Environment-aware AoD and AoA Prediction for Wireless Networks Utilizing Machine Learning

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***Abstract*—The angle of departure (AoD) and the angle of arrival (AoA) are crucial parameters of wireless channels to enable location-aware applications for the sixth generation (6G) communication systems. This paper addresses the problem of predicting the AoD and AoA at locations within the coverage of a deployed base station (BS) utilizing deep machine learning (DML). Unlike exisitng works which rely on user location information and AoA/AoD as direct input and output for DML models, we generate five distinct maps, that characterize different aspects of the transmission environment and use them as the input and output for the DML. Additional, we introduce a method which leverages a user location-specific transmission zone to mask the area with minimum impact on the signal propagation. This helps to reduce the ambiguity of the training dataset, enabling the DML model to learn the relationship between the transmission environment and the AoD and AoA more effectively. The performance of the proposed method is evaluated using DeepMIMO dataset. Simulation results show that the proposed method can predict both the AoD and the AoA with satisfactory accuracy compared to the true AoD and AoA. Furthermore, the proposed method achieves better performance than the methods, which utilized the location information only.**

***Index Terms*—deep machine learning, regression, channel knowledge map, AoD, AoA, geo-location, environment-aware, image, prediction.**

I. Introduction

Recently, channel knowledge map (CKM) has evolved as a key technology to enable environment-aware communications for future sixth generation (6G) networks, by providing insightful location-specific information on channel parameters such as pathloss, path gains, angle of departure (AoD) and angle of arrival (AoA) [1], [2], [2]–[4]. The AoD and AoA are parameters of wireless channels referring to the directions of propagation of radio signals with respect to the transmit and receive antennas. AoD is essential to direct the transmit signals toward specific users or regions [5], whereas AoA is critical in positioning devices as well as receive beamforming design [6].

The recent research efforts on CKM focus on the construction of radio environment map (REM) providing information on signal strength or pathloss of user locations within the coverage, which is mainly used to guide the deployment of new base stations (BSs) [7]–[10]. The REM construction is equivalent to collectively obtaining the signal strength or path loss for all locations within the coverage. On the other hand, CKM also needs to address the problem of predicting channel parameters at specific user locations for a readily deployed BS [4], [7], [11], [12]. In this context, the objective of the CKM is to provide the users with the channel parameters solely based on their location information. This is crucial to achieve energy-efficient communications, especially when the wireless networks become denser and the overhead becomes formidable.

The prediction of channel parameters at user locations without measurements is usually formulated as regression problems. Intensive studies have shown that data-driven deep machine learning (DML)-based methods achieved better performance than statistical methods [7], [8], [13]. There are plenty of research works on the REM construction for signal strength and pathloss employing DML technique. However the works on the prediction of AoD and AoA of readily deployed BSs are very limited. The prediction of AoD of the strongest path was investigated in [11] given the user locations. The prediction of AoD and AoA of multiple paths was studied in [12], by sequentially predicting the AoD and AoA. These two works utilize only the coordinates of the user locations as the input to the DML model.

However, the AoD and AoA are strongly affected by the transmission environment, such as terrain structure, city landscape and texture of the obstacles. To this end, in this paper, we propose a new method to predict the AoD and AoA of a readily deployed BS utilizing the knowledge of transmission environments. Four maps, the city map, the height map, the LOS map and the location map are used to characterize different aspects of the transmission environment.

In collective prediction of signal strength and pathloss of all user locations, images of the whole coverage area of a BS is usually used to train the DML model [7]–[10]. This is reasonable since the training label is a REM image containing the signal strength or path loss of all the user locations. There exists a unique translation from the input image to the label image. However when the prediction of AoD and AoA of a particular user location is concerned, not the whole coverage area affects the signal propagation. If the whole coverage area is still used as input to the DML model, data ambiguity might happen and the DML model will fail to learn the correlation between the user locations and the AoD and AoA.

Therefore, we propose to use a rectangle transmission zone of varying size to characterize the transmission environment between the BS and the particular user location. The irrelevant area less affecting the signal propagation will be masked, so

Fig. 1: The transmission environment considered in this paper [14].

as to have a more deterministic relationship between the user location and the AoD and AoA. Furthermore, the size of the maps remains as constant although the size of the transmission zone varies with the user locations, in order to simply the DML model architecture.

The contribution of this paper is summarized as follows:

- We propose a DML-based method to predict the AoD and AoA exploiting the transmission environments, the location information and the radio U-Net architecture [7].
- Five maps, each characterizing different aspects of the transmission environment, are generated as the training dataset to train the DML model.
- A rectangle transmission zone of various size to characterize the transmission environment between the BS and the particular user locations.

The outline of the paper is as follows. The system model is introduced in Section II. The proposed DML-based AoD and AoA prediction is presented in Section III. The performance achieved by the proposed method is investigated in Section IV, followed by conclusions in Section V.

II. System Model

In this paper, we consider an outdoor urban transmission environment of area $440m \times 600m$, with two streets, one intersection and some buildings, as shown in Fig. 1. The heights of buildings range from 12 meters (m) to 34m, as indicated by the number in the white blocks. We consider only one BS at the location denoted as BS1 in Fig. 1. The BS operates at 60 GHz and is equipped with horizontal antennas $P_t = 6$ and vertical antennas $Q_t = 2$, mounted at a height of 6 meters. Users are equipped with horizontal antennas $P_r = 3$ and vertical antennas $Q_r = 2$ positioned at a height of 2 meters.

The radio signals propagating through the transmission environments suffer scattering, diffraction and refraction. At each user location, the signals might undergo line-of-sight (LOS) transmission, non-line-of-sight (NLOS) transmission or blockage by the surroundings. Each propagation path can undergo a maximum of four reflections before reaching the user.

For the k^{th} user location with coordinate (x_k, y_k, z_k), we assume that there are L_k paths present between the BS and the user location. Note that we have $L_k = 1$ for LOS transmission and $L_k = 0$ for blocked transmission. In this paper we focus on the prediction of AoD and AoA for the strongest path only. Given the location-dependent path parameters, following the classic geometry-based channel model, the wireless channel at the k^{th} location is given as [15]

$$\mathbf{H}_k = \sqrt{M_t M_r} \sum_{l}^{L_k} g_k^{(l)} \mathbf{a}_t^H \left(\beta_k^{(l)}, \varphi_k^{(l)}\right) \mathbf{b}_r \left(\theta_k^{(l)}, \phi_k^{(l)}\right) \quad (1)$$

where M_t, M_r are the number of antennas in the transmitter and receiver; $g_k^{(l)} = Ae^{j\psi}$ denotes the complex path gain of the l^{th} path, with A, ψ being the amplitude and the phase; $\beta_k^{(l)}, \varphi_k^{(l)}$ are the zenith and azimuth of AoD for the l^{th} path at the BS; $\theta_k^{(l)}, \phi_k^{(l)}$ are the zenith and azimuth of AoA for the l^{th} path at the user location; $\mathbf{a}_t, \mathbf{b}_r$ are column vectors representing the BS and user antenna array response, respectively.

The elements of $\mathbf{a}_t$ at the p_t-th horizontal antenna and q_t-th vertical antennas, where $p_t = 0, \ldots, P_t - 1$ and $q_t = 0, \ldots, Q_t - 1$, are given as

$$\mathbf{a}_t^{(p_t,q_t)} \left(\beta_k^{(l)}, \varphi_k^{(l)}\right) = \frac{1}{\sqrt{M_t}} e^{\frac{j2\pi d}{\lambda}\left(p_t \sin\varphi_k^{(l)} \sin\beta_k^{(l)} + q_t \cos\beta_k^{(l)}\right)} \quad (2)$$

The elements of $\mathbf{b}_r$ at the p_r-th horizontal antenna and q_r-th vertical antennas, where $p_r = 0, \ldots, P_r - 1$ and $q_r = 0, \ldots, Q_r - 1$, are given as

$$\mathbf{b}_r^{(p_r,q_r)} \left(\theta_k^{(l)}, \phi_k^{(l)}\right) = \frac{1}{\sqrt{M_r}} e^{\frac{j2\pi d}{\lambda}\left(p_r \sin\phi_k^{(l)} \sin\theta_k^{(l)} + q_r \cos\theta_k^{(l)}\right)} \quad (3)$$

respectively, where λ is the wavelength of the radio signals and d is the spacing between any two adjacent antenna elements.

Based on this model, at a given user location, with the knowledge of the number of paths, path gains, AoDs and AoAs, the channel matrix $\mathbf{H}_k$ can be easily reconstructed, rather than estimated from real-time transmission of reference signals.

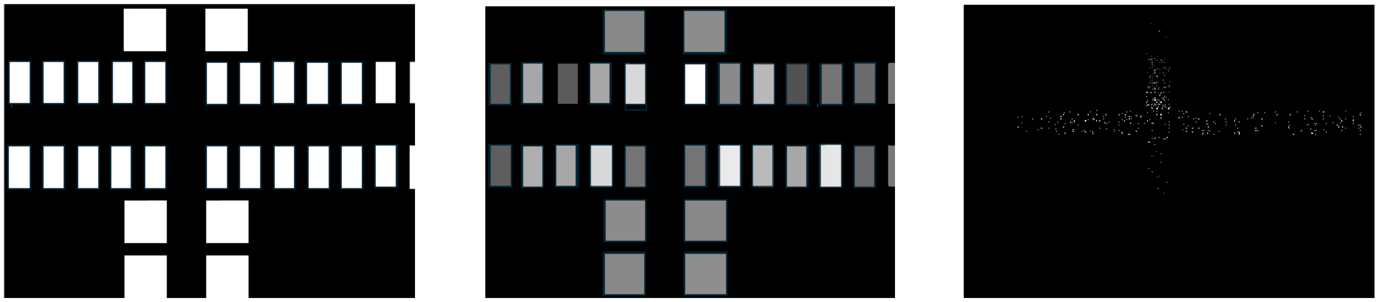
III. Proposed DML-based AoD and AoA Prediction

The prediction of AoD/AoA using the DML technique is formulated as a regression problem, which involves developing a DML model to replace the function $f(\,)$ that maps a location $O_k = (x_k, y_k, z_k)$ to its corresponding AoD (β_k, φ_k) and AoA (θ_k, ϕ_k).

In this section, we will propose a new method for the prediction of AoD and AoA, leveraging the knowledge of the environment. The proposed method will be elaborated in terms of dataset generation and neural network architecture.

A. Dataset Generation

Note that DML models are able to solve regression problems with satisfactory performance only when there are 1) hidden common structures, patterns and features in the training dataset; 2) the input of the neural network and the labels should



((a)) City Map ((b)) Height Map ((c)) LOS Map

Fig. 2: Illustrations of maps.

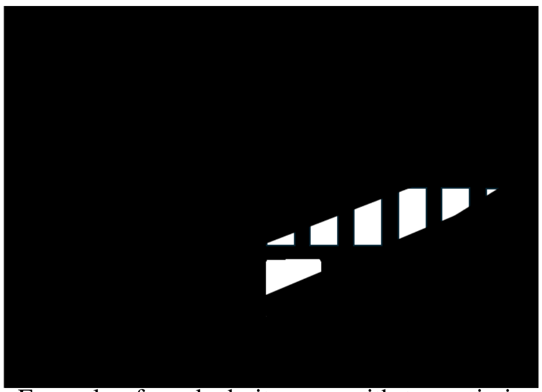


Fig. 3: Example of masked city map with transmission zone.

be correlated deterministically. These ensure the DML model to learn the relationship through multiple layers of abstraction of the neural network.

In this paper, we present our DML model for AoD and AoA prediction, utilizing images as both the input and output. This approach is motivated by two key reasons: (1) images effectively capture the transmission environment between the base station (BS) and the user location, and (2) we can leverage existing neural network architectures, such as Radio U-Net, which are well-established for image processing tasks.

To this end, in this paper, we propose to use five maps as the training dataset, including the city map, the height map, the LOS map, the location map and the AoD and AoA map. The first four maps are images characterizing different aspects of the transmission environment, whereas the AoD and AoA map is an image as the target label.

1) Map Generation:

a) City map: A morphological image showing the placement of the buildings and streets. It contains information on building locations, building size, as well as the street layout, as shown in Fig. 2 (a). The values of pixels inside and outside the buildings are set to be 1 and 0, respectively.

b) Height map: An image containing the information of building heights. The values of pixels inside the buildings are the height of the building, as shown in Fig. 2 (b).

c) LOS map: The LOS map contains the information of LOS indicator at all locations, as shown in Fig. 2 (c). The LOS indicators are $1, 0, -1$ for LOS transmission, NLOS transmission and blockage, respectively. The values of pixels of locations in the LOS map are their respective LOS indicators.

d) Location map: The location map contains the information of the BS location and the user location whose AoD and AoA will be predicted. One image is generated for each user location, where the values of the pixel containing the BS on the map are set as the BS's actual coordinates and the values of the pixel the user location resides on the map are set as its actual coordinates as well. The values of the rest of the pixel values on the location map are all set to be zero.

e) AoD and AoA map: The AoD and AoA at user locations are within range $(-180, 180)$ degrees. In each AoD map and AoA map, the pixel value at the user location is set as its AoD and AoA value, respectively.

The pixel values of all the above maps must be quantized to integer values within $(0, 255)$ before they are applied to the DML model according to the equations below:

$$H_k^{(new)} = uint8\left(\frac{255H_k}{34}\right) \tag{4a}$$

$$LoS_k^{(new)} = uint8\left(\frac{255(LoS_k+1)}{2}\right) \tag{4b}$$

$$\beta_k^{(new)} = uint8\left(\frac{255(\varphi_k+180)}{360}\right) \tag{4c}$$

$$\varphi_k^{(new)} = uint8\left(\frac{255(\beta_k+180)}{360}\right) \tag{4d}$$

$$\theta_k^{(new)} = uint8\left(\frac{255(\theta_k+180)}{360}\right) \tag{4e}$$

$$\phi_k^{(new)} = uint8\left(\frac{255(\phi_k+180)}{360}\right) \tag{4f}$$

where $unit8(\ )$ is a function that converts a number to unsigned 8-bit integer.

2) Generation of Rectangle Transmission Zone: In most of the existing works [7]–[10], the above mentioned maps generally include the whole coverage area of the BS. However, in practical, only the surroundings around the BS, the user location and the path from the BS to the user location affect the AoD and AoA. The rest of the coverage area is irrelevant and will cause data ambiguity if being included in the map. Therefore, given the location of the BS and the user location, we construct new maps comprised of a rectangle transmission zone and a masked area. The rectangle transmission zone has a pre-defined width, whereas the length and the rotation angle are defined based on the locations of the BS and the user as follows.

Given the coordinates of the BS and the user location k as (x_{BS}, y_{BS}, z_{BS}) and (x_k, y_k, z_k) respectively, the coordinates of the center of the transmission zone will be given by

$$x_c = \frac{x_k + x_{BS}}{2} \tag{5}$$

$$y_c = \frac{y_k + y_{BS}}{2} \tag{6}$$

The length S and the rotation angle α of the transmission zone for the user location k are given by

$$S_k = \sqrt{(x_k - x_{BS})^2 + (y_k - y_{BS})^2} \tag{7}$$

$$\alpha_k = \arctan\left(\frac{y_k - y_{BS}}{x_k - x_{BS}}\right) \tag{8}$$

Note that the transmission zone has variable length and rotation depending on the relative location between the BS and the user.

The rectangle transmission zone will then be applied to the city map, the height map and the LOS map. The new maps for the user location k are then constructed by retaining the map information inside the zone, but masking the irrelevant area outside the zone through setting the pixel values as zero. An example of the new city map after applying the rectangle transmission zone is shown in Fig. 3. Note that in this example, the boundary of the rectangle transmission zone is invisible.

With this construction, each user location is associated with a unique set of city map, height map and LOS map. This uniqueness is crucial for the regression problem to translate each specific user location map to AoD and AoA map. Note that although the size of transmission zone varies with the user location, the size of maps remain constant. This consistency will simplify the design of DML model, without the need to address variable size of input images.

B. Neural Network Architecture

We adopt the well developed Radio U-Net as our neural network architecture to predict the AoD/AoA [7]. The U-Net architecture mainly consists of an encoder contractive path, a decoder expansive path, and skip connections.

- Encoder path: making use of convolution and pooling operations to progressively reduce the spatial dimensions of the input while increasing the number of feature channels. This process helps to extract hierarchical representations of the input image.
- Decoder path: converting the feature maps back to the original input size by upsampling, which are used to progressively increase the spatial dimensions and reduce the number of feature channels.
- Skip connections: copying and concatenating the feature maps in the encoder layers to the corresponding feature maps with the same resolution in the decoder layers, resulting an U-shape architecture. The skip connections help preserve spatial information and promote better segmentation.

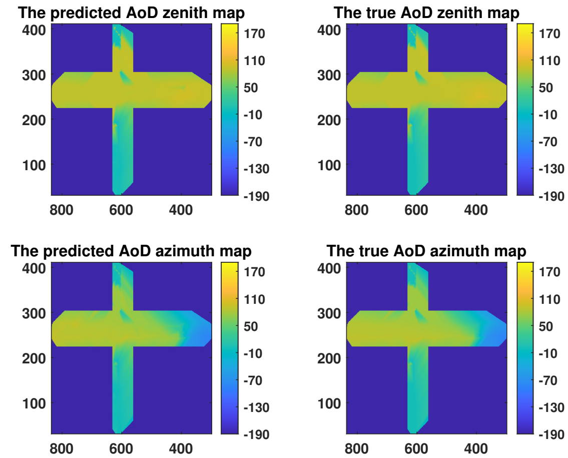


Fig. 4: The colormaps of predicted and true AoD.

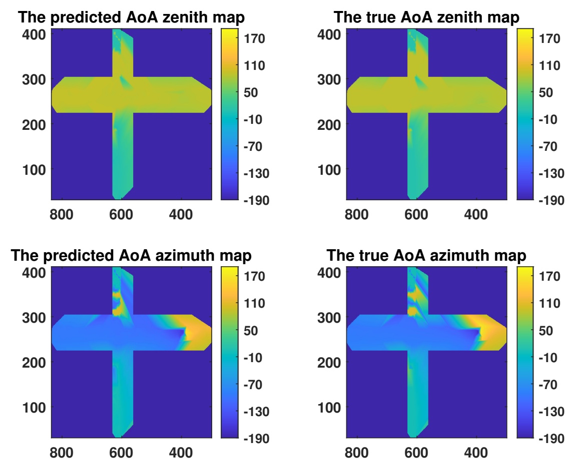


Fig. 5: The colormaps of predicted and true AoA.

The schematic illustration of the architecture of U-Net that we use can be found in Fig. 1 of [16]. The U-Net architecture used in this study has four convolutional layers in the encoder and decoder, with a number of 32, 64, 128, 256 channels respectively, and an activation function of Relu.

In this paper, we utilize U-Net to perform regression instead of classification through image-to-image translation. We stack the city map, the height map, the LOS map and the location map together as a 3-dimensional (3D) tensor and feed it to the U-Net.

In the training of the U-Net, the loss function is defined as the minimum mean square error (MSE) between true AoD and AoA map and the predicted AoD and AoA map. The RMSprop optimizer is adopted to optimize the U-Net.

IV. Performance Evaluation

In this section, we evaluate the performance of the proposed DML models for the prediction of the zenith angle $\beta_k^{(l)}$ and

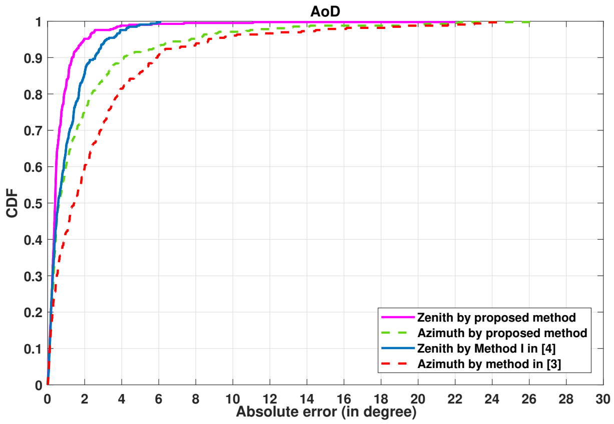


Fig. 6: The CDFs of AoD.

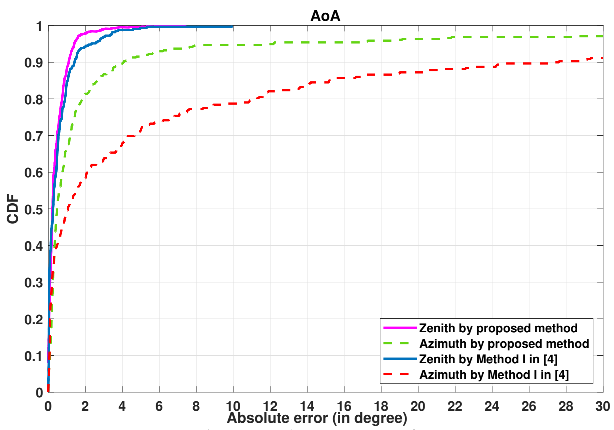


Fig. 7: The CDFs of AoA.

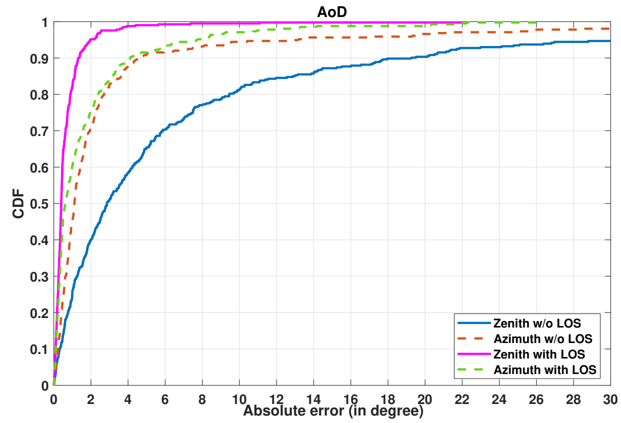


Fig. 8: The CDFs of AoD with and without LOS information.

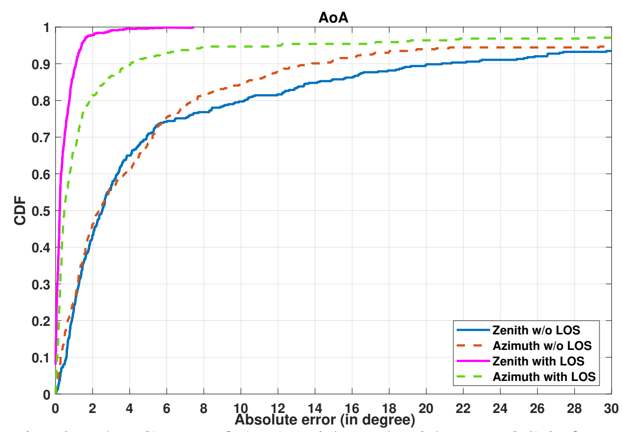


Fig. 9: The CDFs of AoA with and without LOS information.

azimuth angle of $\varphi_k^{(l)}$ of the strongest path of AoD, as well as the zenith angle $\theta_k^{(l)}$, azimuth angle $\phi_k^{(l)}$ of the strongest path of AoA. Each AoD and AoA parameter will have its own model although they share the same U-Net architecture.

In the simulations, we consider the radio signal transmission from BS1 which resides at the right end of the horizontal street as shown in Fig. 1. To train the U-Net, we generate 1320 sets of city map, height map, LOS map, location map and AoA and AoD map, with each set for one user location. All the maps have the same size of 500×702. The user locations are randomly distributed along the main streets which are divided into User Grid 1, 2 and 3. The spacing of user locations in the User Grid 1, 2 and 3 are around $2m$ and $15m$, $15m$ and $2m$, and $10m$ and $2m$ in the horizontal and vertical direction, respectively. The length of the transmission zone is set to be 300 pixels.

We use the DeepMIMO dataset Scenario O1, which is available at https://www.deepmimo.net/scenarios/o1-scenario/, to train the U-Net model [14], [17]. The performance will be evaluated in terms of the colormap and the cumulative distribution function (CDF).

1) Performance in Terms of Colormap and CDF: Fig. 4 and Fig. 5 show the predicted AoD and AoA map (left plots) as well as the true AoD and AoA (right plots) by the proposed DML model. The color bars in the figures show the degrees of respective variables. Fig. 6 to Fig. 9 present the CDFs of the absolute errors between the true AoD and AoA and the predicted AoD and AoA.

It can be seen that all the predicted colormaps match the true colormaps very well, which indicates that the proposed DML models can predict the AoD and AoA with satisfactory accuracy. From the colormaps, we also notice that along the horizontal street, the prediction performance is better. This is because the user locations along the horizontal street usually experience LOS transmission which is more deterministic.

From 6 and Fig. 7, we observe that the prediction of the azimuth is worse than the prediction of the zenith, for example, in the zenith prediction of AoD, nearly 100% of the errors being less than around 5 degrees, whereas in the azimuth prediction of AoD, less than 90% of the error being less than 5 degrees. For the prediction of AoA parameters, it can be seen that, 98% of the errors of zenith prediction is less than 2 degree, while only 90% of errors are less than 5 degree for azimuth prediction. The reason is that zenith angle is generally less affected by surroundings on the horizon. Therefore, it is less random and easy for the DML model to learn the hidden feature.

2) Effects of LOS Information: Fig. 8 and Fig. 9 show the effects of LOS information on the prediction of AoD and AoA. Obviously, the LOS maps provide another dimension of transmission environment which significantly improve the prediction performance, as shown in the figures. Particularly in our example, the prediction on zenith has considerable improvement, from 40% errors to 95% errors less than 2 degree for AoD, and from 42% errors to 98% errors less than 2 degree for AoA.

3) Performance Comparison with Other Methods: We compare the prediction performance achieved by our proposed method with the methods in [11], [12], in terms of CDFs as shown in Fig. 6 and Fig. 7.

It can be seen that, in the prediction of AoD parameters, our porposed method has better performance than the methods in [11], [12], for example, 95% of zenith errors by our method are less than 2 degrees, whereas only 85% of the errors are less than 2 degrees by the methods in [11], [12].

For AoA parameters, our proposed method achieves significantly better performance than the methods in [11], [12] in the prediction of AoA azimuth. For prediction of AoA zenith, our proposed method achieves performance not worse than the method in [12]. We also notice that, our method achieves errors less than 8 degrees with 100%, whereas it is 10 degrees for the method in [12].

V. Conclusions

In this paper, we have developed DML-based method to predict the location-specific AoD and AoA, by leveraging the transmission environment and the user location information, without requiring explicit knowledge of channel models. In the proposed method, five maps, each characterizing different aspects of the transmission environment, have been generated as the training dataset to train the DML model. To further enhance the model's learning capability for regression tasks, a rectangular transmission zone, whose size varies with user locations, is employed to characterize the location-specific transmission environment between the base station (BS) and the user The simulation results have shown that the proposed method can achieve better prediction performance for AoD and AoA zenith and azimuth angles than the methods in [11], [12] which leveraged the user location information only. Future research could explore the use of additional maps, such as map of reflection factor of obstacles, to better characterize the transmission environments and futher enhance the performance of the DML model.

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