mmWave Beam Prediction with the Assistance of UE Location

毫米波波束預測：使用者設備的位置資訊對預測的影響

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Abstract

Millimeter wave (mmWave) [3] is an electromagnetic wave which spectrum ranges from 30 to 300 GHz. This is an important resource for future communication systems since its wide frequency band can provide higher capacity and transmission rate. However, compared to low frequency waves, mmWave is more prone to get attenuated. To cope with this issue, a signal processing technique called "beamforming" [3] is necessary to focus the transmitted signal toward a certain direction. The communication channel between base station (BS) and user equipment (UE) is not stationary, so how to control the beam wisely is important to provide UE with higher quality of transmission.

In my work, I used long short-term memory (LSTM) as my model for making optimal beam decision. The dataset was generated by DeepMIMO [1]. Also, I tried to add the information of UE location into the model to observe whether this information can help increase the performance of the prediction.

Method

1. System model

We consider a communication system with 1 BS and 1 UE, where BS has a uniform linear array (ULA) with M antennas and UE has only single antenna. We can express the mmWave channel model as

$$\mathbf{H}_t = \sum_{l=1}^{L} \alpha_{t,l}\mathbf{a}(\phi_{t,l})$$

Where L is the number of paths, $\alpha_{t,l}$ is the path gain, $\phi_{t,l}$ is the angle of departure (AoD), and $\mathbf{a}(\phi_{t,l})$ is the steering vector of the ULA at the BS.

Suppose $s \in \mathbb{C}$, $|s| = 1$ is the transmitted signal, then the signal received at UE will be

$$\mathbf{y}_t^{(q)} = \mathbf{H}_t^T \mathbf{f}_q s + \mathbf{w}_t$$

$\mathbf{w}_t$ is the additional white Gaussian noise (AWGN) at time t and $\mathbf{f}_q = \frac{1}{\sqrt{M}}\left[1\ e^{j2\pi q/Q} \dots e^{j(M-1)2\pi q/Q}\right]$ is the q-th beamforming vector while Q is the total number of beams.

We need to decide the optimal beam to align with the time-varying AoD due to UE movement. Define the beamforming gain as $G_t = \left|\mathbf{H}_t^T \mathbf{f}_q\right|^2$. The optimal beam index q_t^* is defined as:

$$q_t^* = \mathrm{argmax}_{q\in\{1,2,\dots,Q\}} G_t$$

2. Machine learning model

After UE receives the transmitted signal vector $\mathbf{Y}(t_n) = [\mathbf{y}_{t_n}^{(q)}]_{q\in\mathcal{S}}$ during beam tracking stage, we will use convolution neural networks (CNNs) to extract its feature, denoting the feature vector as $\mathbf{x}(t_n)$. Next, this feature will be fed into a LSTM model to do further feature extraction. Finally, we will use a fully connection (FC) layer and a softmax activation layer to transform the hidden state of the LSTM into probabilities representing each beam in set $\mathcal{S}$ being the optimal one at time t_n. The beam with the highest probability will be chosen.

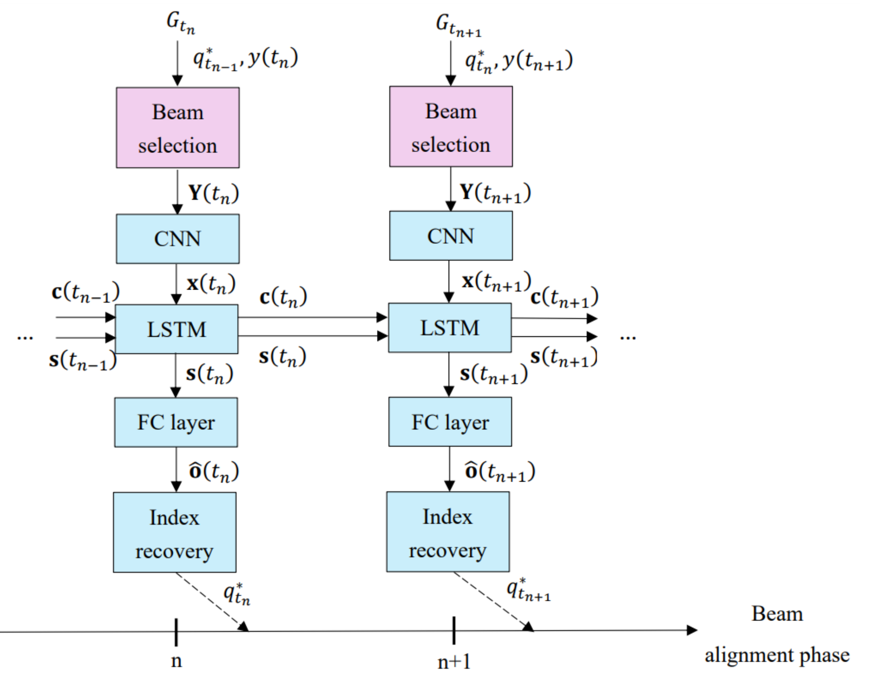


Fig. 1: The model used in beam prediction.

Result

In this experiment, I use DeepMIMO [1], which is widely used in machine/deep learning communication, to generate the mmWave channel dataset. The Outdoor 1 (O1) Scenario, which is shown on Fig. 2, is selected with operating frequency 28 GHz. Also, only user grid 1 (UG1) and base station 1 (BS1) is used.

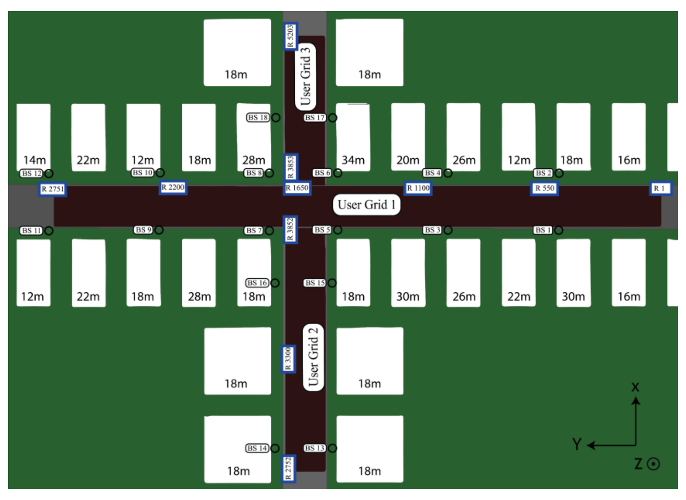
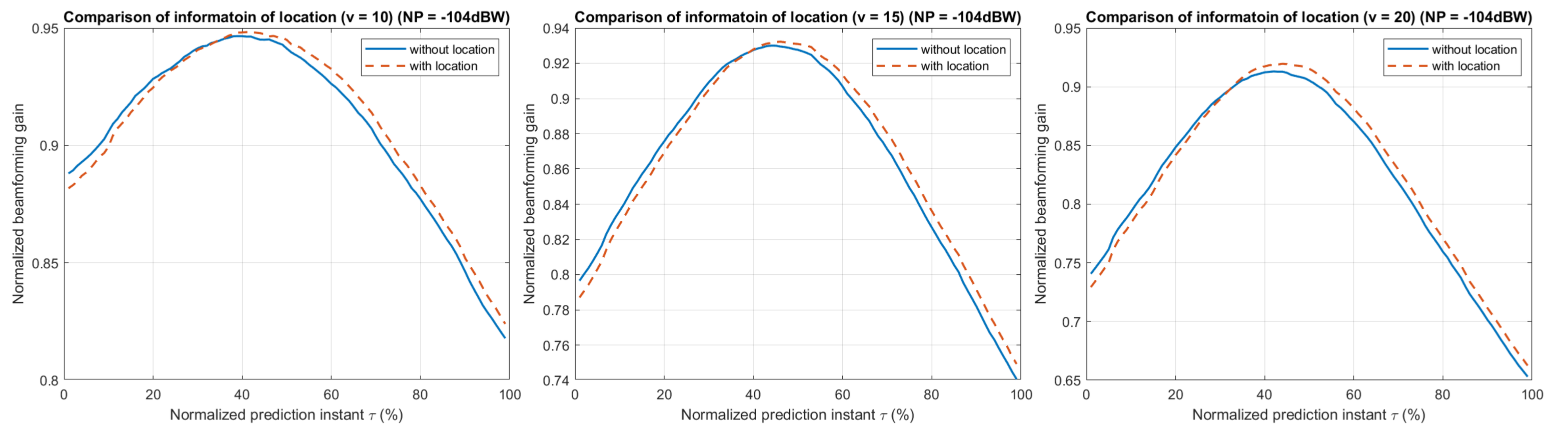


Fig. 2: O1 Scenario from DeepMIMO.

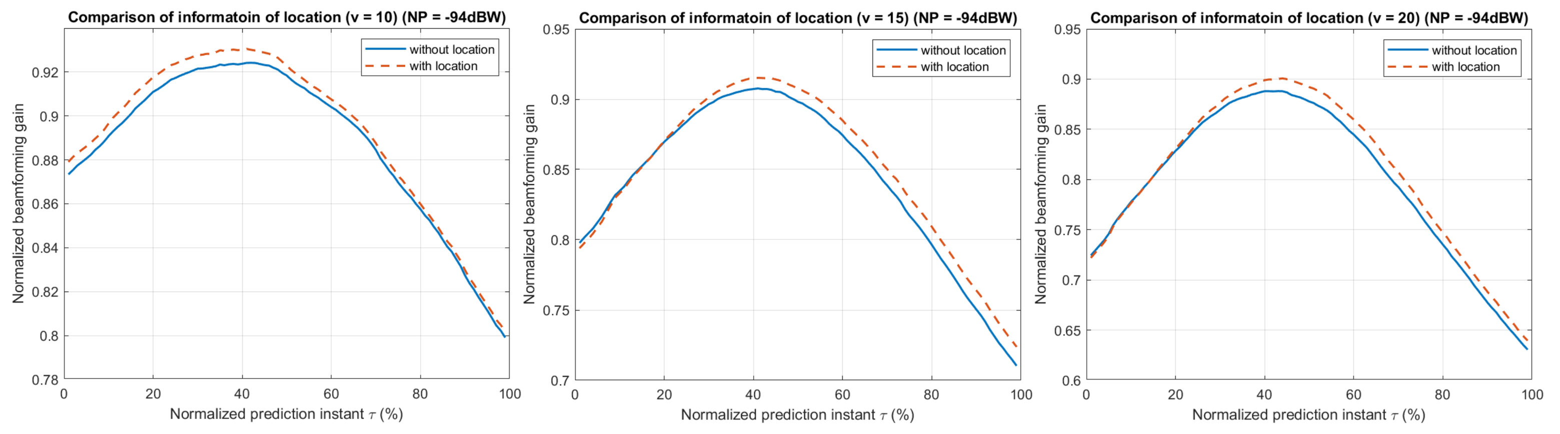
The location of UE will be calculated by $[x(t)\ y(t)] = [x_0\ y_0] + s(t) \times [\cos\theta\ \sin\theta]$, where $x(t)$ and $y(t)$ are the x coordinate and the y coordinate of UE location when time is t, respectively. x_0 and y_0 are the x coordinate and the y coordinate of the initial location of UE, which is randomly selected from row 100 ~ 900 in UG1 shown on Fig. 2. θ is the direction of the UE motion, which is randomly chosen from $[0, 2\pi]$. $s(t) = vt + \frac{1}{2}at^2$ is the displacement of the UE motion, v is the initial velocity with unit m/s, and a = 0.2v (m/s^2) is the acceleration of UE.

The simulation result is shown in Fig. 3, 4, 5. Fig. 3 shows the normalized beamforming gain G_t in 3 cases: UE initial velocity v = 10, 15, 20 m/s, with noise power $\sigma^2 = -104$ dBW (which is the original parameter in [2]). Fig. 4 and Fig. 5 is the same as Fig. 3 except the noise power is set to −94 dBW and −84 dBW, respectively. The total duration of the prediction is 1 second, and the resolution is 0.01 second.



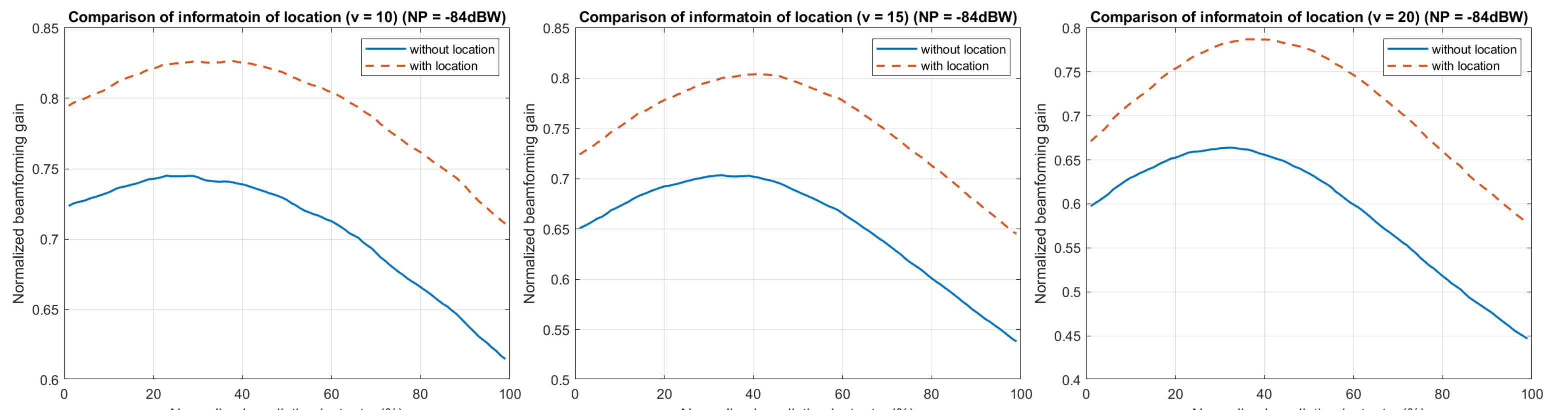
(a) (b) (c)

Fig. 3: Comparison of performance with and without the information of location. UE speed = (a) 10 m/s (b) 15 m/s (c) 20 m/s.



(a) (b) (c)

Fig. 4: Comparison of performance with and without the information of location. UE speed = (a) 10 m/s (b) 15 m/s (c) 20 m/s.



(a) (b) (c)

Fig. 5: Comparison of performance with and without the information of location. UE speed = (a) 10 m/s (b) 15 m/s (c) 20 m/s.

We can observe that the performance decreases as the UE speed increases. Since the channel changes more dramatically as the increasement of speed. Also, the difference between two results becomes more noticeable as the noise power increases. As noise becomes larger, it makes the model harder to predict the correct beam, and the information of UE location becomes more useful in the prediction.

Reference:

[1] DeepMIMO site: https://www.deepmimo.net/

[2] H.-C. Lin and K.-H. Liu, "Simulation codes and details for adaptiveonline beam alignment (AOBA)," https://github.com/kuanghaoliu/Adaptive-online-beam-alignment, 2023

[3] I. A. Hemadeh, K. Satyanarayana, M. El-Hajjar and L. Hanzo, "Millimeter-wave communications: physical channel models, design considerations, antenna constructions, and link-budget," in IEEE Communications Surveys & Tutorials, vol. 20, no. 2, pp. 870-913, 2018.

[4] S. H. Lim, S. Kim, B. Shim, and J. W. Choi, "Deep learning-based beam tracking for millimeter-wave communications under mobility," IEEE Trans. Commun., vol. 69, no. 11, pp. 7458–7469, Nov. 2021.

[5] H. -C. Lin and K. -H. Liu, "Low Overhead Beam Alignment for Mobile Millimeter Channel Based on Continuous-Time Prediction," 2024 IEEE Wireless Communications and Networking Conference (WCNC), 2024, pp. 1-6.