## Chapter 26

# Ultra High Frequency Polynomial and Trigonometric Higher Order Neural Networks for Control Signal Generator

### Ming Zhang

Christopher Newport University, USA

### **ABSTRACT**

This chapter develops a new nonlinear model, Ultra high frequency Polynomial and Trigonometric Higher Order Neural Networks (UPT-HONN), for control signal generator. UPT-HONN includes UPS-HONN (Ultra high frequency Polynomial and Sine function Higher Order Neural Networks) and UPC-HONN (Ultra high frequency Polynomial and Cosine function Higher Order Neural Networks). UPS-HONN and UPC-HONN model learning algorithms are developed in this chapter. UPS-HONN and UPC-HONN models are used to build nonlinear control signal generator. Test results show that UPS-HONN and UPC-HONN models are better than other Polynomial Higher Order Neural Network (PHONN) and Trigonometric Higher Order Neural Network (THONN) models, since UPS-HONN and UPC-HONN models can generate control signals with error approaching 0.0000%.

### INTRODUCTION

The perspective of this chapter will be: introduce the background of HONNs with the applications of HONNs in control area; develop a new HONN model called UPT-HONN for ultra-high frequency control signal generator; provide the UPT-HONN learning algorithm and weight update formulae; applications of UPT-HONN model for control signals.

This chapter is organized as follows: Section background gives the background knowledge of HONNs in control area. Section UPT-HONN models introduces UPT-HONN structure and different modes of the UPT-HONN model. Section learning algorithm of UPT-HONN models provides the UPT-HONN model update formula, learning algorithms, and convergence theories of HONN. Section UPT-HONN testing describes UPT-HONN computer software system and testing results.

DOI: 10.4018/978-1-5225-0788-8.ch026

### BACKGROUND

### **Neural Networks for Control Signals and Control Systems**

Artificial Neural Networks have been widely used in the control area. Studies found that artificial neural networks are good tools for system control and control signal generating. Narendra and Parthasarathy (1990) develop identification and control techniques of dynamical systems using artificial neural networks. Arai, Kohon, and Imai (1991) study an adaptive control of neural network with variable function of a unit and its application. Chen and Khalil (1992) develop an adaptive control of nonlinear systems using neural networks. Hu and Shao (1992) show the neural network adaptive control systems. Yamada and Yabuta (1992) investigate a neural network controller which uses an auto-tuning method for nonlinear functions. Campolucci, Capparelli, Guarnieri, Piazza, and Uncini (1996) learn neural networks with adaptive spline activation function. Lewis, Yesildirek, and Liu, (1996) design Multilayer neural-net robot controller with guaranteed tracking performance. Polycarpou (1996) applies stable adaptive neural control scheme for nonlinear systems. Lewis, Jagannathan, and Yesildirek (1998) build neural network control for robot manipulators and non-linear systems.

Norgaard, Rayn, Poulsen, and Hansen (2000) generate neural networks for modelling and control of dynamic systems, Poznyak, Sanchez, and Yu (2000) investigate differential neural networks for robust nonlinear control. Chen and Narendra (2002) present nonlinear adaptive control using neural networks and multiple models. Diao and Passino (2002) examine adaptive neural/fuzzy control for interpolated nonlinear systems. Holubar, Zani, Hager, Froschl, Radak, Braun (2002) explore advanced controlling of anaerobic digestion by means of hierarchical neural networks. Plett (2003) inspects adaptive inverse control of linear and nonlinear systems using dynamic neural networks. Ge, Zhang, and Lee (2004) probe adaptive neural network control for a class of MIMO nonlinear systems with disturbances in discretetime. Shi and Li (2004) contribute a novel control of a small wind turbine driven generator based on neural networks. Bukovsky, Bila, and Gupta (2005) analyze linear dynamic neural units with time delay for identification and control. Yih, Wei, and Tsu (2005) experiment observer-based direct adaptive fuzzy-neural control for nonffine nonlinear systems. Farrell and Polycarpou (2006) indicate adaptive approximation based control by unifying neural, fuzzy and traditional adaptive approximation approaches. Boutalis, Theodoridis, and Christodoulou (2009) suppose a new neuro FDS definition for indirect adaptive control of unknown nonlinear systems using a method of parameter hopping. Hou, Cheng, and Tan (2009) supply decentralized robust adaptive control for the multiagent system consensus problem using neural networks, Alanis, Sanchez, Loukianov, and Perez-Cisneros (2010) seek real-time discrete neural block control using sliding modes for electric induction motors. Weidong, Yubing, and Xingpei (2010) offer short-term forecasting of wind turbine power generation based on genetic neural network. Kumar, Panwar, Sukavanam, Sharma, and Borm (2011) run neural network-based nonlinear tracking control of kinematically redundant robot manipulators. Pedro, and Dahunsi (2011) grant neural network based feedback linearization control of a servo-hydraulic vehicle suspension system. All of the studies above suggest that artificial neural networks are powerful tools for control signals and control systems

### **Higher Order Neural Networks for Control Signals and Control Systems**

Artificial Higher Order Neural Networks (HONNs) have been widely used in the control area too. Studies also found that artificial higher order neural networks are good tools for system control and generating

32 more pages are available in the full version of this document, which may be purchased using the "Add to Cart" button on the publisher's webpage:

www.igi-global.com/chapter/ultra-high-frequency-polynomial-and-trigonometric-higher-order-neural-networks-for-control-signal-generator/161047

### **Related Content**

# An Observer Approach for Deterministic Learning Using Patchy Neural Networks with Applications to Fuzzy Cognitive Networks

H. E. Psillakis, M. A. Christodoulou, T. Giotisand Y. Boutalis (2011). *International Journal of Artificial Life Research (pp. 1-16)*.

www.irma-international.org/article/observer-approach-deterministic-learning-using/52974

### Structural and Functional Data Processing in Bio-Computing and Deep Learning

Karthigai Selvi S. (2023). Structural and Functional Aspects of Biocomputing Systems for Data Processing (pp. 198-215).

www.irma-international.org/chapter/structural-and-functional-data-processing-in-bio-computing-and-deep-learning/318558

### Active Contour Model for Medical Applications

Ritam Sahaand Mrinal Kanti Bhowmik (2016). *Handbook of Research on Natural Computing for Optimization Problems (pp. 937-959).* 

www.irma-international.org/chapter/active-contour-model-for-medical-applications/153849

### Multi-Objective Optimization Evolutionary Algorithms in Insurance-Linked Derivatives

M. J. Perez (2007). Handbook of Research on Nature-Inspired Computing for Economics and Management (pp. 885-908).

 $\underline{www.irma-international.org/chapter/multi-objective-optimization-evolutionary-algorithms/21172}$ 

### Cell Motility Viewed as Softness

Koji Sawa, Igor Balažand Tomohiro Shirakawa (2012). *International Journal of Artificial Life Research (pp. 1-9).* 

www.irma-international.org/article/cell-motility-viewed-softness/65071