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A novel convolutional neural network based approach to predictions of process dynamic time delay sequences

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ABSTRACT

It is practical that correlated process variables always involve dynamic time-delay sequences. In this paper, a novel convolutional neural network (CNN) based approach is proposed to predict dynamic time delay sequences. Firstly, according to the calculating similarities between correlated process variables, the time delay sequence is extracted offline using a dynamic time delay analysis by elastic windows (EW-DTDA) method. In addition, through an additional correlation analysis between the time delay sequence and process variables data, the process variables majorly influencing the time delay sequences can be obtained. Finally, a deep learning CNN model between the extracted time delay sequence and the obtained majorly influencing variables is constructed to predict the time delay sequence online. In order to validate the effectiveness of the proposed method, the method is applied to a real distillation column for analyzing dynamic time delay sequences, the simulation results conformed the effectiveness of the proposed approach.

1. Introduction

With the prevalence of big data technologies, a huge amount of process data generated from industrial processes has attracted more and more attentions [13]. In this context, data mining is usually employed to acquire the knowledge that significantly contributes to modeling [3,23], fault diagnosis [21,22], and optimal operations [12,20].

[9] presented an method for extracting temporal correlation rules of multivariate time sequences, taking account that the influence of changes of a time sequence on those of another might not be synchronized but with a time delay available. In addition, industrial processes usually suffer large time delays, data dislocation, information missing and other problems which possibly result from direct utilization of associated variables for predictions. So, it is necessary to carry out time delay analysis and select appropriate temporal windows for time series predictions. As a popular correlation analysis method, Cross-Correlation Analysis (CCA) has been used to calculate the Cross-Correlation function (CCF) between variables under different time differences before choosing the time differences corresponding to the maximum value of CCF as the time delay [15]. In this context [17], proposed a cross-correlation and wavelet denoising based method for time series predictions [13]. proposed an improved fuzzy interpolation prediction method to improve the tracking efficiency for oscillating time series sequences.

However, in the above-mentioned time series correlation analysis, the time delay is usually assigned to a constant value, which inevitably ignores dynamic characteristics of the time delay. Moreover, traditional methods by sliding time windows usually face with intrinsic limitations. For example, it is difficult to meet both the validity and the dynamic property of the target delay extraction. In fact, extracting and analyzing the transmission dynamics can make better uses of process data in applications such as effectively estimating process specific states and forecasting abnormalities in time. Furthermore, provided with much supporting information, human operators can intervene processes in a timely and effective way to ensure maintaining stable states of process productions [14]. It is possible that we can effectively and accurately achieve the time delay between correlated variables. However, because the time delay is estimated based on historical data, the current practical conditions cannot be effectively tracked in real time. In response, we are encouraged to use time series predictions based methods to predict and track the time delay sequence of correlated variables in real time.

Traditionally, time series prediction models mainly aim at short time predictions using output time series, such as ARIMA, VAR, SVM [7,8,11]. In addition, neural networks based time series prediction methods draw a lot of attentions from researchers as well [6]. established a dynamic time series prediction model based on BP neural network, in which two BP

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networks with the same structure are employed to conduct offline training and online predictions [5]. proposed a Bayesian adaptive neural network model to predict single-step wind speed time series. However, the algorithms mentioned above have limited abilities in dealing with multi-step predictions. Multi-step predictions usually involve a lot of uncertainty. In response, two basic strategies [1,2] are suggested for multi-step predictions. (1) Iterate approaches: Single-step prediction strategies are iteratively used to calculate the next step values, which inevitably accumulate errors. (2) Direct-based approaches: Inputs are directly used to predict the multi-step values of time series, which demand for a high algorithmic accuracy.

In this paper, the time delay sequence of correlated process variables is estimated offline by EW-DTDA. Subsequently, through additional correlation analysis between the time delay sequence and process variables series data, we can find out major variables influencing the time delay sequence. Furthermore, a deep learning CNN models is established based on the major variables and the time delay sequence before applying to estimating the time delay sequence online. Fig. 1 shows the flow chart of the proposed approach. It can be seen that the accuracy and robustness of the algorithm are improved by the time-delay analysis. Additionally, the activate functions in CNN are able to deal with process nonlinearities involved, resulting in good performances and robustness for multi-step predictions of the time delay sequences.

The rest of this paper is organized as follows: In Section 2, we estimated the time delay sequence associated with correlated process variables using the EW-DTDA approach before the major process variables influencing the time delay sequence are attained through an additional correlation analysis. In Section 3, common models for time series prediction are presented before a deep learning CNN structure is designed for the time delay sequence prediction. Section 4 shows an application to a distillation process experiment, demonstrating the validity of the proposed approach. The conclusions are presented in Section 5.

2. A time delay sequence analysis

In CCF method, assuming that a and b are time series of n observations with means μ_a, μ_b and variances σ_a, σ_b respectively, the cross-correlation function with an assumed lag k is characterized by

$$\phi_{ab}(k) = \frac{E[(a_i-\mu_a)(b_{i+k}-\mu_b)]}{\sigma_a\sigma_b}, k = -n+1, \cdots, n-1. \quad (1)$$

The correlation coefficient is estimated as follows.

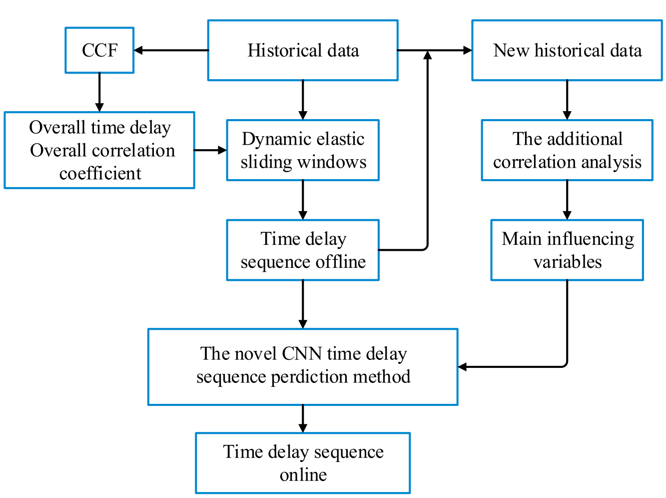

Fig. 1. A flow chart of the approach.

$$\widehat{\phi}_{ab}(k) = \begin{cases} \dfrac{1}{n-k}\displaystyle\sum_{i=1}^{n-k}(a_i-\mu_a)(b_{i+k}-\mu_b)/s_a s_b, & if\ k \geq 0, \\ \dfrac{1}{n+k}\displaystyle\sum_{i=1-k}^{n}(a_i-\mu_a)(b_{i+k}-\mu_b)/s_a s_b, & if\ k < 0. \end{cases} \quad (2)$$

where, s_a and s_b are sampling standard deviations of a and b, respectively.

The CCF method assumes that there is a certain time lag for a time series sequence. Therefore, the maximum absolute value of $\phi_{ab}(k)$ can be regarded as the correlation coefficient, and the corresponding time lag k is the estimation between two variables [16].

Generally, the existence of time delays is bound to affect the accuracy and efficiency of the correlation estimation. The temporal characteristics between correlated process variables are usually different. In addition, the temporal differences are also shifted with changes of variables and time. However, in the traditional association analysis, the time delay is usually regarded as a constant. Accordingly, numerous time delay treatment methods have been circulated in the field, among which, EW-DTDA is acknowledged as a kind of effective and convenient approaches [14].

Here, we present a dynamic time delay analysis with elastic windows shown in Fig. 2, in which, the delay estimation λ and the cross-correlation$\rho$are used to determine the data scanning width λ_k of the traditional off-line analysis, i.e.$\lambda_k = \omega_1 {}^*\lambda, \omega_1 \in [1,5]$. With the relevant parameters specified, the improved dynamic correlation analysis can be employed to calculate the dynamic time delay of time series as follows.

$$\widehat{\phi}_{ab(i)}(k_i) = \frac{1}{n_k}\sum_{j=i}^{i+n_k}\left(a_{j-r}-\mu_{a(j)}\right)\left(b_{j+k-r}-\mu_{b(j+k)}\right)\Big/ s_{a(j)}s_{b(j+k)}, \quad k = 0,1,2\cdots,\lambda_k.\ i = 1,2,\cdots,n \quad (3)$$

Where, (i) stands for time. The contrast width n_k is the size of the sliding window, and r is the radius of the contrast, $r = n_k/2$. The data scanning width λ_k is the moving range of the sliding window. We also can compute the maximum and minimum values$\phi_{ab(i)}^{max} = \max_k\{\phi_{ab(i)}(k_i), 0\} \geq 0$, $\phi_{ab(i)}^{min} = \min_k\{\phi_{ab(i)}(k_i), 0\} \leq 0$, as well as the corresponding arguments $k_i^{max}$and k_i^{min}. Then the estimated certain time lag$\lambda(i)$from a to b is

$$\lambda(i) = \begin{cases} k_i^{max}, & \text{if}\ \phi_{ab(i)}^{max} \geq -\phi_{ab(i)}^{min}\ \text{and}\ \phi_{ab(i)}^{max} \geq \phi_{ab} \\ k_i^{min}, & \text{if}\ \phi_{ab(i)}^{max} < -\phi_{ab(i)}^{min}\ \text{and}\ -\phi_{ab(i)}^{min} \geq \phi_{ab} \end{cases} \quad (4)$$

Comparing $\phi_{ab(i)}^{max}(-\phi_{ab(i)}^{min})$ to the target similarity ϕ_{ab}, the window size can be dynamically adjusted according to the requirements. In the case of small window size, the reverse fault similarity estimation tends to

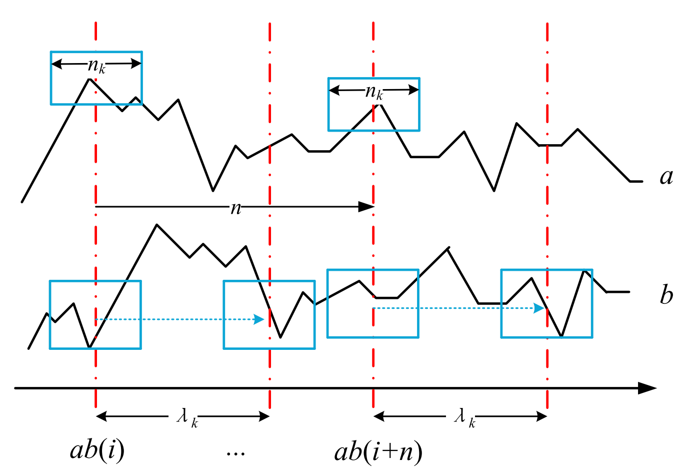

Fig. 2. Sliding windows.