Signpost: Scalable MU-MIMO Signaling with Zero CSI Feedback

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ABSTRACT

Poor scalability is a long standing problem in multi-user MIMO (MU-MIMO) networks: in order to select concurrent uplink users with strong channel orthogonality and thus high total capacity, channel state information (CSI) feedback from users is required. However, when the user population is large, the overhead from CSI feedback can easily overwhelm the actual channel time spent on data transmission. Moreover, due to spontaneous uplink traffic, uplink user selection cannot rely on the access point's central assignment and needs a distributed realization instead, which makes the problem even more challenging.

In this paper, we propose a fully scalable and distributed uplink MU-MIMO protocol called *Signpost*. Firstly, Signpost is scalable, i.e., it achieves *zero CSI overhead* by exploiting a novel orthogonality evaluation mechanism that enables each user to speculate its orthogonality to other users, using its own CSI only. Secondly, Signpost realizes distributed user selection through a two-dimensional prioritized contention mechanism, which can single out the best users efficiently by utilizing both the time and frequency domain resources. The contention mechanism includes a unique collision recovery scheme, which enables Signpost to achieve a collision probability as low as one-tenth compared with traditional 802.11-like mechanism. Software-radio based implementation and testbed experimentation show that Signpost significantly outperforms state-of-the-art user selection methods under various traffic patterns and node mobility.

Categories and Subject Descriptors

C.2.1 [**Computer-Communication Networks**]: Network Architecture and Design—*Wireless Communications*

General Terms

Algorithms, Design, Theory, Performance

Keywords

Multi-user MIMO; MU-MIMO; 802.11ac; User selection

1. INTRODUCTION

MU-MIMO is an emerging wireless technology that allows multiple users to transmit concurrently towards the same multi-antenna access point (AP), or vice versa. It holds the potential to substantially improve network throughput. To fully realize this potential, only the best user group should be served in each MU-MIMO transmission, because users are coupled and their achievable rates depend on the orthogonality of their instantaneous channel states [1, 13]. However, selecting the best user group usually requires a signaling stage, wherein all users feed back their CSI to the AP. When the user population is large, channel time spent on CSI feedback can easily overwhelm the actual channel time spent on data transmission. Therefore, a user selection mechanism must be *scalable* – given a growing user population, it should limit the CSI overhead while maximizing the link capacity, in order to optimize the overall throughput.

Besides, particularly for uplink (UL) MU-MIMO, the user selection mechanism must be fully *distributed* and executed by the users themselves instead of the AP. The users may be mobile, have bursty traffic demands, or join/leave the MU-MIMO cell dynamically. Thus, they should coordinate with each other spontaneously to form the best user group for each UL MU-MIMO transmission.

Recent MU-MIMO protocols have addressed the scalability of *downlink* (DL) MU-MIMO user selection [15, 18]. One state-of-the-art approach is OPUS [18] which bounds CSI overhead via the AP's iterative probing. Suppose M is the number of antennas on the AP and N is the number of client users in the network. OPUS requires only M rounds of CSI feedback from the client users to the AP, instead of N rounds in previous studies.

One may handle the UL scenario in a similar manner as DL (i.e., the AP is in charge of choosing an optimal set of concurrent users, and then the selected users transmit following the AP's commands [17]). However, such an approach falls short of scalability and goes against the distributed nature of UL MU-MIMO. First of all, M rounds of CSI feedback still entail a non-trivial overhead. For example, when $M = 2$, the time spent on CSI feedback is usually more than half of the time spent on data transmission (More details are in Sec. 6). Second, in UL scenarios, a client needs to compete for transmission opportunities upon traffic demand [16, 17]. When the user population grows, collisions happen frequently and network performance degrades severely, which in turn leads to poor MU-MIMO scalability. Due to these challenges, recent wireless standards like 802.11ac, LTE and WiMax only permit MU-MIMO DL, whereas efficient UL MU-MIMO remains an open problem.

In this paper, we propose Signpost – a scalable and distributed user selection protocol for UL MU-MIMO. *Firstly*, Signpost can decide on a high-throughput concurrent user set without requiring any CSI feedback, which means *zero CSI overhead* under any user population. To achieve this, our key observation is that *the orthogonality between users could be speculated through an indirect way instead of directly collecting CSI from users*. Specifically, suppose we want to choose 2 users for concurrent uplink transmission towards a 2-antenna AP. Our basic idea is to predefine two orthogonal channel vectors (called *Signpost directions*). Before each uplink transmission, each user can compute the angle between its own CSI and each signpost direction. Suppose that among all users, user i is best aligned with one Signpost direction, and another user j is best aligned to the other Signpost direction. Then we can conjecture that the two users have strong

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orthogonality, since they are aligned to two orthogonal Signpost directions[1].

One may question whether this indirect method can group orthogonal users as reliably as one that directly collects CSI. We provide a positive answer through both theoretical analysis and a test-bed measurement study in Sec.3. We also find that this desirable benefit is unique to UL scenarios, and does not hold true in the opposite DL scenarios.

Secondly, to facilitate a distributed realization, we design an efficient two-dimensional (2-D) prioritized contention protocol to single out users with strong orthogonality. Instead of equal-chance random access as in 802.11, here the MAC layer contention priority of a user is derived from its PHY layer information of alignment metrics (i.e., how well the user's CSI is aligned to Signpost directions). In this way, we can guarantee that a preferred set of concurrent users will be selected.

In addition, unlike conventional channel contention, here multiple users are contending for multiple Signpost directions simultaneously. Thus, collision rate can easily become overwhelming. To achieve contention efficiency, we utilize different OFDM subcarriers to separate the contention from different Signpost directions. Combining this with the time-domain random backoff, we design a unique collision recovery mechanism that allows users to detect a collision and recover from the collision in a distributed and cooperative way. In a network consisting of 30 users with saturated traffic, the resulting collision probability is only about $2\sim3\%$, whereas that in state-of-the-art work is more than tenfold higher. Signpost's contention mechanism preserves the distributed nature of UL scenarios, and hence works well under various traffic patterns and node mobility.

We have built a prototype of Signpost on the WARP [30] software radio platform, and have conducted extensive experiments under different scenarios to compare its performance with three state-of-the-art user selections works including SAM [16], MIMOMate [17] and OPUS [18]. The main results are as follows:

(i) In terms of PHY-layer throughput, Signpost achieves a gain of $1.16\times$ to $1.70\times$ under saturated-traffic scenarios, $1.13\times$ to $1.56\times$ under non-saturated scenarios, and $1.04\times$ to $1.56\times$ under mobile scenarios, in a typical 802.11 MU-MIMO WLAN with a 2-antenna AP and 14 users.

(ii) After taking the MAC overhead into account, Signpost achieves remarkably higher MAC-layer throughput gain. In particular, it is $1.44\times$ to $2.96\times$, $1.55\times$ to $1.93\times$, and $1.70\times$ to $2.57\times$ under the three scenarios.

(iii) Signpost scales well in medium to large sized networks. For a 3-antenna AP, we vary the number of users from 6 to 46, and for each setting half of the users are statically located and the other half mobile, and traffic on each user is random. The resulting gain is $1.72\times$, $1.56\times$ and $1.49\times$ compared with SAM, MIMOMate and OPUS respectively, averaged over all network sizes.

The rest of this paper is organized as follows. We discuss more related works in Sec. 2, and then present Signpost's indirect user orthogonality evaluation in Sec. 3 and 2-D prioritized contention in Sec. 4, and the complete Signpost protocol operations in Sec. 5. We evaluate Signpost's performance in Sec. 6 and conclude the paper in Sec. 7.

2. RELATED WORK

The potential of MU-MIMO and the impact of user selection have long been recognized in communication theory [1]. Early works [2–8] assumed that perfect CSI is available and focused on designing low-complexity algorithms to approximate the maximum capacity. However, in practice, obtaining CSI incurs huge overhead, which renders these theoretical approaches infeasible [18, 19].

Recently, many experimental studies [9–18] have explored MU-MIMO in practical scenarios. For the DL case [15, 18], MU-MIMO transmission is more straightforward since user selection could be achieved in a centralized manner at the AP side. However, how to realize scalable and distributed MU-MIMO transmission is a far more challenging problem. Existing UL MU-MIMO protocols [13, 16] still adopt the traditional 802.11 random contention mechanism to select concurrent users, which not only fails to select concurrent transmitters according to their channel characteristic, but also wastes much channel time due to high collision probability.

A recent protocol called MIMOMate [17] optimizes UL user selection through a centralized approach, where the AP is in charge of selecting concurrent users. The AP learns the CSI passively, and then matches users into groups according to their CSI. Then for each round of UL transmission, only group leaders are involved in contention, thus saving channel contention time. However, such a centralized approach is not applicable when users are mobile or have non-saturated traffic, since the passively learned CSI usually becomes outdated and leads to an inappropriate selected users set. Moreover, it also adds protocol complexity. To our knowledge, Signpost represents the first distributed UL MU-MIMO mechanism with zero CSI overhead. Therefore, it can maximally deliver the gain of MU-MIMO, as will be verified in Sec. 6.

Signpost's zero-feedback principle shares similar spirit with random beamforming (RBF) [8] which is used for *downlink* MU-MIMO. An RBF AP randomly beamforms to multiple directions, requires users to feed back their alignment with each direction, and then beamforms to users with best alignment. To our knowledge, RBF has only been discussed in theory and lacks a MAC protocol that supports its operations in practice. More importantly, although RBF is asymptotically optimal (i.e, its information-theory capacity grows at the same order as that obtained with known CSI, as the number of users N and the number of antennas M approach infinity [8]), we show that under practical networks with a reasonable number of N and M, RBF has poor performance. This fact indicates that having exact CSI is critical for DL MU-MIMO beamforming in practice. In contrast, we demonstrate that CSI feedback is not necessarily required to achieve high performance in UL scenarios. We contrast Signpost and RBF in more details in Sec. 3.4.

In terms of Signpost MAC, the 2-D prioritized contention mechanism is inspired by the frequency domain contention mechanism Back2F [20], but it differs in several aspects. *First*, Signpost jointly utilizes the resource from both frequency domain and time domain for efficient contention. *Second*, the Signpost MAC supports MU-MIMO through concurrent multi-directional contention, while Back2F is designed for traditional single-transmission scenarios. Finally, Back2F requires at least two antennas to enable concurrent transmission and carrier sensing, which is not needed in Signpost.

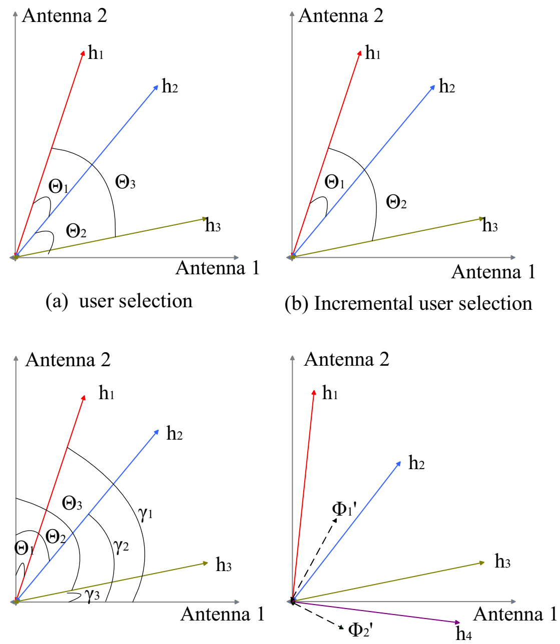
3. INDIRECT ORTHOGONALITY EVALUATION

In this section, we first introduce the relevant background, including the impact of users' CSI orthogonality and traditional direct orthogonality evaluation mechanisms. Then we describe Signpost's indirect approach followed by both analytical and experimental validation.

3.1 Background

In MU-MIMO networks, the throughput of a user depends not only on the user's own channel state, but also on the channel state

[1]Since these predefined orthogonal vectors could be used to indicate client users' direction, we can image them as the signposts along a sidewalk. We thus name our approach "Signpost".



(a) user selection (b) Incremental user selection

(c) Signpost: a round (d) Signpost: the second round

Figure 1: User selection in MU-MIMO.

of other concurrent users [1, 13]. We briefly review this point as follows. Consider a typical MU-MIMO WLAN with a 2-antenna AP, when a single user u_1 transmits a symbol x_1 alone, the received symbol $\boldsymbol{y}$ on the AP is as follows:

$$\begin{cases} y_1 = h_{11}x_1 + n_1 \\ y_2 = h_{21}x_1 + n_2 \end{cases} \tag{1}$$

where $\boldsymbol{h_1} = (h_{11}, h_{21})$ is the channel coefficients between the AP and u_1, and n_i represents zero-mean Gaussian noise with variance N_0. Through Maximal Radio Combining (MRC) [1], we can recover the symbol and the resulting SNR of the symbol, denoted by SNR_{alone}, is:

$$SNR_{alone} = E[\|\boldsymbol{h_1}x_1\|^2]/N_0 \tag{2}$$

Next, suppose another user u_2 transmits a symbol x_2 concurrently with u_1, then the received symbol $\boldsymbol{y}$ can be represented as:

$$\begin{cases} y_1 = h_{11}x_1 + h_{12}x_2 + n_1 \\ y_2 = h_{21}x_1 + h_{22}x_2 + n_2 \end{cases} \tag{3}$$

To recover each symbol, say x_1, the AP migrates the interference from the other symbol using a *zero-forcing* (ZF) technique as in [13]. Specifically, ZF projects $\boldsymbol{y}$ on a direction orthogonal to $\boldsymbol{h_2}$ so as to null out x_2, and gets an estimate of x_1 (denoted by $\hat{x}_1$) as follows:

$$\hat{x}_1 = x_1 + \frac{h_{22}n_1 - h_{12}n_2}{h_{22}h_{11} - h_{21}h_{12}} \tag{4}$$

From (4), we can compute the resulting SNR of x_1, denoted by SNR_{con}:

$$SNR_{con} = SNR_{alone}(1 - \cos^2(\theta)) \tag{5}$$

where θ is the angle between $\boldsymbol{h_1}$ and $\boldsymbol{h_2}$, that is,

$$\cos^2(\theta) = \frac{\|\boldsymbol{h_1}\boldsymbol{h_2}\|^2}{\|\boldsymbol{h_1}\|^2\|\boldsymbol{h_2}\|^2} \tag{6}$$

From (5), we can observe that the channel quality of u_1, SNR_{con}, depends on the angle between the two users' channel coefficients. When the two users are nearly orthogonal (i.e., θ is close to $\frac{\pi}{2}$), the channel quality will be as good as that when u_1 transmits alone. But when θ is small, the channel quality will degrade significantly, which in consequence leads to poor performance. For example, when $\theta = 45°$, SNR_{con} is only half of SNR_{alone}. Therefore, *it is critical to select and group users with strong channel orthogonality.*

A straightforward approach for selecting an optimal user set is to allow the AP to collect all users' CSI first, evaluate the orthogonality of each possible user set, and then choose the one with the best orthogonality. We illustrate this by an example shown in Fig. 1(a), where we assume a 2-antenna AP, and three users u_1, u_2 and u_3 with CSI $\boldsymbol{h_1}$, $\boldsymbol{h_2}$ and $\boldsymbol{h_3}$, respectively. When CSI of all three users is available on the AP, the AP can compute their pairwise angles, and select the two users (in fact, u_1 and u_3) with the most orthogonal angle[2].

However, this approach has many drawbacks in practice. First, obtaining full CSI of all users usually incurs large overhead, which grows linearly with the number of users and can easily overwhelm the actual channel time spent on data transmission [18, 19]. Moreover, even if we can get the full CSI, the computational complexity may become formidable as it increases exponentially with the user population.

To cope with the computational cost, many suboptimal incremental user selection algorithms [4–7] have been proposed, which choose the first user according to a performance metric, and then select additional users one by one that provides the best potential performance when grouped with those previously selected ones. The procedure repeats until M users are selected (M is the number of antennas on the AP). For example, in Fig. 1(b), suppose we choose u_1 as the first user, then by computing the angle θ_1 between u_1 and u_2, and the angle θ_2 between u_1 and u_3, we will find that u_3 should be the next selected user. Although some incremental user selection methods (e.g., SUS [4]) have been shown to well approximate the optimal capacity at low computational complexity [7], they still incur large overhead, since in each round of user selection, identifying the next best user still requires full CSI from all unselected users. To reduce such CSI overhead, a recent work, OPUS [18], proposed a novel incremental user selection method, which requires CSI of M users in each round, instead of full CSI of all users. However, as we will show in Sec. 6, the overhead of OPUS is still high due to its contention and feedback overhead.

In retrospect, these existing approaches could be categorized into a class of **direct** approach for user selection, as the orthogonality is derived by directly computing the angle between the users' CSI. In consequence, CSI is necessary and hence the overhead is unavoidable.

3.2 UL User Selection with Zero CSI Feedback

Now we introduce the principle of indirect user selection in Signpost. The key idea is to allow each user to speculate its orthogonality with others by using its local CSI only.

Suppose we want to determine the orthogonality between two users u_i and u_j with channel gain $\boldsymbol{h_i}$ and $\boldsymbol{h_j}$, respectively. We predefine some vectors (say, $\boldsymbol{\phi_1}$, $\boldsymbol{\phi_2}$, and called Signpost directions) with orthogonal directions. Each user then computes the angles between its channel gain and the Signpost directions. If user i has good *alignment* with $\boldsymbol{\phi_1}$ and j also has good *alignment* with $\boldsymbol{\phi_2}$, we can conjecture that the angle between $\boldsymbol{h_i}$ and $\boldsymbol{h_j}$ is close to orthogonal since $\boldsymbol{\phi_1}$ and $\boldsymbol{\phi_2}$ are orthogonal.

For example, in Fig. 1(c), we can set the directions along two axes of coordinates as the Signpost directions, i.e., $\boldsymbol{\phi_1} = (1, 0)$ and $\boldsymbol{\phi_2} = (0, 1)$. Suppose these Signpost directions are known to all three users, then each user can evaluate its alignment to each Signpost direction, by computing the angle between its CSI and that

[2]Besides angles, some works also take the SNR of each user into account. Here we just use angle for simplicity, but the principle is the same.

Signpost direction. For direction $\boldsymbol{\phi_1}$, the angles are θ_1, θ_2 and θ_3 for the three users respectively. Then u_1 with the smallest angle θ_1 will be selected. Similarly, on the second Signpost direction $\boldsymbol{\phi_2}$, u_3 (with the smallest angle γ_3) will be selected.

Note that if we use a fixed set of Signpost directions, there will be unfairness problem since the same set of users will always be selected. To solve this problem, we predefine multiple sets of Signpost vectors, and use them alternately across different rounds of user selection. For example, in Fig. 1(d), in the second round, we use a different set of Signpost directions (i.e, $\boldsymbol{\phi_1'}$ and $\boldsymbol{\phi_2'}$) than the first round. Consequently, a different set of users (u_2 and u_4) is likely to be selected along the new directions.

We now extend the above basic idea to the general case. For a MU-MIMO network with an M-antenna AP and N users, each client user i computes $g_{i,j}$ ($j = 1, \cdots, M$), the *alignment metric* between its channel state $\boldsymbol{h_i}$ and the j^{th} Signpost vector $\boldsymbol{\phi_j}$ as follows:

$$g_{i,j} = \frac{\|\boldsymbol{h_i}\boldsymbol{\phi_j}\|^2}{\|\boldsymbol{h_i}\|^2} \tag{7}$$

From a centralized perspective, Signpost user selection operates in an iterative manner. *First*, we pick the maximum value among all $g_{i,j}$ ($i \in [1, N]$ and $j \in [1, M]$), and denote it as $g_{i_{max}, j_{max}}$. We then put the corresponding user i_{max} into the set of selected users, and remove the j_{max} Signpost direction out of consideration. *Second*, we find the next maximum alignment metric among the remaining Signpost directions and remaining users, that is, among all $g_{i,j}$ ($i \in [1, i_{max} - 1] \cup [i_{max} + 1, N]$) and $j \in [1, j_{max} - 1] \cup [j_{max} + 1, M]$. Then we can select the second user and remove it and the its corresponding Signpost direction. The process iterates until we select M users (or N if the user population $N < M$). Before describing a decentralized realization of the iterative procedure (Sec. 4), we first justify this design through both analysis and testbed measurement.

3.3 Analytical Verification

One may question whether Signpost's indirect approach can select appropriate user sets that result in large overall throughput. After all, it is an indirect approach, and each user only uses its local CSI without knowing other users' CSI. The following analysis provides a positive answer.

We first analyze the advantage of Signpost by comparing it with a baseline random user selection. We first show, for any Signpost direction, how well the selected users can be aligned. We define the alignment metric (denoted by $\hat{g}$) between the selected user on the j^{th} Signpost direction as:

$$\hat{g} \triangleq \max_{i \in [1,N]} g_{i,j} \tag{8}$$

For a simple case of $M = 2$, we compute a closed-form expression of $E\{\hat{g}\}$ as follows. From the definition of $\hat{g}$, it is clear that for any $cos^2(\theta) \in [0, 1]$, $\hat{g} \leq cos^2(\theta)$ requires that all $g_{i,j}$ ($i \in [1, N]$) should be no larger than $cos^2(\theta)$. Then, we know the probability that $\hat{g} \leq cos^2(\theta)$ is

$$F(\hat{g} \leq cos^2(\theta)) = \prod_{i=1}^{N} F(g_{i,j} \leq cos^2(\theta)) \tag{9}$$

We assume the CSI of any user is a random vector in the M dimension space, then the cosine of the angle between the user and a Signpost direction follows a distribution as that of the minimum of (M-1) i.i.d. uniform random variables in [0,1] (from Lemma 3.2 in [26]). For our specific case of $M = 2$, this means that the angle follows a uniform distribution in [0, $\frac{\pi}{2}$]. So

$$F(g_{i,j} \leq cos^2(\theta)) = 1 - \frac{2\theta}{\pi} \qquad \forall i \in [1, N] \tag{10}$$

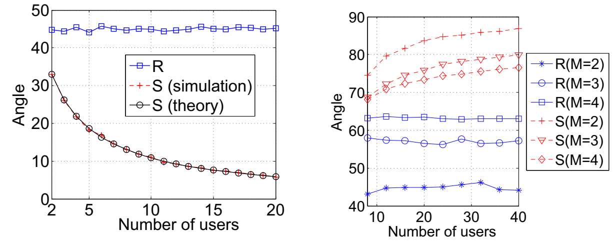


Figure 2: Mean angle (a) between users and signpost directions (b) between selected users.'R' means Random method, and 'S' means Signpost.

Putting (10) into (9), we have

$$F(\hat{g} \leq cos^2(\theta)) = (1 - \frac{2\theta}{\pi})^N \tag{11}$$

Then the expectation of $\hat{g}$ becomes

$$E(\hat{g}) = \int_{\theta=0}^{\frac{\pi}{2}} \Big[cos^2(\theta) N \big(1 - \frac{2\theta}{\pi}\big)^{(N-1)} (-\frac{2}{\pi}) d\theta\Big] \tag{12}$$

Solving the integration above, we can have a closed-form equation as follows,

$$E\{\hat{g}\} = \frac{1}{2}\Big[1 + \sum_{i=0}^{N-1} \frac{(\frac{1+(-1)^i}{2})(-1)^{\frac{i}{2}-1} \prod_{j=0}^{i-1}(N-j)}{\pi^i} + \frac{(1+(-1)^N)(-1)^{\frac{N}{2}-1} \prod_{j=0}^{N-1}(N-j)}{\pi^N}\Big] \tag{13}$$

From (13), we obtain the average angle (denoted by $\hat{\theta}$) between the selected user and the corresponding Signpost direction as:

$$\hat{\theta} = \arccos\big(\sqrt{E\{\hat{g}\}}\big) \tag{14}$$

Fig. 2(a) (the 'theory' Line) plots $\hat{\theta}$ as the number of users N grows from 2 to 20. We also verify the analysis with simulation: for each N, we generate N users with random CSI, and select two users using Signpost and Random method, respectively. We repeat 1000 rounds of simulation for each N setting. The results show that the simulation perfectly match with theory. The angle between a user and its corresponding Signpost direction $\hat{\theta}$ decreases rapidly with N. When $N \geq 12$, $\hat{\theta}$ is smaller than $10°$. In contrast, under random user selection, a selected user always has an average angle of $45°$ to any Signpost direction, regardless of N.

Therefore, our user selection scheme can ensure the selected users are well aligned with the corresponding Signpost directions. Since the Signpost directions are orthogonal, we expect that the selected users will be near-orthogonal. The simulation results in Fig. 2(b) confirm this point. Under $M = 2$, if $N \geq 12$, the angle between two users selected by Signpost is larger than $77°$, and approaches $90°$ as N further increases. We also find that Signpost keeps much advantage over the random user selection as M increases.

3.4 Measurement Validation

Now we show that strong orthogonality achieved by Signpost leads to much higher network performance, using a test-bed based measurement. We set up the test-bed in Fig.12 using WARP [30] on a 20-MHz channel, where we use a 3-antenna AP, and collect CSI of 30 distinct locations by varying the location of the two clients (more details of the implementation are in Sec. 6). Then we feed the CSI into different channel orthogonality evaluation and user selection methods, and compare the resulting per-user SINR from Signpost, Random User Selection (RUS) and the Optimal upbound derived by an exhaustive search among all possible user combinations. The results are given in Fig. 3(a). We can observe that Signpost is much

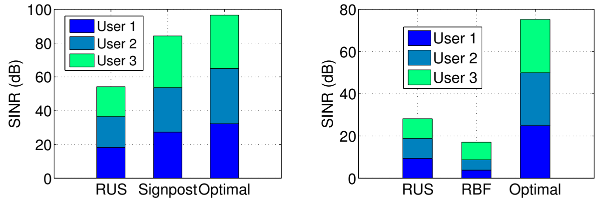


Figure 3: (a) UL SINR (b) DL SINR.

closer to the optimal bound, and the ratio is 87.3%, while that of RUS is only 56.1%.

More importantly, we find that this desirable benefit is unique to UL scenarios, and it does not hold true in the opposite DL scenarios. We plot the result for the DL scenario in Fig. 3(b). Here we compare RUS, the Optimal bound and Random Beamforming (RBF) [8]. RBF could be considered as the DL version of Signpost. Similar to Signpost, RBF also applies indirect orthogonality evaluation without CSI feedback. A RBF AP randomly beamforms to multiple directions, asks the users to feed back their alignment along each direction, and then beamforms to users with best alignment. It is proved in [8] that when both the number of antennas on the AP M and the user population N go to infinity, the information-theory capacity of RBF is at the same order with that of the Optimal. However, as we can observe from Fig. 3(b), RBF exhibits poor performance, even much worse than RUS in practice with reasonable M and N.

We find the reason as follows. After user selection, the AP needs to know the exact CSI to perform precoding before beamforming to users. However, RBF only precodes with the randomly selected directions without CSI feedback, which causes much capacity loss. In contrast, for the UL case, the AP will finally get all CSI after it receives upcoming transmissions, which can be used to decode all of them. In this way, the AP exploits full potential of selected users with strong orthogonality. To sum up, this fact indicates that having exact CSI is critical for downlink beamforming in practice, while Signpost demonstrates that CSI feedback is not necessarily required in uplink scenarios.

4. 2-D PRIORITIZED CONTENTION

Now we present the contention mechanism that realizes the Signpost user selection in a distributed way. Compared with traditional SISO scenarios, it is far more challenging when designing an efficient contention mechanism for MU-MIMO. In traditional SISO networks, the aim is to single out *one random user* while minimizing collisions. For MU-MIMO, the objective is to single out *a preferred set of users with strong orthogonality* while minimizing the contention and collision overhead.

To meet the objective, we propose a cross-layer approach, which connects the alignment metrics computed from PHY layer CSI with the MAC layer contention aggressiveness of users. The larger the metrics, the smaller the contention aggressiveness is. On one hand, this makes users with strong orthogonality more likely to win the contention. On the other hand, this prioritized contention causes an extra difficulty in avoiding collisions. In particular, when different users have similar alignment metrics, they will end up in collision since they have similar contention time. One straightforward method for avoiding collisions is to increase the contention window. For 802.11 contention, this will work since users pick a random contention time in the contention window. The larger the window, the more likely they will choose different contention time so as to avoid collisions. However, this will not work for prioritized contention, since the contention time is not randomly picked but pre-defined by the alignment metrics. One may increase the contention window to a very large value so that close alignment metrics can still be mapped into different contention slots. But clearly, this will waste too much channel time.

Algorithm 1 2-D prioritized contention algorithm.

Input: $\boldsymbol{h}$: the user's CSI; Φ: the Signpost directions; W: the contention window;
Output: *sel*: the selected status of the user;

Initialize: *sel* = 0; the selected Signpost direction $sel\_dir = 0$; contention status *cont* = 1; *slot* = 1;
Compute the alignment metrics using (7)
Create M backoff timers using (15), (16), (17) and (18);
while slot $\leq W$ **do**
  if *cont* == 1 & a timer on any direction m expires **then**
    cont = 0
    sel = 1;
    $sel\_dir = m$;
  end if
  if hear a CA on any direction m **then**
    if *cont* == 1 **then**
      Quit contention on direction m;
      Disable the corresponding timer ;
    end if
    if *cont* == 0 & $sel\_dir == m$ **then**
      sel = 0; ▷ Detect own collision, cancel the selection
    end if
  end if
  if hear multiple CAs on any direction m **then**
    if *cont* == 1 **then**
      Detect other users' collision, keep contention;
    end if
    if *cont* == 0 & $sel\_dir == m$ **then**
      sel = 0; ▷ Detect own collision, cancel the selection
    end if
  end if
  slot++;
end while

To overcome this problem, we design a two-dimensional (2-D) contention method. Besides the time domain backoff used in 802.11, we also utilize frequency domain by using different OFDM subcarriers to separate the contention from different Signpost directions. In this way, we alleviate contention intensity and reduce collision probability. Moreover, by leveraging both time and frequency domain knowledge, we design a unique collision recovery mechanism that allows users to detect collisions, and recover from the collisions in a cooperative and distributed way. Combining these two techniques, Signpost achieves distributed user selection efficiently. Next, we present an overview of the 2-D prioritized contention mechanism, followed by more details for each component.

4.1 Overview

For a network with N users and a M-antenna AP, the contention mechanism works as follows. Recall each user i can locally compute M alignment metrics, one metric per Singpost direction. Thereafter, the user employs a *mapping mechanism* to project each metric to a 2-D coordinate: along frequency (subcarrier index) and time (backoff timer), respectively. Then, a 2-D CSMA-based contention procedure begins. Specifically, each user picks the Signpost direction with smallest backoff timer and starts counting down. After the timer expires, it contends with others by transmitting a contention announcement (CA, the design is in Sec. 5) on the specified subcarrier. If a user hears a CA on this Signpost direction before its timer

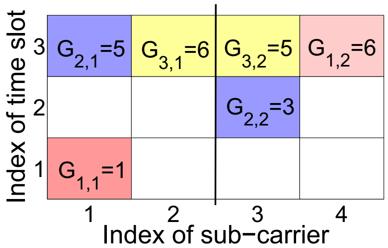


Figure 4: An example of Signpost contention.

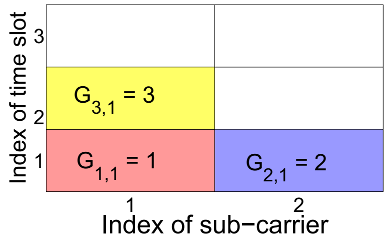


Figure 5: An example of collision recovery

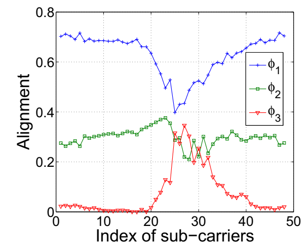


Figure 6: Alignment consistency

expiration, it will infer that someone else has better alignment and then it quits contention on this Signpost direction. Then it contends for next Signpost direction with the second smallest backoff time. However, if a user hears more than one CAs on the same Signpost direction at the same time, it will infer that a collision happens and then it keeps contending to recover from the collision. Once it wins a contention on any direction, it stops contention. The contention procedure running on each user is given in Algorithm 1. Next we explain each component of the algorithm.

4.2 Mapping

An alignment metric is mapped to a specified subcarrier index and a specified backoff timer in two steps. First, we separate contention from different Signpost directions by assigning a different segment of consecutive subcarriers to each Signpost direction. Given S subcarriers in total, we first divide them into M segments, each containing $L \triangleq \lfloor \frac{S}{M} \rfloor$ subcarriers. Then alignment metrics belonging to the j_{th} Signpost direction will be mapped to the j_{th} subcarrier segments. In the second step, we decide the exact subcarrier and backoff timer for each alignment metric. Suppose we use a contention window with length of W time slots. Then an alignment metric $g_{i,j}$ (i.e., the alignment of user i on direction j, $0 \leq g_{i,j} \leq 1$) is first quantized to $G_{i,j}$ as follows:

$$G_{i,j} = \lfloor (1 - g_{i,j})LW \rfloor \tag{15}$$

Then, the backoff timer $t_{i,j}$ is specified as:

$$t_{i,j} = \left\lceil \frac{G_{i,j}}{L} \right\rceil \tag{16}$$

and the subcarrier index $s_{i,j}$ is specified as follows. First we compute

$$\hat{s}_{i,j} = mod(G_{i,j}, L) \tag{17}$$

then we shift this subcarrier into the j^{th} subcarrier segment as:

$$s_{i,j} = (j-1)L + \hat{s}_{i,j} \tag{18}$$

We illustrate the mapping mechanism using an example in Fig. 4, where we assume $M = 2$, $N = 3$, contention window $W = 3$, and number of subcarriers $S = 4$. The alignment metrics for these three users are $\{G_{1,1} = 1, G_{1,2} = 6\}$, $\{G_{1,2} = 5, G_{2,2} = 3\}$, and $\{G_{3,1} = 6, G_{3,2} = 5\}$, respectively. Following the above mapping mechanism, we compute the corresponding subcarrier index and backoff timer for each alignment metric, which is given in Fig. 4. We can see that user 1 will win the contention on the first direction, while user 2 will win on the second direction.

4.3 Collision Recovery

Collision happens when multiple users have the same or very close alignment metric on the same Signpost direction. An example is shown in Fig. 5, with a similar setting as in Fig. 4 but with focus on the contention from the first Signpost direction. The contention on other Signpost directions is similar but independent since we use different subcarrier segments to separate them.

We assume three users with $G_{1,1} = 1$, $G_{2,1} = 2$ and $G_{3,1} = 3$. User 1 and user 2 will transmit a CA each at the same time slot, on subcarrier 1 and subcarrier 2. Note that user 2 has a larger backoff timer and hence a lower contention priority, and ideally it should know that user 1 has won the contention. But in practice, it has no such knowledge. When it transmits a CA on subcarrier 2, it is unable to hear the CA on subcarrier 1 from user 1 since 802.11 radios are half-duplex, which finally leads to a collision.

We design a collision recovery scheme to tackle such challenges. The basic idea is to let other users keep contending on this direction (and will transmit a CA once the nearest timer expires), if they detect multiple CAs in the same slot but on more than one subcarriers. Then, the previous users involved in the collision, after hearing that there are still active contenders, will learn that they have been involved in a collision. In consequence, they will give up the transmissions, and finally avoid the collision. Continuing on the above example, user 3 will hear two CAs on two different subcarriers, thus aware of a collision. Then, instead of quitting the contention, user 3 will still transmit a CA at its backoff timer expiration point, i.e., the second time slot. Meanwhile, user 1 and 2 upon hearing the new CA, will know that they collide and give up the transmissions. Finally, user 3 wins the contention without collision. In this way, the collision is resolved.

Note that the collision recovery mechanism may fail under two cases. The first case is that there are no later users to help collision recovery. In the previous example, if there are only 2 users, the collision cannot be recovered. The second case is that more than one users have exactly the same quantized alignment metric, and hence transmit on the same subcarrier at the same backoff time. For this case, later users cannot detect that more than one users' CAs collide on the same subcarrier, and therefore will not start collision recovery. However, these two kinds of collisions could be limited to a minimum using a reasonable contention window. In Sec. 6, we will show that in a network of 30 users with saturated traffic, the collision probability of Signpost is only about 2$\sim$3%, while that of random contention based methods is more than tenfold.

In the description above, we focus on the single collision domain where all contending users can hear each other, but Signpost can naturally handle multiple collision domains. For example, suppose three contending users A, B and C, where A and B can carrier sense each other, B and C can sense each other, but A and C cannot sense each other. Suppose A wins the contention by first sending out a CA. After hearing this CA, user B in the same domain with user A will quit the contention by not sending out any CA. In consequence, user C can still have a transmission opportunity even when it has a lower contention priority than user B. In this way, Signpost users in different collision domains can transmit in parallel and thus reuse the spatial diversity.

We have assumed that each client only has one antenna for ease of exposition. However, Signpost can be applicable to multi-antenna clients by a straightforward adaptation. The basic idea is to treat each separate antenna as a "virtual" user. All virtual users contend the transmission opportunities following the same 2-D prioritized contention mechanism. In this way, Signpost can still choose an

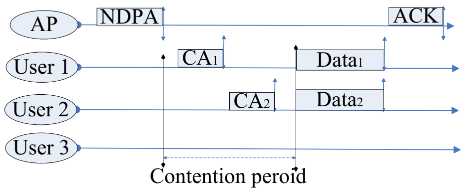


Figure 7: Signpost operations

optimal concurrent user set while simultaneously taking into account the fairness among users with different number of antennas.

5. PROTOCOL OPERATIONS

Now we put the indirect orthogonality evaluation and 2-D prioritized contention mechanisms together to design a complete Signpost uplink MU-MIMO protocol. Fig. 7 illustrates a typical flow of operations in Signpost. Signpost operates in a similar way as the basic operations in 802.11ac, but it works for uplink MU-MIMO and avoids CSI probing. We re-engineer the 802.11ac NDPA packet to indicate the Signpost directions, and add a new packet type called contention announcement (*CA*) to indicate that some users have won contention. At a high level, Signpost works as follows:

(i): First, the AP broadcasts a NDPA packet to start a new *round* of uplink transmission. The NDPA contains a training sequence that allows each user to estimate its own CSI to the AP (assuming calibrated reciprocal channel as in 802.11 beamforming [31, Ch. 20.3.12.1]). In addition, it contains a Signpost index number that indicates to users the corresponding Signpost vectors in this round.

(ii): Each user evaluates its alignment metrics. Specifically, each user i computes the alignment between its channel state vector $\boldsymbol{h_i}$ and each of the M Signpost vectors (directions). Thus, it obtains M orthogonality metrics, one for each direction (Sec. 3.2).

(iii): Then, the users contend for medium access following the proposed 2-D prioritized contention scheme. This scheme ensures that for each Signpost direction, the user that best aligns to it will win with high probability. The winner then declares itself by transmitting a *CA*. Upon hearing the *CA*, others quit contention on this direction, but can still contend on other directions (Sec. 4.3).

(iv): The contention can end up with one winner along each Signpost direction. All the M winners then start uplink transmission concurrently, and the AP acknowledges the reception through a block ACK.

Steps *(i)*-*(iv)* are repeated for each round of uplink transmission. Note that for a new round, a new set of Signpost vectors should be used for fairness among users. We realize this by embedding a new index number in the NDPA. Note that multiple data packets can follow one user-selection procedure, provided that they span much shorter duration than the channel coherence time.

5.1 Design of Signpost Vectors

For a M-antenna AP, the CSI of each user is a M dimension vector. Thus, there can be up to M orthogonal Signpost directions, each being a M dimension vector. These M Signpost vectors constitute a Signpost matrix Φ, which is a unit orthogonal matrix.

To generate a Signpost matrix Φ, we first generate a random unit vector $\boldsymbol{\phi_1}$, and use it as the first Signpost direction. Then we generate other $M-1$ Signpost directions (i.e, $\boldsymbol{\phi_2}$, $\boldsymbol{\phi_3}$, $\cdots$, $\boldsymbol{\phi_M}$) by computing the $\boldsymbol{\phi_1}$'s orthogonal basis: $null(\boldsymbol{\phi_1})$.

We repeat the above to generate P different Signpost matrices, and assign index numbers to them as Φ^1, Φ^2,..Φ^P. Since these Signpost matrices are generated randomly, they have very diverse Signpost directions. In each round of uplink transmission, we use a different Signpost matrix so that different set of users can be selected for fairness. To do so, we should have two preparations. *First*, users should have a consistent knowledge of the collection of Signpost matrices and corresponding index numbers. This is easy to achieve, since the Signpost matrices could be generated off-line and standardized among users. *Second*, we embed an index number in each NDPA, which indicates the Signpost matrix to be used. By hearing the NDPA, all users are synchronized to use the same Signpost matrix in each round.

Note that a very small storage space is required for storing these Signpost matrices in each AP or user device. We use a complex number to represent an element in a Signpost matrix, requiring 64 bit. For a 4-antenna AP and 100 Signpost matrices in total, 12.5KB of storage space suffices.

5.2 Design of Contention Announcement

The contention announcement (CA) is produced by sending a symbol on the mapped subcarrier (using similar technique as in [20]). The length of a symbol is 3.6 μs. Taking into account the propagation delay and hardware circuit delay, we set the duration of CA to be an 802.11 slot length of 9 μs.

5.3 Handling OFDM Systems

Modern wireless systems such as WiFi and LTE widely use OFDM, which decomposes a user's channel into multiple subcarriers. Due to frequency diversity, the subcarriers may have different channel gains, which makes the user selection problem more sophisticated. In particular, for each user, one subcarrier s_1 may be better aligned with a Signpost direction, whereas another subcarrier s_2 may be better aligned to a different direction. In this case, it is hard to tell which Signpost direction the whole channel is close to.

However, we find that in practical OFDM channels, different subcarriers usually have consistency of alignment with Signpost directions, despite minor fluctuation. We presents an experimental example in Fig. 6, which plots the alignment of each subcarrier of an OFDM channel with three Signpost directions $\boldsymbol{\phi_1}$, $\boldsymbol{\phi_2}$ and $\boldsymbol{\phi_3}$. The per-subcarrier CSI is collected from a WARP testbed (Sec. 6) deployed in an office environment with rich multipath reflections (and hence frequency diversity). We can see that although there exist some bumps on some subcarriers, on average the alignment of the entire OFDM channel with three Signpost directions could be clearly separated out in descending order as: $\boldsymbol{\phi_1}$, $\boldsymbol{\phi_2}$ and $\boldsymbol{\phi_3}$.

Based on the above observation, we can define the alignment metric of an OFDM channel with a Signpost direction by averaging the alignment metrics among all subcarriers. Then the user selection process remains the same as introduced before. Our actual experiments of Signpost always focus on OFDM systems. Note that instead of using the averaging approach, one may further improve Signpost performance by incorporating a more advanced multi-subcarrier alignment metric like the effective SNR metric in [27], but this is beyond the scope of our work. Also note that one could select users on a per-subcarrier basis, but this will significantly increase the overhead (e.g., by almost 48$\times$ in 802.11 which has 48 data subcarriers). Therefore, we insist on the simple averaging based metric in Signpost.

6. PERFORMANCE EVALUATION

In this section, we evaluate the performance of Signpost in comparison with existing methods. After introducing the implementation and experimental setup, we first examine the network capacity improvement from Signpost's indirect user selection approach. Then we take MAC overhead into account, and examine the MAC-layer throughput. Finally, we run a system test under various traffic patterns and node mobility.

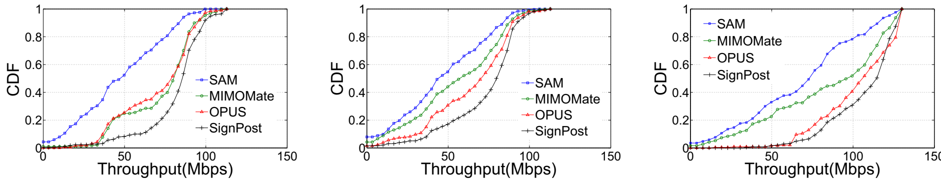


Figure 8: Comparison under (a) saturation, (b) non-saturation (c) mobile.

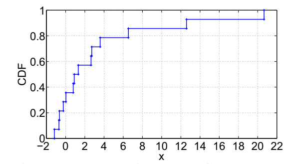


Figure 9: CDF of per-user throughput gap

6.1 Implementation and Experimental Setup

We have prototyped Signpost on top of an 802.11ac-compatible MU-MIMO OFDM library that we built on WARP [30]. The library's PHY-module implements OFDM modulation, packet detection and synchronization, channel estimation and symbol demodulation, and MMSE based MU-MIMO decoding [19]. To realize Signpost, we implement the computation and quantization of the alignment metric, and the 2-D prioritized contention mechanism in the prototype. Due to the interface latency of WARP, we cannot directly implement a real-time version of the Signpost MAC. However, since all WARP radios in our testbed are connected to a PC controller, we emulate the contention on the PC, which then commands the winning contender to start the data transmission over the air. Similarly, we also emulate an optimal bit-rate adaptation on the PC for all comparing user selection methods, so we can separately study the effect of user selection. In practice, rateless coding mechanisms [28, 29] can be used to adapt a user's bit-rate to its channel quality without any channel state feedback.

For performance comparison, we have also implemented three state-of-the-art user selection schemes:

(i): SAM [16]. SAM is the fist experimental work to validate the performance gain of uplink MU-MIMO through implementation on a software radio platform. SAM inherits the traditional 802.11 CSMA contention mechanism and uses a *random* backoff mechanism to select each concurrent user with equal probability, so it does not require CSI feedback.

(ii): MIMOMate [17]. MIMOMate optimizes SAM's user selection by introducing a leader-contention-based contention mechanism. It first matches clients into groups according to their CSI. Then for each round of uplink transmission, it elects a leader through SAM-like random contention, and then the followers matched to the leader transmit one by one without contention. For computing the optimal matching sets, CSI of all users is required, which causes substantial overhead. Therefore, MIMOMate abandons the CSI feedback, and allows the AP to learn CSI passively from normal uplink frames. One problem with the leader-based contention is that a follower may not always have traffic to transmit (i.e., bursty traffic pattern, which is often true in practice). To handle this problem, we combine MIMOMate with a random contention to let other users (i.e., users with traffic but not in the leader's matching set) fill these transmission opportunities [3].

(iii): OPUS [18]. OPUS is a scalable incremental user selection approach for downlink MU-MIMO, but can be readily applied to uplink. OPUS handles the user selection in M rounds. In each round, the AP broadcasts a probing direction. Each remaining user can evaluate its orthogonality metric against the existing selected users by comparing its CSI to the probing direction, and the one with the largest metric will be selected. Unlike Signpost, the probing direction is computed from the CSI of the existing selected user, so in each round, the selected user should feed back its CSI to the AP.

[3]Besides the random contention mechanism, one may use angle-based [17] or SINR-based [18] contention mechanisms to select users to fill the transmission opportunities. However, these mechanisms require CSI exchange among all client users [17], which incurs large overhead. Therefore, in this paper we suppose no CSI exchange between client users and use the random contention when MIMOMate is facing this situation.

Table 1: Average PHY layer throughput (Mbps)

	SAM	MIMOMate	OPUS	Signpost
Saturated	47.7	72.2	70.3	81.2
Non-saturated	46.2	54.7	63.6	72.0
Mobile	68.4	83.51	102.5	106.5

Our experiments are conducted on a testbed located in an office environment. All MU-MIMO transmissions run on a 2.4GHz channel unused and non-overlapping with ambient wireless devices. Other PHY parameters follow the 802.11ac default (e.g., 20MHz bandwidth and 64 subcarriers). Packet size is 1.5KB unless noted otherwise. Due to limited hardware, for experiments involving more than 4 clients simultaneously, we move the testbed nodes to different locations, collect the per-subcarrier uplink channel matrices, and feed the CSI traces to our implementation in place of WARP's over-the-air channel.

6.2 PHY Layer Throughput

We first check whether Signpost can select better user sets and result in larger network capacity, so here we ignore MAC overhead and examine users' time-averaged bit-rates. We run a 2-antenna AP and 14 users, with the topology and user positions shown in Fig. 12.

6.2.1 *Saturated Traffic*

In this experiment, we set all 14 users static with saturated traffic, and run 400 rounds of uplink transmissions. We compute the sum bitrates of all selected users in each round, and plot the CDF of sum bitrates in Fig. 8(a), and also give the average of sum bitrates in Table I. From the results, we see that SAM has much lower throughput than the other three methods, since it selects users randomly without considering their channel characteristics. Moreover, Signpost achieves the highest throughput among all schemes. Its gain is 1.70×, 1.12×, and 1.16× compared with SAM, MIMOMate and OPUS, respectively. The gain comes from the fact that Signpost selects more orthogonal concurrent users.

The experiment results show that an indirect user selection approach can indeed have better performance than direct approaches. We analyze the reason as follows. Essentially speaking, MIMOMate, OPUS and Signpost all use greedy approximation to an exhaustive search, and there is no guarantee that they can find the optimal user set. However, the difference is that both MIMOMate and OPUS are incrementally greedy, that is, they first select a user, and then they find next user best matched to the selected user, and so on. In this case, the decision is made based on more local information. In contrast, Signpost simultaneously considers multiple orthogonal directions, and the decision is made from much more global information.

6.2.2 *Non-saturated Traffic*

We now evaluate Signpost when users have non-saturated traffic. To emulate bursty traffic patterns, we generate packets following a Poisson distribution with rate 0.55 packet/round. Fig. 8(b) plots

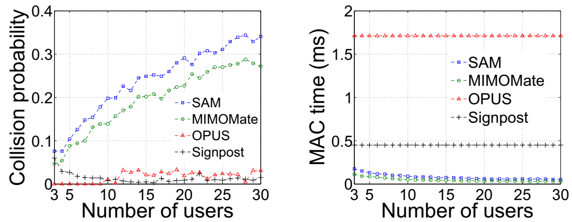


Figure 10: Overhead: (a) collision probability (b) MAC time

the CDF and Table I gives the average per-round throughput. The average gain of Signpost is 1.56×, 1.32× and 1.13× over the other three methods, respectively. The throughput of all four methods drops when compared with the saturated case because there are fewer users to select from. A closer inspection shows that non-saturated traffic affects MIMOMate the most. The throughput of MIMOMate drops by about 24% while that of OPUS and Signpost drops by about 10% and SAM barely changes. This fits our expectation because MIMOMate AP pre-defines each set of selected users. Additional users are selected randomly to fill transmission opportunities when some selected users have no packets to send. As a result, the users that finally transmit concurrently may not form an originally pre-defined set and hence the performance degrades significantly. On the other hand, OPUS and Signpost can still select better concurrent user sets from the users that have traffic.

6.2.3 Mobile Scenario

In this experiment, we set up a mobility environment by letting the client users move at a walking speed. The results (Fig. 8(c) and Table I) show that MIMOMate is affected by the mobility, with throughput about 78% of that of Signpost, in comparison with 89% in static scenario. The reason lies in MIMOMate's passive CSI learning scheme. The passively learned CSI easily becomes outdated under mobile scenarios and hence leads to suboptimal user matching. On average, the gain of Signpost is 1.56×, 1.28× and 1.04× over the other three methods, respectively.

6.2.4 Fairness

We examine Signpost's fairness issue by using SAM as a baseline, since SAM gives equal transmitting probability to all users. Here we present results under the saturated scenario, but the conclusion holds true under other scenarios. For each user, we compute the throughput gap (denoted with x) by subtracting SAM's throughput from Signpost's throughput. We plot the CDF of x in Fig.9 and make two observations *(i)*: Signpost increases throughput for more than 70% users. *(ii)* For users whose throughput drops, the decrease is less than 2Mbps. On the other hand, the increase for other users is much larger and is up to 20Mbps. Overall, we can conclude that Signpost improves throughput by selecting users with strong orthogonality, *not* by unfairly starving a fraction of the users.

6.3 MAC Overhead

In this section, we use our MAC emulator to examine Signpost's MAC overhead, including collision probability and channel time spent on contention. We still use a 2-antenna AP, and vary the number of users from 3 to 30. SAM and MIMOMate inherit the backoff mechanism of 802.11 For MAC parameters. We set the initial contention window to 32 and the contention window doubles if collision happens and up to a maximum of $32 * (2^7) = 4096$. OPUS uses a fixed contention time of 8 contention slots each lasting 27 μs [18]. Signpost use a fixed contention time of $W = 50$ 802.11 slots of 9 μs each (A smaller W leads to less contention time but a larger collision probability, and vice versa. Our experiments show that $W = 50$ achieves the best tradeoff in medium to large sized networks). We run saturated traffic as it incurs the worst-case overhead for Signpost.

6.3.1 Collision Probability

Fig. 10(a) plots the collision probability as the number of users increases. We observe that: *(i)* Random contention based methods, SAM and MIMOMate, have much larger collision probability, which is consistent with previous studies on 802.11 MAC [21–25]. Between them, MIMOMate is better because MIMOMate only needs contention to select the leading user. *(ii)* Prioritized contention methods, OPUS and Signpost, have many fewer collisions. Interestingly, Signpost's collision probability is slightly higher when the number of users N is small. The reason lies in its collision recovery mechanism: with fewer users, there rarely exist any other users for collision recovery (Sec. 4.3), which leads to higher collision probability.

6.3.2 Time Spent on MAC

Fig. 10(b) shows the mean channel time spent on MAC-level signaling before each transmission. OPUS has the largest expense, since it requires two rounds of CSI feedback. Other methods only need to waste time for contention. Also, Signpost and OPUS's MAC time is fixed regardless of the user population, since they use a fixed contention time. Whereas, the MAC time of SAM and MIMOMate decreases as the user population increases, since the contention is fiercer and hence users will be selected faster.

6.4 MAC Layer Throughput

Now we take into account the MAC overhead and check the MAC-layer throughput. The network setting is the same as in Sec. 6.2. Modern high speed wireless standards like 802.11n and 802.11ac widely adopt frame aggregation to amortize MAC protocol overhead across frames. In 802.11ac, a frame can be aggregated up to 5.5ms. In our following experiment, we aggregate 5 frame together, and the final frame duration will be about 2.3ms under an intermediate data rate of 18Mbps.

Fig. 11 presents the average throughput under 3 scenarios. Compared with the PHY throughput in Table I, the advantage of Signpost magnifies significantly under all scenarios. In particular, the throughput of Signpost is 1.93× to 2.96× over SAM, 1.44× to 1.72× over MIMOMate and 1.64× to 1.83× over OPUS. The extra gain over SAM and MIMOMate comes from Signpost's low collision probability, while the extra gain over OPUS comes from Signpost's low MAC time.

6.5 A Comprehensive Test

Finally, we examine the scalability of Signpost in a more complex mixed scenario consisting of a 3-antenna AP and users varying from 6 to 46. For each user population, we set half of the users statically located and the other half mobile. Meanwhile, we set traffic intensity for each user randomly within a range of [0, 1]. As shown in Fig.13, the experiment result has similar trend as in Fig.11: the throughput of MIMOMate and OPUS is not far from SAM, due to the impact of mobility, non-saturation and MAC overhead. Signpost significantly outperforms other schemes, especially as the user population grows. Its throughput is 1.72×, 1.56× and 1.49× compared with SAM, MIMOMate and OPUS, averaged over all network sizes.

7. CONCLUSION

In this paper, we have presented Signpost, a scalable and distributed signaling and user selection protocol for uplink MU-MIMO. Signpost enables a user to speculate its orthogonality with other users by computing the angle between its local CSI and some pre-defined orthogonal directions, without requiring other users' CSI.

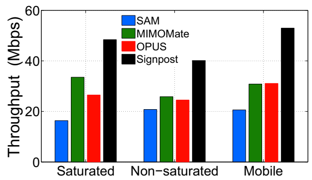


Figure 11: MAC throughput

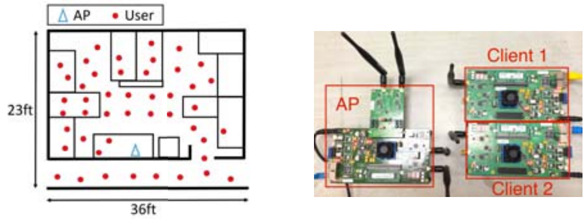


Figure 12: Testbed floor map and software-radio nodes.

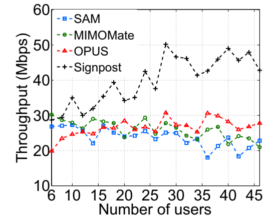


Figure 13: System test.

This lightweight orthogonality evaluation method is integrated with a 2-D prioritized contention mechanism that singles out the best M users for an M-antenna AP. The contention mechanism enables the users to detect and avoid collisions cooperatively in a distributed way so as to achieve an efficient contention with low overhead and low collision probability. Our software-radio based prototype implementation and experiments show that the gain of Signpost is usually more than $1.5\times$ compared with three state-of-the-art MU-MIMO user selection methods, under various network scenarios with static or mobile users, saturated or non-saturated traffic.

Acknowledgements

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