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Original research article

Time series prediction using optimal theorem and dynamic Bayesian network

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ABSTRACT

A novel multi-step-ahead time series prediction model is proposed based on combination of the multi-information fusion optimization model and the dynamic Bayesian network (DBN). Our contribution includes: (1) a theorem of multi-information fusion prediction is proposed and proved. We can obtain the optimal estimate value of prediction based on the proposed fusion estimation theorem. (2) Based on proposed theorem, we consider using the recursion-based DBN to enhance performance of the optimal-based direct prediction model. A novel graph model named the R-DBN that generated from combination of multi-information fusion prediction and DBN is developed to predict multi-step-ahead time series data. The simulation and comparison results show that the proposed model is more effectiveness and robustness.

1. Introduction

In recent years, many researches focus in time series forecasting, most models still keep a watchful eye on one-step-ahead prediction instead of multi-step-ahead prediction. The main reason is that the longer prediction is with the bigger challenges arising from increased uncertainty. In general, multi-step-ahead time series prediction includes two basic strategies [1–3]: iterate-based and direct-based methods. The iterate-based strategy usually builds one-step-ahead prediction framework firstly, and the predicted values are always utilized as known data to forecast the next ones. The direct-based strategy constructs forecasting model to predict one-step-ahead or multi-step-ahead values directly. In iterate-based methods, cumulative errors always impact the prediction accuracy greatly, and in direct-based approaches, computational cost of algorithm usually is a key factor to be considered, especially in multi-step-ahead prediction.

Besides above-mentioned two main trend strategies, there also have other time series data prediction methods, including the multi-input multi-output (MIMO) method [5], the DirRec algorithm [4], and multi-input several multi-outputs (MISMO) prediction model [6,7], and so on. The MIMO and the MISMO strategy focus in higher prediction accurate, on the other hand, it is always with the higher computational cost. The MISMO strategy transform the initial prediction task into subtasks, based on cross-validation, to use the optimal solution to calculate the outputs [8], although the prediction accuracy is always satisfaction, the algorithm complexity usually need further to be optimized.

In this paper, we propose a novel graph-based strategy for multi-step-ahead time series prediction, which incorporates the optimal-based prediction [9,11] and recursion signal processing. The proposed model is presented using the dynamic

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Bayesian network (DBN), which is a strong tool for random signals modeling, analysis and processing. Our motives are described as follow.

Firstly, in recent years, it has been proved that the optimal-based prediction model is promising model for time series prediction. The models have been applied for time series prediction and many others fields successfully [9,11], and we select the optimal-based RBF prediction model as one part of our prediction strategy.

On the other hand, although the optimal-based prediction model is promising for time series prediction, in split of nice prediction accuracy, only short-time time series information is utilized for prediction. For example, in course of real-time prediction [9], only previous a few short-time remembering known data is used as input information to predict h-step-ahead data based on trained model. If we use all previous time series data to predict h-step-ahead data, the prediction currency may be increased and robustness of prediction can be enhanced.

Based on above analysis, we consider combining the short-time-based prediction structure and long-time-based sequence signals processing method together. The sequence signals processing algorithm always utilizes all previous time series data sufficiently. As we known, DBN [13] is an effective method to meet sequence signals data processing, including time series data smoothing, filtering and prediction. The graph-based prediction model is with more flexible representation, at the same time, it can combine with other algorithms easily. Hence, in this paper, we propose a combination frame of the optimal-based RBF neural network prediction model and the DBN, and the frame can be presented using DBN graph model too, it is called the R-DBN prediction model.

The rest parts are arranged as follows. Section 2 describes the detail steps of the R-DBN for multi-step-ahead prediction. Simulation results are analyzed in Section 3, and conclusions are drawn in Section 4.

2. Prediction model

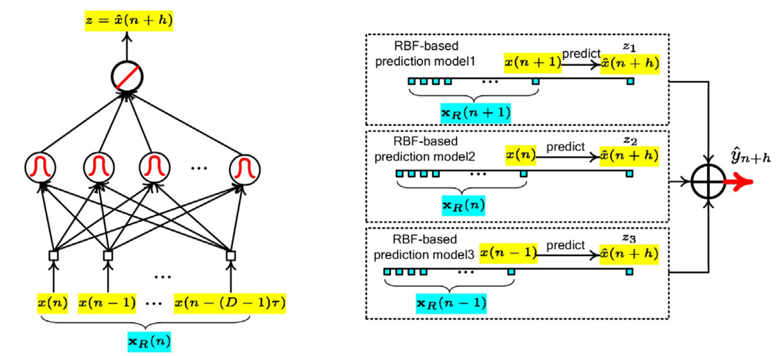
2.1. RBF prediction data fusion

To build a multi-input and one-output nonlinear system model: $f : \mathbb{R}^D \to \mathbb{R}$, which is used for h-step-ahead prediction, and the model is written as: $z = \hat{x}(n+h) = f(\mathbf{x}_R(n))$. The $\mathbf{x}_R(n) = [x(n), \cdots, x(n-(D-1)\tau)]^T$, where the τ is time delay coefficient, the precondition of time series data reconstruction is $D \geq 2d_1 + 1$, where the d_1 is correlation dimension.

In this paper, we proposed a multi-information fusion prediction frame, as shown in Fig. 1. Firstly, we select RBF neural network as h-steps-ahead prediction model, which is a nonlinear system translation model, we can write the model as: $z = \hat{x}(n+h) = f^h_{RBF}(\mathbf{x}_R(n))$, as shown in Fig. 1(a). The next, assume there are 3 time series prediction models based on RBF neural network, as shown in Fig. 1(b), we have:

$$\begin{cases} z_1 = f^{h-1}_{RBF}(\mathbf{x}_R(n-1)) = y_{n+h} + \upsilon_1 \\ z_2 = f^{h}_{RBF}(\mathbf{x}_R(n)) = y_{n+h} + \upsilon_2 \\ z_3 = f^{h+1}_{RBF}(\mathbf{x}_R(n+1)) = y_{n+h} + \upsilon_3 \end{cases} \tag{1}$$

where $f^{h-1}_{RBF}(\cdot)f^{h}_{RBF}(\cdot)f^{h+1}_{RBF}(\cdot)$ are $[h-1]$-step-ahead, h-steps-ahead and $[h+1]$-steps-ahead nonlinear prediction models based on RBF neural network, respectively. And $\mathbf{x}_R(n-1) = [x(n-1), \cdots, x(n-(D-1)\tau-1)]$, $\mathbf{x}_R(n) = [x(n), \cdots, x(n-(D-1)\tau)]$, $\mathbf{x}_R(n+1) = [x(n+1), \cdots, x(n-(D-1)\tau+1)]$ and $y_{n+h} = x(n+h)$. The z_i is prediction value and error is υ_i, we assume all prediction errors are Gaussian distributions, let $\upsilon_1 \sim \mathbb{N}(0, \sigma_1^2)$, $\upsilon_2 \sim \mathbb{N}(0, \sigma_2^2)$, $\upsilon_3 \sim \mathbb{N}(0, \sigma_3^2)$. We have the following theorem:



(a) RBF neural network prediction model (b) Fusion prediction frame

Fig. 1. RBF-based neural network time series prediction fusion model.