

Extended Abstract

(For Ph.D. Open Seminar)

Deep Learning-Driven Transform and Denoising Framework for Efficient CSI Feedback in Next Generation Massive MIMO Systems

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Abstract

The exponential growth of wireless communication, driven by the advent of fifth-generation (5G) and the upcoming sixth-generation (6G) networks, demands advanced transmission technologies. These technologies are expected to be capable of achieving ultra-high data rates, massive connectivity, and superior energy efficiency. In this regard, massive multiple input multiple output (MIMO) has emerged as a pivotal technology, that uses spatial multiplexing and channel diversity to enhance throughput and mitigate multi user interference. However, as the number of antennas at the base station (BS) and user equipment (UE) scales into the hundreds (100) or thousands (1000), channel state information (CSI) acquisition and feedback overhead become major challenges. The difficulty in feedback reduction further increases in frequency division duplex (FDD) systems, where the BS depends on UE feedback for downlink CSI reconstruction. Compressive sensing (CS) has been found as an efficient mechanism for CSI feedback reduction.

Traditional CS techniques mitigate this overhead by exploiting channel sparsity and projecting high dimensional CSI onto a lower dimensional subspace. Despite their efficiency, CS-based methods rely on the discrete Fourier transform (DFT) for sparse domain representation, which increases computational complexity and performs poorly under non-strict sparsity conditions. To overcome these limitations, deep learning (DL) has emerged as a data driven alternative capable of learning nonlinear mappings for efficient CSI compression and reconstruction. Frameworks such as CsiNet, CsiNet+, CRNet, PRVNet, DeepAE, and TransNet have demonstrated notable improvements in feedback efficiency and reconstruction accuracy. Nonetheless, these methods often face challenges related to computational cost, performance degradation in low signal-to-noise ratio (SNR) environments, and limited adaptability to real world deployment.

To address these challenges, this thesis proposes computationally efficient and practically implementable DL-based frameworks designed to achieve accurate and robust CSI feedback in massive MIMO systems. Unlike conventional compressed sensing and existing DL architectures that struggle with complexity and noise sensitivity, the proposed frameworks employ transform-assisted learning mechanisms to achieve effective feature extraction, dimensionality reduction, and enhanced noise resilience. The resulting architectures bridge the gap between theoretical advancements and real-world applicability, enabling efficient, scalable, and energy-aware CSI feedback solutions for next-generation 5G and 6G wireless communication systems.

First, a discrete Rajan transform (DRT)-based DL model is introduced to overcome the inherent trade-off between model complexity and reconstruction fidelity. The DRT, being an orthogonal and computationally efficient transform, facilitates compact CSI representation while preserving essential spatial–frequency features. The proposed DRT-based DL framework effectively reduces the number of trainable parameters without compromising accuracy. Simulation results demonstrate that it achieves a 126.19% improvement in cosine correlation (ρ) and an 81.81% enhancement in normalized mean square error (NMSE) compared with conventional DFT-based DL schemes. These results highlight its ability to deliver high reconstruction precision even under low SNR conditions, thereby making it an excellent candidate for low-power or bandwidth-constrained feedback scenarios.

Building upon this foundation, a Hadamard Transform-based DL framework (HaDLeMO) is developed, which employs the discrete Hadamard transform (DHT) for a low-complexity, permutation-invariant, and energy-compacting CSI representation. The DHT provides fast,

multiplication-free operations, allowing for real-time deployment in large-scale wireless systems. The proposed HaDLeMO framework achieves a 109.52% improvement in cosine correlation (ρ) and a 257.14% enhancement in NMSE compared to DFT-based models. In addition to superior reconstruction accuracy, HaDLeMO exhibits rapid convergence, reduced training complexity, and strong resilience across a wide range of SNR values, making it highly suitable for scalable 5G and emerging 6G deployments.

To further improve CSI reliability under noisy and non-ideal conditions, a DL-based denoising network (DeNoNet) is proposed. DeNoNet integrates a noise suppression module within the CSI encoder–decoder architecture, allowing it to mitigate interference, nonlinear distortions, and environmental noise commonly encountered in practical wireless environments. By encoding CSI into compact and noise-resilient feature representations, DeNoNet ensures accurate reconstruction even under severe signal degradation. Performance analysis reveals that DeNoNet outperforms the DRT-based model by 113.18% in NMSE and 72.72% in cosine correlation (ρ), underscoring its superior denoising capability and robustness in low SNR regimes where traditional approaches tend to fail.

Finally, the thesis undertakes a comparative evaluation of multiple neural architectures, including Convolutional Neural Network (CNN) and Channel Denoising Network (CDN) models, benchmarked against the baseline Deep Autoencoder (DeepAE) framework. The CNN-based DFT model achieves a cosine similarity of 0.770, while the CDN model further improves it to 0.890, compared to 0.567 achieved by DeepAE. Correspondingly, NMSE improves from -5.33 dB (DeepAE) to -11.42 dB (CNN-DFT) and -16.30 dB (CDN). These results demonstrate the effectiveness of spatial feature extraction and denoising integration in enhancing CSI feedback performance, leading to significant gains in structural efficiency, noise resilience, and overall system reliability.

The thesis has been organized as follows:

Chapter 1: Introduction

This chapter provides an overview of the fundamental concepts and existing mechanisms related to CSI acquisition and feedback in massive MIMO systems. It discusses the limitations of traditional CS-based techniques and highlights the motivation for adopting DL-based approaches to enhance compression efficiency, reconstruction accuracy, and robustness under practical conditions. The chapter further outlines the key challenges addressed in this research work and briefly introduces the transform-assisted DL frameworks proposed in this thesis as potential solutions to overcome these limitations.

Chapter 2: A Review on DL applications in CSI Feedback Reduction

This chapter explores the existing literature on the researches on CSI feedback reduction in massive MIMO. Recent research on CSI feedback has focused on enhancing compression efficiency and reconstruction accuracy through both compressive sensing (CS) and deep learning (DL) methods. Adaptive CS-based techniques exploit spatial and block sparsity to reduce pilot overhead and complexity, while iterative models like LASSO and AMP-Net improve sparse signal recovery. DL-based frameworks such as CsiNet and CsiNet+ employ end-to-end encoder decoder architectures for compact CSI representation. Extensions including CRNet, PRVNet, TransNet, DeepAE and CSI-StripeFormer leverage multi resolution and Transformer-based mechanisms for higher accuracy. Despite their success, high computational demands motivate hybrid transform

integrated DL architectures for scalable and energy efficient CSI feedback.

Chapter 3: DRT-Assisted DL- for Massive MIMO CSI Feedback Reduction

This chapter introduces the importance of minimizing channel state information (CSI) feedback overhead which is a critical requirement in fifth-generation (5G) and upcoming sixth-generation (6G) massive multiple input multiple output (MIMO) systems. Although compressive sensing (CS) techniques have been explored to tackle this issue, the use of the discrete Fourier transform (DFT) introduces considerable computational complexity. To overcome this limitation, this study proposes a novel discrete Rajan transform (DRT)-based deep learning (DL) framework for efficient CSI feedback enhancement in massive MIMO networks. Simulation results demonstrate that the proposed DRT-based model achieves performance gains of 126.19% and 81.81% in cosine correlation and normalized mean square error (NMSE), respectively, compared to the conventional DFT-based DL approach across various signal-to-noise ratio (SNR) conditions. Furthermore, the DRT-based algorithm exhibits robust performance under low SNR environments, underscoring its suitability for practical large scale wireless communication systems.

Chapter 4: Hadamard Transform Enhanced DL-for Massive MIMO CSI Feedback Reduction

Building upon the concept of transform-based learning, we presents HaDLeMO, a deep learning framework leveraging the discrete Hadamard transform (DHT). The DHT offers low computational complexity, permutation invariance, and high energy compaction, enabling efficient CSI representation within a compressive sensing deep learning (CS-DL) architecture. Through extensive simulations, HaDLeMO demonstrates significant performance gains achieving improvements of 109.52% in cosine correlation and 257.14% in NMSE compared to the DFT-based DL algorithm. The method exhibits rapid convergence, reduced training complexity, and resilience across diverse SNR scenarios, making it a practical candidate for large scale 5G/6G massive MIMO systems.

Chapter 5: Deep Learning Based Denoising in FDD Massive MIMO

In this Chapter, our research introduces DeNoNet, a deep learning-based denoising network designed to handle the effects of channel interference, noise, and nonlinearities in CSI feedback. DeNoNet encodes CSI into compact, noise resistant representations that facilitate accurate reconstruction under degraded conditions. Simulation analysis indicates that DeNoNet surpasses the DRT-based DL approach by 113.18% in NMSE and 72.72% in cosine correlation (ρ). The model performs exceptionally well under low SNR conditions, where traditional models typically fail, validating its robustness and adaptability for real time wireless communication environments.

Chapter 6: CDN and its Comparison with CNN for CSI Feedback Reduction in Massive MIMO

To further validate the effectiveness of the proposed frameworks, this chapter evaluates the performance of Convolutional Neural Network (CNN) and Channel Denoising Network (CDN) architectures against the baseline DeepAE model. The results show that the CNN-based DFT model achieves a cosine similarity of 0.770, while the CDN model improves this to 0.890, compared to 0.567 for DeepAE. Similarly, NMSE improves from -5.33 (DeepAE) to -11.42 (CNN-based DFT) and -16.30 (CDN). These consistent gains across SNR levels up to 10 dB demonstrate the superior noise handling capabilities and structural efficiency of the proposed DL-

based methods. Furthermore, both the CNN-based DFT and CDN frameworks show strong performance in low SNR environments, underscoring their suitability for real world 5G/6G applications that demand reliability under varying channel conditions.

Chapter 7: Conclusion

This chapter summarizes the key outcomes of the research focused on efficient CSI feedback in massive MIMO systems using transform-assisted DL frameworks. It highlights how the proposed DRT, DHT (HaDLeMO), and DeNoNet architectures achieve improved accuracy, robustness, and computational efficiency compared to conventional DFT-based and autoencoder-based models. The chapter concludes that hybrid mathematical–neural approaches effectively capture channel sparsity and offer a promising direction for low-complexity, high-performance CSI feedback in future 6G networks.

List of Journal Publications:

[1.] Amit Kumar, A. Raza, Shivanshu Shrivastava*, P. Katragunta, M. Barbeau, D. Prahladas Kothari, and T. Verma, “A Novel DRT-Assisted Deep Learning-Based Channel Feedback Mechanism for Massive MIMO,” IEEE Transactions on Consumer Electronics, vol. 71, no. 2, pp. 6734–6743, 2025. (IF: 10.9)

[2.] Amit Kumar, Shivanshu Shrivastava*, and Xiao-Zhi Gao, Enhanced CSI Feedback via Deep Learning Based Denoising in FDD Massive MIMO, Accepted in AEÜ – International Journal of Electronics and Communications, 2025. (IF: 3.2)

[3.] Amit Kumar, A. Raza, Shivanshu Shrivastava*, P. Katragunta, and M. Barbeau, “A Hadamard Transform Enhanced DL-based Channel Feedback Mechanism for Massive MIMO,” IEEE Transactions on Consumer Electronics, 2025 (Under Review). (IF: 10.9)

[4.] Amit Kumar, Shivanshu Shrivastava* and OJ. Pandey, “Performance Evaluation of CNN and CDN for CSI Feedback Reduction in Massive MIMO,” IEEE Transactions on Network and Service Management, 2025 (Under Review). (IF: 5.4)

[5.] Amit Kumar, Shivanshu Shrivastava*, and X. Gao, A Two-Tier Deep Learning Architecture for Efficient CSI Feedback in 5G and Beyond Massive MIMO, Information Sciences (2025) (Under Review). (IF: 6.8)

List of Conference Publications:

[1.] **Amit Kumar** and Shivanshu Shrivastava, Deep Neural Network Denoising for Enhanced CSI Feedback in FDD Multi-User MIMO Systems, Accepted in: 2025 IEEE 17th International Conference on Computational Intelligence and Communication Networks (CICN), IEEE, 20-21 dec, 2025.

