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A novel online adaptive time series prediction model with input and output uncertainties

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ABSTRACT

Only the output uncertainty is usually concerned in many regression models for noisy time series prediction, and a near optimal smooth model will be a close approximation to input–output process function if the input data is noise free and only the output data is corrupted by noise in a smooth input–output process. However, if the input data is also corrupted by noise then the best predictive smooth model based on noisy data need not be an approximation to the actual underlying process; rather, the best predictive model depends on both the underlying process and the noise. In this study, a novel strategy with noise addition is proposed by combining iterated nonlinear filters and the single multiplicative neuron (SMN) model, in which the additive noises describe the internal state uncertainty which can be used to explain the input noise and the output uncertainty. The state vector and the observation equation of nonlinear filters are presented by using the weights and the biases of SMN model and the output of SMN model, and the input vector data of the SMN model are composed of known sequential noisy time series data. To verify the effectiveness of the proposed methods, the noisy Mackey–Glass time series, the noisy Box–Jenkins dataset and the noisy electroencephalogram data are employed. The experimental results have demonstrated that the proposed methods are effective for noisy time series prediction.

1. Introduction

Time series prediction is an active research area that has drawn considerable attention for applications in variety of areas. With the time series approach to prediction, historical observations are collected and analyzed to determine a model to capture the underlying data generating process, then the model is used to predict the future. Much effort has been devoted over the past several decades to the development and improvement of time series prediction models, which are applied to many domains such as finance [1–5], engineering [5–20] and science [16–21].

Artificial neural networks (ANNs) represent a recent approach to time series prediction. There has been an increasing interest in using ANNs to model and predict time series over the last decade. ANNs have been found to be a viable contender to various traditional time series models [1–21]. Among different types of ANNs, multi-layer perceptron (MLP) neural networks are quite popular [22]. Recently single multiplicative neuron (SMN) model has been proposed as an alternative to the general MLP–ANNs. The SMN model derives its inspiration from the single neuron computation in neuroscience [23,24]. The SMN model is much simpler in structure than the conventional MLP–ANNs and can offer better performances if properly trained [25,26]. So far, the SMN model has been successfully applied to several time series prediction tasks. In [27], Yadav et al. presented a single multiplicative neuron model for time series prediction. Zhao and Yang [28] applied the SMN model to the time series prediction by using particle swarm optimization to estimate the SMN model parameters. Based on adaptive neuro–fuzzy inference system, Samanta [29] proposed a SMN model for different time series prediction. In [30], a high order fuzzy time series forecasting approach in which multiplicative neuron model was used to define fuzzy relations was proposed and a particle swarm optimization method was utilized to train the multiplicative neuron model. These methods could improve the prediction accuracy of noise-free time series, but for the noisy nonlinear series, the quality of these methods had not been proved or demonstrated.

Developing a model of a real physical dynamical system and comparing the results of the modelling with an observed signal,

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we always observe departures of the model from the real dynamics. These departures are caused by two reasons. First, some contaminations can be superimposed on the real signal during an observation process. We assume that these contaminations do not change dynamics of the system, but rather result from imperfections of the observation process. Therefore, this kind of contamination is called observed noise. However, noise can enter dynamics in a more complex way. Namely, the applied deterministic model of the dynamics can be inexact and the system can rather evolve according to a rule consisting of combined deterministic and stochastic components. This kind of contaminations is called dynamical noise. Dynamical noise usually represents an intrinsic random process being superimposed on deterministic dynamics. Observed noise is a relatively simple case to work with, even for such complex time series as those generated by chaotic dynamical systems. On the contrary, dynamical noise is a much more difficult case, mainly because this kind of contamination is strongly involved in nonlinear dynamics of the systems [31].

In this study, an improved SMN model with noise addition is proposed to predict the noisy nonlinear time series by combining the SMN model with iterated nonlinear filters, in which the uncertainties from internal states and outputs are meanwhile considered. The SMN model is used to generate the dynamic filters' nonlinear observed mapping, and the dynamic filters are used to online training the SMN model sequentially by adjusting the model parameters within a minimum variance framework. As far as the dynamic filters are concerned, the extended Kalman filter (EKF) is a well-known approach in the integration of the nonlinear system, and the iterated EKF (IEKF) can effectively reduce the bias and the estimation error by increasing iterative operations [32,33]. In addition, enlightened by the development of IEKF as well as the superiority of UKF, a recently developed filtering technique called iterated Unscented Kalman filter (IUKF) is proposed as well and has been used in different fields such as [34,35]. Therefore, we take the IEKF and the IUKF as the online training algorithm for the SMN model and call them as the IEKF-based-SMN model and the IUKF-based-SMN model, respectively. The contribution of this paper lies in the following three aspects. First, compared with most existing models, the proposed prediction strategies based only on the most recent data may have better performance. Second, the proposed algorithms can be used to fine tune the SMN-based prediction model online once new information becomes available and to perform forward prediction from the given inputs. Finally, the implementation process of the proposed method is much easier than that of the classical ANNs-based time series prediction model.

Section 2 introduces the iterated nonlinear filters simply and the SMN model. The new proposed methods are presented in Sections 3. The implementation results of different datasets and discussions are given in Section 4. Final section concludes the paper.

2. The iterated nonlinear filters and the SMN model

2.1. The iterated nonlinear filters

Suppose that a state vector $\boldsymbol{x}_k$ at instant k is propagated through the following nonlinear state transition equation.

$$x_{k+1} = f(x_k) + v_k, \tag{1}$$

where $f(\bullet)$ is the state transition function and $\boldsymbol{v}_k$ is the process noise with covariance matrices $\boldsymbol{Q}_k$. The observation equation is given as.

$$y_k = h(x_k, u_k) + w_k, \tag{2}$$

where $h(\bullet, \bullet)$ is the observation equation, $\boldsymbol{u}_k$ is the known input vector and $\boldsymbol{w}_k$ denotes the observation noise with covariance matrices $\boldsymbol{R}_k$.

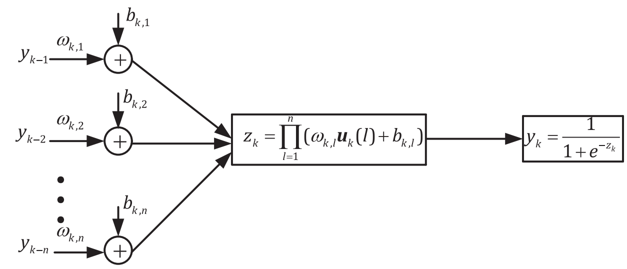

Fig. 1. The diagram of single multiplicative neuron model.

As for the detailed descriptions of iterated nonlinear filters, the reader can refer to Bell and Cathey [32] on IEKF and Xie and Feng [35] on IUKF.

2.2. The SMN model

The SMN model derives its inspiration from the single neuron computation in neuroscience [24], and only the input connections need to be determined during the learning process. Therefore, the SMN model is much simpler in structure and lower in computational complexity than the conventional ANNs and can offer better performances if properly trained [25,26].

Assumed that the noise-free time series data are $y_{idea} = \begin{bmatrix} y_{idea,1} & y_{idea,2} & \cdots \end{bmatrix}$, and the noisy time series is

$$\begin{aligned} \boldsymbol{y} &= \boldsymbol{y}_{\text{idea}} + s \times var(\boldsymbol{y}_{\text{idea}}) \times \text{randn}(\text{Length}(\boldsymbol{y}_{\text{idea}}), 1) \\ &= \begin{bmatrix} y_1 & y_2 & \cdots \end{bmatrix}, \end{aligned} \tag{3}$$

where scalar value s is varied from 0.01 to 0.05 in increments of 0.02 in the experiments of Section 4. The input vector of the SMN model at instant k is

$$\boldsymbol{u}_k = \begin{bmatrix} y_{k-n} & y_{k-n+1} & \cdots & y_{k-1} \end{bmatrix} \quad (k \geq n+1). \tag{4}$$

Fig. 1 shows the diagram of SMN model used in our study, and $(\omega_{k,1} \quad \omega_{k,2} \quad \cdots \quad \omega_{k,n})$ and $(b_{k,1} \quad b_{k,2} \quad \cdots \quad b_{k,n})$ (where n is the input vector dimension of SMN model.) are the weights and the biases of SMN model, respectively. The multiplication node z_k is transformed to the output function y_k with the *logsig* function defined as follows.

$$y_k = \frac{1}{1+e^{-z_k}} \quad \left(z_k = \prod_{l=1}^{n} (\omega_{k,l} u_{k,l} + b_{k,l}) \right). \tag{5}$$

The general SMN model can also refer to literatures [27–29].

3. The iterated nonlinear filters based SMN model for time series prediction

In general, we can view the online optimization of the weights and the biases of SMN model as a minimum mean squared error (MSE) problem, where the error vector is the difference between the outputs of SMN model and the target values. In order to cast the optimization problem in a form suited for iterated nonlinear filters, we let the weights and the biases of SMN model constitute the state vector and the outputs of SMN model constitute the observation equation of iterated nonlinear filters, then the state vector of the dynamic model at instant k can be represented as

$$x_k = \begin{bmatrix} \omega_{k,1} & \omega_{k,2} & \cdots & \omega_{k,n} & b_{k,1} & b_{k,2} & \cdots & b_{k,n} \end{bmatrix}^T \tag{6}$$

The state vector $\boldsymbol{x}_k$ thus consists of $2n$ parameters of the SMN model arranged in a linear array. In order to execute a stable nonlinear filtering algorithm, we add some observation noises $\boldsymbol{w}_k$ and