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Research on air interface performance based on AI

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Abstract: with the continuous development of artificial intelligence, the excellent nonlinear processing ability of deep neural network shows important application potential in wireless air interface, which is of great significance to the research of 6G technology. As the wireless environment becomes more and more complex, the performance of traditional wireless air interface is more and more unable to meet. How to improve the performance of wireless air interface has become an important issue. In this paper, an enhancement method based on deep neural network is proposed for CSI prediction, channel estimation and polar code decoding, and its performance is verified by simulation.

Key words: deep learning; CSI forecast; Channel estimation; Polar code

1introduction

Ai/ml air interface mainly studies CSI feedback enhancement and channel estimation based on reference signal. CSI feedback enhancement includes CSI compression, CSI prediction and CSI measurement accuracy improvement. Channel estimation based on reference signal mainly includes channel estimation based on DMRs and SRS for uplink / downlink. This paper mainly simulates CSI prediction, channel estimation based on DMRs and decoding scheme based on deep cyclic neural network, and analyzes the improvement of system performance after the introduction of AI / ml algorithm.

2 csi prediction

2.1 Basic process

GNB sends CSI reference signal periodically or aperiodically, and UE measures CSI (cqi/pmi/ri) and gives feedback on PUCCH or Pusch; Between UE measurement and UE reporting D1 The time difference of CSI transmission from UE side to GNB side on air interface will also introduce transmission delay D2, but usually smaller; When the CSI measurement report arrives at the base station side, the signaling is transmitted from the physical layer to the MAC layer, and the MAC layer schedules several time slots in advance and sends the service from the air interface. The D3 Time difference.

CSI is measured from ue to GNB, i.e D1+D2+D3 The total delay is about several milliseconds to ten milliseconds, because the CSI used in service transmission is D1+D2+D3 Previous UE measurements, while the current wireless channel environment has changed, which will affect the transmission performance of the current service.

Wireless AI technology can well reflect the nonlinear characteristics of wireless channel, which makes it possible to accurately predict the wireless channel after several milliseconds to ten milliseconds. In the AI based CSI prediction model, the measured results of historical CSIS are used as the input of CSI prediction model to predict one or more CSIS values in the future. AI based CSI prediction block diagram is shown in Figure 1 CSI prediction depth learning model is shown in Figure 2:

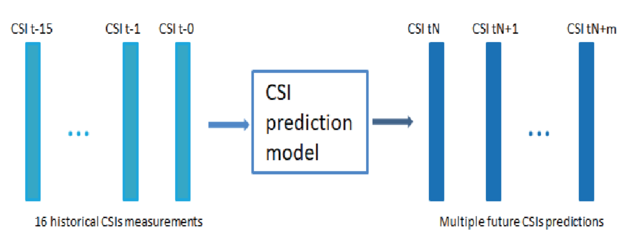

Figure 1 AI based CSI prediction block diagram

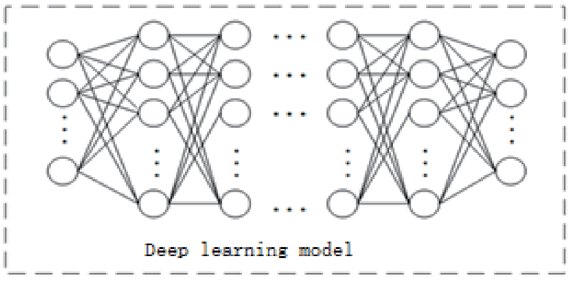

Figure 2 deep learning model diagram

2.2 Performance evaluation

We simulated the CSI prediction results of rnn and lstm neural networks, and compared them with the baseline without CSI prediction and the average CSI. The simulation data adopts the measured CQI, the feedback time interval is 10ms, and the UE moving speed is 10km / h. The number of samples is 20000, including the first 16000 samples as the training set and the last 4000 samples as the test set. During model training, 16 continuous CQIs are input and 1 CQI predictive value is output. The simulation diagrams are used separately without CQI prediction; Average the historical value of CQI as the predictive value of CQI; RNN; The four models of LSTM are compared. The accuracy of CQI ± 1 order of each model was similar; The CQI prediction accuracy of LSTM was the highest, reaching 70.8%; The CQI accuracy of the average, RNN and LSTM models were 5.1%, 10% and 13.8% higher than that of the non prediction models, respectively. The average spectral efficiency of the three models of average, RNN and LSTM increased by 6.2%, 9.1% and 10.6% respectively compared with the unpredicted.

3 Channel estimation scheme based on deep convolutional network

We first introduce a channel estimation scheme based on deep convolutional networks. In the process of Pusch transmission, the channel estimation and equalization module at the receiver can use the deep convolutional network instead of to reduce pilot overhead and bit error rate.

3.1 Deep convolution network architecture

The convolution layer of deep convolution network mainly adopts deep separable convolution, which can reduce the amount of calculation of the network. among N_c=2N_r+1 It is necessary to(N_r Is the number of receiving antennas), QM is related to the modulation order. The input data of the network is a mixture of received signal and pilot information.

3.2Performance evaluation

We simulate the performance of channel estimation based on deep convolution network, and compare it with the common MMSE algorithm. The simulation results are shown in Figure 3. The simulation performance index is measured by BER. It can be seen that with two DMRs symbols, when BER = 1e-2, the deep convolution network is about 5dB higher than MMSE, and when BER = 1e-3, the difference between the two is about 4.5db.

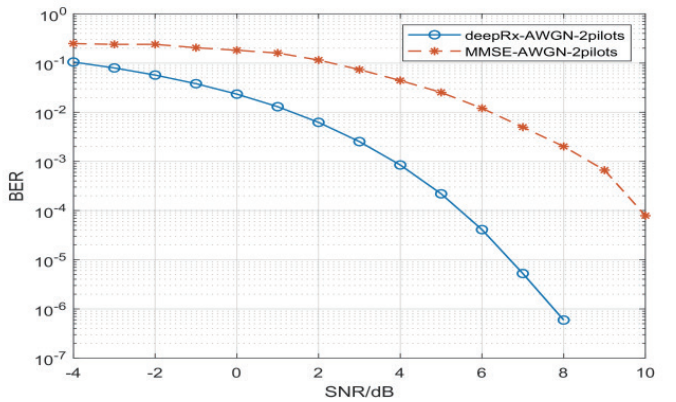

Figure 3 performance comparison diagram for two DMRs symbols

4 Decoding scheme based on deep recurrent neural network

4.1 Deep loop decoding network architecture

The deep convolution network mainly adopts the cyclic convolution network structure, and uses the pre coding signal generated by MATLAB and the signal after AWGN as the training set. The decoding network structure is shown in Figure 4. The main body of the network is LSTM.

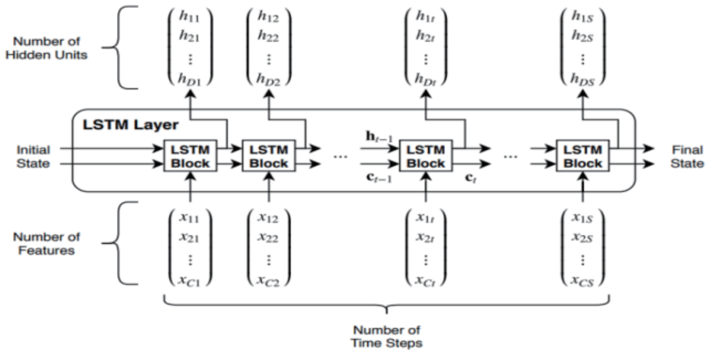

Figure 4 deep loop decoding network structure

4.2 Performance evaluation

We simulated the decoding performance of polar code based on LSTM, and compared it with the common SC algorithm.

4.3 simulation result

The simulation results are shown in Figure 5. The decoding performance of LSTM is up to 0.3dB higher than that of SC decoding.

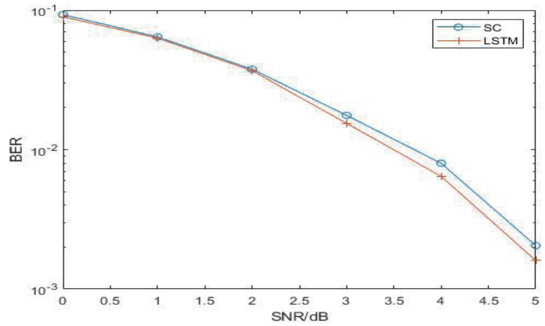

Figure 5 decoding performance comparison chart

5 summary

The AI based CSI prediction model can improve the accuracy of CSI prediction relative to the baseline. The CQI accuracy of LSTM network can be improved by 13.8% and the average spectral efficiency can be improved by 10.6%. The performance of channel estimation based on AI / ml is better than that of traditional channel estimation. When two DMRs symbols are configured, the BER is improved by about 5dB at 1e-2 and 4.5db at 1e-3. The decoding performance of polar code based on deep cyclic neural network is improved by 0.3dB at most. The subsequent work can further improve the accuracy and performance of the deep neural network, and replace the simulation conditions.

References

[1]Rp-212708New Sid on ai/ml for NR air interface, moderator (Qualcomm) [s], 3GPP TSG ran\94e, electronic meeting, 2021: 1-22

[2]W. Jiang, H. D. schottenNeural network based channel prediction and its performance in multi antenna systems[c], 2018 IEEE 88th vehicular Technology Conference (VTC fall), 2018: 1-6

[3]W. Jiang, H. D. schottenRecurrent neural network based frequency domain channel prediction for broadband communications[c]2019 IEEE 89th vehicular Technology Conference (vtc2019 spring), 2019: 1-6

[3]S. Hochreiter, J. schmidhuberLong short term memory[J]Neural computing, 1997, 9 (8): 1735-1780

[4]M. Honkala, D. korpi, J. M. J. huttunenDeeprx: fully revolutionary deep learning receiver[J]IEEE Transactions on wireless communications, 2021, 20 (6): 3925-3940

[5]M. E. morocho cayamcela, H. Lee, and w. limMachine learning for 5g/b5g mobile and wireless communications: potential, limitations, and future direction[J]IEEE access, 2019, 7 (1): 137184-137206

[6]Technical specification group radio access network; NR; Physical channels and modulation, document TS 38.211 version 16.1.0 release 16[s], 3GPP, ETSI, Sophia Antipolis Cedex, France, 2020: 1-136

[7]Z. Chang, Y. Wang, H. Li, and Z. wangComplex CNN based equalization for communication signal[c]IEEE 4th int. conf. signal image process (icsip), 2019: 513-517

[8]H. He, S. Jin, C. K. Wen, F. Gao, G. y. Li, and Z. xuModel driven deep learning for physical layer communications[c]IEEE wireless commun, 2019, 26 (5): 77 – 83

[9]F. CholletXception: deep learning with profound separable conflicts[c]IEEE conf. computeVisPattern recognizit(CVPR), 2017: 1800-1807

[10]E. ArikanChannel polarization: a method for constructing capacity achieving codes for symmetric binary input memoryless channels[J]IEEE Transactions on information theory, 2009, 55 (7): 3051-3073

[11]B. Yuan and K. K. parhiEarly stopping criteria for energy efficient low latency belief propagation polar code decoders[J]IEEE transSignal process, 2014, 62 (24): 6496-6506

[12]J. Yang, C. Zhang, H. Zhou, et al. pipelined belief propagation polar decoders[c]2016 IEEE International Symposium on circuits and systems (ISCAS), 2016: 413-416

[13]W. Xu, Z. Wu, Y. L. ueng, et al. improved polar decoder based on deep learning[c]2017 IEEE International Workshop on signal processing systems (SIPS), 2017: 1-6

[14]N. Doan, S. A. Hashemi, e. n. mambou, t. tonnellier, and W. J. grossNeural belief dissemination coding of CRC polar concatenated codes[c]IEEE int. conf. commun(ICC), 2019: 1-6