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ChanEstNet: A Deep Learning Based Channel Estimation for High-Speed Scenarios

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***Abstract*—Aiming at the problem that the downlink channel estimation performance is limited due to the fast time-varying and non-stationary characteristics in the high-speed mobile scenarios, we propose a channel estimation network based on deep learning, called *ChanEstNet*. *ChanEstNet* uses the convolutional neural network (CNN) to extract channel response feature vectors and long short-term memory (LSTM) recurrent neural network (RNN) for channel estimation. Through performing offline training to the learning network, takes advantage of the nonlinear mapping features of deep learning, the channel state information (CSI) in the training samples can be effectively utilized to adapt to the characteristics of fast time-varying and non-stationary channels in the high-speed mobile scenarios. The simulation results show that in the high-speed mobile scenarios, compared with the traditional methods, the proposed channel estimation method has low computational complexity and significant performance improvement.**

***Index Terms*—OFDM, channel estimation, high-speed channel, deep learning, fast time-varying channel, non-stationary channel**

I. Introduction

With the rapid development of the high-speed railways, mobile communication systems in high-speed environments has become a research hotspot. For orthogonal frequency division multiplexing (OFDM) systems, downlink channel estimation has received widespread attention [1]. The channel frequency is not stationary with time due to the influences of multipath and Doppler in high-speed environments, which leads to time and frequency selective fading channels (doubly selective fading) and the channels are not stationary [2]. The performance of traditional channel estimation methods are not suitable in this environment.

Traditional channel estimation methods are divided into time-domain estimation and frequency-domain estimation, which have different performances and complexities [3]. For the frequency-domain channel estimation, the channel frequency response (CFR) at the pilot will be estimated at first and then the CFR at the data symbol is estimated by interpolation. The method of frequency-domain channel estimation is relatively simple and frequently used, such as the least squares (LS) [4], the linear minimum mean square error (LMMSE) [3], whose both are assumed that the channel changes linearly and channel information of the data position is estimated by interpolation. The channel impulse response (CIR) shall be assumed to be continuous in an OFDM symbol in the frequency-domain channel estimation. But this assumption is not true in high-speed environments, so the traditional frequency-domain estimation is not suitable for high-speed environments. As for time-domain channel estimation, since it can directly estimate CIR, inter-carrier interference (ICI) can be eliminated, which can be used to estimate doubly selective channel. But CIR of each path need be estimated in time-domain channel estimation method, which will lead that the estimation parameters are too plentiful. To solve the problem, [5] proposes the basis expansion model (BEM)-based LS algorithm, which can reduce the estimation parameters by using BEM. However, due to LS estimation algorithm features lower estimation performance, it is not suitable for high-speed scenarios. [6] proposes the BEM-based extended kalman filter (EKF) and BEM-based EKF-rauch-tung-striebel smoother (RTSS) algorithm, which can reduce estimation parameters by using BEM, and the data symbol channel information is obtained by EKF based on iteration decoding. Although this method is suitable for doubly selective channel, its estimation complexity is too high. So it is a challenge to find a high-performance and low-complexity channel estimation method.

Deep learning methods which have been developed in recent years can map input data to output through non-linear transformation [7], and it has been successfully applied in wireless communications [8], [9]. To solve weaknesses of the traditional channel estimation, this paper proposes a channel estimation method based on recurrent neural network (RNN), which can estimate channels through the non-linear mapping of deep learning. The main contributions in this paper are described as follows: Firstly, an offline training and online channel prediction estimation network with convolutional neural network (CNN) and long short-term memory (LSTM) network is designed. The learning network can be trained by using perfect offline channel data, so the network can learn change features of high-speed channels. The trained network is used to estimate channels and improve estimation precision; Secondly, for the time-domain channel estimation, the estimation parameters are too plentiful, so the maxpooling network is used to reduce dimensions of the estimation parameters to minimize estimation complexity to most extent in this paper; Finally, the computing complexity of the proposed algorithm and the traditional channel estimation methods are analyzed and their estimation performance in different environments is analyzed by the communication system simulation.

II. System Model

The channel estimation is divided into the blind estimation, semi-blind estimation and pilot-aided channel estimation (non-blind estimation), which depends on whether pilot is used or not. Since the CIR of channels is assumed as a wide-sense stationary (WSS) process in the blind estimation and semi-blind estimation [10], for non-stationary doubly selective channels, the pilot-aided channel estimation method is more suitable [3]. Some pilots pattern suitable for OFDM have been extensively applied, such as comb pilot pattern, block pilot pattern and grid pilot pattern, etc. [11]. The pilot pattern used in a communication system is the foundation for further research. For the block pilot pattern, the pilot symbols are inserted into all subcarriers in an OFDM symbol, namely the pilot symbols are fully inserted into the frequency domain, so it can effectively overcome frequency-selective fading. The block pilot pattern are used by some mobile communication protocols, such as IEEE 802.11p [12], it indicates that the channel estimation based on the block pilot mode is applied extensively. We use block pilot channel estimation in this paper. The block pilot pattern and frame structure used in this paper is shown in Fig.1.

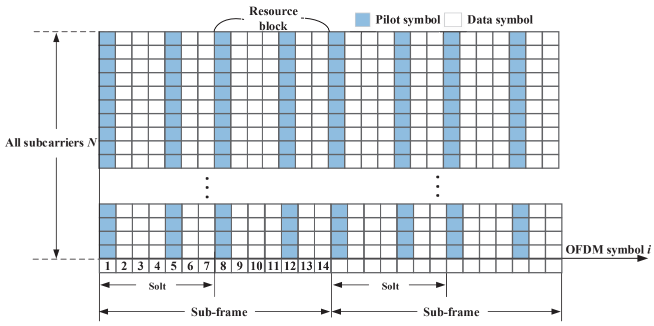

Fig. 1. Frame structure and pilot pattern.

For an OFDM system with N subcarriers and LTE pilot pattern, the pilot symbols sent in i-th OFDM symbol are expressed as $\mathbf{x}_i$, so the system model can be obtained

$$\mathbf{y}_i = \mathbf{h}_i \otimes \mathbf{x}_i + \mathbf{z}_i \tag{1}$$

where $\mathbf{x}_i = [x_i(1), \cdots, x_i(N)]^T$, $\mathbf{h}_i = [h_i(1), \cdots, h_i(N)]^T$ is the transmitted pilot symbols and the channel response vector at i-th OFDM pilot symbol, respectively. $\mathbf{y}_i$ is the received i-th OFDM pilot symbol vector, $\mathbf{z}_i$ is the zero-mean additive complex Gauss noise and the covariance matrix is $\mathbf{Q}_z = \sigma_z^2 \mathbf{I}_N$, where σ_z^2 is the variance of $\mathbf{z}_i$. $\otimes$ denotes the circular convolution. After removing the cyclic prefix (CP) and performing discrete fourier transform (DFT), the received frequency signal is

$$\mathbf{Y}_i = \mathbf{H}_i * \mathbf{X}_i + \mathbf{Z}_i \tag{2}$$

where $\mathbf{Y}_i$, $\mathbf{H}_i$, $\mathbf{X}_i$ and $\mathbf{Z}_i$ are the DFT of $\mathbf{y}_i$, $\mathbf{h}_i$, $\mathbf{x}_i$ and $\mathbf{z}_i$, respectively. The channel estimation aims to make the receiver estimate the channel matrix $\mathbf{H}_i$ through the known $\mathbf{Y}_i$ and $\mathbf{X}_i$.

III. *ChanEstNet* CHANNEL ESTIMATION

For the issue in the traditional interpolation method, this paper proposes a channel estimation method based on RNN. Firstly, the channel state information (CSI) at the pilot is initialized by LS, then the CSI at the data symbol can be estimated through the non-linear mapping of the RNN network.

A. *ChanEstNet Structure*

The *ChanEstNet* is divided into offline training and online prediction. Its framework is shown in Fig.2.

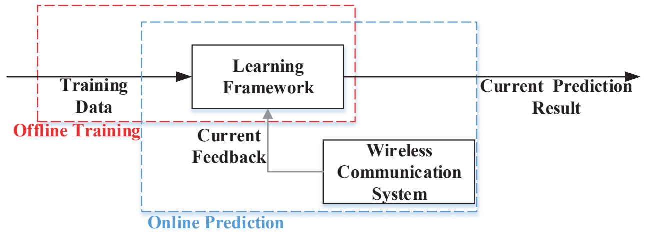

Fig. 2. The channel estimation framework for *ChanEstNet*.

As shown in Fig. 2, we use a learning network to train and predict the CSI, and use perfect offline data to train the learning network so that the learning network can learn the characteristics of the channels changing. The learning network includes the One Dimension (1D) CNN, the 1D MaxPooling, the LSTM and fully connected neutral network. The framework of learning network is shown in Fig. 3.

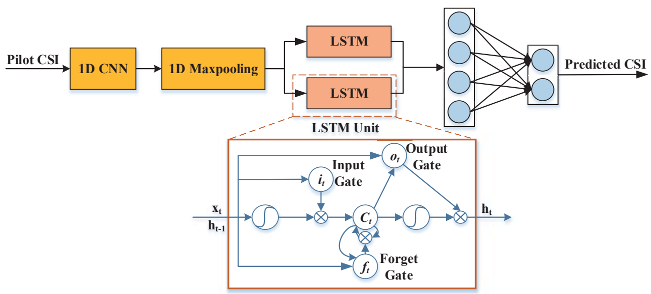

Fig. 3. The learning framework.

The 1D CNN network is mainly used to initialize the input data and extract the pilot sequence feature values, which is composed of a series of parallel filters. These filters are connected to the input signal through a set of weights, and the convolution is calculated along the input frequency-domain. The output is expressed as

$$\mathbf{y} = f(\mathbf{x} * \mathbf{w} + \mathbf{b}) \tag{3}$$

where $\mathbf{w}$ is the weight vector, $\mathbf{b}$ is the offset vector and $f(\cdot)$ is the activation function.

The 1D Maxpooling layer mainly reduces dimensions of the estimation parameters. For the frequency-domain channel estimation, its estimation parameters are less, so this layer can be ignored. For the time-domain channel estimation, its expression is

$$x^* = \max(\mathbf{x}) \tag{4}$$

The LSTM networks are used to predict the data. One of the LSTM networks is used for forward data prediction and another LSTM network is used for reverse prediction. Each LSTM network is composed of several LSTM units. Each unit is composed of the input gate, forget gate, output gate and memory unit. This paper uses the bi-direction RNN based on the current channel information not only related to the previous moment but also related to the latter moment, which can overcome the error propagation caused

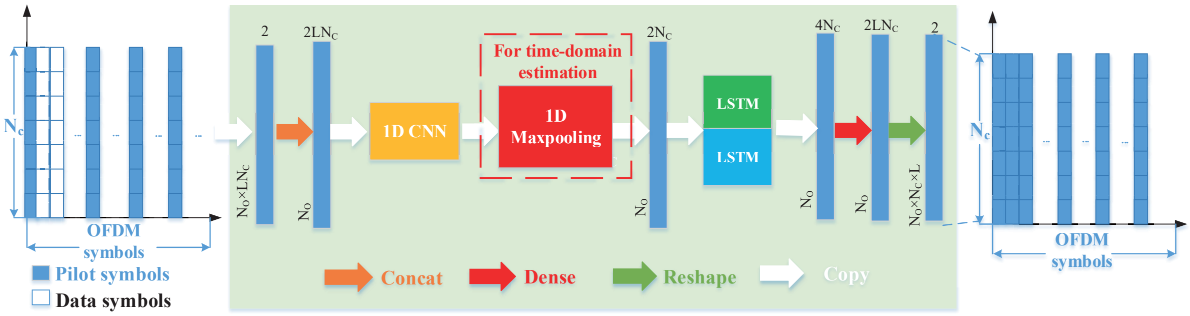

Fig. 4. Data flow of learning network. The N_c, N_o and L are the number of the subcarriers, OFDM symbols and multi-path, respectively. In the frequency-domain channel estimation, L is set as 1.

by one-way prediction. The prediction precision is improved through forward and backward prediction. The mathematic description of the LSTM structure is shown as

$$\mathbf{i}^{(t)} = \sigma\left(\mathbf{b}_i + \mathbf{U}_i x^{(t)} + \mathbf{W}_i \mathbf{h}^{(t-1)}\right) \tag{5}$$

$$\mathbf{f}^{(t)} = \sigma\left(\mathbf{b}_f + \mathbf{U}_f \mathbf{x}^{(t)} + \mathbf{W}_f \mathbf{h}^{(t-1)}\right) \tag{6}$$

$$\mathbf{c}^{(t)} = \mathbf{f}^{(t)} \odot \mathbf{c}^{(t-1)} + \mathbf{i}^{(t)} \odot \sigma\left(\mathbf{b}_c + \mathbf{U}_c \mathbf{x}^{(t)} + \mathbf{W}_c \mathbf{h}^{(t-1)}\right) \tag{7}$$

$$\mathbf{o}^{(t)} = \sigma\left(\mathbf{b}_o + \mathbf{U}_o \mathbf{x}^{(t)} + \mathbf{W}_o \mathbf{h}^{(t-1)}\right) \tag{8}$$

$$\mathbf{h}^{(t)} = tanh\left(\mathbf{c}^{(t)}\right) \odot \mathbf{o}^{(t)} \tag{9}$$

where $\mathbf{i}^{(t)}$, $\mathbf{f}^{(t)}$, $\mathbf{o}^{(t)}$, $\mathbf{c}^{(t)}$ and $\mathbf{h}^{(t)}$ are the input gate, forget gate, output gate, memory unit and hidden tier vector, respectively. $\mathbf{U}_i$, $\mathbf{W}_i$, $\mathbf{U}_f$, $\mathbf{W}_f$, $\mathbf{U}_c$, $\mathbf{W}_c$, $\mathbf{U}_o$ and $\mathbf{W}_o \in R^{d\times d}$ are the weight matrix of LSTM, $\mathbf{b}_i$, $\mathbf{b}_f$, $\mathbf{b}_c$ and $\mathbf{b}_o \in R^d$ are the offset of LSTM. The weights and offsets are learned by training, σ is the sigmoid function, $tanh$ is the double tangent activation function, $\odot$ is the element multiply and d is the input sequence dimension, which is the number of OFDM subcarriers in this paper, t is the number of input sequences, which is the number of OFDM symbols, in another word, it is the number of LSTM units.

The update equation of each LSTM unit can be simplified as (10)

$$\mathbf{h}_t = LSTM\left(\mathbf{h}_{t-1}, \mathbf{x}_t, \mathbf{\Theta}\right) \tag{10}$$

where $LSTM\left(\cdot\right)$ is the combination of (5)-(9) and $\mathbf{\Theta}$ is all parameters of the LSTM network.

B. Data Flow In ChanEstNet

The input data of *ChanEstNet* will vary for different estimation method. Its data flow is shown in Fig. 4, where the N_c, N_o and L are the number of the subcarriers, OFDM symbols and multi-path, respectively. In the frequency-domain channel estimation, L is set as 1.

In particular, original data will be pre-processed at first because the LSTM network requires time sequences as input data, so we extract the real part and imaginary part of the input data as the third dimension and the real part and the imaginary are synthesized as a dimension as the input data of the 1D CNN network. The frequency feature vector is extracted through the convolution network and this feature vector is fed to the bi-direction LSTM network. The LSTM network can predict the frequency vector at the data symbol. Finally, the channel estimation vector is outputted through the fully connected layer. For the time-domain channel estimation, the CIR is directly estimated. Therefore, the original data includes an additional time delay dimension compared to the frequency-domain channel. Unlike the frequency-domain estimation, a 1D Maxpooling layer is added to compress the estimation parameters. The following part introduces the input data, extraction of the frequency feature value and channel estimation in details.

(1) Input data. The input data of the learning network is CRM at the pilot symbols, which can be obtained through the pilot estimation based on LS. The input data is expressed as

$$\mathbf{H}_P = \left[\mathbf{h}_p^{(1)}, 0, \cdots, \mathbf{h}_p^{(5)}, 0 \cdots, \mathbf{h}_p^{(8)}, 0 \cdots, \mathbf{h}_p^{(12)}, 0, 0\right]^T \tag{11}$$

where $\mathbf{h}_p^{(t)} \in R^{N_c\times L}$ is the CSI at the pilot and $\mathbf{H}_P \in R^{N_c\times L\times N_o}$, the CSI is set as 0 at the data symbols. The channel data is the complex number, so the data shall be pre-processed before the learning network is inputted. The real part and imaginary part of the channel data are extracted as the third dimension and the real part and imaginary part are combined, so the input data is changed as $\tilde{\mathbf{H}}_P \in R^{N_o\times 2LN_c}$ and $\tilde{\mathbf{h}}_p^{(t)} \in R^{1\times 2LN_c}$.

(2) Extraction of frequency feature vector. The input data is pre-processed and sent to the 1D CNN network. The main task of CNN is to extract and select the frequency feature vector.

Generally a CNN is composed of multiple convolutional filters. Each filter can handle data in different time sequences and calculate the convolutional sum of the frequency data through the sliding window, the size of the sliding window is the size of the filter. Based on (3), the signal output after 1D CNN is

$$\hat{\mathbf{h}}_p^{(t)} = f\left(\tilde{\mathbf{h}}_p^{(t)} * \mathbf{w}_{i,t} + \mathbf{b}_{i,t}\right) \tag{12}$$

where $\mathbf{b}_i$ is the offset, $\mathbf{w}_i$ is the weight and f is the activation function.

After data are processed by the convolutional network, the output dimensions do not change, namely $\hat{\mathbf{h}}_p^{(t)} \in R^{1\times 2N_c}$. In particular, for time-domain estimation, the output of the CNN will be reduced by maxplooing, and its output is $\mathbf{H}_P^{*} = \left[\hat{\mathbf{h}}_p^{*(1)}, 0, \cdots, \hat{\mathbf{h}}_p^{*(5)}, 0 \cdots, \hat{\mathbf{h}}_p^{*(8)}, 0 \cdots, \hat{\mathbf{h}}_p^{*(12)}, 0, 0\right]^T$.

(3) Channel estimation. Our mentioned learning network

aims to predict the current channel information based on the past and current feedback and future data. Considering the LSTM network is excellent in learning of the sequence task, so the LSTM network is used to predict the current channel information in this paper, because it can facilitate learning of long-term dependence.

Based on (10), we can get the channel prediction sequence as

$$\mathbf{h}_{ST1}^{(t)} = LSTM\left(\mathbf{h}_{ST1}^{(t-1)}, \hat{\mathbf{h}}_p^{*(t)}, \mathbf{\Theta}_1\right) \tag{13}$$

$$\mathbf{h}_{ST2}^{(t)} = LSTM\left(\mathbf{h}_{ST2}^{(t-1)}, \hat{\mathbf{h}}_p^{*\dagger(t)}, \mathbf{\Theta}_2\right) \tag{14}$$

$$\mathbf{h}_{ST}^{(t)} = Concat\left(\mathbf{h}_{ST1}^{(t)}, \mathbf{h}_{ST2}^{(t)}\right) \tag{15}$$

where $\mathbf{h}_{ST1}^{(t)}$ and $\mathbf{h}_{ST2}^{(t)}$ are the output of two LSTM network, $\mathbf{h}_{ST}^{(t)}$ is the output of bi-direction LSTM network, $\hat{\mathbf{h}}_p^{*(t)}$ and $\hat{\mathbf{h}}_p^{*\dagger(t)}$ are the forward input and backward input of the LSTM network, $Concat\left(\cdot\right)$ is the function which can combine two vectors by specified dimensions.

The fully connected network is used to reduce output dimensions of the LSTM network. It is expressed as

$$\mathbf{h}_{f}^{(t)} = linear(\mathbf{W}_{f,t}\mathbf{h}_{ST}^{(t)} + \mathbf{b}_{f,t}) \tag{16}$$

where $\mathbf{W}_{f,t}$ and $\mathbf{b}_{f,t}$ are the weight and offset of the full connection layer, so the predicted loss of our model is described as

$$loss = \frac{1}{T}\sum_{t=0}^{T}\left(\mathbf{h}_{f}^{(t)} - \mathbf{h}^{(t)}\right)^2 \tag{17}$$

C. The Algorithm Flow For ChanEstNet

The signal processing flows of the *ChanEstNet* is summarized as the algorithm 1.

Algorithm 1 *ChanEstNet*

Input: CSI at the pilot $\mathbf{H}_{\mathrm{P}}$;
Output: Estimated values of CSI $\hat{\mathbf{H}}$;
Step 1: Initialization of CSI at the pilot, estimated by LS estimation;
Step 2: Pre-process the input data, combine the real part and imaginary part by using the $Concat$ function and represent it with $\tilde{\mathbf{H}}_P$;
Step 3: After the data is pre-processed, the data is inputted to the 1D CNN layer to extract the frequency-domain feature values. The output of the convolution layer is $\hat{\mathbf{H}}_P = f\left(\tilde{\mathbf{H}}_P * \mathbf{w} + \mathbf{b}\right)$;
Step 4: For time-domain channel estimation, the output of 1D CNN will reduce the dimension of the estimated parameters by 1D Maxpooling, and its output is $\mathbf{H}_P^* = \max\left(\hat{\mathbf{H}}_P\right)$. For frequency-domain channel estimation, $\mathbf{H}_P^* = \hat{\mathbf{H}}_P$ and jump to Step 5;
Step 5: The output of the convolution layer or max-poling layer is used as the input of the bi-directional LSTM network. The CSI at the data symbols is estimated by the LSTM network. Each LSTM's outputs are $\tilde{\mathbf{H}}_{st1}^{(t)} = LSTM\left(\tilde{\mathbf{H}}_{st1}^{(t-1)}, \hat{\mathbf{H}}_P^{*(t)}, \mathbf{\Theta}_1\right)$ and $\tilde{\mathbf{H}}_{st2}^{(t)} = LSTM\left(\tilde{\mathbf{H}}_{st2}^{(t-1)}, \hat{\mathbf{H}}_P^{*\dagger(t)}, \mathbf{\Theta}_2\right)$, the total network output is $\tilde{\mathbf{H}} = Concat\left(\tilde{\mathbf{H}}_{st1}, \tilde{\mathbf{H}}_{st2}\right)$;
Step 6: The output dimensions of the bi-direction LSTM network is reduced by the fully connected layer. The real part and imaginary part of the channels can be obtained via $Reshape$ function, and the real part and imaginary part are added to get the final output $\hat{\mathbf{H}}$.

IV. Complexity Analysis

Table I shows the comparison of the computational complexity (the number of times) for several classical channel estimation methods, similar channel estimation methods and the proposed *F-ChanEstNet* method and *T-ChanEstNet* method in an OFDM symbol, where the *F-ChanEstNet* and *T-ChanEstNet* are the frequency-domain estimation and time-domain estimation, respectively,where the Q is the dimensions of BEM base vector. Q is set as 16 in [6].

TABLE I: Comparison of computational complexity.

Algorithms	Complexity
LS	N
LMMSE	N^2
F-ChanEstNet	N
T-ChanEstNet	NL
BEM-based LS	$2(QL)^3$
BEM-based EKF	$7(QL)^3 + 5(QL)^2$
BEM-based EKF-RTSS	$14(QL)^3 + 7(QL)^2$

The LS, LMMSE and *F-ChanEstNet* are the frequency-domain channel estimation methods in the table I and have lower complexities. The *T-ChanEstNet*, BEM-based LS, BEM-based EKF and BEM-based EKF-RTSS are the time-domain channel estimation. The BEM-based LS method could consider the ICI, but since the measurement matrix is not a diagonal matrix as traditional LS method, which would increase the complexity of matrix inversing. For the BEM-based EKF and BEM-based EKF-RTSS algorithm, the EKF is used to estimate channel response. Complexity is very high due to some matrix inversion operations. For proposed algorithm in this paper, the channel is estimated via the non-linear mapping, so the complexity is low.

V. Analysis On Simulation Results

In this section, we will evaluate the performance of time-domain channel estimation and frequency-domain channel estimation of the proposed methods in different environment. We use the high-speed channel model WINNER-II D2a [13] with fast time-varying and non-stationary features. The MATLAB and Python simulation platform are used for simulation analysis of the mentioned methods. The training, validation, and testing sets contain 10000, 2000, and 1000 samples, respectively, and are obtained from the WINNER-II D2a channel model [13]. The parameters of simulation system are shown in Table II.

A. Normalized Mean Square Error

The Fig. 5 compares normalized mean squared error (NMSE) performance of the frequency-domain estimation LS

TABLE II: Parameters of simulation system.

Parameters	Value
Frequency of carrier	2.8GHz
Bandwidth	5MHz
Number of subcarriers	300
Length of FFT	512
Length of CP	36
Modulation	QPSK
Non-stationary channel	WINNER-II D2a [13]

[4] method, LMMSE [3] method and the proposed frequency-domain estimation *F-ChanEstNet* method, The Fig. 6 compares the time-domain estimation BEM-based LS method [5], BEM-based EKF [6] method, BEM-based EKF-RTSS [6] method and the proposed time-domain estimation *T-ChanEstNet* method in different speed environment.

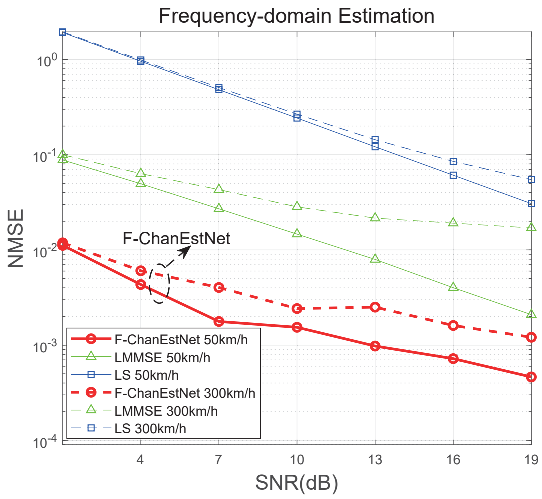

Fig. 5. NMSE comparison of frequency-domain estimation method.

The simulation results show that NMSE of three frequency-domain methods are very different. When the speed is 50km/h, the signal-to-noise ratio (SNR) gain of the LMMSE is about 16dB higher than that of LS and the SNR gain of the *F-ChanEstNet* is about 9dB higher than that of LMMSE. This is because the LS algorithm is simpler than LMMSE algorithm, the estimation error is higher due to ignoring noise, the LMMSE can improve estimation precision by using the channel statistics information. At a speed of 300 km/h, the NMSE of the three methods is on an upward trend compared to 50 km/h, and the SNR gain of LMMSE methods to LS method is 5dB averagely. At this time, the SNR gain difference between of *F-ChanEstNet* and LMMSE is large, the main reason is that the hypothesis of linear interpolation that the change of CIR is linear is not applicable for high speed channel. The proposed method first learns the characteristics of channel variation through training, and then estimates the response at the data symbol through nonlinear mapping, so it is more suitable for high-speed scenario and is also excellent in a low-speed environment.

For time-domain estimation, the NMSE performance of various methods is very close at different speeds. Since the

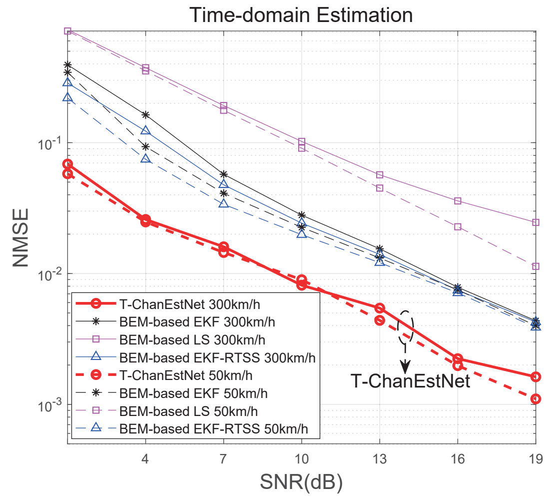

Fig. 6. NMSE comparison of time-domain estimation method.

time-domain estimation estimates the channel gain for each path, so the ICI caused by the Doppler shift can be estimated. The Fig. 6 shows that the NMSE of BEM-based EKF and BEM-based EKF-RTSS is approximate and its SNR gain is about 3.5dB higher than that of BEM-based LS and the SNR gain of *T-ChanEstNet* is 4dB higher than that of BEM-based LS, because the CIR linear change theory is not suitable for high-speed channel. Although the BEM-based EKF and BEM-based EKF-RTSS methods are similar to *T-ChanEstNet* at this time, the estimation time is too long due to higher complexity. Therefore, the proposed method can also have higher performance in time-domain estimation.

In a word, the non-linear mapping estimation method in this paper shows higher NMSE performance both in time-domain estimation and frequency-domain estimation. For the low-speed scenarios, the SNR gain of the proposed method will gradually reduce with the increase of SNR. For a high-speed scenarios, the proposed method features excellent NMSE performance.

B. Bit Error Rate

The bit error rate (BER) performance is the macro index to measure the influences of the channel estimation method on the whole system performance. The Fig. 7 and Fig. 8 compare the BER performance of different algorithms at speeds of 50km/h and 300km/h.

For the frequency-domain channel estimation, it can be seen from Fig. 7 that at 50 km/h, the LMMSE algorithm has about 4.5dB SNR gain to the LS algorithm, the BER performance of *F-ChanEstNet* algorithm and LMMSE algorithm is equivalent at a low SNR (SNR$\leq$10dB) and *F-ChanEstNet* algorithm has about 6dB SNR gain compared to LS algorithm. However, in the case of high SNR (SNR$>$10dB), the BER of *F-ChanEstNet* method decreases rapidly and its BER performance is significantly superior to that of LMSE algorithm. At 300 km/h, the LMMSE algorithm has an SNR gain of about 4 dB to the LS algorithm. Similarly, at a low SNR, The *F-ChanEstNet* method has the same BER performance as the LMMSE algorithm, and has an SNR gain

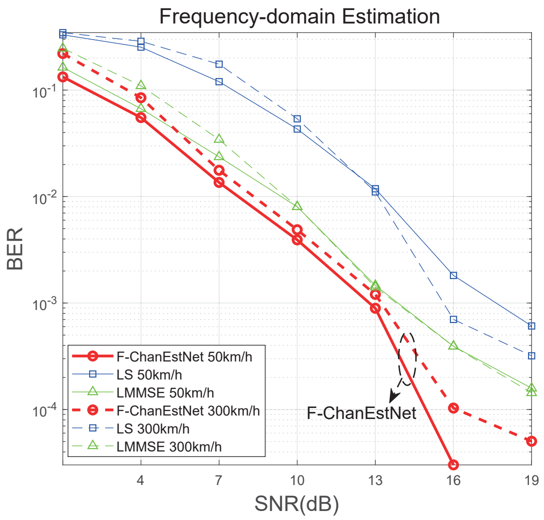

Fig. 7. BER comparison of frequency-domain channel method.

about 5dB to LS. In the case of high SNR, the *F-ChanEstNet* method has about 4dB SNR gain to LMMSE algorithm.

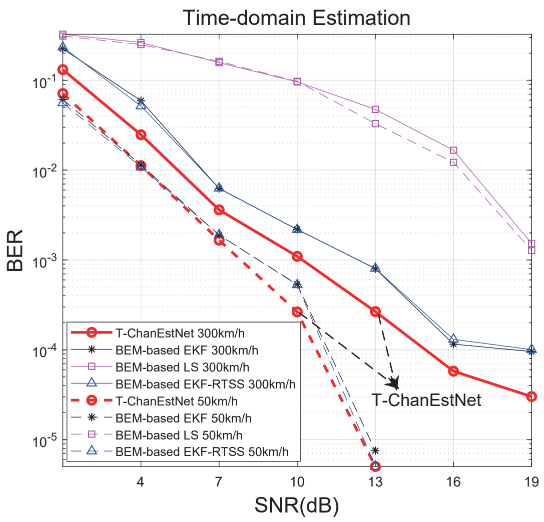

Fig. 8. BER comparison of time-domain estimation method.

For the time-domain estimation, as shown in Fig. 8, the BER performance of *T-ChanEstNet* are equivalent to that of BEM-based EKF method and BEM-based EKF-RTSS method at 50km/h, but the its BER performance is significantly superior to that of BEM-based LS method, because the CIR change tends to be stationary in a low-speed environment and BEM-based EKF and BEM-based EKF-RTSS algorithms are also suitable well, but the estimation algorithm of the LS method is too simple, so the BER performance is not better. The BER performance of different channel estimation methods will tend to converge with the growth of SNR at 300km/h due to influences of the channel environment. The BER performance of BEM-based EKF and BEM-based EKF-RTSS algorithm are nearly overlapped, its SNR gain is about 6.5dB to BEM-based LS, at this time, the SNR gain of the *T-ChanEstNet* algorithm is about 2dB compared to BEM-based EKF and BEM-based EKF-RTSS algorithm and its SNR gain reaches about 9.5dB to BEM-based LS algorithm.

Overall, the BER performance of the proposed method is superior to that of other algorithms both in the frequency-domain estimation and time-domain estimation at a high-speed scenarios, which reflects the overall performance that is more adaptive to high-speed scenarios.

VI. Conclusions

In the paper, for the weakness of the traditional channel methods in a high-speed scenarios, a channel estimation method based on deep learning is proposed. The nonlinear mapping characteristics of deep learning can better adapt to the changing characteristics of high-speed channels, and the channel information in the offline training sample can be effectively used to improve the accuracy of channel estimation. Finally the performoance of the *ChanEstNet* method is analyzed in a high-speed scenarios through simulation comparison of the time-domain estimation and frequency-domain estimation. The simulation results show that in the case of low estimation complexity, the channel estimateion precision and whole system performance of the *ChanEstNet* method is both superior to that of the traditional methods.

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