Deep Learning Approach for Precise Positioning of Millimeter Wave in 5G for V2V Links

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Abstract. The millimeter-wave of 5G will usher in a new era in Vehicle-to-Vehicle (V2V) communication. The ensuing radiation from a millimeter-wave of 5G bounces off most visible things, creating enriched multi-directional environments, particularly in sub-urban scenarios. Physical impediments were once primarily connected with signal attenuation; nevertheless, their existence now introduces complicated, non-linear phenomena such as reflections and scattering. As a result of the impediments faced, a multipath propagation environment emerges, suggesting the presence of concealed spatial information within the received signal for a dense vehicular environment. The key contributions of this research are to discuss and evaluate a self-proposed deep neural network for the beamformed fingerprint location problem in connected cars. Training of deep learning model and simulation environment has been performed using AMD Ryzen 7 GPU environment. Results show that in a realistic outdoor sub-urban scenario with predominantly non-line-of-sight (NLoS) positions, average estimation errors of less than 1.69 m can be achieved, paving the way for novel positioning systems beneficial for V2V links with low computational power. Furthermore, the self-proposed deep learning model is compared with the long-short-term memory (LSTM) in terms of computational complexity. Self-proposed DNN outperform LSTM in terms of training time by 50 min.

Keywords: V2V Technology · V2X · 5G · mmWave of 5G · Deep learning · AIoT

1 Introduction

The introduction of 5G is expected to deliver new Vehicle-to-Vehicle(V2V) capabilities, but it will also bring new challenges. The introduction of millimeter- wave communication is one of the 5G's revolution, opening a substantial block of previously unused capacity [1]. The propagation properties of mmWave alter dramatically. The resulting radiation has significant excess path loss features and reflects on most visible barriers, which can be disastrous in a vehicle and a vehicle-related environment [2]. As a result, any mmWave communication between two locations that are not in direct line-of-sight (LoS) communication may only be accomplished through an indirect propagation path, such as a reflection. To overcome the aforementioned characteristics, beamforming (BF)

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is commonly utilized in systems using multiple-input multiple-output (MIMO) antennas, allowing for a steerable and directional radiation pattern that may subsequently be used for non-line-of-sight (NLoS) communications [3]. The recent focus on mmWave communications led to the development and research of more sophisticated V2V environments with new vehicle location systems [4]. In certain environments, ultra- dense line-of-sight (LoS) communications are used incorporating mmWave of 5G for outstanding results [5]. For best V2V environments, localization and position system of connected cars should be precise in NLoS settings, where communication link formation is a difficult task, which had been enhanced using mmWave of 5G. In contrast, model-centric communication approaches were determined by analyzing fingerprint positioning [6]. Fingerprint positioning methodologies helped to target numerous areas [7]. Fingerprint contains important information from a certain link, which can be a useful data collection method in mmWave of 5G for dense vehicular network.

Machine Learning (ML) approaches can be used in prediction of different parameters of V2V links. ML precisely in domain of communications creates accurate solutions, but with increased complexity. Beamforming Fingerprint (BFF) helps to collect dataset and important information from V2V links, which can be processed in ML models. The key problem with the fingerprint dataset is choosing the right parameters. A model can be as good as data is big and clean, else it would produce differences in results. Even beamforming fingerprint datasets were used with deep learning approaches before in 4G networks, but the median error of prediction was 65 m. In order to enhance the and estimate error rate precisely, mmWave of 5G was used with sub-urban realistic positionings for connected vehicles using a self-proposed deep learning model with the introduction of the GRU layer to reduce computational complexities and training time. Contributions of this paper are summarized as follows:

1) Self-proposed deep learning model is introduced to enhance and predict channel estimation in V2V links using mmWave of 5G with NLoS positions in sub-urban scenarios.
2) Dataset has been created using beamforming fingerprint pattern technique that contained crucial information for V2V links.
3) Simultaneous behavior for connected cars over time are observed, computational complexity is analyzed and compared with state-of-the-art long-short-term-memory (LSTM).

Paper organization is as follows:

Section 2 contains a literature review and previous research gaps. Section 3 contains dataset and its relation with DNN. Section 4 contains detailed architecture of self-proposed neural network for estimation error in V2V links. Section 5 consists of results & discussion analysis. Furthermore, Sect. 6 contains conclusion.

2 Literature Review

Available signal bandwidth increases the temporal resolution of received signal which shows that mmWave of 5G can improved up to extra-ordinary accuracy. In theoretical analysis and experimental analysis, it is proved that inaccuracy is as minimum as 1m for LoS environment, whereas, on the other hand previous techniques were not that superior specifically in positioning methods which is key factor in V2V assessments. Producing accurate estimations for NLoS placements, as indicated in the previous section and proven in [8], is a difficult undertaking. The works created in [9] aim to find vehicles in both LoS and NLoS outside settings, addressing the aforementioned concern. Different access points are employed to construct and locate finger point database of received powers with a specific parameter of angles-of-arrival (AoA) [10], whereas, different (beam forming) BF transmissions are used with iterative algorithms to check positions and distance from vehicle-to-vehicle [11].

Similar, techniques were used to determine angles of arrival AoA, time of arrival (ToA) and angle of departure (AoD) from one car to another car by incorporating LoS, and NLoS transmissions.

In research [12], it was assumed that each car is always within specific range of different static transceiver's, moving further in details, issue analyzed by this scenario was assessed NLoS locations, which required different transmission paths with at least 3–4 different surface reflection for mmWave of 5G. This problem was addressed with solution in [13], which overcomes the limits noted by NLoS locations by providing fingerprint database features for uplink of mmWave of 5G for V2V links. For successful pilot testing, single massive MIMO base stations with many scattered antennas were used as experimental settings, over small area. In other work [14], root-mean-square-error (RMSE) was obtained of 34m by using Gaussian regression methods to solve the issue of position in vehicle to vehicle. Currently, for practical connected cars the technology used so far was long-term-evolution (LTE) and global-navigation-satellite-system (GNSS) based observed time difference with respect to position [15]. But, this method is costly, and inaccuracies can sometimes enhance to more than 10m. Moreover, for a regular GNSS receiver's accuracies can be superior, averaging at around 3m for continuous measurements scenarios [16], because of high use of Kalman filters. But, in NLoS environment for V2V with or without channel tracking there is huge performance differences. Specifically, for mmWave of 5G performance parameters are much more precise in V2V environment as compared to current existing techniques of V2V.

Workflow of our research is that majority of barriers for 5G BSs, which are likely to be positioned in elevated areas in metropolitan environments, will be buildings, which will remain static for an extended period of time. Unless there is a major change in environment, recursive measures for power delay profile (PDP) at a specific position shall remain similar. Receiver can receive many PDP by broadcasting BS using concentrated and directed sequence of BFF patterns to cover whole area for vehicular network. Information in BFF is series of non-linear concatenations. In order to solve non-linearity of BFF and estimate correct error for V2V links, deep neural network approaches emerged as strong option for solving non-linearity of BFF for dense vehicular networks. Deep neural network also consumes less power, whereas in previous studies high power consumption was analyzed for V2V environment. The physical constraints of brief series of positions are investigated in this research using sequence learning to improve the BFF vehicle positioning system by estimating error analysis.

3 Dataset

Stability is a very crucial and important parameter for any trainable dataset since it helps the deep neural system to extract useful information from a trained model using transfer learning, or can also be helpful to get useful results from the cold start of the model without transferable weights. In our case for V2V links error estimation, BFF analysis and data extraction are important. BFF contains crucial information about specific V2V links. Information such as interference, transfer rate, and obstacle tackling analysis is present. In our analysis, specifically for V2V links, the resolution of information is stored in BFF. In BFF, the direction of beam and radiation effects determine the quality of data. So, there is a direct relationship between the directivity of transmission and specific V2V links carrying more concentrated information for specific propagation channels. Furthermore, by concentrating the directed radiation, a number of information is enhanced which in results increases the possible coverage of V2V routes and links. By close observation of data, it is analyzed that visual patterns emerged when sequence BF are transmitted with concentration. In more detail, we observe that measurements of patterns from the same position contain more comparable clusters with some redundant information as well. Similarly, we observe that by decreasing BFF directivity there is an increase in redundancy and decreased accuracy for position inference. So, data is formed in terms of special resolutions by increasing directivity of BFF, collecting samples, and after proper data cleaning, insertion in a deep neural network for further analysis.

Data set gathering structure can be depicted in Fig. 1. V2V links information is collected and analyzed in the form of beamformed prints inculcating important information of mmWave of 5G for vehicle positioning and obstacle analysis. V2V links are shown in Fig. 2. These sample beamformed prints would be passed through proposed deep learning architectures for further analysis. Deep neural network contains good capacity to predict training samples. For appropriate results, generalization of information is necessary during training steps in order to get effective unknown evaluative parameters. Generalization can be more important for a deep neural network when network is noisy or dense, as in our case vehicular network is dense as well as noisy. In order to achieve generalization of information, deep neural network should have large training data amalgam with regularization methods (specifically for wireless communication's data). An efficient deep learning-based system must collect data fast, and efficiently. Moreover, Beam formation fingerprint systems, its employ's GNSS to identify the acquired input data correctly, which is than processed in deep neural network for analysis. System input and dataset is in the form of beamformed prints. Beamformed prints contains each and every information of specific V2V links. System input is in the form of dataset in specific neural network for further processing.

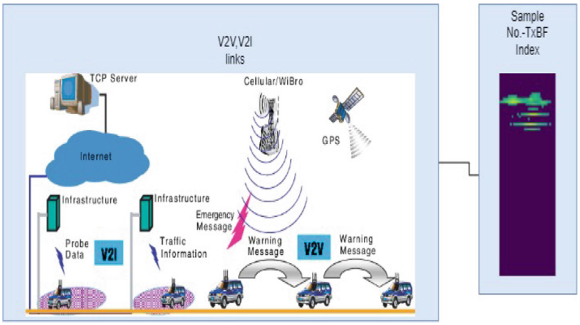

Fig. 1. Beam Formation Fingerprint structure for V2V links.

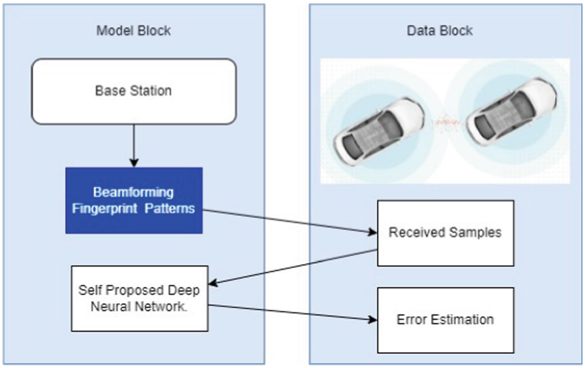

Fig. 2. Detailed architecture of V2V and DNN.

4 Architecture of Self-proposed Deep Neural Network

The self-proposed deep neural network has been introduced. Useful data is extracted from Vehicle-to- Vehicle links. A neural network of three hidden layers has been introduced with maximum pooling layers after every hidden layer, Similarly, after hidden layers the test data was stated up to 20% and train data up to 80%. A gated recurrent layer is added to enhance the optimization and reduce computational complexity as compared to LSTM. Furthermore, robust dense layers are introduced to develop efficient model error estimations in vehicle-to-vehicles links. Detailed architecture can be viewed in Figure 3.

The detailed layer modelling can be shown in Fig. 4. It contains batch normalization as parameter for fast and stable network. Input layers with parameter details are used. Connection of one layer to another layer is described in detail in the model. Convolutional layers are introduced with activation function at different connections.

Hyperparameters of the DNN for training analysis and experimental settings are listed in Table 1. Reason for choosing above mentioned parameters are to reduce computational complexity. Learning size is enhanced at two decimal places for appropriate learning analysis of DNN. Furthermore, NMSE is most appropriate criteria to cross check the error for DNN. Adam is one of the most sophisticated optimizers with low

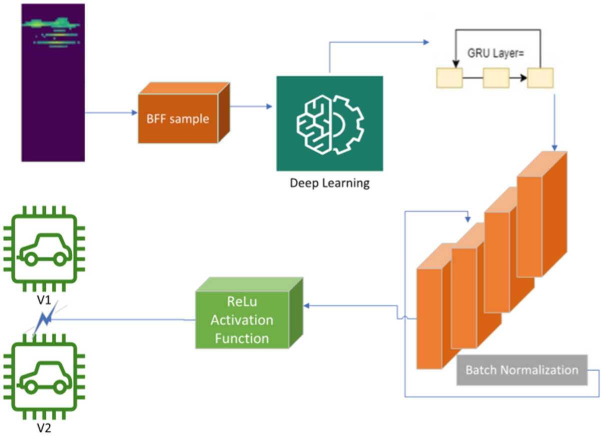

Fig. 3. Detailed architecture of self-proposed DNN.

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	[(None, 256, 256, 3)]	0	[]
conv2d (Conv2D)	(None, 256, 256, 16)	448	['input_1[0][0]']
batch_normalization (BatchNormalization)	(None, 256, 256, 16)	64	['conv2d[0][0]']
activation (Activation)	(None, 256, 256, 16)	0	['batch_normalization[0][0]']
conv2d_2 (Conv2D)	(None, 256, 256, 16)	64	['input_1[0][0]']
conv2d_1 (Conv2D)	(None, 256, 256, 16)	2320	['activation[0][0]']
batch_normalization_1 (BatchNormalization)	(None, 256, 256, 16)	64	['conv2d_2[0][0]']
add (Add)	(None, 256, 256, 16)	0	['conv2d_1[0][0]', 'batch_normalization_1[0][0]']
batch_normalization_2 (BatchNormalization)	(None, 256, 256, 16)	64	['add[0][0]']
activation_1 (Activation)	(None, 256, 256, 16)	0	['batch_normalization_2[0][0]']
conv2d_3 (Conv2D)	(None, 128, 128, 32)	4640	['activation_1[0][0]']
batch_normalization_3 (BatchNormalization)	(None, 128, 128, 32)	128	['conv2d_3[0][0]']
conv2d_5 (Conv2D)	(None, 128, 128, 32)	544	['add[0][0]']
activation_2 (Activation)	(None, 128, 128, 32)	0	['batch_normalization_3[0][0]']
batch_normalization_4 (BatchNormalization)	(None, 128, 128, 32)	128	['conv2d_5[0][0]']
conv2d_4 (Conv2D)	(None, 128, 128, 32)	9248	['activation_2[0][0]']
add_1 (Add)	(None, 128, 128, 32)	0	['batch_normalization_4[0][0]', 'conv2d_4[0][0]']

Fig. 4. Layer specifications for self-proposed model for V2V links analysis and estimation error.

Table 1. Hyperparameters for self-proposed DNN.

Hyper-Parameters	Values
Kernel/Convolutional Layer	10
Learning rate	0.005
Loss function criterion	NMSE
Optimizer	Adam
Epoch size	5670

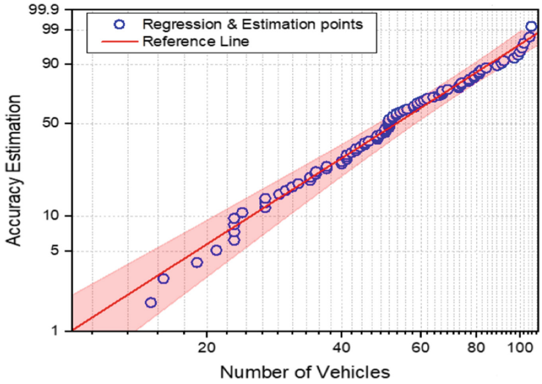

Fig. 5. Error estimation over number of vehicles.

computational power. Moreover, epoch size is increased to 5670 for least error and high accuracy, because accuracy is directly proportional to high epoch size and large dataset.

5 Results and Discussions

Results are analyzed in three different categories. Firstly, channel error is estimated for BFF patterns using a self-proposed deep learning model. Secondly, V2V links has been observed for three different vehicles in dense environments with the least estimated errors. Thirdly, the computational costs are analyzed for self- proposed DNN, computational cost and the effect of GRU on computational cost are also analyzed. Firstly, in Fig. 5, it is observed that accuracy estimation improved by increase in number of vehicles. This regression analysis shows that with the increment of vehicular environment, error estimation is reduced. It is observed that error estimation at median calculation came out to be 1.69m, which is quite competitive. Error estimation is observed from formula in Eq. 1:

$$\partial = |V_0 - V_{ref|} \tag{1}$$

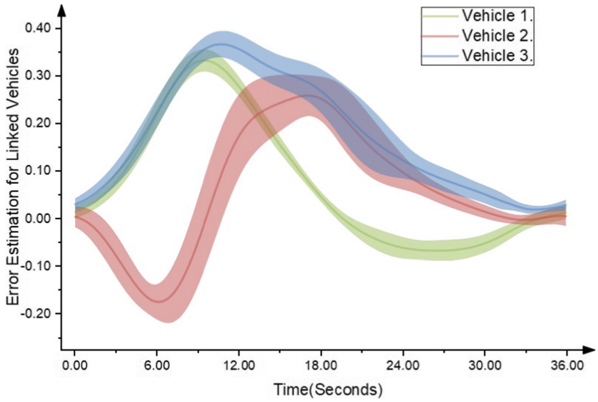

Fig. 6. Vehicle-to-Vehicle (V2V) connectivity analysis Over time for 3 connected cars.

Secondly, three vehicular connectivity was observed as shown in Fig. 6 with respect to obstacle and dense environment. So, in error vs time graph, the stable connectivity of vehicles was achieved at 36^{th} second with continuous safety message exchange using mmWave of 5G which represented reliability and precision of mmWave for V2V environments. The results were analysed using simulated environment by setting up MATLAB toolbox for 5G and incorporating BFF patterns obtained for deep learning modules. Least error was incorporated and observed with time analysis.

Thirdly, the computational cost is computed for self- proposed DNN. Initially in Figure 7, loss and accuracies for DNN are observed for estimation of channel analysis at specific obtained datasets. Loss are decreased smartly, after 50 epoch size, and accuracies started enhancing after 50 epoch size which shows that the addition of the GRU layer made DNN more stable and faster.

Moreover, computational power was analyzed. Computational complexity and utilization of GPU was analysed for self-proposed DNN model with GRU layer and was compared with long-short-term-memory (LSTM) on defined beamforming fingerprint (BFF) dataset. Outcomes are shown in Table 2. As shown in Table 2, there is a significant time difference between GRU and LSTM networks. Even though LSTM slightly outperformed from GRU, but at the cost of computational resources which is inevitable factor for vehicular a connected cars environment.

As shown in Table 2, 11.7% of time is saved by adding GRU layer with respect to LSTM. Even though LSTM slightly outperformed from GRU, but at the cost of computational resources which is inevitable factor for vehicular a connected cars environment.

LSTM layer had been incorporated before in the same vehicular network for estimation. Reason to compare proposed GRU system with standard state of the art LSTM system was to cross-verify computational complexity and procedural settings.

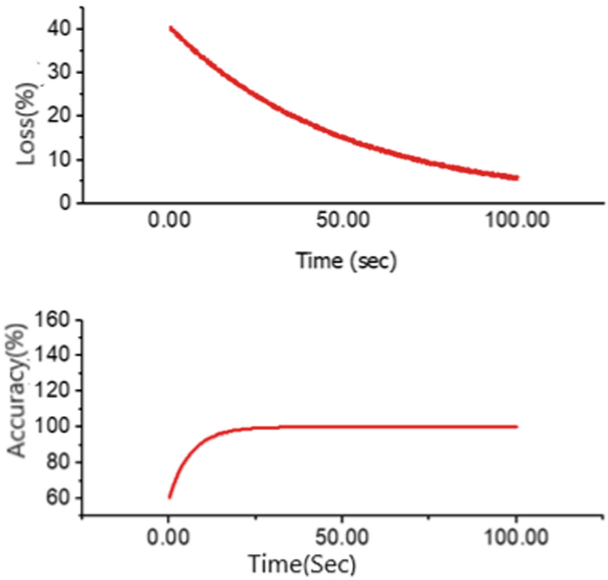

Fig. 7. Loss and accuracy graphical analysis for self- proposed deep learning model on BFF dataset for V2V environment.

Table 2. Computational comparison of self-proposed DNN with GRU layer and self-proposed DNN with LSTM.

Methods	Training Times	Accuracy	mAP
Self-proposed DNN (with GRU layer)	7 h and 6 min	91%	92.6%
DNN with LSTM layer	7 h and 56 min	91.16%	93.12%

6 Conclusion

In a nutshell, Vehicle-to-Vehicle networks with increased density start's creating several issues, such as increased errors between V2V links. In order to improve this scenario, mmWave of 5G has been used and errors are estimated using self-proposed deep learning model. Initially, dataset was formed using beamforming patterns which contained crucial information for mmWave of 5G. After this, deep neural network has been proposed with GRU as its added layer for reduced computationalcomplexities.Furthermore, hyperparameters of DNN inculcated 0.005 as learning rate, Adam as optimizer. Training was performed for 5670 epoch size, and results were analyzed by four different dimensions. Firstly, error estimation of V2V links were analyzed, and it resulted out to be 1.69m, a very competitive figure. Secondly, connected environment, and connectivity were observed over time for mmWave of 5G among 3 cars. Moreover, computational complexity was analyzed keeping in view accuracy and precision, so GRU outperformed state of the art LSTM in terms of training time. For future work, mmWave of 5G cyber secure analysis shall be conducted for V2V environments, because safety parameters are very important. Moreover, Blockchain techniques can be added by combining to V2V architecture for secure and sound vehicular environment to avoid cybersecurity and personal breach attack.

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