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Robust identification of nonlinear complex systems using low complexity ANN and particle swarm optimization technique

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ABSTRACT

The paper introduces a novel method of adaptive robust identification of complex nonlinear dynamic plants including Box Jenkin, Mackey Glass and Sunspot series under the presence of strong outliers in the training samples. The identification model consists of a low complexity single layer functional link artificial neural network (FLANN) in the feed forward path and another on the feedback path. The connecting weights are iteratively adjusted by a population based particle swarm optimization technique so that a robust cost function (RCF) of the model-error is minimized. To demonstrate robust identification performance up to 50% random samples of the plant output is contaminated with strong outliers and are employed for training the model using PSO tool. Identification of wide varieties of benchmark complex static and dynamic plants is carried out through simulation study and the performance obtained are compared with those obtained from using standard squared error norm as CF. It is in general observed that, the Wilcoxon norm provides best identification performance compared to squared error and other RCFs based models.

1. Introduction

The objective of identification is to determine a suitable mathematical model of a given system/process useful for predicting the behavior of the system under different operating conditions. Its another objective is to design a controller which allows the system to perform in a desired manner. Most of the practical plants and systems are nonlinear and dynamic in nature and hence identification of such complex plants is a challenging task. Accurate and fast identification of real time nonlinear complex processes is still a difficult problem. Further, in many practical situations, building of a proper model of a plant becomes difficult when outliers are present or few data are missing from the output samples of the plant or the training signal. Under such adverse conditions the training of models becomes ineffective when conventional learning algorithms such as the least mean square (LMS) or recursive least square (RLS) type algorithms are used. But all these derivative based algorithms have been derived by minimizing the square of the error as the cost function. In recent past many bioinspired and evolutionary computing tools such as genetic algorithm (GA), particle swarm optimization (PSO), bacterial foraging optimization (BFO) and ant colony optimization (ACO) have been reported and have been applied for optimization and identification tasks. In case of the derivative free algorithms conventionally the mean square error (MSE) is used as the fitness or cost function. Use of MSE as cost function leads to improper training of adaptive model when outliers are present in the desired signal. Therefore there is a need for identification of complex plants which are nonlinear and dynamic in nature. It is a fact that the traditional regressors employ least square fit which minimizes the Euclidean norm, while the robust estimator is based on a fit which minimizes another rank based on a norm called Wilcoxon norm (McKean, 2004). It is known in statistics that linear regressors developed using Wilcoxon norm are robust against outliers. Using such norm new robust machines have recently been proposed for approximation of nonlinear functions (Hsieh, Lin, & Jeng, 2008). In the present investigation we develop a new method of robust identification of nonlinear dynamic systems or plants by minimizing robust cost function (RCF) (McKean, 2004; Tsai & Yu, 2000; Wang, Lee, Liu, & Wang, 1997) of errors of a functional link artificial neural network (FLANN) model using a derivative free PSO technique. The identification performance of the new method is evaluated through simulation study and is compared with the results obtained from corresponding Euclidean norm-based PSO technique. Hence the main contribution of the paper is the formulation of complex identification task as a robust optimization problem of RCF of the FLANN model. The second contribution is the effective minimization of this norm employing a population based derivative free PSO technique which essentially adjusts the connecting weight of

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feed forward and feed back paths of the model. The third contribution is the selection of appropriate FLANN structure as the backbone of the model which is a single layer ANN structure and offers low complexity. The robust identification performance in presence of outliers in the training signal is then shown through simulation of some bench mark nonlinear dynamic identification problems. Many research papers have been reported in the literature to identify both static and dynamic nonlinear systems. The Artificial Neural Network (ANN) has been employed for many identification and control purpose (Haykin, 1994; Parlos, Chong, & Atiya, 1994; Sastry, Santharam, & Unnikrishnan, 1994) but at the expense of large computational complexity. Narendra and Parthasarathy (1990) have used the MLP architecture with back propagation learning algorithm for effective identification and control of dynamic systems (Nguyen & Widrow, 1991) and robot arm control (Cembrano, Wells, Sarda, & Ruggeri, 1997). Similarly the Radial Basis Function (RBF) network has been introduced to develop system identification model of nonlinear dynamic systems (Chen, Billings, & Grant, 1992; Elanayar & Shin, 1994). In recent past the wavelets in place of RBF has been suggested in neural network (Pati & Krishnaprasad, 1993; Zhang & Benveniste, 1992) to develop efficient identification model. Further, the Functional Link Artificial Neural Network (FLANN), a computationally efficient single layer ANN, has been reported in the literature as an useful alternative to MLP for many applications. This single layer ANN has also been successfully employed for identification of nonlinear systems (Patra, Pal, Chatterji, & Panda, 1999). Recently Chebyshev-FLANN has been proposed for identification of nonlinear dynamic systems (Patra & Kot, 2002).

Particle swarm optimization (PSO) is a stochastic, population based and self-adaptive evolutionary computational technique first introduced by Kennedy and Eberhart (1995). It is an optimization algorithm which is inspired by the social behavior of animals like fish schooling and bird flocking. In comparison to other population based stochastic optimization methods the PSO offers equivalent or even superior search performance for many complex optimization problems with faster and more stable convergence rates (Kennedy & Eberhart, 2001). The PSO exploits a population of individuals to probe promising regions of the search space. The population is called a swarm and the individuals are called particles. Each particle moves with an adaptable velocity within the search space and retains in its memory its historical best position and the neighborhood best position. These two positions are derived according to problem-defined cost function. The movement of each particle progressively evolves to an optimal or near optimal solution. According to some authors it is a computational intelligence (Valle, Ganesh Kumar, Salman, Jean-Carlos, & Harley Ronald, 2008) based or bioinspired technique which is not largely affected the size and nonlinearity of the problem and can converge to the optimal solution in many problems where most analytical methods fail to converge. The research papers published on PSO during the last thirteen years have mainly concentrated on two issues. Developing powerful PSO algorithms (Valle et al., 2008) by incorporating some variations in the main concept and applying PSO and its variants to many fields to solve engineering problems. Recently reported papers on applications of PSO are function approximation (Yanping, Shaozi, & Changle, 2007), image segmentation (Liu, Sui, Zhang, Lu, & Liu, 2007), design of antennas (Baskar, Alphones, Suganthan, & Liang, 2005), stock market prediction (Majhi, Panda, Sahoo, & Panda, 2008), design of tree structures (Schutte & Groenwold, 2003), learning to play games (Messerschmidt & Engelbrecht, 2004), biomedical image registration (Wachowiak, Smolikova, Zheng, Zurada, & Elmaghraby, 2004), design of adaptive IIR filters (Krusienski & Jenkins, 2004), identification of nonlinear systems (Panda, Mohanty, Majhi, & Sahoo, 2007), reactive power and voltage control (Yoshida, Kawata, Fukuyama, Takayama, & Nakanishi, 2000; Zhao, Guo, & Cao, 2005), economic dispatch (Park, Lee, Shin, & Lee, 2005; Aruldoss, Victoire, & Jeyakumar, 2005; Gaing, 2003; Chen, Peng, & Jian, 2007), power system reliability and security (Kassabalidis, El-Sharkawi, Marks, Moulin, & Silva, 2002), generation expansion problem (Kannan, Slochanal, & Padhy, 2004; Kannan, Slochanal, & Padhy, 2005), state estimation (Abido, 2002; Vlachogiannis & Lee, 2005), controller tuning (Abido, 2002; Gaing, 2004), system identification and control (Chia-Feng, 2004; Liu, Zhu, Zhang, & Wang, 2004), capacitor placement (Esmin, Torres, & Zambroni, 2005; Yu, Xiong, & Wu, 2004), short term load forecasting (Huang, Huang, & Wang, 2005), generator contribution to transmission systems (Vlachogiannis & Lee, 2005), industrial applications (Ling et al., 2008), task assignment problem (Ho, Lin, Liauh, & Ho, 2008), to solve the Sudoku puzzle (Moraglio, Chio, Cecilia, Togelius, & Poli, 2008), electromagnetic design (Coelho, 2007), unit commitment problem (Ting, Rao, & Loo, 2006) and global optimization of multimodal functions (Liang, Qin, Suganthan, & Baskar, 2006).

In the past many robust learning algorithms have been proposed for training different adaptive networks. A robust BP learning algorithm that is resistant to the noise effects has been derived in (Chen & Jain, 2004). However the convergence of this algorithm is very slow. Another robust learning algorithm has been reported (Connor, Martin, & Atlas, 1994) for recurrent neural network. This algorithm is based on filtering outliers from data followed by estimating parameters from the filtered data. The new method makes better prediction of electrical demand compared to conventional methods. In a letter (Sanchez, 1995) a robust learning method has been proposed for RBF network and has been applied for function approximation. Kadir Liano has reported (Liano, 1996) a mean log squared error (MLSE) cost function (CF) and has shown that the new cost function yields algorithm which is robust compared to conventional squared error based cost function. In another publication the authors have used the fuzzy neural network and β-spline membership function for function approximation with outliers in training data (Wang et al., 1997) and have shown that their algorithm is more flexible and efficient than the one reported in (Chen & Jain, 2004). In 1998 a robust interval regression analysis has been suggested which provides robust performance against outliers as well as improvement in rates of convergence (Huang, Zhang, & Huang, 1998). A robust objective function is suggested in (Lee, Chung, Tsai, & Chang, 1999) for RBF networks to reduce the influence of outliers. The authors have shown that the proposed objective function yields better function approximation compared to its least square (LS) counterpart. In (Tsai & Yu, 2000), the authors have proposed robust learning algorithms of fuzzy neural network to reduce the outlier effects during training. They have tested the robustness of their algorithm through simulation of various function approximation problems. Chuang et al have recently proposed (Chuang, Su, & Chen, 2001) a robust TSK fuzzy modeling approach with improved performance for function approximation in presence of outliers. A novel regression approach has recently been reported (Chuang, Su, Jeng, & Hsiao, 2002) to enhance the robust capability of the support vector regressor. In their approach they have used a cost function which works satisfactorily when maximum 10% outliers are present in the training set. In 2004, a robust analysis of linear models is presented using Wilcoxon norm (McKean, 2004) and it has been shown the proposed norm is more robust to outliers compared to its least square counterpart. Recently Hsieh et al. have proposed robust learning rules for neural network, fuzzy neural network and kernel based regressor using a Wilcoxon norm (Hsieh et al., 2008) which is different from other norms and have shown that the new norm-based algorithm exhibits robust better performance when the percentage of outlier is as high as 40%. The organization of the paper proceeds as follows.