LSTM-based Beam Tracking for mmWave Vehicular Networks

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***Abstract*—The use of millimeter wave (mmWave) frequency bands for transmission can improve data rate with the help of beamforming technology to overcome the high path and penetration losses. However for vehicle, the high mobility of vehicle results in extremely frequent beam alignment and significant overhead. In this paper, a long short-term memory (LSTM)-based beam tracking method was proposed for reducing overhead brought by beam alignment in mmWave Vehicular Networks, by predicting angles of beam pair at next time step through known angles of beam pairs at a certain number of consecutive time steps as features. To train this network, an time series array antenna channel data was set up by statistical channel model using time series vehicle information generated from road traffic simulation software named "Simulation of Urban MObility (SUMO)". Simulation results show that proposed LSTM-based method outpreforms Kalman filter based method, and can prevent frequent beam alignment to reduce overhead while ensuring acceptable signal-to-noise ratio (SNR).**

***Index Terms*—beam tracking, mmWave vehicular networks, LSTM, Kalman filter**

I. INTRODUCTION

MmWave is one of the important technology for the future development of communications [1], relies on abundant spectrum resources. In order to apply mmWave better, the high path and penetration loss caused by high frequency of mmWave need to be overcome [2]. Thanks to the small wavelength of mmWave, it is possible to integrate array antennas into small chip and use beamforming technique to constrained signal power in specified direction for high gain [3].

Unlike conventional omni-directional antennas, array antennas are directional [4], which means that if higher antenna gain needs to be achieved, it is important to ensure that the beams generated by array antennas at the receiver and transmitter are aligned with each other. Otherwise the misalignment of the beam pairs will result in serious gain reduction, degrading communications performance. A hierarchical codebook design was proposed in [5], which essentially exploit binary search algorithm to reduce overhead by using different widths of beams at different stages to perform beam search. However, this algorithm requires a high quantization level phase shifter and potentially multiple RF chains to implement, which results in high cost. In [6], Zhang et al. proposed a Kalman filter based method for beam tracking using exhaustive search. However, the number of measurements and protocol overhead for exhaustive search required increases with the number of elements in antenna. On the other hand, [7] exploits extended Kalman filter and requires only a single measurement, making it more suitable for beam tracking in fast-changing environments.

Providing reliable beam alignment for high speed vehicles is more challenging than for low speed terminals, due to vehicles move out of the beam coverage faster. To ensure that the vehicles are always covered by high gain beams, high frequency beam alignment is required, and it can further increase system overhead, especially when high resolution code books are used. Fortunately, due to the sparsity of mmWave channel [8] and the correlation between the angle of arrival (AoA) and angle of departure (AoD) of a millimeter-wave channel and the location of the receiver and transmitter [9], the angle of beam pair of a vehicle traveling along a road under LOS condition should be well predicted.

In this paper, a LSTM-based beam tracking method is proposed. By using LSTM network to learn the historical channel state information (CSI) which was obtained from exhaustive beam search, AoA and AoD of current channel between vehicle and BS can be predicted to reduce system overhead. Meanwhile, a road traffic simulation software is use to generate time seires vehicle information (e.g. position, speed, etc.) to set up time seires CSI with a statistical channel model for training the network. Compared to [6], [7], this paper differs in the following ways: 1) More realistic channel model; 2) Simultaneous prediction of AoA and AoD; 3) The outage judgment is based on the SNR of the receiver instead of the angle difference; 4) Fewer beam measurements required on average in a tracking cycle. In addition, beam search is performed more realistic than [7], by using a quantized phase shifter based beamforming.

The following notation will be used in this paper. Matrices, vectors and scalars are denoted by bold uppercase letters (e.g. $\mathbf{A}$), bold lowercase letters (e.g. $\mathbf{a}$) and lowercase letters (e.g. a), respectively. $(\cdot)^T$ denote transpose and $(\cdot)^H$ denote conjugate transpose (Hermitian). $[\mathbf{A}]_{m,:}$, $[\mathbf{A}]_{:,n}$ and $[\mathbf{A}_{m,n}]$ denote the mth row, nth column and the mth row nth column entry of $\mathbf{A}$, respectively. $[\mathbf{a}]_n$ denote the nth entry of $\mathbf{a}$. Besides, $\|\cdot\|_2$ denote ℓ_2-norm of a vector. $\mathbb{C}$ denote the set of complex number and $\mathbb{R}$ denote the set of real number. Gaussian, complex Gaussian, wrapped Gaussian and exponential distribution are denoted by $\mathcal{N}$, $\mathcal{CN}$, $\mathcal{WN}$ and $\mathcal{E}$, respectively.

II. System Model

A mmWave vehicular networks scenario including a vehicle with M_r antenna as receiver and a Base Station (BS) with M_t antenna as transmitter are considered. Both of them equips with uniform linear array (ULA) of half wave interval antenna as shown in Fig. 1, and adopted analog beamforming used quantitative phase shifter which connect with single analog radio frequency (RF) chain. The array response vector of a uniform linear array with M half wave interval antenna is given by:

$$\mathbf{a}(M,\varphi)=\frac{1}{\sqrt{M}}\left[1,e^{j\pi cos(\varphi)},...,e^{j\pi(M-1)cos(\varphi)}\right]^T \quad (1)$$

where φ is the arrival angle of the signal. When AoA of the vehicle is ϕ and AoD of the BS is θ, the array response vectors of both are $\mathbf{a}_r(\phi)=\mathbf{a}(M_r,\phi)$ and $\mathbf{a}_t(\theta)=\mathbf{a}(M_t,\theta)$, respectively.

The statistical 28 GHz mmWave channel model in [10] was used, which is modeled by real experimental data collected in New York City. The narrowband time-varying L subpaths channel matrix between the vehicle and BS at nth time step is $\mathbf{H}_n \in \mathbb{C}^{M_r\times M_t}$, which is given as:

$$\mathbf{H}_n=\frac{1}{\sqrt{L}}\sum_{l=1}^{L} g_{ln}\mathbf{a}_r(\phi_{ln})\mathbf{a}_t^H(\theta_{ln}) \quad (2)$$

where $g_{ln}\in\mathbb{C}$ is complex small-scale fading gain on subpath l at nth time step, ϕ_{ln} is AoA of the lth subpath signal received by the vehicle at nth time step, and θ_{ln} is AoD of the lth subpath signal transmitted by the BS at nth time step. $\phi_{ln}=\phi_n+\Delta\phi_{ln}$ and $\theta_{ln}=\theta_n+\Delta\theta_{ln}$, where ϕ_n and θ_n is the AoA and AoD of the cluster at nth time step, $\Delta\phi_{ln}\sim\mathcal{WN}(\delta_{rn}^2)$, and $\Delta\theta_{ln}\sim\mathcal{WN}(\delta_{tn}^2)$. The complex small-scale fading gain is given by:

$$g_{ln}=\overline{g}_{ln}e^{j2\pi t_n f_{D,max}cos(\omega_{ln})},\overline{g}_{ln}\sim\mathcal{CN}\left(0,10^{-0.1PL_n}\right) \quad (3)$$

where t_n is the signal transmission time at nth time step, $f_{D,max}=v_n/\lambda_c$ is maximum doppler shift, v_n is the speed of vehicle at nth time step, λ_c is the carrier wavelength, $\omega_{ln}=\phi_{ln}-\pi/2$ is the AoA of subpath l relative to the direction of vehicle at time step n, and PL_n is omnidirectional path loss at nth time step, which is defined as:

$$PL_n=61.4+20\log(d_n)+\xi\ [dB] \quad (4)$$

where d_n is distance between the vehicle and BS at nth time step, and $\xi\sim\mathcal{N}(0,\sigma_p^2)$. Note that only the case of single cluster under line-of-sight (LOS) condition is considered in this paper. In addition, the cluster angle depends on the geometric position of the vehicle and base station.

For a transmitted signal x_n from the BS, received signal y_n in the vehicle at nth time step is:

$$y_n=\mathbf{w}_n^H\mathbf{H}_n\mathbf{f}_n x_n+\mathbf{w}_n^H\mathbf{v}_n \quad (5)$$

where $\mathbf{w}_n$ and $\mathbf{f}_n$ are combining vector and beamforming vector at nth time step, respectively. $\mathbf{v}_n$ is Gaussian noise at time step n and $\mathbf{v}_n\sim\mathcal{CN}(0,\sigma_v^2\mathbf{I}_{M_r})$.

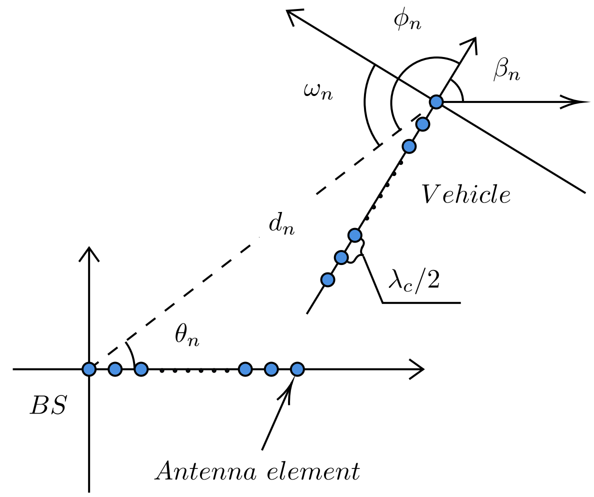

Fig. 1. Channel geometry

III. Data Generation

A. Channel Matrix

A road traffic simulation software named "SUMO" was used to generate time series information of the vehicle in the scene mentioned in Section II, which including a vehicle, a BS and a road with a curve as shown in Fig. 2. The vehicle departs from $(0,100)$ at first time step, and arrives $(100,0)$ at final time step. Note that the speed of vehicle is different at each time step, that means the variation of vehicle position and beam angles is non-linear.

The generated vehicle time series information is composed of position, v_n and directional angle β_n of the vehicle at each time step. For nth time step, the position of vehicle is given by (x_{rn},y_{rn}), v_n is used to determine maximum doppler shift in (3), and β_n is used to calculate ϕ_{ln} and ω_{ln}.

Once the position of the vehicle and the BS are obtained, θ_n and ϕ_n can be calculated by simple geometric methods as following:

$$\begin{cases}\theta_n=\arg(\Gamma_{xn}+j\Gamma_{yn})\\ \phi_n=\arg(\Gamma_{xn}+j\Gamma_{yn})-\beta_n\end{cases} \quad (6)$$

where $\Gamma_{xn}=x_{rn}-x_{tn}$, $\Gamma_{yn}=y_{rn}-y_{tn}$, (x_{tn},y_{tn}) are coordinates of the BS, β_n is directional angle of the vehicle. Furthermore, $t_n=d_n/c$, $d_n=\sqrt{\Gamma_{xn}^2+\Gamma_{yn}^2}$, and c is light speed. Now the channel matrix at each time step can be obtained from (2), (3), (4) and (6).

B. AoAs and AoDs

In this paper, Downlink (DL) configuration scheme is considered for beam management. The beam management procedure is as follows. The reference signals are sent to the vehicle from the BS, the vehicle measures and determines the optimal beam for communication, then transmits beam reporting back to the BS.

AoAs and AoDs measured from exhaustive beam search method is used to train the network, rather than using the

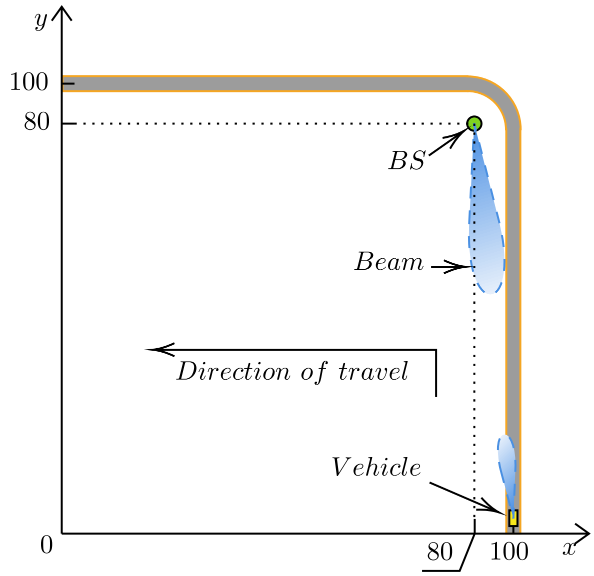

Fig. 2. Scene of mmWave vehicular networks for data generation

generated CSI directly. The advantage of training with radian value instead of the codeword index is that it allows the proposed beam tracking solution to be generalized under terminals with different antenna configuration and beamforming techniques, without increasing computation load and transimtted data. To reduce the overhead of beamforming, a discrete resolution b-bit codebook is adopted to perform beam search, where b is the number of bits for quantized phase shifters, which is assumed to be $2log_2 M$ for a M-element antenna terminal. Assume the number of beam patterns of a codebook is equal to its quantized bits in this paper. So, for a terminal with M-element antenna, the candidate beam angles vector $\mathbf{b}_M$ is given by:

$$\mathbf{b}_M = \left[\frac{1}{2M}\pi, \frac{2}{2M}\pi, ..., \pi\right] \tag{7}$$

In other words, there are $2M_r$ beam patterns for the vehicle, and $2M_t$ beam patterns for the BS. Note that another codebook which achieves uniform maximum gain in all direction is not used for this solution, beacause its low spatial resolution near 0 and π radians resulting in network underfitting. The beam codebooks of the vehicle and the BS are:

$$\begin{aligned} \mathbf{W} &= [\mathbf{a}_r([\mathbf{b}_{M_r}]_1), \mathbf{a}_r\left([\mathbf{b}_{M_r}]_2\right), ..., \mathbf{a}_r\left([\mathbf{b}_{M_r}]_{2M_r}\right)] \\ \mathbf{F} &= [\mathbf{a}_t([\mathbf{b}_{M_t}]_1), \mathbf{a}_t\left([\mathbf{b}_{M_t}]_2\right), ..., \mathbf{a}_t\left([\mathbf{b}_{M_t}]_{2M_t}\right)] \end{aligned} \tag{8}$$

where $\mathbf{W} \in \mathbb{C}^{M_r \times 2M_r}$ is the codebook matrix of vehicle, and $\mathbf{F} \in \mathbb{C}^{M_t \times 2M_t}$ is the codebook matrix of BS. Each column of the codebook matrix represents a beam pattern, each entry in the column is phase rotation for corresponding antenna element to generate directional beam.

Assume $x_n = 1$ is sent as refernece signal, the observation matrix comprises all measurement of exhaustive search now can be given by:

$$\mathbf{Y}_n = \mathbf{W}^H \mathbf{H}_n \mathbf{F} + \mathbf{V}_n \tag{9}$$

where $\mathbf{V}_n \in \mathbb{C}^{2M_r \times 2M_t}$ is Guassian noise matrix composed of independent identically distribution (i.i.d.) elements, which are the noise part of (5). $\mathbf{Y}_n \in \mathbb{C}^{2M_r \times 2M_t}$, $[\mathbf{Y}_n]_{i,j}$ is the received signal of using $[\mathbf{W}]_{:,i}$ as combining vector and $[\mathbf{F}]_{:,j}$ as beamforming vector.

For each time step, both of the vehicle and the BS use their beam codebook to perform exhaustive beam search to find the optimal beam pair. The indexs of optimal beam pair can be obtained by solving a optimization problems as following:

$$\begin{aligned} (i_n^*, j_n^*) = &\underset{i_n, j_n}{\operatorname{argmax}} \|[\mathbf{Y}_n]_{i_n, j_n}\|_2 \\ &s.t. \; i_n \in [1, 2M_r], \\ &\quad\;\; j_n \in [1, 2M_t] \end{aligned} \tag{10}$$

A simple nested loop algorithm can be expolited to solve this problem. Then, at nth time step, the optimal combining vector $\mathbf{w}_n^*$ and the optimal beamforming vector $\mathbf{f}_n^*$ are $\mathbf{w}_n^* = [\mathbf{W}]_{:,i_n^*}$ and $\mathbf{f}_n^* = [\mathbf{F}]_{:,j_n^*}$, respectively. And the estimated AoA ϕ_n^e and AoD θ_n^e used to training network are given by:

$$\begin{cases} \phi_n^e = i_n^* \pi / (2M_r) \\ \theta_n^e = j_n^* \pi / (2M_t) \end{cases} \tag{11}$$

Note that due to limitation of the resolution of the beam codebook and the noise received at the vehicle, there will be some errors in the estimation of the AoAs and AoDs, which is reflected in fluctuations in the estimated time series AoAs and AoDs. To reduce the fluctuations due to errors, a first order Savitzky-Golay filter [11], with frame length 11 (corresponding to a time window of 1 second) was used to smooth the estimated AoAs and AoDs.

IV. LSTM-based Beam Tracking Solution

A. The LSTM Network

The purpose of beam tracking is to obtain current precise beam angles with as few channel estimates as possible for reducing overhead. Since the vehicle must travel in a particular direction on the road and the beam of the mmWave is correlated with the position of the vehicle, the problem of obtaining the current beam angle can be viewed as a time series regression problem when the CSI of historical vehicles is known.

An artificial neural network named LSTMs network was used to solve this regression problem. LSTMs have been implemented successfully in several fields such as machine translation, image captioning, speech recognition, and even stock prices prediction in economy. As one of the recurrent neural networks (RNNs), LSTMs are generally considered to be more robust to long time series than simpler vanilla RNN implementations [12]. LSTMs are powerful for handling time series data, beacase relying on three gates which are forget, input and output gate composed of NNs in LSTM cells, it can learn long-term relations between features.

Fig. 3 show the structure of the network, which is a sequential model comprises LSTM layer with 50 hidden units, a dropout layer with 0.2 probability, a LSTM layer with 50

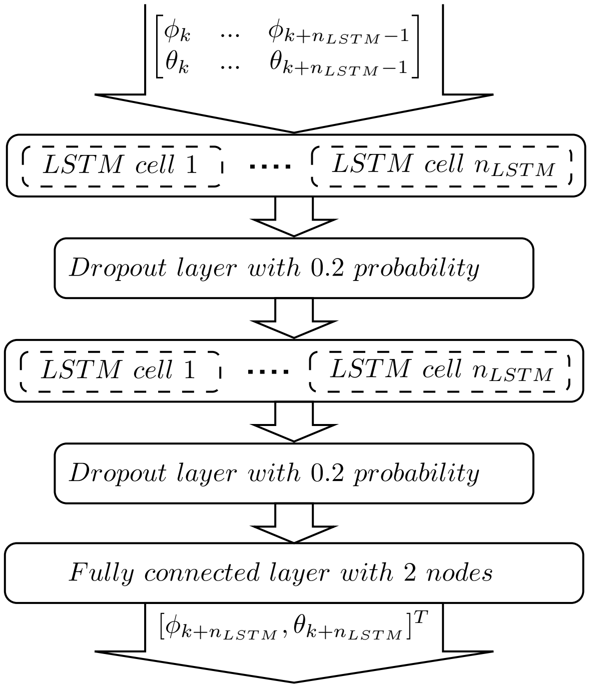

Fig. 3. Structure of network

hidden units, a dropout layer with 0.2 probability and a fully connected layer with 2 nodes. The output of the first LSTM layer is a sequence of length n_{LSTM}, which is used as the input of the second LSTM layer. And two dropout layers are set to prevent overfitting.

B. Procedure of the Beam Tracking

At the begining of the beam tracking, the LSTM network takes the estimated AoAs and AoDs of n_{LSTM} consecutive time steps as features, and the AoA and AoD at next time step as responses. In other words, the network will use the AoAs and AoDs from $(n - n_{LSTM})$th to $(n-1)$th time steps to predict the AoA and AoD at n time step.

Then, the predicted AoA and AoD at nth time steps will be used to compose new feature which from $(n - n_{LSTM} + 1)$th to nth time steps to predict the AoA and AoD at $(n+1)$ time step. For every time step, SNR under current predicted AoA and AoD will be calculated and compares with a threshold T_{SNR}. When the calculated SNR is less than the threshold, a new round of estimation and prediction will be repeated.

C. Loss Function

A straightforward idea is to take the negative of the dot product of the estimated angle and predicted angle array response vectors plus a positive constant as the loss function. Calculating this function, however, requires array response vectors of estimated angle and predicted angle at the corresponding time step, which will increase the computational cost when training network.

V. Simulation Results and Discussion

Acknowledgment

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