Numerical Simulation and Design Assessment of Limited Feedback Channel Estimation in Massive MIMO Communication System

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ABSTRACT: The Internet of Things (IoT) has attracted a great deal of interest in various fields including governments, business, academia as an evolving technology that aims to make anything connected, communicate, and exchange of data. The massive connectivity, stringent energy restrictions, and ultra-reliable transmission requirements are also defined as the most distinctive features of IoT. This feature is a natural IoT supporting technology, as massive multiple input (MIMO) inputs will result in enormous spectral/energy efficiency gains and boost IoT transmission reliability dramatically through a coherent processing of the large-scale antenna array signals. However, the processing is coherent and relies on accurate estimation of channel state information (CSI) between BS and users. Massive multiple input (MIMO) is a powerous support technology that fulfils the Internet of Things' (IoT) energy/spectral performance and reliability needs. However, the benefit of MIMOs is dependent on the availability of CSIs. This research proposes an adaptive sparse channel calculation with limited feedback to estimate accurate and prompt CSIs for large multi-intimate-output systems based on Duplex Frequency Division (DFD) systems. The minimal retro-feedback scheme must retrofit the burden of the base station antennas in a linear proportion. This work offers a narrow feedback algorithm to elevate the burden by means of a MIMO double-way representation (DD) channel using uniform dictionaries linked to the arrival angle and start angle (AoA) (AoD). Although the number of transmission antennas in the BS is high, the algorithms offer an acceptable channel estimation accuracy using a limited number of feedback bits, making it suitable for 5G massively MIMO. The results of the simulation indicate the output limit can be achieved with the proposed algorithm.

Keywords: *IOT, MIMO, DFD, 5G*

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1. INTRODUCTION

Massive MIMO is an evolving technology that uses antenna arrays of several hundred antennas that serve several dozen endpoints at the same time. The promises of this technology, which make it suitable for wireless 5 G next-generation systems, are considerable improvement in spectral performance, improved chain response and simpler transceiver designs (Wang et al., 2014; Akyildiz et al., 2014). The 5 G wireless infrastructure is forecast to provide the power of today's mobile networks as much as 1000 times. In order to serve current and new applications better, the 5 G mobile infrastructure can also handle substantially more cellular Chapters 1 10 connexions. No single technology will comply with the rigorous 5 G QoS specifications, such as improved delay, reliability, higher spectrum and energy efficiency. There is also a need to build and jointly incorporate a range of wireless technologies (Gavrilovska et al . 2016). Until now, much of the research work on the broad MIMO was solely theoretical, mostly due to its practical constraints on hardware design and massive and voluminous dimensions of the antenna range.

At 5 G, even if our mobile phone is in one bar or two, or we're thinking about video chatting and streame blockbuster movies, we can't even think of downloaded a file twice. Often, it is as seamless as streaming music to conduct such practises. 5 G NR (New Radio) technology is one of the key elements to activate these 5 G user interactions. Multiple Input Multiple output (MIMO) technology.And with the global rollout of 5 G, consumer aspirations also grow as the capacities of today's mobile networks significantly increase. We have covered mm Wave 's concepts for mobile, beam shaping and low latency in our ongoing series of blog postings to illustrate our breakneck innovations that make 5 G a reality. Now we can view huge 5 G NR MIMO and how this technology improves mobile device users as well as networks.Huge MIMO is the secret to allowing very high data speeds of 5 G and aims to increase the capacity of 5 G to a new stage. The principal benefits to the network and end users of massive MIMO can be summarised as follows:

Increased network capacity: Network capability is defined as the total amount of data that can be provided to a user or the maximum number of users who can be supported by a certain service level. Massive MIMO will improve capabilities first by allowing 5 G NR deployment in Sub-6 GHz (e.g. 3.5 GHz), and second through use of MU-MIMO, where many users are supported with the same frequency and time resources.

Improved coverage: Customers have a more uniform network experience with huge MIMO, including on the cell front – enabling users to anticipate a high-data rate service almost anywhere. 3D beamforming also allows for complex coverage needed for moving users (e.g. travellers travelling in vehicles or connected cars) and changes the coverage for user locations, even where the network coverage is relatively small.

User experience: In short, the two above advantages result in a great user experience – wherever life takes users to upload massive data files or watch movies or use data-hungry applications on the go.

As previously mentioned, MIMO has been used for several years in wireless communications. But now, with 5G, a massive MIMO changes dramatically the way we use our mobile devices and how they use them. If we're in a good place to download or upload big files we no longer have to second guess. A major leap forward is on the verge of user interface.

The main purpose of the dissertation is to provide an efficient 5G network by efficient channel estimation and precoding. To achieve the goal following steps of work as objectives are considered:

- To design and simulate Massive MIMO Communication System Model.
- To analyse the challenges in channel estimation and precoding of Massive MIMO system.
- To design and implement efficient hybrid precoding scheme for massive MIMO systems.
- To design and implement support detection (SD)-based/machine learning/deep learning based efficient channel estimation for massive MIMO system.
- To analyze the figure of merits and perform comparative assessment of proposed system.

2. LITERATURE REVIEW

[Hengtao He et.al, 2018] The channel calculation is very difficult because the recipient has an ampl chain (mmWave) mm-wave (MF) in multiple input and multiple output systems. We use an approximate message centred on the denoising network of moving networks (LDAMP) in order to solve this problem. This network is in a position to learn the channel structure and to estimate a large amount of training knowledge. Data for preparation. Furthermore, on the asymptotic efficiency of the channel estimator. Building on the new compressed sensing, our LDAMP neuronal network research and simulation results even surpass if the receiver has a limited algorithm. RF chains number. In this article Huge MIMO systems for beamspace mmWave we present our initial findings in profound learning. Apply a standard 2D image channel matrix Approximate message transmission (LDAMP) depending on denotation network denotative convolution (DNCNN) channel estimate signal recovery algorithm Much of this study is the first to use our expertise in depth. Technology for estimating channel beamspace. The network uses as many data training on channel matrices as can be used for a variety of choices. The research framework also provides the asymptotic output of LDAMP on the channel evaluation. The results of the analyses and simulations are from LDAMP. With few RF chains the network reaches advanced compressed sensing (CS). [1]

[Shiguo Wang et.al , 2019] discussed Huge multiple input output is a big technology in 5 G, It allows many users to use pre-coding or beam forming techniques in the same frequency block, thereby increasing power, reliability and efficiency in energy. A key issue in a large MIMO is the power allocation for each antennas to achieve a specific goal , i.e. to optimise the minimum user energy. This is an NP-hard issue that has to be addressed promptly, since the status of the channels is changing in due course, with the power allocation still in sequence. Although several heuristics have been suggested for the resolution of this dilemma, they require a substantial amount of time. As a consequence, power allocation can not be assured on time with the present methods. We propose a deep neural network (DNN) to solve this problem. A DNN has a low time complexity; however, before it is operational, a rigorous training phase is required. The DNN that we propose consists of two convolutionary layers and four layers. It takes the long term data fading as an input and provides every consumer with the power for each antenna feature. We are limited to sub 6GHz networks based on the Time-Division (TDD). Numeric results show that the results of a widely used heuristic based on the bisectional algorithm are very approximated by our DNN-based method. [2]

[Yu Zhao et al, 2020] The author says the combination of cell-free multi-input (MIMO) systems with a microwave (mmWave) tape is indeed one of the most promising technical enablers to the imagined wireless Gbit / s experience. The author says. However, both massive antennas and broad bandwidth at mmWave trigger high computer complexity to use a precise approximation of the channel state information. With the sparse channel matrix of the mmWave being a natural image, we propose a realistic and accurate channel estimation method on the basis of the fast and versatile FFDNet. Unlike earlier methods of profound learning, FFDNet is ideal for a broad spectrum of signal / to noise levels, with the input being a versatile noise level map. In particular, we deliver a detailed study to refine the Channel Estimator based on FFDNet. Extensive simulation results confirm that FFDNet 's training speed is more rapid than state-of-the-art channel estimators without sacrificing standardised mean square error efficiency. FFDNet is a handy channel estimator for large MIMO systems using cell-free mmWave. [3]

[Yu Jin et.al, 2019] Wireless networks are complex, huge and demanding on capacity increased demand led to difficulties in network component management and monitoring. Smart data-driven designs and methods would also be required to reform the 5th generation (5 G) of mobile networks for self-organization. So mathematical models have been developed and adapted between modems in the last decade. This article offers a full overview of recent research into in-depth models of learning for strong MIMO systems. The main part of the work includes the reconstruction of the traditional communication system using deep learning models. This can include channel encoding, decoding, tracking, antenna identification, modulation, etc. It is important to understand that a deeper-learning autoencoder, convolutionary neural networks, etc, replaces a communication system with a fundamentally new architecture. These deep learning models show promising performance improvements with some limits and can be used in huge MIMOs efficiently. [4]

[Vandana Bhatia et al , 2020] In this paper, the author briefly describes how the calculation of the multiple input channel (MIMO) for vehicle communication is highly demanding because of the shift in channel and low latency. In this paper, the newly emerging and popular deep neural network is used to improve the accuracy and reduce the delay of massive MIMO channel evaluation to learn the sparing information in the MIMO channel and to more reliably and more rapidly estimate the channel. First, a new massive MIMO Channel Evaluation scheme (DLCE) based on profound learning is proposed, which achieves an efficient balance between accuracy and channel delay assessments. In addition, an improved method called spatial correlated DLCE (SC-DLCE) is proposed to further improve the accuracy of the channel estimate, especially in a low signal-to - noise environment, using the spatial correlation of the multiantenna channel. Results from simulations have shown that the two schemes proposed will increase substantially the accuracy of a broad estimate of the MIMO channel by reducing process time in realistic terminals relative to the new benchmarking schemes. [5]

3. PROPOSED WORK

Nowadays, numerous cellular networks are using more efficient systems for symmetric traffic and delay-sensitive applications for frequency division duplexing (FDD). So in Massive MIMO we use FDD. However, FDD systems have some challenges such as downline training for CSI, while training and overhead feedback are commensurate with BS antenna number. To address the problem of a small feedback system for downlink channel, we can implement DD models. We will use the virtual sparse image of the downlink channel under this model. Each channel path is parameterised by the DD model using the BS departure angle (AoD) and a UE (AoA)[1]. When quantizing both AoD and AoA, it is possible to construct over a whole dictionary which includes steering vectors for the actual angle of arrival and exit. Then we will evaluate the channel state information in this parametrization using the greedy orthogonal pursuit matching (OMP) algorithm at UE.

Following an approximation of the CSI instant downlink in the UE, the UE sends the best matched code block index to minimise the likelihood of errors and to increase the communication over a small channel[1]. The spatially linked channel codebooks are associated with the Lloyd algorithm which helps find non-zero elements of a sparse vector with known BS threshold.

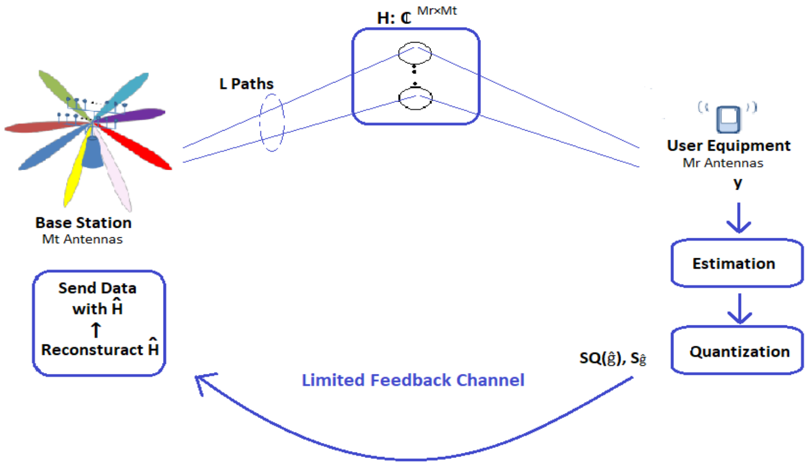

Figure 3.1 Block diagram of the Limited Feedback Channel Estimation

3.1 Modeling of Physical Layer

FDD cellular systems were our main priority. It is made up of BS antennas that serve K active UE terminals. BS estimates the downlink channel using the EU feedback channel. MT antennas are used in the BS and MR antennas contain UE. BS provides CSI input from active UE terminals for downlink transmission. The signal is then built with symbols of Ntr training. The vector Yn = H sn+ n n=1,2....Ntr,(1) below is given where sn is transmitted as a training signal, and H is a complex baseball channel [1].

$$Y_n = \mathbf{H}s_n + \mathbf{n}_n n = 1,2 \dots . N_{tr} \qquad (3.1)$$

where ***sn*** is transmitted training signal and **H** is complex baseband channel [1].

The main aim is to estimate the exact channel by providing some feedback. We tend to use a DD model with L paths in order to implement this concept. Parametry of L paths with a sparse virtual representation can be implemented. However, this sparse representation may lead to an overall and complex computational feedback regime. In the following equation the downlink channel can be described:

$$\mathbf{H} = \sqrt{\frac{M_T M_R}{L}} \sum_{l=1}^{L} \alpha_l a_{\mathrm{R}}(\phi_l) a_{\mathrm{T}}^{\mathrm{H}}(\phi_l') e^{j\varphi t} \qquad (3.2)$$

The channel downlink parameters of αl are small sizes with Rician parameters, Śl and µl's are the angle of arrival of azimuth (AoA) and the angle of departure of the azimute (AoD), steering vectors are transmitted and the signal receipt is αT (.) and αR(.).

$$\boldsymbol{a}_{\mathrm{T}}(\phi) = \sqrt{\frac{1}{M_T}} \Big[1 \quad e^{\frac{-j2\pi d_y}{\lambda}} \sin(\phi) \quad \dots \quad e^{\frac{-j2\pi d_y (M_{T-1})}{\lambda}} \sin(\phi) \Big] \qquad (3.3)$$

With carrier wavelength µ and distance between antenna elements fading across the y axis, the BS directional vector is given.

The BS steering vector is given by with carrier wavelength λ and distance between the antenna elements dy through the y axis.

This channel parameters can represent more compact form as a below.

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$\boldsymbol{A}R$=[aR(ϕ1)……. aR(ϕL)] : receive steering matrix form with its vectors

$\boldsymbol{A}T$=[aT(ϕ1′)……. aT(ϕL′)] : transmit steering matrix form with its vectors

We can also simply arrange the combination of the path loss and phase shift component;

$$\alpha = \sqrt{\frac{M_T M_B}{L}}\,[\alpha_1 e^{-j\varphi_1} \ldots \alpha_L e^{-j\varphi_L}]^T \tag{3.4}$$

Finally, via the simplest forms above we can get a more compact form instead of canal in Equation. We could get sparse representation of the channel.

$$\boldsymbol{H}=\boldsymbol{A}\mathrm{R}d(\boldsymbol{\alpha})\boldsymbol{A}\mathrm{TH} \tag{3.5}$$

First of all, we quantized AoA and AoD as dictionaries using angular space discretion. In angular areas [a, b) [-α, α] these dictionaries are defined uniformly. The dictionaries GT and GR are participants.

$$\boldsymbol{P}_T = \left\{a + \frac{j(b-a)}{G_R+1}\right\}_{j=1}^{G_T} \boldsymbol{P}_R = \left\{a + \frac{j(b-a)}{G_R+1}\right\}_{j=1}^{G_R} \tag{3.6}$$

The following dictionary matrices are the approximation of the AR and AT matrices.

$$\tilde{\boldsymbol{A}}R=\{aR(\phi) : \phi\in \boldsymbol{P}R\} \in CMR\times GR \tag{3.7}$$

$$\tilde{\boldsymbol{A}}\mathrm{T}=\{aT(\phi) : \phi\in \boldsymbol{P}T\}\in CMT\times GT \tag{3.8}$$

3.5 Modeling of Channel Estimation

The training sequence can be transmitted via the unperfect channel and error channel parameters are given in the received signal at UE. We have a measuring matrix at the UE that includes the channel steering vector information and true training sequence.

The parameters of the error channel were shown below:

$$\begin{aligned} \phi_{er} &= \phi + \beta \\ \tilde{A}_{Rer} &= \{a_R(\phi_{er}) : \phi_{er} \in P_{Rer}\} \in C^{M_R \times G_R} \\ \tilde{A}_{\mathrm{Ter}} &= \{a_T(\phi_{er}) : \phi_{er} \in P_{Ter}\} \in C^{M_T \times C_T} \\ H_{er} &\approx \tilde{A}_{Rer} G \tilde{A}_{Ter}^H \end{aligned} \tag{3.9}$$

Where β is the deflection angle, $\tilde{\boldsymbol{A}}Rer$ and $\tilde{\boldsymbol{A}}Ter$ are steering vectors the error channel.

So we can use OMP algorithm to estimate the channel status information which channel vectors can operate and send this information from UE to BS using compression and removal of inactive paths with feedback bits restriction on active pathways. This information can be used. Then the CSI can be sent from the UE through the BS and the small feedback channel estimated for the BS can be restructured for adaptive communication.

$$\boldsymbol{H}\approx\tilde{\boldsymbol{A}}R\boldsymbol{G}\ \tilde{\boldsymbol{A}}TH \tag{3.10}$$

The matrix G — the matrix CGR — the matrix and its interaction matrix, which are similar to the matrix AR and AT. Therefore we can say the kth angle PT is active when the interaction matrix is not equivalent to zero. G matrix is typically sparse if the active paths are fewer

$$\mathrm{Y}= \tilde{\boldsymbol{A}}R\boldsymbol{G}\ \tilde{\boldsymbol{A}}TH\boldsymbol{S}+\boldsymbol{N} \tag{3.11}$$

$$\begin{gathered} y = \left(\left(s^{\top}\tilde{A}_T^*\right) \otimes \tilde{A}_R\right) g + n = Qg + n \\ \text{where } y \cong \mathrm{vec}\,(Y) \in C^{M_R N_{tr}}, g \cong \mathrm{vec}\,(G) \in C^{G_T \times G_R}, n \cong \mathrm{vec}\,(N) \in C^{G_R M_R} \\ \mathbf{Q} \cong \left(s^T \tilde{A}_T^*\right) \otimes \tilde{A}_{R\in} \in C^{M_R N_{lr} \times G_T G_A} \end{gathered} \tag{3.12}$$

We need to apply a vectorizing property since vectors are easier to analyse than matrices. The obtained signal for baseband can be written when the vectorization property as the received baseband signal can be written.

4. SIMULATION

The main objective of this research work is to study the limitations of the existing channel estimation and precoding methodologies in massive MIMO system. The prime objective of the research is to enhance the spectral efficiency of the existing system and to compare the performance of system with existing and contemporary methodologies. The proposed methodology will also address the problem of power allocation and channel estimation in massive MIMO system with less complexity, accuracy and inclusion of machine learning and artificial intelligence techniques. Investigators have found channel estimates to be exceedingly difficult when the receiver is fitted with a small number of RF chains in large input and multi-output beam space mm wave (mm Wave) systems. Investigators also suggested that unregulated completely digital precoding for its necessity of antenna antenna dedicated radio frequency chain is excluded for large multiple input multiple output systems due to high cost and electric consumption. The allocation of power to individual antennas to accomplish a particular target is the main issue in massive MIMO, e.g. the maximisation of limited user-assured energy. Literature review shows that massive antennas at mmWave access points and broad bandwidth cause high computer complexity to accurately estimate the state of the channel.The massive antennas in access point and broad bandwidth on MM Wave also revealed, after extensive analysis, that high computational complexity is needed to accurately estimate channel state information There are also research fields which have a significant alteration between the wireless channel and the massive MIMO systems due to the fading of the channel.

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4.2 Recovery of Feedback Channel and Performance Evaluation

In this work, to study the recovery performance of the CS based OMP-SQ technique, average Normalized Mean Squared Error (NMSE) and sum capacity are investigated under different quantization bits.

In literature, there are several calculation techniques for NMSE. One of them calculates NMSE between perfect channel and the reconstructed channel. And, the other one calculates NMSE regarding reconstructed channel. ‖.‖ represents the L2-norm.

NMSE between the estimated channel and perfect channel was found below formula [9]:

$\boldsymbol{NMSE}=\|(\tilde{\boldsymbol{H}}-\boldsymbol{H})\|2(\tilde{\boldsymbol{H}}\boldsymbol{m}\times\boldsymbol{Hm})$ (4.1)

$\|(\tilde{\boldsymbol{H}}-\boldsymbol{H})\|\mathbf{2}=\mathbf{1}\boldsymbol{N}\Sigma(\tilde{\boldsymbol{H}}-\boldsymbol{H})\mathbf{2}\boldsymbol{Ni}=\mathbf{1}$ (4.2)

where $\tilde{\boldsymbol{H}}$ is reconstructed channel and $\boldsymbol{H}$ is perfect channel, $\tilde{\boldsymbol{H}}m$ represented average reconstructed channel and $\boldsymbol{H}m$ represented average of perfect channel.

Shannon Capacity of a MIMO Channel [9]:

$Cr=[\det(IMR+SNRMT\tilde{\boldsymbol{H}}\times\tilde{\boldsymbol{H}}\boldsymbol{H}]$ (4.3)

$Cp=[\det(IMR+SNRMT\boldsymbol{H}\times\boldsymbol{HH}]$ (4.4)

$Cer=[\det(IMR+SNRMT\boldsymbol{H}\times\boldsymbol{HerH}]$ (4.5)

where Cr is estimated channel capacity and Cp is perfect channel capacity and Cer is error channel capacity,IMR is the $MR\times MR$ identity matrix.

Furthermore, hij, an element of the matrix H defines the complex channel coefficient between the ith receive antenna and jth transmit antenna. It is obvious that the channel capacity (in bits/sec/Hz) is highly dependent on the structure of matrix H. The equation (4.3), (4.4) and (4.5) were used to calculate perfect, estimated and error channel capacities and directly related to the SNR.

4.3 Proposed Solution

We are offering the OMP and SQ algorithms for compress sensing to find active paths both transmitter and receiver side. Thus, the section 3.1 for OMP and 3.2 for SQ was explained below.

CSI with OMP:

Our aim is to solve the problem of the sparse vector maximum estimation approach with minimum noise. To solve it in practice; some compress sensing approximation algorithm will need to be used such as OMP based.

OMP has high capabilities of reliably recover of a high-dimensional sparse signal based on a small number of noisy linear measurements a signal with nonzero entries. OMP is a recursive greedy algorithm. At each step of it, the column which is most correlated with the residual is chosen. The OMP algorithm has rules to limit the feedback bits and recover the received signal. According to (5), it indicates that OMP algorithm with high possibility would estimate the sparse vector, under these conditions on the reciprocal incoherence and the minimum magnitude of the non-zero components of the signal [5].

$\boldsymbol{Input}:\boldsymbol{Q},\bar{,}Step$ 1: t=0 $Initialize$: r=y $\boldsymbol{S}$ĝ=∅

$Step$ 2: $\boldsymbol{While}$ $\|\boldsymbol{Q}H\boldsymbol{r}t\|\infty > \in$ $\boldsymbol{and}$ $t<\bar{\boldsymbol{L}}$ $\boldsymbol{do}$ $Step$ 3: $t=t+1$ $Step$ 4: $\boldsymbol{p}t=\boldsymbol{Q}H\boldsymbol{r}t$

$Step$ 5: $nt*=argmaxj=1,2$ ..(|$\boldsymbol{p}t,j$|) $Step$ 6: $\boldsymbol{S}$ĝ=$\boldsymbol{S}$ĝ ∪$nt*$

$Step$ 7: ĝ$\boldsymbol{S}$ĝ=0 and ĝ$\boldsymbol{S}$ĝ=$\boldsymbol{Q}$:,ĝH y

$Step$ 8: $\boldsymbol{r}=\boldsymbol{y}-\boldsymbol{Q}$ĝ $Step$ 9: $\boldsymbol{end\ while}$

$\boldsymbol{Output}$: ĝ , $\boldsymbol{S}$ĝ

The procedure of iterative algorithm OMP can be explained step by step;

Step 1: We initialized the residual $\boldsymbol{r}=\boldsymbol{y}$ and index set $\boldsymbol{S}$ĝ=∅ and t=0;

Step 2: We increased the iteration of algorithm.

Step 3: While the norm of residual is bigger than ∈ and t is less than $\bar{\boldsymbol{L}}$, we iterated the residuals and continued the other steps. "∈" will be a boundary to get small error when finding acceptable measurement matrix. After that, OMP would recover original signal with high probability [6]. Moreover, we limited the iteration number with feedback overload.

Step 4: We applied the QR decomposition to find sparse ĝ because the matrix $\boldsymbol{Q}$ has knowledge of the dictionary at which the signal is received. $\boldsymbol{p}t=\boldsymbol{Q}H\boldsymbol{r}t$

Step 5: Using sparse ĝ vector, we found max probability of active path indexes. Its mean, maximum correlation and minimum noise could be provided. $nt*=argmaxj=1,2$ ..G(|$\boldsymbol{p}t,j$|)

Step 6: The indices of active paths was added in an index set and index set was augmented. $\boldsymbol{S}$ĝ=$\boldsymbol{S}$ĝ ∪nt

Step 7: The estimated sparse vector was initialized, and estimation could continue until the iteration end.

ĝ$\boldsymbol{S}$ĝ=0 ĝ$\boldsymbol{S}$ĝ=$\boldsymbol{Q}$:,ĝH y

Step 8: The new approximation of the received signal and the new residual was calculated. $\boldsymbol{r}=\boldsymbol{y}-\boldsymbol{Q}$ĝ

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Step 9: While $t<\bar{\boldsymbol{L}}$, algorithm will return to Step 3 during this process, when the limit is exceeded the loop could break and end the process.

Also, we shouldn't forget that the residual $\boldsymbol{r}$ is always orthogonal to the columns of $\boldsymbol{Q}$.

After the estimation sparse vector which is associated with sparse interaction matrix Ĝ we applied the feedback technique with quantizing non-zero elements of ĝ with index set. For quantization of ĝ , we can apply max Lloyd scalar quantizing technique as a compress sensing, and after we would obtain Ĝ with reshaping the sparse ĝ vector. Then, receiving bits which are related to non-zero indices of ĝ , BS can reconstruct the channel according to equation (4.6).

$$\boldsymbol{H} \approx \tilde{\boldsymbol{A}} R \boldsymbol{G}\ \tilde{\boldsymbol{A}} T H \qquad (4.6)$$

4.4 Lloyd Scalar Quantization for Limitation

The input field, which is associated with each quantizer, is divided into the regions expressing around the code word. Designing quantities to find the codebook and portion rule which is making a minimization the overall average distortion measure.

Two necessary conditions prove that it is necessary for the design of the quantizer. First, it is the so-called centroid condition that is necessary for the optimization of the codebook, which means that for each region, the average decay measure over that region or the optimal codeword must be selected to minimize the local mean distortion. Second is the nearest neighbor rule that is required for the optimization of the channel space partition, which allows all input vectors closer to the code word to be assigned to more neighbors or regions than another code word. The generalized Lloyd algorithm reexamines the two conditions necessary to find the optimal codebook and channel space partition [7].

Lloyd Algorithm

Step 1: Initialize the valid codebook (ĝ).

Step 2: Apply the nearest neighbor rule to find the optimal regions for ĝ.

Step 3: Apply the centroid condition to determine the optimal codewords for optimal regions.

Step 4: Continue these steps until convergence.

Because of the centroid condition and the nearest neighbor rule, the overall average distortion reduces monotonically. This means that in each iteration, we can estimate the non-zero elements of the sparse channel. After quantization, we can dequantize the sparse vector at BS using known thresholds.

The number of feedback bits is the non-zero elements of the ĝ :

$$\bar{\boldsymbol{L}} = \log 2G + 2Q \qquad (4.7)$$

where 2Q is the quantization bit number for one Q is real part another imaginary part of the CSI, and G is the dictionary members multiplication ($\boldsymbol{G}R\boldsymbol{G}T$) and $\bar{\boldsymbol{L}}$ is related to directly OMP algorithm for limitation of feedback bits.

4.5 Results and Discussions

To understand difference between perfect, non-perfect and estimated channel we examined the normalized mean-squared error (NMSE) because the matrix dimensions are not the same and we calculated the channel capacities. The uplink feedback channel is considered error-free. Also, below the table we can see simulation parameters.

The Channel was constructed according to Mt and it is directly related NMSE so, we can see the above graph the relation of NMSE and Mt. While increasing the Mt, NMSE is decreasing as it is expected according to equation (18) and (19). Also, after 256 transmitter antennas number NMSE is keeping the same NMSE value so 128 is optimum number of antennas.

Furthermore, we can see the effect of Lloyd algorithm quantization level. Lloyd is limited the feedback channel and it is over the feedback burden and it decrease the NMSE.

The graph is provided that the increased SNR values capacity is increasing as an expected according to equation. The estimated channel capacity is shown with red line and its capacity less than perfect and error channel's. Also, perfect channel capacity is higher than the error channel's because error decrease the capacity of the channel.

Mt was used to construct the channel, and Mt is directly connected to NMSE, as seen in the graph above. NMSE decreases as Mt increases. Furthermore, after 256 transmitter antennas, the NMSE value remains constant, indicating that 128 is the optimal number of antennas.

We can also see the impact of the Lloyd algorithm quantization level. Lloyd has narrowed the feedback channel, which has resulted in an increase in the feedback burden and a decrease in the NMSE.

The graph shows that as the SNR values increase, the power increases as predicted by the equation. With a red line, the estimated channel capacity is shown, as well as its capacity less than perfect and error channels. Furthermore, the capacity of a perfect channel is greater than that of an error channel because errors minimise the capacity of the channel.

The output was assessed using the figure of merits process. The output plot of normalised mean square error (NMSE) with respect to the number of antennas was used to examine the characteristic. The output was also evaluated in terms of channel capability and signal-to-noise ratio (SNR). The results were examined to show and analyse the shift in channel ability and NMSE in relation to the proposed methodology. The figure of merits demonstrates the algorithm's applicability and dependability.

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Table 4.1

Simulation Parameters

Parameters	Values
Carrier Frequency (f_c)	$2\ GHz$
Carrier Wavelength (λ)	$\lambda = c/f_c$
Noise power (σ^2)	$10^{-10}\ Watts$
Path number (L)	Discrete uniform in $[5, 6, \ldots, 19, 20]$
AoA and AoD (ϕ_l *and* ϕ_l')	$\phi_l\ , \phi_l{}' \sim U[-\pi/2, \pi/2]$
Path loss exponent (η)	$\eta \sim N(2.8, 0.12)$
Rician parameter (κ_l)	$\kappa_l \sim U[0, 50]$
Multipath gain (α_l)	$\alpha_l \sim CN(\sqrt{\frac{\kappa_l}{\kappa_l+1}}, \frac{1}{\kappa_l+1})$
Path delay (φ_l)	$\varphi_l \sim U[0, 2\pi]$
Deflection angle(β)	$\beta \sim U[-5, 5]$

Channel state information (CSI) at the base station (BS) is important for beamforming and multiplexing gains in multiple-input multiple-output (MIMO) systems. Current restricted feedback schemes for 5G massive MIMO require feedback overhead that scales linearly with the number of BS antennas, which is prohibitively expensive. This paper proposes new restricted feedback algorithms that alleviate this burden by exploiting the inherent sparsity in DD MIMO channel representation using overcomplete dictionaries. These dictionaries are linked to angles of arrival (AoA) and departure (AoD), which are used to account for antenna directivity patterns on both ends of the link.

The proposed algorithms achieve adequate channel estimation accuracy with a small number of feedback bits, even when the number of transmit antennas at the BS is huge, making them suitable for 5G massive MIMO. They outperform a number of popular feedback schemes in simulations, emphasising the importance of using angle dictionaries that suit the antenna directivity patterns rather than uniform dictionaries. Since the proposed algorithms are computationally light, particularly on the user equipment side, they are ideal for use in real-world 5G systems.

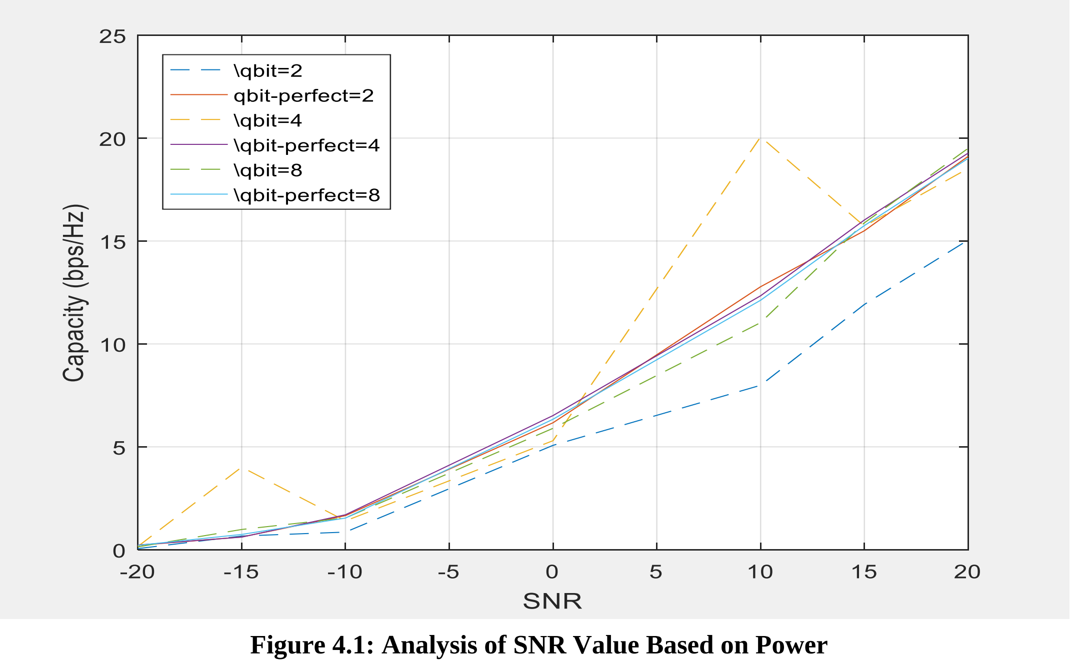

Figure 4.1: Analysis of SNR Value Based on Power

The graph shows that as the SNR values increase, the power increases as predicted by the equation. With a red line, the estimated channel capacity is shown, as well as its capacity less than perfect and error channels. Furthermore, the capacity of a perfect channel is greater than that of an error channel because errors reduce the capacity of the channel.

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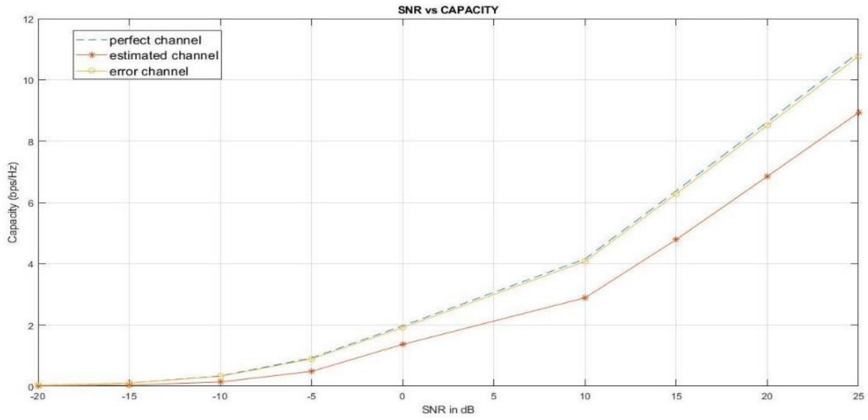

Figure 4.2: Analysis of Channel Capacity With Respect to SNR (dB)

Mt was used to construct the channel, and Mt is directly connected to NMSE, as seen in the graph above. As the Mt is increased, the NMSE decreases, as predicted by the equation. Furthermore, after 256 transmitter antennas, the NMSE value remains constant, indicating that 128 is the optimal number of antennas. We can also see the impact of the Lloyd algorithm quantization level. Lloyd has restricted the feedback channel, which has resulted in an increase in the feedback burden and a decrease in the NMSE.

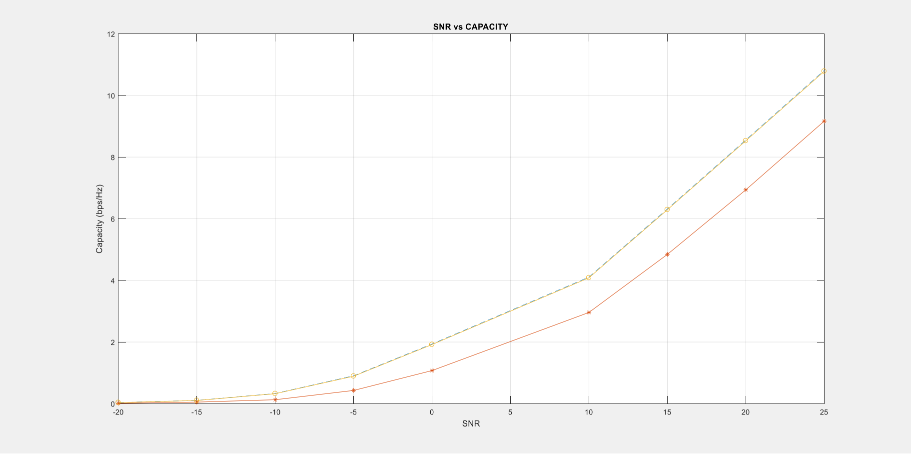

Figure 4.3: Plot of Channel Capacity v/s Signal to Noise Ratio

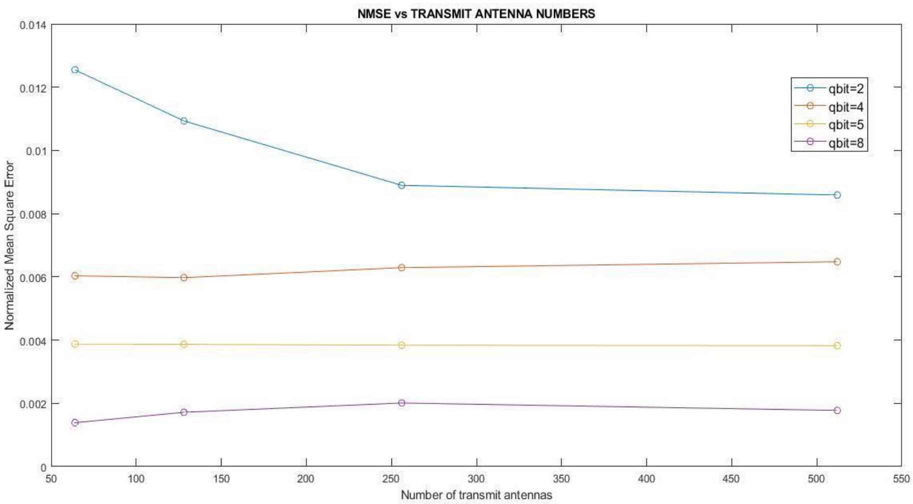

Figure 4.4: Plot of Normalized Mean Square Error v/s Number of Transmit Antennas

Dictionary-based sparse channel estimation algorithms were used to develop the minimal feedback method. The antenna path is explained in the dictionaries, and they may propose high capacity while requiring less feedback. To maintain a certain level of efficiency, the number of feedback bits should grow in lockstep with the number of BS antennas. The number of feedback bits for the OMP can be controlled by the designer, and they can achieve better output with a much smaller bit budget. When the number of transmit antennas is rational and the SNR is high in the large MIMO regime, the proposed OMP-SQ algorithm achieves the predicted capacity efficiency.

5. CONCLUSIONS AND FUTURE SCOPE

The benefit of MIMOs is dependent on the availability of CSIs. This research proposes an adaptive sparse channel calculation with limited feedback to estimate accurate and prompt CSIs for large multi-intimate-output systems based on Duplex Frequency Division (DFD) systems. The minimal retro-feedback scheme must retrofit the burden of the base station antennas in a linear proportion. This work offers a narrow feedback algorithm to elevate the burden by means of a MIMO double-way representation (DD) channel using uniform dictionaries linked to the arrival angle and start angle (AoA) (AoD). Although the number of transmission antennas in the BS is high, the algorithms offer an acceptable channel estimation accuracy using a limited number of feedback bits, making it suitable for 5G massively MIMO. The results of the simulation indicate the output limit can be achieved with the proposed algorithm. The limited feedback system was constructed using dictionary-based sparse channel estimation algorithms. The dictionaries explain the antenna direction and they can proposal high capacity while requiring less feedback burden. The feedback bits number should increase with the BS antennas number proportionally to keep a certain performance level. The number of feedback bits for the OMP is under designer control, and they can achieve better performance using a significantly lower bit budget. The proposed OMP-SQ algorithm reaches the expected capacity performance when the number of transmit antennas is reasonable and SNR is high in the massive MIMO regime.

Future Scope:

- Channel Estimation- Improved learned denoising-based approximate message passing (ILDAMP) network, Modified support detection (SD)-based channel estimation techniques.
- Efficient Precoding by- hybrid singular value decomposition (SVD) technique.
- System Design, Result analysis and comparative assessment.

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