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A new hybrid enhanced local linear neuro-fuzzy model based on the optimized singular spectrum analysis and its application for nonlinear and chaotic time series forecasting

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ABSTRACT

This paper develops a hybrid method for nonlinear and chaotic time series forecasting based on a local linear neuro-fuzzy model (LLNF) and optimized singular spectrum analysis (OSSA), termed OSSA–LLNF. Nonlinear and chaotic time series often exhibit complex behaviour and dynamics, turning their forecasting (particularly in multi-step ahead horizons) into a difficult task. In this paper, SSA is utilized for data processing, resulting in the elimination of noisy components and improvement of forecasting performance. The SSA parameters are fine-tuned using the particle swarm optimization algorithm. Then, the processed time series is modelled and forecasted via the LLNF model. The proposed OSSA–LLNF model is applied to forecast several well-known time series with different structures and characteristics. The comparison of the obtained results with those of several old and recently developed methods indicates the superiority and promising performance of the proposed OSSA–LLNF approach.

1. Introduction

1.1. Motivation and aims

Modelling and prediction of nonlinear and chaotic time series have always been a challenge to the research community. Such time series, which are commonly encountered in real world phenomena e.g. physics, biology, medicine, and engineering, usually exhibit seemingly unpredictable behaviour [28]. They are composed of various components such as trend, seasonality, impulse, steps, model exchange and other uncontrolled features, e.g. non-stationary behaviour, making traditional mathematical and statistical methods unsuitable for their modelling and prediction [33]. Hence, due to the wide application of time series analysis in fields such as engineering, economics and medicine [6], and the increasing importance of accurate modelling and prediction, this problem continues to remain open for further development of more sophisticated modelling approaches.

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1.2. Literature review

From a general perspective, time series prediction techniques can be categorized into two broad categories, namely statistical, e.g. auto-regressive (AR) and auto-regressive integrated moving average (ARIMA) models, and computational intelligence (CI) approaches, such as neural networks and fuzzy systems. An overview of time series prediction techniques, with the main focus on CI-based approaches, is presented in Table 1.

The statistical time series modelling approaches, among them the well-known AR, ARIMA, and generalized autoregressive conditional heteroskedasticity (GARCH) models employ some prominent features of time series, such as trend and seasonality to build the prediction model [28]. However, they often assume several restrictive assumptions, such as linearity, stationarity and normality, which are seldom satisfied in the case of nonlinear and chaotic time series. Hence, there is an ongoing need for the development of more dependable approaches which are able to model the complex behavior of nonlinear and chaotic time series.

Through the last two decades, CI techniques have been proposed as appropriate alternatives for identification, modelling, and prediction in complex dynamic systems and processes [11–44]. Artificial neural networks, neuro-fuzzy models and support vector machines are three well-known CI approaches widely used for time series prediction.

Among the available CI approaches, artificial neural networks (ANNs) and neuro-fuzzy models, as synergistic integration of ANNs and Takagi–Sugeno fuzzy inference systems, have gained a strong popularity in the area of nonlinear time series prediction [68,36,5,52,15]. These CI approaches are data-driven modelling techniques which construct a mapping between the past values of a time series and its future. They usually do not require any specific assumption about the nature of the time series, its behaviour, stationarity and complexity. With CI approaches, the prediction model is built upon the available historical data of the time series.

ANNs were originally motivated by the biological structures in the brains of humans and animals, and are extremely powerful for tasks such as information processing, learning, function approximation and prediction [47,32,17]. There are several variants of ANNs, such as multi-layered perceptron (MLP) neural networks, radial basis function (RBF) neural networks and recurrent neural networks. For instance, in [36] a RBF neural network was developed for chaotic and noisy time series prediction. In [67], Yan proposed a generalized regression neural network (GRNN) for effective modelling of the large-scale business time series, and modular neural networks were developed for time series forecasting in [41,42].

The neuro-fuzzy (NF) models, which inherit the learning and parallel processing capabilities of ANNs and incorporation of a priori knowledge in fuzzy systems, are data-driven fuzzy inference systems not solely designed by expert knowledge but instead partly learned from data [47]. Owing to these capabilities, the NF models have been proved as high-performance approaches for identification and prediction of complex nonlinear processes, e.g. time series [70,3,45,1].

In [70], a multi-input–multi-output-adaptive-network-based fuzzy inference system (MANFIS) was developed for chaotic time series prediction and applied to Mackey–Glass chaotic time series and a Duffing forced-oscillation system. Bodyanskiy and Vynokurova proposed a wavelet-neuro-fuzzy system with a five-layered structure for chaotic time series identification [3]. In this work, wavelets were used as membership functions in the antecedent layer, and the adaptive multidimensional wavelets as activation functions in the consequent layer [3]. In another recent study, Miranian and Abdollahzade [45] combined the powerful least-squares support vector machines with neuro-fuzzy models and applied their developed model to predict several different chaotic and nonlinear time series.

Time series modelling and prediction by ensemble NF models has been also pursued by researchers in [50,43,71]. For instance, integration of type-2 fuzzy systems in ensemble neural networks for time series prediction has been proposed in [50]. In [51], a genetic algorithm-based optimization method was proposed for ensemble neural network models with fuzzy aggregation of responses for complex time series prediction. In [14], Gaxiola et al. employed a genetic algorithm to optimize the three neural networks in an ensemble mode. Their method was applied to time series prediction as well as

Table 1
Summarization of time series prediction methods with a main focus on CI-based techniques.

Authors/years	Methodology
Jang (1993) [48]	ANFIS
Cho and Wang (1996) [4]	RBF adaptive fuzzy system
Zhang and Morris (1999) [5]	Recurrent neural network
Leung (2001) [9]	RBF neural networks
Castillo and Melin (2002) [13]	Hybrid system using neural networks and fuzzy logic
Chen et al. (2004) [44]	Neural trees
Melin et al. (2006) [16]	Modular neural networks and fuzzy Sugeno integral
Juang and Tsao (2008) [53]	Self-evolving type-2 fuzzy neural network
Lin et al. (2009) [55]	Neural fuzzy networks
Yilmaz and Oysal (2010) [6]	Fuzzy wavelet neural networks
Pulido et al. (2011) [20]	Ensemble neural network
Melin et al. (2012) [22]	Ensembles of ANFIS
Miranian and Abdollahzade (2013) [18]	LSSVM-based neuro fuzzy model
Gaxiola et al. (2013) [21]	Type-2 fuzzy neural network
Pulido and Melin (2013) [19]	Ensemble neural networks with type-2 fuzzy integration
Pulido and Melin (2014) [67]	Ensemble neural networks with fuzzy aggregation and PSO