Water Level Prediction Model Based on GRU and CNN

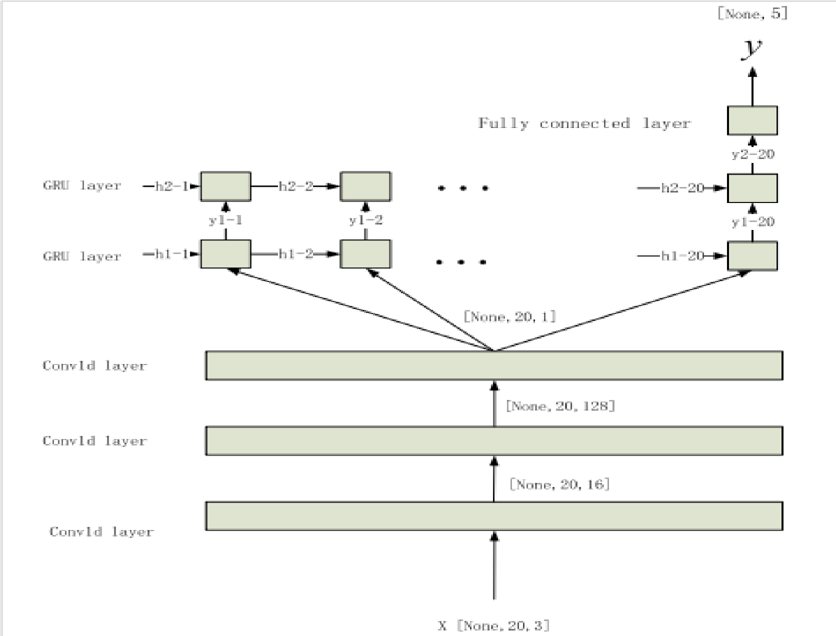
Introduction

Massive amount of water level data has been collected by using Internet of Things (IoT) techniques in the Yangtze River and other rivers. In this paper, utilizing these data to construct deep neural network models for water level prediction is focused. To achieve higher accuracy, both the factors of time and locations of data collection sensors are considered to perform prediction. And the network structures of gated recurrent unit (GRU) and convolutional neural network (CNN) are combined to build a CNN-GRU model in which the GRU part learns the changing trend of water level, and the CNN part learns the spatial correlation among water level data observed from adjacent water stations. The CNN-GRU model that using data from multiple locations to predict the water level of the middle location has higher accuracy than the model only based on GRU and other state-of-the-art methods including autoregressive integrated moving average model (ARIMA), wavelet-based artificial neural network (WANN) and long-short term memory model (LSTM), because of its ability to decrease the affections of abnormal value and data randomness of a single water station to some extent. The results are verified on an experiment dataset that including 30-year observed data of water level at several collection stations in the Yangtze River. For forecasting the 8-o'clock water levels of future 5 days, accuracy of the CNN-GRU model is better than that of ARIMA, WANN and LSTM models with three evaluation factors including Nash-Sutcliffe efficiency coefficient (NSE), average relative error (MRE) and root mean square error (RMSE).

CNN-GRU-Based Prediction Model

In GRU-based prediction model, the correlation of adjacent water stations was considered in some extent. However, it is difficult to reflect the spatial relationship between the water stations only by the simple structural design of the input layer. The data correlative degrees of neighboring stations with different distances are not considered carefully.

As is well known, in image and audio recognition, and other fields, CNN has excellent performance because of its excellent ability at capturing spatially related features. In order to better reflect the spatial distribution characteristics of water stations, CNN is further combined with the GRU network to build the water level prediction model. Its structure is shown in figure below.



The network consists of three convolution layers and three GRU layers. The shape of the input layer is [None, 20, 3], ‘3’ represents three water level values of the three adjacent water stations; the shape of the output layer is [None, 5], ‘5’ represents the predicted water level value of the next 5 days in the middle water station. The three convolutional layers, namely C1, C2, and C3, all are one-dimensional convolutional layer, they can be expressed as:

$$C = f\,(wx + b)$$

f is the activation function, and all three layers are set to the ‘relu’ function. C1 has 16 convolution kernels, C2 has 128 kernels, and C3 has one kernel. So the final shape of the output of convolutional layers is [None, 20, 1]. It means the three values from three water stations are abstracted into one value according to their correlative degrees to the middle station. These values will have better smoothness than the original water level value of the middle water station, they then enter the first GRU layer. The rest part of GRUs is consistent with the one for single water station.

Conclusion

In this paper, deep neural networks are used to investigate water level prediction of inland rivers. The GRU-based prediction model is used to extract the time series wave shape features of water level changes, and a prediction model based CNN-GRU with multiple water stations is proposed for water level prediction. Practical experiments based on a 30-years water level dataset of the Yangtze River were performed to evaluate the proposed model.

The proposed CNN-GRU-based prediction model is superior to the classical ARIMA and WANN models. It has higher prediction accuracy, as it considers more data from multiple water stations with spatial correlation to predict the water level of a middle station, which is helpful for it to decrease the affection of the data randomness of a single water station to some extent.

Even the CNN-GRU-based model, its prediction errors increase with the forecasting days. Therefore, in practice, the long-term prediction more than 5 days is not very efficient.

In the future, cluster methods can be used to analyze the water levels of different river segments for clustering and extracting important environmental factors. Furthermore, the clustered datasets can be adopted to train the CNN-GRUbased prediction model for the improvement of water level prediction