

博士論文(要約)

**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ー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)

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Nonlinear time-series prediction (NTP) is one of the challenging research topics in machine learning due to complex non-stationarity in temporal dynamics. Artificial Neural Networks (ANNs) are a subset of machine learning methods and have been widely used in nonlinear time-series prediction tasks. The most widely used ANN is the Feed-forward Neural Network (FNN). However, since the architecture of the FNN is not suitable for extracting the temporal dependency from the input time-series data, the corresponding performances on various NTP tasks are not ideal. Recurrent Neural Networks (RNNs), as another representative category of ANN approaches, are capable of extracting temporal dependency from the input time-series data and have been widely used in dealing with nonlinear time-series prediction 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 its representation ability and improving predictive performances. To remedy this problem, a multiple reservoir-based paradigm named Multi-Reservoir Echo State Network (MRESN) was proposed recently. In this thesis, we focus on improving prediction performances on NTP tasks for the MRESN models by leveraging three improving schemes.

In the first work, 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, which is composed of a resampling unit, a group-wise reservoir unit, and a collection unit. Based on the modified encoder and decoder, we propose three novel MRESN models, DeepESN with Every-layer Sequence Resampling (DeepESN-ESR), DeepESN with Last-layer Sequence Resampling (DeepESN-LSR), and GroupedESN with Input-layer Sequence Resampling (GroupedESN-ISR). Numerical results on six challenging nonlinear time-series prediction 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 multi-reservoir ESN 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 second work, we propose the 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, including the original input time series data points, the input time slices of the repeated type, and the input time slices of the random type. Experimental results demonstrate that our proposed schemes 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 more 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 third work, 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 addition, performance comparisons between the HP-MRESN and related MRESN models with other preprocessing methods show the benefit of time series decompositions using the HP filter.

In the above three works, we conclude that our proposed schemes can effectively improve prediction performances on NTP tasks with very high efficiency for MRESN models. Since the nonlinear time series prediction is a fundamental procedure of some other temporal processing tasks such as time series anomaly detection and time series missing data imputation. Our works would be beneficial for improving performances on the other kinds of temporal processing tasks for MRESN models.