ARTICLE IN PRESS

Mechanical Systems and Signal Processing ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/ymssp

Cascaded evolutionary algorithm for nonlinear system identification based on correlation functions and radial basis functions neural networks

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ARTICLE INFO

Article history:
Received 8 August 2014
Received in revised form
19 May 2015
Accepted 27 May 2015

Keywords:
System identification
Nonlinear systems
Magnetorheological damper
Correlation tests
Input selection
Evolutionary algorithms

ABSTRACT

The present work introduces a procedure for input selection and parameter estimation for system identification based on Radial Basis Functions Neural Networks (RBFNNs) models with an improved objective function based on the residuals and its correlation function coefficients. We show the results when the proposed methodology is applied to model a magnetorheological damper, with real acquired data, and other two well-known benchmarks. The canonical genetic and differential evolution algorithms are used in cascade to decompose the problem of defining the lags taken as the inputs of the model and its related parameters based on the simultaneous minimization of the residuals and higher orders correlation functions. The inner layer of the cascaded approach is composed of a population which represents the lags on the inputs and outputs of the system and an outer layer represents the corresponding parameters of the RBFNN. The approach is able to define both the inputs of the model and its parameters. This is interesting as it frees the designer of manual procedures, which are time consuming and prone to error, usually done to define the model inputs. We compare the proposed methodology with other works found in the literature, showing overall better results for the cascaded approach.

1. Introduction

Natural computing paradigms, which are methods developed on the basis of inspiration in processes found in nature, have found many applications in mechanical systems, with artificial neural networks being a prominent example [1]. Among the problems successfully tackled by such techniques, we can cite fault diagnosis [2,3], data and sensor fusion [4,5], parameter extraction [6,7], optimization [8,9] and system identification [10,11].

The task of building mathematical abstractions of dynamical plants is pursued by system identification techniques. Among them, whenever the assumption that input and output data is available, black-box modeling is an interesting option for the designer. It might be prohibitively complex, too expensive, unadvisable due to uncertainties or even too time consuming to model the physics underlying the process and, in such scenario, one could try to capture the dynamics which

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http://dx.doi.org/10.1016/j.ymssp.2015.05.022
0888-3270/

govern the system by using data acquired from experimentation [12,13]. As the concept of system is broad and encompasses many aspects in applied engineering, techniques for black-box system identification are powerful tools for their wide scope of application [14].

However, as no a priori information is assumed to be available in the case of black-box modeling, there are different issues that the designer faces in order to build a model, in contrast with the specificity and the first principles of each system as in white-box modeling. The input design is the first step when designing an experiment, for details see [15]. It is important as the input sequence should be set to extract the dynamics adequately when measuring the outputs and should cover the bandwidth and amplitude range of interest. Poor datasets will probably lead to poor models. Once data are available, the architecture of the model must be set, with the definition of the inputs and the complexity of the model, such that the model parameters are estimated and checked according to some predefined validation criteria.

As an inadequate set of inputs for the model will often lead to invalid mathematical abstractions, the input selection is a crucial step in the case of black-box system identification. Moreover, as the number of possibilities for the set of inputs of the model grows very rapidly with respect to the possible candidates on the inputs and outputs of the system, it may not be feasible to test all of them. Thus, in the specialized literature it is possible to find many relevant works on the topic of input selection. These algorithms can be categorized into model-free and model-based [16]. Even though selecting an appropriate set of model inputs is an important step in system identification, this task is done many times on the basis of the expertise and intuition of the designer [17].

In [18], the authors introduce a methodology for input selection based on the continuity of nonlinear representations. In this method, a suggestion is made for the orders of the system, solely on the basis of input and output data. However, the analysis and interpretation of the outcome of the algorithm are subjective and depend on the interpretation of the user. Clustering techniques have been used in input selection as in the case of nearest neighbours [19,20] and fuzzy clustering [21,16]. These methods have the advantage of not requiring a model to be estimated. As such, they may serve as a good starting point for the designer, which may then fine tune the choice for the inputs of a given model by trial-and-error, successively changing the initial set of inputs and estimating the parameters of the model. This practice, however, is time consuming, repetitive and prone to errors.

Model-based techniques are designed for a given model structure to define their adequate inputs. On this matter, Evolutionary Algorithms (EAs) have been extensively applied due to their global search capability. Genetic programming is employed to build nonlinear polynomial models in [22,23] together with orthogonal least squares. Another scheme for constructing polynomial models is given by [24] where the authors propose a different individual encoding and an improved objective function based on the correlation function coefficients of the residuals, solved by the Genetic Algorithm (GA). Loghmanian et al. [25] applied a multiobjective GA for the purpose of automatic input selection, complexity and parameter definition used to validate the methodology three simulated systems and the Box–Jenkins gas furnace. In [26] the authors propose a hybrid of the backpropagation and multiobjective Differential Evolution (DE) algorithms for the task of selecting the inputs and the parameters of an Artificial Neural Network (NN) model for an unmanned aerial vehicle. A novel multiobjective automatic building algorithm was given by [27], based on the cuckoo search algorithm and on the minimization of the error, correlation function coefficients and a regularization term, which was able to define the model inputs, complexity and related parameters. In [28] the authors propose a cascaded approach for automatic input selection and related parameter definition targeting the minimization of the error and the correlation function coefficients, using for this end a canonical GA and the free search DE algorithm.

On the other hand, many works have been proposed in the topic of automatic input selection and parameter estimation in the case of NNs with EAs for different types of applications. In [29] a hybrid methodology based on metaheuristic algorithms and backpropagation was proposed for the purpose of parameter estimation and architecture definition, which may also perform input selection as the input nodes are subject to pruning. The estimation of distribution algorithm is used together with support vector machines in [30] and with multilayer perceptrons in [31] to perform input selection and parameter estimation for the purpose of time series forecasting. In [32] the authors use a modified multiobjective micro-GA to perform feature extraction and parameter estimation in the case of human motion detection and classification task, aiming at the minimization of the number of inputs and the maximization of the overall performance. A methodology for input selection and parameter estimation of multilayer perceptrons is proposed in [33], to perform time series forecasting with feature selection based on chaotic time series analysis and correlation functions together with hybrid Levenberg–Marquardt and DE algorithms.

In the present work, we analyse the application of a cascaded evolutionary algorithm composed of GA and DE for the purpose of system identification. The algorithm uses an improved objective function based on the minimization of the errors and the autocorrelation function coefficients of the residuals and the higher order cross-correlation function coefficients of the residuals and the system inputs as suggested in [34]. Being so, as in [28] the present work aims at the extension to a more general class of models of [24]. We extend the analysis done in [28] to the application to a higher number of case studies, differently use the DE algorithm to perform the parameter estimation and analyse statistically the optimization outcomes of the overall procedure. The methodology is applied to identify a MagnetoRheological (MR) damper [35,11,36], a simulated system [37] and also the Box–Jenkins gas furnace [38] – which are frequently used as benchmarks in system identification. We found that the methodology provides overall better results in the MR damper and Box–Jenkins gas furnace cases when compared to other works and methodologies for input selection and is able to find the true set of lags for the simulated system.