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Human Mobility Prediction for Seamless Coverage: An Intelligent LoS Enabling Framework

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Abstract—Despite all the benefits 60 GHz networks bring about, such as high network bandwidth, effective data rates, etc., one of its main application scenarios, Line-of-Sight (LoS) communications, still has troubles in actual indoor environments due to its high directionality. Traditional beam training methods are inaccurate and time-wasting, leading to unstable and inefficient wireless networks. Therefore, in this paper, we attempt to address this problem from a new aspect, i.e., assisting the signal adaptation with human mobility prediction. A state-of-the-art long short-term memory (LSTM) model is adopted to analyze the past trajectories and predict the future position, which can serve as an important reference for the transmitters to proactively adjust their beams and provide seamless coverage. In addition, we also design an algorithm to optimize the beam selection problem and improve the network quality. To the best of our knowledge, this is the first work in the field to use deep learning models for the beam selection problem. Simulations demonstrate that our approach is robust and efficient, and outperforms the state-ofthe-art in several related tasks.

I. Introduction

As a next-generation network for the future, 60 GHz networks promise to empower the commonly-used wireless networks with the extremely-high data rate, up to 100 gigabits per second as defined in IEEE 802.11ay protocol [1]. However, just as other Line-of-Sight (LoS) methods, applying 60 GHz communications in widely-used wireless networks, Wi-Fi as an example, is still an open problem. Due to the intrinsic highdirectionality of 60 GHz signals, it is a challenging task to deliver the wireless beams consistently to the end devices, especially when these devices move randomly with user's mobility.

A typical indoor environment is shown in Fig. 1, where two 60GHz-enabled wireless Access Points (APs) exist. The dotted lines represent the human motion trajectories. The colored figure is the real position p at one specific point of the timeline, while the white one behind it shows its past position p^o that is slightly behind p. As we can see in Fig. 1, during the user's movement, the APs attempt to deliver signal beams to the users' actual position p. Since the autoadaptive feature defined in IEEE 802.11ad [2] is implemented by some beam training protocols, which certainly have some time cost, the user position stored in APs' memories has been outdated. Therefore, although the user has moved to p, the AP still transmits their beams to point p^o. As the 60 GHz signal is highly directional, the network status on the user side is deteriorated. This is an inevitable phenomenon in current millimeter wave (mmWave) based networks and the performance loss is negligible. According to some recent results [3], even when the end device is kept within the Fieldof-View (FoV) of the AP's signal, the user may still face an up to 50% loss in the network throughput, compared with the stationary cases. Another problem in this scenario is that the signal is lost when the user steps behind an obstacle. As shown in the right-bottom corner of Fig. 1, AP2 choose to directly deliver its beam to the user device, because it believes that the route is clear and the destination is reachable. However, due to the slight lag in beam transmitting, the user has been undetectable from AP2's FoV, resulting in the failure of the wireless network.

To avoid the network degradation resulted from beacon training, we propose a new LoS communication strategy from a new aspect. The proposed system is called Intelligent Defined LoS (ID-LoS), which is based on the state-of-theart recurrent neural network (RNN). The main workflow is as follows. First, we can obtain the approximate positions of the network users, as the 60 GHz beam is highly-directional and its signal strength has a direct relationship with the transmitting distance. Then we can analyze the motion trajectory of the device, which is in its owner's hands, and predict its future positions with deep learning methods. Finally, the APs can prepare for the beam changing in advance and assure seamless coverage. In addition, some existing methods simply assume that the location information is provided by the global positioning system (GPS), gyroscope, or other onboard sensors. However, when other mobile devices with no location sensors are used in 60 GHz networks, these methods become unavailable. Therefore, we desire to develop a method to predict user trajectories using only the data obtained from the network signals.

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The main contributions of our work include:

- We adopt a long short-term memory (LSTM) model to predict the future position of the LoS network users, using their past trajectories.
- We formulate the beam selection problem as an optimization process. By minimizing the error estimation and maximizing relative received signal strength (RSSI), the proposed ID-LoS system can accurately find the optimal beam settings in real-time.
- We design a simple yet effective approach to infer the initial user position, which is the essential input of the proposed LSTM model.

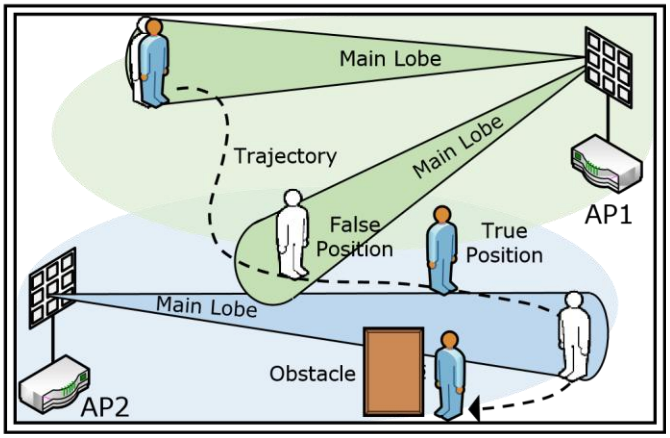


Fig. 1. An indoor 60GHz-based wireless network. A regular LoS communication system without mobility prediction.

II. Related Work

A. LoS and 60 GHz Networks

As the 60 GHz networks is strong-directional and easily blocked by obstacles in the signal path, people work out several approaches to bypass the barriers and improve the signal coverage. Abari *et al.* propose a software-controlled signal mirroring method [4] to reflect the 60 GHz signals, which are transmitted from the APs, to the desired receiver, a VR device in their work. This is a novel solution to avoid the inevitable failure when there is an obstacle in the transmitting route. With this method, they also implement a programmable hardware and design an algorithm to find the proper angles of incidence and reflection.

As mentioned in existing work [5], the communication between transmitter and receiver is only transmitted via a

few of LOS or reflection paths, resulting high vulnerability when the transmitter or receiver moves, due to the highdirectional link. Aiming to improve the link quality of 60 GHz networks, Anfu Zhou *et al.* [6] propose a model-driven beam steering method, called beam-forecast, which can predict the optimal beams directly. The method predicts multiple possible beam directions, then selects the best one by a computational process, thereby saving the time for beam scanning. And the experiments illustrate that the model-driven method can achieve the optimal prediction and high throughput in various scenarios.

Building the robust communication in 60GHz networks also needs to consider the channel dynamics, which can be impacted by small movements of obstacles. In order to measure the channel environment, Christopher Slezak *et al.* [7] introduce a system for measurement and analysis, to estimate the obstacles over multiple paths between transmitters and receivers. The system adopts 60 GHz phased arrays with several elements, and measurements are performing among various combinations of transmitters and receivers. With the measurements they conduct, the authors present a modeling method to select paths with low-rank tensor factorization of the measurement data.

Generally, the obstacles involved in the channel model are floor, windows, tables, etc. However, A. K. M. Baki *et al.* [8] take finer structures into account for 60 GHz networks, such like chairs and lamps, and utilize two different environments, i.e. IEEE 8.2.11ad living room and Full-3D ray residential apartment, for investigation. The main goal of the investigation is to estimate the effect of side lobe level (SLL) among RMS Delay Spread (RDS) in scenarios of LOS/NLOS paths, transmitters-receivers distances and others. And it has been proved that RDS can be reduced once SLL is decreased into a lower level.

B. Trajectory Prediction Approaches

Trajectory prediction for human plays an important role in the motion pattern analysis, navigation for the blind, interaction and location-based services. A plenty of research work has been done in recent years.

Qiao *et al.* [9] come up with the algorithm called Hidden Markov model-based Trajectory Prediction(HMTP). The method can be used to forecast the continuous positions of moving objects. In addition, they consider the situation that objects move with different speeds dynamically in reality. They modify the algorithm into a new self-adaptive parameter selection algorithm called HMTP*, which is able to adjust parameters automatically according to the real world scene. Hu *et al.* [10] try to predict the trajectory with the matrix representation method. The current and previous trajectories are represented as the matrix. The method is effective to preserve the users' privacy because the matrix processing and trajectory prediction are both conducted at the mobile client.

Alahi *et al.* [11] present a RNN-based motion estimation method called Social-LSTM, which can predict the human trajectory in streaming videos of crowded scenes, using their past positions. The most significant advantage in their work is that the authors take the correlation of the adjacent sequences into account and introduce a specially-designed layer to analyze the social interactions. Xue *et al.* [12] work out a novel method named Bi-Prediction to solve the problem of pedestrian trajectory prediction, considering the impact of the intended destinations of the human. Their work can be divided into two stages. First, they apply the bidirectional LSTM to predict the possible destination regions of the user with the historical trajectories. After that, they estimate the trajectory of different destinations with the differently trained LSTMS. Bartoli *et al.* [13] design a "context-aware" recurrent neural network LSTM model for human trajectory prediction in crowded spaces in videos. They comprehensively consider the influence of the human-human and human-space interactions on the human motion and forecast the trajectory based on the past positions and the static elements in the scene.

Naserian *et al.* [14] propose a new pattern to estimate the location by applying the information of the users' current movement along with the travel group type. In contrast to the existing studies, their work considers the influence of travel group movement pattern on the specific user. Song *et al.* [15] address this problem with Optimized Neural Network, which has the advantage of processing data nonlinear. Besides, they overcome some problems of the BP Neural Network, for example, the slow convergence speed, by optimizing the weights and thresholds with ant colony algorithm.

III. Mobility Prediction Model

As an essential input, we need to obtain the user initial positions at first. Due to the high directionality of LoS communications and regular loss characteristic of 60 GHz signals, we adopt a simple yet effective strategy to infer the locations of user devices.

As shown in Fig. 2, we create a coordinate system in the room plane and fix the APs in several pre-defined locations A = $\{a_1,\ldots,a_n\}$, where a_i represents the position for AP i. The task is to estimate the initial positions of the human users U = $\{u_1,\ldots,u_m\}$. The main principle is to average each AP's perception point, which is the specific position that the AP feels the user locates in, and the result is regarded as the final estimation point of the mobile device. For one user position u_j, the equation is as below.

$$\begin{aligned} 0<\phi\left(b_{x_i}\right)\leqslant\frac{\pi}{2}, x_{u_j}&=\tfrac{1}{n}\sum_{i=1}^{n}\left(x_{a_i}-d_j(b_i)\cdot cos\phi(b_i)\right) \\ \frac{\pi}{2}<\phi\left(b_{x_i}\right)<\pi, x_{u_j}&=\tfrac{1}{n}\sum_{i=1}^{n}\left(x_{a_i}+d_j(b_i)\cdot cos\phi(b_i)\right) \\ 0<\phi\left(b_{y_i}\right)\leqslant\frac{\pi}{2}, y_{u_j}&=\tfrac{1}{n}\sum_{i=1}^{n}\left(y_{a_i}-d_j(b_i)\cdot sin\phi(b_i)\right) \\ \frac{\pi}{2}<\phi\left(b_{y_i}\right)<\pi, y_{u_j}&=\tfrac{1}{n}\sum_{i=1}^{n}\left(y_{a_i}+d_j(b_i)\cdot sin\phi(b_i)\right) \end{aligned} \tag{1}$$

where n is the AP number, $\varphi(b_i)$ is the angle value between beam b_i and positive axes and $d_j(b_i)$ represents the distance between beam b_i and user u_j. As a mainstream in current beam selection methods, APs decide one desired beam index in the codebook [16], which consists of many discretized beamforming parameters as available beam patterns. Therefore, although the beams may have some side lobes, their main lobes are fixed and consistent during actual communication process. Given a specific beam index for AP i, we can obtain its angle information $\varphi(b_i)$ immediately. Then the question is how to get the distance values.

Given the general path loss function in indoor environments,

$$L(d) = a + 10b\log(d) + \eta, \quad \eta\sim N(0,\sigma^2) \tag{2}$$

where a,b are model parameters and η represents the shadowing, we can obtain distance d as

$$d=10^{\frac{L-\eta-a}{10b}}, \quad \eta\sim N(0,\sigma^2). \tag{3}$$

TABLE I
Main Notations

Notation	Description
A	Set of the APs A = $\{a_1,\ldots,a_n\}$.
U	Set of the users U = $\{u_1,\ldots,u_m\}$.
a_i	Position of AP i, $a_i = (x_{ai}, y_{ai})$.
u_j	Position of user j, $u_j = (x_{uj}, y_{uj})$.
b_i	Signal beam delivered from AP i.
$\varphi(b_i)$	Angle value between beam b_i and positive axes.
$d_j(b_i)$	Distance between beam b_i and user u_j.
$L(\cdot)$	Path loss function during signal delivering.
$A(\cdot)$	Signal loss caused by angular error.
$\overrightarrow{\text{beam}_{id}}$	Selected beam pattern from the codebook.

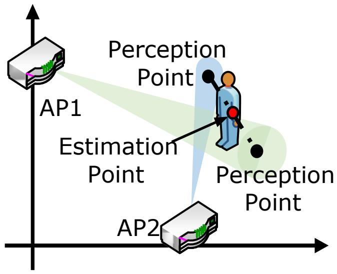


Fig. 2. Infer the initial user positions with APs' perception points.

Eq. (2) is a generalized case of Friis transmission formula and its parameter settings can be easily obtained through some simple measurements in actual deployments, and path loss value can also be directly acquired in receiver devices.

Although the perception points are all approximate points, they can contribute to the further improvement of the estimation accuracy by averaging the coordinates, as shown in Fig. 2. The system keeps observing users' locations for a small period, using the default beam training strategies. After we obtain all users' motion data using Eq. (1), we can import them into the RNN model for analysis and prediction, as detailed below.

The adopted LSTM network is based on a state-of-theart RNN model [11], whose most significant advantage is that the deep model can take into account the relationships among multiple people. As the main application scenario in our research is indoor environments, where people may have strong interactions with others. Therefore, the concept of "social-LSTM" proposed in [11] is of great help in this work. Based on their work, we successfully adapt the LSTM model to the user device tracking for 60 GHz beam selection.

Fig. 3 gives an example of the interaction layer. In figure (a), u_1 is the target user to be analyzed and $u_2 \sim u_5$ are other users around. When estimating the future moves of u_1, several other users within a pre-defined distance should also be considered as they may have some influences on the u_1's movement. In this figure, $u_2 \sim u_4$ are in the interaction circle and will contribute to the LSTM inference of u_1. Figure (b) shows the concentrate way of the interaction layer, which should preserve the spatial information of the adjacent users. The concatenation method is presented in Algorithm 1

The training process is to minimize the negative log-

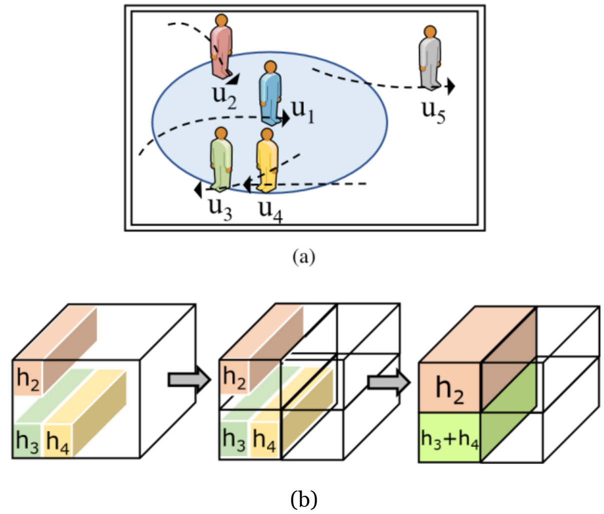


Fig. 3. The interaction layer in the adopted LSTM model.

Algorithm 1: Interaction Concatenation&LSTM Inference

Input: Hidden States in Time $t-1$ H_{t-1}, User Set U, Neighbouring Circle Radius r, Grid Size s Output: Hidden States for user i in Time t h^i_t

foreach u *in* U do

→– if $|ui|$ >

r then

continue; . Not adjacent user row, column

= . Find the target grid c^i_t[row][column] += h^u_{t-1};

. Concatenate layer ReLU(c^i_t); . Concatenate layer Activation ReLU(x^i_t,y^i_t); . Current Position Activation h^i_t = LSTM(h^i_{t-1}, ReLU(c^i_t),ReLU(x^i_t,y^i_t))

return h^i_t;

likelihood loss. The back-propagation is performed to each participants in the interaction layer. With a well-trained model, the system can indicate accurate positions for all the users in the user list.

IV. Adaptive LoS Networking

The objective of this work is to implement a LoS network, which is shown in Fig. 4. With the prediction results of the RNN model, the proposed ID-LoS system can prepare for the beam changing in advance and precisely transmit the beams to user positions. A special scenario is that the user steps behind some obstacles, as shown in Fig. 1. To increase the available signal paths and ensure seamless coverage in our system, we also adopt some software-defined reflectors, which is introduced in [4], to provide new possibilities. In following, we will describe a beam-selection method to optimize the indoor network quality.

Having user estimated position $u^o = (x^o, y^o)$, we can assume that the real location $u = (x, y)$ is within a circle centered at u^o with a radius r. The distribution function is

$$u_i = (x_i, y_i), \qquad x_i \sim N(0,1), \qquad y_i \sim N(0,1) \tag{4}$$

where $0 \leq x_i - x^o \leq r$ and $0 \leq y_i - y^o \leq r$.

Essentially, each possible u follows a normal distribution around point u with different possibilities. The probability density function can be expressed as

$$f(x_i, u, \sigma) = \frac{1}{\sqrt{2\pi}} exp(-\frac{(x-u)^2}{2\sigma^2}) \tag{5}$$

where u, σ are the parameters for the normal distribution. Then the probability distribution can be written as

$$p(c < x_i < d) = \int_c^d \frac{1}{\sigma\sqrt{2\pi}} exp(-\frac{(x-u)^2}{2\sigma^2}) dx_i \tag{6}$$

where c, d are two variables.

Then the possibilities can be expressed as

$$p(x_i) = \int_{x'}^{x'+r} \frac{1}{\sqrt{2\pi}} e^{-\frac{x_i^2}{2}} dx_i$$
$$p(y_i) = \int_{y'}^{y'+r} \frac{1}{\sqrt{2\pi}} e^{-\frac{y_i^2}{2}} dy_i \tag{7}$$

where $(x_i - x^o)^2 + (y_i - y^o)^2 \leq r^2$. Also,

$$p(u_i) = p(x_i) \cdot p(y_i). \tag{8}$$

Then we can calculate the signal loss S for a specific case that user locates in u_s.

$$\begin{aligned} S(u_s, \frac{\overrightarrow{au_s} \cdot \overrightarrow{\text{beam}_{\text{id}}}}{|\overrightarrow{au_s}| \cdot |\overrightarrow{\text{beam}_{\text{id}}}|}) &= L(|\overrightarrow{au_s}|) + A(\frac{\overrightarrow{au_s} \cdot \overrightarrow{\text{beam}_{\text{id}}}}{|\overrightarrow{au_s}| \cdot |\overrightarrow{\text{beam}_{\text{id}}}|}) \\ &= a + 10b \log |\overrightarrow{au_s}| + \eta + A(\frac{\overrightarrow{au_s} \cdot \overrightarrow{\text{beam}_{\text{id}}}}{|\overrightarrow{au_s}| \cdot |\overrightarrow{\text{beam}_{\text{id}}}|}) \end{aligned} \tag{9}$$

$$\eta \sim N(0, \sigma^2)$$

where $L(\cdot)$ is the path loss defined in Eq. (2), $|\overrightarrow{au_s}|$ is the distance d, $A(\cdot)$ is the signal loss caused by angular error, and $\frac{\overrightarrow{au_s} \cdot \overrightarrow{\text{beam}_{\text{id}}}}{|\overrightarrow{au_s}| \cdot |\overrightarrow{\text{beam}_{\text{id}}}|}$ is the angle value. In addition, $A(\cdot)$ is determined by the antenna array installed in the AP.

According to the above functions, the expectation of network loss can be written as

$$E(\frac{\overrightarrow{au_s} \cdot \overrightarrow{\text{beam}_{\text{id}}}}{|\overrightarrow{au_s}| \cdot |\overrightarrow{\text{beam}_{\text{id}}}|}) = \sum_{l=1}^{\infty} S(u_l, \frac{\overrightarrow{au_s} \cdot \overrightarrow{\text{beam}_{\text{id}}}}{|\overrightarrow{au_s}| \cdot |\overrightarrow{\text{beam}_{\text{id}}}|}) \cdot p(u_l). \tag{10}$$

It can be seen that Eq. (10) is a equation only related with $\overrightarrow{u_s}$ and $\overrightarrow{\text{beam}_{\text{id}}}$, and it can be transformed into the RSSI, which directly reflects the network quality in the user side. RSSI is given by

$$\text{RSSI} = \text{TxPower[in dBm]} - E\text{[in dB]} \tag{11}$$

where TxPower indicates the strength that APs transmit the signal, and L is the path loss calculated by Eq. (2).

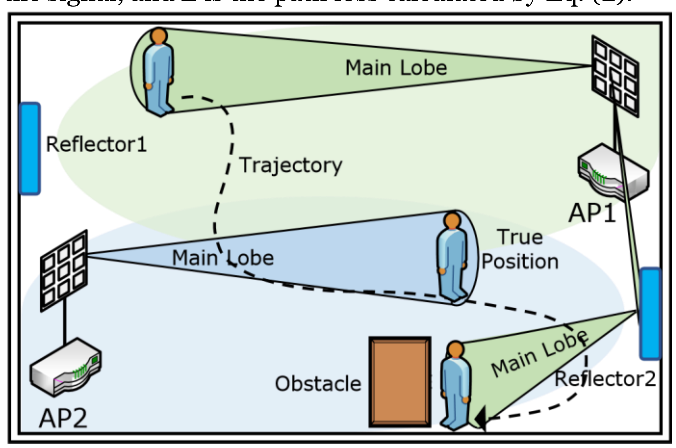


Fig. 4. The proposed ID-LoS network with the ability of mobility prediction.

Then the problem becomes how to find the optimal beams to maximize the RSSI value. The optimization objective can be expressed as

$$\max_{\text{id}} \ \text{TxPower} - E(\frac{\overrightarrow{au_s} \cdot \overrightarrow{\text{beam}_{\text{id}}}}{|\overrightarrow{au_s}| \cdot |\overrightarrow{\text{beam}_{\text{id}}}|}). \tag{12}$$

Notice that TxPower is determined by the APs and all of a, b, η are known values, so the only variable in this function is the beam index t. However, finding a optimal solution of this problem is complicated and time-wasting.

To implement a real-time communication system which provides seamless connections, we must design an efficient algorithm to accelerate the optimization speed, as shown in Algorithm 2.

Algorithm 2: Optimal Beam Selection

Input: Beam Pattern Set B, User Set U, User Next Position Set P_u, Sampling Number S Output: Optimal Beam Pattern b_o foreach b *in* B do gain = 0;

. The overall gain for each beam index.

foreach u *in* U do

if *obstacle* then

continue; . Signal is unvaliable for user u

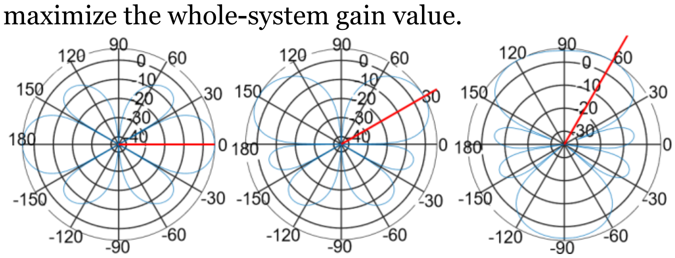
sum = 0 for $s \leq S$ do

sum = sum + L(·) + A(·) . Eq. (9) s += 1;

gain = gain + $\frac{sum}{S}$; . Calculate the expectation b_o = argmax$_b$ gain; . The beam to maximize the gain

return b_o;

With Algorithm 2, the proposed ID-LoS system can quickly find the optimal beam pattern. The selected path can address occlusion using the available reflectors. By combining each AP's pattern set, we can further empower this algorithm with the ability to jointly consider multiple APs. It will check each possible combination of the beams from different APs, and select the optimal one to maximize the whole-system gain value.



(a) (b) (c)

Fig. 5. Three example beam patterns with different main lobe angles.

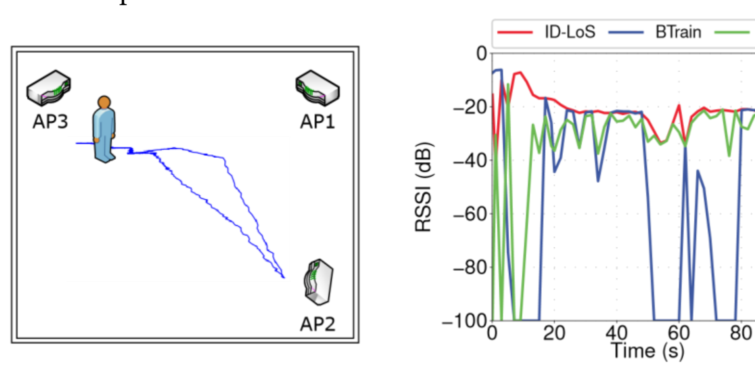
V. Performance Evaluation

To demonstrate the feasibility and performance of the proposed ID-LoS system, we implement a simulation environment to conduct several comparison experiments. The 60 GHz APs we adopt are capable of delivering signal beams into many directions according to the codebook. In Fig. 5, we present three example signal patterns with different main lobe angles, and the environmental setup is shown in Fig. 6(a), where three APs are available. The blue line is the moving trajectory of the user and its mobile device. It first goes toward the rightbottom corner and then turns back, and walks along the upper line.

The first simulation is conducted with all these three APs, and a human walks inside the room while using the 60 GHz wireless network. We keep monitoring the RSSI values in the user devices and present the records in Fig. 6(b). We compare three beam-selection approaches in this experiment, i.e., the proposed ID-LoS method, the beam training method, and the RNN method, which is also a mobility prediction based strategy. The difference is that our approach is based on a state-of-the-art LSTM model, and the RNN method is a common used model without the interaction analysis ability.

As shown in Fig. 6(b), we can see that both beam training method and RNN method suffer from drastic changes of the RSSI levels. As a comparison, the proposed ID-LoS method can assure a stable network performance in most cases. To quantitatively compare these three methods and find the differences when deploying different numbers of APs, we conduct another experiment as shown in Fig. 6(c).

We respectively adopt AP1, AP1&AP2, AP1&AP2&AP3 in the environments. As we can see, in all these scenarios, the proposed ID-LoS system outperforms other two methods with a significant advantage. An interesting thing is, although the beam training method improves with the increase of AP number, the deep learning based methods do not show too much differences. That means these two methods have found a near-optimal solution for the 60 GHz communication system in a small room, where the angular loss is dominant while the path loss is not significant. Therefore, adding more APs into the simulation environment does not have much influence on their network performance.



(a) (b)

Fig. 6. Experimental results. (a) The simulation scenario. (b) The real-time RSSI change

VI. Conclusion

In this paper, we design a new strategy for stable 60 GHz communications. To provide seamless coverage in indoor environments, we change the traditional beam training process with a new approach, i.e., empowering the APs with the ability to predict the future user positions and prepare for the beam adaption in advance. To implement this feature, we use a widely-used RNN model to analyze the past trajectories and perform the estimation regarding the next movements. One important work in this research is that we formulate an optimization function to minimize the network loss and find the optimal beam index. The experimental results prove that our model is stable and robust, and is able to effectively improve the signal level on the user side.

In the future, we will continue to modify the network model for higher prediction accuracy. In addition, we plan to take some other factors into account, for example, the possible interactions with static objects, which may have some influences on the user mobility.

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