Blockage Prediction and Fast Handover of Base Station for Millimeter Wave Communications

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***Abstract*— We propose a blockage prediction and fast base station (BS) handover (BP-FBSH) scheme based on the reference signal received power (RSRP) of the mobile terminal (MT) and the indices of the BS transmit beams for millimeter wave communications. Using a specific beam tracking method called neighborhood beam search, the BS transmits multiple neighborhood beams to the MT and collects the RSRPs of these beams from the MT. Then, the BP-FBSH scheme uses the beam-associated information sequences composed of the RSRPs and the indices of the BS transmit beams to train a long short-term memory (LSTM)-based blockage prediction neural network (BPNN). If the BPNN predicts the MT is to be blocked, the scheme triggers a handover of this MT to an adjacent BS as well as determining an initial access (IA) beam for it by an LSTM-based BS handover neural network. Simulation results based on Wireless Insite software show that the scheme can achieve high success rate for both the blockage prediction and the IA beam prediction.**

***Index Terms*— Blockage prediction, base station (BS) handover, reference signal received power (RSRP), long short-term memory (LSTM), millimeter wave (mmWave) communications.**

I. Introduction

As one of the key technologies of 5G and even 6G, millimeter wave (mmWave) massive MIMO communications play important roles in improving system capacity and spectral efficiency [1], [2], [3]. However, many challenging problems need to be solved for mmWave communications, including the weak diffraction characteristics and high penetration loss of the mmWave signal, which heavily relies on a line-of-sight (LoS) link to obtain sufficient received signal power [2], [4], [5]. Therefore, mmWave communications are highly sensitive to the channel blockage. Once the LoS link is blocked, it will lead to a sudden link failure and the transceivers will start to search for another effective link, during which a handover of another base station (BS) may be triggered. How to avoid the sudden link failure by accurately predicting the blockage and then performing a fast BS handover is on focus.

Current works on blockage prediction for mmWave communications mainly consider the blockage due to the mobile obstacles in the environment [4], [6], [7], [8] and the blockage due to the mobile terminal (MT) [9], [10], [11]. To predict the blockage due to the mobile obstacles, the visual data captured by cameras equipped on the BS [4], the unique diffracted signal patterns associated with approaching obstacles [6], [7], and the pre-blockage wireless signatures for blockage prediction with received signal power sequences of different beams [8], are considered. To predict the blockage due to the mobility of MT, the acquired sub-6 GHz channel state information [9], the sequences of beam indices of the BS [10], and the sequences of the signal-to-interference-plus-noise ratio of the MT [11], are used. Since beam tracking is typically employed in mmWave mobile communications, it is important that the blockage prediction can be implemented with the beam tracking methods.

Different from the existing works, in this letter we propose a blockage prediction and fast BS handover (BP-FBSH) scheme for mmWave mobile communications based on the reference signal received power (RSRP) of the MT and the indices of the BS transmit beams with a specific beam tracking method. The contributions of this letter are mainly summarized as follows.

1) Using a beam tracking method called neighborhood beam search, the BS transmits multiple neighborhood beams to the MT and collects the RSRPs of these beams from the MT. Then the beam-associated information sequence composed of the RSRPs and the indices of the BS transmit beams is used to train a long short-term memory (LSTM)-based blockage prediction neural network (BPNN) to predict the future blockage state of the MT.
2) If the BPNN predicts the MT is to be blocked, a BS handover is triggered so that this MT is connected to an adjacent BS and an initial access (IA) beam for this MT will be determined by an LSTM-based BS handover neural network (BHNN).

Notations: Symbols for matrices and vectors are written in boldface. $a, \boldsymbol{a}, \boldsymbol{A}$ denote a scalar, a vector and a matrix, respectively, while $(*)^{\mathrm{T}}$ and $(*)^{\mathrm{H}}$ denote the transpose and the conjugate transpose, respectively. $|a|$ represents the absolute value of a. $\mathbb{R}$ and $\mathbb{C}$ represent the set of real numbers and the set of complex numbers, respectively. $\otimes$ represents the Kronecker product.

II. System Model

An mmWave BS equipped with a half-wavelength uniform planar array (UPA) of $M \times N$ antennas serves an MT equipped with a single antenna. For the UPA, the channel steering vector can be expressed as

$$\begin{aligned}\boldsymbol{a}(\phi,\theta) = \ & \frac{1}{\sqrt{MN}}\big[1, e^{j\pi\theta}, \cdots, e^{j\pi(N-1)\theta}, e^{j\pi\phi}, e^{j\pi(\theta+\phi)}, \\ & \cdots, e^{j\pi[(N-1)\theta+(M-1)\phi]}\big]^{\mathrm{T}} = \boldsymbol{v}_M(\phi)\otimes\boldsymbol{v}_N(\theta)\end{aligned} \tag{1}$$

where $\phi \in (-1,1)$ and $\theta \in (-1,1)$ are the elevation and azimuth angles for a channel path, respectively. Note

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that ϕ and θ can be expressed as $\phi \triangleq \sin(\psi)\cos(\omega)$ and $\theta \triangleq \sin(\psi)\sin(\omega)$, respectively, where $\psi \in [0, \pi/2)$ and $\omega \in [0, 2\pi)$ are denoted as the physical elevation and azimuth angles, respectively. $\boldsymbol{v}_N(\theta)$ is the channel steering vector for a half-wavelength uniform linear array with N antennas, and can be expressed as

$$\boldsymbol{v}_N(\theta) = \frac{1}{\sqrt{N}}\left[1, e^{j\pi\theta}, \cdots, e^{j\pi(N-1)\theta}\right]^{\mathrm{T}}. \tag{2}$$

It is demonstrated that the mmWave channel only has a few channel paths, including one LoS path and $L-1$ non-LoS (NLoS) paths, while the channel power is concentrated on the LoS path. At the tth time frame, the mmWave channel between the BS and a single-antenna MT, denoted by $\boldsymbol{h}_t \in \mathbb{C}^{MN}$, can be written as

$$\boldsymbol{h}_t = \sqrt{\frac{MN}{L_t}}\sum_{l=1}^{L_t}\alpha_{t,l}\boldsymbol{a}\left(\phi_{t,l}, \theta_{t,l}\right) \tag{3}$$

where $\phi_{t,l}$ and $\theta_{t,l}$ denote the elevation and azimuth angles of departure (AoDs), respectively, and $\alpha_{t,l}$ denotes the complex-valued channel gain of the lth path, for $l = 1, 2, \ldots, L_t$. We define $\mathcal{M} \triangleq \{1, 2, \ldots, M\}$ and $\mathcal{N} \triangleq \{1, 2, \ldots, N\}$.

The BS performs analog beamforming to steer the beam to MN different directions, by changing the phases of the phase shifter network. Furthermore, to make the beams cover the whole angle space, ϕ and θ are quantized according to the resolution of $1/M$ and $1/N$, respectively. As shown in Fig. 1, the MN beams corresponding to MN different directions form a two-dimensional grid. Therefore, a predefined beamforming codebook can be denoted by $\boldsymbol{\mathcal{F}}$, where $\boldsymbol{f}_{m,n} = \boldsymbol{a}\left(-1 + (2m-1)/M, -1 + (2n-1)/N\right), \forall m \in \mathcal{M}, \forall n \in \mathcal{N}$, denotes the $(N(m-1)+n)$th codeword of $\boldsymbol{\mathcal{F}}$. At $t = 0$ time frame, the BS performs beam sweeping, which exhaustively tests all the codewords in $\boldsymbol{\mathcal{F}}$ by using them as the BS transmit beams. Then the signal received by the MT is expressed as

$$y_{m,n}^{(0)} = \boldsymbol{h}_0^{\mathrm{H}}\boldsymbol{f}_{m,n}x + \eta_{m,n}, \ \forall m \in \mathcal{M}, \ \forall n \in \mathcal{N}, \tag{4}$$

where x denotes the transmit pilot symbol with normalized power $|x| = 1$, and $\eta_{m,n} \sim \mathcal{CN}\left(0, \sigma^2\right)$ is the additive white Gaussian noise with zero mean and the variance being σ^2. Based on the block fading channel model, we assume $\boldsymbol{h}_0$ keeps constant during the beam sweeping. The indices of the best BS transmit beam in $\boldsymbol{\mathcal{F}}$, also known as the IA beam, are

$$[\widetilde{m}_0, \widetilde{n}_0] = \arg\max_{m\in\mathcal{M}, n\in\mathcal{N}} |y_{m,n}^{(0)}|. \tag{5}$$

Starting from $t = 1$ time frame, the BS performs beam tracking, which can utilize previous information to assist the search for the best beam at the current time frame, therefore reducing the overhead of transmitting beams compared to the beam sweeping. Suppose the indices of the best BS transmit beam obtained at the $(t-1)$th time frame are $[\widetilde{m}_{t-1}, \widetilde{n}_{t-1}]$, $t = 1, 2, \ldots, T$, where T is the total number of time frames for beam tracking. For the beam tracking at the tth time frame, to reduce the overhead, the BS uses a beam tracking method called neighborhood beam search, which only tests a small number of beams adjacent to $\boldsymbol{f}_{\widetilde{m}_{t-1}, \widetilde{n}_{t-1}}$. Suppose

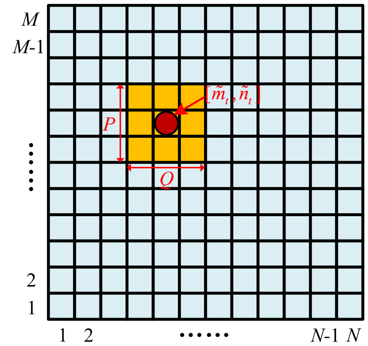

Fig. 1. Illustration of the neighborhood beam search method.

the neighborhood sizes in elevation and azimuth are denoted by odd integers P and Q, respectively, where $P \ll M$ and $Q \ll N$, as shown in Fig. 1. For the beam tracking at each time frame, the BS only tests PQ beams, which results in the reduced overhead of beam tracking by $MN - PQ$ compared to the beam sweeping. We define

$$\mathcal{P}_t \triangleq \{\widetilde{m}_{t-1} - \frac{P}{2} + \frac{1}{2}, \widetilde{m}_{t-1} - \frac{P}{2} + \frac{3}{2}, \ldots, \widetilde{m}_{t-1} + \frac{P-1}{2}\}, \tag{6}$$

$$\mathcal{Q}_t \triangleq \{\widetilde{n}_{t-1} - \frac{Q}{2} + \frac{1}{2}, \widetilde{n}_{t-1} - \frac{Q}{2} + \frac{3}{2}, \ldots, \widetilde{n}_{t-1} + \frac{Q-1}{2}\}. \tag{7}$$

Then the signal received by the MT at the tth time frame can be expressed as

$$y_{m,n}^{(t)} = \boldsymbol{h}_t^{\mathrm{H}}\boldsymbol{f}_{m,n}x + \eta_{m,n}, \ \forall m \in \mathcal{P}_t, \ \forall n \in \mathcal{Q}_t. \tag{8}$$

The RSRP sequence of the MT is defined as

$$\boldsymbol{r}_t \triangleq \left\{|y_{m,n}^{(t)}|, \ \forall m \in \mathcal{P}_t, \ \forall n \in \mathcal{Q}_t\right\} \tag{9}$$

which is required to be fed back from the MT to the BS. The indices of the best beam obtained at the tth time frame are

$$[\widetilde{m}_t, \widetilde{n}_t] = \arg\max_{m\in\mathcal{P}_t, n\in\mathcal{Q}_t} |y_{m,n}^{(t)}|. \tag{10}$$

Based on $[\widetilde{m}_t, \widetilde{n}_t]$, we perform the neighborhood beam search at the $(t+1)$th time frame in the similar procedure to obtain $[\widetilde{m}_{t+1}, \widetilde{n}_{t+1}]$ until finishing a period of T time frames for beam tracking. After that, a new period including one time-frame beam sweeping and T time-frame beam tracking will be performed.

III. Blockage Prediction and Fast BS Handover

As shown in Fig. 2, there are two BSs, represented by BS1 and BS2, to provide mmWave communication service for several MTs that move according to certain traffic rules on the urban road. Suppose one MT is first served by BS1 and there is a LoS link between BS1 and it for mmWave communications. But when this MT turns a corner, the LoS link is suddenly blocked and only much weaker NLoS links exist, resulting in a severe drop in signal strength. In this context, it is necessary to predict the future blockage state of this MT and trigger a handover to an adjacent BS, i.e., BS2, if the MT is to be blocked. Furthermore, the IA beam of the handover BS, i.e., BS2, needs to be determined for the MT after the handover.

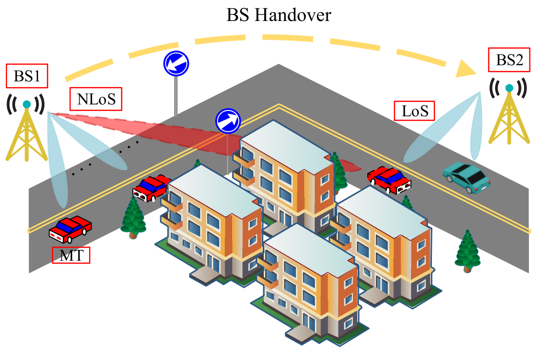

Fig. 2. Illustration of blockage prediction and BS handover.

We define $w_t \in \{0, 1\}$ as the blockage state of the MT at the tth time frame. If $w_t = 1$, it means that the LoS link is blocked; otherwise, it means that the LoS link is unblocked. Since the LoS link is much stronger than the NLoS link, the RSRP of the MT with the LoS link is much larger than that of the NLoS link. We define an RSRP threshold δ. Then we have

$$w_t = \begin{cases} 0, & \text{if } \ |y_{\widetilde{m}_t, \widetilde{n}_t}| \geq \delta, \\ 1, & \text{else.} \end{cases} \tag{11}$$

To indicate whether there will be a blockage occurrence in the future R time frames, we define

$$b_t \triangleq \begin{cases} 0, & \text{if } w_{t+i} = 0, \quad \forall i \in \{1, 2, \ldots, R\} \\ 1, & \text{otherwise} \end{cases} \tag{12}$$

where R is a predefined parameter. If the MT moves at a high speed, we may set R large; otherwise, we may set R small. In fact, $b_t = 0$ indicates the blockage will not occur from the $(t+1)$th to $(t+R)$th time frames; otherwise, the blockage will occur and a handover of the MT to the other BS may be considered.

Different from the existing works that need additional information of the MT, in this letter, we use the indices of the BS transmit beams as well as the RSRPs, which are generally available to the BS, to predict the blockage state of the MT.

According to the neighborhood beam search method, the beam-associated information collected by the BS at the tth time frame is composed of the RSRPs and the indices of the BS transmit beams, and can be defined as

$$\boldsymbol{g}_t \triangleq \{\widetilde{m}_{t-1}, \widetilde{n}_{t-1}, \boldsymbol{r}_t\}. \tag{13}$$

Since $\widetilde{m}_t$ and $\widetilde{n}_t$ can be determined by $\widetilde{m}_{t-1}$, $\widetilde{n}_{t-1}$ and $\boldsymbol{r}_t$, they are not included in the beam-associated information.

To unify the data size for the blockage prediction, we define a beam-associated information sequence $\boldsymbol{G}_t$ at the tth time frame including R_{ob} time-frame beam-associated information as

$$\boldsymbol{G}_t \triangleq \left\{\boldsymbol{g}_{t+i}, \ i = -R_{\text{ob}} + 1, \ldots, 0\right\}. \tag{14}$$

Given $\boldsymbol{G}_t$, the objective is to maximize the probability that the blockage prediction is consistent with the actual blockage state, and can be expressed as

$$\max_{\widehat{b}_t} \ \mathbb{P}\left(\widehat{b}_t = b_t \middle| \boldsymbol{G}_t\right) \tag{15}$$

where $\widehat{b}_t$ is the predicted value of b_t.

If the blockage will occur from the $(t+1)$th to $(t+R)$th time frames, a BS handover will be triggered for the MT so that this MT is connected to an adjacent BS and an IA beam of the handover BS for this MT needs to be determined. To reduce the overhead of beam sweeping when determining the IA beam, the objective is to maximize the probability that the IA beam prediction is consistent with the best beam obtained by beam sweeping. Then the objective can be expressed as

$$\max_{\widehat{d}_t} \mathbb{P}\left(\widehat{d}_t = d_t \middle| \boldsymbol{G}_t, b_t = 1\right) \tag{16}$$

where d_t is the index of the best beam in $\boldsymbol{\mathcal{F}}$ obtained by the beam sweeping of the handover BS and $\widehat{d}_t$ is the predicted value of d_t.

In fact, (15) and (16) are highly nonlinear, which makes them difficult to be solved by traditional methods. Many studies have already shown that data-driven deep learning can effectively handle nonlinear problems. In particular, the LSTM networks are good at dealing with such problems related to data sequences [12], which inspires us to solve (15) and (16) using an LSTM-based BPNN and an LSTM-based BHNN, respectively. During the offline training, the data sets for the BPNN and the BHNN are $\{\boldsymbol{G}_t, b_t\}$ and $\{\boldsymbol{G}_t, d_t\}$, respectively. During the online deployment, the BPNN is used to make a real-time blockage prediction. If the BPNN predicts that the blockage will occur, the MT will be connected to an adjacent BS and the BHNN will be used to predict the index of an IA beam for fast BS handover.

As shown in Fig. 3(a), the BPNN is composed of four modules, including the preprocessing module, full connection (FC) module, LSTM module and binary classifier module. The preprocessing module normalizes $\boldsymbol{g}_{t+i}$, for $i = -R_{\text{ob}} + 1, -R_{\text{ob}} + 2, \ldots, 0$, and can be expressed as

$$\overline{m}_{t+i-1} = \frac{\widetilde{m}_{t+i-1}}{M}, \ \overline{n}_{t+i-1} = \frac{\widetilde{n}_{t+i-1}}{N}, \ \overline{\boldsymbol{r}}_{t+i} = \frac{\boldsymbol{r}_{t+i}}{Z_{t+i}} \tag{17}$$

where

$$Z_{t+i} \triangleq \max_{m \in \mathcal{P}_{t+i}, n \in \mathcal{Q}_{t+i}} |y_{m,n}^{(t+i)}| \tag{18}$$

based on (9). The FC module consists of two FC layers and the numbers of neurons in them are set as 128 and 64, respectively. The activation function adopted in the FC layers is the ReLU function. The LSTM module consists of one LSTM layer and the number of neurons in it is set as 256. The binary classifier module including an FC layer with 2 neurons and a Softmax activation layer, is used to output the probability of blockage, denoted as $\mathbb{P}_{b_t=0}$ and $\mathbb{P}_{b_t=1}$ in Fig. 3(a). The BPNN is trained by $\boldsymbol{G}_t$ and the corresponding blockage label b_t based on the cross entropy loss. The adaptive moment estimation (Adam) optimizer is used to track the gradient and update the weight parameters.

As shown in Fig. 3(b), the structure of BHNN is mostly the same as that of BPNN, while their difference is that the BHNN uses the multiple classifier module to output the predicted index of the IA beam of the handover BS. The multiple classifier module including an FC layer with MN neurons and a Softmax activation layer, is used to obtain the probability that each of the MN beams is the best beam obtained by the

Algorithm 1 Blockage Prediction and Fast BS Handover (BP-FBSH) Scheme

Input: $\boldsymbol{G}_{t-1}$, $\widetilde{m}_{t-1}$, $\widetilde{n}_{t-1}$

Output: $\boldsymbol{G}_t$, $\widetilde{m}_t$, $\widetilde{n}_t$ for beam tracking or $\widehat{d}_t$ for fast BS handover.

BS transmits neighborhood beams based on (6) and (7).
BS collects the RSRP and obtains $\boldsymbol{r}_t$ via (9).
Determine $\widetilde{m}_t$ and $\widetilde{n}_t$ via (10).
Obtain $\boldsymbol{g}_t$ via (13).
Obtain $\boldsymbol{G}_t$ via (14).
Use the BPNN to predict the blockage state $\widehat{b}_t$ via (19).
if $\widehat{b}_t = 1$ **then**
    Use the BHNN to obtain $\widehat{d}_t$ via (20).
    Perform the BS handover.
end if

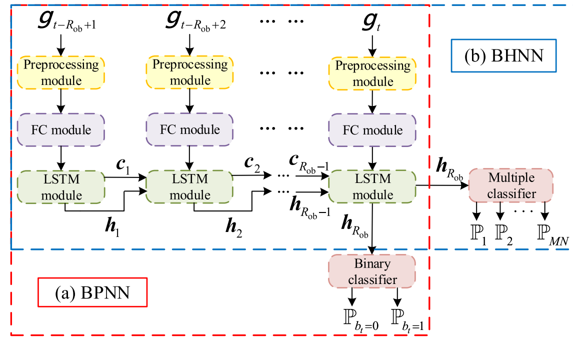

Fig. 3. Illustration of the proposed BPNN and BHNN.

Fig. 4. Simulated mmWave mobile communications in Rosslyn.

beam sweeping, denoted as $\mathbb{P}_1, \mathbb{P}_2, \ldots, \mathbb{P}_{MN}$ in Fig. 3(b). The BPNN is trained by $\boldsymbol{G}_t$ and the corresponding IA beam label d_t based on the cross entropy loss and Adam optimizer.

During the online deployment of the trained BPNN and BHNN, the BS first transmits PQ neighborhood beams based on (6) and (7), and then collects the RSRP fed back from the MT to determine $\boldsymbol{r}_t$ via (9). We can determine $\widetilde{m}_t$ and $\widetilde{n}_t$ via (10) for the beam tracking in the $(t+1)$th time frame. After $\boldsymbol{G}_t$ is obtained via (13), we determine $\boldsymbol{G}_t$ via (14). Then the BPNN predicts the blockage state based on $\boldsymbol{G}_t$, which can be expressed as

$$\widehat{b}_t = f_{\mathrm{BPNN}}\left(\boldsymbol{G}_t\right). \tag{19}$$

If $\widehat{b}_t = 1$, indicating that the blockage will occur, $\boldsymbol{G}_t$ is input into the BHNN to predict the IA beam of the handover BS, which can be expressed as

$$\widehat{d}_t = f_{\mathrm{BHNN}}\left(\boldsymbol{G}_t\right). \tag{20}$$

Then the BS handover can be fast performed. If $\widehat{b}_t = 0$, the BS handover will not be triggered and $\boldsymbol{G}_t$, $\widetilde{m}_t$ and $\widetilde{n}_t$ are output for the beam tracking at the $(t+1)$th time frame.

The detailed steps of the BP-FBSH scheme are summarized in **Algorithm 1**.

IV. Simulation Results

As shown in Fig. 4, we evaluate different schemes using Wireless Insite software [13], where mmWave mobile communications in Rosslyn, Virginia, are considered. The MT is first served by BS1. When the MT turns a corner, the channel blockage will occur, and the BS handover will be triggered so that the MT is served by BS2. In particular, we consider the turning situations of the two intersections in Fig. 4. For each turning situation, dozens of trajectories are generated to cover the actual trajectories of the MT. The mmWave BS working at 28 GHz is equipped with a UPA including $MN = 1024$ antennas and the MT is equipped with a single antenna. The detailed simulation parameters are given in Table I.

The speed of the MT is set as 60 km/h. The interval of two adjacent time frames for beam tracking is set as 60 ms. We use Wireless Insite software to generate the channel matrices between two BSs and the MT at each time frame. The neighborhood sizes are set to $P = Q = 3$ for simplicity and the number of $\boldsymbol{g}_t$ in $\boldsymbol{G}_t$ is set to be $R_{\mathrm{ob}} = 20$.

TABLE I
Detailed Parameters For Simulation

Parameter	value
Height of the BS	10m
Height of the UE	2m
Antenna element	Omnidirectional
Carrier frequency	28 GHz
Bandwidth	100 Mhz
Transmit power	30 dBm
Noise PSD	-174 dBm/Hz
Ray power threshold	-250 dBm
Propagation model	X3D ray model

Inspired by [10], we also use the beam-associated information sequences composed of only the indices of the BS transmit beams, i.e., $\bar{\boldsymbol{g}}_t \triangleq \{\widetilde{m}_{t-1}, \widetilde{n}_{t-1}\}$, to train the LSTM networks for blockage prediction and beam prediction, which is named as comparison scheme.

Fig. 5 shows the success rate of the blockage prediction with $R = \{3, 4, 5\}$. For an MT that is to be blocked, if the blockage can be predicted within R time frames before the occurrence of the blockage while the non-blockage is predicted in the other time frames, the blockage prediction for the MT is defined to be successful; otherwise, it is defined to be failed. It can be seen that the success rate of the BP-FBSH scheme can reach higher than 90% at SNR $=$ 15dB and is much larger than that of the comparison scheme, which implies that only using the indices of the BS transmit beams is not enough to catch the moving information of the MT. Moreover, larger R leads to the better success rate, where the reason is that larger R provides more tolerance of time frames for blockage prediction.

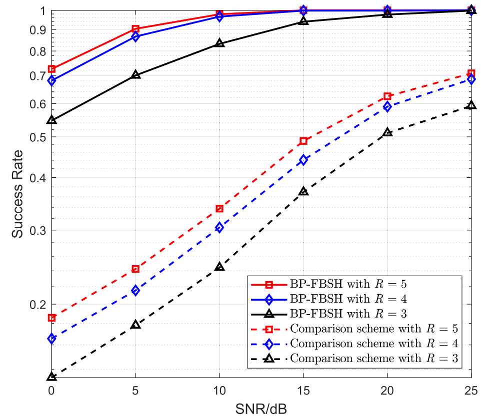

Fig. 5. Success rate of blockage prediction with different R.

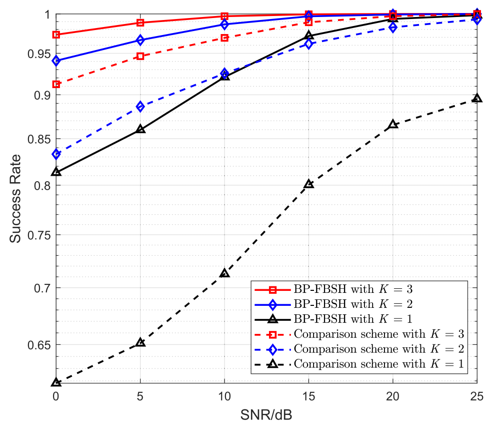

Fig. 6. Success rate of IA beam prediction for the handover BS.

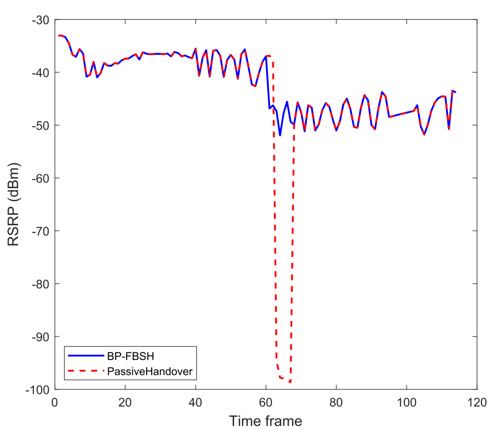

Fig. 7. Comparisons of RSRP between the BP-FBSH and the passive handover schemes.

Fig. 6 shows the success rate of IA beam prediction for the handover BS. In practice, if the blockage is predicted to occur, we may need to predict K IA beams instead of only the best IA beam, so that the handover BS has more candidate beams for the MT. Therefore, if the predicted K IA beams include the actual best IA beam, the beam prediction is defined to be successful; otherwise, it is defined to be failed. From Fig. 6, the performance of the BP-FBSH scheme is much better than that of the comparison scheme, where the former can reach higher than 95% at SNR $= 15$ dB.

Fig. 7 compares the RSRP between the BP-FBSH and the passive handover schemes, where the RSRP of tth time frame is defined to be the best one of $\boldsymbol{r}_t$. For the passive handover scheme, the handover BS performs beam sweeping to determine the IA beam once the blockage occurs. Therefore, the BP-FBSH scheme can proactively predict the blockage and fast determine the IA beam for the handover BS, which prevents severe drop in signal strength caused by the blockage.

V. Conclusion

In this letter, the BP-FBSH scheme has been proposed for mmWave mobile communications. Based on the neighborhood beam search method, the BP-FBSH scheme uses the beam-associated information sequences composed of RSRPs and the corresponding indices of the BS transmit beams to train LSTM networks. High success rates for both the blockage prediction and the IA beam prediction have been achieved. Fast BS handover has been accomplished to avoid severe drop in signal strength caused by the channel blockage. In the future, we will extend our work to the MT with multiple antennas.

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