MU-MIMO Optimization on Downlink Commodity Wi-Fi

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ABSTRACT

We study the impact of environmental factors that affect Mu-MIMO user selection compared to conventional models. MU-MIMO is a technique in802.11 ac that improves spectral efficiency by allowing concurrent communication between one AP and multiple clients. In practice, the expected gain is not always achieved and is sometimes even negative. 802.11ac joint MU-MIMO user grouping and scheduling is important for many applications over Wi-Fi applications. Although Mu-MIMO is introduced in 802.11ac to improve spectral efficiency by allowing concurrent communication, it may introduce high delays and low throughput if AP selects the wrong users to group in an MU-MIMO transmission, as users with correlated channels cause high packet losses due to interference. Therefore, using a commodity 802.11ac AP, we experimentally show that the factors such as user mobility or user device with low SNR can reduce Mu-MIMO throughput below that of single-user transmissions.

1 INTRODUCTION

MU-MIMO is introduced in 802.11ac and ax to improve spectral efficiency by allowing concurrent communication, it may introduce high delays and low throughput if AP selects the wrong users to group in an MU-MIMO transmission, as users with correlated channels cause high packet losses due to interference. Factors that impact MU-MIMO user grouping and consequently impact the performance of multi-user applications are crucial for running efficient multi-user applications over 802.11ac/ax. In this work, we have selected multi user VR (mu-VR) as the target application over 802.11ac/ax. Despite recent efforts on VR research, providing high-quality, immersive multi-user experience still poses numerous challenges. While some of them, such as limited battery life and computation power, have been considered for single-user VR [7, 15], little research has been conducted on multi-user VR, which brings a new set of scalability and heterogeneity challenges. How to support tens of untethered users interacting simultaneously over the state-of-the-art wireless infrastructure? How to make the server scale when executing complex scheduling and rendering operations? How to accommodate user devices with heterogeneous hardware configurations? The last one is an important and practical requirement, given that "BYOD" (bring-your-own-device) policies are becoming increasingly popular in enterprises. By taking a cross-layer, interdisciplinary approach, we study the novel opportunities in both the application-layer design and VR-aware wireless network optimizations.

To our best knowledge, this work presents a first research proposal of designing a multi-user VR system for untethered COTS mobile devices, by incorporating cross-layer system design, wireless networks, and machine learning. We first describe the proposed cross-layer design with the main focus on Mu-MIMO group selection for Multi user VR over commodity Wi-Fi. We then present the preliminary results to further motivate and demonstrate the feasibility of our approach.

2 RELATED WORK

Current trend on the problem of emerging MAC protocols with machine learning focuses mainly on new medium-access policies. The research mostly focused on contentioned-based policies [14], [13], Dynamic Channel Access (DSA) such as [2, 3, 8]. The recent works [9], [12], [11], [10] focus on random access MAC protocol design in 802.11 LANs by selecting appropriate protocol blocks. In addition, there are recent works that particularly focus in Mu-MIMO optimizations in physical and mac layer [1, 4–6, 16] using machine learning techniques.

3 SYSTEM DESIGN

In network level optimization, our approach seek to save bandwidth, increase throughput, and reduce delay. We describe our system design elements in the following.

MU-MIMO Grouping and Scheduling. Joint MU-MIMO user grouping and scheduling is crucial for multiuser applications over 802.11ac/ax. The grouping protocol may introduce high delays and low throughput if it selects the wrong users to group in an MU-MIMO transmission, as users with correlated channels cause high packet losses due to interference. For scheduling, ideally the protocol has to be short-term fair to ensure low access delay for all users; the protocol should also determine the optimal frame duration based on the traffic dynamics. We propose to group users by minimizing interference and to avoid delays by crafting VR-aware frame aggregation. Specifically, we propose two optimizations. First, we can blacklist groups with SFER yielding prohibitive delays whose threshold could be set by the server based on the VR QoE requirements. Second, the server can also inform the AP about the size distribution of the data to be transmitted (e.g.,GOPs of rendered frames). The AP can then use this information to make strategic frame aggregation decisions, such as limiting the transmission duration, to maintain the proper scheduling granularity without delaying other users.

In our approach, a client needs to continuously transmit uplink (UL) meta-data that contains the user's position, orientation, and controller inputs. Due to the heavy downlink (DL) traffic that causes CSMA/CA deferrals or collisions, users might experience tens of ms delay for meta-data transmissions over 802.11ac. 802.11ax Wi-Fi can also incur delays, as users need to send buffer status reports (BSR) to earn OFDMA UL slots from the AP. To reduce the UL delay while maintaining good DL performance, one approach would be to schedule uplink meta-data over another medium such as Bluetooth. In 802.11ax OFDMA, transmissions are completely controlled by the AP which can periodically schedule all clients with small uplink meta-data on a single frame transmission.

4 EXPERIMENTAL EVALUATION

In this section we first identify the factors that affect MU-MIMO grouping that are directly correlated to the performance in application layer for mu-VR. We mainly focus on two important factors:

Client Motion As shown in Section IV-B, the channel state experienced by a client can be significantly different at positions a few centimeters apart from each other. On the other hand, in order to limit the overhead of CSI feedback, the typical sounding interval in an 802.11ac network is on the order of one tenth of a second [20]. It follows that a client moving at walking speed can lead to a non-trivial CSI difference within a sounding period, and that the CSI used for the MU-MIMO beamforming is inaccurate in part of the period. This leads to higher PER and throughput degradation when the MU-MIMO group includes moving clients. To quantify the performance loss associated with client movement, we conduct experiments using the same one spatial-stream laptops and the same saturating UDP traffic as in the previous subsection. Each experimental run involves a different number of moving clients at walking speed within a 12 feet range, and the AP configured to exclusively transmit in either SU or MU mode. UDP throughput of the clients with different numbers of moving clients in the network. We remark that the moving clients are indexed with lower indices in the results. For example, client I and II are moving while client III is stationary in the case of two moving clients. The results indicate that both SU and MU performance degrades in the presence of moving clients, and the throughput of MU-MIMO drops more drastically. In the scenario with one moving client, although the MU throughput of the two stationary clients (II and III) still outperforms that in SU mode, the MU throughput of the two clients decreases by one half in comparison to the scenario where all three clients are stationary. The MU throughput of the moving client (Client one) decreases to around 10-15 Mbps which under-performs its SU mode. In the scenarios with two or more moving clients, the MU mode under-performs the SU mode for all three clients. Therefore, to realize the promised performance gain of the MU-MIMO, it is necessary to exclude the moving clients from the MUMIMO transmissions. This motivates us to look for indications of client mobility in the client screening algorithm.

Device Type The previous two subsections show that client motion and low SNR are two major factors that limit the performance of MU-MIMO mode. It follows that excluding the moving clients and the clients with low SNR from participating in MU-MIMO will be beneficial. However, as different types of clients have different characteristics , the performance degradation due to motion and low SNR may vary from device to device. It may not work well if one criterion is used to screen all clients for MU-MIMO grouping. For instance, different types of device support different numbers of spatial streams, resulting in different performance gains from choosing MU-MIMO over SU-MIMO. Different designs of firmware and antenna positioning may also lead to different levels of sensitivity to motion and low SNR. To evaluate the impact of device type on MU-MIMO performance, we conduct experiments by varying the device type for Client I. The MU-MIMO group further includes either one or two additional laptops equipped with the one-antenna USB adaptors, so that the total number of spatial streams is three. Client I is the only client in the group with motion or low SNR. The experiment for each device type is repeated multiple times where Client I follows approximately along the same path at the same speed. The AP is configured to switch between SU and MU mode every 15 milliseconds (ms), so that we can compare the performance in both modes in approximately the same channel condition. We quantify the performance gain of operating in MU over SU mode in terms of the ratio between the two throughput values. result shows the CDF of MU-MIMO throughput gain over SU-MIMO for different device types. The results demonstrate that it is rather common for MU-MIMO to under-perform SU transmissions. In addition, the degree of degradation can be significant. The five clients spend between half of their time operating in the suboptimal MU-MIMO mode while losing throughput. On the other hand, it is obvious that the MU-MIMO performance gain varies significantly across device types. For example, although both the 2-stream USB adapter and the 2-stream laptop has two receive antennas. It is therefore important for the client grouping scheme to explicitly account for different device types.

802.11ac MU-MIMO Performance. We experimentally investigate the multi-user performance of 802.11ac in an emulated VR context. We modify the firmware of an enterprise-grade AP to collect statistics and to use either MU- or SU-MIMO. We first demonstrate that MU-MIMO can yield significant gains if properly configured for a small number of users. In our setup, we distribute three clients in a large lab emulating a VR room. The clients have un-correlated channels, as verified by the channel state information. They are first grouped with MU-MIMO and then using SU-MIMO to concurrently download data from a local server. Results uncovers that MU-MIMO can yield more than half of throughput gains compared to SU-MIMO. We plan to conduct similar performance analysis for 802.11ax when it becomes available on commodity mobile devices in the near future.

Our design enables high-quality multi-user VR on untethered COTS mobile devices over 802.11ac and the next-generation 802.11ax Wi-Fi. Our design consists of both application and wireless layer innovations, whose synergy helps realize the key goals of achieving the scalability, providing good content quality, and embracing clients' heterogeneity. Some of our proposed ideas, in particular those pertaining to the network-level optimizations, can be applied to other bandwidth-intensive applications, such as video conferencing and social AR.

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