論 文 の 内 容 の 要 旨

論文題目　　Extended Models based on Multi-Reservoir Echo State Networks for Nonlinear Time Series Prediction(非線形時系列予測のためのマルチリザバーエコーステートネットワークに基づく拡張モデルに関する研究)

氏　　名　　李　子強

In the first chapter, we introduce some basis about Nonlinear Time-series Prediction (NTP) task. We focus on a subset of the most powerful machine learning methods, Artificial Neural Networks (ANNs), which have been widely used in NTP tasks. Recurrent Neural Networks (RNNs), as representative ANN approaches, can extract temporal dependency from the input time-series data and have been widely used in dealing with NTP tasks. However, this complicated architecture of the RNN leads to difficulties and expensive computational costs in training an RNN. In the Reservoir Computing (RC) framework, RNNs can be trained efficiently by optimizing only a part of connection weights. Such a model is called the Echo State Network (ESN), which consists of an untrainable reservoir and a trainable readout. This simple training scheme of ESN inevitably brings a limitation in enhancing predictive performances. To remedy this problem, a multiple reservoir-based paradigm named Multi-Reservoir Echo State Network (MRESN) was proposed recently. We focus on improving prediction performances on NTP tasks for the MRESN models by leveraging three improvement schemes.

In the second chapter, we focus on describing details of MRESN. Based on the modular architecture, we introduce three representative models for MRESN and analyze the corresponding computational complexities for the three models.

In the third chapter, we introduce the scheme of sequence resampling for MRESN models. This scheme can enrich the temporal features used for training the readout part with batch learning and lead to better prediction performance. To implement the proposed scheme, we propose a modified encoder of the MRESN for extracting temporal features from resampled input data. Based on the modified encoder and decoder, we propose three novel MRESN models, including the DeepESN-ESR, the DeepESN-LSR, and the GroupedESN-ISR. Numerical results on six challenging NTP tasks show that the proposed models outperform some state-of-the-art multi-reservoir ESN models. An evaluation of computational time shows that our proposed three models require less computational cost for learning than many existing MRESN models in practice. Moreover, a comprehensive comparative analysis reveals that our proposed models are able to memorize longer temporal information and generate richer dynamics from the reservoir states than some existing models.

In the fourth chapter, we propose a scheme of feeding input time slices into MRESN models. The input time slices of the consecutive type contain richer temporal information than the original input time series data points. We extract temporal features from this kind of input data for enhancing the computational ability of MRESN models. We implement the proposed scheme on the three tested models, including the ESN, the DeepESN, and the GroupedESN. Moreover, to better show the effectiveness brought about by the input time slices of the consecutive type, we set the other three kinds of input data for comparison. Experimental results demonstrate that our proposed scheme can improve the performances on both the nonlinear time-series prediction tasks and the time-series classification tasks. The corresponding analysis on the richness of reservoir dynamics reveals that input time slices of the consecutive type can effectively improve the richness of the three tested models. Moreover, the analysis of the computational complexity demonstrates the high efficiency of our proposed scheme.

In the fifth chapter, we propose a scheme of feeding decomposed components of an input time slice into each corresponding reservoir encoder. To implement this scheme, we propose a new model called an HP-MRESN by combining an MRESN with the Hodrick-Prescott (HP) filter for nonlinear time series prediction. The proposed HP-MRESN comprises three basic components: a time series decomposer, a reservoir state extractor, and an ensemble decoder. In the time series decomposer, we recursively leverage the HP filter to decompose original time-series data into multiple trend and cycle components. In the reservoir state extractor, each time series component is fed into a corresponding reservoir-state encoder for generating a reservoir state which is extracted as it is or through the principal component analysis. In the ensemble decoder, the states of multiple reservoirs are collected and processed to produce model outputs. Moreover, we propose an evolutionary algorithm to automatically find the best architecture of HP-MRESN. Through analyzing the computational complexities of the above models, we show that the increases in computational complexities brought about by the proposed schemes are negligible. Experimental results on a total of 24 nonlinear time-series prediction tasks with 6 real-world datasets demonstrate that our proposed HP-MRESN not only can outperform some existing representative MRESN models and fully-trained RNN models but also can have a relatively low training time.

In the sixth chapter, we conclude that our proposed schemes can effectively improve prediction performances on NTP tasks with very high efficiency for MRESN models. Moreover, we also point out that our works would be beneficial for improving performances on the time series anomaly detection and time series missing data imputation for MRESN models.