

Poster: *Hawkeye*–Predictive Positioning of a Ceiling-Mounted Mobile AP in mmWave WLANs for Maximizing Line-of-sight

Yubing Jian, Mohit Agarwal, Yuchen Liu, Douglas M Blough and Raghupathy Sivakumar

Georgia Institute of Technology

{yubing,me.agmohit,yuchen.liu,doug.blough,siva}@ece.gatech.edu

ABSTRACT

Line-of-sight (LOS) is a critical requirement for mmWave communication. In this work, we make the case for a ceiling-mounted mobile (CMM) AP by comparing its performance with other types of AP mobility and single static AP. We then present *Hawkeye* to solve the optimal location discovery problem for a CMM AP using a machine learning (ML) algorithm. *Hawkeye* relies purely on the connectivity matrix between STAs and the AP to decide if and where the AP should move to for maximizing LOS connectivity. Using a prototype implementation, we show that the throughput of *Hawkeye* is 219% and 129% compared with single static AP and other approaches for AP mobility, respectively.

KEYWORDS

Infrastructure mobility; mmWave WiFi; CMM AP; ML

ACM Reference Format:

Yubing Jian, Mohit Agarwal, Yuchen Liu, Douglas M Blough and Raghupathy Sivakumar. 2019. Poster: *Hawkeye*–Predictive Positioning of a Ceiling-Mounted Mobile AP in mmWave WLANs for Maximizing Line-of-sight. In *The 25th Annual International Conference on Mobile Computing and Networking (MobiCom '19)*, October 21–25, 2019, Los Cabos, Mexico. ACM, New York, NY, USA, 3 pages. <https://doi.org/10.1145/3300061.3343395>

1 INTRODUCTION

The mmWave WiFi standard (e.g., 802.11ad) operates in the 60GHz frequency band. 802.11ad can deliver multi-gigabit (~7 Gbps) performance with a bandwidth of 2160MHz. While the potential performance is quite promising, the technology is vulnerable to non-LOS (NLOS) conditions compared to conventional WiFi. In this context, it is likely that mmWave networks can deliver considerably better performance, but that the performance cannot be assured and will be dependent on the existence of LOS conditions. LOS conditions are

a function of the physical environment, but communication technologies hitherto have had no ability to improve the conditions when necessary. In recent years, related works have started exploring *infrastructure mobility* as a degree of freedom that can be exploited to better the physical channel conditions [1]. In other words, the WiFi AP, if mobile, can discover an optimal location for itself and move to that location to offer the best possible performance for the network. AP mobility is especially an attractive degree of freedom for mmWave technology, where the creation of LOS with STAs can have a profound impact on network performance.

Since the primary focus of this work is to enable mobility to create better LOS conditions, we explore the model of a *CMM AP that can move on a simple 1D linear actuator*. We show through a simulation-based evaluation that a CMM AP can perform better than a static ceiling mounted AP and other types of AP mobility. For the CMM AP, the *discovery* problem is the most challenging. Explicitly, we define the discovery problem as how the AP figures out the ideal location for itself to move to in order to serve the greatest number of STAs with LOS conditions timely. We present *Hawkeye*, an ML algorithm based solution for the calculation of the optimal AP position that relies solely on the connectivity matrix between the STAs and the AP in the network. The algorithm trains itself to predict, simply based on the connectivity matrix, whether a STA in the network is likely to have LOS connectivity to the different AP positions.

2 NETWORK MODEL

We consider a single room with a linear actuator mounted at arbitrary locations. An AP is attached to the platform and able to move to P discrete positions on the platform. There are M STAs that intend to connect with the AP using 60GHz at a time instance. For the AP and STAs, we assume both 5GHz and 60GHz are available. The information on STAs' intention to connect to the AP and the current position information of the AP are communicated through 5GHz.

3 THE CASE FOR AP MOBILITY

Evaluation Methodology: We perform a simulation-based comparison of CMM AP against floor-based, wall-based AP mobility, and single static AP mounted at the center of the ceiling. The main metrics that we focus on are *LOS* and *throughput* between the AP and STAs. LOS is defined as a

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).

MobiCom '19, October 21–25, 2019, Los Cabos, Mexico

© 2019 Copyright held by the owner/author(s).

ACM ISBN 978-1-4503-6169-9/19/10.

<https://doi.org/10.1145/3300061.3343395>

binary with 1 representing LOS between the AP and STA, and 0 representing NLOS between the AP and STA. With respect to STA m , $LOS_{m,p}$ and $Thpt_{m,p}$ representing LOS status and throughput between AP and the STA at location p . Here, we utilize the maximum LOS ($\max_p(LOS_{m,p})$) and maximum throughput ($\max_p(Thpt_{m,p})$) as the metric for evaluation of both static AP and AP mobility.

Simulation Platform: To incorporate the features of indoor configurations and 802.11ad, we make the following modifications to the default ns-3 simulator. We use the 802.11ad model based on [2]. To simulate an indoor scenario, a room is simulated as a specific three-dimensional space. To simplify the simulations of indoor obstacles, we assume that the obstacles are modeled as cuboids and that they are placed on the floor. The center of the obstacle follows a Poisson point process. It defines the locations and probability of the number of obstacles to be placed in the indoor scenario. The x , y , and z dimension of obstacle follow a truncated normal distribution. The material of the obstacles is uniformly chosen from a set of materials of varying penetration losses.

The Benefits of AP Mobility: The simulation parameters are derived from a real-life physical space (a lab environment) as a guiding example, where the room size is $9m \times 6m \times 3m$ the expected number of the obstacle is 43. A single STA is positioned in the room following uniform distribution across 100 different trials. The platform length is set as 3m with 0.1m step size. Intuitively, as the AP is located on the ceiling, the performance should be the best compared to the AP placed on the floor, on the walls, on the floor or single static AP. Fig. 1a and 1b illustrate the maximum LOS and normalized maximum throughput performance when the AP platform is located on the floor, on the walls, the ceiling, and single static AP. It can be observed that CMM has the best LOS and throughput performance, and the maximum LOS performance is proportional to maximum throughput performance. The expected throughput gain for the CMM varies between 101% to 130% compared with other types of AP mobility and static AP. Clearly, the floor-based platform has the worst performance due to the high probability of blockage leading to NLOS connection. The reason for the high performance of the right wall is most obstacles are located at the left side of the room.

4 HAWKEYE: SOLVING THE CMM AP DISCOVERY PROBLEM

The critical algorithmic problem that needs to be solved to enable a CMM AP is the determination of the ideal position of the CMM AP on the rail both during network start up, and when network conditions change. We term this problem as the *discovery problem*. A trivial brute-force solution to the discovery problem is to have the AP periodically traverse the

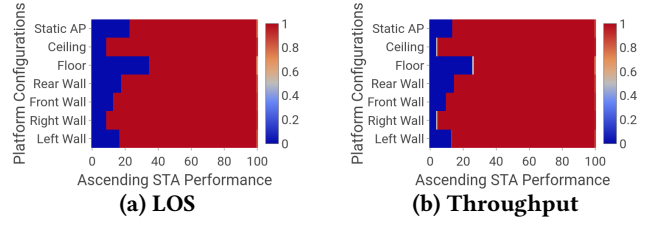


Figure 1: AP Mobility vs. a Static AP

entire length of the rail, explicitly determine LOS connectivity from each position, and then move to the optimal location that provides LOS to the most number of STAs. However, the time complexity of such an approach is inordinately high because of the overheads of physical mobility. We now present an ML-based solution that relies only on the adjacency matrix of the network comprising of the different STAs, the current location of the AP, and any previous positions of the AP to predict what is likely to be the best location for the AP to move to. Such an approach can potentially reduce the expected time complexity by a factor of 3, and more drastically in other typical scenarios.

ML Problem Formulation: We now formalize the problem definition and present an algorithm for data-driven learning to predict the LOS connectivity between STAs and possible AP locations. We consider an environment with M STAs with known LOS connectivity and distances between STAs to STAs and STAs to possible AP locations. As the $(m+1)^{th}$ STA become active in the environment, the LOS connectivity and distances of $(m+1)^{th}$ STA with other STAs can be estimated by the STAs [3]. Given this information, our goal is to predict the LOS connectivity ($LOS_{m+1,p}$) of $(m+1)^{th}$ STA with all possible P AP locations. In this simple scenario, we assume a static environment, i.e., the obstacle map and the STA locations are fixed.

ML Algorithm: For a given obstacle map in a 3D environment, the LOS connectivity of two points can be easily computed. In case the obstacle map is fixed but unknown, a set of labeled examples can reveal the information about unknown obstacle map (to some extent), which could further be utilized to predict the LOS connectivity for the newly added STA. Thus, keeping the fact in mind that the underlying relationship between input and output is actually a skewed representation of the fixed obstacle map, we utilize parametric function approximation approaches to learn this latent structure.

Input features and the output: The input data is present in the format of LOS connectivity matrix between STA-STA, $STA_STA_{LOS} \in \{0, 1\}^{(m+1) \times (m+1)}$, the distance matrix between STA-STA, $STA_STA_{Dist} \in \mathbb{R}^{(m+1) \times (m+1)}$, and LOS connectivity matrix and distance matrix of M STAs and AP locations, $STA_AP_{LOS} \in \{0, 1\}^{M \times P}$, $STA_AP_{Dist} \in \mathbb{R}^{M \times P}$. The labels (ground truth) are present in the format of $STA_AP_{LOS}^{m+1} \in$



Figure 2: Platform

$\{0, 1\}^{1 \times P}$ i.e., the LOS connectivity matrix of $(m + 1)^{th}$ STA with the P AP locations. We extract only informative bits from all four matrices, and concatenate these informative bits to form a feature vector of size $M * (M + 2P + 1)$ represented as X . The network outputs $\hat{Y} \in [0, 1]^P$, a P sized probability vector representing the probability of LOS connectivity of $(m + 1)^{th}$ STA with P locations.

Network: We use a multi-layer perceptron network with a different number of hidden layer and neurons depending upon the value of M . We model the non-linearity in the model using ReLU activations and use softmax layer for output to transform the logits to probability vectors. We use weighted cross-entropy loss, defined as:

$$H_y(l) = \sum_i^P -(y_i \log(l_i) * w + (1 - y_i) \log(1 - l_i)) \quad (1)$$

Here, l represents the probability of output logits, and w is calculated as the ratio of NLOS vs. LOS connectivity using training data. Using the available training data bank of N i.i.d samples, $DB = \{(X_1, Y_1), (X_2, Y_2), \dots (X_N, Y_N)\}$, the loss function is minimized using stochastic gradient descent with momentum optimizer. Learning rate is decreased over time to optimize performance and increase the convergence rate.

System Operation: To identify the CMM AP location that will provide the maximum number of LOS STAs, *Hawkeye* works as follows: 1) Initialization: brute force discovery to collect LOS and distance connection matrices for AP-STAs and STAs-STAs; 2) AP Movement: identify and move to the closest location with the maximum number of LOS STAs; 3) For any network changes: i) when an STA becomes inactive, the CMM AP identifies and moves to the optimal location based on history; ii) when a new STA joins the network, the CMM AP uses ML feedback to predict the closest location with maximum LOS probability and move to that location.

5 PERFORMANCE EVALUATION

Evaluation Methodology: We compare three solutions in the evaluation: 1) single static AP mounted on the center of the ceiling, 2) brute-force search as described in Section 4, and 3) *Hawkeye*. We mount a 1m long Progressive Linear Actuator PA-18 (with moving speed 4cm/s) on the center of the ceiling in a lab environment. This unit is controlled by a central controller through Arduino UNO and Mega Moto Plus. The AP mounted on the actuator is Tp-link Talon ad7200.

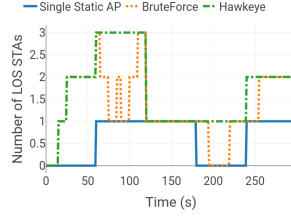


Figure 3: LOS

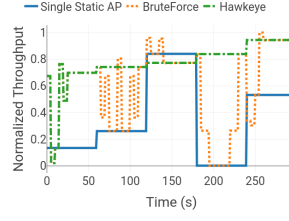


Figure 4: Throughput

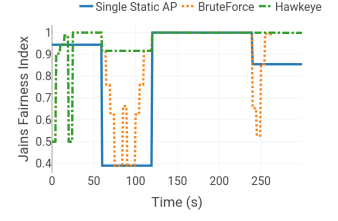


Figure 5: Fairness

The platform is shown in Fig. 2. We use 3 Acer Travelmate P648 laptops as STAs. STAs join or leave the network following Poisson distribution. When an STA joins the network, it chooses a specific one of 10 candidate locations as its location. To collect training data for ML, the LOS and distance matrices of 10 possible locations are hard-coded, where we also consider a distance estimation error model based on [3].

Experimental Evaluation: For the environment setup, initially, there are 2 STAs in the network. The overall evaluation time is set as 5 minutes. Specifically, the STA numbers change at each minute as $\{+1, -2, +1/-1, +1\}$. Fig. 3, 4, and 5 illustrate the number of LOS STAs, throughput, and Jain's fairness index for the aforementioned three approaches at various time instants. For *Hawkeye* and brute-force with an initial location at the edge of the platform, there is one STA in the LOS condition. For the single static AP case, the 2 STAs are in NLOS condition. Initially, *Hawkeye* tries to explore the entire platform to collect network information (same as brute-force). In the first 60s, *Hawkeye* and brute-force take 25s to reach the location that has LOS w.r.t. to both STAs. Clearly, at the location with maximum LOS STAs, the network achieves good fairness and throughput. During the first 60s for *Hawkeye*, the number of LOS STA is increased by 50%, the throughput is increased by 10%, and Jain's fairness index has also increased by almost 50%. The expected throughput performance of *Hawkeye* is 219% and 129% compared with brute-force and single static AP, and expected Jain's fairness index is 115% and 108% compared with brute-force and single static AP. Overall, we can observe *Hawkeye* dynamically adapts to network conditions and achieves the best performance among brute-force and single static AP.

ACKNOWLEDGMENTS

This work was supported in part by the National Science Foundation under grants CNS-1513884, IIP-1701115, CNS-1813242, and CNS-1837369, and the Wayne J. Holman Chair.

REFERENCES

- [1] Jian et al. Toward a self-positioning access point for wifi networks. In *Proceedings of the 16th MobiWac*, pages 19–28, 2018.
- [2] Assasa et al. Implementation and evaluation of a wlan ieee 802.11 ad model in ns-3. In *Proceedings of Workshop on ns-3*, pages 57–64, 2016.
- [3] Ioannis et al. Accurate 3d localization for 60 ghz networks. In *Proceedings of the 16th SenSys*, pages 120–131, 2018.