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Novel continuous function prediction model using an improved Takagi–Sugeno fuzzy rule and its application based on chaotic time series

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ABSTRACT

A novel continuous function prediction model (CFPM) is proposed to resolve prediction problem whose input and output are both continuous functions (CFs). CFPM can simplify sample space reconstruction by using the coefficients of CFs, and use an improved Takagi–Sugeno (TS) fuzzy rule to predict output CF by optimizing the tendency of input CFs. The improved TS fuzzy rule handles each input CF as a consequent parameter and can obtain the nonlinear tendency. After learning process by using opinion-leader-based particle swarm optimization, output CF is determined. In the data prediction based on chaotic time series, CF can either be obtained directly or be fitted by discrete data points, thus the prediction range is enlarged because more discrete data points can be generated once output CF is determined.

Two experiments and three cases based on chaotic time series are performed to validate CFPM. The Mackey–Glass chaotic time series is used to prove CFPM validation, while the NN3 time series is used to evaluate CFPM performance. The cases on exhaust gas temperature (EGT), EGT margin and delta EGT are used to show that CFPM is valuable in health status prediction for a particular aircraft engine in the practical engineering field.

1. Introduction

Fuzzy theories have got more and more attention recently, because they can be used to solve many actual problems which are either strong nonlinear or high uncertain, such as numerical optimization (Ahmad et al., 2013; Kim and Sakthivel, 2012), pattern recognition (Chu et al., 2014; Mitra and Pal, 2005), big data mining (He et al., 2015; López et al., 2015), fuzzy clustering (Izakian et al., 2015; Wu et al., 2011), and prediction (An et al., 2014; Pan et al., 2014). Based on fuzzy theories, two mainly fuzzy model exist: Mamdani fuzzy model (Mamdani and Assilian, 1975) and Takagi–Sugeno (TS) fuzzy model (Takagi and Sugeno, 1985). Many scholars have carried on thorough research to TS fuzzy model, because TS fuzzy model is more intuitive and has a relatively simple structure.

Prediction with high accuracy is a key issue in these years, and the prediction based on chaotic time series is still a hot area. Many new models and algorithms are proposed to solve the problems, such as adaptive natural gradient method (Zhao and Yu, 2015), adaptive step size kernel least mean square algorithm (Shoaib et al., 2015), and others (Abdollahzade et al., 2015; Gan et al., 2015; Shi et al., 2015). Nowadays, the data based on chaotic time series can be predicted by two mainly kinds of methods. The first is using the discrete data points, while the second is using the continuous functions (CFs). The discrete data points are usually collected from the time-varying system that outputs discrete values such as concentration, temperature, and humidity. CFs are usually collected from the time-varying system that outputs waveforms such as voltage signal, sound waves and alternating current. In fact, for the time-varying system, discrete data point is a special case of CF; therefore, there is a great value in using CFs as samples to predict the practical engineering data based on chaotic time series in the following time.

Many methodologies exist to predict the chaotic time series data using CFs. Some typical methodologies are described as follows. The methodology based on dynamic time warping (DTW) shows the satisfactory result, and the typical method proposed recently is multiclass support vector machines with weighted DTW kernel function (Jeong and Jayaraman, 2015) which provides

Abbreviations: CFPM, continuous function prediction model; CF, continuous function; TS, Takagi–Sugeno; DTW, dynamic time warping; PNN, process neural network; PTS, process TS; PSO, particle swarm optimization; OLB-QPSO, quantum-behaved PSO; FGS, function group sample; EGT, exhausted gas temperature; EGTM, EGT margin; DEGT, delta EGT; MIN, maximum iteration number; CC, convergence condition; CR, coefficient range; PN, particle number; CIN, current iteration number; BPNN, back propagation neural network; pbest, personal best position; mbest, mean best position; gbest, global best position

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a flexible and robust kernel function for time series classification between non-aligned time series data; but prediction accuracy sometimes has to be affected by the similarity between two time series. The methodology based on Gauss process shows many actual applications in prediction, and the typical method propose recently is Gaussian mixture copula model based localized Gaussian process regression approach (Yu et al., 2013) which can deal with the random uncertainty and shows higher prediction accuracy and reliability; but the deterministic function is difficult to describe time series characteristics sometimes because of regression in essence. The methodology based on Hidden Markov Models shows the good robustness, and the typical method proposed recently is imprecise hidden Markov models (Antonucci et al., 2015) which achieves classification by extending the k-NN approach to interval data; however, the transfer of each state depends on the formal several states in most of these methods, but the number of state is difficult to be confirmed for many time series.

Most of the above methodologies do not fully consider the effect of time accumulation and space aggregation for the engineering data based on chaotic time series, whereas both time and space can influence the prediction accuracy (Xingui et al., 2001) in the actual applications. Therefore, some new methodologies are also proposed, such as process neural network (PNN) (Xingui et al., 2001) and process TS (PTS) (Xie et al., 2014). The typical PNN is a further improved model based on traditional neural network, which consists of lots of process neurons. Each process neuron essentially is a typical time-varying system, and has the characteristic of both time accumulation (by integral operation) and space aggregation (by addition operation). Nowadays, many improved models based on the typical PNN are gradually appearing, such as parallel feedforward process neural network (Gang and Zhong, 2005), cascade-forward process neural network (Yao-ming et al., 2012), and continuous wavelet process neural network (Shisheng et al., 2007). Those models are used in many areas such as aircraft engine lubricating oil monitoring (Ding and Zhong, 2006), time series prediction (Gang and Zhong, 2005), and helicopter engine performance prediction (Yao-ming et al., 2012). Because the integral operation is used, when the inputs are more, the efficient decreases. Although input functions and weight functions are expanded based on the orthogonal basis to simplify the integral operation, the information about samples maybe loses. Therefore, convolution sum discrete process neural network (Shisheng et al., 2011) is proposed, which uses convolution and operation to obtain the effect of time accumulation. But, the model based on the typical PNN generally uses CF as input while discrete value as output. Once the output is CF, the structure complexity will be increased. To solve the problem, PTS is proposed. PTS uses the any relational clustering algorithm (Corsini et al., 2004) to cluster CF samples, modifies the consequent part of the fuzzy rule by using the function input to replace the discrete input, and transforms the parameters identification of consequent part of the fuzzy rule to be an unconstrained optimization problem to avoid the integral operation. After the parameters are identified, a particular PTS model is established. Experiments show PTS decreases the computational complexity and can approximate a CF as output.

Both PNN and PTS are proposed based on the time accumulation and space aggregation, but they only can represent the outputs using the model, so the details of output CF cannot be obtained. To solve that problem, CFPM is proposed based on a new problem solving structure. Its core contributions are as follows. First, CFPM uses the coefficients of input CFs to generate samples to process learning, which can simplify sample construction and reduce computation load. Second, CFPM uses coefficients learning to replace time aggregate for obtaining output CF, which is a process of learning the sample generation tendency in essence. Third, CFPM extends the form of TS fuzzy model, which makes the nonlinear tendency for output CF can be obtained. Fourth, once output CF is determined, more discrete data points can be obtained, therefore, for the discrete values, the prediction range is enlarged. Fifth, some experiments and cases in this paper show that using CFPM to predict the data based on chaotic time series is capable of obtaining satisfied results.

CFPM can use evolutionary algorithm to learning itself by optimizing the parameters in it, and usually the satisfied solutions can be obtained after iterations. There are many evolutionary algorithms such as genetic algorithm (Holland, 1975), ant colony optimization (Dorigo, 2006), and particle swarm optimization (PSO) (Eberhart and Shi, 2001). PSO has good computational efficiency, and which requires both low memory space and CPU speed, and has few parameters to adjust (Khare and Rangnekar, 2013). Thus, PSO is used in CFPM. However, many improved methods based on PSO exist, to accelerate the learning process, opinion-leader-based quantum-behaved PSO (OLB-QPSO) (Lin et al., 2015) is used, whose description is in Section 3.1.

In the engineering application, many practical cases exist, whose samples can be generated by a lot of discrete data points. This paper progresses the research based on a particular aircraft engine health status. The aircraft engine health status is used to monitor running capability of aircraft engine under the normal operation. Generally speaking, health status includes normal, degradation and failure. Aircraft engine health condition prediction mainly refers to the prediction in the phrase of performance degradation. To ensure the flight safety and decrease the maintenance cost of aircraft engine, monitoring aircraft engine health status is very significant and necessary. And then, as the typical chaotic time series data, exhausted gas temperature (EGT), EGT margin (EGTM), and delta EGT (DEGT) were used in the practical cases, which were all collected from a particular aircraft engine and the detail descriptions are in Sections 5.1, 5.2, and 5.3, respectively. To show the practical engineering application value, the cases' samples in this paper came from an airlines company in China.

This paper is organized as follows. In Section 2, model description is discussed, through the stepwise refinement to propose the solution for the approach, including: (1) constructing function group sample (FGS) using CFs; (2) obtaining FGS output based on tendency curve; (3) building improved fuzzy rule with CFs; (4) representing CF with discrete values; and (5) collecting CFs. In another word, in learning process, the correct steps should be (5), (4), (3), (2), and (1). In Section 3, learning process is provided, including both OLB-QPSO and algorithm description. In Section 4, two experiments are presented: the Mackey–Glass chaotic time series are used to show the prediction validation because the data generated by a deterministic function; the NN3 chaotic time series are used to show the accuracy of the propose model because the data is drawn from the homogeneous population of empirical business time series. In Section 5, three practical cases are presented, including aircraft engine EGT, EGTM and DEGT data. All the cases' data are employed to demonstrate the performance of the proposed model in the practical engineering application. Finally, conclusion remarks and further research are provided in Section 6.

2. Model description

In this section, model description is discussed. Here is a precondition: the types of different CFs are same and known. For the time-varying system that only generates discrete data points, function fitting should be used to generate CFs. Thus, this section provides the solutions one by one according to the concerns for different steps.