Machine Learning-based Channel Tracking for Next-Generation 5G Communication System

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Abstract—**The use of millimeter-wave (mmWave) frequencies is a promising technology for meeting the ever-growing data traffic in next-generation wireless communications. A major challenge of mmWave communications is the high path loss. To overcome this issue, mmWave systems adopt beamforming techniques, which require robust channel estimation and tracking algorithms to maintain an adequate quality of service. In this study, we propose the machine learning-based channel tracking algorithm for vehicular mmWave communications. In this paper, we propose a long short-term memory (LSTM)-based channel tracking algorithm for vehicle-to-infrastructure mmWave communications. The bidirectional LSTM is leveraged to track the channel. Simulation results demonstrate that the proposed algorithm efficiently tracks the mmWave channel with negligible training overhead.**

Keywords— Channel tracking, Machine learing, Long short-term memory, Millimeter-wave, MIMO;

I. INTRODUCTION

The use of millimeter-wave (mmWave) frequencies is a promising technology for supporting high data rates for next-generation wireless communications [1], [2]. However, mmWave communications possess shortcomings, such as signal attenuation and reduced transmission distance, owing to their short wavelength and high frequencies [3], [4]. However, millimeter waves are suitable for use in massive multiple-input–multiple-output (MIMO) systems, wherein multiple antennas are installed within a small space. Based on these features, many studies have been performed to overcome the large path losses encountered in mmWave bands through the use of a highly directional beamforming technique [5]-[7]. To perform high directional beamforming, it is necessary to estimate and track channels for all transmitter and receiver antenna pairs. In this paper, we propose a long short-term memory(LSTM)-based channel tracking algorithm in millimeter-wave Vehicle-to-Infrastructure (V2I) communication. The composition of this paper is as follows. In Section II, we introduce the system and channel models for mmWave vehicular communications, and in Section III, we describe the proposed channel trackng, and the simulation results. Finally, the paper is concluded in Section IV.

II. SYSTEM MODEL & CHANNEL MODEL

Because of the large path loss in mmWave communications, We consider the coordinated mmWave communication system, where *N* base stations (BSs) simultaneously serve one mobile user, as illustrated in Fig. 1.

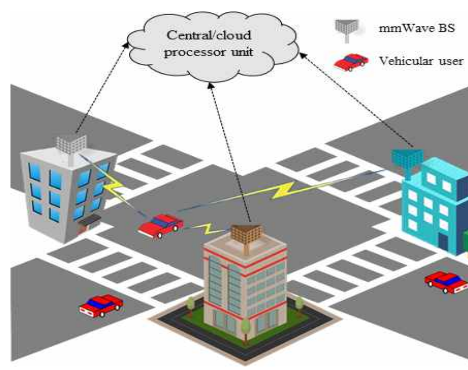

Fig. 1. Illustration of the considered coordinated mmWave system.

Each BS is equipped with M(= $M_h \times M_v$) antennas, which form a uniform planar array (UPA), and the UE has only one antenna. The BSs are assumed to be connected to each other so that they can share the uplink training signals received from the mobile user. For millimeter wave systems in this paper, we consider wideband geometric channel models of L clusters. In this model, each of the clusters contributes one ray that has a time delay, $\tau_{n,l}$, and an AoA, $\theta_{n,l}$. If *p(t)* denotes the pulse-shaping function, the delay-*d* channel vector between the user and *n*th BS can be written as

$$h_{d,n} = \sqrt{\frac{M}{\rho}} \sum_{\ell=1}^{L} g_{n,\ell}\, p(dT_s - \tau_{n,\ell})\, \mathrm{a}_n(\phi_\ell, \theta_\ell) \qquad (1)$$

III. Channel Tracking & simulation result

A. LSTM-based Channel Tracking

LSTM is an artificial recurrent neural network (RNN) architecture that effectively overcomes the vanishing gradient issue in a naively designed RNN [8]. The LSTM cell has the input layer, xt, and the output layer, yt, during time slot t. An LSTM is composed of a memory cell, an input gate, an output gate and a forget gate. The cell stores values over arbitrary time intervals. The three gates regulate the flow of information into and out of the cell. The architecture of the LSTM model is illustrated in Fig. 2. The forget gate, ft, input gate, it, and output gate, ot, are calculated as

$$\mathrm{f}_t = \sigma(\mathbf{W}_{fx}\mathrm{x}_t + \mathbf{W}_{fh}\mathrm{h}_{t-1} + \mathrm{b}_f), \tag{2}$$

$$\mathrm{i}_t = \sigma(\mathbf{W}_{ix}\mathrm{x}_t + \mathbf{W}_{ih}\mathrm{h}_{t-1} + \mathrm{b}_i), \tag{3}$$

$$\mathrm{o}_t = \sigma(\mathbf{W}_{ox}\mathrm{x}_t + \mathbf{W}_{oh}\mathrm{h}_{t-1} + \mathrm{b}_o). \tag{4}$$

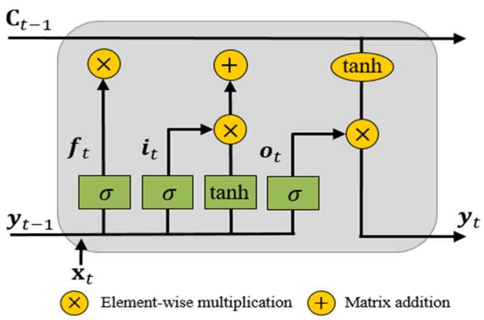

Fig. 2. Structure of the LSTM.

A bidirectional LSTM (Bi-LSTM) has two hidden layers by forward and backward processes, which then feed forward to the same output layer [9]. The function of this hidden layer can be defined as follows [10]:

$$\mathrm{y}_t = \sigma(\overset{t}{\underset{h}{\rightarrow}} \oplus \overset{t}{\underset{h}{\leftarrow}}). \tag{5}$$

Note that notations → and ← denote the forward and backward processes, respectively. Both the forward and backward layer outputs are calculated using the standard LSTM updating equations: Eqs. (2)–(4). The Bi-LSTM layer generates an output vector in which each element is calculated by Eq. (5). For the channel tracking system considered by us, the sequence of the most recent T channel estimation results, $\tilde{h}_{t-T+1},\ldots,\tilde{h}_t$ is the input of the Bi-LSTM. Furthermore, the next time slot-estimated channel $\tilde{h}_{t+1}$ is the desired output, which correspond to x_t and the desired output y_t, respectively, in the Bi-LSTM model. In the Bi-LSTM training procedure, the prediction results are improved continuously based on advanced memory, by discarding some of the ineffective information from the past. The predicted channel vector $\bar{h}_{(t+1)}$ after the training is the output of the Bi-LSTM. The difference between this vector and the actual channel vector at the next time $\tilde{h}_{(t+1)}$ is negligible. Fig. 3 illustrates an example of the Bi-LSTM structure with three hidden layers and three time slots for the estimated channel sequence.

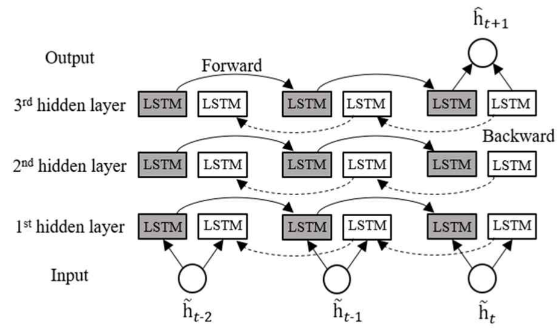

Fig. 3. Structure of the Bi-LSTM.

B. Simulation Result

The simulation setup was based on the publicly-available generic DeepMIMO[11] dataset with the parameters. The system and channel models are as shown in Section II, and channel vectors are generated using parameters such as AoA, AoD, and path loss. The millimeter wave frequency is 60 GHz. The four BSs have UPA antennas and a single antenna vehicle UE. To estimate and track the channel vectors of the vehicle UE, the travel speed is considered at 10 m/s to 30 m/s. The proposed machine learning system evaluates its performance via Normalized MSE (NMSE). The NMSE between the estimated/tracked channel vector ($\hat{\mathrm{h}}$) and the actual channel vector (h) is defined as follows.

$$\mathrm{NMSE} = \frac{\|h-\hat{h}\|^2}{\|h\|^2} \tag{6}$$

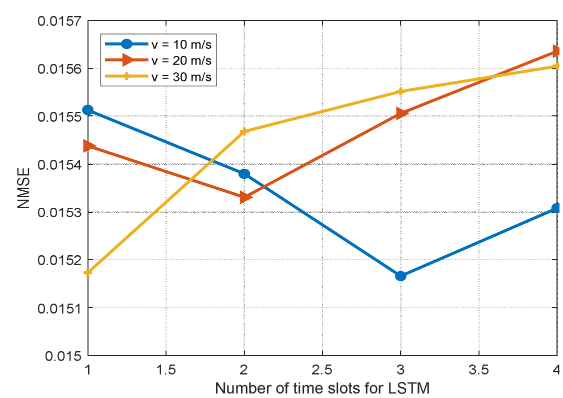

Fig. 4. The NMSE performance of Bi-LSTM with different number of time slots.

Figure 4 shows the NMSE performance of Bi-LSTM with different numbers of time slots. The time slots of the Bi-LSTM input shorten as the vehicular UE speeds up. Furthermore, the performance degrades as the time slot of Bi-LSTM increases, even for high vehicular UE speed. This is because the estimated channel was outdated and the long-predictions inaccurate. Based on Fig. 4, we adopt the numbers of time slots according to the vehicular environment. For example, Bi-LSTM adopts one time slot in a high-speed environment such as a freeway, and three time slots in a dense urban environment.

To demonstrate that our algorithm can reduce the pilot overhead, we introduce the beam coherence time and effective achievable rate, which is a recent concept in mmWave communications to represent the average beam training time [12]. The effective achievable rate can be characterized as

$$R_{eff} = (1 - \frac{N_{tr} T_p}{T_B}) \log_2(1 + \frac{\left|\sum_{n=1}^{N} \tilde{h}_n^T f_n\right|^2}{\sigma^2}) \qquad (7)$$

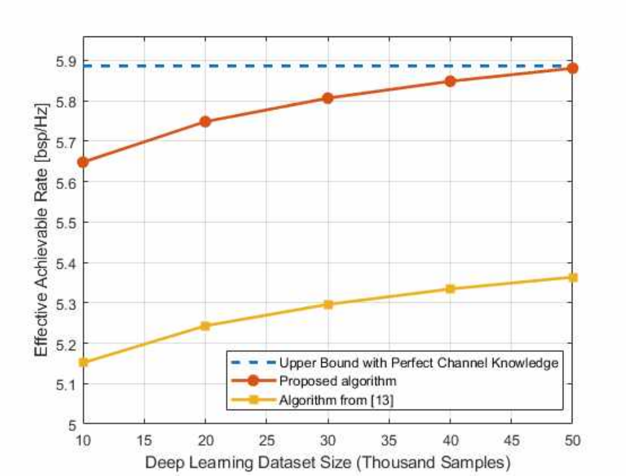

Fig. 5. The effective achievable rate performance.

Fig. 5 shows the achievable rate. The algorithm in [13], which incurs a higher overhead, has a lower effective achievable rate than that of our algorithm. When the number of training pilots is increased, the performance difference increases. This clearly illustrates the capability of the proposed deep learning-based algorithm in supporting highly-mobile mmWave applications with negligible training overhead.

IV. Conclusion

In this study, we proposed a novel method integrating machine learning and channel tracking, and develop its machine learning modeling for vehicular mmWave communications. More specifically, Bi- LSTM was leveraged to track the channel. Bi-LSTM employes the past channel to promote the prediction of the user's channel. The simulation results demonstrated that the proposed algorithm tracking the mmWave channel efficiently, incurring a negligible training overhead.

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