Navigating the Complexities of 60 GHz 5G Wireless Communication Systems at 60 GHz Frequency Band for Secure V2V Communication

Capstone Report

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Abstract:

Road safety concerns have increased with the rising surge in vehicular traffic and can be tackled by breakthrough solutions. One of such approaches which has drawn much attention is Vehicular-to-Vehicular communication through Massive MIMO at 60 GHz mmWave technology in the 5G spectrum. Massive MIMO utilizes multiple antennas to improve spectral efficiency, throughput, coverage, energy efficiency, and reduce latency. Installation of Massive MIMO for mmWave technology entails greater complexities more so in channel estimation. The problem is solved in this paper as this work designs a sparsity adaptive algorithm that manages the tradeoff between accuracy and computational complexity. The algorithm works for real-time V2V communication taking massive MIMO into consideration and especially for 60 GHz environments. The authors conducted research from which this paper is designed to compare existing channel estimation techniques' effectiveness in different environments. It offers prospects for improvement in V2V communication hence better road network in the traffic scenario.

Contents

Preface

The increasing future potential that 5G technology is expected to offer, especially in the automotive and intelligent transportation systems sectors, makes the research on their applications more critical. This capstone project paper addressed the transformation expected from 5G communications with a specific interest in 60 GHz millimeter-wave technology, Massive MIMO systems, and vehicle-to-vehicle communications technologies. The research objectives were to further investigate complexity, conceptualize the challenge, and propose solutions or alternatives on how 5G should be done in the future. I would like to express my heartfelt appreciation to my current supervisor, Professor Sultangali Arzykulov, whose visionary leadership and support have been instrumental in my academic and research journey. His thoughts and commentary helped guide the direction of the research and will have played a part in determining its outcomes. I am also grateful to my former supervisor, Professor Ikechi Ukaegbu, who played a part in the initial development and direction of the project. The intention was to merge academic discourse, and practical suggestions and recommendations that could achieve significant improvements in the performance and efficiency of 5G networks in supporting automotive systems. I am confident that the examination covered in this report will add valuable classroom and industry insights for consideration. I would, therefore, argue that through this examination process, I was able to uncover a lot about the wireless technologies and the complexities that exist in 60 GHz frequency bands and the Massive MIMO and the importance of the V2V technology in promoting safety and efficiency.

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Chapter 1

Introduction

As 5G technology advances, it brings increased demand for faster data, low latency, and reliable communication. In the automotive field, we expect 5G to support various safety applications, improving Intelligent Transportation Systems (ITS). This includes enhancing road perception and emergency handling, which currently rely on line-of-sight methods like GPS, radar, and video monitoring. Wireless communication will expand these capabilities, enabling intelligent vehicle sensing, enhancing situational awareness, and ensuring connectivity even in non-line-of-sight situations [1]. V2V communication is vital for connected vehicles, enhancing transportation safety and efficiency. In wireless communication, there's a rising emphasis on using Massive

MIMO in 5G for V2V communication. MIMO (Multiple-Input Multiple-Output) technologies play a crucial role in enhancing 5G V2V (vehicle-to-vehicle) communication systems, effectively addressing the growing traffic demands within 5G wireless networks [2]. Particularly, Massive MIMO, with its numerous base station antennas, significantly improves spectral and energy efficiency, elevating overall network performance [3]. The integration of antennas, radios, and spectrum in Massive MIMO is pivotal for boosting 5G network capacity and speed, making it a fundamental technology for emerging wireless standards [4]. As stated in [5], massive MIMO exhibits a spectral efficiency exceeding tenfold when compared to point-to-point MIMO in practical transmission scenarios, while employing less complex signal processing algorithms. Additionally, smart antennas in massive MIMO systems significantly boost wireless system capacity by reducing signal interference and adapting radiation patterns to the signal environment [3]. Massive MIMO's multiplexing and beamforming capabilities enable simultaneous data capture from multiple sensors, reducing latency and improving data rates and connectivity. In smart sensor applications, massive MIMO is vital for real-time data transmission and central monitoring [4]. In wireless communication, massive MIMO offers advantages like high spectral efficiency, reliability, reduced signal processing complexity, energy efficiency, and favorable propagation characteristics [6].

Millimeter-wave (mmWave) communication in the 60 GHz range is emerging as a potential solution to meet the demand for higher transmission speed and capacity in V2X communication [7]. In wireless communication, researchers are exploring the use of the 60 GHz mmWave band for mobile cellular communication. This is driven by cost-effective integrated circuits at 60 GHz, the demand for high data rates, wide signal bandwidths, and other factors. In 5G deployment, many small cells like microcells and picocells may be installed, and low-powered base stations (BSs) on streetlamps are also considered [8]. IEEE 802.11ad Wi-Fi and WiGig standards operate in the 60 GHz spectrum, offering data rates up to 7 Gbit/s. The 60 GHz ISM band provides ample bandwidth while minimizing interference [9]. The 60 GHz frequency is a key player in the millimeter-wave spectrum, particularly in unlicensed spectrum use. It leads to high-bandwidth wireless communication, enabling strong data transmission [10]. The 60 GHz band (57-71 GHz) enables short-range, high-speed wireless communication exceeding 1 Gbps. Unlike the limited bandwidth of current 4G bands (up to 100 MHz), 60 GHz offers several GHz of bandwidth. It provides better security against sabotage and immunity from external noise sources like power systems. This frequency range is suitable for stationary point-to-point or mobile applications due to low RF power and strong antenna gain [11].

This research paper explores 60 GHz 5G communication complexities, identifies challenges, and suggests effective strategies and technologies. It examines the 60 GHz frequency band's characteristics and their impact on 5G deployment, focusing on channel estimation algorithm solutions.

Chapter 2

Background

Research in wireless communication has shown that at 28 GHz and 38 GHz, rain and oxygen absorption effects are negligible up to 200 meters [12]. However, at 60 GHz, these effects become significant under similar conditions, with air absorption ranging from 15 to 30 dB/km and path loss increasing by 20 to 40 dB, depending on atmospheric circumstances [13]. The short wavelength of 60 GHz electromagnetic waves results in a heightened susceptibility to obstruction around large objects [12]. Moreover, variations in path length due to reflections, scattering, and different materials introduce delays and attenuation in each multipath component, leading to dynamic channel characteristics [13]. Historically, millimeter-wave frequencies in wireless communication were expensive and primarily employed for non-consumer and government applications [14].

Massive MIMO, with more antennas, leads to increased pilot overhead, complexity, and reduced throughput [15]. Despite aiming for higher capacity and spectral efficiency, challenges like circuit power consumption, antenna spacing, and hardware imperfections persist [16]. Effective transceiver algorithms are required to mitigate phase noise issues [17]. In multi-cell massive MIMO systems, non-orthogonal nearby cell user pilots, compounded by pilot shortages, cause pilot contamination, and directed inter-cell interference, impacting system performance [5]. The problem can be solved by using a proper channel estimation. Finally, the "large" number of antennas utilized makes it difficult to implement and estimate the channel accurately because of high costs and complexity [18].

Chapter 3

Proposed Algorithm

Notations: Vectors and matrices are denoted, respectively, by lowercase and uppercase characters; $()^{-1}$, $()^T$, $()^H$ represent a matrix's inverse, transpose, and conjugate transpose, respectively.

3.1 Channel Model of Sparse Multipath

The base station (BS) employs MIMO systems with Q transmitting antennas to transmit OFDM signals. Each individual antenna transmits an OFDM signal of length L, and a subset of P carriers (where $0 < P < L$) is selected as the pilot to estimate the channel. The channel length is denoted as C. Each transmit antenna, indexed as i (ranging from 1 to Q), follows a unique pilot pattern, denoted as $t(i)$. The pilot patterns for different antennas, $t(i)$ and $t(j)$, are disjoint $t(i) \cap t(j) = \emptyset$, except when $i \neq j$. At the receiving end, after the transmission, the pilot signal corresponding to each antenna is received and represented as $r(t(i))$, which can be denoted as $r^{(i)}$. The basic channel model may be stated as follows:

$$r^{(i)} = G^{(i)} F^{(i)} c^{(i)} + n^{(i)}, \quad i = 1, 2, \ldots, Q \tag{3.1}$$

In this context, the matrix $F^{(i)}$ represents a sub-matrix with dimensions $P \times C$, derived from a Fourier matrix associated with a Discrete Fourier transform (DFT) matrix of size $L \times L$. The elements of this sub-matrix are selected from the pilot lines, while the columns are limited to the first C columns. On the other hand, $G^{(i)}$ is a diagonal array represented by the pilot pattern $t(i)$ for antenna i. It effectively diagonalizes the matrix and allows for individual processing of the pilot patterns. Additionally, the term $n^{(i)}$ denotes Gaussian white noise with a variance of σ^2 and a mean of 0, contributing to the overall noise in the system. To the j-th antenna, the corresponding channel impulse response (CIR) is $c^{(i)} = \left[c^{(i)}(1), c^{(i)}(2), \ldots, c^{(i)}(C)\right]^T$. Equation (3.1) now includes the following extra equation after changing $H^{(i)} = G^{(i)}F^{(i)}$:

$$r^{(i)} = H^{(i)}c^{(i)} + n^{(i)}, \quad i = 1, 2, \ldots, Q \tag{3.2}$$

Here, the equation $\text{supp}\{c^{(i)}\} = \{l : |c^{(i)}(l)| > p_{\text{th}}, 1 \leq l \leq C\}$ represents the index set that defines the support for the i-th sub-channel. The support set consists of indices for which the absolute value of $c^{(i)}$ exceeds a specific noise threshold p_{th}. Recent studies show that in massive MIMO, as transmission distance increases, the base station's antenna array can be reduced. Sub-channels between different antennas exhibit consistent delay characteristics, with the sparse support set remaining unchanged across users and transmitting antennas [19].

$$\text{supp}\{c^{(i)}\} = \text{supp}\{c^{(j)}\}, \quad i \neq j \tag{3.3}$$

3.2 SAMP Algorithm

3.2.1 Estimation of Sparseness

The problem of finding the minimum ℓ_0 norm can be solved by applying compressed sensing techniques to the channel estimation problem.

$$\hat{c} = \arg\min \|c\|_0, \quad \text{subject to} \quad \|r - Ac\|_2 \leq \epsilon \tag{3.4}$$

The expression $\|c\|_0$ represents the ℓ_0 norm of vector h, which corresponds to the count of non-zero elements in the vector. According to [20], it has been proven that when the following condition is met:

$$\|c\|_0 < \frac{1}{2}\text{spark}(A) \tag{3.5}$$

It is possible to recover only the channel impulse response (c). The parameter $\text{spark}(A)$ indicates the smallest count of linearly dependent columns within matrix A. It is clear from analysis that $2 \leq \text{spark}(A) \leq \text{rank}(A) + 1$. If matrix A represents a partial Fourier matrix with dimensions $P \times C$ and $P < C$, it follows that $\|c\|_0 < \frac{1}{2}(P + 1)$.

In wireless communication, the channel impulse response is sparse, with most energy concentrated on a few taps, and only a few taps exist above the noise threshold. Non-zero taps are much fewer than the channel length (L). Leveraging channel sparsity enables accurate estimation with fewer pilot symbols, improving spectrum utilization. Equation (3.5) provides a means to determine an appropriate level of pilot overhead, ensuring efficient utilization of resources.

$$X = \begin{cases} \frac{P}{2}, & \text{if } P \text{ is even} \\ \frac{P+1}{2}, & \text{if } P \text{ is odd} \end{cases} \tag{3.6}$$

Based on the analysis, the channel vector contains at most X non-zero taps, while $C - X$ elements are considered noise. An initial sparseness estimation is made, selecting elements within this range. In scenarios with better signal quality, where signal-to-noise ratios are higher, channel tap gain exceeds noise amplitudes. Thus, the restored elements are sorted in descending order. Disparity between adjacent elements helps select elements for the current iteration and estimate sparsity. The support set includes elements before the largest backward difference, which may contain channel information.

When certain conditions are met by the observation matrix (represented by A), the task of recovering sparse signals can be transformed into a convex optimization problem. The parameter δ_x, known as the Restricted Isometry Property (RIP) parameter, corresponds to the minimum value of δ that satisfies (3.7).

$$(1 - \delta_x)\|c\|_2 \leq \|Ac\|_2 \leq (1 + \delta_x)\|c\|_2 \tag{3.7}$$

Here, c denotes the sparse signal corresponding to x. If the value of δ_x is less than 0.5, the xth order RIP condition is satisfied by the matrix A [21]. Moreover, if the matrix's δ_x parameter is smaller than the value of $\sqrt{2} - 1$, the problem of restoration can be transformed into a minimization problem involving the ℓ_1 norm.

$$\hat{c} = \arg\min \|c\|_1, \text{ subject to } \|r - Ac\|_2 \leq \epsilon \tag{3.8}$$

3.2.2 Channel Estimation

To address the joint sparsity observed in the channel, a transformed channel vector can be represented as $v = [v_1^T, v_2^T, \ldots, v_C^T]^T$, where v_i corresponds to the ith sub-block of v and contains elements $[c^{(1)}(i), c^{(2)}(i), \ldots, c^{(Q)}(i)]^T$, where $i = 1, 2, \ldots, C$. The consequence of this transformation is the concentration of non-zero elements within the channel vector. The received pilot signal is similarly transformed to $y = [y_1^T, y_2^T, \ldots, y_P^T]^T$, where $y_i = [r^{(1)}(i), r^{(2)}(i), \ldots, r^{(Q)}(i)]^T$, $i = 1, 2, \ldots, P$. The noise is also transformed to $e = [e_1^T, e_2^T, \ldots, e_P^T]^T$, where e_i corresponds to the ith sub-block of e and equals to $[n^{(1)}(i), n^{(2)}(i), \ldots, n^{(Q)}(i)]^T$, $i = 1, 2, \ldots, P$. Considering all transmitting antennas, the expression of the received signal can be formulated as follows:

$$y = Mv + e \tag{3.9}$$

Here, $M = [M_1, M_2, \ldots, M_C]$; $M_i = [a^{(1)}(i), a^{(2)}(i), \ldots, a^{(T)}(i)]$, $i = 1, 2, \ldots, C$, $a^{(T)}(i)$ is matrix $A^{(T)}$'s ith column. By performing matrix multiplication between (3.3) and the conjugate transpose of matrix M, denoted as M^H, we can estimate v. This estimation employs compressed sensing techniques in scenarios where the sparsity of the channel is unknown.

$$M^H y = M^H(Mv + e) = v + (M^H M - J)v + M^H e \tag{3.10}$$

Here, J represents the $QC \times QC$ unit matrix. Since the matrix M does not exhibit complete orthogonality, $M^H M - J$ is a matrix with small element values but not zero. The representation of the energy dispersion resulting from the non-orthogonality of the observation matrix is represented by $e' = (M^H M - J)v + M^H e$. As a result, (3.10) can be stated as:

$$M^H y = v + e' \tag{3.11}$$

Define a $QC \times 1$ vector E during iteration.

$$E = \left| M^H q \right| \tag{3.12}$$

Here, the variable q denotes the iterative residuals, initially set as y. The absolute values of the elements in the conjugate transpose of matrix M multiplied by q are denoted by $|\cdot|$. The elements in vector V' are defined as the summation of the squared values in each set of Q' elements within vector E.

$$V(j) = \sum_{(j-1)\times Q+1}^{j\times Q} |E(i)|^2, \quad i = 1, 2, \ldots, QC; \quad j = 1, 2, \ldots, C \tag{3.13}$$

Here, the ith element in vector E is denoted by $E(i)$, and the jth element in vector V is denoted by $V(j)$. To obtain vector V_s, the elements in vector V must be sorted in descending order. The maximum sparsity of the channel is X. After the first iteration, only e' in (3.11) generates the last $C - X$ elements in V_s. In the wireless communication domain, when considering the subsequent $C - X$ elements, their energy is assigned a specific threshold, denoted as t. In order for a tap energy in the channel to be considered significant, it must exceed this threshold value. Consequently, only elements in vector V_s that surpass this threshold are expected to be included in the support set.

The algorithm estimates sparseness in two key steps. Firstly, it sets an upper sparsity limit using a threshold based on wireless channel properties to prevent overlooking channel taps. Secondly, it estimates sparseness by identifying the maximum difference within this range to distinguish channel taps from noise. Unlike other compression-aware algorithms, it accounts for Gaussian white noise factors and energy dispersion due to observation matrix non-orthogonality. Additionally, it employs regularization to filter support set elements, improving accuracy through secondary screening. Consequently, this algorithm surpasses existing ones in estimation performance.

Chapter 4

Results

MATLAB was employed to simulate the proposed algorithm. The parameters for the simulation setup were configured as follows: the system featured 500 transmit antennas, a signal length of 256, and 16 pilot symbols, which were positioned randomly. The channel length was set at 60. Due to system limitations, only a simplified version of the proposed algorithm could be tested. Figure 4.1 illustrates the results obtained from the simulation of the algorithm.

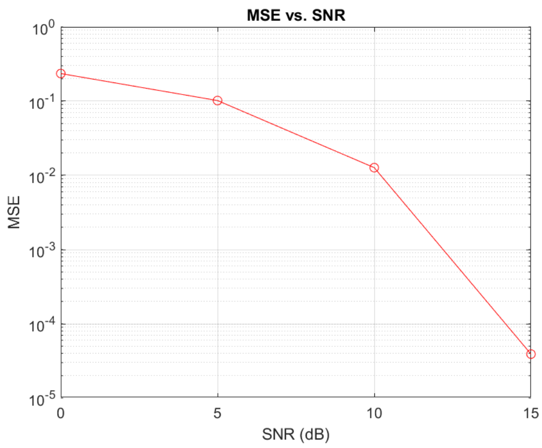

Figure 4.1: MSE of the proposed algorithm.

The challenges of Massive MIMO systems at the 60 GHz frequency band include high path loss, short propagation range, high cost, and high computational complexity, which can result in large estimation errors in channel estimation algorithms. Due to that, several classical algorithms have been proposed to address these challenges, including Least Square (LS), Least Mean Square (LMS), Orthogonal Matching Pursuit (OMP), and so on. The widely used least squares (LS) method in pilot-aided channel estimation, recognized for its simplicity and limited reliance on channel statistics, suffers from performance degradation due to its neglect of noise impact during solution computation. To mitigate this drawback, article [22] introduces an innovative LS method tailored for Orthogonal Frequency Division Multiplexing (OFDM) systems, focused on noise suppression. This method seeks to ameliorate the influence of noise on channel estimation, ultimately enhancing estimation accuracy. The Least Mean Square (LMS) algorithm is a commonly employed adaptive filter algorithm in signal processing. However, its convergence rate is relatively slow as it relies on the eigenvalue spread of the input correlation matrix [23]. The primary objective of the LMS algorithm is to dynamically adjust weights to optimize the signal-to-noise ratio of the desired signal in a specific direction while minimizing the mean square error [24]. The Orthogonal Matching Pursuit (OMP) algorithm is an iterative, greedy algorithm used for signal recovery and approximation. Compared to other methods, OMP has a major advantage in its simplicity and fast implementation [25]. However, there are other novel, effective algorithms which can be a possible solution for the challenges of Massive MIMO systems at the 60 GHz frequency band. In Table 4.1 was proposed a list of algorithms with their advantages and disadvantages.

Table 4.1: List of Algorithms for Navigating the Complexities of 60 GHz 5G Wireless Communication Systems.

Citation	Proposed algorithms	Advantages	Disadvantages
[26] Khan et al. (2018)	BSAMP is a channel estimation technique used in huge MIMO installations. It manages sparsity in these channels effectively by using block sparsity and dynamically modifying the amount of sparsity. This method reduces processing loads while retaining high channel estimation performance.	BSAMP offers low computational complexity by exploiting inherent block sparsity in massive MIMO channels, distinguishing it from other estimation methods. BSAMP dynamically adjusts sparsity levels, making it suitable for real-time adaptation to changing channel conditions in dynamic environments.	BSAMP assumes channel sparsity, requiring known or estimated sparsity levels. If the channel is not sparse or sparsity levels are inaccurately estimated, BSAMP's performance may lag other methods. BSAMP's block-wise processing approach has limitations in large-scale MIMO systems.
[27] Lichao et al. (2022)	In this paper, a new 5G signal detection algorithm based on deep learning of multiple MIMO antennas was presented, which achieves better performance and complexity reduction. The sMPD algorithm was used for iterative optimization, leading to the creation of an effective "neural" signal detection system in massive MIMO for signal transmission.	Improved detection due to improved error rates and detection robustness resulting from utilizing deep learning. Additionally, irrespective of the method of detection used, the algorithm iteratively optimizes network parameters, thereby decreasing the computational complexity of deep neural networks. An increase in efficiency ensures that this method can be effectively used to manage the complexity of large-scale MIMO systems.	One might note that the effectiveness of the given approach is focused on the channel environment. In case of less optimal conditions; the effectiveness of the algorithm might remain low. Thus, it is also critical to take into account the environmental factors associated with the channel during this iteration.

[28] Salah et al. (2022)	The Butterfly Optimization Algorithm (BOA) emulates butterfly behavior and pheromones for a distinct optimization approach. In terms of accuracy and error rate for best solutions, it helps to combat pilot contamination in 5G massive MIMO systems by means of training sequence generation and better signal detection.	Another interesting finding is that the BOA algorithm is better in the number of respondents and the error rate for the optimal solution. The search operation is implemented in the BOA by two search modes; once during the random movement to the optimal solution, and once more through a brief exposure to the pheromones of the other butterflies. This extension of the search has a great chance to find the optimal solution.	It is difficult to choose a set of parameters good enough, such as the release rate of pheromone or the number of butterflies. The definition of the optimal value for the given problem is not trivial. The first published BOA used random numbers, relying on the training process. Each run had a different result due to the unpredictability of the number generation process. A lack of repeatability is not acceptable in some cases.
[29] Zheng et al. (2016)	In this paper, a new and improved channel estimation method for OFDM systems has been presented. It minimizes the effect of the noise relative to the traditional least squares method. The channel estimation based on LS method with noise suppression can achieve substantially better estimation precision than the standard LS method.	The proposed method aims to improve channel estimate accuracy in OFDM systems by reducing noise influence. It's based on the least squares criterion, which is a widely used and well-understood method for parameter estimation.	There is also a limitation in these simulations carried out using the assumption of an AWGN channel which might not generally be the case and hence the performance will significantly deteriorate when faced with more complex channel conditions. The algorithm assumes knowledge of noise variance, which can be challenging to accurately estimate in practice.

[30] Fan et al. (2014)	The paper presents an algorithm for channel parameter estimation in a static indoor 60GHz wireless communication system with multiple receiving antennas. It addresses the challenge of estimating numerous channel parameters within the 60 GHz band using a tailored system model designed for this frequency-selective environment.	The algorithm addresses the challenge of estimating numerous 60 GHz channel parameters, a critical issue in wireless communication systems at this frequency. The algorithm efficiently estimates multiple channel parameters, accommodating systems with numerous antennas.	The algorithm assumes a static indoor scenario, so the results may not be generalizable to other scenarios, such as outdoor or mobile environments. The algorithm assumes channel effects from oxygen absorption, rain attenuation, and wall reflections but may overlook factors like multipath fading and shadowing in practice.
[31] Soltani et al. (2019)	The paper presents a deep learning framework for estimating channels in OFDM systems, where the channel response's time-frequency grid is treated as a 2D image and the estimated channel is considered a high-resolution (HR) image.	Incorporating advanced CNN algorithms like SRCNN for super-resolution (SR) and DnCNN for image restoration (IR) networks enhances channel estimation precision.	The use of deep learning-based methods can be considered as a disadvantage as they may be computationally complex and require a large amount of data for training.

[32] Gao et al. (2014)	This paper delves into a 60-GHz millimeter-wave beamforming algorithm for wireless communication, emphasizing signal optimization in challenging conditions through beam training and channel response estimation. Specifically, it centers on the matching pursuit (MP) algorithm, which sequentially estimates channel taps using correlated dictionary matrix columns and residual signals.	The MP algorithm performs well in sparse channels, especially in beam alignment scenarios with minimal reflection loss. By applying a precise stopping rule, the algorithm removes noise in specific zero taps, resulting in a substantial decrease in estimation error compared to the least-squares (LS) algorithm in sparse channels.	The algorithm may yield significant estimation errors in dense multipath scenarios, leading to poor performance. The algorithm needs to have a prior knowledge of channel probability distribution, which is not always available in beam training. Complexity: The algorithm can be computationally complex, especially when used in combination with other methods for refining the estimation.
[33] Belaoura et al. (2019)	This paper presents an innovative "forward-backward channel estimation algorithm" for 60 GHz STBC-FBMC systems in underground mines. It aims to enhance spectral efficiency and service quality in low SNR conditions by using compressive sensing to reduce training overhead. The algorithm adopts a forward-backward approach, akin to OMP, for efficient channel component estimation without prior sparsity knowledge.	The algorithm is crafted to withstand challenging channel conditions, especially in low SNR ranges, by mitigating channel effects. Designed for low computational complexity, the algorithm leverages temporal sparsity via compressive sensing (CS) to estimate channel parameters efficiently, minimizing training overhead. The algorithm does not require any prior knowledge of the channel's sparsity level.	Tailored for underground mine wireless communication at 60 GHz, this algorithm necessitates extremely high sampling rates to meet the Shannon criteria, posing potential challenges and limitations due to the high-frequency nature. Limited to specific environment. The algorithm's performance can be affected by the choice of the stopping rule, emphasizing its sensitivity to this decision, which in turn impacts its effectiveness.

[34] An et al. (2022)	The paper introduces an OFDM channel estimation algorithm using LS and MMSE techniques with pilot-frequency sequence interpolation. LS minimizes squared errors, while MMSE leverages channel and noise variance to reduce signal discrepancies.	The LS-based estimation algorithm is less complex and has better real-time performance. The MMSE channel estimation algorithm uses channel and noise statistics to minimize signal discrepancies.	Conventional interpolation using the pilot-frequency sequence neglects channel time-frequency correlation and noise influence. Conventional algorithms struggle in complex RF environments, leading to reduced estimation accuracy in challenging wireless communication scenarios.
[35] Kang et al. (2022)	The CAGAN algorithm improves wireless communication channel estimation by combining a concrete autoencoder (Concrete AE) and a conditional generative adversarial network (cGAN) into a single deep neural network. It optimizes pilots and estimates channels through offline training and uses the trained generator with optimized pilots for precise channel estimation during online testing. This method enhances pattern optimization and accuracy.	A combination of the Concrete AE algorithm successfully extracts critical positions on the time-frequency grid for pilot allocation, generating a very successful and nearly ideal pilot pattern for distinct channel models. The shareholder loss function creates a discriminator optimization methodology by determining the variance amongst estimated and real wireless communication channels.	The algorithm may not work effectively in noisy or interference-prone wireless communication environments. Because the CAGAN algorithm is not robust against adversarial attack, the algorithm should constantly update and upgrade to be able to operate. The algorithm may not support the dynamic changes within the wireless communication environment, including changes in the channel condition.

[36] Sarnin et al. (2016)	The MIMO-OFDM system technique, proposed in this research, is based on the utilization of adaptive filtering and RLS and employs training sequences to estimate and track channels. The integrated algorithm relies on EW-RLS and NLMS and uses a decision-directed to estimate channel responses based time and frequency.	The MIMO-OFDM system utilizes adaptive filtering in order to estimate and keep updating the character of the channel to respond favorably to changes. By employing EW-RLS, NLMS, and DD, the resilience to interference and overall robustness of the algorithm are improved.	The numerical experiments conducted confirmed that the use of this method of RLS algorithm for such a task will lead to increased computational complexity.The algorithm may not be suitable for channels with very high mobility, as the assumption of the channel remaining fixed during the observation interval may not hold in such cases.
[37] Bhoyar et al. (2013)	The paper introduces a novel algorithm named Modified Variable Step Size Leaky Least Mean Square (MLLMS), an adaptive channel estimator for MIMO-OFDM systems based on Leaky LMS. MLLMS is computationally efficient, robust to system changes, and less complex than competing methods like variable-step LMS and recursive least square while maintaining effectiveness.	The algorithm uses the LMS technique, which is computationally efficient and robust to dynamic variations in the system. The computational complexity of the MLLMS algorithm is less than other methods such as the Variable step size LMS and Recursive Least Square. The MLLMS method gives better performance in a noisy environment.	The algorithm is slightly computationally complex compared to the LMS algorithm.

[38] Tapio et al. (2019)	The paper introduces three CSI estimation algorithms for millimeter and terahertz wave bands in 5G and future wireless networks. It recommends a hybrid beamforming approach due to hardware constraints. The algorithms discussed include LASSO optimization, OMP, and Bayesian learning with RVM, compared to least squares in terms of performance and complexity, assessed through operation count. The paper also outlines a system model for the channel between transmitter and receiver antenna arrays.	Among the various tested cases, the estimator based on Relevance Vector Machine (RVM) consistently demonstrates superior accuracy in channel estimation. The OMP algorithm performs similarly to the RVM when the number of iterations aligns with the channel's reflecting clusters, especially when there are few clusters. For complex multiplications, additions, and singular value decomposition (SVD) calculations, RVM is less complex than OMP.	In all cases evaluated, the performance of the algorithm based on LASSO consistently demonstrates the lowest level of performance. The RVM-based algorithm's computation time fluctuates due to time spent on add, delete, or re-estimate branches during estimations. The performance of the OMP algorithm is not as good as the RVM-based estimator in terms of estimation accuracy. OMP's computational complexity is intermediate between the lower-complexity LS estimator and the higher-complexity RVM.
[39] Mohammed et al. (2022)	In this paper, the authors have discussed two channel estimation algorithms that include the deep neural network and long short-term memory algorithm. The LSTM resolves the issue of vanishing gradients for recurrent neural networks by simulating input sequences and determining results through recurrent functions and equations.	LSTMs can handle sequential data which is common in wireless channel estimation. LSTMs can retain memory of past inputs, which can help in modeling the time-varying channels. LSTMs can address the "vanishing gradient" problem that can occur in RNNs.	LSTMs can be computationally expensive to train and use. LSTMs are more difficult to interpret compared to other models, which can make it harder to understand the relationship between the inputs and outputs. LSTMs can be prone to overfitting if the model is too complex, or the training dataset is not representative of the test dataset.

Chapter 5

Discussion

Table 4.1 summarizes channel estimation algorithms for MIMO-OFDM and massive MIMO systems, highlighting their positives and possible drawbacks. It helps gauge algorithm suitability across diverse scenarios and applications. Researchers have examined various algorithms, each with its pros and cons. For example, BSAMP is low in complexity but relies on sparsity assumptions, while methods like deep learning and BOA offer improved performance but require extensive data and complexity. In V2V communication, algorithm choice should consider factors like vehicle mobility, computational efficiency, adaptability, protocol compatibility, and system characteristics. In Figure 4.2, the three papers focus on the topic of channel estimation for wireless communication systems operating exactly in the 60GHz frequency band. The comparison is based on the Mean Square Error (MSE) of their respective algorithms.

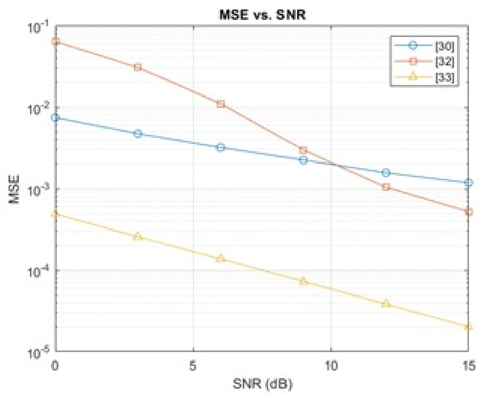

Figure 5.1: MSE of channel estimation algorithms based on mmWave(60Ghz).

The comparison of the three papers' channel estimation methods reveals insights into their performance. Paper [30] excels with an efficient algorithm for accurate low-SNR channel estimation. Paper [32] introduces an effective SDCE-

NTD method with improved MSE in dense and sparse channels. Paper [33] offers a low-complexity approach with potential, though slightly higher MSE. These insights aid researchers in choosing appropriate 60GHz wireless communication channel estimation techniques based on performance needs and scenarios. From Table I, the two exceptional techniques present in mmWave systems include BOA and MLLMS algorithm. The BOA has global and local search capabilities and is appropriate for complex mmWave channels. MLLMS, which has reduced complexity, is proper for dynamic changes in the system. Both these techniques are critical in ensuring accurate channel estimation for frequently varying mmWave conditions. The selection of mmWave channel estimation technique is crucial because of the problems associated with high-frequency bands that are susceptible to route loss, air absorption, and blockages. The factors to consider should include computational complexity, multi-antenna processing, real-time responsiveness, data rates, and how to deal with sparsity encountered in mmWave channels with very few significant routes among others. Figure 4.3 shows a comparison of MSE values for three deep learning-based channel estimation algorithms in papers [31], [34], and [35] at different SNR levels, aiming to enhance accuracy and efficiency.

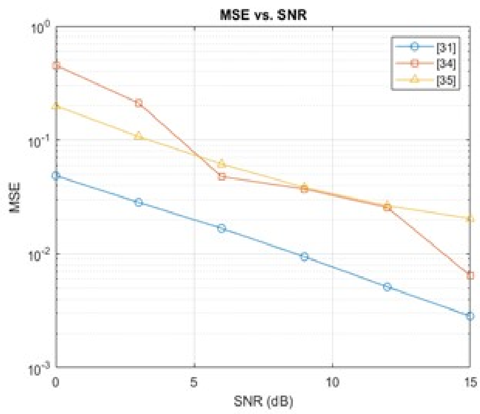

Figure 5.2: MSE of channel estimation algorithms based on Deep learning.

In [31], the algorithm demonstrates the lowest MSE across all SNR levels, highlighting deep learning's effectiveness in challenging conditions. In [34], MSE is higher than [31] but lower than [35], showing good performance with inverse convolutional networks. [35] has the highest MSE but uses fewer pilots, suggesting effective pilot optimization for acceptable channel estimation.

Except for the method given in [33], the suggested algorithm has a lower MSE at all SNR levels when compared to the techniques shown in Figures 4.2 and 4.3. The algorithm in [33] performs noticeably better than the suggested method. Nonetheless, the suggested method and the algorithm in [33] provide nearly equal outcomes for SNR levels of 10 and 15. Furthermore, after an SNR of 10, as seen in

Figure 4.1, there is a notable and abrupt drop in MSE. Therefore, when the SNR level is more than 15, the suggested algorithm may perform better than the other techniques mentioned.

Effective mmWave channel estimation requires algorithms that exploit sparsity, like LASSO or OMP. Adaptability to dynamic channel conditions is vital, so RLS or MLLMS are valuable. Robust interference handling is crucial; Bayesian or deep learning approaches excel. In massive MIMO mmWave systems, support for spatial multiplexing and interference cancellation is key for enhanced capacity and performance.

Massive MIMO, through deploying a large number of antennas on base stations, can significantly boost the performance of mmWave communication systems. Firstly, spatial diversity and beamforming reduce path loss by focusing energy on users, which serves as a mechanism to compensate for path loss at mmWave frequencies. Secondly, reduced signal-to-noise ratio through spatial separation and less interference between users ensures more reliable communications and system performance. Lastly, a significant number of antennas in massive MIMO systems can enable several users simultaneously via spatial multiplexing, increasing system capacity and supporting multi-Gbps data rates due to beamforming, which is particularly beneficial for mmWave communications with ultra-high bandwidth requirements.

Chapter 6

Conclusion

In this paper, a novel channel estimation algorithm is proposed that addresses the problems of massive MIMO channels by efficiently exploiting the sparsity of massive MIMO channels. This analysis, achieved by block sparsity with adaptive updating, supports a low algorithmic complexity method with satisfactory channel estimation performance; this technique is appropriate for active channels whereby the channel conditions fluctuate. The algorithm can periodically monitor these fluctuations and adjust the sparsity in real-time. Moreover, the computational complexity of the presented algorithms is entirely achievable in practice for large MIMO systems. Furthermore, we present a detailed literature study based on the mmWave and massive MIMO approaches to channel estimation algorithms. There is also a requirement for simulation and implementation-based modification and enhancement of the algorithm to overcome the limitations of the proposed algorithms and effectively take advantage of its perks to improve these methods. To thoroughly evaluate the performance of the proposed method, it is recommended to conduct simulations with appropriately adjusted system setup parameters, specifically targeting SNR levels above 15. This approach will allow for a detailed assessment of the MSE performance under conditions where the proposed algorithm might demonstrate superior effectiveness.

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Appendix A

Appendix

The iteration process of the proposed algorithm is as follows:

Proposed Algorithm
Input: receive pilot signal y, Observation matrix M, The number of antennas T Output: channel estimate z'. Initialize the block support set location index $S_{LI1} = \emptyset$, Support set location index $S_{LI2} = \emptyset$, $z' = 0$, The threshold $t = E\left\{[V_s(i)]^2, i = G+1, G+2, \ldots, C\right\}$, $r_{es} = y$. **Iteration process** 1: Calculate vector V, arrange the elements in V in descending order to obtain a vector V_s and the corresponding index set S_{LI1}. 2: Select the elements in V_s larger than the threshold t and set the element number to n; if n is 0, exit; otherwise, go to Step 3. 3: Select the vector $V_s(1:n+1)$ and the maximum backward difference between adjacent elements is labeled as d. 4: Regularize the elements in the vector $V_s(1:d)$. make $v = V_s(1:d)$, $s = S_{LI1}(1:d)$, All elements in v follows $\lvert v(i)\rvert \leq 2\lvert v(j)\rvert, i, j \in s$. Divided into a number of groups, select the energy of the largest group of a selected support set. The location of the selected elements is indexed U, and if the length of the vector U is L_v, $S_{LI2} = S_{LI2} \cup \{(U(k)-1)T+1 : U(k)T\}, k = 1, 2, C, L_v$. 5: According to the location index S_{LI2}, find the matrix of the corresponding columns in the observation matrix $M_{S_{LI2}}$. 6: Solve the estimated channel using the least square method $z' = \left(M_{S_{LI2}}^H M_{S_{LI2}}\right)^{-1} M_{S_{LI2}}^H y$; 7: Update the residual $r_{es} = y - M_{S_{LI2}} z'$, make $S_{LI1} = \text{null}$, $L_v = \text{null}$; 8: Return to Step1.