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Channel State Information Prediction Using Autoencoder and Transfer Learning

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Abstract: Accurate channel state information (CSI) is essential for optimizing wireless communication performance. Traditional models, such as parameter-based and autoregressive approaches, suffer from noise interference and adaptability issues. In response, this paper proposes a novel deep learning framework combining a deep convolutional autoencoder with CNN-BiLSTM to enhance CSI prediction. The autoencoder denoises and refines CSI data, while the CNN-BiLSTM extracts both local and global temporal features. To address time-varying channel dynamics, transfer learning is employed, enabling the model to adapt to new environments with minimal data. Comparative analysis with traditional and deep learning methods demonstrates that the proposed approach significantly improves prediction accuracy, optimizes resource allocation, and enhances overall communication quality.

Keywords: Channel Prediction; Deep Convolutional Autoencoder; CNN; BiLSTM; Transfer Learning.

1. Introduction

Channel state information (CSI) quantifies the quality of the radio link [1], and largely determines the physical layer parameters and schemes of wireless communication deployment to a large extent, so obtaining accurate CSI is crucial to ensure the link performance of wireless communication system. Channel prediction technology [2] provides an effective method to directly improve the quality of CSI without spending additional wireless resources, which has attracted great attention of researchers. Traditional channel prediction models include parameter model [3] and autoregressive model [4]. The parameter model is easily affected by channel changes, which leads to the expiration of estimated parameters, while the autoregressive model is vulnerable to noise interference [5].

With the rapid development of deep learning, the neural network method based on data modeling has been proposed. Its main feature is to adaptively capture the inherent characteristics of data through training a large number of data. Among them, Liao [6] proposed a neural network model based on back-propagation to predict the CSI in the future. However, BP neural network is a feedforward neural network, which does not fully consider the time correlation of the prediction sequence. A three- dimensional wireless channel feature prediction model [7] based on back-propagation neural network is proposed. Navabi [8] proposed to use the correlation between base station characteristics and user characteristics to predict the characteristic parameters of user. In the process of neural network development, recurrent neural network (RNN) has strong time series prediction ability [9]. Liu [10] proposed the application of RNN to build a narrowband single-antenna channel predictor, and further expanded to MIMO channels in [11]. Jiang [12] adopted real-valued RNN to implement multi-step predictor, and further verified its effectiveness in MIMO system [13]. A hybrid of convolutional neural network and short and long term memory [14] is proposed to obtain the CSI of downlink channel based on the CSI of uplink channel. On the contrary, it focuses on predicting the future CSI from the past value of the same frequency and subcarrier. Deep transfer learning [15] is proposed to solve the problem of high training cost of the downlink CSI feedback neural network. Considering the variability of the real channel, Zeng proposed to incorporate meta learning to further reduce the cost of model training [16]. It is proposed to use channel state information (CSI) of a small number of antennas to extrapolate CSI of other antennas and reduce training costs [17]. A sparse complex neural network (SCNet) [18] is proposed to approximate the mapping function from uplink to downlink. The downlink CSI is predicted directly from the estimated uplink CSI without the need for upstream and downstream link feedback.

These studies demonstrate the potential of neural networks for wireless channel prediction, but they have some limitations such as data availability, model complexity, and accuracy. In order to alleviate the problems mentioned above as much as possible, we propose a channel prediction combining deep convolutional autoencoder and CNN-BiLSTM to enhance the characterization energy capability of the received CSI data by removing the introduced noise during transmission, and then extract the local and global features of the data by a lightweight feature fusion prediction model based on CNN and BiLSTM. Also considering the time-varying channel characteristics, we explore the use of transfer learning to accurately predict new CSI in order to prevent the single trained prediction network model from being unsuitable for time-varying fading channels.

2. Channel System

We consider a wireless channel based on Rayleigh fading, where electromagnetic waves propagate through multiple paths and fade at different moments after reaching the receiver superposition, and the probability density function of the received signal obeys the Rayleigh distribution. The symbol period is defined as t_s , the maximum Doppler frequency shift is f_d , the system bandwidth B $1/t_s$,the change frequency of channel state is mainly affected by ts and f_d . Discrete sampling of baseband signal, the discrete representation of the received signal is:

$$y(n) = h(n)x(n) + w(n)$$

Where, $x(n)$ is the transmitted signal at the symbol period n , $w(n)$ is the complex Gaussian noise subject to zero mean, and $h(n)$ is the complex channel gain, denoted as:

$$h(n) = h_r(n) + jh_i(n)$$

3. Channel Prediction

3.1 Deep Convolutional Autoencoder Network

Noise interference is inevitable in the wireless transmission process, especially in the process of signal modulation and demodulation, which ultimately leads to the change of channel state. We constructs a convolutional autoencoder network with a relatively simple model, in which the length of input data is N×1. The input is encoded through convolution and pooling operations. In order to recover the de- noised data, convolution and up-sampling operations are used to recover the length of N×1, as in Figure 1.

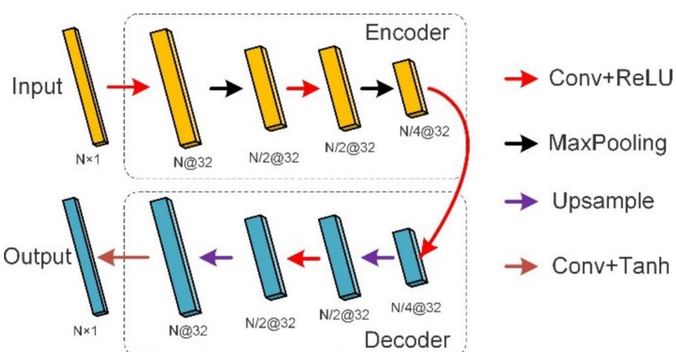

Figure 1. Deep convolutional autoencoder denoising model

3.2 CNN-BiLSTM

3.2.1 BiLSTM

LSTM [19] avoids the problem of long-term dependence by setting forgetting gates, input gates and output gates, and the worthless connection information in the sequence is eliminated and the relevant information is retained, but there is the problem of learning sequence relevance only in the forward direction. BiLSTM [20] adds a reverse LSTM to the LSTM, which is able to capture the before and after contextual information features of the sequence simultaneously by bi-directional processing, and reduce the overfitting problem. The update process of BiLSTM is shown in Figure 2 as follows:

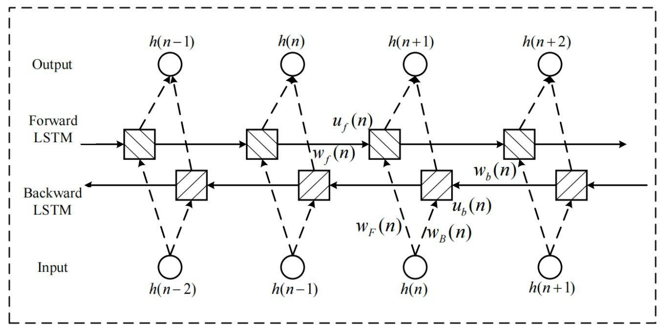

Figure 2. Schematic diagram of BiLSTM

$$u_f = LSTM^{+}\left(w_f(n)u_f(n-1) + w_F(n)h(n)\right)$$

$$u_b = LSTM^{-}\left(w_b(n)u_b(n+1) + w_B(n)h(n)\right)$$

Where: $h(n)$ is the input at the current moment. $u_f(n)$ and u_b (n) denote the forward-propagating and backward-propagating hidden states, respectively. LSTM and LSTM operations are the neural network operations mentioned above; $w_f(n)$ and $w_F(n)$ are the forward weight values respectively; $w_b(n)$ and $w_B(n)$ are the reverse weight values.

$$h(n+1) = concat(u_f, u_b)$$

3.2.2 Architecture

The prediction characteristics of wireless communication channels are characterized by strong time series correlation, the channel signal value in the past time seriously affects the prediction performance. We construct a multi-scale feature fusion model, which is named CNN-BiLSTM, based on 1D CNN and BiLSTM, including a 1D CNN network branch, a BiLSTM branch and a branch combined with 1D CNN and BiLSTM. It is adopted to fully learn the hidden features of data from different dimensions and improve prediction performance. In order to make use of the features along the positive direction of the time axis in the channel signal, 1D CNN is used to extract the local non- correlation features, so as to obtain more time features. In order to make full use of the two-way global time characteristics in the channel, BiLSTM is used to process the input, and the local non-correlation features extracted from the 1D CNN are fused to form a three-channel bidirectional global and local time characteristics. The dropout layer is introduced to prevent the model from over-fitting, and finally the regression prediction is carried out through the full connection layer. The model structure is shown in Figure 3.

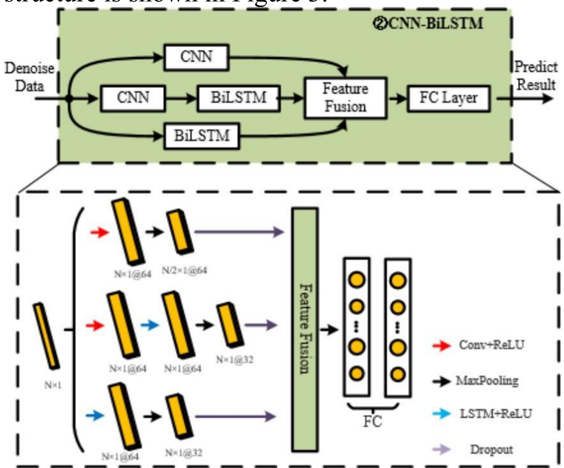

Figure 3. CNN-BiLSTM Hybrid Model

4. Algorithm Evaluation

4.1 Predict result

The proposed fusion model based on convolutional denoising autoencoder and CNN-BiLSTM is compared with ELM, CNN, LSTM and variants of the proposed algorithm, which are CNN-BiLSTM (without noise reduction module) and Deno-BiLSTM (without feature fusion module). Tables 1 and 2 show the average prediction performance of the two datasets and it can be seen that the proposed algorithm outperforms the prediction accuracy of the other methods. As shown in Figure 6, the fitted curves are very close to the true values and achieve more than 97% accuracy even under fast fading channel conditions. the CNN-BiLSTM is slightly worse than our model, which is due to noise interference, but has better feature learning capability than the other networks due to the fact that the CNN can extract local nonlinear features of the data, while the BiLSTM can learn the time axis of bidirectional information. The prediction performance of other algorithms is relatively poor because they only learn a single feature and may overfit the training set.

Table 1. Comparison of single-step prediction performance on CSIdata-0.01 dataset

Method	RMSE	MAE	R2
ELM	0.1364	0.1273	0.9334
CNN	0.1371	0.1283	0.9322
LSTM	0.1406	0.1317	0.9278
Deno-BiLSTM	0.1252	0.1174	0.9429
CNN-BiLSTM	0.1013	0.0870	0.9608
Ours	0.0784	0.0565	0.9764

Table 2. Comparison of single-step prediction performance on CSIdata-0.1 dataset

Method	RMSE	MAE	R2
ELM	0.1432	0.1210	0.8974
CNN	0.1323	0.1168	0.9167
LSTM	0.1337	0.1176	0.9152
Deno-BiLSTM	0.1201	0.1053	0.9312
CNN-BiLSTM	0.0909	0.0814	0.9599
Ours	0.0728	0.0648	0.9745

5. Conclusion

Aiming at the problems of noise interference, rapid change of channel quality and outdated channel parameters in wireless communication transmission, this paper combines the deep learning method to predict signal CSI from the perspective of signal prediction. Build a deep convolutional autoencoder network model to preprocess the signal, fuse the mixed model of CNN and BiLSTM, extract the global and local time characteristics of the signal, and use small sample data to transfer and learn the trained model. The proposed method is compared with the traditional method and the deep learning method. The results show that the proposed method can effectively improve the accuracy of channel CSI prediction, help to provide basis for channel parameters and adjustments, improve communication quality, and save resources.

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