



Research article

Bi-LSTM based deep learning method for 5G signal detection and channel estimation

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Abstract: The advanced neural network methods solve significant signal estimation and channel characterization difficulties in the next-generation 5G wireless communication systems. The number of transmitted signal copies received through multiple paths at the receiver leads to delay spread, which in turn causes interference in communication. These adverse effects of the interference can be mitigated with the orthogonal frequency division modulation (OFDM) technique. Furthermore, the proper signal detection methods optimal channel estimation enhances the performance of the multicarrier wireless communication system. In this paper, bi-directional long short-term memory (Bi-LSTM) based deep learning method is implemented to estimate the channel in different multipath scenarios. The impact of the pilots and cyclic prefix on the performance of Bi LSTM algorithm is analyzed. It is evident from the symbol-error rate (SER) results that the Bi-LSTM algorithm performs better than the state of art channel estimation methods known as the Minimum Mean Square and Error (MMSE) estimation method.

Keywords: deep learning; LSTM; Bi-LSTM; OFDM; channel estimation

1. Introduction

The next-generation 5G wireless communication provides very high data rates, ultra-low latency, increased capacity, improved quality of service (QoS) for current wireless networks applications [1]. In the wireless communication system, multipath delay spread and Doppler shift cause frequency

selective fading in the channel. The modeling of the time-varying wireless channel is crucial in 5G wireless communication systems [2]. The implementation of OFDM makes the complex equalization and decoding much simple by transforming the frequency-dependent fading channels into a form of frequency-independent fading channels [3]. The OFDM technique is capable of mitigating intersymbol interference and enhances the capacity [4]. Hani et al [5,6] successfully demonstrated that switchable dual-wavelength fiber laser is an effective millimeter wave signal source for 5G wireless communication and diverse 5G-supported microwave-photonic systems. The conventional Least Square (LS) estimation method requires no statistical information of the channel. The MMSE method results in better performance by utilizing statistical Information [7]. The performance of 5G wireless communication systems in different scenarios is degraded due to imperfections and nonlinearities. The mathematical modeling of 5G wireless channels is challenging. Deep neural networks (DNN) are promising machine learning methods to model the 5G wireless channel characteristics. The DNN based methods do not require a mathematically tractable model and optimization becomes simple for such imperfections. The prediction process of loss estimation in the varying wireless channel is a regression problem [8]. To detect/predict the time series events with time lags of variable size are studied with the LSTM type deep learning architecture [9]. A Bidirectional LSTM is implemented to rectify the issues in the LSTM. The model is trained using input data sequences in the past and future of a specific time frame [10]. The LSTM based neural network is trained to estimate the channel [11]. The neural network method is implemented and found that NN model is performed better than conventional LS and MMSE estimation methods, particularly at a lower Number of the pilot and omitting the cyclic prefix. Le et al [12] demonstrated that Bi-LSTM algorithm performance is better in reduction of channel estimation error and the bit error ratio in a MIMO-OFDM system with different scenarios of fading multi-path channel models based on the Tapped delay line type C model defined in the 5G networks. This paper implements the Bi- LSTM channel estimation method and obtains much better SER performance at the fewer pilot symbols and omits the cyclic prefix for in single out (SISO) wireless communication system.

2. The Mathematical model for Bi LSTM

We have considered a typical single in single out (SISO) wireless communication system. The distorted transmitted signal at the receiver input is represented as

$$y = \mathbf{H}x + n, \quad (1)$$

where n is additive white Gaussian noise (AWGN), \mathbf{H} is the channel impulse response. We proposed a Bi LSTM based framework to estimate the channel. The simplest linear deep learning model $f(\mathbf{u}, \mathbf{w}) = \sum_{i=1}^n u_i w_i$ where $\{u_1, u_2, \dots, u_n\}$ are set of n inputs to the model, \mathbf{w} and $f(\cdot)$ represent the weights and output of the network, respectively. The LSTM architecture is shown in Figure 1. The gate structure is considered to add or remove the information from the cell state. It has an input gate, forget gate, and output gate.

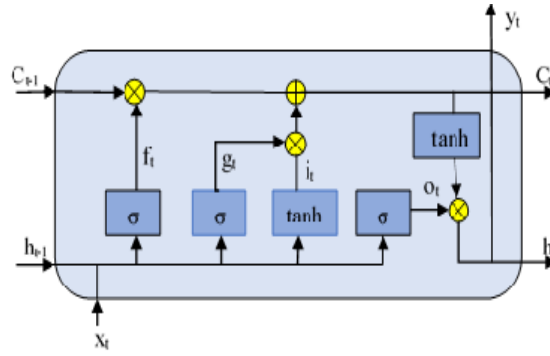


Figure 1. LSTM block diagram.

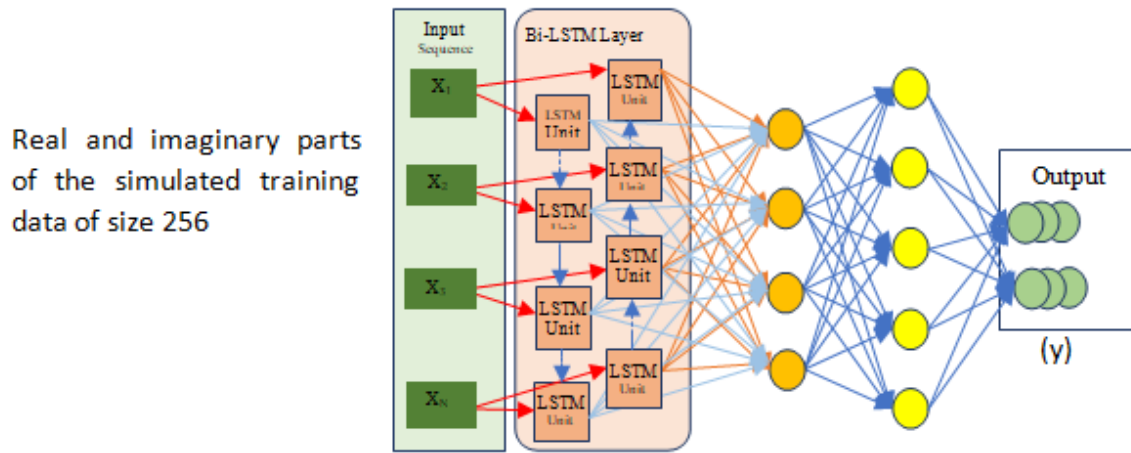


Figure 2. Bidirectional LSTM architecture.

Bidirectional Long Short-Term Memory architecture consists of two LSTM layers side by side, as shown in Figure 2. One layer of LSTM is trained with the input sequence in the forward direction. The input sequence is provided in reverse order for training another LSTM layer in the backward direction. The input sequence of size 256 is used to train the model in both directions. These input sequences have the real and imaginary parts of the simulated training data. We have provided the input sequence of size 256 as-is as input to the one layer and provided a reversed copy of the input sequence to the next layer.

The LSTM neural network is considered to rectify the vanishing gradient issue in RNNs for long sequence data. The LSTM four gates can be represented as,

$$f_t = \sigma(W_f x_t + R_f h_{t-1} + b_f), \quad (2)$$

$$g_t = \tanh(W_g x_t + R_g h_{t-1} + b_g), \quad (3)$$

$$i_t = \sigma(W_i x_t + R_o h_{t-1} + b_i), \quad (4)$$

$$o_t = \sigma(W_o x_t + R_o h_{t-1} + b_o), \quad (5)$$

where R_f, R_g, R_i, R_o denotes the weights matrices for the previous short-term state h_{t-1} . $W_f, W_g, W_i,$

W_o are the weight matrices in the current input state x_t , and b_f , b_g , b_i , and b_o are the bias terms.

The current long-term state of the network c_t can be calculated by

$$c_t = f_t \otimes c_{t-1} + i_t \otimes g_t, \quad (6)$$

And the output y_t of the network is

$$y_t = h_t = o_t \otimes \tanh(c_t). \quad (7)$$

where, c_{t-1} represents the previous long-term state.

Thus, the current output depends on the current long-term state, current input, and the previous short-term state.

Algorithm: Bi-LSTM based DNN training algorithm for channel estimation.

Input: the training data, i.e., generated using simulation, transmitted signal vector x —output: Bi-LSTM based DNN.

- 1: Start simulation to generate a wireless channel, and mix noise or distortion into the channel.
- 2: The training sequences are generated, and every OFDM symbol consists of a specified number of pilots and data symbols.
- 3: Design the proposed Bi-LSTM based DNN framework. Also, set the appropriate learning rate and the loss rate, and set the error threshold as $\gamma = 10^{-6}$.
- 4: while error $\geq \gamma$: Train the BiLSTM based with given input sequences according to the learning by ADAM optimization.
- 5: The weights of the training network are replaced with update values, and the output of each layer of the BiLSTM based DNN.
- 6: end while
- 7: return: BiLSTM based DNN.

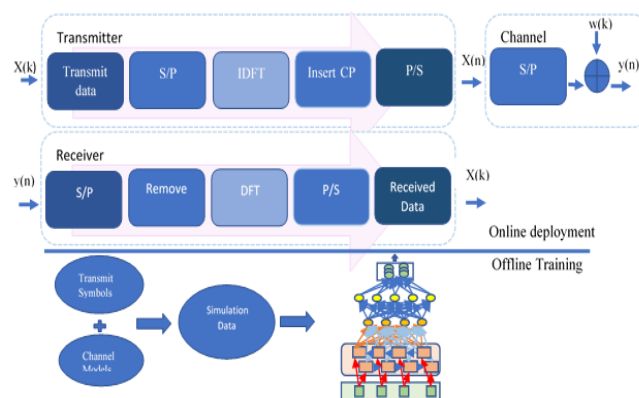


Figure 3. Architecture of OFDM system with Bi LSTM.

Figure 3 illustrates the architecture of the OFDM system with BiLSTM based signal detection and channel estimation. The transmitted data is converted into a parallel stream, and the frequency domain signal is transformed to the time domain by inverse discrete Fourier transform (IDFT). The CP is inserted to mitigate the inter-symbol interference of the signals. The training data is generated

by simulating channel models with transmitted symbols. The Proposed Bi LSTM model consists of one input layer, three hidden layers, and a single output layer. The size of the input layer is 256, and the output layer is 4. The input layer's size equals the sum of real and imaginary parts of the 2 OFDM blocks. Each OFDM block contains transmitted symbols and pilots. In this research work, we have demonstrated the performance of the Bi-LSTM learning method for the detection of signal and the channel estimation in OFDM wireless communication systems. The training data is generated by transmitting the OFDM frames through existing channel models. The required training data contains the received OFDM signal, which is distorted by current channel characteristics and noise and the original transmitted data. An LSTM and Bi-LSTM models are trained with the simulated data in offline. In this paper, offline training is considered for the channel state information of different environments from simulations. However, offline training has a constraint due to the complexity of the back-propagation process. In the deployment phase, the signals are detected with the already obtained channel estimations. The results indicated that the Bi-LSTM method is performed better than the traditional wireless channel estimation methods in terms of the symbol error rates (SERs) under different symbol energy to noise ratios ($\frac{E_s}{N_o}$). The LSTM and Bi-LSTM deep learning-based approaches are robust than LS and MMSE methods. The algorithms are tested under different scenario cases, where fewer training pilot symbols and no cyclic prefix is used. A 64 subcarriers OFDM wireless communication system with the CP of length 16 symbols is considered, maximum delay 16 sampling period with 24 paths is considered. The typical urban scenario, where multipath channels with maximum delay are equal to 16 sampling time intervals and the maximum number of paths equals to 24. The M-ary PSK of order 4 is selected as the modulation method.

3. Results

3.1. Performance analysis with number of pilots

The proposed Bi-LSTM method is compared with LS, MMSE, LSTM, Bi LSTM algorithms for channel estimation and detection, when 64 pilots and without CP (Figure 4). It is observed that the LS method has the worst performance when compared to all other algorithms. The LS 64 pilots method doesn't consider the statistical knowledge of the wireless channel, whereas MMSE considers the second-order statistics of the channel. It is noted that MMSE algorithm performance is better than the LS algorithm. The SER of Bi LSTM model is the lowest value ($10^{-2.5}$) reached at 20dB of E_s/N_0 than the LSTM, MMSE, and the LS methods without CP (Figure 4).

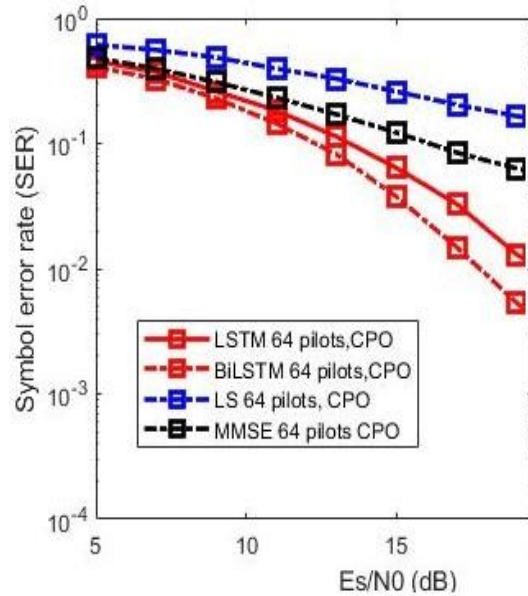


Figure 4. SER results without Cyclic prefix.

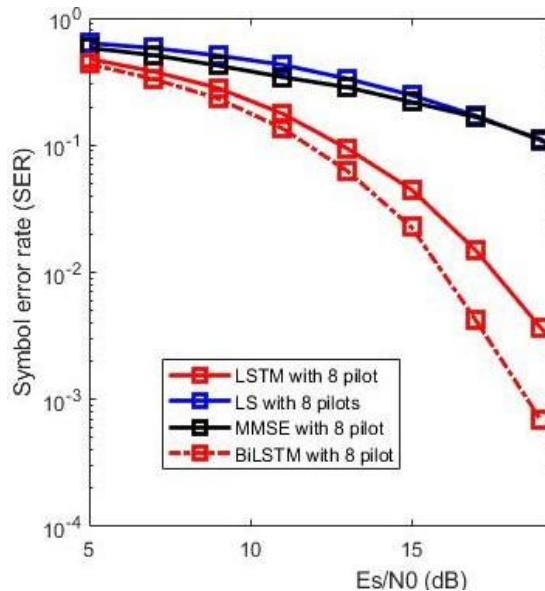


Figure 5. SER results with 8-pilots.

The multipath simulation scenario with the maximum delay in the multipath channel is 16 sampling periods, and very few pilots (8 pilots) is considered to evaluate the spectral efficiency of the proposed Bi-LSTM method. The SER curve of the LS and MMSE estimation methods saturates at lower values of SER at 15 dB of E_s/N_0 (Figure 5). The LSTM and Bi LSTM model shows SER reduction as E_s/N_0 increases. The Bi-LSTM model performed better than the LSTM model with 8 pilots and learned the characteristics of the wireless channel.

3.2. Performance analysis with cyclic prefix

The CP converts the process of linear convolution into circular convolution and mitigates ISI. However, it reduces the spectral efficiency. The impact of the CP on the channel estimation efficiency of the OFDM wireless communication system is analyzed and shown in Figure 6. The

simulation scenario of 8 pilots and omitting the cyclic prefix is considered to evaluate the SER performance of the Bi-LSTM model. The LSTM and Bi-LSTM deep learning models outperformed as compared to traditional LS and MMSE estimation methods. The Bi-LSTM SER reached minimum values of 10^{-3} at 20 dB of E_s/N_0 , indicating the robustness of SER reduction (Figure 6).

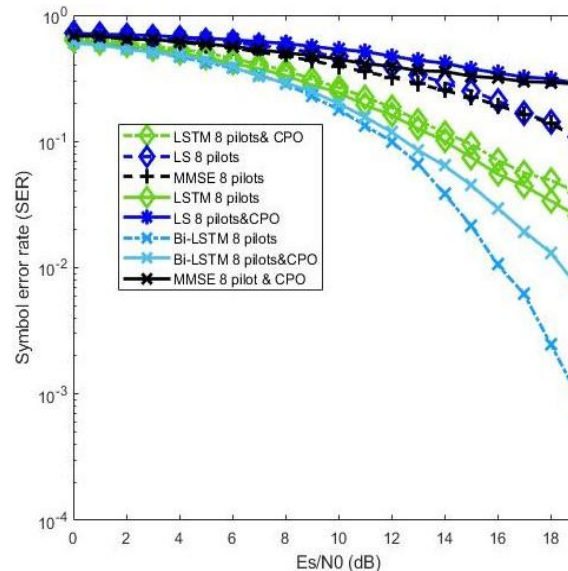


Figure 6. SER results with few pilots and without cyclic prefix.

4. Conclusions

We have demonstrated the LSTM and Bi-LSTM deep learning methods to detect and OFDM signal and channel estimation. The deep learning model is trained in offline mode with simulated data with the help of the wireless channel models. The results indicate that the Bi-LSTM method has better learning ability and performs better than the traditional Least square estimation and MMSE methods. Furthermore, the Bi-LSTM are trained in both forward and backward directions of the input data; hence the model performs better than the traditional methods and the LSTM. Furthermore, the Bi LSTM model can effectively remember and analyze the distorted wireless channel with a smaller number of pilots s and without the CP Even. Therefore, the performance of the Bi-LSTM based estimation is better in reducing SER than the LSTM, LS, and MMSE methods. The deep learning models are potential candidates for channel modeling for 5G and beyond wireless communication systems.

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Conflict of interest

The authors declare that there is no conflict of interest.

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