Chapter 15

PERFORMANCE ANALYSIS OF DYNAMIC CELL STRUCTURES

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Abstract As a special type of Self-Organizing Maps (SOM), the Dynamic Cell Structures (DCS) network has topology-preserving adaptive learning capabilities that can, in theory, respond and learn to abstract from a wide variety of complex data manifolds. However, the highly complex learning algorithm and non-linearity behind the dynamic learning pose serious challenge to validating the performance of DCS and impede its spread in control applications, safety-critical systems in particular.

In this paper, we analyze the performance of DCS network by providing sensitivity analysis on its structure and confidence measures on its predictions. We evaluate how the quality of each parameter of the network (e.g., weight) influences the output of the network by defining a metric for parameter sensitivity for DCS network. We present the validity index (VI), an estimated confidence associated with each DCS

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output, as a reliability-like measure of the network's prediction performance. Our experiments using artificial data and a case study on a flight control application demonstrate that our analysis effectively measures the network performance and provides validation inferences in a real-time manner.

Keywords: Dynamic Cell Structures, Validity index, sensitivity analysis, performance estimation, confidence measures, neural networks.

1. Introduction

Often viewed as black box tools, neural network models have a proven track record of successful applications in various fields. In safety-critical systems such as flight control, neural networks are adopted as a major soft-computing paradigm to support on-line adaptation and damage-adaptive control. The appeal of including neural networks in these systems is in their ability to cope with a changing environment. Unfortunately, the validation of neural networks is particularly challenging due to their complexity and nonlinearity and thus reliable performance prediction of such models is hard to assure. The uncertainties (low confidence) existing in the neural network predictions need to be well analyzed and measured during system operation. In essence, a reliable neural network model should provide not only predictions, but also a confidence measure of its predictions.

The Dynamic Cell Structure (DCS) network [1] is designed as a dynamically growing structure in order to achieve better adaptability. DCS is proven to have topology-preserving adaptive learning capabilities that can respond and learn to abstract from a wide variety of complex data manifolds [2, 3]. The structural flexibility of DCS network has gained it a good reputation of adapting faster and better to a new region than most SOMs [2, 3]. A typical application of DCS is the NASA Intelligent Flight Control System (IFCS)[4]. DCS is employed in IFCS as online adaptive learner and provides derivative corrections as control adjustments during system operation. In this application, it outperforms Radial Basis Function (RBF) and Multi-Layer Perceptron (MLP) network models [5]. As a crucial component of a safety critical system, the DCS network is expected to give quality performance in the entire operational domain.

Relying upon learning/training/approximation, a neural network model raises issues in its quality (e.g., [6]). Two aspects are of importance here: if the model has been trained with a set D of input values X, the model should produce the correct (or almost correct) values for these data. In learning theory, this is called *recall*. On the other hand,