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Deep Learning-Based Channel Estimation Method for Mimo Systems in Spatially Correlated Channels

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Abstract

Receivers can usually estimate CSI with the use of known pilot signals. The BS is able to measure the down-link CSI using pilots in uplink broadcasts in the special case of time-division duplex (TDD) mode, courtesy of channel reciprocity. The BS uses UE feedback to approximate downlink CSI in frequency division duplex (FDD) mode because the channel reciprocity of the uplink channel and the downlink channel is less than 100 rather limited. One important consideration is how to reduce feedback bandwidth while keeping downlink CSI predictions correct; this is known as the CSI feedback scheme. Deep learning-based alternatives to CS approaches for compressed CSI estimation have been proposed in recent studies. In order to derive compressed versions of high-dimensional CSI, these suggested approaches usually make use of convolutional neural networks (CNNs). The CNN-based research has two broad types of deep learning architecture. Convolutional neural networks (CNNs) networks for autoencoders fall into the first group. These networks have two subnetworks: one that learns a low-dimensional representation from the original data and estimates the original data using this representation. The second kind of CNN is an unrolled optimization network, which takes its cues from the aforementioned CS techniques by constructing the CNN based on a set of small number of repeated blocks, which resembles an iteration of a particular CS algorithm. We also enhance those which came before where the homogeneous differential encoders are used by the heterogeneous differential encoder which utilizes different network architectures per time slot, giving more accurate estimations.

Keywords: Deep Learning, Mimo, CNN, Algorithm and Frequency

1. Introduction

Through with the application of multiple-input multiple-output (MIMO) systems, wireless communication has advanced and significant advancements have been achieved in the data rates, network performance, and the spectrum efficiency. Various 5G networks and other telecommunications standards now use various multiple-input multiple-output (MIMO) technology. It involves a high number of transmitting and receiving antennas. The constant demand to have a reliable and fast connection implies that MIMO systems will be even more crucial to the 6G implementation. These systems are required in the cases where more reliability is needed across diverse environments since it offers greater capabilities such as beamforming, spatial multiplexing and diversity gain. Given this environment, MIMO systems have become an essential technology for meeting the growing need for reliable, high-capacity communication.

MIMO systems take use of spatial diversity to improve signal quality and data throughput by using at the sender and receiver sides of the communication are a number of antennas. chain. Manual beamforming setup and power regulation are two examples of conventional approaches to optimize MIMO systems; however, these approaches are becoming more inadequate in increasingly complex IoT contexts. The Intelligent Reflecting Surface (IRS) is a set of passive components that may modify the amplitude, phase, and direction of incoming electromagnetic waves; it offers a potential answer to this problem. IRS are a cost-effective and energy-saving manner of. improve the performance of a network since they may reflect signals towards the receiver while using very little power.

Incorporating IRS into MIMO systems adds a new level of adaptability, which might help with signal fading, interference, and general communication quality, especially where a direct line-of-sight. connection is blocked. The benefits of IRS in IoT networks can only be realized, however, with precise channel state information (CSI). Accurate channel information between the IRS, receiver, and transmitter is crucial for MIMO communication to work, since it allows the system to fine-tune the reflection settings. In recent years, AI and ML have developed into potent resources for addressing the difficulties of CSI acquisition and IRS optimization. Using AI and ML algorithms, we can adjust IRS parameters instantly, adapt to ever-changing network conditions, and substantially enhance the precision and efficacy of MIMO channel estimates. More autonomous, scalable, and intelligent MIMO systems for the Internet of Things should be possible as a result of these advancements., guaranteeing that they can manage the burden of contemporary communication applications.

2. Literature Review

Balasoupramanien, Rajarajeswarie *et al*. (2020) [1]. The goal of achieving fast data transfer rates with little delay is driving the present mobile infrastructure to its limits, since the quantities of mobile traffic are growing at an exponential pace. As a result of its great data rate and system throughput, massive MIMO is a very promising technology for 5G wireless communication networks. The tremendous computational complexity and the considerable difficulty in using the multiple antenna systems are the key obstacles in this technology. Therefore, The goal of this survey research is to analyze the problems with 5G wireless networks' Massive MIMO systems and how intelligence may help fix them so that users have a better experience and radio resources are used more efficiently. Consequently, this article offers a concise overview of the use of AI in 5G wireless systems to address many issues with the Massive MIMO system.

Asimiyu, Zainab. (2024) [2]. Improving IRS-Assisted MIMO Systems with Advanced Internet of Things Connectivity with the Use of AI and ML. Rapid growth in the number of Internet of Things (IoT) devices has accelerated the need for innovative approaches to address connectivity, scalability, and performance issues plaguing dense wireless networks. This research explores the potential integration of AI, ML, and Intelligent Reflecting Surfaces (IRS) to enhance Multiple-Input Multiple-Output (MIMO) systems, which are essential for current Internet of Things (IoT) connectivity. Using AI-driven ML models, the research delves into new ways to optimize IRS configurations, improve channel estimation accuracy, and enable real-time network adaptation. Featured are uses in autonomous systems, smart cities, healthcare, and the industrial internet of things; discussed in depth are technological hurdles and potential avenues for further study. More robust, efficient, and intelligent wireless networks are on the horizon, thanks to this study's emphasis on AI and ML's revolutionary potential to redefine IoT connection.

Sun, Bule *et al*. (2023) [3]. This document is a detailed account of the WAIC (Wireless Advanced Information Competition) track that employs AI for channel estimation in the second edition. The 5G+AI Work Group, which is part of the IMT-2020(5G) Promotion Group, is hosting the track. To begin, you'll need to provide the demodulation reference signal (DMRS) and the dataset that will be used to solve the channel estimation problem. Following that, we will discuss several approaches to enhance the performance of AI-based channel estimates, taking into account data analysis, pre-processing, critical components, and backbone network designs. Finally, the final results of the competition are in, and they contained a range of solutions. The second WAIC's channel estimation track, which is based on AI, might provide useful recommendations for researchers and businesses alike.

Xiang, Bingtong *et al*. (2023) [4]. An FDD large Downlink channel estimation is the main topic of this letter, which focuses on multiple-input multiple-output (MIMO) systems. Obtaining the downlink channel state information (CSI) is more complex as the number of antennas grows, which limits the performance of communication systems. Without feedback, a deep learning system estimates the downlink CSI. The uplink cluster is first obtained using the receiving signals in the proposed method. After that, the uplink cluster data is sent into a neural network to forecast the downlink channel. The results of the simulation show that the proposed method may successfully achieve higher achievable spectral efficiency.

He, Hengtao *et al*. (2018) [5]. In beamspace millimeter-wave (mmWave) large MMI/O systems, channel estimation becomes very difficult when the receiver only has a few RF chains. Our approach involves using an LDAMP network, which is based on learnt denoising, to address this issue. As a result of its ability to learn from a huge amount of training data, this neural network can estimate channels and understand their structure. Our study also includes providing a mathematical basis for the asymptotic performance of the channel estimator. Our simulation and analysis demonstrate that the LDAMP neural network outperforms state-of-the-art approaches based on compressed sensing, even when the receiver only contains a few RF chains. As a result, mmWave channel estimation is greatly enhanced by deep learning.

3. Research Methodology

3.1 System Model: This research takes a look at large proposed a uniform planar array (UPA) as an effective approach for antenna placement in multiple-input multiple-output (MIMO) systems that use non-directional (NT) transmit and non-radiative (NR) receive antennas. To get over multipath fading channels, the cyclic prefix orthogonal frequency division multiplexing (CP-OFDM) method is used. The signal that was picked up vector y (k, n) = y1 (k, n)··· ynr (k, n)··· yNR (k, n) T, which is linked to the kth subcarrier and the nth symbol interval, may be written as follows, assuming perfect synchronization at the receiver side:

$$\mathbf{y}(k,n) = \sqrt{\gamma}\mathbf{H}(k,n)\, s(k,n) + v(k,n)\,,$$

3.2 Improving Computational Efficiency

This dissertation reviews previous work that has enhanced deep neural networks' performance for CSI compression by using domain knowledge. Here we take a look at a few ways to make these networks more efficient.

Estimating the shortened delay domain using frequency domain pilots at the UE. Using Further computational and memory resources are added by the P2DE at the UE. load, even if it's sparsity beneficial to obtain the delay domain CSI at the UE. Go back to Algorithm 4.1 and think about the P2DE estimator. The algorithm multiplies matrices iteratively across the Nb antennas $_{d;i}Q^{\#}{}_{c;j}$ the course of each cycle. To execute the algorithm, N_bM_f (N_f 1) FLOPs are required[1], and 2D (M_f N_f) Using the P2DE at the UE might lead to an extra charge, therefore parameters must be stored 2. 1:04 10^6 FLOPs and 2:62 10^5 parameters.

3.3 Proposed Deep Learning-Based Channel Estimation Method

Here we present the channel estimation method that uses deep learning to reduce the workload of pilot symbol-assisted channel estimation in spatially correlated MIMO channels. This is achieved by the suggested technique cut down on the ratio of pilot symbols to transmit antennas, that is, $N_T^{\text{pilot}} < N_T$. Both P and N are sets of indices of transmit antennas; P contains those that convey pilot symbols, whereas N does not. After that, $U=P \cup N$ is an array that contains all transmit antenna indices. It should be noted that P and N have cardinalities of $|\mathcal{P}| = N_T^{\text{pilot}}$ and $|\mathcal{N}| = N_T - N_T^{\text{pilot}} = N_T^{\text{null}}$. For ease of notation, we will now omit (k, n), the subcarrier and symbol interval indices.

4. Results

Our goal is to assess the efficacy of reusing models and direct frequency-domain CSI input using Indoor and outdoor CSI data generated by the COST2100 model settings. Using ISTANet+ with spherical normalization, we conduct all tests.

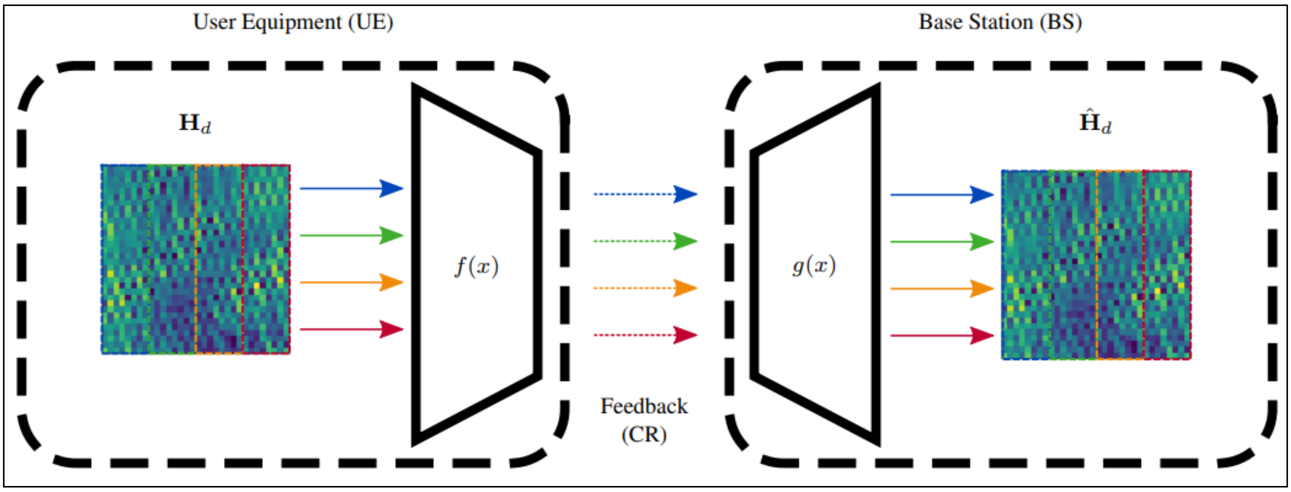

Fig 1: Compressive CSI estimation with model re- use

In place of reducing the input data size to zero, H_d, by compressing K adjacent subcarriers from the input, the encoder produces $^{M}{}_{K}{}^{f}$ feedback payloads (shown by various colours in the image above). Base station (BS) decoders use the $^{M}{}_{K}{}^{f}$ the complete estimate in the frequency domain is generated by combining the encoded and decoded payloads.

4.1 Simulation Results

Here, we use Monte Carlo simulations to assess how well in MIMO-OFDM systems, the proposed channel estimation method is effective. The simulation parameters utilized in the system and DNN are detailed in Tables 1 and 2, respectively. We estimate the channel using the LMMSE algorithm and recognise symbols using the zero-forcing decoder; both methods are based on the pedestrian channel models found in. As a point of reference, we also assess how well the traditional channel estimate approach works in. To follow the standard procedure, NT pilot symbols are sent by every transmit antenna. On the receiving end, NT pilot symbols are used to produce NT estimated channel vectors h^nt, and an LMMSE algorithm is employed. At long last, we can get a predicted MIMO channel matrix using linear interpolation. $\hat{\mathbf{H}} = \left[\hat{\mathbf{h}}_1 \cdots \hat{\mathbf{h}}_{n_t} \cdots \hat{\mathbf{h}}_{N_T}\right]$ for each and every subcarrier and interval of symbols.

Table 1: System parameters for simulations.

Parameters	Values
Antenna configuration, (N_T, N_R)	(64, 2), (128, 2)
Number of pilot symbols, N_T^{pilot}	$r = 0.875$: 56, 112, for $N_T = 64, 128$
	$r = 0.938$: 60, 120, for $N_T = 64, 128$
	$r = 0.969$: 62, 124, for $N_T = 64, 128$
Modulation scheme	QAM
Modulation order	4
Correlation coefficient, ρ	0.7, 0.8, 0.9
Subcarrier spacing	15kHz
Number of subcarriers	1024
Pilot spacing in the frequency domain	12
Pilot spacing in the time domain	16
Channel model	3GPP pedestrian A
Interpolation method	Linear [44]
Precoder	DFT precoding [55]

Table 2: DNN parameters for simulations.

Parameters	Values
Number of nodes of input, output layers, $\{d_0, d_{M+1}\}$	$r = 0.875$: $\{224, 256\}$, $\{448, 512\}$ for $N_T = 64, 128$ $r = 0.938$: $\{240, 256\}$, $\{480, 512\}$ for $N_T = 64, 128$ $r = 0.969$: $\{248, 256\}$, $\{496, 512\}$ for $N_T = 64, 128$
Number of nodes of hidden layers, $\{d_1, \cdots, d_M\}$	$\{1024, 1024, 1024\}$
Activation function	ReLU
Learning rate	1×10^{-5}
Number of epochs	500
Batch size	32
Optimizer	Adam [56]

To start, there's the NMSE performance, which is

$$\mathrm{NMSE} = \mathbb{E}\left[\frac{\left\|\mathbf{H} - \bar{\mathbf{H}}\right\|_F^2}{\|\mathbf{H}\|_F^2}\right]$$

is assessed using different r and ρ values. Illustrations 4.11 and 4.10 indicate that the channel estimate accuracy improves with increasing SNR when using the standard technique, which delivers pilot symbols for all transmit antennas and runs the LMMSE algorithm. But The proposed technique outperforms the conventional channel estimation methodology in terms of NMSE performances are worse, and the problem becomes worse as r gets smaller. This is due to the fact that the suggested approach uses a DNN to forecast the CSI of transmit antennas that do not broadcast pilot signals. This means that r has to be carefully selected to ensure the communication system has good link reliability, as the suggested method's NMSE performance is limited even when SNR values are increased. In this study, we'll use r=0.875, 0.938, and 0.969 to get BER performances that are almost identical to those of the traditional technique. By examining the correlation coefficient, ρ, at NT=64, NR=2, and r=0.969, Fig. 4 illustrates the NMSE performances of the traditional and suggested methods. For strongly correlated channels, the standard technique shows poor NMSE results (Fig. 4). In contrast to the traditional approach, it is evident that the NMSE performances of the suggested strategy deteriorate with decreasing ρ values. This is to be expected, given that the DNN in the suggested strategy is tasked with discovering the unknown variables only via spatial correlation, without pilot symbols. Moving forward, we will solely assess the ρ=0.9 instance to demonstrate the performance benefit of the suggested strategy.

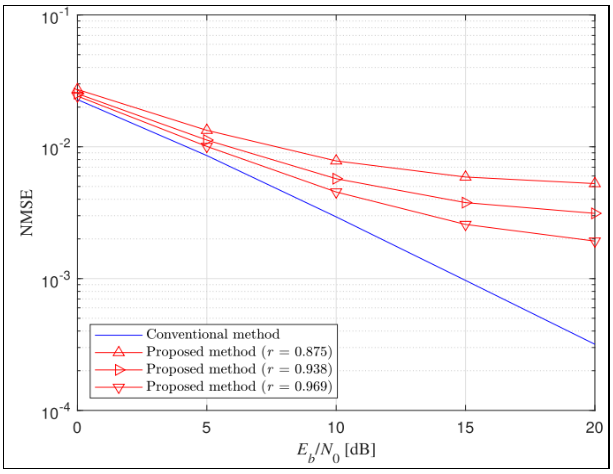

Fig 2: Comparison of NMSE performances (nt=64 and nr=2).

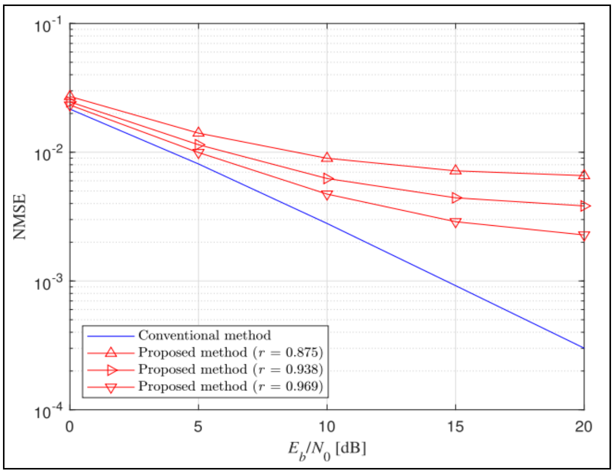

Fig 3: Comparison of NMSE performances (nt=128 and nr=2).

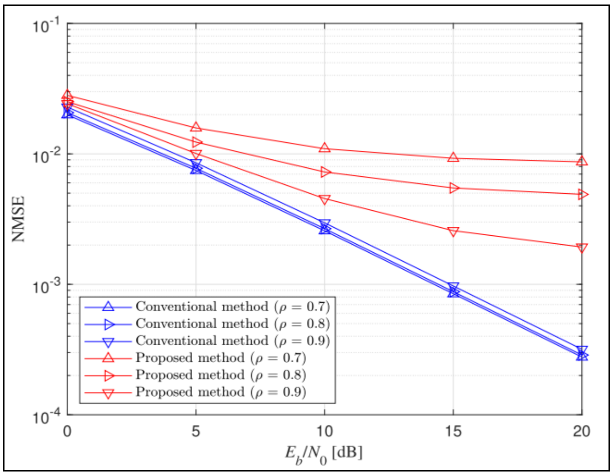

Fig 4: Comparison of NMSE performances according to the correlation coefficient, ρ (nt=64, nr=2 and r=0.969).

Figures 5 and 6 show the BER results for the traditional and suggested approaches, respectively. In contrast to the NMSE performance, the suggested technique shows almost identical BER performance to the traditional method with r=0.969, independent of antenna configurations. The findings show that the suggested technique meets the NMSE performance requirements to keep the BER performance of the traditional method, with a correlation coefficient of 0.969. On top of that, we can see that NMSE performance degrades significantly as r drops, yet BER performance decline is almost nonexistent.

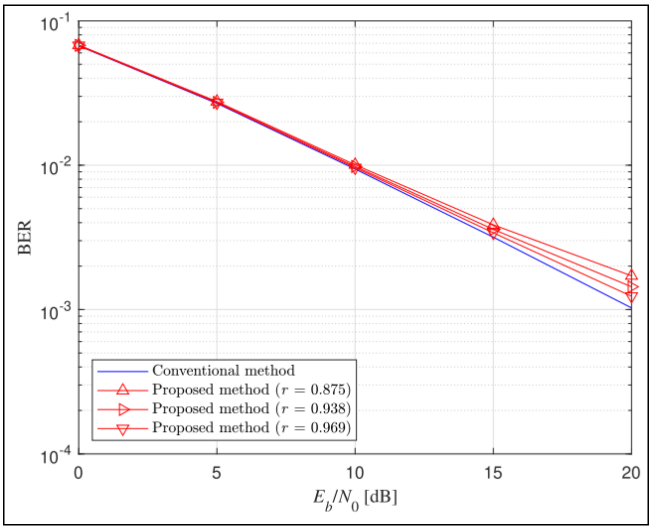

Fig 5: Comparison of BER performances (nt=64 and nr=2).

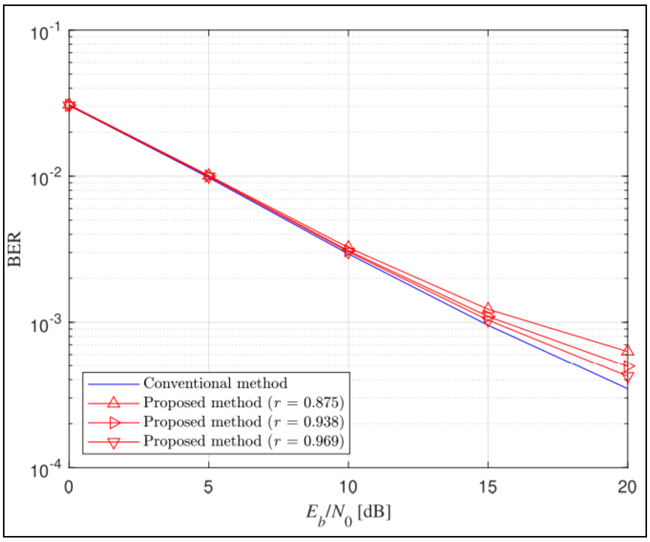

Fig 6: Comparison of BER performances (nt=128 and nr=2).

Figures 7 and 8 show an analysis of the conventional methods' throughput capacity in contrast to the suggested approaches. By reducing the number of pilot symbols used while keeping BER performances the same, the suggested technique outperforms the standard method from a throughput perspective. Furthermore, the proposed method outperforms the throughput performances of other scenarios, although displaying relatively high BER performance decrease (r=0.875). So, reducing pilot overhead has a disproportionately significantly affects throughput. The objective BER performance of the proposed technique is disappointing, unfortunately. will be unsatisfied if the number of pilot symbols is drastically lowered. Hence, r has to be carefully selected to sacrifice throughput and BER performance, depending on the cases where the suggested approach is used.

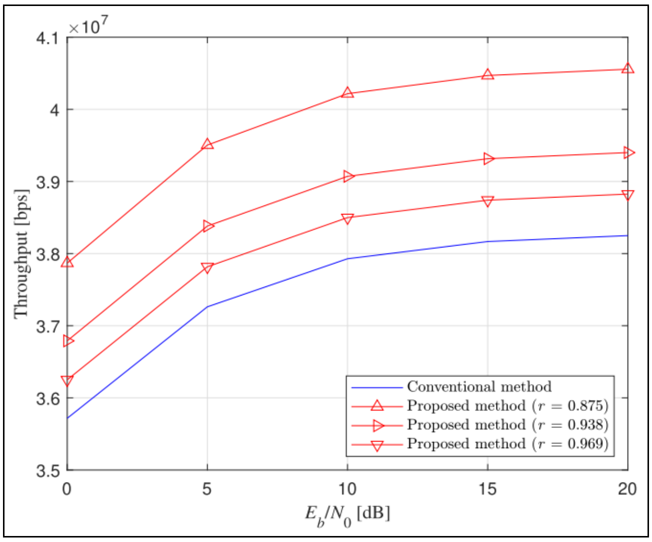

Fig 7: Analyzing throughput performances (nt=64 and nr=2).

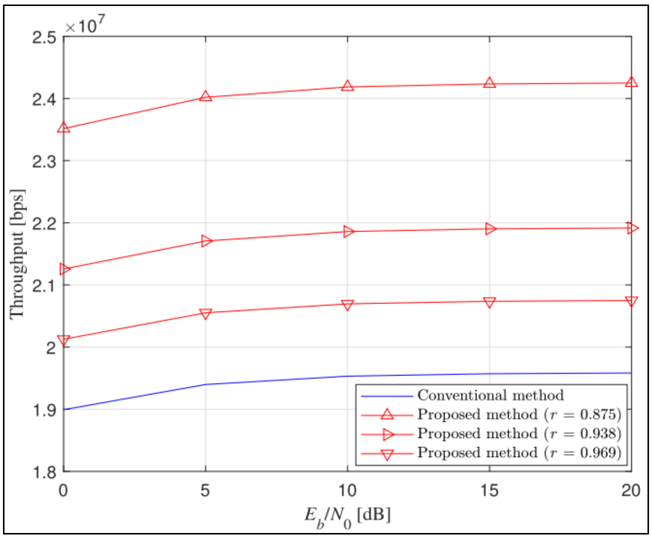

Fig 8: Comparison of throughput performances (nt=128 and nr=2).

The suggested method's NMSE performances are somewhat poorer in the NT=128 case compared to the NT=64 case when comparing the results according to the antenna configurations. Because it is able to obtain a bigger diversity gain, the NT=128 case has superior BER performance compared to the NT=64 case. It should be noted that improving BER performance will not result in greater throughput performance compared to NT=64 as both instances use the same modulation order and the NT=128 scenario requires additional pilot overhead for channel estimation. The NT=128 example, when applied to real-world systems, takes use of adaptive modulation and diversity gain to achieve a higher modulation order, leading to better throughput. When using channel estimation in massive MIMO systems using pilot symbols, it is crucial to reduce the pilot overhead, as we can see from these considerations.

5. Conclusion

we looked at methods that improved computing efficiency and estimate accuracy by using domain knowledge of the wireless channel in a way that better followed 3GPP standards. Similar strategies that use wireless channel, communications protocol, or CSI data properties should be used in future CSI compression studies. Our proposal for multiple-input multiple-output (MIMO) systems in spatially correlated channels that relies on deep learning. The goal is to decrease the amount of pilot symbols that are required. The suggested approach uses a DNN to forecast the CSI of transmit antennas that aren't transmitting pilot symbols and to recreate the predicted MIMO channel matrix. Through a comparison of different performances with the traditional channel estimation approach, the results of the simulation prove that the proposed technique is valid. Through the application of the proposed deep learning-based method to data-aided channel estimation, we aim to improve the accuracy and performance of channel estimation in time-varying channels method in future research.

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