Intelligent Reflective Surface Assisted Wireless Communication BER Estimation LSTM vs BiLSTM

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Abstract

Intelligent reflective surfaces (IRS) are used in wireless communication to direct the electromagnetic wave towards the user. This technique can help to reduce noise in the communication system and improve the user experience. However, the channel estimation technique is very hard due to the number of elements that makes the mathematical model complex. Machine learning approaches are very useful tools to make channel estimation for IRS-based system. In this study, we compare the performance of long short-term memory (LSTM) and BiLSTM for IRS-based wireless communication system. The simulations results show that BiLSTM has better bit error rate performance as compared to LSTM technique.

Ⅰ. Introduction

Intelligent reflective surface (IRS) is a meta-surface filled with a large number of low-cost passive elements operated by a smart controller to adjusting the amplitude or phase of the reflected signal [1]. IRS is considered as a potential technique to mitigate the challenges of sixth generation (6G) mobile communications [2]. However, because of the prohibitive pilot overhead, acquiring channel state information (CSI) is a difficult operation in IRS-assisted massive multiple-input multiple-output (MIMO) systems due to the high-dimensional channel of IRS links and the passive feature of IRS. It is also very challenging task to make analytical model and make optimization approach for IRS based communication. In solution to this issue, machine learning (ML) models can be applied to estimate the channel by using data driven approach. We can use the black box approach to find the optimal solution for channel estimation problems. Different types of ML approaches are available for estimating channel of IRS based communication. In this study, we focus on recurrent neural network (RNN) as it can handle variable length input data. Two variations of RNN named long short-term memory (LSTM) and bidirectional long short-term memory (BiLSTM) are considered. We simulate wireless channels using IRS and use the collected data to train both models.

Ⅱ. System Model

In this paper, we consider multiple input single output (MISO) system to simulate IRS based wireless communication. The proposed system is visualized in Figure 1. We consider a based station (BS) having n antennas and each user (U) has single antenna. The IRS has n reflecting elements, and which can be controlled by a controller connected to the base station. From Figure 1 we can see there are two separate channels available which needs to be combined for IRS based downlink communication. First one is BS to IRS channel and the second one is IRS to U.

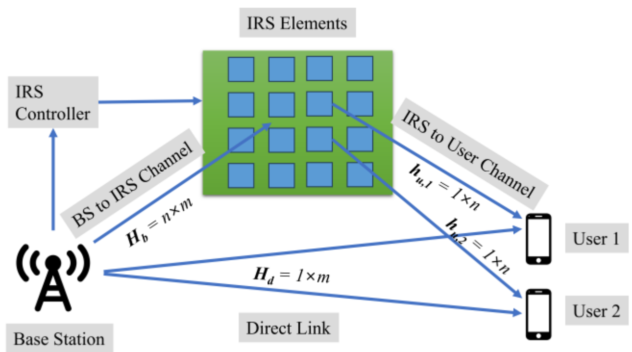

Figure 1. Proposed system illustration for IRS-based wireless communication.

The channel from BS to IRS can be expressed as follows [3]:

$$H_b = \sqrt{\frac{mn}{L_1}} \sum_{l=0}^{L_1-1} \alpha_l a_r(\phi_{r,l}, \theta_{r,l}) a_t(\phi_{t,l}) \quad (1)$$

where Hb is the channel matrix between BS to IRS, m is the number of antennas in BS, n is the number of reflecting elements, $\sqrt{\frac{mn}{L_1}}$ is the normalization factor L1 is the number of scatterers, complex gain of l scatter is αl which have zero mean and 1 standard deviation, a_r is the array response vector associated with IRS, and a_t is the array response vector associated with BS, azimuth angle of departure $\phi_{r,l}$, zenith angle of departure $\theta_{r,l}$ and $(\phi_{t,l})$ is the angle of arrival. The total channel for BS to U is expressed as:

$$H_t = H_b \Phi h_{u,i} + H_d + k_i, \qquad (2)$$

where H_t is the total channel, H_b is the channel between BS to IRS, $h_{u,i}$ is the channel IRS to i-th user, H_d is the direct channel between BS and user and k_i is the noise present in the communication channel. Using the above we generated simulation data for training. In the second part we construct LSTM and BiLSTM model to evaluate the bit error rate (BER) performance. LSTM can remember long term dependencies for series data and can forget unnecessary data. However, BiLSTM has capability of capturing feature in forward and backward direction of LSTM cell. Each technique is trained using simulated data and BER performance is evaluated.

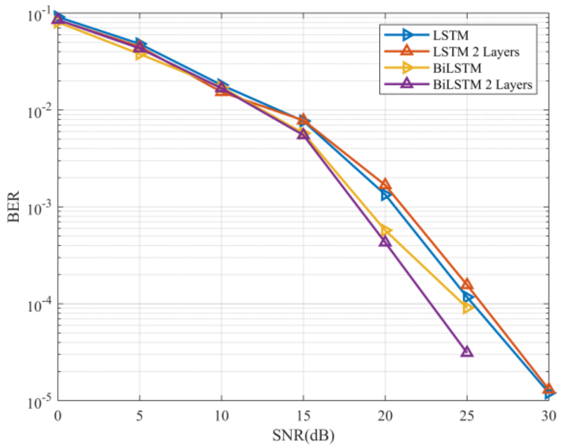

Figure 2. BER performance of LSTM and BiLSTM comparison for IRS-based communication.

Ⅲ. Experiment Results

The experiment results are described in this section. First the performance of LSTM is described for single layer and double layer is presented. Figure 2 shows the BER performance of LSTM for proposed IRS-based communication. LSTM single layer can achieve BER around 10^{-5} in 30 dB SNR value. In contrast, using two layers of LSTM has less BER performance as SNR increases. As shown in Fig. 2 the performance is similar however the BER of two-layer LSTM. LSTM with two layers is not capable of extracting features from input data. In the case of BiLSTM the performance is much better than normal LSTM as it can extract features in both directions. As we can see from Fig. 2 the single BiLSTM layer shows better performance as compared to LSTM after 15 dB SNR. Again, two-layer BiLSTM has better performance as compared to single layer BiLSTM. Which indicates that increasing the layer number can extract data features more efficiently.

IV. Conclusion

In this paper we simulate the IRS-based wireless communication system and used ML techniques to estimate BER performance. We used two RNN approaches LSTM and BiLSTM and compared the result against the BER. The experiment results shows that BILSTM can provide better BER performance as compared to LSTM. Also, by increasing one more layer in BiLSTM can reduce BER for IRS-based communication.

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