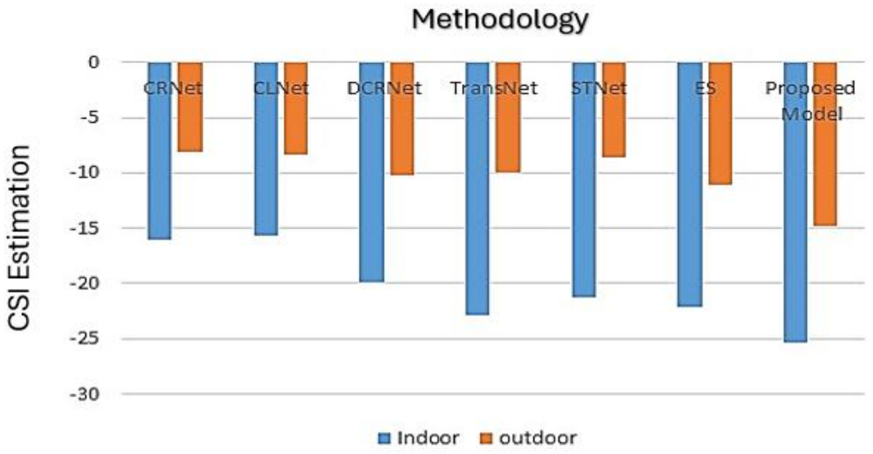

Figure 3. CSI reconstruction results for compression ratio 1/8 from 0 to -40

Table 2. CR results for 1/8

CR	Classical CSI methods	Indoor	Outdoor
	CRNet [15]	-16.01	-8.04
	CLNet [16]	-15.6	-8.29
	DCRNet [18]	-19.92	-10.17
1/8	TransNet [19]	-22.91	-9.99
	STNet [20]	-21.28	-8.53
	ES [21]	**-22.13**	**-11.04**
	Proposed Model	-25.36	-14.78

In the comparison of various models for CSI estimation, the table reflects their performance in both indoor and outdoor settings. Starting with CsiNet, it shows the least effectiveness, scoring -8.65 indoor and -4.51 outdoor. CRNet and CLNet demonstrate improvements, with CRNet at -11.35 indoor and -5.44 outdoor, and CLNet slightly behind at -11.15 indoor and -5.56 outdoor. DCRNet marks a significant enhancement, particularly indoors, scoring -14.02 indoor and -6.35 outdoor. TransNet and STNet further advance the performance, with TransNet achieving -15 indoor and -7.82 outdoor, and STNet showing -15.28 indoor and -5.72 outdoor. ES is comparable, scoring -15.29 indoor and -7.04 outdoor. The Proposed Model outshines all, leading with the most effective scores of -18.98 indoor and -9.76 outdoor, indicating its superior ability in CSI estimation across both environments. This progression indicates ongoing advancements in CSI estimation methodologies, with the Proposed Model at the forefront.

4. CONCLUSION

This research advances the field of wireless communication by introducing a deep learning-based spatial delay feature aware encoder decoder module (SDFEFD) for enhanced CSI Feedback in Massive MIMO systems. The novel approach combines spatial delay feature extraction with parameter tuning optimization, improving CSI processing in uplink and downlink scenarios. The research demonstrates SDFEFD's effectiveness through rigorous evaluation using the COST 2100 dataset, where it significantly outperforms existing methods in terms of Normalized Mean Squared Error. This indicates its potential to revolutionize CSI feedback in massive MIMO systems, marking a substantial progression in the optimization of wireless network performance.

ACKNOWLEDGEMENT

We would like to express our sincere gratitude to all those who have supported and contributed to this research project. Primarily, we extend our heartfelt thanks to our guide for his unwavering guidance, invaluable insights, and encouragement throughout the research process. No funding is raised for this research.

FUNDING INFORMATION

No funding is raised for this research.

AUTHOR CONTRIBUTION

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Parinitha Jayashankar	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			✓	
Chigalakkappa Rangaswamy	✓	✓	✓	✓		✓		✓	✓	✓	✓	✓	✓	
Byrappa N. Shobha	✓	✓	✓	✓	✓	✓	✓		✓	✓				

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST

Author declares no conflict of interest.

DATA AVAILABILTY

Dataset is utilized in this research mentioned in reference [21].

REFERENCES

[1] L. Lu, G. Y. Li, A. L. Swindlehurst, A. Ashikhmin, and R. Zhang, "An overview of massive MIMO: benefits and challenges," in *IEEE Journal of Selected Topics in Signal Processing*, vol. 8, no. 5, pp. 742-758, Oct. 2014, doi: 10.1109/JSTSP.2014.2317671.

[2] G. N. Kamga, M. Xia, and S. Aïssa, "Spectral-efficiency analysis of massive MIMO systems in centralized and distributed schemes," in *IEEE Transactions on Communications*, vol. 64, no. 5, pp. 1930-1941, May 2016, doi: 10.48550/arXiv.1601.04829.

[3] V. W. Wong, R. Schober, D. W. K. Ng, and L.-C. Wang, "Key technologies for 5G wireless systems," Cambridge, U.K.: Cambridge University Press, 2017, doi: 10.1017/9781316771655.

[4] W. Xu *et al.*, "Edge learning for B5G networks with distributed signal processing: semantic communication, edge computing, and wireless sensing," in *IEEE Journal of Selected Topics in Signal Processing*, vol. 17, no. 1, pp. 9-39, Jan. 2023, doi: 10.1109/JSTSP.2023.3239189.

[5] W. Shen, L. Dai, Y. Shi, B. Shim, and Z. Wang, "Joint channel training and feedback for FDD massive MIMO systems," in *IEEE Transactions on Vehicular Technology*, vol. 65, no. 10, pp. 8762-8767, Oct. 2016, doi: 10.1109/TVT.2015.2508033.

[6] K. Wei, J. Xu, W. Xu, N. Wang, and D. Chen, "Distributed neural precoding for hybrid mmwave MIMO communications with limited feedback," in *IEEE Communications Letters*, vol. 26, no. 7, pp. 1568-1572, July 2022, doi: 10.1109/LCOMM.2022.3167712.

[7] J. Guo, C. -K. Wen, and S. Jin, "Deep learning-based CSI feedback for beamforming in single- and multi-cell massive MIMO systems," in *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 7, pp. 1872-1884, July 2021, doi: 10.1109/JSAC.2020.3041397.

[8] Z. Hu *et al.*, "MRFNet: a deep learning-based CSI feedback approach of massive MIMO systems," in *IEEE Communications Letters*, vol. 25, no. 10, pp. 3310-3314, Oct. 2021, doi: 10.1109/LCOMM.2021.3099841.

[9] Z. Lu, J. Wang, and J. Song, "Binary neural network aided CSI feedback in massive MIMO system," in *IEEE Wireless Communications Letters*, vol. 10, no. 6, pp. 1305-1308, June 2021, doi: 10.1109/LWC.2021.3064963.

[10] H. Ren *et al.*, "Performance analysis for RIS-aided secure massive MIMO systems with statistical CSI," in *IEEE Wireless Communications Letters*, vol. 12, no. 1, pp. 124-128, Jan. 2023, doi: 10.1109/LWC.2022.3218961.

[11] P. Pujar, A. Kumar, and V. Kumar, "Efficient plant leaf detection through machine learning approach based on corn leaf image classification," in *IAES International Journal of Artificial Intelligence*, vol. 13, no. 1, pp. 1139-1148, March 2024, doi: 10.11591/ijai.v13.i1.pp1139-1148.

[12] S. H. Sreedhara, V. Kumar, and S. Salma, "Efficient big data clustering using adhoc fuzzy C-means and auto-encoder CNN," in *Lecture Notes in Networks and Systems*, vol. 563, Springer, 2023, doi: 10.1007/978-981-19-7402-1_25.

[13] Z. Gu, Z. Chen, J. Zhang, X. Zhang and Z. L. Yu, "An online interactive paradigm for P300 brain–computer interface speller," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 2, pp. 152-161, Feb. 2019, doi: 10.1109/TNSRE.2019.2892967.

[14] Q. Cai, C. Dong, and K. Niu, "Attention model for massive MIMO CSI compression feedback and recovery," in Proceedings of *IEEE Wireless Communications and Networking Conference (WCNC),* Marrakesh, Morocco, 2019, pp. 1-5, doi: 10.1109/WCNC.2019.8885897.

[15] J. J. Podmore, T. P. Breckon, N. K. N. Aznan and J. D. Connolly, "On the relative contribution of deep convolutional neural networks for SSVEP-based bio-signal decoding in BCI speller applications," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 4, pp. 611-618, April 2019, doi: 10.1109/TNSRE.2019.2904791.

[16] A. Vaswani *et al.*, "Attention is all you need," in *Proceedings of the 31st International Conference on Neural Information Processing Systems,* 2017, pp. 6000-6010, doi: 10.48550/arXiv.1706.03762.

[17] Y. Xu, M. Yuan, and M. -O. Pun, "Transformer empowered CSI feedback for massive MIMO systems," in *Proceedings of the 30th Wireless and Optical Communications Conference (WOCC),* Taipei, Taiwan, 2021, pp. 157-161, doi: 10.1109/WOCC53213.2021.9602863.

[18] S. Kundu and S. Ari, "MsCNN: A deep learning framework for P300-based brain–computer interface speller," in *IEEE Transactions on Medical Robotics and Bionics*, vol. 2, no. 1, pp. 86-93, Feb. 2020, doi: 10.1109/TMRB.2019.2959559.

[19] L. Liu *et al.*, "The COST 2100 MIMO channel model," in *IEEE Wireless Communications*, vol. 19, no. 6, pp. 92-99, Dec. 2012, doi: 10.1109/MWC.2012.6393523.

[20] C. -K. Wen, W. -T. Shih, and S. Jin, "Deep learning for massive MIMO CSI feedback," in *IEEE Wireless Communications Letters*, vol. 7, no. 5, pp. 748-751, Oct. 2018, doi: 10.1109/LWC.2018.2818160.

[21] Z. Lu, J. Wang and J. Song, "Multi-resolution CSI feedback with deep learning in massive MIMO system," *ICC 2020 - 2020 IEEE International Conference on Communications (ICC),* Dublin, Ireland, 2020, pp. 1-6, doi: 10.1109/ICC40277.2020.9149229.

[22] S. Ji and M. Li, "CLNet: Complex input lightweight neural network designed for massive MIMO CSI feedback," in *IEEE Wireless Communications Letters*, vol. 10, no. 10, pp. 2318-2322, Oct. 2021, doi: 10.1109/LWC.2021.3100493.

[23] S. Tang, J. Xia, L. Fan, X. Lei, W. Xu, and A. Nallanathan, "Dilated convolution based CSI feedback compression for massive MIMO systems," in *IEEE Transactions on Vehicular Technology*, vol. 71, no. 10, pp. 11216-11221, Oct. 2022, doi: 10.1109/TVT.2022.3183596.

[24] S. M. Bathala, S. Amuru, and K. Kuchi, "A spatially separable attention mechanism for massive MIMO CSI feedback," *arXiv preprint,* 2022, doi: 10.48550/arXiv.2208.03369.

[25] A. Chakma, S. S. Alam, M. H. Rahman, and Y. M. Jang, "Deep decoder CsiNet for FDD massive MIMO system," in *IEEE Wireless Communications Letters*, vol. PP, no. 1, pp. 1-1, 2023, doi: 10.1109/LWC.2023.3307164.

BIOGRAPHIES OF AUTHORS

Parinitha Jayashankar earned her Bachelors of engineering in Telecommunication Engineering and Master's degree in Digital communication and Networking from Visvesvaraya Technological University (VTU), Belgavi. Currently she is a pursuing her Ph.D. in Electronics and communication engineering from S J C institute of technology, VTU, Belgavi. She is working as an assistant professor with a total experience of 11 years. She has guided over 11 under graduate projects and published 10 papers in various Journals. She can be contacted at email: parinithaj_12@rediffmail.com.

Chigalakkappa Rangaswamy has received Ph.D. from Reva University Bengaluru and M.Tech. Degree from Visvesvaraya Technological University, Belagavi, Karnataka. Currently working as Professor and Head in the Department of Electronics and Communication Engineering SJC Institute of Technology, Chickballapur. He has 25 years of experience in teaching. His area of research interests includes Image Processing, Communication. He is IETE life member. He has published 18 papers in leading reputed Journals/International Conferences/National Conferences. He can be contacted at this email: crsecesait@gmail.com and hodece@sjcit.ac.in.

Dr. Byrappa N. Shobha is Principal of B G S Institue of Technology, BG Nagar Nagamangala, Mandya. She is having a total experience of 31 years. She is qualified in Bachelor and Master Degrees in Electronics from Bangalore university, and Ph.D. from Karpagam University in the field of Electronics. She has guided over 60 undergraduate projects, 45 post graduate projects and guiding 4 Ph.D. students. She has published over 28 papers in various Journals and have 6 patents in her name. Her area of interest is bio–Sensor image processing computer vision embedded system IoT. She can be contacted at this email: bnshobha67@gmail.com.