

Chapter II

An Introduction to Artificial Neural Networks

Introduction

The design of the first computers were influenced by the power of the human brain and attempts to create **artificial intelligence**, yet modern day digital computers are very different from what we understand about human neural processing. Most computers today are sequential (or only partially parallel) and have no (or very limited) learning capability. We have succeeded in building machines that can reliably store and quickly access information from large databases of data but we have only recently been able to create control mechanisms that enable robots to walk on two legs on flat surfaces. However, as far as image recognition is concerned, and in particular face recognition, our attempts to replicate the power of our own visual systems have been very limited. Our own biological visual systems are still much more advanced than current artificial models. For example, human visual systems are able to recognise people's faces from various distances and angles, or when we are shown a picture of a person when they were much younger, and even when someone is in disguise. If we could artificially recreate even some of the most

powerful parallel processing or learning capabilities of the brain then it would be very worthwhile. Whether for learning, generalisation, modelling complex nonlinear functions, or intelligent data compression, artificial neural networks can be also be useful in game design and development.

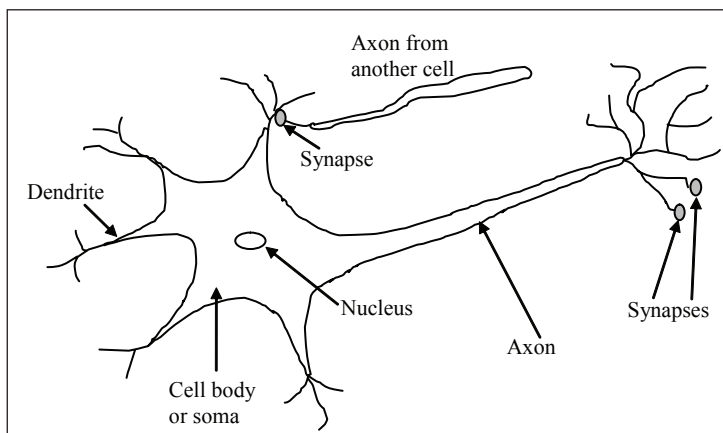
In the next chapters we discuss the two main forms of neural network learning in detail: supervised and unsupervised learning. This will then be used as a base for us to outline a number of practical applied examples for digital games. First we will explain the background and basic ideas surrounding artificial neural networks.

Biological Neural Networks

The first neural cells were discovered in 1873 by Italian scientist Camillo Golgi who found when brain tissue was stained in Silver Chromate solution that a small percentage of neurons became darkly stained. The **human brain** contains approximately 95-100 billion of these neurons (grey matter), each between 0.01 and 0.05 mm in size, and each neuron may have up to 10 000 connections (white matter). The following diagram illustrates the structure and main components of a typical biological neuron.

In a real neuron, signals are transmitted between neurons by electrical pulses (action-potentials or “spike” trains) travelling along the axon. Information is received by the neuron at synapses on its dendrites. Each **synapse** represents the junction of an incoming axon from another neuron with a dendrite of the neuron represented

Figure 1. The structure of a biological neuron



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