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FEEDBACK MECHANISMS FOR CENTRALIZED AND DISTRIBUTED MOBILE SYSTEMS

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FEEDBACK MECHANISMS FOR CENTRALIZED AND DISTRIBUTED MOBILE SYSTEMS

A Dissertation Presented to the Graduate Faculty of the

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Doctor of Philosophy

with a

Major in Electrical and Computer Engineering

by

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The wireless communication market is expected to witness considerable growth in the immediate future due to increasing smart device usage to access real-time data. Mobile devices become the predominant method of Internet access via cellular networks (4G/5G) and the onset of virtual reality (VR), ushering in the wide deployment of multiple bands, ranging from TV White Spaces to cellular/WiFi bands and on to mmWave. Multi-antenna techniques have been considered to be promising approaches in telecommunication to optimize the utilization of radio spectrum and minimize the cost of system construction. The performance of multiple antenna technology depends on the utilization of radio propagation properties and feedback of such information in a timely manner. However, when a signal is transmitted, it is usually dispersed over time coming over different paths of different lengths due to reflections from obstacles or affected by Doppler shift in mobile environments. This motivates the design of novel feedback mechanisms that improve the performance of multi-antenna systems.

Accurate channel state information (CSI) is essential to increasing throughput in multiinput, multi-output (MIMO) systems with digital beamforming. Channel-state information for the operation of MIMO schemes (such as transmit diversity or spatial multiplexing) can be acquired by feedback of CSI reports in the downlink direction, or inferred from uplink measurements assuming perfect channel reciprocity (CR). However, most works make the assumption that channels are perfectly reciprocal. This assumption is often incorrect in practice due to poor channel estimation and imperfect channel feedback. Instead, experiments have demonstrated that channel reciprocity can be easily broken by multiple factors. Specifically, channel reciprocity error (CRE) introduced by transmitter-receiver imbalance have been widely studied by both simulations and experiments, and the impact of mobility and estimation error have been fully investigated in this thesis. In particular, unmanned aerial vehicles (UAVs) have asymmetric behavior when communicating with one another and to the ground, due to differences in altitude that frequently occur. Feedback mechanisms are also affected by channel differences caused by the user's body. While there has been work to specifically quantify the losses in signal reception, there has been little work on how these channel differences affect feedback mechanisms.

In this dissertation, we first investigate the key challenges in channel feedback performance, including transmitter-receiver imbalance, channel coherence, and effective noise for mobile systems. We evaluate IEEE 802.11ac-based implicit and explicit feedback schemes with both emulated MIMO channels and in-field UAV-based transmissions. We additionally evaluate the impact of frequency offset asymmetry on the performance of distributed mobile systems. Our analysis shows that implicit feedback is susceptible to channel reciprocity errors, while explicit feedback is more sensitive to Doppler effects. Based on this analysis, we propose a hybrid feedback mechanism that outperforms conventional feedback framework, we explore two specific real-world scenarios: (*i*.) sub-6 GHz networks where UAVs transmit in-flight to and from the ground, and (*ii*.) wireless networks that are subject to user-induced losses, which we study across a wide range in carrier frequency from 900 MHz to 60 GHz (mmWave networks).

To study the air-to-ground scenario, we design a UAV-based software defined radio (SDR) platform and perform a measurement study between the aerial platforms and a terrestrial user in practical scenarios such as hovering, encircling, and linear topologies. In particular, our experiments include cellular (900 MHz and 1800 MHz) and WiFi (5 GHz) bands. Furthermore, we address three baseline issues for deploying drone-based beamforming systems: channel reciprocity, feedback overhead, and update rate for channel estimation. Numerical

results show that explicit CSI feedback can significantly improve the throughput performance over implicit feedback and the optimal update rate are similar across frequencies. We additionally analyze the reciprocity error and find that the amplitude error remained steady while the phase error depends on mobility.

Finally, we explore the role of feedback mechanisms when subjected to user-induced losses. To better understand these losses, we first perform a measurement study to explore the user-induced effects on radio wave propagation with varying line-of-sight conditions and environments across multiple frequency bands. To do so, we conduct a baseline experiment that characterizes the propagation channel in this environment. We show that the propagation differences for ground-to-ground communication and tower-to-ground communication are frequency dependent. Then, we measure signal quality as a function of the on-body location of the receiver, directional heading of the user with respect to the transmitter, vegetation type, frequency band, and propagation distance. We find that the body can act like an antenna, significantly increasing the signal reception and system throughput over a reference node at the same distance. Lastly, we progress to mmWave channels to study feedback in the context of the IEEE 802.11ad with body-induced losses. We find that the blocking probability can reach up to 90% with an aggressive feedback interval and lower modulation scheme is more preferred than high modulation.

TABLE OF CONTENTS

LIST	ГOF	FIGURES	xi
LIST	ГOF	TABLES	xv
CHA	APTE	L'R	
1.	Intro	oduction	1
	1.1.	Challenges	3
	1.2.	Contributions of this Thesis	4
	1.3.	Thesis Overview	6
2.	Bacl	ground	7
	2.1.	IEEE 802.11 Standard	7
	2.2.	Software Defined Radio Platform	11
	2.3.	Azimuth Wireless Channel Emulator	16
	2.4.	Beamforming with Channel Feedback	17
3.	Feed	back Mechanisms for Mobile Beamforming Systems	20
	3.1.	Channel Feedback Mechanism	20
	3.2.	Channel Reciprocity Model and Feedback Design	24
		3.2.1. Beamforming Framework	24
		3.2.2. Channel Reciprocity Emulation Model	25
		3.2.3. Channel-differential Feedback Mechanism	27
		3.2.4. Hybrid Feedback Mechanism	29
		3.2.5. Channel-aware Feedback Mechanism	31
	3.3.	Experimental Settings	33
	3.4.	Experimental Evaluation with Channel Emulation	34
		3.4.1. Transmitter-Receiver Imbalance Impact Evaluation	35

		3.4.2. Doppler Effect Impact Evaluation	37
		3.4.2.1. Characterization of Doppler Effect	38
		3.4.2.2. Analysis of Joint Effects	39
		3.4.2.3. Characterization of Channel Accuracy	40
		3.4.3. Effective Noise Impact Evaluation	41
		3.4.4. Hybrid Feedback Mechanism Evaluation	42
		3.4.5. Channel-Aware Feedback Mechanism Evaluation	44
		3.4.6. Distributed Beamforming Evaluation	45
	3.5.	Related Work	47
	3.6.	Summary	50
4.	Droi	ne-Based Beamforming and Feedback System	51
	4.1.	Motivation	51
	4.2.	System Model	52
		4.2.1. Drone-based Beamforming Framework	52
		4.2.2. Channel Feedback Framework	54
	4.3.	Experimental Settings	57
	4.4.	In-Field Evaluation with Hovering Experiments	59
		4.4.1. Baseline Experiments	60
		4.4.2. Path Loss Evaluation	61
		4.4.3. Link Performance Evaluation	64
	4.5.	In-Field Evaluation with Encircling Experiments	65
		4.5.1. Channel Reciprocity Evaluation	65
		4.5.2. Update Rate for Channel Estimation	69
	4.6.	In-Field Evaluation with Linear Experiments	70
	4.7.	Related Work	72

4.8. Summary				
5. Wireless Propagation and Channel Feedback with User-Induced Effects				
5.1. User-induced Effects		74		
5.2. System Path Loss Model		78		
5.3. Experimental Settings		78		
5.4. Baseline Propagation Prediction		80		
5.4.1. Baseline Experiment Method		80		
5.4.2. Ground-to-Ground Propagation Evaluation		81		
5.4.3. Tower-to-Ground Propagation Evaluation		84		
5.5. Propagation Evaluation with User-induced Effects \ldots		85		
5.5.1. Single-User Linear Evaluation		85		
5.5.2. Multi-User Radial Evaluation		89		
5.5.3. Directionality-Aware Propagation Prediction		92		
5.6. Channel Feedback Evaluation with User-induced Effects		94		
5.6.1. Sweep-based Feedback Framework		94		
5.6.2. Feedback Interval Evaluation		97		
5.6.3. Training Overhead Evaluation		99		
5.7. Related Work		100		
5.8. Summary		102		
6. Conclusion		104		
BIBLIOGRAPHY		107		

LIST OF FIGURES

Figure		Page
2.1.	802.11a OFDM PHY Frame Structure	8
2.2.	The architecture of Typical IEEE 802.11 Systems: (a) Transmitter (b) Receiver [1]	9
2.3.	USRP N210 with WBX board	12
2.4.	Frequencies channels used in commercial carriers. [2]	13
2.5.	Software Defined Radio block diagram with USRP N210 and GNU Radio. [3]	14
2.6.	USRP E312 (Battery-powered and MIMO Capability)	15
2.7.	System beamforming with antenna array [4]	18
3.1.	Channel Feedback Mechanisms. (a) Explicit (b) Implicit	21
3.2.	Feedback Analysis Scheme	26
3.3.	Schematic diagram of epoch of 802.11ac-based feedback mechanism: (a) Implicit (b) Explicit	28
3.4.	Schematic diagram of hybrid feedback mechanism.	30
3.5.	5-Tap Rayleigh Channel Model with Doppler Effects: (a) Time Domain (b) Frequency Domain	31
3.6.	Channel Aware feedback. (a) 32 Samples (b) 16 Samples	32
3.7.	Experimental Setup (a) WARP and Azimuth Wireless Channel Emulator (b) Channel Emulation via Director II software	34
3.8.	RF mismatch for transceiver paths	35
3.9.	TX-RX Imbalance Evaluation (a) Throughput vs. Phase Error Percentage, and (b) Throughput vs. Amplitude Error Percentage	37

3.10.	TX-RX Imbalance Evaluation: Throughput vs. Joint Amplitude and Phase Errors	38
3.11.	Doppler Effect Evaluation: Throughput vs. UE Velocities	39
3.12.	Doppler Effect Evaluation: Throughput Performance vs. Changing Velocities.(a) Implicit (b) Explicit	40
3.13.	Channel Accuracy Analysis (a) Impact of CRE on Channel Accuracy (b) Impact of Doppler Effect on Channel Accuracy	42
3.14.	Effective noise Impact Analysis (a)(b) $SNR = 8 \ dB \ (c)(d) \ SNR = 4 \ dB \ (e) \\ SNR = 2 \ dB \ \dots $	43
3.15.	CDF of calibrated throughput for feedback Mechanisms:(a) Constant (b) Binary	44
3.16.	CAF Mechanism Evaluation: Throughput vs. Joint Amplitude and Phase Errors.	45
3.17.	Experimental Setup (a) Experimental Diagram (b) System Emulation (c) Feedback Analysis Flow	46
3.18.	Distributed link performance analysis	48
4.1.	IEEE 802.11 PHY frame Structure	54
4.2.	Timeline of CSI Feedback for proposed beamforming scheme	55
4.3.	BER Simulation under different feedback approaches.	56
4.4.	Equipment settings for experiments. (a) Beamformer USRP mounted on a drone (b) UE USRP mounted on a tripod	58
4.5.	Channel Feedback Evaluation Topologies: (a) Hovering (b) Encircling \ldots	59
4.6.	Physical location of UABeam propagation experiments.	60
4.7.	Ground-Based Reference Measurements. (a) Setup (b) Path Loss	61
4.8.	Variable-Range, Variable Altitude. (a) Path Loss (b) Signal Quality	61
4.9.	 BER vs. Distance plot of the air-to-ground channel: (a) 900 MHz (b) 1800 MHz (c) 5 GHz; Throughput vs. Distance plot of the air-to-ground channel: (d) 900 MHz (e) 1800 MHz (f) 5 GHz; Normalized Throughput Gain vs. Distance plot of the air-to-ground channel: (g) 900 MHz (h) 1800 MHz (i) 5 GHz. 	63
4.10.	Distribution Analysis for CRE. (a) Amplitude (b) Phase Gradient	66

4.11.	Timeline of Implicit Feedback. 68		
4.12.	Throughput results of beamforming system with channel reciprocity		
4.13.	. Throughput for various frame lengths: (a) Hovering (b) Encircling		
4.14.	Instantaneous Throughput vs. Distance. (a) Setup (b) 900 MHz \ldots	71	
5.1.	Long Term Measurements Locations	75	
5.2.	Measurement Scenario for both LOS and NLOS Environments	76	
5.3.	Received Signal Strength vs Distance on Four Frequency Bands	77	
5.4.	Forest Propagation Measurements.	81	
5.5.	Ground-to-Ground Path Loss Model above 1 m Reference on Four Frequency Bands	82	
5.6.	Tower-to-Ground Path Loss Model above 1 m Reference on Four Frequency Bands	82	
5.7.	Spatial Depiction of Linear LOS Measurements	85	
5.8.	Hand Facing Towards/Turning Away the Transmitter in Linear LOS Measure- ments		
5.9.	Backpack Facing Towards/Turning Away the Transmitter in Linear LOS Measurements.		
5.10.). Pocket Facing Towards/Turning Away the Transmitter in Linear LOS Measurements.		
5.11.	Overhead Image of Throughput Performance Measurement	88	
5.12.	Comparison of Throughput among Three Receiver Setups	89	
5.13.	3. Spatial Depiction of Radial NLOS Measurements		
5.14.	Estimated User-Induced Loss in Tree Area.		
5.15.	Estimated User-Induced Loss in Brush Area.	91	
5.16.	Averaged User-Induced Loss Based on Aggregate User Effects	92	
5.17.	802.11ad Sweep-based Beamforming Scheme [5]	95	
5.18.	Snapshot of 10 users in one trail	96	

5.19.	CCDF of interference vs. feedback intervals	98
5.20.	Evaluation of training overhead on blocking probability and SINR reaching	
	probability	100

LIST OF TABLES

Table		Page	;
3.1.	IEEE 802.11ac based Frame Parameters	25	
4.1.	IEEE 802.11 based Frame Parameters	58	
4.2.	Estimated Log-distance Path Loss Model Parameters	62	
4.3.	Statistic Parameters of Channel Reciprocity Error Results	67	
5.1.	Path Loss Calibration based on 1 m Reference Distance	80	
5.2.	Estimated Log-distance Path Loss Model Parameters	83	
5.3.	Estimated User-Induced Loss After Linear Fitting	87	
5.4.	Estimated Propagation Parameters With User-induced Effects	93	
5.5.	Estimated Gain Loss using MCS1 Training Frame	99	1

Chapter 1

Introduction

Modern wireless communications are indispensable in people's common life by changing the way we study, work and enjoy entertainment. With the development of communication standardization such as the next generation of WiFi techniques (e.g., IEEE 801.11ax and ad), fifth generation mobile networks (5G), and Internet of Things (IoT), having ubiquitous access to wireless spectrum becomes increasingly indispensable to almost all kinds of mobile devices, such as smart phones, laptops, tablets, smart watches, UAVs, and vehicular wireless devices [6]. People now require more and more applications based on mobile computing and data rate, which require more transmission bandwidth not only in larger transmission bands but at higher carrier frequencies. The wireless data traffic is expected to increase a thousand-fold over the next decade [7]. However, all of those developments aggravate the contradiction between the limited wireless resources and the increasing demand of wireless data. Many transmission features in these modern radio-access technologies closely depend on the availability of more or less detailed knowledge about different characteristics of the radio channel information over which a signal is to be transmitted. Beamforming is one of these key techniques that maximize the signal power at the receiver side by manipulating each transmit antenna with appropriate weighting (phase and gain), known as beamforming precoding. The design of precoding expects to fully utilize the channel properties to improve the system throughput. Such channel properties are usually denoted as channel state information (CSI) demanded to feed back to the beamformer in a timely manner. Investigating the performance of channel feedback schemes and proposing novel design are essential to increasing throughput in the increasing deployed modern wireless systems, such as the IEEE 802.11ax/ad and 5G cellular networks.

It is well understood that the performance of channel feedback is essential for systems equipped with multiple antennas, denoted as multiple input multiple output (MIMO) systems. The wireless industry is working feverishly on spatial dimension innovations, falling under the category of channel estimation and feedback mechanisms for MIMO systems, which help deliver significant network capacity and performance [8]. With robust channel estimation and feedback, the key concept is to perform digital signal processing on CSI acquired by measurements on either the transmitter side or receiver side of a radio link. The design of beamforming requires implementation of multiple antennas to enable multiple concurrent transmissions. CSI for operation of MIMO schemes can be acquired by feedback in the downlink (from beamformer to beamformee), or directly using uplink (from beamformee to beamformer) measurements, denoted as channel reciprocity.

Furthermore, to address the data requirement, wireless standards have recently sought to increase the total bandwidth per channel access and explore the optimal channel feedback schemes for MIMO systems. First, in WiFi networks, IEEE 802.11a uses up to 20 MHz, IEEE 802.11n uses up to 40 MHz, IEEE 802.11ac and IEEE 802.11ax use up to 160 MHz, and IEEE 802.11ad 60 GHz standard will use nearly 1 GHz of available bandwidth [9]. The abundant spectrum available is capable of delivering unprecedentedly high data speeds and capacity that will reshape users' data experience. Second, a single device can support a wide range of carrier frequency bands for future networks. In order to address growing connectivity demands in modern wireless systems, 5G technologies will extend spectrum bands to 3.5 GHz (sub-6 GHz) and making above 28 GHz and 39 GHz, loosely known as mmWave spectrum, available for cellular broadband communications for the first time [10]. UAV-based beamforming systems and distributed beamforming networks (multiple independent radios coordinate their transmissions to form a distributed node) systems are believed to open a new degree of freedom and space for enhancing network capacity. Also, the receiver directionality and on-body location caused by human behavior can strongly affect the reception of electromagnetic waves. Investigating the performance of feedback frameworks with involvement of user behaviors, antenna elevation, or scatter distributions provide new insights to future network optimization in terms of the user-side.

In this dissertation, we perform system-level simulations, implement design with a software defined radio platform, conduct in-field experiments for various wireless communication systems to analyze different channel feedback mechanisms. To explore the feedback mechanism, we then explore two specific real world scenarios, including UAV-based beamforming communications, and user-induced feedback systems.

1.1 Challenges

To maximize the received signal power, accurate knowledge of the wireless channel profile is required at the transmitter. However, most works make the assumption that uplink channel estimation can perfectly predict downlink CSI, which is often not the case in practice due to poor channel estimation and imperfect channel feedback. The explicit feedback mechanism is realized through the CSI feedback based on transmission of known training signals. Such information reflects the instantaneous downlink channel quality in the time and frequency domains, as well as other information necessary to determine the appropriate antenna processing in the case of MIMO scheme processing. In the implicit feedback mechanism, the channel estimates can be derived from a reference signal transmitted from the beamformee for which the beamformee estimates the uplink CSI first. Although the implicit feedback mechanism can save lots of training overhead, it does not always hold the perfect channel reciprocity. Channel estimation error introduced can be evaluated by both simulations and experiments, yet the impact of mobility is mostly addressed by simulations. Sufficient knowledge about the impact factors key to the feedback performance is lacking in current research literature, and the design of novel channel feedback mechanisms is highly demanded.

Also, there has been little work to propose a beamforming design optimized for UAVbased MIMO systems with theoretical analysis and in-field experiments. The future development of airborne wireless communication necessitates precise channel characterization and system level performance analysis due to increasing deployments of aerial communication systems and their resulting data services. The high mobility and the noise power cast serious challenges to information security and call for optimized transmission design against conventional MIMO systems. Lacking such knowledge will significantly affect many UAV applications, such as search and rescue, reconnaissance, and disaster recovery. Furthermore, directionalization using beamforming technology can boost the transmission range with optimized feedback mechanisms. However, the high mobility and flight conditions of UAVs can threaten the ability to receive accurate CSI feedback in a timely manner. Although current works have simulated air-to-ground channels in urban environments, most of the aforementioned works lack in-field data with real geographical features, which are crucial to UAV-based applications.

Lastly, the performance of wireless propagation and MIMO feedback are subject to large user-induced losses, where few literature has fully covered the carrier frequency ranging from 900 MHz to 60 GHz mmWave band. The receiver directionality and on-body location caused by human behavior can strongly affect the reception of electromagnetic waves, especially at higher frequency bands. In user-induced wireless systems, the receiver directionality and on-body location caused by human behavior, and changing environments are believed to impact the performance by causing fluctuations in channel quality. User behaviors have been shown to cause increasing impact on the signal propagation with the increase of frequency and decreasing of the cell size. Also, the emergence of mmWave communicating systems encourages the implementation of new applications in wearable and on-body communication networks, ranging from e-health to wearable entertainments. Antenna array beamforming is essential for realizing mmWave communication systems, especially for anticipated high attenuation at mmWave band and extra large body-induced losses due to body blocking. However, current works fail to study feedback performance with user-induced losses for mmWave-based wireless body networks.

1.2 Contributions of this Thesis

In this thesis, we first analytically and experimentally study the feedback mechanism for centralized and distributed mobile MIMO systems. Then, we perform spatial processing to improve the performance of UAV-based communication systems by making use of novel feedback designs, optimal channel update rate, and channel reciprocity analysis. Lastly, we investigate the effects of user induced spatial locations on signal propagation for white space, cellular/WiFi frequency bands, and explore general feedback framework for mmWave band.

First, we explore the impact of key factors that degrade the performance of channel reciprocity, such as TX-RX imbalance, Doppler effect due to mobility, and noise profile. We first build a channel reciprocity error model that makes use of the channel emulation to evaluate the MIMO throughput performance in terms of the phase error, amplitude error and their joint effects on channel reciprocity. Since high mobility can bring large Doppler frequencies that introduces errors to channel estimation process, we additionally analyze the impact of Doppler effect on explicit and implicit feedback. As a result, motivated by the feedback evaluation of implicit feedback and explicit feedback under various contexts, we propose and evaluate a hybrid feedback mechanism that takes advantage of both conventional feedback schemes. We successfully demonstrated that our proposed hybrid feedback approach can improve the channel estimation significantly by evaluating the joint effects of channel reciprocity and Doppler effect. Also, we investigate the joint impacts of mobility and frequency offset on the performance of distributed feedback scheme for distributed nodes with emulated channels, which consists of a large number of distributed beam array nodes, such as UAV swarms.

Second, we propose the first beamforming prototyping system on UAVs that realizes airto-ground communication using beamforming techniques across three commonly-used frequency bands (900 MHz, 1800 MHz, and 5 GHz). In particular, we implement our proposed beamforming system on a Universal Software Radio Peripheral (USRP) platform by developing a PHY and MAC design that allows explicit feedback for beamforming using IEEE 802.11-ac signaling. In order to reduce the overhead during CSI feeding back, we propose a channel-differential feedback approach that expedites CSI feedback and saves computational cost at the receiver compared to existing feedback approaches. To experimentally evaluate the performance of our proposed UAV-based beamforming system, we conduct experiments within a repeatable variable range scenario to characterize the air-to-ground channel and link performance of airborne beamforming, showing significant performance improvement over the conventional IEEE 802.11 scheme. We additionally evaluate channel reciprocity with three in-the-field scenarios to compare explicit and implicit feedback for UAV-based beamforming, demonstrating that implicit feedback can largely degrade system performance. Finally, we investigate the optimal update rate for channel estimation in airborne communications and find that the optimal rate is mostly independent of carrier frequency.

Lastly, in order to understand user-induced effects on signal reception across multiple frequency bands and evaluate channel feedback performance with mmWave channels, we experimentally characterize the effects of various on-body locations and directional heading of the user on the performance of mobile devices and perform IEEE 802.11ad beamformed transmissions with body-induced losses. In this work, we first conduct a baseline experiment that characterizes the propagation channel in this environment. We show that the propagation differences for ground-to-ground communication (common in Ad-Hoc and WiFi scenarios) and tower-to-ground communication (common in cellular scenarios) are frequency dependent. Then, we measure signal quality as a function of the on-body location of the receiver, directional heading of the user with respect to the transmitter, vegetation type, frequency band, and propagation distance. Our assessment reveals that the user directionality with respect to the transmitter can reduce received signal strength up to 20 dB and reduce throughput by 20.9% at most. We also find that the body can act like an antenna, increasing reception by 4.4 dB and throughput by 14.4% over a reference node at the same distance. Finally, we progress to mmWave channels to study user-induced feedback performance with changing feedback intervals and training overheads in the context of the IEEE 802.11ad. We find that the blocking probability can reach up to 90% with an aggressive feedback interval and lower order modulation for training overhead outperforms higher order modulation in throughput improvement considering the trade-off between overhead payload and training accuracy. Since our study spans many critical network frequency bands, we believe these results will have far-reaching impact on a broad range of network types, ranging from 900 MHz to 60 GHz mmWave.

1.3 Thesis Overview

In Chapter 2, we discuss the background of this work, including the basic knowledge related to this work and the hardware/software tools that we use. In Chapter 3, we analytically and experimentally study the feedback mechanism for centralized mobile MIMO systems, including digital beamforming and analog beamforming. Chapter 4 evaluate key factor for channel feedback and provides novel feedback methods. In Chapter 5, we explore the user effects on radio wave propagation environments across multiple frequency bands and study the user-induced feedback performance with 802.11ad mmWave channels. Finally, we conclude our work for this thesis in Chapter 6.

Chapter 2

Background

In this chapter, we introduce the background of our research, including the specific description of related technologies, and software tools that we implement in our proposed beamforming framework, and the hardware that we use to evaluate our proposed feedback mechanisms.

2.1 IEEE 802.11 Standard

IEEE 802.11 refers to the set of standards that define communication for wireless local area networks (WLAN). The technology behind 802.11 is branded to consumers as WiFi [11]. As the name implies, IEEE 802.11 is overseen by the IEEE, specifically the IEEE LAN/MAN Standards Committee (IEEE 802) [12]. In other words, IEEE 802.11 is the set of technical guidelines for implementing WiFi. Selling products under this trademark is overseen by an industry trade association by the name of the WiFi Alliance [13]. IEEE 802.11 has its roots from a 1985 decision by the U.S. Federal Commission for Communication that opened up the ISM band for unlicensed use. The standard was formally released in 1997. That original standard was called IEEE 802.11-1997 and is now obsolete [14]. The earlier versions of IEEE 802.11 specify the operation for single antenna systems (e.g., IEEE 802.11a/b/g/p), while the later versions adopt multiple transmit and receive antennas and/or multiple simultaneous users (e.g., IEEE 802.11n/ac), or Gigabit bandwidth transmissions on mmWave (e.g., IEEE 802.11ad). IEEE 802.11 transceivers have been widely applied in laptops, and smart phones (nearly each laptop or smart phone has an IEEE 802.11 transceiver). It's common to hear people refer to "802.11 standards" or the "802.11 family of standards." However, to be more precise, there is only one standard (IEEE 802.11-2007) but many amendments. Commonly known amendments include 802.11a, 802.11b, 802.11g, 802.11n, 802.11ac, and 802.11ad [15].

In this work, we start with a single-antenna, single-user system and then extend it to

a multiple-antenna, multiple-user beamforming topology. For the single-antenna, singleuser scheme, one frame defined in IEEE 802.11ac is composed of a short preamble, a long preamble, a header symbol, and several data symbols, as shown in Figure 2.1 (from Figure 2 in [16]). The short preamble is a pre-defined signal at the beginning of the received signal, assisting the receiver to detect the beginning of the frame, Automatic gain control (AGC). The purpose of AGC is to provide a controlled signal amplitude at its output, despite variation of the amplitude in the received signal. The receiver will amplify too weak a received signal, or attenuate too strong a received signal to achieve good performance. A short preamble is also used for the receiver to detect the signal strength to perform channel estimation and fine frequency shift offset correction.



Figure 2.1: 802.11a OFDM PHY Frame Structure

In the IEEE 802.11 standard, Carrier Sense Multiple Access (CSMA) is the one used to allow Multiple Access. To be exact, IEEE 802.11 releases use CSMA/CA (Collision Avoidance) instead of CSMA/CD (Collision Detection) which is used in wired networks [12]. Current 802.11 design, OFDM is used as an advanced digital modulation scheme which divides the data stream being exchanged between the node and the access point (AP) to multiple individual streams of lower rate and transmits them on different, closely-spaced carrier frequencies simultaneously (multiplexing). Making the signal more robust against error-thus allowing higher data rates. OFDM divides a given channel into many narrower subcarriers. The spacing is such that the subcarriers are orthogonal, so they won't interfere with one another despite the lack of guard bands between them. This comes about by having the subcarrier spacing equal to the reciprocal of symbol time. All subcarriers have a complete number of sine wave cycles that upon demodulation will sum to zero [17].



Figure 2.2: The architecture of Typical IEEE 802.11 Systems: (a) Transmitter (b) Receiver [1]

According to the IEEE 802.11ac standards and the function of each part of the frame, a physical layer transmitter and receiver block diagram is shown in Figure 2.2 (from Figure 2 and 3 in [1]). For IEEE 802.11 devices, the transmitter and the receiver use separate oscillators, resulting in slightly different carrier frequencies. The transmitter needs to construct the transmission frame using the input bit streams. In particular, the processing includes Scrambling, Encoding and Interleaving. Extra components such as pilot, preamble, and

cyclic redundancy check (CRC) will be added to the payload. The control information is carried in the header symbol, and the payload is carried in the data symbols of the frame. The receiver needs to first detect the incoming frame, compensate carrier frequency difference, and estimate the channel information. In order for the transmitter to correctly decode the received signal, for which the short preamble is also used. Prior channel status estimation methods usually take advantage of the long preamble, which is another pre-defined signal transmitted after the short preamble. After that, each data symbol is demodulated to a soft value per coded bit. Then, interleaved democulation, Decoding, and scrambling demodulation will be be performed in order.

IEEE 802.11 standard used OFDM for data transmissions. OFDM is a prevalent scheme for wideband communication across wired and wireless mediums and used in applications such as digital television and audio broadcasting, DSL Internet access, wireless networks, and mobile communications [18–22]. The primary advantage of OFDM over single-carrier schemes is its robustness to severe fading conditions without complex equalization filters. Another major advantage of OFDM is that it allows devices to easily manipulate the signals on different sub-carriers and allow sub-channels to be apportioned according to the frequency selectivity [23]. In [23], the OFDM sub-carriers are grouped into Physical Resource Blocks (PRBs), and the AP allocates different PRBs to different users, which provides significant flexibility in allocating bandwidth to users according to their respective demands. OFDMA is a method to add multiple access in OFDM systems by assigning subsets of subcarriers to different users. IEEE 802.11ax is the first WLAN standard to introduce OFDMA into WLAN networks. In [24–26], OFDMA enables efficient use of available spectrum by allowing multiple users with varying bandwidth needs to be served simultaneously. The specification defines a four times larger FFT, multiplying the number of subcarriers while preserving the existing channel bandwidths. One critical feature with 802.11ax is that the subcarrier spacing for OFDM has been reduced to one fourth compared with previous 802.11 standards. In contrast, we demonstrate the feasibility of beamforming capabilities on different bands of an OFDM system using FPGA-based software defined radio platforms.

2.2 Software Defined Radio Platform

The FPGA-based platform we use for our implementation and experimental evaluation is the USRP, as shown in Figure 2.3. USRP is a range of software-defined radios designed and sold by Ettus Research and its parent company, National Instruments (NI). Developed by a team led by Matt Ettus, the USRP product family is intended to be a comparatively inexpensive hardware platform for software radio, and is commonly used by research labs, universities, and hobbyists [27]. USRP is a useful wireless communication system supporting a fully customized cross layer real-time design. WARP combines a large FPGA and multiple radio-frequency interfaces. Mainly, the physical layer implementation is in the FPGA logic fabric, and the higher layers exist as programming code on an embedded processor or standalone PC. USRP is widely used by nearly a hundred academic and industrial research labs for protocol implementation. Furthermore, USRP has been cited hundreds of times and there are hundreds of published papers using WARP(Wireless Open-Access Research Platform) for their protocol/system implementation and evaluation [27]. Most USRPs connect to a host computer through a high-speed link, which the host-based software uses to control the USRP hardware and transmit/receive data. Some USRP models also integrate the general functionality of a host computer with an embedded processor that allows the USRP device to operate in a stand-alone fashion. The USRP family was designed for accessibility, and many of the products are open source hardware. The board schematics for select USRP models are freely available for download; all USRP products are controlled with the open source USRP Hardware Driver (UHD) driver, which is free and open source software [28]. USRPs are commonly used with the GNU Radio software suite to create complex software-defined radio systems.

The software defined radio platforms can used for frequency-agile experiments. Frequency is everything when it comes to choosing or designing wireless equipment. Knowledge of the electromagnetic (EM) spectrum is essential for all engineers working with wireless equipment and systems [29]. It affects what you can transmit as well as how and where, determining everything from rates and range to capabilities and cost. In order to achieve high levels of capacity and reliability in wireless networks, measuring the wireless channel across key carrier frequencies is critical for designing and implementing effective systems. The term of "white



Figure 2.3: USRP N210 with WBX board

space band " denotes the below 1 GHz frequencies channels previously used by analog TV broadcasts. Figure 2.4 (from Table 1 in [29])shows the complete range of radio applications expressed in frequency bands and wave categories. For example, full power analog television broadcasts operate between the 54 MHz and 806 MHz television frequencies. The 802.11ac is working on 2.4 GHz and 5 GHz. The 802.11ad is working on 60 GHz mmWave band.

Channel measurements have been done in different environments and frequency bands [2, 30–35]. In [2], the authors measure the channel heterogeneity and temporal stability to guide their system design. In [30], the authors investigated the temporal, spatial, and spectral fading in home and office environments on the 5.2 GHz band. Power-delay profile characteristics are measured in [32]. In [31, 34], channel characteristics of millimeter wave signals are measured to study the feasibility of next generation wireless networks in that band. Frequency selectivity and time selectivity are the two key wireless channel effects that each pose a challenge to system designers. Frequency selectivity typically corresponds to the multi-tap

Name	Frequency range	Applications
Low frequency (LF)	30 to 300 kHz	Navigation, time standards
Medium frequency (MF)	300 kHz to 3 MHz	Marine/aircraft navigation, AM broadcast
High frequency (HF)	3 to 30 MHz	AM broadcasting, mobile radio, amateur radio, shortwave broadcasting.
Very high frequency (VHF)	30 to 300 MHz	Land mobile, FM/TV broadcast, amateur radio
Ultra high frequency (UHF)	300 MHz to 3 GHz	Cellular phones, mobile radio, wireless LAN, PAN
Super high frequency (SHF), millimeter-wave range	3 to 30 GHz	Satellite, radar, backhaul, TV, WLAN, 5G cellular
Extremely high frequency (EHF)	30 to 300 GHz	Satellite, radar, backhaul, experimental, 5G cellular
Terahertz , tremendously high fequency (THF) or far infrared (FIR)	300 GHz to IR	R & D, experimental

Figure 2.4: Frequencies channels used in commercial carriers. [2]

effect, while time selectivity typically corresponds to channel fading.

In this work, we use R&S FSH 8 hand-held spectrum analyzer to record the data for postprocessing. The R&S FSH 8 spectrum analyzer is designed for portable measurements with applications in multiple environments, especially for in-field measurements. Its low weight, its simple, well–conceived operation concept and the large number of measurement functions make it an indispensable tool for anyone who needs an efficient measuring instrument for outdoor work. We employ the FSH 8 in our indoor and outdoor measurements to collect data in multiple bands. FSH 8 is able to sense the signal in the air from 9 KHz to 8 GHz. The spectrum analyzer could sense both 802.11 signals and non-802.11 signals in the air. Through the time stamp, we could merge data from Gateworks platform and FSH 8 platform to perform our algorithms and frameworks.

One of the important application frameworks is GNU Radio. GNU Radio is a free & open-



Figure 2.5: Software Defined Radio block diagram with USRP N210 and GNU Radio. [3]

source software development toolkit that provides signal processing blocks to implement software radios. It can be used with readily-available low-cost external RF hardware to create software-defined radios, or without hardware in a simulation-like environment. It is widely used in hobbyist, academic and commercial environments to support both wireless communications research and real-world radio systems [28]. One example of how to use GNU Radio to control and communicate with USRP N210 is shown in Figure 2.5 (from Figure 1 in [3]). GNU Radio performs all the signal processing. You can use it to write applications to receive data out of digital streams or to push data into digital streams, which is then transmitted using hardware. GNU Radio has filters, channel codes, synchronization elements, equalizers, demodulation, decoders, and many other elements (in the GNU Radio jargon, we call these elements as blocks) which are typically found in radio systems. More importantly, it includes a method of connecting these blocks and then manages how data is passed from one block to another. Extending GNU Radio is also quite easy; if you find a specific block that is missing, you can quickly create and add it. Since GNU Radio is software, it can only handle digital data. Usually, complex baseband samples are the input data type for receivers and the output data type for transmitters. Analog hardware is then used to shift the signal to the desired centre frequency. That requirement aside, any data type can be passed from one block to another - be it bits, bytes, vectors, bursts or more complex data types. GNU Radio applications are primarily written using the Python programming language, while the supplied, performance-critical signal processing path is implemented in C++ using processor floating point extensions, where available. Thus, the developer is able to implement real-time, high-throughput radio systems in a simple-to-use, rapid-application-development environment.



Figure 2.6: USRP E312 (Battery-powered and MIMO Capability)

In this work, we use USRP N210 to perform in-field experiments and characterize the effects of user-induced behaviors on wave propagation. The USRP N210 provides highbandwidth, high-dynamic range processing capability, as shown in Figure 2.3. The USRP N210 is intended for demanding communications applications requiring this type of rapid development. The product architecture includes a Xilinx Spartan 3A-DSP 3400 FPGA, 100 MS/s dual ADC, 400 MS/s dual DAC and Gigabit Ethernet connectivity to stream data to and from host processors. The FPGA also offers the potential to process up to 100 MS/s in both the transmit and receive directions. The FPGA firmware can be reloaded through the Gigabit Ethernet interface [36]. On the other hand, we use the other USRP E312 to design and implement drone-based beamforming communication framework, as shown in Figure 2.6. The USRP E312 provides a larger FPGA than the USRP N210 for applications demanding additional logic, memory and DSP resources. Furthermore, it is battery-powered and supports MIMO capability. The battery operated USRP E312 offers a portable stand-alone software defined radio platform designed for field deployment. The flexible 2x2 MIMO AD9361 transceiver from Analog Devices provides up to 56 MHz of instantaneous bandwidth and spans frequencies from 70 MHz – 6 GHz to cover multiple bands of interest. The USRP Embedded Series platform uses the Open-embedded framework to create custom Linux distributions tailored to application specific needs [37].

2.3 Azimuth Wireless Channel Emulator

Emerging carrier-grade 3G/4G wireless access promises speeds of 100 to 350 Mbps for delivery of high-speed data, video and voice services. High throughput delivery for LTE and Worldwide Interoperability for Microwave Access (WiMAX) is achieved using orthogonal frequency-division multiplexing (OFDM) and advanced antenna techniques such as Multiple-Input, Multiple-Output (MIMO). MIMO performance depends on the radio channels in which it operates, and accurate and repeatable lab characterization of RF environmental effects such as multipath and fading is critical for reliable testing of conformance, performance and interoperability of the systems. Testing such conditions can only be achieved through the use of channel emulation [38].

The Azimuth wireless channel emulator is a state-of-the-art channel emulator, purposebuilt to support MIMO transmissions and architected to meet the demanding RF needs of OFDM based systems. The channel emulator can be controlled by TCL customized scripts that generate controllable and repeatable channel conditions as a function of frequency, Doppler shift, and scenario type for complex wireless environments. The Azimuth wireless channel emulator combines industry-leading channel emulation capabilities in a comprehensive design to deliver a range of configurations for MIMO and/or SISO system testing, with uni- and bi-directional configurations.

2.4 Beamforming with Channel Feedback

One of the key technologies in unlocking additional carrier frequencies for greater capacity in wireless networks is directionality in the form of beamforming. The beamforming is used for sensor arrays directional signal transmission and reception in spatial division [4]. It has provision to change both amplitude and phase which helps in power variation as well as beam steering in the desired directions and cause destructive interference in undesired directions, as shown in Figure 2.7. The antenna arrays with separate provision for amplitude/phase variation is used in beamforming for both the transmission as well as reception. The improvement compared with the conventional omni-directional transmission is known as the directivity gain of the antenna array. Besides, beamforming can be used at both the transmitting and receiving ends in order to achieve spatial selectivity. Beamforming can be used for radio or sound waves. It has found numerous applications in radar, sonar, seismology, wireless communications, radio astronomy, acoustics and biomedicine [39]. In analog beamforming, amplitude/phase variation is applied to analog signal at transmit end. The signals from different antennas are summed up before the ADC conversion in analog beamforming at receive end. Beamforming plays a significant role in the spectral efficiency and data transmission in wireless systems, especially for OFDM systems, which have been successfully implemented in widelydeployed wireless infrastructures, including IEEE 802.11 wireless LAN standards (WiFi), IEEE 802.16 Wireless MAN standard (WiMax), and 3GPP Long-Term Evolution (LTE).

Beamforming requires precoding for spatial processing at beamformer. In codebook based transmission, very few bits is utilized by wireless networks to feed back so that beamformer can select a preferred precoding matrix from a given set of tables based on channel quality and channel rank, while non-codebook based transmission scheme is introduced in 5G to further feedback group of bits indicating the MIMO channel matrix and enable implicit feedback to support massive MIMO that fully utilize the spatial properties of channel to boost data rate.

Beamforming can be divided into Analog Beamforming and Digital Beamforming [40]. In analog beamforming, amplitude/phase variation is applied to analog signal at transmit end. The signals from different antennas are summed up before the Analog to Digital Con-



Figure 2.7: System beamforming with antenna array [4]

verter (ADC) conversion in analog beamforming at receive end. In digital beamforming, amplitude/phase variation is applied to digital signal before Digital to Analog Converter (DAC) conversion at transmit end. The reverse process is done after ADC operations are performed. As shown the received signals from antennas are first passed from ADC converters and digital down converters before summation operation. The benefits of digital beam forming include: improved dynamic range, controlling of multiple beams, and better and faster control of amplitude and phase.

The CSI information feedback is the key to increasing throughput in multiple antenna systems, ranging from rough knowledge of the radio-channel path loss for transmit-power adjustment to detailed knowledge about the channel amplitude and phase in the time, frequency, and/or spatial domains. IEEE 802.11 standards specify two types of feedback mechanisms: implicit feedback and explicit feedback. Both IEEE 802.11ax and 802.11ac implement explicit feedback scheme from UE to calculate the optimal transmit signal weights [41]. Explicit feedback approach is realized through the CSI feedback by the beamformee or the receiver to the beamformer or transmitter based on transmission of known training signals. Such information reflects the instantaneous downlink channel quality in both the time and

frequency domains, as well as other information (e.g., channel rank and channel quality) to determine the appropriate antenna processing in the case of MIMO scheme processing. In the implicit feedback approach, the CSI necessary for downlink MIMO processing can be based on a reference signal transmitted from the receiver for which the transmitter estimates the uplink channel and assumes channel reciprocity. Channel feedback mechanism is based on the Singular Value Decomposition (SVD) of the channel. However, this procedure can bring large computation cost [42]. While explicit feedback can provide more accurate CSI, it introduces large overhead in terms of time and feedback control bits. For implicit feedback, the transmitter does not need to measure and send the CSI to the beam former. Implicit Beamforming is also implemented 802.11n [43]. However, implicit beamforming requires frequent calibration operation between the transmitter and receiver when practical channel is not reciprocal, which can complicate the 802.11ac MIMO framework design [41].
Chapter 3

Feedback Mechanisms for Mobile Beamforming Systems

In this Chapter, we will quantify the impact of key factors that degrade the performance of IEEE 802.11ac MIMO techniques and feedback mechanisms, including channel reciprocity error caused by transmitter-receiver imbalance, Doppler shifts related to a time-varying channel, and noise power divergence between transmitter and receiver. Then, we propose novel feedback mechanisms which are robust to channel reciprocity error and channel coherence to improve the system performance.

3.1 Channel Feedback Mechanism

Accurate CSI is essential to increasing throughput in MIMO systems with digital beamforming. CSI can be acquired by channel estimation and reported via feedback mechanisms. While the training and feedback overhead are typically proportional to the number of antennas, uplink measurements can be utilized to predict downlink CSI assuming perfect channel reciprocity. However, most works make the assumption that channels are perfectly reciprocal, which is often not the case in practice due to poor channel estimation and imperfect channel feedback. In this chapter, we investigate the key challenges in channel feedback performance, including transmitter-receiver imbalance, channel coherence, and interference for mobile systems. We evaluate IEEE 802.11ac-based implicit and explicit feedback schemes with both emulated MIMO channels and in-field UAV-based transmissions (described in the previous chapter). We additionally evaluate the impact of frequency offset asymmetry on the performance of distributed mobile systems. Our analysis shows that implicit feedback is susceptible to channel reciprocity errors, while explicit feedback is more sensitive to Doppler effects. Finally, we propose a hybrid feedback mechanism that outperforms conventional feedback methods by 32 percent in throughput performance.

The key to increasing the throughput of MIMO systems is the design of robust and

efficient channel feedback mechanisms, which is essential to IEEE 802.11 networks. With the mobile wireless demands of users exploding in recent years, network operators have increasingly deployed multiple antenna systems to support the growing number of highbandwidth, streaming functionalities. Multiple antennas at the transmitter can perform spatial processing in order to support the growing number of multimedia functions targeted to user terminals (UE). This technology requires antenna coordination with the aid of CSI feedback to direct beams for large data transmission. In this work, we focus on channel estimation and feedback mechanisms focused in IEEE 802.11 systems to enhance the UE downlink throughput.

In the current IEEE 802.11 standards, typical feedback mechanisms roughly fall into two categories: implicit feedback and explicit feedback [41, 43, 44], as shown in Figure 3.1. In 802.11ac explicit feedback, the transmitter first sends null data packet (NDP) as a sounding/training frame to the UE in the downlink. After decoding the received signal, the UE performs channel estimation and sends back the compressed CSI to the transmitter [41]. Implicit feedback is first supported in 802.11n, where the transmitter implicitly obtains an estimate of the downlink channel by taking the transpose of uplink CSI assuming that downlink and uplink channels are perfectly reciprocal [43]. Current feedback mechanisms use compressed data representation that causes CSI mismatch and lacks flexibility to address practical non-ideal channel reciprocity issues.



Figure 3.1: Channel Feedback Mechanisms. (a) Explicit (b) Implicit

Statistical models for predicting channel reciprocity error have been proposed [42,45–51]. With perfect channel reciprocity, implicit feedback will incur less overhead and improve throughput performance. However, most of these works overlook the fact that in practice, the downlink and uplink channels may not be reciprocal. The key factors that introduce non-ideal channel reciprocity and degrade the performance of implicit feedback include channel reciprocity error caused by transmitter-receiver imbalance [42,46,47], noise power difference between transmitter and receiver [48,49], as well as channel estimation error introduced by device movement [50,51]. To the best of our knowledge, none of the current published works discuss the isolated and joint effects of channel reciprocity error, channel coherence variation due to mobility, and changing effective noise power on the feedback performance.

Lastly, we leverage our evaluation of drone-based mobile systems to investigate feedback protocols in a real-world context, as discussed in Chapter 4. The future development of airborne wireless communication necessitates precise channel characterization and MIMO support due to increasing deployments of aerial networks and their resulting data services. Theoretical studies have characterized air-to-ground channel estimation with theoretical simulations but lack experimental validation in the field [52–56]. Although these works have simulated air-to-ground channels in urban environments, most of the aforementioned works lack channel reciprocity evaluation in explicit and implicit feedback for drone-based beamforming due to the assumptions inherently made within the simulation environment.

In this chapter, we will quantify the impact of key factors that degrade the performance of IEEE 802.11ac MIMO techniques and feedback mechanisms, including channel reciprocity error caused by transmitter-receiver imbalance, Doppler shifts related to a time-varying channel, and noise power divergence between transmitter and receiver. In particular, the Doppler shift is attributed to a channel that has a coherence time that is shorter than the OFDM training period, resulting in frequency shifts in the received OFDM symbol [49]. The performance of channel feedback is sensitive to CSI mismatch over Doppler spread channels. The noise power can be denoted by an additive effective noise due to different interference power profiles between transmitter and receiver. For instance in airborne communications, very different background noises, spatial separations, interference sources can present between UAV in the air and ground station on the ground. Thus, the effective noise greatly reduce the validation of channel estimation. Furthermore, we analyze the joint effects of channel reciprocity error on feedback performance for centralized and distributed MIMO systems. Although channel reciprocity error can be evaluated by both simulations and experiments, the impact of mobility in only addressed by simulations in current works. Then, we propose novel feedback mechanisms which are robust to channel reciprocity error and channel coherence to improve the system performance. Lastly, we build an IEEE 802.11ac-based signaling mechanism across the media access control and physical layers to explore in-field beamforming (UAV-based transmissions), demonstrating that a properly optimized drone-based digital beamforming system can provide significant throughput improvements using explicit versus implicit feedback.

The main contributions of this chapter are as follows:

- 1. We analyze the joint effects that degrade the performance of feedback mechanism in 802.11ac, including TX-RX imbalance, Doppler effects, and effective noise showing that implicit feedback is susceptible to channel reciprocity errors, while explicit feedback is more susceptible to channel coherence.
- 2. We propose a channel-differential feedback mechanism and proves our design expedites CSI feedback and saves computation cost.
- 3. We propose a novel hybrid feedback mechanism that is robust to both channel reciprocity error and channel coherence and demonstrate system performance improvement.
- 4. We prove the concept of channel aware feedback mechanism aiming at dynamically adjusting overheads for feedback matrix based on flatness properties of channel, leveraging the novel insight for next generation network design.
- 5. We extend our evaluation to distributed MIMO systems, revealing that the asymmetrical errors can degrade the performance of feedback mechanisms.
- 6. We propose the first prototyping system on UAV that realizes air-to-ground communication using beamforming techniques in representative realistic channels.

The rest of the chapter is organized as follows. In Section 3.2, we propose our channeldifferential and hybrid feedback mechanism designs. Then, we discuss hardware setup for our beamforming schemes in Section 3.3. In Section 3.4, we present our channel reciprocity measurements for the repeatable channel conditions on a channel emulator. Note that the channel reciprocity with in-fied experiments will be covered in the Chapter 4. We discuss related works in Section 3.5 and conclude our work for this chapter in Section 3.6,

3.2 Channel Reciprocity Model and Feedback Design

In this section, we introduce a beamforming framework based on a channel reciprocity model. We first consider channel reciprocity based on channel feedback performance by examining the main factors that affect the performance of channel reciprocity. Then, we introduce our proposed channel feedback mechanisms that improve the performance of the MIMO channel.

3.2.1 Beamforming Framework

Consider a typical beamforming system with M transmit antennas at the access point and a single receive antenna on the UE side. Each transmit chain at the transmitter can be digitally controlled by phase and amplitude separately.

In this dissertation, we use an IEEE 802.11 PHY frame structure for data transmission, which is composed of a preamble, a header symbol, and payload symbols. At the k-th subcarrier, the same copies of normalized complex signal symbol s(k) is coded by the beamformer prior to being sent to the UE from the m-th transmit antenna. Let K denote the number of subcarriers of an OFDM structure. We consider a spatially-independent Rayleigh fading channel. Thus, the received signal vector at the k-th subcarrier, denoted as r(k), can be expressed as:

$$r(k) = \sum_{m=1}^{M} p_m h_m(k) w_m(k) s(k) + n(k).$$
(3.1)

Here, p_m , $w_m(k)$, and $h_m(k)$ represent, respectively, the power gain, normalized beamforming precoding vector, and downlink channel coefficient vector in the frequency domain at the k-th

subcarrier from the *m*-th transmit antenna. n(k) is the additive white noise with standard deviation σ_n .

The estimated CSI can be obtained by transmitting known training symbols prior to frame decoding via either implicit or explicit feedback. In this dissertation, we use a conjugate beamforming vector to maximize the signal-to-noise ratio (SNR) at the receiver, described as:

$$w_m = \frac{h_m(k)^*}{\|h_m(k)\|}.$$
(3.2)

Here, * denotes the complex conjugate operator. Other parameters of our testbed are shown in Table 3.1.

Parameters	Preamble	Data
Modulation Schemes	BPSK	BPSK/QPSK/64QAM
Total Subcarriers	52	52
Occupied Subcarriers	52	48
Pilot Subcarriers	0	4
FFT size	64	64
CP Interval	0.25	0.25

Table 3.1: IEEE 802.11ac based Frame Parameters

3.2.2 Channel Reciprocity Emulation Model

According to the literature discussed above, increasing the accuracy of the estimated channel $\bar{h_m}(k)$ is essential for the operational performance of the beamforming scheme. However, implicit feedback can never obtain perfect CSI due to the none-ideal reciprocity with imperfect channel estimation and finite rate feedback between the downlink and uplink channels and the induced Doppler effect due to mobility. There are three major contributing factors to reciprocity errors: TX-RX imbalance, effective noise, and channels with Doppler effects. TX-RX imbalance is the mismatch between the transmit and receive RF chains of the same hardware device and the resulting amplitude/phase differences. In addition, mobility and noise introduce significant channel estimation error under different feedback schemes. However, few works model and quantify the joint effects of Channel Reciprocity Error (CRE) and Doppler effects in terms of practical mobile MIMO systems.

The contributions of these key factors can be modeled by channel emulation with basedband pre-distortion, as shown in Figure 3.2. Specifically, RF impairments can be controlled by connecting the transmitter and receiver with an RF cable for synchronization and to compensate for phase differences. Then, baseband distortion can be modelled by multiplying the amplitude and phase shift in the baseband signal processing blocks to create controllable distortion levels. Finally, channel emulation is used to predict the uplink channel information based on downlink channel information as a function of frequency, mobile velocity, and propagation environments.



Figure 3.2: Feedback Analysis Scheme

The systematic CRE introduced by the joint impacts of these key factors is given by:

$$h_m(k) = E(k)\bar{h_m}(k) \tag{3.3}$$

$$= e_{env}(k)e_{syn}(k)\bar{h_m}(k). \tag{3.4}$$

Here, $h_m(k)$ and $\bar{h_m}(k)$ are the downlink and uplink channel information, respectively. $e_{env}(k)$ denotes the propagation reciprocity error component caused by TX-RX imbalance, antenna mismatch, and channel estimation errors due to noise/interference. Moreover, $e_{syn}(k)$ denotes the reciprocity error component introduced by imperfect synchronization between transmitter and receiver. The lack of synchronization stems primarily from the frequency mismatch caused by Doppler effects, since OFDM signals are much more sensitive to frequency offsets [57]. Both TX-RX imbalance and noise will lead to amplitude error and phase error during channel estimation. Thus, the propagation reciprocity error introduced can be expressed as:

$$e_{env}(k) = A_m(k)e^{j\theta_m(k)}.$$
(3.5)

Here, $A_m(k)$ and $\theta_m(k)$ are modeled as normally-distributed and uniformly-distributed random variables, respectively. The synchronization reciprocity error e_{syn} due to the Doppler shift can be expressed as:

$$e_{syn}(k) = e^{\frac{4\pi k \delta_p}{K}}.$$
(3.6)

Here, δ_p is the slope of the phase error denoted by the phase gradient due to the Doppler shift on phase changing. Following the above discussion, systematic CRE E(k) in Equation 4.7 is equivalent to:

$$E(k) = A_m(k)e^{j(\theta_m(k) + \frac{4\pi k\delta_p}{K})}.$$
(3.7)

Considering the issue of asymmetric synchronization in distributed nodes which are equipped with independent oscillators, we include the joint impacts of frequency offset Δf , creating a changing phase rotation at each subcarrier where Equation 4.10 will become [50]:

$$e_{esyn}(k) = e^{j(\frac{4\pi(k(N+N_{CP})+N_{CP})\Delta f}{Kf_{scs}} + \frac{4\pi k\delta_p}{K})}.$$
(3.8)

Here, N is the symbol duration, N_{CP} is the cyclic prefix duration, and f_{scs} is the OFDM subcarrier spacing.

3.2.3 Channel-differential Feedback Mechanism

In the current 802.11ac compressed explicit feedback scheme, prompt and accurate CSI feedback is expected for the design [41]. Large feedback overhead or mismatched CSI will greatly degrade the throughput performance. Existing works have focused on the precoder codebook to choose the matrix index [58–61]. In these works, the receiver needs to compress the CSI and prepare the feedback with extra computational cost. We propose a channel-

differential feedback approach that expedites CSI feedback by eliminating CSI-processing cost at the receiver with a relay procedure [62].



Figure 3.3: Schematic diagram of epoch of 802.11ac-based feedback mechanism: (a) Implicit (b) Explicit.

Figure 3.3(a) illustrates implicit transmission epochs with 2 transmit antennas in 802.11ac. The receiver sends the sounding NDP frame to the transmitter that serves two purposes: to acknowledge the previous epoch transmission and to perform uplink channel estimation for the next transmission epoch. The NDP only includes a general 802.11 PHY preamble frame that consists of a short training sequence (STS) followed by a long training sequence (LTS) and the signal field (SIG). The timeline of our proposed channel-differential feedback method based on IEEE 802.11ac explicit feedback is shown in Figure 3.3(b). In each epoch, CSI information is "relayed" to the transmitter by fully eliminating CSI processing at the receiver, which greatly expedites the feedback as well as limits power consumption. In particular, the transmitting antenna takes turns sending M sounding frames (NDPs) to the receiver. Instead of performing CSI estimation on these received messages, the receiver directly attaches the received LTS to the end of the feedback message to be sent. Note that the feedback contains (M + 1) LTSs, in which M LTSs have been processed in the downlink direction and one original LTS in the preamble afterward. When the receiver sends back the feedback, all the LTSs are then processed by the uplink path. The received symbol $r_{pre}(k)$ derived from the preamble LTS directly sent from UE at k-th subcarrier is given by:

$$r_{pre}(k) = p_m \overline{h}_m(k) s(k) + \overline{n}(k).$$
(3.9)

The received symbol $r_{rel}(k)$ for the *m*-th relayed LTS propagating across both downlink and uplink channels are given by:

$$r_{rel}(k) = p_m \overline{h}_m(k) h_m(k) s(k) + \overline{h}_m(k) n(k) + \overline{n}(k).$$
(3.10)

Here, n(k) and $\overline{n}(k)$ denote the addictive noise in downlink and uplink, separately. Assuming $p_m \gg \sigma_n^2$, dividing $r_{pre}(k)$ by $r_{rel}(k)$ gives the channel difference:

$$\frac{r_{rel}(k)}{r_{pre}(k)} = \frac{p_m \overline{h}_m(k) h_m(k) s(k) + \overline{h}_m(k) n(k) + \overline{n}(k)}{p_m \overline{h}_m(k) s(k) + \overline{n}(k)}$$
(3.11)

$$=h_m - \frac{h_m(k)\overline{n}(k) + \overline{h}_m(k)n(k) + \overline{n}(k)}{p_m\overline{h}_m(k)s(k) + \overline{n}(k)}$$
(3.12)

$$\approx h_m.$$
 (3.13)

Downlink CSI can be assumed to be accurately derived at high SNR. Then, the data symbols are precoded by the beamformer at the transmitter prior to being sent to the receiver.

3.2.4 Hybrid Feedback Mechanism

In this part, we set forth a framework to construct a novel feedback mechanism that combines channel estimates obtained from both implicit and explicit feedback to improve the channel estimation accuracy.

As depicted in Figure 3.4, we consider implementing explicit feedback using the channeldifferential protocol previously described. Additionally, implicit CSI can also be acquired from feedback or messages that make use of known preambles across the uplink channel. Channel coherence can be estimated through the obtained channel impulse response and delay spread. Channel reciprocity error can be known by sending a training overhead in both the uplink and downlink channels. Both channel coherence and channel reciprocity error will decide how implicit and explicit CSI jointly impact our hybrid channel estimation, which is given by:

$$h_b(k) = \alpha h_m(k) + (1 - \alpha) \bar{h_m}(k)$$
 (3.14)

Here, α is the factor parameter that decides the ratio to distribute the contribution between implicit and explicit CSI that improve channel estimation accuracy. In this dissertation, we explore the impact of α with two patterns: constant and binary. For a constant pattern, ratio parameter α with a fixed value of 0.5 means equal contribution from both schemes. For a binary pattern, α will decide 0 or 1 based on channel contexts based on estimated Doppler and CRE. For instance, a factor parameter equal to 1 denotes only utilizing explicit CSI in the channel estimate. The combination of implicit and explicit feedback enables our hybrid feedback scheme to significantly improve channel estimation accuracy with known information of channel coherence and channel reciprocity error. The ratio parameter and feature mode can be dynamically indicated in the 802.11ac VHT-SIG field for the recipients to support and process the hybrid feedback transmissions.



Figure 3.4: Schematic diagram of hybrid feedback mechanism.

3.2.5 Channel-aware Feedback Mechanism

Although the optimal rate for channel estimation can be evaluated by both simulation and experiments in prior work, fixed overheads have been used for each feedback operation. In our previous experiments, we emulated a Rayleigh fading channel with 5 taps and implemented 64 uniformly-distributed element vectors for OFDM transmissions at each transmit antenna to describe the channel properties in the frequency domain. As shown in Figure 3.5, the channel taps can be modeled as a Finite Impulse Response (FIR) filter with a frequency response given by:

$$h_m(k) = \frac{1}{N} \sum_{n=-\infty}^{\infty} c(n) e^{-j2\pi nk\Delta_f}.$$
(3.15)

Here, $h_m(k)$ represents the channel vectors (in the frequency domain) that are estimated by training overhead, depending on the specific feedback mechanisms. The FIR channel tap is c(n).



Figure 3.5: 5-Tap Rayleigh Channel Model with Doppler Effects: (a) Time Domain (b) Frequency Domain

We anticipate the payload of feedback will only increase as the antenna number increases for massive MIMO systems. Also, since channels can be frequency-selective or frequencyflat [9], this motivates the design of a channel-aware feedback (CAF) mechanism which dynamically implements a proporational feedback matrix based on flatness properties of channel for each transmit antenna. Assuming the available feedback vector length is limited to set $I \in \{64, 32, 16, 8\}$, considering FFT/IFFT implementation in DSP chip design, the predicted vector length *i* with satisfied channel estimation performance is derived by:

$$_{i \in I}MSE(h_{m,i} - h_{m,64}) < T.$$
 (3.16)

Here, T denotes the MSE threshold, and $h_{m,i}$ is the estimated 64 channel vectors by a linear curve-fit of an i element vector. With T = 0.1, when the channel spectrum tends to be more flat, less estimation points can be potentially deployed to describe and recover the channel with high precision. The idea here is to perform an i-point FFT on sounding signals and obtain i-element channel estimations with equal subcarrier spacing. We then use linear fitting to derive 64 elements and compare with the 64-point FFT full channel estimation for the MSE calculation. We have demonstrated that reduced channel vector leads to reduced training overhead while achieving satisfactory estimation performance. For example, in Figure 3.6(a), a MSE of 0.073 is achieved with 32-element estimates for channel feedback, while Figure 3.6(b) shows another case that the number of required points is 16 with an MSE of 0.089.



Figure 3.6: Channel Aware feedback. (a) 32 Samples (b) 16 Samples

3.3 Experimental Settings

In this section, we first describe the design of our channel evaluation and outline the main factors that impact channel reciprocity. We then discuss our beamforming framework that is optimized for UAVs and the 802.11ac MIMO scheme that allows CSI feedback in our mobile system.

We evaluate channel reciprocity error using a software-defined radio platform and WARPLab with channel emulator. WARPLab enables users to implement the OFDM functionalities in MATLAB and encode/decode actual signals using synchronized radios [63]. Then, the coded and modulated data samples are transferred to the WARP board via an Ethernet cable. WARP is then triggered to transmit data samples over the air. The receiver samples the received signal over the air and then transfers the raw samples to the PC, where the receiver also leverages MATLAB to process the received data. During our experiments, one WARP board with two antennas acts as the beamformer/transmitter with precoding, and the other WARP board acts as a client device that is equipped with one antenna as a beamformer/receiver. We use an Azimuth Wireless Channel Emulator and Director II software to investigate the factors that affect the system performance [38]. The channel emulator can be controlled by TCL customzied scripts that generates controllable and repeatable channel conditions as a function of frequency, Doppler shift, and scenario type for complex wireless environments. The hardware setup, for this channel emulation is shown in Figure 3.7.

In addition to the experimental setup, we evaluate the system with step controlled factors and then their joint effects on feedback performance. We include a reference result which is the zero CRE error as the baseline case for our evaluation. The distance between antennas along each side of the square is 20 cm, which is approximately the size of a mobile device. Moreover, with the use of 5 GHz band, this antenna separation allows little correlation between the channels from different transmit antennas. The transmit signal bandwidth is 20 MHz, which is the maximum bandwidth currently supported by the WARP radio. We use an OFDM scheme with 64 sub-carriers in our experiment, which is compatible for the next generation WLAN technologies working with a 20 MHz bandwidth. The experimental plan of our proposed CRE evaluation is shown in Figure 3.8.

Our experiments are conducted over three carrier frequencies: 900 MHz, 1800 MHz, and



Figure 3.7: Experimental Setup (a) WARP and Azimuth Wireless Channel Emulator (b) Channel Emulation via Director II software

5 GHz. At the PHY layer, we use the same transmission framework as channel emulation platform, as described in Fig. 3.3. We measure both BER and throughput to evaluate the beamforming system performance. While many works use the Shannon Capacity to map the SNR or BER to the ideal information rate [9], for a practical frame-based system, the throughput depends closely on the hand-shaking overheads and successful decoding of the received frames. In this work, link throughput (Mbps) is obtained by monitoring the bit error rate (BER) statistics, number of successfully recovered packets (N_s) , and total transmission time (T) at each experiment, given by the following equation:

$$Throughput = \frac{256 * 8 * N_s * (1 - BER)}{T}$$
(3.17)

3.4 Experimental Evaluation with Channel Emulation

Current IEEE 802.11 protocols adopt a single feedback scheme, which inherently could be beneficial in some scenarios and inefficient in others. In this section, we quantify the effect of key factors on channel feedback mechanisms for 802.11ac beamforming precoding, including transmitter-receiver imbalance, Doppler effects, and effective noise power. We additionally evaluate the joint effect of these factors on centralized and distributed beamforming networks to approach practical transmission scenarios.



Figure 3.8: RF mismatch for transceiver paths

3.4.1 Transmitter-Receiver Imbalance Impact Evaluation

We refer to TX-RX imbalance as the error in terms of amplitude and phase, stemming from the reliance on the transmitter and receiver chain difference without channel impacts. To study the impact of phase error on system link performance, the null data packet (NDP) sounding frames are sent bi-directionally with a constant channel attenuation of 70 dB to simulate the propagation path loss. Automatic gain control (AGC) is turned off during the experiments to ensure control of this attenuation. The channel is modeled as a Rayleigh fading channel with 5 taps that we embed in our channel emulation scripts. For each test, we fix the channel amplitude to be the same for downlink and uplink channels and measure the throughput as a result of changing the phase error percentage by increasing it from 0 to 80%. The throughput is calculated based on equation (3.17).

Figure 3.9(a) illustrates the results of throughput performance according to the range of values for phase error percentage. The phase error percentage is denoted as the ratio of error deviation compared to the recorded reference channel taps. In this plot, we can observe that with two transmit antennas, the implicit feedback incurs less overhead and improves throughput performance by up to 61% with no phase error. This link performance difference between explicit and implicit feedback is explained by the explicit overhead directly. However, the performance of implicit feedback degrades sharply as phase error increases. For example, when we increase the phase error to approximately 80% we find that the throughput of implicit feedback would be less than 3 Mbps. This is for the fixed bandwidth of 20 MHz at a

carrier frequency of 5 GHz. If the bandwidth is increased (*e.g.*, 160 MHz, as in 802.11ac and 802.11ax, 1.76 GHz, as in 802.11ad), the transmitted signal becomes more susceptible to the potentially destructive effects of fading such as phase dispersion and frequency-selective fading. In addition, from a hardware complexity perspective, the analog-to-digital converter can be easily saturated by the large amount of sampled and quantized signals, leading to delay and jitter in baseband processing. As a result, severe channel estimation errors and channel reciprocity degradation occurs in contrast to more narrow bands. If, however, narrow-band signals are in use, these effects are negligible as the signal experiences flat fading where all of its components are attenuated, phase shifted, and time delayed by approximately the same amount. In the narrow-band case, delays in baseband processing are minimal.

To quantify the impact of amplitude error, we repeat the experiments with a fixed phase error and evaluate the link throughput performance across different amplitude error percentages. As shown in Figure 3.9(b), we observe that the performance of implicit feedback stays almost the same as amplitude error increases, and then degrades more sharply from 29.3 Mbps to 18 Mbps as the amplitude error reaches the 60% to 80% range. Since the amplitude error percentage is found to be less than 20% in the large majority (95%) of practical instances in Chapter 4, the effect of amplitude error is far less significant as compared to phase error.

To examine the joint effect of phase and amplitude error on link performance, we fix the error value of one factor and change the value of the other factor for each experimental condition. The result is shown in Figure 3.10, where we use the same repeatable 5-tap, equal-power Rayleigh distribution model for this experiment via channel emulation scripts. We observe that, in a relatively good channel reciprocity condition, implicit feedback can outperform explicit feedback, by 21% on average. This is due to the advantage of saving overhead with implicit feedback (and relying on channel reciprocity) compared to explicit feedback with the same time-domain resources. Phase error, on the other hand, has a more significant impact on system performance. This is explained by the performance separation curve that varies more severely along the phase axis. The separation curve is calibrated by different TX-RX switching times and based on our platform to investigate the performance of the different commercial transmitters. Our calibrated switching time rises from 8 μs to 1



Figure 3.9: TX-RX Imbalance Evaluation (a) Throughput vs. Phase Error Percentage, and (b) Throughput vs. Amplitude Error Percentage

ms. Since we use the WARP platform for experimentation in this section, we use a TX-RX switch time of 200 μs .

3.4.2 Doppler Effect Impact Evaluation

We now seek to enhance and extend current works on the evaluation of diverse feedback mechanisms in the presence of mobility. In particular, we evaluate the link performance of beamformed transmissions using the aforementioned experimentation setup in the emulated channel by introducing various levels of Doppler effects at a carrier frequency of 5 GHz. We use a channel emulator with a 3GPP R36 5-tap Rayleigh distribution model, which is typical for small cell coverage with NLOS conditions (*e.g.*, an auditorium, playground, or open-roof stadium). By implementing the Rayleigh fading model, the coherence time can be approximately by:

$$t_c = \frac{9}{16\pi f_d}.$$
 (3.18)

Here, f_d represents the Doppler frequency shift and is given by $\frac{vf_c}{c}$.

High device mobility is known to affect channel estimation and feedback performance. In channel emulation, we use a central carrier frequency of 5 GHz for channel emulation. We



Figure 3.10: TX-RX Imbalance Evaluation: Throughput vs. Joint Amplitude and Phase Errors

vary the UE velocity to create different Doppler effects over the channel. Moreover, we use the IEEE 802.11ac implicit feedback as a comparison to the performance of different channel feedback approaches. In order to consider the system performance at low and high velocity scenarios, we increase the velocity to 100 m/s across the various emulated channels.

3.4.2.1 Characterization of Doppler Effect

Figure 3.11 depicts how the throughput decreases as Doppler frequency increases, an effect which is induced by UE mobility. For each test, we repeatedly send 10k frames and analyze the successfully decoded payload in one second, which is interpreted as throughput. The results are shown for both explicit and implicit feedback schemes. The theoretical throughput (the blue line on the y-axis) is based on zero bit rate and 64-QAM, considering a training overhead of 10 ms. We observe that, by increasing the emulated Doppler velocity from 0 to 100 m/s, throughput in both feedback approaches decreases by 85 percentage.



Figure 3.11: Doppler Effect Evaluation: Throughput vs. UE Velocities

However, the throughput of the implicit feedback scheme degrades more severely than with explicit feedback. Furthermore, the peak throughput of implicit feedback when no Doppler shift is applied can, on average, reach 28.9 Mbps, which means the predicted value is very close to the theoretical throughput reference of 30 Mbps. Our evaluation demonstrates that it is necessary to eliminate phase error to improve channel estimation.

3.4.2.2 Analysis of Joint Effects

We present the throughput performance of the beamforming techniques based on explicit and implicit feedback schemes, as illustrated in Figure 3.12(a) and Figure 3.12(b), respectively. We observe that, for a fixed phase error, an increase in Doppler velocity significantly reduces the estimated throughput. For example, at a phase error of 20%, the Doppler effect reduces throughput by 60 to 90 percent beyond a velocity of 20 m/s. With the largest velocity setting, 100 m/s extended for channel emulation, the impact of channel coherence introduced by mobility becomes stronger, resulting in less throughout with implicit feedback. However, for explicit feedback, the performance degrades slower compared to implicit feedback scheme. This is explained by the fact that explicit feedback is robust enough to combat channel reciprocity errors by its capability to obtain accurate CSI in the downlink direction. Thus, we can conclude that implicit feedback is more susceptible to the impact of channel coherence.



Figure 3.12: Doppler Effect Evaluation: Throughput Performance vs. Changing Velocities. (a) Implicit (b) Explicit

3.4.2.3 Characterization of Channel Accuracy

Prompt and accurate channel feedback is essential for robust beamforming design. In this part, we compare the performance of explicit and implicit channel accuracy by excluding the impact of overhead. The channel accuracy is characterized by comparing the configured channel vectors with estimated channel estimates. We first calibrate the recorded channel vectors provided by channel emulation at different levels of Doppler velocities and phase errors. Then, we evaluate and compare the accuracy of the estimated channel of implicit and explicit feedback schemes. The channel accuracy is based MSE and given by:

$$\delta = 1 - \frac{1}{M} \sum_{m}^{M} \frac{||h'_m - h_m||}{||h_m||} \times 100\%.$$
(3.19)

Figure 3.13(a) shows how channel estimation accuracy changes with increasing phase

errors introduced over the emulated uplink channel. The channel accuracy is an average estimation over 20k transmission epochs (as shown in Figure 3.3) at each phase error condition. The estimated SNR during our experiments is as high as 53 dB considering only thermal noise. By comparing both implicit feedback and implicit feedback under the same condition and isolating the overhead for explicit, we observe that the explicit feedback can perfectly capture the downlink channel information with an estimation accuracy approaching 1. However, the estimation accuracy of implicit feedback, due to channel reciprocity error (CRE), decreases from 1 to 0.12 as phase errors increase, which means that implicit feedback is highly susceptible to CRE.

Figure 3.13(b) shows the impact of increasing Doppler velocity on channel accuracy using our explicit and implicit feedback schemes. Although a Doppler velocity of 100 m/s can introduce a Doppler frequency of approximately 1.7 kHz in the emulated channel model, it has less impact on implicit feedback than explicit feedback. For example, the accuracy of implicit channel decreases by 80% while that explicit channel decreases by around 95%. Of particular note in our evaluation is that implicit feedback is susceptible to channel reciprocity errors, while explicit feedback is more susceptible to Doppler effects. This motivates the need for a hybrid feedback scheme that could make use of either scheme at the appropriate time according to the most favorable channel factor for that scheme. By further increasing the Doppler velocities, the performance degradation of channel characteristic estimation decreases gradually.

3.4.3 Effective Noise Impact Evaluation

We have previously addressed the effects of channel reciprocity error and Doppler velocity in the absence of effective noise. Now, we explore the impact of co-channel noise power on the performance of channel estimation to anticipate similar effects in practical channels. To do so, we extract and compare the channel estimates based on transmissions of NDP sounding frames with various levels of the signal-to-noise ratio (SNR) applied at the receiver. The effective noise denote the joint impact of interference power and thermal noise. By varying the values of p_i , we can emulate different noise power profiles between the transmitter and receiver and evaluate our system under different SNR conditions.



Figure 3.13: Channel Accuracy Analysis (a) Impact of CRE on Channel Accuracy (b) Impact of Doppler Effect on Channel Accuracy

Figure 3.14 depicts channel estimation accuracy for implicit and explicit feedback with 6 different groups of SNR values. There are two interesting findings from these result: (i) The effects of Doppler velocity and phase error are clearly the most dominant at high SIR values, and (ii) Implicit and explicit schemes result in approximately the same performance under the impact of Doppler effects with low SNR values. These curves infer significant performance degradation of implicit feedback under low SNR values.

3.4.4 Hybrid Feedback Mechanism Evaluation

In this part, we discuss our hybrid feedback mechanism that combines channel estimates obtained from both implicit and explicit feedback to improve the channel accuracy. As depicted in Figure 3.4, we consider implementing explicit feedback that obtains explicit CSI via our proposed channel-differential feedback scheme. In addition, the implicit CSI is obtained based on the LTS field in the feedback message sent from the UE. The transmitter will dynamically and jointly utilize the explicit or implicit CSI to improve the channel accuracy.

Figure 3.15 presents the statistical CDF of the calibrated throughput with different channel accuracy estimates. Monte Carlo experiments are used to create the random samples of channel coherence and channel reciprocity errors. We do this for two scenarios of the factor α configurations: constant and binary patterns, as described in Section 3.2.4. By



Figure 3.14: Effective noise Impact Analysis (a)(b) SNR = 8 dB (c)(d) SNR = 4 dB (e) SNR = 2 dB

performing hybrid feedback for different test cases, the channel estimates are predicted and then translated to throughput estimates. We observe that using our factor parameter results in outperforming the explicit/implicit schemes by 32%, on average. This proves that



Figure 3.15: CDF of calibrated throughput for feedback Mechanisms: (a) Constant (b) Binary

beamforming with the proposed hybrid feedback mechanism shows significant performance gain. We believe our analysis also laid the foundation for future works towards determining the optimal ratio parameter yields the best prediction performance.

3.4.5 Channel-Aware Feedback Mechanism Evaluation

We evaluate the performance the CAF mechanism in the context of phase and amplitude errors, following the same experimental setup in Section 3.4-A. The results are shown in Figure 3.16, where we repeat the experiments with the same Rayleigh distribution channels for explicit/implicit channel estimation and beamforming. However, we implement a reduced feedback matrix instead of the fixed 64 vectors based on the optimal feedback vector length selection according to Equation 3.16. We observe that, with changing channel properties in flatness, both implicit feedback and explicit throughput increase more than that without CAF implementation by 7.3%, due to the overhead saving. Considering that an 1024 and 4096 FFT IP will be deployed as the bandwith processing increases and more flexibility will be given to feedback vector length selection, our design and concept of CAF will allow flexibility in OFDM-based WiFi and cellular network feedback design.



Figure 3.16: CAF Mechanism Evaluation: Throughput vs. Joint Amplitude and Phase Errors.

3.4.6 Distributed Beamforming Evaluation

We extend our analysis to a distributed beamforming scheme with asymmetrical synchronization. For this scenario, wireless radios are now situated on distinct transmission nodes, which have independent oscillators and amplifiers that introduce different frequency and phase offsets. This means that extra estimation error will result due to oscillators mismatch. In addition, mobility of transmission nodes can, as previously explained, significantly impact the feedback schemes. Therefore, it is essential to investigate the impact of these joint factors with asymmetrical synchronization on the link performance of a distributed beamforming system.

In order to evaluate the effects of frequency offset and Doppler shift, we design and perform our experiments using an Azimuth ACE-MX channel emulator and generate a controlled and repeatable propagation channel and fading parameters. The setup for this section is shown in Figure 3.17. For the beamformer, we use two WARP boards and connect them with the Azimuth ACE-MX via RF cables that run from the transmission ports to the two emulator input ports. A third WARP board is used as the beamformee connected to the emulator output port. We control the channel emulator with a TCL script that generates repeatable 5-tap Rayleigh distributed samples. The channel emulator is controlled over an Ethernet cable from the control PC by the Director-II software, from which we can configure the channel characteristics such as the distribution model, channel taps, path-loss, Doppler effects, and input/output attenuation.



Figure 3.17: Experimental Setup (a) Experimental Diagram (b) System Emulation (c) Feedback Analysis Flow

We evaluate the impact of asymmetrical synchronization using a software-defined radio platform, WARPLab. WARPLab enables users to implement PHY and MAC layer functionalities in MATLAB and transmit/receive actual signals using RF radios. Then, the coded and modulated data samples are transferred to the WARP board via an Ethernet cable. WARP is then triggered to transmit data samples over the air. The receiver samples the signal and then transfers the raw samples to the PC, where the receiver also leverages MAT-LAB to demodulate and decode the transmitted data for post-processing and data analysis. The feedback test scheme is depicted in Figure 3.17(c). In order to introduce an asymmetrical frequency offset for the two transmitting nodes, we introduce a shifting parameter to the digital samples with various frequency offset settings. The frequency offset is the carrier frequency difference between the distributed nodes, which can be emulated by multiplying the samples with a time-based exponential shift (sampling rate = 40 MHz). Since the WARP board is reported to have an a oscillator deviation of 3 ppm (15 KHz as the worst offset), we configure the frequency error to be in the range of 100 Hz, 200 Hz, and 1 KHz. Then, we evaluate the impact of mobility introduced by the channel emulator. We also use an RF synchronization cable to create zero frequency offset as a reference for our evaluation.

The impact of the resulting channel and its translation to throughput are shown in Figure 3.18. It shows how various frequency offsets and Doppler frequencies with explicit and implicit feedback schemes can affect the calibrated throughput. We observe that, with perfect synchronization, feedback performance based on distributed MIMO can achieve the same throughput performance as a centralized MIMO scheme due to perfect channel estimation accuracy. Furthermore, the levels of frequency offset can significantly affect MIMO performance. With a frequency offset of 100 Hz, the channel accuracy drops by 10%. However, the channel accuracy significantly degrades to 80% with a frequency offset of 1 kHz. This result shows that the frequency offset can significantly degrade the distributed beamforming link performance.

3.5 Related Work

This work has relevance across the following areas: (i.) Channel Reciprocity, (ii.) Feedback Mechanism, and (iii.) Beamforming.

Feedback Mechanism: IEEE 802.11 standards specify two types of feedback mechanisms: implicit feedback and explicit feedback. Both IEEE 802.11ax and 802.11ac implement



Figure 3.18: Distributed link performance analysis.

explicit feedback scheme from UE to calculate the optimal transmit signal weights [41]. Channel feedback mechanism is based on the Singular Value Decomposition (SVD) of the channel. However, this procedure can bring large computation cost [42]. While explicit feedback can provide more accurate CSI, it introduces large overhead in terms of time and feedback control bits. For implicit feedback, the transmitter does not need to measure and send the CSI to the beam former. Implicit Beamforming is also implemented 802.11n [43]. However, implicit beamforming requires frequent calibration operation between the transmitter and receiver when practical channel is not reciprocal, which can complicate the 802.11ac MIMO framework design [41].

Channel Reciprocity: In perfect channel reciprocity, implicit feedback will incur less overhead and improve throughput performance [42, 45–51]. However, most works ignore the possibility that the channel is not perfectly reciprocal in practice. This is due to three reasons: signal travelling imbalance between transmitter and receiver, noise power difference between transmitter and receiver, and channel estimation error introduced by device movement. Channel reciprocity estimation failure due to TX-RX impairment has been fully discussed. For example, experiments have showed significant performance losses with implicit feedback due to non-reciprocity between the forward and reverse signal travelling when transceiver calibration is neglected [45]. Still other work has modeled the reciprocity error

(gain mismatch) caused by the difference in transmit/receive analogue front-ends electronics under a narrow band assumption [42]. The different mutual coupling (MC) of transmitters and receivers, which can destroy the reciprocity in compact antenna array scenario, is also considered [46]. However, sufficient knowledge about the joint effects of channel reciprocity error and mobility on feedback performance is still lacking in current literature. Another work investigates the reciprocity error in OFDM systems and finds that the phase of reciprocity error rotates linearly in frequency domain which is caused by phase/amplitude imbalance between the transmitter and receiver [47]. Albeit insightful, this work only describes the phenomenon observed during experiments without further analysis of the internal cause and the impact of such OFDM-based phase errors on system link performance. Furthermore, the effective noise profile at the transmitter and receiver sides may be significantly different [48]. This causes the signal quality to be different between the forward and reverse link. A MMSE method has been proposed to minimize the demodulation error, assuming knowledge of the effective noise distribution [49]. The closest work to ours that investigates the impact of mobility on feedback performance is given by [50]. Channel reciprocity can theoretically be assumed for channels in which uplink and downlink transmissions share the same frequency spectrum and when the coherence time of the channel is much greater than the packet period. However, this is only true for channels with low Doppler spread 51. In high mobility scenarios, we have observed frequency domain phase distortion and significant degradation with implicit channel feedback.

Beamforming: The key features for the next generation wireless standard development is the scaling of MIMO. Beamforming technique is one of the dominant approaches to improve system capacity and network coverage by enabling multiple concurrent transmissions using the same frequency spectrum reuse, especially suitable for high frequency bands due to their high path loss and poor penetration ability. Beamforming can improve the received signal strength of the intended user and reduce noise interference to unintended users [5,64]. Relative to the in-field experimentation of this work, beamforming systems are particularly suitable for air-to-ground wireless communications due to the following attributes: (i.) combating high levels of channel fluctuations introduced by hovering and flying the aircraft, (ii.)overcoming the limited range of omni-directional antenna patterns, and (iii.) leveraging spatial diversity to improve wireless transmissions [65-67]. To address these uncertainties, we first analytically evaluate the feedback overhead and then investigate it via experiments.

3.6 Summary

In this Chapter, we have examined the key factors that degrade the performance of channel reciprocity, such as transmitter-receiver imbalance, Doppler effect due to mobility, and effective noise impact. First, we reviewed the current IEEE 802.11 channel feedback schemes and their challenges. Then, we have presented our proposed channel feedback mechanisms to increase CSI accuracy and further improve throughput, which are possibly considered for future WLAN systems. Also we have evaluated implicit channel feedback and explicit feedback scheme in both emulated MIMO channels and in-field study with UAV communications. Our evaluation shows that channel estimation can be significantly affected by channel coherence due to mobility and our proposed hybrid feedback scheme can efficiently improve channel estimation accuracy and link performance by 32%. Our in-field assessment demonstrates that a properly optimized drone-based beamforming system can provide significant throughput improvement using explicit versus implicit feedback.

Chapter 4

Drone-Based Beamforming and Feedback System

In this chapter, we design a prototyping testbed which implements drone-based beamforming using a software defined ratio platforms. We develop an IEEE 802.11-based mechanism to support the channel feedback required for beamforming with variable-range experimental evaluation.

4.1 Motivation

Commercial drones are taking the world by storm — the global market for drones is expected to reach \$22.15 billion by 2022 [68]. Recently, the deployment of low altitude platforms (LAPs) or UAVs has enabled wireless communication for ground-based terminals in applications such as disaster relief systems, public safety, and military communications. Drones can play a significant role in search and rescue operations, communication system recovery, and damage assessment for natural disasters like earthquakes, volcanoes, floods, or wildfires [69], due to rapid deployment and access to "hard-to-reach" geographic regions such as rivers, mountains and forests. In the public safety sector, UAVs have delivered broadband data rates in emergency and public safety situations, such as law enforcement and fire rescue [70]. Another emerging application is military communications where the role of drones has expanded from conventional missions like surveillance and reconnaissance to special forces for such applications as electronic interference, node swarms, and long-haul communication relays, each of which has traditionally relied upon soldiers or terrestrial-based vehicles [71, 72].

In this chapter, we design a prototyping testbed which implements drone-based beamforming using a USRP-based SDR platform (a battery-powered 2×2 MIMO Ettus E312) mounted via 3D printing to a DJI Matrice 100 drone. We develop an IEEE 802.11-based mechanism to support the channel feedback required for beamforming. Then, we conduct variable-range propagation experiments and characterize air-to-ground links as a function of distance, frequency, and drone altitude by analyzing the dominant propagation parameters (e.g., the path loss and shadowing) on a wide range of frequency bands. We additionally evaluate the system-level performance of beamforming in terms of Bit Error Rate (BER) and throughput with in-field measurements. To evaluate the channel feedback required for drone-based beamforming gains, we use the three distinct scenarios of hovering, encircling, and linear: (i.) in the hovering case, the drone is hovering at a fixed altitude and location, (ii.) in the encircling case, the drone moves at a steady speed around a circle with the user equipment (UE) in the center, and, (iii.) in the linear case, the drone is passing by the ground receiver in a straight line.

4.2 System Model

In this section, we discuss the challenges that beamforming presents to UAVs, the 802.11based signaling mechanism that allows CSI feedback in our UABeam system, and quantify the feedback overhead that exists in such a system.

4.2.1 Drone-based Beamforming Framework

Beamforming systems are particularly suitable for air-to-ground wireless communications due to the following abilities: (*i*.) combating high levels of channel fluctuations introduced by hovering and flying the aircraft, (*ii*.) overcoming the limited range of omnidirectional antenna patterns, and (*iii*.) leveraging spatial diversity to improve wireless transmissions [65–67]. The performance of beamforming can be further enhanced in terms of BER and throughput if CSI is obtained in a timely and efficient manner, assuming multiple antennas can be mounted and sufficiently spaced at the transmitter. However, there are three major uncertainties to evaluate when it comes to deploying beamforming systems on an UAV. First, will the overhead induced by feeding back the CSI consume any beamforming gain, especially in highly mobile scenarios common to drones. Second, can channel reciprocity be assumed or exploited in some capacity to minimize feedback overhead. Third, how frequently does CSI have to be fed back to the transmitter to support various drone topologies and mobility patterns and what relationship does this update rate have with the carrier frequency. To address these uncertainties, we first analytically evaluate the feedback overhead and then investigate it via experiments.

We implement a completely real-time OFDM beamforming system with flow control, synchronization, signal processing, and performance analysis functionalities by means of GNU Radio. Consider a typical beamforming system with M transmit antennas, one single receive antenna, and K subcarriers. At the kth subcarrier, the same copies of signal symbol s(k) ($E[|s|^2] = 1$) is coded by the beamformer prior to being sent to the UE from the mth transmit antenna. For the purpose of eliminating inter-symbol interference (ISI) introduced by frequency-selective multipath channel, the cyclic prefix (CP) is added at each OFDM symbol. We represent $h_m(k)$ as the complex channel information obtained in the path from the mth transmit antenna to the single receive antenna at the kth subcarrier. The length of one OFDM data frame is assumed to contain a fixed number of L OFDM symbols. The preamble has two OFDM symbols with known training data. Therefore, the received symbol at the kth subcarrier and lth OFDM symbol interval (l = 1, ..., L) can be written as:

$$r(k,l) = \sum_{m=1}^{M} h_m(k) w_m(k) s(k,l) + n(k,l)$$
(4.1)

Here, $w_m(k)$ represents the beamforming vector at the kth subcarrier, and n(k, l) denotes the additive noise. Empirically, $h_m(k)$ can be assumed to be constant within one epoch (a brief period of message exchange consisting of training, feedback, and beamforming) and changes independently from other epochs with velocities less than 8 m/s when timely feedback schemes and proper packet lengths are configured [73]. A short packet length will lead to excessive header overhead and resulting low throughput, while a long packet length could cause relatively high BER due to outdated CSI. Hence, we experimentally examine these independence assumptions and the impact of the packet length for drone-based systems.

In this thesis, we choose conjugate beamforming at the beamformer due to its simplicity and efficiency [74]. However, the above beamforming model can also be applied with other beamforming techniques like Zero-Forcing or Singular Value Decomposition. The conjugate beamformer is given by:

$$w_m(k) = \frac{\tilde{h}_m(k)^*}{\|\tilde{h}_m(k)\|} \tag{4.2}$$

Here, $(\cdot)^*$ is the conjugate transpose operation, and $\tilde{h}_m(k)$ is the estimated channel information based on training symbols.

4.2.2 Channel Feedback Framework

We use the IEEE 802.11 PHY frame as the frame structure in this thesis, as shown in Figure 4.1. One frame is composed of a preamble, a header symbol, and OFDM-based data symbols of payload length L. The preamble consists of short training sequences (STS) and long training sequences (LTS). Both the STS and LTS have the duration of two training OFDM symbols, and the header has a duration of one OFDM symbol.



Figure 4.1: IEEE 802.11 PHY frame Structure

In the conventional IEEE 802.11 standard, a CTS packet is required when the receiver successfully decodes an RTS packet. In this thesis, RTS and CTS frames are assumed to have zero-sized data payloads. The preamble serves two purposes: synchronization and channel estimation. The receiver detects the existence of a frame based on the correlation of the received stream with the known information in the time domain. The preamble of the RTS sent by the transmitter is also used for channel estimation in the frequency domain.

In order to efficiently achieve beamforming, the receiver broadcasts back its estimate of CSI to the transmitter via the time division duplex (TDD) schedule. Considering aerial communication, one challenge is trying to expedite the feedback procedure at minimal loss, since a large feedback overhead will greatly degrade the throughput rate. However, existing works that have attempted to optimize the CSI feedback have not directly addressed air-to-ground situations [75–80]. A previously proposed criterion is used to determine the matrix

in this precoder codebook out of which to choose. By means of Grassmannian subspace packing, [75] proposed an efficient method to determine the optimal codebook. In [76], the OFDM subcarriers are divided into clusters, and only the Karcher mean vector is used. [77] allows feedback compression with fewer bits for MIMO systems. However in these works, the receiver still needs to process the CSI and prepare the feedback with extra computational cost.



Figure 4.2: Timeline of CSI Feedback for proposed beamforming scheme.

The MAC layer operation of our proposed CSI feedback method is shown in Figure 4.2. In each epoch, CSI information is "relayed" to the transmitter by fully eliminating CSI processing at the receiver, which greatly expedites the feedback as well as limits power consumption. In particular, the transmitting antenna takes turns sending M RTS training messages to the receiver. Instead of performing CSI estimation on these received messages, the receiver directly attaches the received LTS to the end of the CTS feedback message to be sent. Note that the CTS contains M + 1 LTSs, including M LTSs processed in the downlink direction, and one original LTS in the preamble. When the receiver sends back the CTS, all the LTSs are then processed by the uplink path. Assuming one training symbol from the LTS at the kth subcarrier is denoted as s_t , then the received symbols for M LTSs are given by:

$$r(s_t) = \overline{h}_m h_m s_t \tag{4.3}$$

The received symbol for the preamble LTS is given by:

$$\overline{r}(s_t) = \overline{h}_m s_t \tag{4.4}$$
where \overline{h}_m is the uplink channel gain. Then, it is straightforward to obtain the downlink CSI by dividing $r(s_t)$ by $\overline{r}(s_t)$. Then, the data symbols are precoded by the beamformer at the transmitter prior to being sent to the receiver.

We compare our proposed feedback method with three previously-discussed approaches via simulation: (*i.*) G-subspace Codebook Index [75], (*ii.*) K-means Clustering [76], and (*iii.*) Vector Quantization [77]. For the convenience of this evaluation, we assume the transmitter and receiver are perfectly synchronized. We also assume the CSI can be perfectly obtained at the receiver. Now, the problem becomes how to feed back the CSI to the transmitter. For practical channel relevance, we implement the IEEE 802.11 Channel Model B with 11 taps [78]. We also implement conjugate beamforming at the transmitter equipped with two antennas but vary the transmission power. We evaluate the BER of the different feedback approaches as a function of SNR sensed by the receiver. We use QPSK as the data constellation order and calculate the BER for each method.



Figure 4.3: BER Simulation under different feedback approaches.

Figure 4.3 shows the simulation results of BER values for a 2×1 beamforming system employing our proposed approach, G-subspace Codebook Index, K-means Clustering, and Vector Quantization. Note that our proposed approach completely eliminates the feed-

back overhead at the receiver without sacrificing beamforming gain, while all other feedback schemes require various computational costs. A perfect feedback scenario is one where the receiver is assumed to feed back the CSI without any CSI loss with zero overhead cost. Our proposed approach has a BER improvement of 1.63 dB on average over that of K-means Clustering and 2.35 dB over that of Vector Quantization, respectively. At the low SNR, our proposed approach still provides the lowest BER of all four feedback schemes and comparable BER to perfect feedback. This can be explained by the channel quality having more impact on the conventional feedback schemes, which introduce extra feedback overhead and compression loss.

4.3 Experimental Settings

To build UABeam for drone-based beamforming experimentation, we have designed and printed mounts for an Ettus E312 and two antennas to be secured on a DJI Matrice 100 (1-kg load capability), as shown in Figure 4.4. To do so, we have used a ROBO 3D printer and CAD software to ensure that a 10-cm separation exists between two antennas for diversity purposes and allows repeatability in testing to position them in the same location. For a given experiment with a carrier frequency of 900 MHz and 1800 MHz, we mount two dual-band VERT900 omni-directional antennas, and for a given experiment at 5 GHz, we mount two dual-band VERT2450 antennas. Both antenna types provide a gain of 3 dBi. We have designed and implemented PHY and MAC layers that carry out the IEEE 802.11like channel feedback signaling discussed in the previous section (Section 4.2) using GNU Radio [81]. The receiver configuration is matched for the USRP hardware, but is housed on a tripod at a height of 1 m above the ground. The received signals are amplified and down modulated to baseband. The digital samples are processed by GNU Radio blocks running on a Linux-based laptop.

Our experiments are conducted over three carrier frequencies: 900 MHz, 1800 MHz, and 5 GHz. At the PHY layer, we implement an OFDM scheme with 64 subcarriers operating with 20-MHz bandwidth, which is common for 802.11 systems. The preamble and header OFDM symbols use BPSK modulation but the data OFDM symbols use QPSK. The payload length is set to 256 bytes. At the MAC layer, we follow the periodic timeline schedule



Figure 4.4: Equipment settings for experiments. (a) Beamformer USRP mounted on a drone (b) UE USRP mounted on a tripod.

Parameters	Preamble	Data
Modulation Schemes	BPSK	QPSK
Total Subcarriers	52	52
Occupied Subcarriers	52	48
Pilot Subcarriers	0	4
FFT size	64	64
CP Interval	0.25	0.25

Table 4.1: IEEE 802.11 based Frame Parameters

described in Figure 4.2. We measure both BER and throughput to evaluate the beamforming system performance in the transmission environment. While many works use the Shannon Capacity to map the SNR or BER to the ideal information rate [82], for a practical frame-based system, the throughput depends closely on the hand-shaking overheads and successful decoding of the received frames [73]. In this thesis, the throughput (Mbps) is defined as the number of payload bits successfully recovered from the successfully decoded packets over the transmission time.

We conduct two different sets of experiments in the field. In the first set, we design experiments to evaluate the propagation and link performance at various transmitter-receiver separation distances, ranging from 10 to 100 m with 10-m granularity, and different drone hovering altitudes, ranging from 10 to 30 m with 10-m granularity. At each measurement position, the recording lasted 15 s, collecting 20M samples/s for each of the three carrier frequencies and in the 2×1 beamforming configuration. After the signal processing occurs, the received signal strength (RSS), BER, number of successfully decoded packets, and transmission period are extracted and then exported into a comma-separated format for post-processing.



Figure 4.5: Channel Feedback Evaluation Topologies: (a) Hovering (b) Encircling

In the second set of in-field experiments, we first evaluate channel feedback approaches with both hovering and encircling scenarios to address the issues of channel reciprocity and update rate for channel estimation, as shown in Figure 4.5. During our experiments, the average daily wind speed is reported to be approximate 5.7 m/s. In the hovering case, the drone maintains a height of 10 m and has a horizontal distance of 10 m from the receiver on the ground. In the encircling case, the drone follows a circular pattern at a horizontal radius of 10 m from the ground node in the middle of the circle with velocities reaching 6 m/s (this is full throttle in GPS mode due to the 500-g payload). To account for representative drone-based applications, we further evaluate the linear case, in which the drone is flying in a straight line approaching and leaving the ground node location. Additional details for the latter scenario can be found in Section 4.6.

4.4 In-Field Evaluation with Hovering Experiments

In this section, we perform in-field measurements to characterize the air-to-ground propagation channel and evaluate the link performance of beamforming. The transmitter and receiver have an unobstructed path as depicted in Figure 4.6 with variable distances, carrier frequencies, and drone altitudes.



Figure 4.6: Physical location of UABeam propagation experiments.

4.4.1 Baseline Experiments

For reference purposes, we first conduct SISO-based omni-directional experiments when the transmitter is on the ground (see Figure 4.7(a) below) and hovering in the air (see Figure 4.5(a)) at altitudes of 10 m, 20 m, and 30 m. With each transmitter location, the receiver is mounted on a tripod at a 1-m height at the specified ground-based distances from the transmitter's location. Based on the signal level at the receiver, we calculate the path loss exponent and shadowing component for each carrier frequency and transmitter altitude. The channel model from the transmitter to receiver can be described by the widely-used log-distance path loss model [67, 83–85], given by:

$$P_{RX} = P_{TX} - PL_{d_0} - 10\gamma \log_{10}(\frac{d}{d_0}) + X_s$$
(4.5)

Here, PL_{d_0} is the path loss at a reference distance d_0 , P_{RX} is the received signal strength, and P_{TX} is the transmission power. The term $10\gamma log_{10}(d/d_0)$ corresponds to the log-distance path loss, where d denotes the transmitter-receiver separation distance. Lastly, X_s is the shadow-fading parameter that follows a normal distribution with zero-mean and standard deviation σ . We use linear regression fitting to estimate the path loss exponent γ and the standard deviation σ .



Figure 4.7: Ground-Based Reference Measurements. (a) Setup (b) Path Loss



Figure 4.8: Variable-Range, Variable Altitude. (a) Path Loss (b) Signal Quality

4.4.2 Path Loss Evaluation

We use a close-in (e.g., 1 m) free-space reference distance to linearly fit the path loss (dB) as a function of distance (m) [73]. Assuming λ is the carrier wavelength, the path loss at the free space reference distance d_0 is given by:

$$PL_{d_0} = 20 \log_{10}(\frac{4\pi d_0}{\lambda})$$
(4.6)

Figure 4.7(b) shows the path loss for the ground-based experiment after linearly fitting the

measured values as a function of distance and frequency. We see that the 5-GHz path has the least path loss exponent of 1.85, which is less than free space. This can be explained by the existence of scatters that produce strong signal reflections in that frequency band. However, other frequency bands, such as 1800 MHz, show relatively larger path loss exponents.

Then, we repeat our experiments with different drone altitudes, ranging from 10 m to 30 m to investigate practical air-to-ground links influenced by the operation of drones. Figure 4.8(a) presents the 900-MHz path loss behavior in the air-to-ground scenario. Surprisingly, the path loss exponents are far less than the expected free space value. Actually, this phenomenon happens in all of the frequency bands. Table 4.2 gives the estimated result of path loss exponent λ and shadowing standard deviation σ for each frequency band.

Table 4.2: Estimated Log-distance Path Loss Model Parameters

Parameter (Altitude)	$900 \mathrm{~MHz}$	$1800 \mathrm{~MHz}$	$5~\mathrm{GHz}$
$\gamma(10 \text{ m})$	1.91	1.99	0.68
$\gamma(20 \text{ m})$	1.15	1.7	0.45
$\gamma(30 \text{ m})$	0.364	1.59	0.07
σ (10 m)	4.47	3.56	1.30
σ (20 m)	5.34	4.13	2.21
σ (30 m)	6.12	5.25	2.34

To dive deeper on why this odd phenomenon is occurring, Figure 4.8(b) shows the 900-MHz band propagation results of the signal reception with the measurement data and resulting curve fit depicted as the solid lines. The signal reception based on the measurement position seem to follow the expected pattern when the drone is on the ground and at 10-m altitude: the received signal strength decreases as the distance increases. However, a curious pattern emerges at the higher altitudes: the received signal strength increases with distance at the shorter distances, and then decreases from the maximum value at greater distances. For example, 900 MHz has a peak value of -78 dBm at the distance increases, as you would expect from the log-distance path loss model. A similar effect occurs for 1800 MHz and 5 GHz. The reason is that the metal body of the drone is blocking the transmission at higher altitude and shorter distances. As the distance increases, the omni-directional transmission pattern is no longer blocked by the body. Additionally, Table 4.2 shows that the shadowing

standard deviation increases as the altitude increases. In addition to the blocking problem already noted, the increase in shadowing at greater altitude could also be due to the increasing effect of the wind for the same weather conditions at increasing altitudes above the tree and building heights. In order to better describe the air-to-ground channel, we consider higher-order polynomials as shown in Figure 4.8(b). The results at 20 m and 30 m of drone altitude are fit with a third-order polynomial function, creating a parabolic shape. However, the results at 10-m altitude still match a linear fit.



Figure 4.9: BER vs. Distance plot of the air-to-ground channel: (a) 900 MHz (b) 1800 MHz (c) 5 GHz; Throughput vs. Distance plot of the air-to-ground channel: (d) 900 MHz (e) 1800 MHz (f) 5 GHz; Normalized Throughput Gain vs. Distance plot of the air-to-ground channel: (g) 900 MHz (h) 1800 MHz (i) 5 GHz.

4.4.3 Link Performance Evaluation

We now move to understanding the link performance of beamformed (2×1) transmissions that are housed on a drone at various heights (0-30 m) with a receiver at a 1-m height on a tripod and horizontal distances from 10-100 m. Figure 4.9(a)(b)(c) and Figure 4.9(d)(e)(f)present the BER and throughput, respectively, as a function of drone altitude, distance, and carrier frequency (900 MHz, 1800 MHz, and 5 GHz). Regarding BER, the two greatest altitudes (20 and 30 m) have a parabolic shape where the BER is initially reduced by increasing the distance and then increases with increased distance. This has a parallel to the SISO-based path loss experiments presented in the previous subsection, where the body of the UAV appears to be a blocking the signal at high altitude and short distances. Another interesting observation can be seen in Figure 4.9(c), where there is a sizable difference in BER between the lower and higher altitudes as the distance increases. Unlike 900 and 1800 MHz, the hypotenuse of the triangle that forms between the altitude and the horizontal distance from sender to receiver is substantial in the 5 GHz case and causes substantially more loss. Regarding throughput, the increased height of 10 m has advantages at the greatest distances over the ground across all carrier frequencies. However, the throughput decreases from the ground-based transmission in all other cases except the 20-m altitude for 900 MHz (Figure 4.9(d)). In particular, the 10 m altitude provides higher throughput at beyond around 75 m horizontal distance for 900 MHz and 1800 MHz, and around 50 m at 5 GHz, with an average throughput improvement of 89.3%, 76.5%, and 21.1%, respectively.

To quantify the throughput improvement compared with the conventional IEEE 802.11 SISO scenario without beamforming, we plot the normalized throughput gain of beamforming versus the SISO case under different drone altitudes in Figure 4.9(g)(h)(i). We observe that beamforming always produces gains over SISO for 900 MHz at distances from 10-100 m (Figure 4.9(g)), with at most a 39% throughput improvement. As the carrier frequency increases, the beamforming gains are restricted to a shorter range for the highest altitude with 1800 MHz (Figure 4.9(h)) and for all altitudes with 5 GHz (Figure 4.9(i)). The most air-to-ground gains across each carrier frequency occurs at a hovering altitude of 10 m, where beamforming provides improvements of up to 31%, 29%, and 21%, respectively, from lowest to highest carrier frequency.

4.5 In-Field Evaluation with Encircling Experiments

In this section, we use drone mobility to experimentally evaluate the specific issues of channel reciprocity and estimation update rate. The two forms of mobility include: (*i*.) a UABeam transmitter hovering in place and sending to a ground node and (*ii*.) a UABeam transmitter encircling a ground node with differing linear velocities (1 m/s, 3 m/s, and 6 m/s).

4.5.1 Channel Reciprocity Evaluation

In the current IEEE 802.11 standard, two CSI feedback methods are defined: implicit feedback and explicit feedback. In both cases, CSI is estimated from the known training symbols in the preamble. For implicit feedback, the receiver sends the training symbols to the transmitter so that the transmitter can estimate the uplink channel. Since the downlink and uplink channels are assumed to be reciprocal, the transmitter implicitly obtains an estimate of the downlink channel by taking the transpose of uplink CSI. For explicit feedback, the transmitter first sends the training symbols to the receiver. After decoding the received signal, the receiver sends back the CSI to the transmitter. While explicit feedback can provide more accurate CSI, it introduces overhead in terms of time and feedback control bits.

The channel reciprocity assumption could be ill-suited for air-to-ground channels due to the severe mismatch in height of the communicating nodes and the susceptibility to severe channel fading with high levels of mobility. Therefore, we design baseline experiments using the UABeam system to explore and validate the performance of both feedback methods. To clearly demonstrate the effect of channel reciprocity, we first evaluate the relationship between the downlink and uplink channel information h_m and \overline{h}_m . Then, we investigate the throughput performance in both the hovering and encircling scenarios introduced in Section 4.3. We capture the information mismatch between the uplink and downlink channel measured on consecutive forward and reverse traffic exchanges by defining the channel reciprocal error (CRE). The CRE at a specific subcarrier k is given by:

$$E_{cre} = \frac{h_m}{\overline{h}_m} \tag{4.7}$$



Figure 4.10: Distribution Analysis for CRE. (a) Amplitude (b) Phase Gradient

Previous works [57, 86] modeled the CRE as $E_{cre} = e_{env} \cdot e_{syn}$, where e_{env} denotes the propagation reciprocity error component contributed by hardware factors such as RF gain mismatch and antenna imperfections and environmental factors such as humidity, temperature, and altitude differences. e_{syn} denotes the reciprocity error component introduced by imperfect synchronization between the transmitter and receiver. The lack of synchronization stems primarily from the difference of arrival time between uplink and downlink channels (for TDD systems) and the frequency mismatch of the local oscillators, since OFDM signals are much more sensitive to frequency offsets [57]. The propagation reciprocity error can be expressed as:

$$e_{env} = A_{env} e^{j\theta_{env}} \tag{4.8}$$

Here, A_{env} and θ_{env} are modeled as normally-distributed and uniformly-distributed random variables, respectively. The synchronization reciprocity error e_{syn} can be expressed as:

$$e_{sum} = e^{j4\pi k\delta_p/N} \tag{4.9}$$

Here, δ_p is the slope of the phase error denoted by the phase gradient, k is the subcarrier

index, and N is the number of occupied subcarriers. Then, Eq. 4.7 is equivalent to:

$$E_{cre} = A_{env} e^{j(\theta_{env} + 4\pi k \delta_p/N)} \tag{4.10}$$

Case	Frequencies	$Mean(A_{env})$	$\operatorname{Std}(A_{env})$	$\operatorname{Mean}(\delta_p)$	$\operatorname{Std}(\delta_p)$
	900 MHz	1.19	0.016	0.031	0.13
Hovering	$1800 \mathrm{~MHz}$	1.06	0.029	-0.045	0.17
	$5~\mathrm{GHz}$	0.85	0.038	-0.034	0.19
	900 MHz	1.20	0.029	-0.026	0.14
1 m/s	1800 MHz	1.07	0.033	-0.034	0.19
	$5~\mathrm{GHz}$	0.85	0.039	-0.028	0.26
	900 MHz	1.23	0.033	-0.019	0.20
3 m/s	$1800 \mathrm{~MHz}$	1.10	0.036	0.028	0.25
	$5~\mathrm{GHz}$	0.81	0.043	-0.026	0.26
	900 MHz	1.22	0.048	0.027	0.24
6 m/s	$1800 \mathrm{~MHz}$	1.16	0.057	-0.026	0.26
	$5~\mathrm{GHz}$	0.79	0.059	0.016	0.29

Table 4.3: Statistic Parameters of Channel Reciprocity Error Results

During our experiments, the measured CRE results, such as amplitude error and phase error, are calculated as a function of the subcarrier obtained from every single sample measurement in both hovering or encircling experiments. The extraction of major parameters in the reciprocal error expression (4.10) are based on the minimum mean-square error (MMSE) criterion along obtained CRE results. Figure 4.10 depicts a histogram in the form of four lines (superimposed to compare them) for each experiment for the different transmitting-drone velocities at 900 MHz. To form the histograms, the statistical distribution of parameters A_{env} and δ_p have bins of 0.005 and 0.02, respectively. These bins are extracted from 10000 channel samples for hovering and encircling experiments at 900 MHz. The solid line is a normally-distributed curve fit based on their mean and standard deviation. We found that A_{env} has a relatively narrow spike around an amplitude value. However, the width of various δ_p depends on the velocity of the drone, allowing either a positive or negative slope in the phase error. Similar results can also be found in other frequencies, as shown in Table 4.3. Therefore, our analysis shows that while the amplitude error is approximately constant for both hovering and encircling experiments, the phase error for channel reciprocity highly depends on velocity.



Figure 4.11: Timeline of Implicit Feedback.

Beamforming systems will experience severe throughput degradation if imprecise channel feedback is obtained. As a result, we explore the impact of the reciprocity error on the throughput of the downlink conjugate beamforming system. We maintain the same experimental setup as before and have distinguished the downlink data transmissions with downlink CSI (explicit feedback) from the downlink data transmissions with uplink CSI (implicit feedback). Since implicit feedback does not necessarily require an RTS and CTS exchange, experiments with implicit feedback obtain CSI estimates based on the ACK message from the previous epoch, as shown in the timeline schedule in Figure 4.11.



Figure 4.12: Throughput results of beamforming system with channel reciprocity.

We have conducted an extensive set of experiments with the following traffic pattern: a packet payload of 256 bytes and average epoch interval of 200 ms over an experimental duration of 300 s. Figure 4.12 shows the throughput results from a wireless experiment using downlink and uplink CSI for beamforming data transmissions at different frequencies and velocities. The beamforming throughput using explicit feedback (labeled Downlink CSI) can increase the throughput by 67.8%, 93.2%, and 103.9% over that using implicit feedback (labeled Uplink CSI) for 900 MHz, 1800 MHz, and 5 GHz in the hovering cases, respectively. The gains of explicit feedback are even greater when it comes to the encircling cases with a throughput improvement over implicit feedback of up to 92.6%, 111.6%, 123.9% for the aforementioned frequencies, respectively. We expect even greater throughput improvement for explicit feedback with higher velocities.

4.5.2 Update Rate for Channel Estimation

We investigate the update rate for airborne communications in terms of the number of OFDM symbols in a single data frame, denoted by L. First, we explore the influence of the data length on the performance of BER and throughput for a given scenario and estimate the optimal length that leads to the maximum throughput for a given carrier frequency. This also corresponds to the optimal update rate for channel estimation. Second, we examine the optimal data length across different frequencies under the same experimental context.

We now test the hovering and encircling scenarios with the complete feedback signaling timeline shown in Figure 4.3. As previously discussed, the downlink CSI is fed back using our proposed approach for every data frame, but the frame data length varies. We generate the packet source with the following packet lengths: $L \in \{32, 64, 128, 256, 512, 1024, 2048, 4096\}$ and maintain the same transmission bandwidth. Note that 4096 is the maximum payload allowed in a single data frame according to the IEEE 802.11 standard.

The optimal packet length for the hovering scenario can be found in Figure 4.13(a). For 900 MHz and 5 GHz the optimal rate is less than 512 bytes per data frame, while for 1800 MHz, the optimal rate is approximately 256 bytes per frame. In Figure 4.13(b), the throughput decreases for the encircling scenario as drone velocity increases. However, the optimal update rates of 512 and 256 hold for their respective carrier frequencies regardless of the velocity. Based on these results, a reasonable universal packet size for UABeam communications would be 256 bytes across carrier frequencies.



Figure 4.13: Throughput for various frame lengths: (a) Hovering (b) Encircling

4.6 In-Field Evaluation with Linear Experiments

In the previous section, we kept the physical distance constant between the transmitter and receiver in a hovering and encircling scenario to maintain a fixed average received power, but allow channel fluctuations according to the vibrations and mobility of a drone in flight. In this section, we consider the scenario where the drone is flying in a straight line from one edge of the range, coming closer to the ground station, and then on to the other edge of the range. The reason for doing this experiment is to introduce an additional variable beyond the channel fluctuations: a change in the average channel quality over the course of the experiment.

To do so, we design this linear experiment (see Figure 4.14(a) below) where the drone maintains a height of 10 m, beginning at a distance of approximately 30 m from the ground station, progressing in a straight line toward the ground station, and ending at a distance of 30 m from the ground station. We then iterate over three different speeds (1 m/s, 3 m/s, and 6 m/s) and the aforementioned two different feedback mechanisms of explicit (labeled Downlink CSI) and implicit (labeled Uplink CSI). We seek to investigate the impact of channel reciprocity on beamforming performance when there is movement in the average channel quality coupled with the previously tested channel fluctuations. In other words, this scenario accounts for the comprehensive impact of channel fluctuation introduced by both changing velocities and ranges. We feel that the experiments now cover a wide range of scenarios that would be representative for various applications such as public safety, package

delivery, and search and rescue. In these particular cases, the drone is rapidly approaching or moving away from the destination node while trying to maintain reliable communication links.



Figure 4.14: Instantaneous Throughput vs. Distance. (a) Setup (b) 900 MHz

Figure 4.14(b) shows the in-field experimental results of instantaneous throughput for 900 MHz for the six iterations previously mentioned. The three velocities are indicated by different colors and markers of the same shape (blue circles for 1 m/s, green triangles pointing up for 3 m/s, and red triangles pointing down for 6 m/s). The solid lines represent the Downlink CSI, and the dotted lines represent the Uplink CSI. The relative distance is defined as the horizontal distance between drone and receiver UE. The instantaneous throughput is calculated over each 1 second window period of the experiment. The first observation is that compared to the hovering and encircling experiments (approximately 25 Mbps), the peak throughput values are lower for the linear topology (approximately 17 Mbps) even though the drone actually comes closer to the ground station. There are two factors contributing here: (i) the optimal beamforming weights are challenging to find even though the mobility is only 1 m/s and (ii) there is reduced received power directly below the drone (see Figure 4.8). Second, we observe that explicit outperforms implicit feedback again in the linear topology with average throughput increases of 37.8%, 88.1%, and 105.1% for 1, 3, and 6 m/s, respectively. We see the greatest distinction occur at a relative distance of 17 m, which has a gain of 177.3% for explicit versus implicit.

4.7 Related Work

The future development of airborne wireless communication necessitates precise channel characterization and system-level performance analysis due to increasing deployments of aerial communication systems and their resulting data services. Theoretical studies that have characterized air-to-ground radio propagation for aircrafts have been widely conducted but mainly limited to simulation works that lack experimental validation [52–56]. Although these works have simulated air-to-ground channels in urban environments, most of the aforementioned works lack in-field data with real geographical features, which are crucial to drone-based applications.

While one work conducted in-field experiments with 970 MHz and 5.6 GHz with a single antenna, none of these works housed a software defined radio (SDR) platform on a drone to implement and evaluate beamforming techniques, which are gaining ever-increasing relevance for future generations of wireless networks. Beamforming plays a significant role in the spectral efficiency and data transmission in wireless systems, especially for orthogonal frequency division (OFDM) systems, which have been successfully implemented in widelydeployed wireless infrastructures, including IEEE 802.11 wireless LAN standards (WiFi), IEEE 802.16 Wireless MAN standard (WiMax), and 3GPP Long-Term Evolution (LTE). Many works have studied the benefits of beamforming [87], but the vast majority of these works focus on terrestrial networks which are not completely applicable to practical dronebased networks. For example, the cellular tower will always be fixed in location and lack the vibrations of a hovering drone. Lastly, many works assume ideal channel knowledge or errorfree, instantaneous feedback [74], motivating the need for an in-field analysis of air-to-ground channel characterization and feedback analysis for UAV-based beamforming systems.

4.8 Summary

In this Chapter, we designed a system to evaluate propagation, link performance, and channel feedback mechanisms for drone-based beamforming in representative practical scenarios. To do so, we built a complete IEEE 802.11-like signaling mechanism across the MAC and PHY layers using a SDR platform. Then, we conducted in-field, variable-range hovering experiments to characterize the air-to-ground channel and link performance at various heights and distances. Next, we investigated implicit and explicit feedback with hovering, encircling, and linear experiments as well as reciprocity error evaluation. Our assessment covers a wide range of UAV communication bands, and numerical results demonstrate that a properly optimized drone-based beamforming system can provide significant throughput improvement using explicit versus implicit feedback. We believe these results will have farreaching impact on the future design of real-world UAV MIMO communications.

Chapter 5

Wireless Propagation and Channel Feedback with User-Induced Effects

In this Chapter, we performed experiments under LOS and NLOS settings to explore the signal attenuation and give quantitative analysis on user-induced effects. Then, we progress to mmWave channels to study user-induced feedback performance with changing feedback intervals and training overheads in the context of the IEEE 802.11ad.

5.1 User-induced Effects

In wireless telecommunications, radio signals can suffer from various degrees of channel impacts when propagating from the transmitter to the receiver through complex wireless channels. The most dominant element that affects wireless propagation is the multipath effect, which results from the radio signals reaching the receiving antenna by two or more paths with reflection, scattering, and diffraction [88]. Obstacles, such as human bodies, atmospheric ducting, water bodies, and terrestrial objects, exist between and around the transmitter and receiver, creating multiple signal copies with each having differences in attenuation, delay, and phase. Large-scale shadowing is the fading due to variation or the attenuation of a signal that occurs on a large scale, which corresponds to conditions that may vary as one turns a corner, moves behind a large building, or enters a building. Shadowing fading is often modeled as a random process. Fading variations are usually assumed to follow a log-normal distribution, which means that when measured in dB they follow a Gaussian distribution. Consequently shadowing effects are usually incorporated into path loss estimates by the addition of a zero-mean Gaussian random variable.

In this thesis, we first study the effects of transmitter elevation on radio wave propagation in two practical channels: ground-to-ground communication (Ad Hoc and WiFi scenarios) and tower-to-ground communication (cellular scenarios), characterized by antenna height and transmission power. We investigate signal attenuation caused by the environment as a function of frequency, distance, and antenna height. Then, the dominant propagation parameters (path loss exponent and shadowing standard deviation) are extracted and analyzed. In order to achieve a representative sample of the environment, experiments are performed on up to 10 randomly-selected NLOS paths for each frequency band in both the ground-to-ground scenarios and tower-to-ground scenarios.



Figure 5.1: Long Term Measurements Locations.

Second, we implement a measurement-driven framework to collect and analyze aggregated data sets to study the effects of different user-induced behaviors on signal reception. This framework is applied at multiple frequency bands (500, 800, 1800 and 2400 MHz) at several geographical locations near a campus (SMU-in-Taos) in Northern New Mexico over a month-long measurement campaign, shown by an aerial map in Fig. 5.1. We measure the RSS under diverse conditions characterized by on-body location of the receiver, directional heading of the user with respect to the transmitter, vegetation type, frequency band, and propagation distance, quantitatively revealing the user-induced effects on signal reception from relatively distant transmitters. Directional heading refers to the two-dimensional representation of user location in relation to the transmitter. The signal quality received by a mobile device is observed to also depend on the antenna directionality (facing directly towards or turning away from the radiation source) and on-body locations (in the hand or in the front pants

pocket).

We perform measurements in a Line-of-Sight (LOS) setting with a single user (SU) focusing on the effects of diverse mobile phone positioning on the body and the direction the user with respect to the transmitter. Fig. 5.2(a) shows our setup with the receivers in the hand and pocket when squarely facing the transmitter, while the backpack is on the opposite side of the transmitter. By conducting measurements in a LOS path and comparing three different on-body locations, including holding the receiver in the hand, placing in a backpack, and putting in the pants pocket, our results indicate that users facing the transmitter can receive up to 20 dB greater signal quality versus reverse-facing users at the same location. However, these user-induced effects are more pronounced at shorter distances. Moreover, we find that a forward-facing user can act like an antenna that receives up to 4.4 dB over a reference node mounted on a tripod at the same distance.



(b) Hardware Setup for Experiments

Figure 5.2: Measurement Scenario for both LOS and NLOS Environments.

Considering many real applications are Non-Line-of-Sight (NLOS), we further explore the



Figure 5.3: Received Signal Strength vs Distance on Four Frequency Bands.

effects of directional heading by conducting NLOS experiments with multiple users (MU) at each of the cardinal directions at varying distances. These radial experiments are performed in two NLOS environments: a densely treed environment and a brush environment. While we still observe a dominant effect of directional heading in all directions (up to 20 dB), our results show that received signal quality is severely susceptible to environmental impacts and largely depends on frequency. We find that the forward versus reverse facing directionality loss is more pronounced in the tree environment (6-8 dB) as opposed to the brush environment (3-7 dB). Motivated by recent LTE standardization that allows user devices to feed back Key Performance Indicators to cellular towers, we consider the impact of the aforementioned userinduced effects on crowdsourcing wireless channel characteristics. Our assessment reveals that the directional heading of facing towards the transmitter results in higher path loss exponents than turning away in channel propagation, and user directionality can have more than triple the shadowing effect in a given environment.

Finally, due to the heavy reliance of mmWave communication systems on directional links, beamforming with large number of antenna arrays is essential for overcoming the high path loss introduced by user-induced losses at such frequencies. This motivates us to investigate user-induced feedback system-level performance with customized feedback design based on sweep-based beamforming framework, which has been widely used in IEEE 802.11ad communication systems [34]. Specifically, we propose a multiple-node coexistence simulation framework to investigate the impact of various feedback intervals and training overheads on system link performances, such as blocking probability and SINR performance.

5.2 System Path Loss Model

In this section, we discuss relevant path loss models which will be used in characterizing the propagation channel over multiple frequency bands.

Multipath propagation effects can be modeled through fast-fading that typically follows a Rician or Rayleigh distribution [89] with even slight movements by the receiver or scatters potentially causing significant variations in RSS [83]. Complex environmental factors, such as dense and deciduous forest groups, foliage vibration, and capricious weather conditions, can largely affect the signal reception [90]. Such uncertainty caused by location dynamics or multiple paths is usually denoted as shadow-fading. The propagation channel from the transmitter (TX) to receiver (RX) can be described by the widely-used log-distance path loss model in addition to a shadow-fading component [83, 91], given by:

$$P_{RX} = P_{TX} - PL_{d_0} - 10\lambda \log_{10}(\frac{d}{d_0}) + X_s$$
(5.1)

Here, PL_{d_0} is the path loss at a reference distance d_0 , P_{RX} is the received signal strength, and P_{TX} is the transmission power. The term $10\lambda log_{10}(\frac{d}{d_0})$ corresponds to the log-distance path loss model, where d denotes the transmitter-receiver separation distance. Lastly, X_s is the shadow-fading parameter that is typically zero-mean, normally-distributed with standard deviation σ . Linear regression fitting is implemented to estimate the path loss exponent λ and the standard deviation σ .

5.3 Experimental Settings

In this Section, we describe the experimental setup and ambient noise experiments we performed before beginning the measurements on user-induced effects.

The experiments are carried out using the Universal Software Radio Peripheral (USRP) N210 as the transmitter controlled by a Simulink diagram running on a laptop to generate continuous waves at 500, 800, 1800, and 2400 MHz. The transmitter USRP is equipped with a SBX daughterboard that covers a frequency range from 400 to 4400 MHz and provides a bandwidth of 40 MHz. The continuous waves are produced by feeding a tone of zero frequency directly to an amplitude modulator. An omni-directional, multi-band antenna

with a gain of 4 dBi is implemented at the transmitter at various heights according to the scenarios described. A Nuts About Nets Handheld RF Explorer is working as a spectrum analyzer (SA) to capture received signal strengths (dBm) during in-field experiments per user. The handheld SA operates in the frequency range of 15 to 2700 MHz with an NA-773 dual band extendable whip antenna used at the receiver. Using the on-board memory of a Samsung S5 via a USB interface, the data sets are collected in real-time with the Nuts About Nets Touchstone-Pro mobile application. For each experiment, we collect a minimum of 80 samples and later export them in a comma-separated format for post-processing. During measurements, any unnecessary user movement is restricted in order to suppress human movement as much as possible. Fig. 5.2(b) depicts the hardware setup for our experiments.

In-lab calibration of USRP RF transmission power on four frequency bands is performed by directly connecting the Rohde & Schwarz FSH8 SA to the transmitter USRP using two SMA connectors and a coaxial 50 Ω cable. Besides, in order to calibrate the frequency based gain caused by the multi-band antenna and fairly characterize the large-scale coverage distances over all frequency bands, we use a close-in free space reference distance as to perform linear fitting for path loss (dB) as a function of distance (m) [89]. The path loss at the free space reference distance d_0 is given by:

$$PL_{d_0} = 20 \log_{10}(\frac{4\pi d_0}{\theta}) \tag{5.2}$$

Here, θ is the carrier wavelength. We first measure the RSS at a fixed distance of 1 m with the calibrated transmission power and then calculate the relative path loss (PL) for each measurement position. The path loss scatters can be plotted by adding the relative PL on the reference PL obtained from Equation (5.2). Table 5.1 gives an example of the PL calibration at a measurement position of 20 m. Before exploring user-induced effects, we also explore the ambient noise over four frequency bands in our selected measurement environments while disabling our USRP transmitter. It is observed that the noise floor for is generally less than -98 dBm under test.

Frequency	500 MHz	$800 \mathrm{~MHz}$	$1800 \mathrm{~MHz}$	$2400 \mathrm{~MHz}$
RSS at 1 m	-31.3 dBm	-46.4 dBm	-41.3 dBm	-40.8 dBm
RSS at 20 m	-58.7 dBm	$-68.7~\mathrm{dBm}$	$-72.0~\mathrm{dBm}$	$-73.4~\mathrm{dBm}$
Relative PL	27.4 dB	22.3 dB	$35.7 \mathrm{~dB}$	32.6 dB
Reference PL	26.42 dB	30.50 dB	$37.55 \mathrm{dB}$	$40.05~\mathrm{dB}$
PL at 10 m	53.82 dB	52.80 dB	$73.25~\mathrm{dB}$	$72.65~\mathrm{dB}$

Table 5.1: Path Loss Calibration based on 1 m Reference Distance

5.4 Baseline Propagation Prediction

In this section, we set up a baseline experimental framework that predicts the propagation in our experimental environment while controlling for the user behaviors.

5.4.1 Baseline Experiment Method

In this baseline setup, the experiments are performed in two practical channels: a groundto-ground scenario and a tower-to-ground scenario, which enable the study of the effects of transmitter elevation on signal reception, and of controlled user behaviors at diverse user positions. The user always faces the transmitter and the on-body location of the receiver is the hand. The transmitter is located to a height of 1 m above ground in the ground-toground setup, while the transmitter antenna is fixed at 10 meters above the receiver antenna to imitate the tower-to-ground cellular networks. The user holds the handheld spectrum analyzer (SA) in-hand facing the transmitter and takes at least 80 measurements of the received signal strength at each measurement position while moving within a radius of ten times the wavelength to average out fast fading effect throughout our experiments [89]. We then characterize the channel with measurement data and path loss model to study the propagation for our experiments.

For reference purpose, we first conduct measurements in a LOS path where no obvious objects might interfere with the transmission. Results show that 800 MHz LOS path has the least path loss exponent of 1.87, which is slightly less than free space. This is accounted for by the existence of neighbor scatters that produce strong signal reflections in that frequency band. However, other frequency bands, such as 1800 MHz, show relatively larger path loss exponents.



(c) Ground-to-Ground Paths

(d) Tower-to-Ground Paths

Figure 5.4: Forest Propagation Measurements.

5.4.2 Ground-to-Ground Propagation Evaluation

The ground-to-ground setup mimic the communication scenarios similar to WiFi networks and Ad Hoc networks, as shown in Fig. 5.4(a), where there is no direct LOS. We evaluate the propagation by performing measurements in ten random selected NLOS paths with dense foliage coverage, with the overhead image shown in Fig. 5.4(c). The USRP transmission power is calibrated to 12 dBm for all four frequency bands. In order to get a general understanding of the propagation channel, the path loss exponent and shadowing standard deviation are extracted for all paths.

Fig. 5.3 presents the multiple bands propagation results of Path 3 in the ground-toground scenario, with the measurement data and resulting fitted curves depicted as the



Figure 5.5: Ground-to-Ground Path Loss Model above 1 m Reference on Four Frequency Bands.



Figure 5.6: Tower-to-Ground Path Loss Model above 1 m Reference on Four Frequency Bands.

solid black lines. The transmitter-receiver separation distance ranges from 5 to 100 meters with 5 meter granularity, and measurement positions are identical across all frequency bands measured. Table 5.2 gives the estimated path loss exponent λ and shadowing standard deviation σ for each frequency band. The signal reception based on the measurement position at different frequency bands seem to follow the same pattern: the received signal strength decreases as the distance increases. However, the peak patterns for all four frequency bands based on RSS and distance are not consistent for the chosen geographic paths and user positions. For example, 500 MHz has a peak value of -62 dBm at the distance of 80 m and 800 MHz has a peak value of -67 dBm at 65 m, while no comparable peak values can be found at higher frequency bands; this reveals that the channel quality is closely frequency dependent. On the other hand, the environment is another factor that greatly affects the wave propagation. The fact that a low frequency does not strictly obtain better propagation is also explained by the complex obstructions that increase the attenuation and absorption intermittently blocking signals based on frequency. Next, We extend our evaluation to ten geographic paths and use a free space reference distance to perform linear fitting for spectral path loss analysis.

Parameters	500 MHz	$800 \mathrm{~MHz}$	$1800 \mathrm{~MHz}$	$2400 \mathrm{~MHz}$
SA bandwidth (MHz)	40	40	40	40
Sampling Interval (s)	1.13	1.13	1.16	1.19
λ	3.36	3.99	3.42	3.68
σ (dB)	2.98	3.39	2.30	2.27
Route	Fig. 5.3 (a)	Fig. 5.3 (b)	Fig. 5.3(c)	Fig. 5.3 (d)

Table 5.2: Estimated Log-distance Path Loss Model Parameters

5.5 shows the path loss scatters for the ground-to-ground propagation on four Fig. frequency bands generalizing all measurement areas. The path loss exponents and shadowing standard deviation are given for the reference LOS path (LOS), the best path (NLOS,B), the worst path (NLOS,W), and average path (NLOS,A). The so-called best path has the least path loss exponent, which is mostly preferred by future cellular system. The worst path is the one that has the highest path loss component. The average path is defined to average on the propagation parameters of all independent measurement paths in order to describe the overall channel quality in selected experimental area. In addition to measurement data collection, all path loss characterizations are based on a free space reference distance of 1 meter, as previously described in Table 5.1. It is obvious that for all frequency bands, NLOS paths lead to higher path loss exponents than LOS paths by an increase ranging from 0.46 to 1.34. Compared with free space, the pass loss can be as high as 23 dB at the distance of 50 meters and 38 dB at the distance of 100 meters. Interestingly, in terms of averages, the LOS path for 800 MHz has the least path loss exponent of 1.87, while the 800 MHz NLOS path has the largest path loss reaching 3.88, comparable with 2400 MHz that has a path loss exponent of 3.81. If considering the best path alone, all four frequencies have similar path loss exponent of nearly 3.3. On the other hand, the largest path loss exponent happens to result from 800 MHz, indicating the worst path. Our evaluation also reveals that higher frequency bands (1800 and 2400 MHz) have smaller fluctuation in shadowing than lower frequency bands (500 and 800 MHz), with 2400 MHz actually presenting the least shadowing standard deviation of 1.99 dB.

5.4.3 Tower-to-Ground Propagation Evaluation

Tower-to-ground propagation is characterized by the fact that the transmitter usually has a higher elevation and transmission power than the receiver, with typically omni-directional radiation from rooftop to ground. Several experimental contexts have been found near an institutional campus, characterized by a terrain of steep cliffs with a depth ranging from 5 to 15 meters. Similar to the ground-to-ground communication, the tower-to-ground also implements the same basic measurement setup, but has a transmitter elevation height of around 10 meters by fixing the antenna on a tripod on the roof of a car and polling by the edge of cliff face, as shown in Fig. 5.4(b). By conducting measurements under the cliff with spatial measurement positions in ten different radiation paths, the vertical difference forms a cellular alike communication scenario. During our experiments, the transmitter power is aligned to 19 dBm (the highest transmission power available) for all four frequency bands. Independently, we also evaluate up to ten paths radiated by a fixed transmitter position with respect to the tower-to-ground setup, as shown in Fig. 5.4(d), and characterize these channels with path loss calibration.

The path loss scatter diagrams are given in Fig. 5.6 to summarize the tower-to-ground channel path loss distributions at multiple bands. Compared with the ground-to-ground scenario, 500 and 800 MHz propagation channels are observed to be more favored in tower-to-ground setup due to their slightly smaller path loss exponents. One reason for the reduced path loss is the existence of the relatively fewer objects blocking the propagation path in the view from tower to ground. It is interesting to observe that at 500 MHz the tower-to-ground path has the least path loss exponent of 2.84, compared with 2.31 in the LOS path. Furthermore, we detect an increase in shadowing standard deviation, ranging from 0.5 to 1 dB at 1800 and 2400 MHz, due to the large fluctuations of tree branches and foliage under the influence of wind. Considering that a typical forest environment usually contains rich scatters, and any slight movement in the transmitter antenna location will greatly affect the propagation channels, it is very likely that significant fluctuations can be present in tower-to-ground networks. *Finding: The Tower-to-ground scenario results in much higher shadowing standard deviations than the ground-to-ground scenario.*

5.5 Propagation Evaluation with User-induced Effects

5.5.1 Single-User Linear Evaluation

In this section, we describe the linear LOS experiment to explore the user-induced effect of a single user on wave propagation. Specifically, we conduct measurements in a selected LOS path and investigate the effects of on-body positioning and directional heading of the receiver with respect to the transmitter, as shown in Fig. 5.7. The transmitter and receiver have an unobstructed path between them only affected by various on-body locations, as depicted in Fig. 5.2(a), as a function of whether the user is forward facing or reverse, propagation distance, and frequency band under test.



Figure 5.7: Spatial Depiction of Linear LOS Measurements.

During our experiments, the transmitter power is set at 19 dBm for all four frequency bands, and the height is fixed at 2 m above the ground to maintain better radiation. We simultaneously measure the signal receptions at three different on-body locations, including the receiver in the hand, backpack, and pocket, at a transmitter-receiver separation distance ranging from 20 to 200 meters with 20 meter linear granularity. Except the three on-body receivers, an extra receiver is vertically mounted on a tripod at a height of 1 meter as reference (with a clear LOS path to the transmitter). Each on-body location is used for two directional heading scenarios at each distance: facing directly towards the transmitter and turning away from the transmitter.

Fig. 5.8, Fig. 5.9 and Fig. 5.10 show the measurement results with the reference reception



Figure 5.8: Hand Facing Towards/Turning Away the Transmitter in Linear LOS Measurements.



Figure 5.9: Backpack Facing Towards/Turning Away the Transmitter in Linear LOS Measurements.



Figure 5.10: Pocket Facing Towards/Turning Away the Transmitter in Linear LOS Measurements.

after linear fitting as a function of distance, frequency and receiver directional heading for the each of the three on-body locations: hand, backpack, and pocket.¹ Throughout this work, we use the term user-induced loss (dB) to denote the RSS difference between the direction facing respect to the transmitter and turned away from the transmitter. We expect that

 $^{^{1}}$ It should be noted that the backpack facing term refers to the scenario where the backpack (receiver) is actually facing the transmitter, not the user.

when facing towards the transmitter that the RSS is stronger than facing away in all cases. Table 5.3 provides the quantitative evaluation on user-induced loss for each of the three

Location	User-Induced	500 MHz	800 MHz	1800 MHz	2400 MHz
	Loss (dB)				
	Min	9.32	2.56	2.47	0.27
Hand	Max	13.42	7.02	15.10	19.15
	Mean	10.73	5.48	6.81	6.77
	St Dev	0.81	0.93	4.12	6.01
	Min	2.81	0.65	3.36	0.35
Backpack	Max	4.96	2.96	11.11	8.55
	Mean	3.55	1.44	5.71	3.17
	St Dev	0.68	0.73	3.10	2.89
	Min	6.02	3.79	0.50	0.38
Pocket	Max	10.71	8.04	16.46	9.04
	Mean	7.63	5.25	5.99	3.36
	St Dev	1.49	1.21	5.08	3.75

Table 5.3: Estimated User-Induced Loss After Linear Fitting

on-body locations. For the location of the receiver held in the hand, we observe that the user-induced loss ranges from 9.32 to 13.42 dB and from 2.47 to 15.10 dB at 500 and 1800 MHz, respectively. The highest user-induced loss occurs at the shortest distance. As distance increases there is only a slight decrease at 500 MHz, however, at 1800 MHz, user-induced loss drops to almost zero. One reason might be the large path loss experienced at higher frequencies that causing clipping beyond the sensitivity level of the receiver as compared to the shorter distances where the forward and reverse heading are both in the receivable received signal quality region. This is also supported by the fact that relatively higher values of standard deviation (St Dev) with regard to user-induced loss occur at higher frequencies. Hence, the full range of user-induced loss can be measured at shorter distances (20 to 120 meters) as opposed to more distant distances (140 to 200 meters).

Although similar patterns can be found at the other two locations, it is interesting to note that the location inside the backpack shows the least loss out of the three locations, ranging from 3 to 11 dB; while the location of receiver held in the hand has the largest difference, ranging from 9 to 17 dB. When the user is facing the transmitter, this results in higher received signal strength than the reference node in all cases except Fig. 5.10(c)(d), indicating that the user can act as an antenna and cause higher signal reception. *Findings: The effects of user behaviors tend to be more critical on received signal strength at relatively close distances. The location in the hand presents the largest user-induced loss out of all* three locations. Users can act like an antenna and cause signal reception of up to 4.4 dB more than the reference node.



Figure 5.11: Overhead Image of Throughput Performance Measurement.

In order to further justify that the user can act as an antenna, we perform extensive experiments to compare the throughput performance among three receiver setups: in the hand facing towards the transmitter (handfacing), in the hand turning away from the transmitter (handaway), and a reference location (same elevation without human interference). In our experiments, one USRP board operates as the transmitter with a fixed position, while another USRP board operates as a receiver, located at four positions randomly selected on a circle with a radius of 7 m. At each position, We evaluate the throughput performance of each of the three receiver setups. We place the two USRP boards in an outdoor area, as shown in Fig. 5.11. We implement an OFDM scheme with 600 subcarriers, similar to LTE devices. This transmission scheme requires a 10-MHz bandwidth with a sampling rate of 15.36 MHz. To adjust the transmission rate, we choose between three different modulation schemes: QPSK, 16QAM, and 64QAM. We send training OFDM symbols to synchronize the reception of all OFDM symbols in our implementation. The throughput for handfacing, handaway and reference location are shown in Fig. 5.12 for the three modulation schemes. Our evaluation reveals that with the same transmission power, the location of the in-hand facing receiver can achieve an average of 13% (ranging from 11.0% to 14.4%) improvement in terms of throughput than the reference node, and an average of 19% (ranging from 18.1% to 20.9%) improvement than the in-hand receiver that is facing away from the transmitter.



Figure 5.12: Comparison of Throughput among Three Receiver Setups.

5.5.2 Multi-User Radial Evaluation

In this section, we discuss the radial NLOS experiment that investigates the effects of cardinal direction forming a radial pattern, as opposite to the single path in linear LOS experiment, and directional heading of the user with respect to the transmitter on signal reception. We conduct the radial experiments with four simultaneous users of resemble size taking samples at each of the cardinal directions in two distinct propagation scenarios: a densely treed environment and a brush environment, as shown in Fig. 5.13. During the time of measurements, the shrubbery is found to have mature and full leaves in brush environment, while in densely treed environment, the pine trees are observed to have sparse foliage but possess a larger trunk with much greater height. Compared with LOS experiments, we perform radial NLOS experiments on one on-body location (in the hand) in order to focus on the investigation of the spatial effects. The path between the transmitter and the receiver is affected by diverse cardinal directions, whether the user is facing directly towards or turning

away from the transmitter, propagation distance and frequency band under test.



(a) Radial Tree Area(b) Radial Brush AreaFigure 5.13: Spatial Depiction of Radial NLOS Measurements.

In each area, measurements are performed along the four cardinal directions to explore the areal effects at distances ranging from 20 to 80 meters outward, with 20 meter granularity. The transmitter is centered radially at a same distance of 2 meters above ground level. Along each directional heading, each individual user is required to follow the uniform pattern to conduct measurements under both directional headings.

Fig. 5.14 and Fig. 5.15 show the quantitative evaluation on user-induced loss extracted from the measurement data sets as a function of distance, frequency and cardinal direction for the tree and brush environment, respectively. A positive value of user-induced loss denotes that user location facing towards the transmitter has a higher value of received signal strength than the reverse heading, while a negative value means the opposite. We expect that positive values are more likely to occur in our experiments. Both areas reveal that, given a certain distance and vegetation type, analysis along the four cardinal directions



Figure 5.14: Estimated User-Induced Loss in Tree Area.



Figure 5.15: Estimated User-Induced Loss in Brush Area.

does not follow an identical pattern affecting the results of user-induced loss. For instance, by looking at Fig. 5.14(a), at 800 MHz a high positive loss of 17 dB is detected in the east, compared with the unexpected -4 dB in the west; which results in a signal reception difference of 21 dB. However, at 1800 MHz band, all cardinal directions suffer a uniform user-induced loss of approximately 8 dB. Similar results can be found in the other figures, with received signal strength differences in various cardinal direction pairs ranging from 1 db (1800 MHz, Fig. 5.14(a)) to 25 dB (500 MHz, Fig. 5.15(d)). As a result, we conclude that the distinct propagation channels in different cardinal directions indeed impact the measurement results in complex forest environments. *Finding: Received signal quality is severely susceptible to environmental impacts.*

Furthermore, we find that the treed environment actually presents less outcomes of negative user-induced loss than brush environment, which is likely due to the less dense foliage distribution and sparse undergrowth in the pine tree area. Besides, higher frequency bands are observed to present more results of positive user-induced loss than lower frequency bands, which demonstrates that the higher frequency signals tend to be easily absorbed within the environment. Our evaluation reveals that the average user-induced losses are 4.05, 5.53, 5.60 and 7.01 dB for 500, 800, 1800 and 2400 MHz, respectively. *Finding: Users can affect received signal strength up to 20 dB, and the user-induced losses varies with frequency.*

Fig. 5.16 shows the averaged user-induced loss based on the aggregate user effects aligned in all cardinal directions and frequency bands. It is interesting to observe that the averaged user-induced loss decreases to 5.7 and 2.9 dB at 60 m for tree and brush area, respectively, and then obtains a slight increase at 80 m. The tree area presents apparently higher user-
induced loss than brush area by average, which agree well with our previous conclusion that RSS is severely susceptible to environmental impacts. It is assumed that the relatively sparse vegetation distribution in tree area provides a better propagation environment than brush area. Combined with the results from LOS experiment, our evaluation reveals that users can affect received signal strength by an average of 5.6 dB.



Figure 5.16: Averaged User-Induced Loss Based on Aggregate User Effects.

5.5.3 Directionality-Aware Propagation Prediction

In this section, we consider the user-induced impact of cellular providers crowdsourcing and inferring wireless channel characteristics from users via LTE Key Performance Indicators. To do so, we experimentally quantify the role of directional heading of the user with respect to the transmitter on propagation parameters derived from previous discussed linear LOS and radial NLOS experiments. The path loss exponent and shadowing standard deviation are extracted by analyzing the measurement data sets in terms of three aspects for each band: when the user is facing towards the transmitter, when the user is turning away from the transmitter, and mixed directionality when data sets in both directional headings are jointly considered. In radial NLOS experiments, we examine the aggregate user effects aligned in all cardinal directions to remove the spatial differences.

Table 5.4: Estimated Propagation Parameters With User-ind	uced	Effects
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	500 MHz						800 MHz						1800 MHz						2400 MHz					
Scenario	Facing Away Mix		lix	Facing		Away		Mix		Facing		Away		Mix		Facing		Away		Mix				
Parameters	λ	σ	λ	σ	λ	σ	λ	σ	λ	σ	λ	σ	λ	σ	λ	σ	λ	σ	λ	σ	λ	σ	λ	σ
Linear LOS	2.78	3.26	2.58	3.37	2.69	4.54	3.15	3.02	2.45	3.00	2.79	8.78	3.11	2.37	2.97	2.19	3.05	2.76	3.51	2.75	2.15	2.85	2.83	9.84
Tree NLOS	3.80	3.27	3.66	3.19	3.74	3.89	3.63	3.06	2.79	3.73	3.18	7.06	3.52	3.53	3.87	3.38	3.68	6.49	3.79	2.87	2.84	2.96	3.31	8.77
Brush NLOS	3.74	3.08	4.67	2.85	4.22	8.18	4.39	3.15	3.98	2.44	4.20	6.33	3.67	3.78	2.21	2.61	2.91	9.07	3.87	3.24	2.59	3.16	3.24	9.21

Table 5.4 provides the results of propagation parameters as a function of directional heading and mixed directionality across the frequency bands. In the LOS setting, the path loss exponent ranges from 2.78 to 3.51 and from 2.58 to 2.97 in the directional headings of facing towards the transmitter and turning away from the transmitter, respectively. We conclude that facing the transmitter results in higher values of path loss exponent than away. However, this can be misleading because the starting point of the received signal of user facing forwards is much higher than the starting point of the received signal of away. Hence, the path loss exponents derived from measurements with regard to reverse heading are often clipped at the largest distance. Furthermore, the forward facing path loss exponent is not always less than that of reverse heading (see NLOS settings). For instance, the higher path loss exponents have occurred in the direction of turning away at 1800 MHz in tree area and 500 MHz in brush area. This is likely due to the large impact introduced by the complex NLOS environments that cause higher fluctuation as compared LOS environments containing fewer objectives that can interference with the radiowave transmission. With regard to the values of shadowing standard deviations, it turns out that the received signal suffers very close fluctuations for both directions in LOS setting, while in NLOS settings, the difference between the deviation of facing directly toward the transmitter and that of turning away varies, ranging from 0.08 to 1.17 dB. While mixed directionality produces a path loss exponent that lies between the two directional headings (*i.e.*, perhaps leading to the conclusion that the user directionality impact is nominal), an extremely large increase in shadowing standard variance has been observed. Finding: User directionality can more than triple the shadowing effect in a given environment.

5.6 Channel Feedback Evaluation with User-induced Effects

In this section, to explore the channel feedback performance body-induced losses, we perform a multi-node coexistence simulation framework to evaluate the impact of various feedback intervals and training overheads on the performance sweep-based feedback framework in IEEE 802.11ad.

5.6.1 Sweep-based Feedback Framework

MmWave with large bandwidth available has been considered as the most promising frequency band for future wireless communications. The IEEE 802.11ad is operating on 60 GHz mmWave and have attracted significant attention to short distance transmission scenarios, such as wireless local area network and wearable device communications [34]. There are limited spectra in cellular bands and nowadays increasingly congested spectrum has been observed in the existing 802.11 WLANs, such as 802.11n and 802.11ac. The large aperture size of antenna at low frequency bands discourage the widely deployment of MIMO technology.

Due to specific hardware architecture and cost estimation of 802.11ad solution for wearable applications (each on-body beamformer and beamformee device is equipped with battery, based-band processor and RF component, which is connected to phase array with large number of antenna elements), digital beamforming is more difficult to realize on such design than analog sweep-based beaforming design [92]. Therefore, we implement sweep-based beamforming framework, known as sector level sweep (SLS) method in IEEE 802.11ad, to evaluate the performance of channel feedback for user-induced transmissions, as shown in Figure 5.17. Figure 5.17(a) depicts the timing framework for sweep-based design in IEEE 802.11ad, where the beamformer first transmit multiple and continuous training frames to the beamformee. Each training frame is coded by pre-defined beam pointing to different directions. The beamformer ereplies to the beamformee with feedback frames that indicate the received frame strength for successfully received training beams. As shown in Figure 5.17(b), the beamformer sweeps all beams that cover all directions and the beamformee selects the most strongest received training frame and feedback to the beamformer. Although sweepbased feedback design is robust for high path loss scenarios, such as and long distance communications, large overhead significantly reduces the throughput performance for delay sensitive applications, such wearable VR/AR. Moreover, the long training period and extra overhead introduce strong coexistence interference for multiple beam-based links. Therefore, it is essential to explore the trade-off between interference power that largely reduces channel access capability (denoted by blocking probability) and throughput gain (denoted by SINR reaching probability) that benefits from efficient channel feedback.



Figure 5.17: 802.11ad Sweep-based Beamforming Scheme [5]

In this work, we propose a multi-node simulation framework to explore the feedback performances in term of changing feedback intervals and training overheads. To study the system performances with user-induced communications in practical scenarios, we assuming two categories of use cases, including on-body users and off-body users. During each simulation trail, a number of total 10 users are randomly distributed in office-like environments, As shown in Figure 5.18. For on-body users, both beamformer and beamformee are on the same body, with mmWave directional links from head to leg. For off-body users, one of the node is away from the body on a table with around one meter in horizontal distance. Assuming each beamforming pairs use their independent device clock and are capable of sending 64 training frames with 64 different directions in a 3D dimension. The path loss and beam steering gain are calculated to derive the desired link power and interference link power. Based on these results and carrier sense threshold, we are able to obtain the blocking performance as well SINR for rate adaptation. In order to provide an good approximation of system-level performance analysis, 40000 Monte Carlo trails are randomly generated to capture the statistically properties for evaluation. The sweep-based feedback framework is given by



Figure 5.18: Snapshot of 10 users in one trail

$$R_{n\times 1} = W_{RX}^H H_n m W_{TX} s + N \tag{5.3}$$

Here, $R_{n\times 1}$ is the received training symbol carrier by training frame sent from beamformer.

 W_{RX} and W_{TX} are the transmit and receive beam weights, in respectively. s is the transmitted training symbol. The feedback interval is denoted by X, which means that beamformer perform 64-beam sweep-based feedback every X ms.

The performance of sweep-based feedback closely depends on the design of feedback interval X and training overhead s. Reduced feedback interval results in better accuracy in predicting the best beam with less latency in beam tracking for a mobile beamformee, however, too frequent feedback process causes serious interference power to coexistent performance due to the increased possibility of directional beam sweeping towards other legacy users. It is essential to understand the statistical system performance under each impact factor via simulation.

5.6.2 Feedback Interval Evaluation

The data payload ratio increases proportionally to the increase of feedback intervals X to offer enough throughput benefits for beamformed transmissions, yet introduce high interference power to other coexistent users. Hence, the assessment to the impact of various feedback intervals should be explored accordingly to reveal the performance of sweep-based feedback scheme. To investigate the impact of various channel intervals, we simulate a 10-user randomly distributed scenario, as described in Figure 5.18. For each simulation trail, We calculate the interference power from other beamformed pairs and desired link power based its associated beamformer. For statistical analysis, we compare the interference power with detection thresholds and infer the blocking probability in CCDF. The detection thresholds denote the carrier sense capability, includes control frame detection threshold, single carrier detection threshold for data packet, and energy detection threshold. Interference power beyond each threshold will be counted as "carrier sense blocking" so that exponential back-off will be initiated at that beamforming pair. In order to maintain a minimum video refresh rate of 60 Hz, the value of feedback interval is set in a range from 1 ms to 16 ms in the simulation configuration.

In Figure 5.19, we depict the impact of changing feedback interval through training control functionality and payload length in both beamformer and beamformee. When varying the value of X, we have the same background configurations for the Monte Carlo trails

for the purposes of our analysis. We construct a 10-user office area with an inter-user separation spacing which is normalized from 0.05 to 0.1 as described in Figure 5.18. In CCDF interference curve of figure 5.19, we observe that as the feedback interval X increases, the blocking probability decreases significantly. At 16 ms of feedback interval, blocking probability is 35% for control frame detection and 5% for energy detection, while at 1 ms of feedback interval, the blocking probability increases to 90% and 12% for control frame detection and energy detection individually. Reduction from the peak blocking probability occurs slowly with interference power less than -65 dBm due to the low threshold value when performing carrier sensing using control frame and single carrier payload frame, respectively. By comparing frame detection with energy detection, we find that the reduction amount of blocking probability remain the same for different feedback intervals, and the blocking probability is severe for small values of X. However, if energy detection is used, the difference of blocking probability provided by energy detection is marginal.



Figure 5.19: CCDF of interference vs. feedback intervals

5.6.3 Training Overhead Evaluation

We further study the impact of two type of training overhead on system-level performance. We use the same simulation configuration setup as described before but fix the feedback intervals to 8 ms. Before constructing the training frame, we process the training symbol *s* via MCS0 (BPSK) or MCS1 (QPSK) to create two different patterns of training overheads. By changing the modulation type to QPSK for training symbol, we generally shorten the length of training overhead by half, but at a cost of beamforming gain loss due to potentially prediction error and larger constellation distance. The Table 5.5 describes the HFSS 3D electromagnetic software simulated gain loss at different steering angles when MCS1 is used for training frame structure. The BF gain loss in Table 5.5 represent the average gain loss due to reduction of beam prediction accuracy. Note that gain loss will be fixed to -7.7 dB with steering angle increasing beyond 50 degrees. This is explained by the increasing grating lobes that compensates for the drops of predicted gain due to prediction error.

Table 5.5: Estimated Gain Loss using MCS1 Training Frame

Steering Angle	BF Gain Loss (dB)
0	-13.4
20	-11.3
50	-7.7
50	-7.7

In Figure 5.20(a), we observe that the blocking probabilities for training symbol s modulated with MCS0 and MCS1 are almost the same at first, and decreases later as the received interference power increases. This is a similar notion that is depicted in Figure 5.19, but this time the blocking probability with control frame detection and signal carrier payload frame detection 82% and 80% respectively. This proves that training symbol MCS0 has almost the same blocking performance with training frame modulated with MCS1 when frame detection threshold is assumed. Figure 5.20(a) depicts the CDF distribution for different rate adaptation thresholds, which is directly depending on the SINR performance. The SINR performance is denoted by SINR reaching possibility when rate adaptation level is determined. At rate adaptation threshold based on lower MCS index, we observe that the SINR probability can reach 80%, For example at rate adaptation of MCS0, 92% and 98% of trails have reached the SINR requirement when for MCS1 and MCS0 modulated training frame, respectively. Similarly, at rate adaption of MCS8, 80% and 93% of trails have reached the SINR requirement when for MCS1 and MCS0 modulated training frame, respectively. This demonstrates that in most scenarios, MCS8 can be reached with at least 80%. We also find that although the difference between MCS1 and MCS0 training overhead tends to get smaller at different rate adaption thresholds, training frame using MCS0 always outperforms MCS0 for SINR probability performance.



Figure 5.20: Evaluation of training overhead on blocking probability and SINR reaching probability

5.7 Related Work

Wave propagation knowledge of user-induced effects has recently been of increasing interest for military communications, cellular network deployments, and device antenna design [93–98]. The receiver directionality and on-body location caused by human behavior can strongly affect the reception of electromagnetic waves. When there is a change in user behavior, antenna elevation, or scatter distributions, the channel quality can vary, resulting in fluctuations in signal reception within the same environment. Depending on the magnitude of the variation, the received signal strength (RSS) can drastically change the user experience, especially on the outer edges of the propagation range. According to [93], some early measurements of mobile phone network performance relating to orientation and position were conducted by Lehne. Myllymaki [94] proposed a method for evaluating the user-induced load on a cellular antenna on different hand grip positions. Khan [95] investigated the impacts of body shapes on the radio propagation, but his work ignored multiband and shadowing effects. Independently, Huang [96] and Chetcuti [97] performed similar techniques simulating the effects of human movements on signal reception of mobile receiver, but both lacked adequate experimental support. In this thesis, we experimentally investigate the human body induced effects on path loss analysis and shadowing parameters over multiple frequency bands and diverse propagation environments. Our measurement study has impact on future WiFi and cellular deployments for potential crowdsourcing applications and Ad Hoc networks such as when designing military networks.

Theoretical studies for characterization and modeling of radio wave propagation have been conducted for a number of years [99–101], and measurement-driven designs have also been conducted under different practical scenarios. Measurement results for near-ground propagation were presented by Joshi [102]. By using narrowband and wideband channels at 300 and 1900 MHz, Joshi characterized the effects of antenna height on signal reception. Meng [103] developed an experiment to study near ground radio wave propagation at 240 and 700 MHz on an island in Singapore. However, most of these works focus on a particular environment type at a particular frequency band without varying the on-body location and directional heading of the user. To the best of our knowledge, this work is the first to quantitatively analyze these user-induced propagation effects over a wide range of UHF frequency bands at transmitter distances similar to typical WiFi and cellular base stations.

Also, the emergence of mmWave communicating systems encourages the implementation of new applications in wearable and on-body communication networks, ranging from ehealth to AR/VR. Propagation between two antennas on a human body in millimeter-wave frequency band have been investigated empirically [5, 92, 104, 105]. However, most works have been mainly concentrated on on-body communicating systems working around low frequency bands [5, 104]. Although [92, 105] provide very accurate static propagation models for body-induced 60 GHz mmWave transmissions, but none of them considers the necessity of beamforming that usually incorporates with mmWave to overcome the high path loss and shadowing introduced by body blocking or fading at 60 GHz. Antenna array beamforming is essential for realizing mmWave communication systems, especially for anticipated high attenuation at this frequency with large body-induced losses. Therefore, we progress to mmWave channels to study user-induced feedback performance in the context of the IEEE 802.11ad.

5.8 Summary

In this Chapter, we performed a measurement study of user-induced effects on wireless reception across multiple frequency bands under various conditions characterized by onbody location of the receiver, directional heading, propagation distance, vegetation type, and elevation. We first established a baseline knowledge of the propagation channels by comparing the ground-to-ground and tower-to-ground scenarios. The induced propagation channels were characterized by the propagation parameters using a path loss model. We found that the shadowing standard deviations are elevated in the tower-to-ground setup, especially for higher frequency bands.

We also performed experiments under LOS and NLOS settings to explore the signal attenuation and give quantitative analysis on user-induced effects. In the linear LOS experiments, we reported that the location of held in the hand having the greatest user-induced loss out of all locations. We find that a forward-facing user can act like an antenna that receives up to 4.4 dB over a reference node mounted on a tripod at the same distance. Considering many real applications are Non-Line-of-Sight (NLOS), we further explore the effects of directional heading by conducting NLOS experiments with four simultaneous users at each of the cardinal directions at varying distances. Motivated by recent 5G standardization that allows user devices to feed back Key Performance Indicators to cellular towers, we consider the impact of the aforementioned user-induced effects on crowd-sourcing wireless channel characteristics. Our assessment reveals that the directional heading of facing towards the transmitter results in higher path loss exponents than turning away in channel propagation, and user directionality can have more than triple the shadowing effect in a given environment. In radial NLOS experiments, we observed that RSS is severely susceptible to environmental impacts and the user directionality can affect received signal strength up to 20 dB. Our evaluation on user directionality-aware propagation showed that user directionality can more than triple the shadowing effect. Lastly, we progress to mmWave channels to study user-induced feedback performance with changing feedback intervals and training overheads in the context of the IEEE 802.11ad. We find that the blocking probability can reach up to 90% with an aggressive feedback interval and lower modulation scheme is more preferred than high modulation. we estimated that the impact of user effects will only increase with the growth of higher frequency bands such as those with millimeter wavelengths. These measurement results have impact on the next generation network design of WiFi, cellular, Ad-Hoc networks, mmWave networks of all types.

Chapter 6

Conclusion

In this dissertation, we investigated multiple aspects of channel feedback to optimize or improve the wireless system performance in terms of design of novel feedback feedback mechanisms, evaluation of UAV-based beamforming networks, and evaluation of user-induced communications. Feedback mechanisms have been considered to be a promising approach to in the telecommunication to optimize the utilization of radio spectrum and minimize the cost of system construction. The key advantages of implementing Feedback mechanisms in wireless networks include fully utilization of channel information with optimization method and optimized design for channel feedback scheme.

In our evaluation process, in order to understand the challenges in channel feedback performance, we first study the impact of key factors that degrade the performance of channel reciprocity, such as transmitter-receiver imbalance, Doppler effect due to mobility, and effective noise impact. We review the current IEEE 802.11 channel feedback schemes and their challenges. Then, we have presented our proposed channel feedback mechanisms to increase CSI accuracy and further improve throughput, which are possibly considered for future WLAN systems. Also we have evaluated implicit channel feedback and explicit feedback scheme in both emulated MIMO channels and in-field study with UAV communications. Our evaluation shows that channel estimation can be significantly affected by channel coherence due to mobility and our proposed hybrid feedback scheme can efficiently improve channel estimation accuracy and link performance by 32%. Our in-field assessment demonstrates that a properly optimized drone-based beamforming system can provide significant throughput improvement using explicit versus implicit feedback.

Second, precise air-to-ground propagation modeling is imperative for many unmanned aerial vehicle applications such as search and rescue, reconnaissance, and disaster recovery. In this work, we design a UAV-based SDR platform and perform a measurement study to characterize the air-to-ground channel between the aerial platforms and a terrestrial user in practical scenarios such as hovering, encircling, and linear topologies. Our experiments cover multiple carrier frequencies, including cellular (900 MHz and 1800 MHz) and WiFi (5 GHz) bands. Furthermore, we address three baseline issues for deploying drone-based beamforming systems: channel reciprocity, feedback overhead, and update rate for channel estimation. Numerical results show that explicit CSI feedback can increase throughput by 123.9% over implicit feedback and the optimal update rate are similar across frequencies, underscoring the importance of drone-based beamforming design. We additionally analyze the reciprocity error and find that the amplitude error remained steady while the phase error depends on mobility. Since our study spans many critical frequency bands, these results serve as a fundamental step towards understanding drone-based beamforming systems.

Lastly, we perform explore user effects on radio wave propagation and channel feedback performances with varying line-of-sight conditions and environments across multiple frequency bands, including white space (500 and 800 MHz), cellular (1800 MHz), WiFi (2400 MHz) frequency bands, and mmWave (IEEE 802.11ad 60 GHz). To do so, we first conduct a baseline experiment that characterizes the propagation channel in this environment. We show that the propagation differences for ground-to-ground communication and tower-to-ground communication are frequency dependent. Then, we measure signal quality as a function of the on-body location of the receiver, directional heading of the user with respect to the transmitter, vegetation type, frequency band, and propagation distance. Our assessment reveals that the user directionality with respect to the transmitter can reduce received signal strength up to 20 dB and reduce throughput by 20.9% at most. We also find that the body can act like an antenna, increasing reception by 4.4 dB and throughput by 14.4% over a reference node at the same distance. Also, we progress to mmWave channels to study user-induced feedback performance with changing feedback intervals and training overheads in the context of the IEEE 802.11ad. We find that the blocking probability can reach up to 90% with an aggressive feedback interval and lower modulation scheme is more preferred than high modulation.

Since our study spans many critical frequency bands including mmWave networks, we believe these results will have far-reaching impact on a broad range of network types. We believe that this work will serve as a fundamental step in extending the next generation feedback schemes taken by wireless deployment. These measurement results will have impact on the next generation network design of WiFi, cellular, and Ad Hoc networks of all types.

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