Chapter 24
Neural Networks:
Evolution, Topologies, Learning Algorithms and Applications

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ABSTRACT

Artificial neural networks form a class of soft computing tools, which are made up of interconnected computational primitives for the analysis of numeric data. These are inspired by the functional behavior of the human nervous system comprising millions of nerve cells or neurons. Different artificial neural network architectures have been evolved over the years based on the storage, transmission, and processing characteristics of the human nervous system.

These networks generally operate in two different modes, viz., supervised and unsupervised modes. The supervised mode of operation requires a supervisor to train the network with a training set of data. Networks operating in unsupervised mode apply topology preservation techniques so as to learn inputs. Representative examples of networks following either of these two modes are presented with reference to their topologies, configurations, types of input-output data and functional characteristics. Recent trends in this computing paradigm are also reported with due regards to the application perspectives.

INTRODUCTION

A neural network is a powerful data-modeling tool that is able to capture and represent complex input-output relationships (Haykin, 1999; Kumar, 2004). The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform intelligent tasks similar to those performed by the human brain. These tasks include understanding, cognition, perception, control of human body parts etc. Above all, the brain being the pivotal organ of the human body is also entrusted with the synchronization of these actions to avoid functional disorders with the help of the central nervous system, which by itself is an information

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processing entity. This multifaceted functionality of the human brain is attributed to the inherent massively parallel computing structure gifted by a highly dense structure of interconnected computing units referred to as *neurons* (approximately more than 10 billion in number), which evoke appropriate responses to external world signals (Rojas, 1996). These neurons or neuronal cells, which form the human nervous system, imbibe a series of biochemical reactions for the purpose of reception, storage, processing and transmission of information incident from the real world.

The neural cell body or *soma* houses the nucleus and is connected to treelike networks of nerve fibers called *dendrites* (Rojas, 1996). A single long fiber referred to as the *axon* extends from the soma. This axon eventually branches into strands and substrands to connect other neurons through junctions referred to as *synapses*. Complex biochemical reactions enable the transmission of signals from one neuron to another via the intermediate synapses when some transmitter compounds are released from the sending end of the junction. These compounds either raise or lower the electrical potential inside the body of the connected receiving soma. When the electric potential reaches above a threshold value, the signal pulse is sent from the sending soma to the receiving soma via the axon. At this point, the receiving cell is activated or fired. Thus, it is evident that the functioning of the nervous system is mainly carried out by the neurons (Rojas, 1996).

Artificial neural networks are targeted to model the information processing capabilities of the nervous system. The initial steps in this direction were envisaged by the introduction of the simplified neuron by McCulloch and Pitts in 1943 (McCulloch 1943). An artificial neural network comprises several computing primitives interconnected together in different topologies for processing and propagation of information. In analogy with the human nervous system, these primitives are referred to as neurons or *nodes*. The synapses or junctions between these neurons are represented by connection strengths (or *weights*), which weight or modulate the incident input signals. The nonlinear processing power of these neurons is guided by a characteristic *activation/transfer* function. To be precise, the impinging weighted signals from the anterior neurons sum up to generate a neuronal impulse by means of a transformation in the posterior neuron. In this way incident input information gets processed and propagated from the preceding neurons to the following ones. Eventually, relevant features of the information are learnt by the individual neurons by means of an application specific learning algorithm, which entails the adjusting of the interconnection weights until the desired precision is attained (Haykin 1999; Kumar, 2004). This learning of information content by the neurons of an artificial neural network is referred to as the training of the neural network. So much so forth, this trained information is manifested in the adjusted weights in a neural network.

A plethora of literature (Egmont-Petersen, 2002; Huang, 2009) is available on the possible incarnations of the artificial neural network models, which have evolved through the ages. These models differ in their structures, topological connectivities, operational modes, learning algorithms, activation characterizations etc. Since the functioning of the nervous system inspires these models, a proper understanding of the biological mechanisms involved inside the nervous system is a prerequisite for designing artificial neural network models appropriate for a specific task.

The proposed chapter is targeted at providing an understanding of the essence of the neural networking paradigm with reference to the biological processes involved in the nervous system. The following section discusses the mechanisms of transmission, storage and cognition of information in the nervous system. A detailed analysis of the artificial neural networking paradigm is presented in the subsequent section with reference to the basic neuronal model, its mathematical formalism, constituent components, structure and topology.

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