Deep Learning-Based Vehicle-to-Everything Communication for Beyond 5G Millimeter-Wave Vehicular Networks

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***Abstract*—Communication at millimeter wave (mmWave) offers a promising future for the vehicular network beyond the fifth generation (B5G), where high-throughput data exchange is required. However, due to the high mobility and channel attenuation in vehicular environments, it becomes more challenging to establish an efficient mmWave Vehicle-To-Everything (V2X) communication. To overcome the beam misalignment problem, we propose a new deep learning approach based on bidirectional long short-term memory (BiLSTM) model followed by a fully connected layer to predict the suitable beam pair in real-time, i.e., the Angle of Departure (AoD) at the mmWave base station side and Angle of Arrival (AoA) at vehicle side (AoD/AoA) for which the received signal power is maximized. The BiLSTM-BPP is performed to identify automatically the most robust beam pair that connects the mmBS to the vehicle for each vehicle position. After a set of simulations, the results showed that BiLSTM-BPP achieves the lowest beam prediction error between the predicted and the real AoD/AoA compared to traditional machine learning algorithms. We evaluated the performance of our proposal in terms of Mean Squared Error (MSE), Mean Absolute Error (MAE), Median Absolute Error (MedAE), and Root Mean Square Error (RMSE).**

***Index Terms*—Beyond 5G Network, Millimeter Wave, Vehicular Communication, Deep-Learning, Beam alignment.**

I. Introduction

Nowadays, Millimeter Wave (mmWave) communication has become the critical element of Beyond fifth-generation (B5G) in autonomous vehicular networks [1] [2]. The large bandwidth of these band frequencies, from 30 GHz to 300 GHz, allows a high transmission rate and a low latency for Vehicle-To-Everything (V2X) communication, especially in high dynamic scenarios [3].

However, it is well-known that the central communication issue at mmWave frequency is the path loss due to the short-range propagation distance and the signal attenuation caused by the surrounding static and/or dynamic obstacles [4]. Many antenna elements should be used with beamforming technology to overcome this drawback and align the beams on the millimeter-wave base station (mmBS) and the autonomous vehicle (AV) sides. This will provide a high overall beamforming gain and ensure a reliable communication link in a high mobility environment [5].

The beam alignment process has been the focus of most vehicular mmWave communications research in B5G networks. The research in this field is divided into three main categories; the first is called Beam Sweeping (exhaustive search), which examines all possible beam directions at 360° to select the pair where the signal power is maximum. This process must be repeated frequently, resulting in a high time and energy loss [6] [7]. The second category is a vision-aided scheme, which uses information from radar [8], from Lidar [9], and from the camera [10]. The third one is called Angle of Departure/Angle of Arrival prediction, which explores the contextual information, such as a vehicle and base station locations, to avoid the amount of computation and beam selection overhead that beam-sweeping and vision-aided approaches require.

In this study, we propose a new deep learning approach to predict the strongest beam pairs on both sides that connect each vehicle to mmBS, i.e., *Angle of Departure (AoD)* in azimuth at the mmBS and the *Angle of Arrival (AoA)* in azimuth at the vehicle. More specifically, we formulate the beam alignment procedure as a regression problem, using AoA and AoD in azimuth, the location information of mmBS and vehicles, the path-loss, the received signal power, and the distance between the vehicle and the mmBS as input to our proposed BiLSTM-BPP model. The latter comprises four bidirectional Long Short Term Memory (BiLSTM) layers and one Fully Connected (FC) layer.

II. System model

This section presents the adopted mmWave massive Multiple-Input Multiple-Output (MIMO) system and a channel model based on our study. Specifically, *the received signal power (RSP), angle of departure (AoD), and angle of arrival (AoA).*

We consider a downlink mmBS-AV massive MIMO mmWave vehicular communication system with multiple mmBS equipped with $N_A := N_A^h \times N_A^v$ antennas, where N_A^h arrays are placed horizontally and N_A^v arrays are placed vertically. We assume the same for autonomous vehicles that are equipped with $M_A := M_A^h \times M_A^v$, where M_A^h arrays are placed horizontally and M_A^v arrays are placed vertically. In addition, the antennas at the mmBS and autonomous vehicles are placed in uniform planar arrays (UPAs). At time instant k, the downlink signal received $y_k \in \mathbb{C}$ at the vehicle is given by:

$$y_k = f_k^H \mathbf{H} \omega_k s_k + z_k, \tag{1}$$

where, $f_k \in \mathbb{C}^{M_A \times 1}$ is the receive beamforming vector, $\omega_k \in \mathbb{C}^{N_A} \times 1$ is the transmit beamforming vector, $\mathbf{H} \in \mathbb{C}^{N_A \times M_A}$ represents the channel matrix, and $z_n \in \mathbb{C}$ is the additive white Gaussian noise (AWGN) with zero mean and variance of σ^2. For the mmWave vehicular network, the mmWave MIMO channel matrix of the transmission from mmBS to the autonomous vehicle $\mathbf{H} \in \mathbb{C}^{N_A \times M_A}$ is expressed as follows:

$$\mathbf{H} = \sqrt{\frac{N_A M_A}{L}} \sum_{l=1}^{L} \beta_l \alpha_{\mathbf{r}}(\theta_l) \alpha_{\mathbf{t}}^{\mathbf{H}}(\varphi_l), \tag{2}$$

where, L is the number of multi-paths, β_l is the complex gain of the lth path. θ_l and φ_l are the angle of departure (AoD) and the angle of arrival (AoA) of the l path, respectively, where the angles AoD and AoA $\in$ [-180°, 180°]. α_r and $\alpha_t^{\mathbf{H}}$ represent the steering vectors at the vehicle and the mmBS, given by:

$$\alpha_{\mathbf{r}}(\theta_l) = \frac{1}{\sqrt{M_A}}[1, e^{j\frac{2\pi d}{\lambda}cos\theta_l}, ..., e^{j\pi(M_A-1)\frac{2\pi d}{\lambda}cos\theta_l}]^T \tag{3}$$

$$\alpha_{\mathbf{t}}(\varphi_l) = \frac{1}{\sqrt{N_A}}[1, e^{j\frac{2\pi d}{\lambda}cos\varphi_l}, ..., e^{j\pi(N_A-1)\frac{2\pi d}{\lambda}cos\varphi_l}]^T \tag{4}$$

where λ represents the carrier wavelength, d is the space between two adjacent antenna, which is set in the mmWave communication as $\lambda/2$.

III. Deep Learning-Based beam pair selection

We propose a novel BiLSTM-based Beam Pair Prediction approach (BiLSTM-BPP) for LOS millimeter vehicular networks. The location information establishes a reliable data transmission with a reduced error probability and beam search overhead. The procedure scheme is shown in Figure 1. In the following, we present the main steps of the beam pair prediction approach by implementing the proposed BiLSTM-BPP model: database generation, data processing, and beam pair prediction, as described in algorithm 1.

A. Data generation and processing

Our study uses the DeepMIMO (version 2) dataset. The dataset is built based on a 3D ray-tracing scenario simulator, which Remcom develops, Wireless InSite (WI) [11]. The ray-tracing simulator is used to model radio propagation, and through the path tracing in the simulation, we obtain the deepMIMO datasets. The dataset includes AoD in azimuth and elevation, AoA in azimuth and elevation, phase, received signal power, path-loss, time-of-arrival, delay spread, mmBS location, vehicle location, and distance between the mmBS and the vehicle.

After generating dataset channels from the environment simulation, we obtain the contextual channel information of the vehicular communication environment. The BiLSTM-BPP is trained with 60% data where we divide the entire database into three sets such as training, validation, and test sets based on the ratio 6:2:2. However, before inputting data into the model, we normalize input data due to the difference in units between the features.

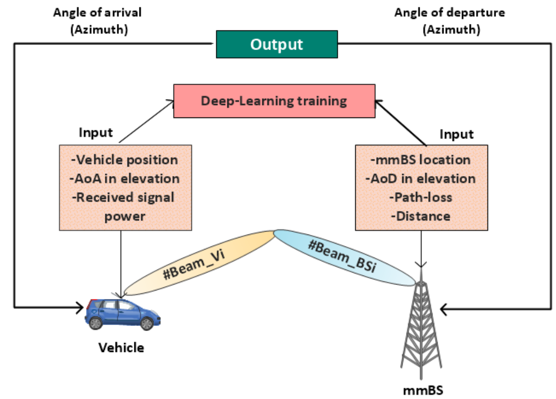

Fig. 1. Deep-Learning Beam Pair Prediction scheme

B. The proposed BiLSTM-BPP model for Beam Pair Prediction

Our study considers the beam misalignment problem as a regression problem, and we use a supervised learning method to train our proposed model. The input features for our proposed BiLSTM-BPP model are AoD and AoA in azimuth, received signal power, path-loss, vehicle position, mmBS location, and distance between mmBS and vehicle. With the BiLSTM approach, the model executes the same command twice.

The architecture of our proposed approach is presented in Figure 2, aiming at reaching the best results after several trials. The architecture consists of one (01) input layer with nine (09) input features and four (04) BiLSTM layers with hidden sizes of 256, 128, 64, and 50 neurons, respectively, followed by a Batch Normalization layer. We then flatten the output and pass them through a fully connected (FC) layer of size 32 with a ReLU activation function where $Relu(x) = max(x, 0)$ and another FC of two outputs with a linear activation function. We choose Linear activation because it does not modify anything in the input and returns the value directly.

IV. Simulations and numerical results

The experimental setup is described in this section, and then we discuss the performance of the obtained results for beam pair angle prediction using the proposed BiLSTM-BPP model.

A. Simulation setup

We have considered an outdoor vehicular communication scenario to validate this proposal to evaluate the proposed beam pair prediction performance. We have applied the LOS 'O1 60' scenario operating at a frequency of 60 GHz where all

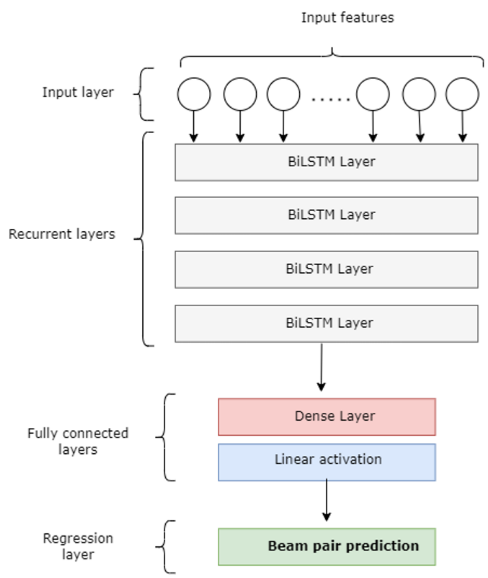

Fig. 2. The proposed BiLSTM-BPP architecture

the vehicles have a Line-of-sight (LOS) communication with mmBS.

The objective of the BiLSTM-BPP training is to reduce the loss function, which is given by the MSE metric between the predicted value of the BiLSTM-BPP model and the actual value θ_i at every step time. As shown in Table I, the optimizer used was Adam [12] with a learning rate of 0.0001. At the same time, the loss function was the mean squared error between the predicted and actual angles, which is widely used in a regression problem. The proposed beam pair angle prediction is obtained after testing several model configurations. In this research, we evaluate the performance of our proposed approach by calculating the error probability between the predicted angle values and the actual values. We observe that when we minimize the loss function (MSE), we are maximizing the received signal power.

TABLE I
BiLSTM-BPP TRAINING HYPER-PARAMETERS.

Parameters	Values
Optimizer	Adam
Learning rate	0.0001
Loss function	MSE
Batch size	1024
Epoch	250
Data size	300.000
Data split	60:20:20

B. The obtained results

As shown in Figure 3 and 4, we have evaluated the performance of our proposed model during the training process by measuring two metrics, including the loss function (MSE) and mean absolute error (MAE). The curve starts to flatten and converge over 250 epochs to maintain at the last epoch a shallow level of 0.0268 for MSE and 0.1036 for MAE, which is very acceptable for the beam pair prediction model. We can also observe that the validation and training curves of MSE and MAE are close, which means that the proposed BiLSTM-BPP model did not suffer from overfitting.

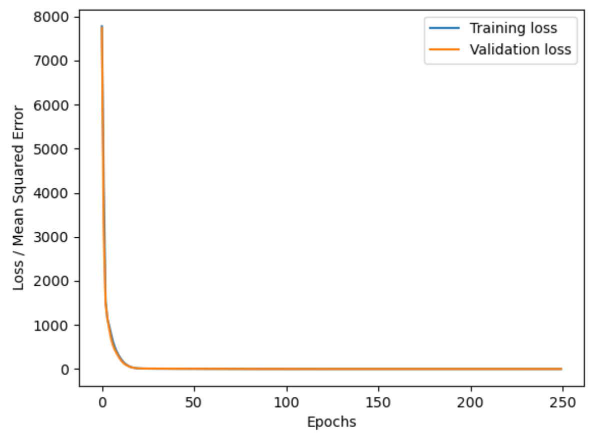

Fig. 3. Training and validation loss (MSE) plot of the proposed BiLSTM-BPP model.

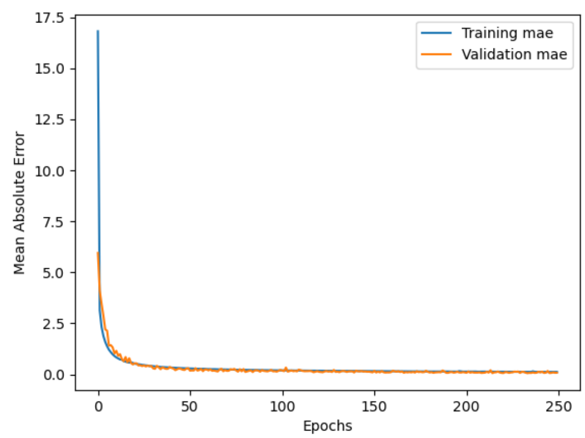

Fig. 4. Training and validation MAE plot of the proposed BiLSTM-BPP model

To evaluate our proposed model performance, we have plotted the predicted angle values by the BiLSTM-BPP model and the actual angle values from the testing set. We can observe from Figure 5 that the predicted and actual values of AoD (the top curve) and AoA (the bottom curve) are almost equal, i.e., there is a strong approximation between the two values, which confirms that our proposed model has achieved high accuracy. This analysis affirms that our proposed BiLSTM-BPP can successfully predict the optimal beam angle pair (AoD/AoA) for each vehicle position with low error probability once the BiLSTM-BPP is sufficiently trained. Moreover, the performance of our proposed approach is validated in terms of evaluation regression metrics, as presented below.

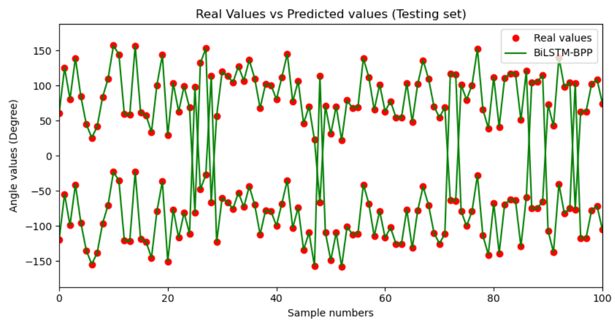

Fig. 5. Comparison between the predicted and actual values for beam pair angle prediction.

Table II shows the results of the evaluation metrics comparison between our proposed BiLSTM-BPP model and other regression models. We have performed five machine learning algorithms, including Linear regression, SVR, KKN regressor, Decision tree, and random forest, using the same training parameters to check their performance for the beam pair prediction approach. From the results obtained, it can be observed that BiLSTM-BBP outperforms the results of the other regression models and offers the best prediction performance, achieving the smallest values of 0.11, 0.99, 0.0816, 0.0121,0.06 for RMSE, R Squared, MAE, MSE, MedAE, respectively.

The above results conclude that the proposed BiLSTM-BPP model performs better than the traditional machine learning algorithms. The proposed solution can automatically identify the strongest beam pair angle that connects the mmBS to the vehicle for each vehicle position, maximizing the received signal power in B5G vehicular networks. This enhancement ensures efficient communication between mmBS and the moving vehicle for each position in a short search beam time, compared to traditional beam searching methods that scan 360° beams to select the best beam angle to use in a highly dynamic environment.

TABLE II
COMPARISON OF EVALUATION METRICS RMSE, R-SQUARED, MAE, MSE, MEDAE FOR REGRESSION MODELS.

Models	**RMSE**	**R-Squared**	**MAE**	**MSE**	**MeAE**
Linear regression	14.92	0.93	12.11	222.7	10.92
SVR	1.26	0.95	0.28	1.61	0.17
KNN regressor	0.44	0.97	0.19	0.59	0.14
Decision Tree	0.36	0.99	0.17	0.06	0.12
Random Forest	0.24	0.99	0.08	0.05	0.11
BiLSTM-BPP	**0.11**	**0.99**	**0.0816**	**0.0121**	**0.06**

V. CONCLUSION

This paper proposes a new deep learning-based beam pair prediction model called BiLSTM-BPP to reduce the beam search time in B5G vehicular networks. This proposal consists of four BiLSTM layers, which enable the use of the past and future channel information, followed by a fully connected layer. Furthermore, the BiLSTM-BPP is proposed to predict the optimal beam pair angle between the mmBS and vehicle that aligns the beams reliably and continuously for each vehicle position. After a set of simulations, we observe that the calculated error probability obtained by our proposal is the lowest compared to those obtained by the traditional machine learning algorithms, namely, Linear regression, SVR, KNN, decision tree, and random forest in terms of MSE, MAE, MeAE, and RMSE. In future research directions, we will investigate how to make our learning model take Non-line of sight (NLOS) paths due to blockage caused by surrounding obstacles and mobility.

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