Springer Geophysics

Alireza Hajian
Peter Styles

Application of Soft Computing and Intelligent Methods in Geophysics

Springer

Springer Geophysics

The Springer Geophysics series seeks to publish a broad portfolio of scientific books, aiming at researchers, students, and everyone interested in geophysics. The series includes peer-reviewed monographs, edited volumes, textbooks, and conference proceedings. It covers the entire research area including, but not limited to, applied geophysics, computational geophysics, electrical and electromagnetic geophysics, geodesy, geodynamics, geomagnetism, gravity, lithosphere research, paleomagnetism, planetology, tectonophysics, thermal geophysics, and seismology.

More information about this series at http://www.springer.com/series/10173

Alireza Hajian · Peter Styles

Application of Soft Computing and Intelligent Methods in Geophysics

Springer

Alireza Hajian
Department of Physics
Najafabad Branch, Islamic Azad University
Najafabad
Iran

Peter Styles
Applied & Environmental Geophysics Research Group, School of Physical and Geographical Sciences
Keele University
Keele
UK

ISSN 2364-9127 ISSN 2364-9119 (electronic)
Springer Geophysics
ISBN 978-3-319-66531-3 ISBN 978-3-319-66532-0 (eBook)
https://doi.org/10.1007/978-3-319-66532-0

Library of Congress Control Number: 2018938772

Printed on acid-free paper

This Springer imprint is published by the registered company Springer International Publishing AG part of Springer Nature
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Preface

Inferences regarding the interior structure of the Earth, ranging from over 6000 km to just the first few hundred meters of depth, have to be made to assess the potential for geohazards as well as to explore for and extract Earth's many invaluable resources and even to evaluate the possibility of safely storing materials underground which we wish to remove from the atmosphere (carbon dioxide) or the surface (radioactive or hazardous wastes). These inferences are based on the measurement, analysis, and interpretation of external geophysical fields. These include potential fields such as gravity and magnetic data which are intrinsically nonunique, i.e., there are many interpretations, each with their inherent measurement uncertainties, which can be derived from a single set of measurements, and electrical, electromagnetic, or seismic data which similarly offer multiple applicable models. It is understood intuitively and intellectually by practitioners within the discipline that the interpretations are intrinsically "FUZZY". In some cases, it is possible to drill down to quite considerable depths to "prove" an interpretation, even if the answer is only actually applicable to a very small region of subsurface space. However, this is very costly and in some cases, the invasive nature is not appropriate, e.g., where the act of drilling may compromise the integrity of a structure such as a radioactive waste repository or quite simply the target may be too deep; here, geophysical methods are invaluable.

Geophysical research over the past few decades has witnessed a flurry of activity especially related to soft computing and intelligent methods. Working in the interdisciplinary field of soft computing and intelligent methods applications in geophysics and geotechnical aspects for the past 10 years has motivated us to publish a textbook on this important area of multi-interdisciplinary applied science. When Prof. Peter Styles was writing his book on the application of geophysics to environmental and civil engineering, I proposed that he added a section within a chapter or a chapter about the application of neural networks and fuzzy logic in gravity interpretation. However, upon reflection, it was felt that this subject was too advanced to be included. He then encouraged me to develop a specialist book on this topic. We agreed to collaborate on a draft for a book on the application of soft computing and intelligent methods in geophysics combining my expertise in the application of these mathematical tools and his wide-ranging expertise across the fields of applied, environmental, and engineering geophysics. We finally developed the blueprint which is applied in this book.

During the more than a decade that we have worked on the application of neural networks, fuzzy logic, and neuro-fuzzy aspects, there have been many graduate students who were very eager to apply soft computing and intelligent methods (SCIMs) to their own geophysical problems but the books to introduce them to the topic and guide them in its application, either weren't available, didn't explain the applications to engineering geophysics or for the main part focused on applications in oil exploration with a principal emphasis on seismic reflection interpretation. Our book, in contrast, tries to cover the application of SCIM to a broad spectrum of geophysical methods. In addition, we provide the tools to design and test SCIM applications using MATLAB software, and these are presented as simply as possible, so that the reader can apply the MATLAB routines themselves and therefore learn the necessary skills in a practical manner.

The book has four main parts: Neural Networks, Fuzzy Logic, Combination of Neural Networks and Fuzzy Logic, and Genetic Algorithms.

In Part I, Chap. 1 outlines the principles of neural networks (NNs) and their design in MATLAB with practical examples, and in Chap. 2, the application of NNs to geophysical applications is presented with many varied examples.

In Part II, Chap. 3 develops the principles of fuzzy logic with the related fuzzy arithmetic and provides various examples in order to practically train the reader to grasp this new fuzzy viewpoint. In Chap. 4, we investigate the application of fuzzy logic to various geophysical methods.

In Part III, Chap. 5, we explain the application of the combination of NNs with Fuzzy logic as Neuro-Fuzzy Methods, with instructions for using the MATLAB ANFIS Toolbox through practical examples. In Chap. 6, the application of these Neuro-Fuzzy methods to geophysical analysis and interpretation is presented.

In Part IV, Prof. Mrinal Sen and Prof. Mallick, the additional contributors to this book, present the Genetic Algorithm and its applications in geophysics with many varied and interesting practical examples.

Readers of the book will find chapters dealing with preliminary aspects as well as advanced features of SCIMs. With a unique focus toward geophysical applications but with applicability to other physical and measurement sciences, this book will serve as a valuable reference for graduate students, research workers, and professionals interested in learning about these useful computing tools. The goal of this book is to help SCIMs find greater acceptability among researchers and practicing geophysicists alike.

It gives us both great pleasure to express our appreciation and thanks to a number of individuals who have helped us, either directly or indirectly, toward starting and eventually completing this book. I am grateful to past Ph.D. students especially R. Kimiaefar (who graduated in 2015 and is now a board member of Physics Department at IAUN) for help with MATLAB codes for NN design to attenuate seismic noise, and also my present Ph.D. student M. Rezazadeh Anbarani, who helped develop the MATLAB guides in Chapters 1 and 5. My colleague

Dr. Kh. Soleimani (board member of Mathematics Department at IAUN) provided invaluable help in the utilization of Fuzzy arithmetic. I will never forget my advisers for my Masters and Ph.D. degrees, Prof. V. E. Ardestani who first motivated me to use ANN in gravity interpretations in my M.S. thesis and Prof. H. Zomorrodian for his kindness and encouragement in combining neural and fuzzy methods in my Ph.D. thesis to interpret microgravity data. A very special mention is due to Prof. Caro Lucas (previously a board member of the Electrical Engineering Department at the University of Tehran) who is not now among us in this mortal world having passed away about a year before I defended my Ph.D. I am especially appreciative of having such a mentor who always encouraged me to go deeper into multi-interdisciplinary researches in soft computing.

I would also like give to a very special thanks to Dr. Pasandi, Assistant Professor of Geology, University of Isfahan and to record my sincere appreciation to Dr. A. Bohlooli, Assistant Professor in the Faculty of Computer Engineering at the University of Isfahan for his key guidance in arranging the book chapters.

Peter Styles would like to thank, en masse, the legions of Ph.D. and M.Sc. students from Swansea, Liverpool, and Keele Universities who worked with him in collecting a vast array of geophysical data, from which we select unique examples for this book, and who gave him such pleasure in their company, often despite adverse conditions and difficult circumstances. He is enormously grateful to his long-suffering wife Roslyn, who once again has had to put up with his chosen, strongly focused, writing modus operandi!

I especially want to give my thanks and express my deep appreciation of my wife Mohaddeseh and my daughter Elina for their support, over the course of more than a year, in writing this book and their understanding; therefore, that I could not spend all of my spare time with them.

Last, but not least, I am indebted to my parents: Mohammad Hassan and Ozra, for the continued appreciation and support that I have received in all my educational pursuits. I will never forget my Mother's endeavors in training me how to think deeply about the philosophy of work and life.

Najafabad, Iran

Alireza Hajian
Department of Physics
Najafabad Branch, Islamic Azad University

Keele, UK

Peter Styles
Applied & Environmental Geophysics Research Group
School of Physical and Geographical Sciences
Keele University

Contents

Part III Combination of Neural Networks and Fuzzy Logic

Part I
Neural Networks

Chapter 1
Artificial Neural Networks

– Principles of neural networks
– Design and test of neural networks
– Neural Networks toolbox in Matlab: NNTOOL

1.1 Introduction

Artificial neural networks are perhaps the most common method amongst intelligent methods in geophysics and are becoming increasingly popular. Because they are universal approximations, these tools can approximate any continuous function with any arbitrary precision.

Neural networks are increasingly being used in prediction, estimation, pattern recognition and optimization problems (Bohlooli et al. 2011) (Fig. 1.1). Neural networks have gained popularity in geophysics this last decade (Gret et al. 2000). Elavadi et al. (2003), Hajian (2008) and Hajian et al. (2011a) used a Hopfield neural network in order to obtain depth estimates of subsurface cavities. Osman et al. (2007) used forced neural networks for forward modeling of gravity anomaly profiles. Styles and Hajian (2012) used Generalized Regression Neural Networks (GRNN) for cavity depth estimation using microgravity data. Hajian and Shirazi (2015) used GRNN for depth estimation of salt dome using gravity data.

In the geophysical domain, neural networks have been used for waveform recognition and first-peak picking (Murat and Rudman 1992; McCormack et al. 1993); for electromagnetic (Poulton et al. 1992), magneto telluric (Zhang and paulson 1997), and seismic inversion purposes (Röth and Tarantola 1994; Langer et al. 1996; Calderón-Macías et al. 1998); neural networks (Elawadi 2001; Osman et al. 2007, Hajian et al. 2012); multi-adaptive neuro—fuzzy interference systems (Hajian et al. 2011b).

The fundamental important step is the mapping of a geophysical problem onto a neural network solution which can have various applications in geophysics for both non-potential and potential methods.

A. Hajian and P. Styles, *Application of Soft Computing and Intelligent Methods in Geophysics*, Springer Geophysics,
https://doi.org/10.1007/978-3-319-66532-0_1

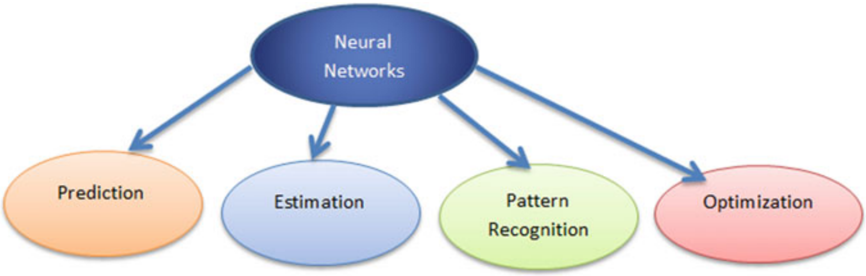


Fig. 1.1 Various fields of neural networks applications

1.2 A Brief Review of ANN Applications in Geophysics

A comprehensive look at all geophysical application for ANNs is impractical. However, a glance at the popular publications in journal books and conference proceedings provides illustrative examples. Geophysical applications include various disciplines which are short listed below:

- Petrophysics:
  - Modeling permeability in tight gas sands using well-log responses
  - predicting permeability from petrographic
  - Porosity estimation, lithofacies mapping,
- Seismic data processing:
  - Wave Form Recognition
  - Picking Arrival Times
  - Trace Editing
  - Velocity Analysis
  - Elimination of Multiples
  - Deconvolution
  - Inversion Of Velocity Model (Moya and Irikura 2010)
  - Random Noise Attenuation
  - Joint Inversion
  - Tracking Horizons And Classifying Seismic Traces
  - Initial Impedance, Impedance Model Estimation
  - Scatter Distribution (Neural Wavelets)
  - 4D Filtering (Fu 1999)
  - Seismic attribute analysis
- Gas detection from absorption and amplitude measurements versus offset (Clifford and Aminzadeh (2011)
- Cross-borehole geological interpretation model based on geotomography (Kumar et al. 2002)

- Geological pattern recognition and modeling from well logs and seismic data processing (Huang and Williamson 1994)
- Classification of seismic windows (Diersen et al. 2011)
- Rock Mass and Reservoir characterization
  - Horizon tracking and facies maps, time lapse interpretation
  - Predicting log properties, Rock/Reservoir characterization
  - Assessing Enhanced Oil Recovery (EOR) methods for reservoirs
- Seismology:
- Regional seismic event classification (Dysart and Pulli 1990)
  - Seismic discrimination
  - Non-linear Dynamic behavior of earthquakes
  - Automatic classification of seismic signals (Scarpetta et al. 2005)
  - Earthquake predictions (Reyes et al. 2013)
  - Prediction of seismicity cycles (Sharma and Arora 2005)

    Identification of earthquake phases under increased noise level conditions (Fernando et al. 2010)
    Earthquake magnitude prediction using artificial neural network (Alarifi et al. 2012)

  - Volcanology:
    - Predicting eruptions
    - Classification of eruptions

    - EM:
      - Detection of cavities and tunnels from magnetic anomaly data (Elawadi 2001)
      - Interpretation of electromagnetic elasticity soundings for near—surface objects (Poulton 1992)
      - Extracting IP parameters from TEM data (Poulton 1992)
      - Magnetic anomaly separation using cellular Neural Networks (Albora 2001)
      - Detection of Airborne Electromagnetic Method (AEM) Anomalies corresponding to dike structures
      - Interpretation of Geophysical surveys of Archeological sites
      - Piecewise Half-space interpretation
      - Inverse modeling of EM data with neural networks
      - Mineral potential mapping using EM, Gravity & geological data
      - Pattern recognition of subsurface EM images (Poulton 1992)
      - Forecasting solar activities (Uwamahoro et al. 2009)
      - Automatic detection of UXO from Airborne Magnetic Data (Salem et al. 2001)

- Solar Cycle prediction (Petrovay 2010)

- Gravity:
  - Depth estimation of cavities using microgravity data
  - Shape factor estimation of gravity anomalies
  - Prediction of linear trends
  - Adaptive learning 3D gravity inversion for salt-body imaging 4D gravity time series prediction
  - Attenuation of the effect of atmospheric temperature and pressure (as noise) on microgravity continuously record by gravimeters
  - Boundary detection for iron ore deposits (Wavelet Cellular Neural Networks)
- Geodesy:
  - Optimal Interpretation of the Gravity of the earth
  - Predicting vertical displacement of structures
  - Orbit propagation for small satellite missions
  - Sea-level prediction using satellite altimetry
  - Determination of structure parameters (Kaftan and Salk 2009)
- Resistivity:
  - Layer boundary picking, locating layer boundaries with unfocused resistivity tools
  - Inversion of DC resistivity data (EL-Qady and Ushijima 2001)
  - Obtaining formation resistivity and layer thickness from vertical electrical sounding (VES)

The most common Neural Networks used in geophysics are:

- Back-propagation
- SVM (Support Vector Machine)
- GRNN (General Regression Neural Networks)
- Cellular Neural Networks, Wavelet Cellular neural networks (CNN)
- Modular Neural Networks (MNN)
- Forced Neural Networks (FNN)
- Radial Basis Function Neural Networks (RBF)

In this chapter we first explain neural network concepts and introduce some of the important types of neural networks which are most common in geophysical problems.

1.3 Natural Neural Networks

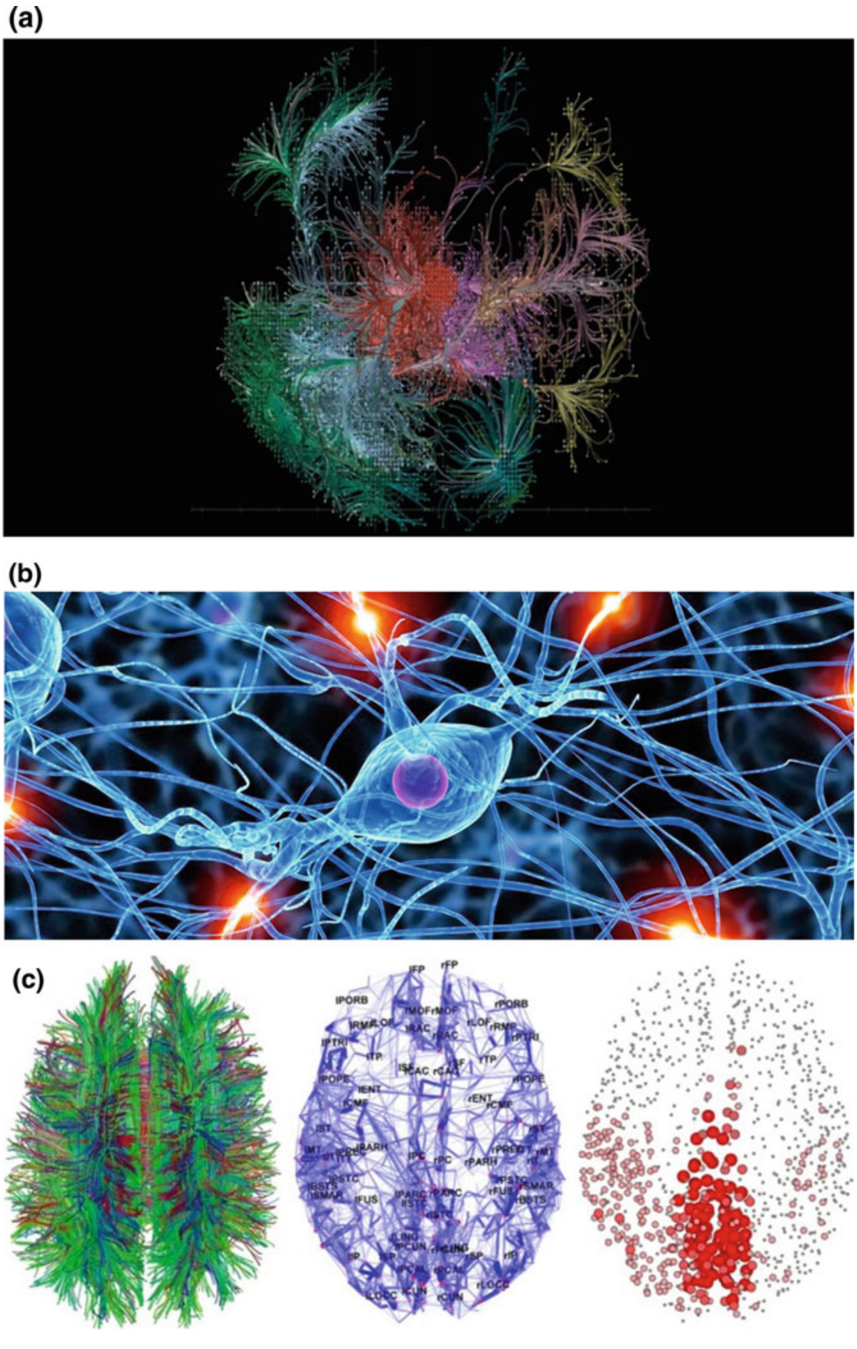
The human brain is a complex organism with great powers of learning and generalization from specific data. The human brain is one of the great mysteries of our time and scientists have not reached a consensus on exactly how it works. Two theories of the brain exist namely: the “grandmother cell theory” and the "distributed representation theory". The first theory asserts that individual neurons have high information capacity and are capable of representing complex concepts such as 'your grandmother' or even 'Jennifer Aniston'. The second theory asserts that neurons are much simpler and the representation of complex objects is distributed across many neurons. Artificial neural networks are loosely inspired by the second theory. Up to now much research has been done by neuroscientists to explore the nature of the human brain operation and structure. These scientists have explored the map of a mouse brain which is shown in Fig. 1.2a. This is the First Detailed Map of a Mammal's Neural Network; if this looks like an incredibly complex wiring diagram to you, it's because it is: you're looking at the Allen Mouse Brain Connectivity Atlas, the first detailed map of any mammal's neural network. It's not a full connectome—the name given to maps of every single interconnection between neurons in a brain—but it's the most detailed rendering of interconnections in any mammalian brain yet. It traces connections between tiny cubes, called voxels, of brain tissue containing between 100 and 500 neurons. Hongkui Zeng and colleagues at the Allen Institute for Brain Science in Seattle, Washington, injected the brains of 469 mice with a virus that introduced a fluorescent protein into the neural network. Because each animal was injected at a slightly different location, when taken together, the fluorescing proteins gave a snapshot of the network's shape. Next, the team diced up each brain into 500,000 pieces each measuring 100 cubic micrometers. Based on the strength of fluorescence in the cubes, they generated a 3D map of how each of the 469 different signals spread through the brain's thoroughfares and quieter by roads (www.gizmodo.com.au).

Human brains have a lot of cells namely "neurons" (Fig. 1.2b, c) and the number of these elements is approximately 10^{11} neurons with perhaps 10^{15} interconnections over transmission paths that may range a metre or more.

1.4 Definition of Artificial Neural Network (ANN)

> A single neuron in the brain is an incredibly complex machine that even today we don't understand. A single "neuron" in a neural network is an incredibly simple mathematical function that captures a minuscule fraction of the complexity of a biological neuron. So to say neural networks mimic the brain, that is true at the level of loose inspiration, but really artificial neural networks are nothing like what the biological brain does.—Andrew Nigrin.

An artificial neural network is a processing method which is inspired by how the human brain and the nervous system are interconnected with neurons. Azoff (1994) states that, "A neural network may be considered as a data processing technique that maps, or relates, some type of input streams of information to an output stream of data". Nigrin (1993) described a neural network based on circuit concepts as" a circuit composed of a very large number of simple processing elements that are


(a)
(b)
(c)

◀**Fig. 1.2** **a** The first detailed map of a mammal's neural network (*source* http://www.gizmodo.com.au/2014/04/this-is-the-first-detailed-map-of-a-mammals-neural-network/). **b** Schematic of neurons in human brains (*source* http://detechter.com/10-interesting-facts-about-the-human-brain). **c** Some very interesting views of the brain as created by state of the art brain imaging techniques (*source* http://www.turingfinance.com/misconceptions-about-neural-networks/#comment-10376)

neutrally based. Each element operates only on local information. Furthermore, each element operates asynchronously; thus there is no overall system clock".

There are numerous alternative definitions of artificial neural networks. One of the commonest is: "Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements" (Schalkoff 2011).

An artificial neural network is composed of a number of interconnected units (artificial neurons) each unit has an input/output (I/O) characteristic and implements a local computation or function. The output of any unit is determined by its I/O characteristics, its interconnections to other units, and (possibly) external inputs. Although "hand crafting" of the network is possible, the network usually develops an overall functionally through one or more forms of training. It is necessary to mention that numerous alternative definitions about ANN exist and the one we select above is a somewhat generic definition.

Commonly, neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is shown in Fig. 1.3. There, the network is adjusted, based on comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are used, in this supervised learning, to train a network.

The overall computing model of an ANN consists of a reconfigurable interconnection of simple elements namely "neurons". The neuron model will be described in detail in the next section. Corresponding to the interconnection

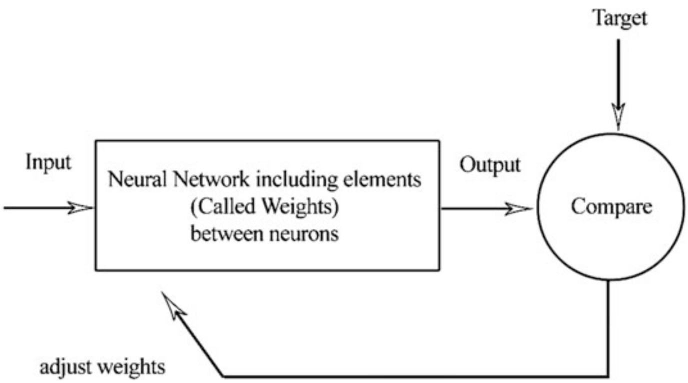


Fig. 1.3 Diagram of a neural network operation

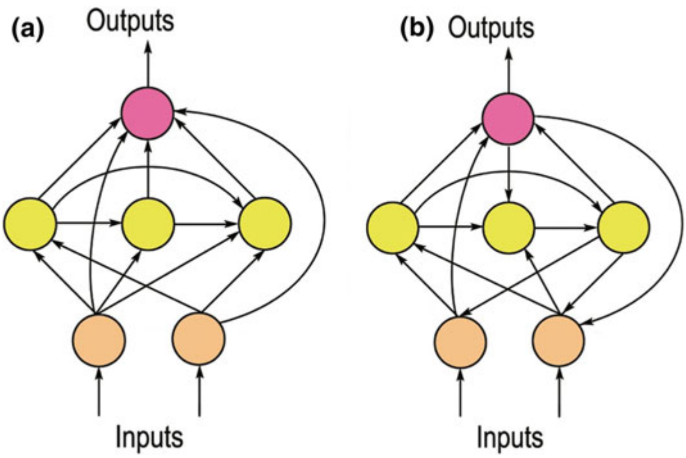


Fig. 1.4 **a** Non-recurrent, **b** recurrent neural networks (Hajian et al. 2012)

direction ANNs can be placed into one of three classes based on their feedback link connection structure ANN's topology: non-recurrent (e.g. feed forward) recurrent (global feedback connections). Local recurrent structure (local feedback connections, e.g. cellular NN).

The non-recurrent ANN contains no closed interconnection paths but in the recurrent ANN the interconnection has arbitrary interconnection flexibility which allows closed-loop (feedback) paths to exist. This allows the network to exhibit far more complex temporal dynamics compared with the (open-loop) strategy, illustrated in Fig. 1.4a, b.

1.5 From Natural Neuron to a Mathematical Model of an Artificial Neuron

Artificial neural networks are a very much simplified model of the natural neural networks of the human nervous system. As we mentioned in the last sections the biological nervous system is built of cells called neurons. Each neuron shares many characteristics with the other cells in the human body and has the capability to receive process and transmit electrochemical signals over the neural pathways that comprise the brain's communication system. The schematic drawing of a Biological Neuron is shown in Fig. 1.5.

1. Dendrites: extend from the cell body out to other neurons where they receive signals at a connection point called "Synapse".
2. The axon is a single long fiber that carries the signal from the cell body out to other neurons.

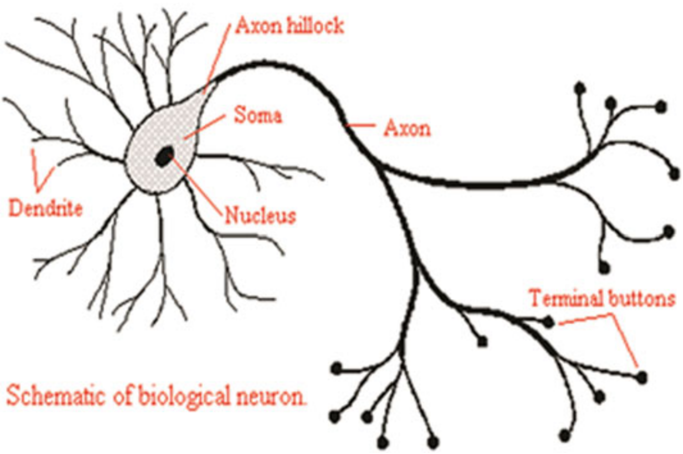


Fig. 1.5 Schematic of a biological neuron. Redrawn from Van der Baan and Jutten (2000)

On the receiving side of the synapse, these inputs are conducted through the cell body out to other neurons. There they are summed; some inputs tend to excite the cell, others tend to inhibit its firing.

When the cumulative excitation in the cell body exceeds a threshold, the cell fires, sending a signal through the axon to other neurons. This basic functional outline has many complexities and exceptions; nevertheless, most Artificial Neural Networks contain only these simple characteristics (Gret and Klingele 1998). Artificial neural networks comprise a set of highly interconnected but simple processing units called nodes which are such neurons. The nodes are arranged in a series of layers that are interconnected through functional linkages. The mathematical model of a simple neuron or 'perception' is presented in Fig. 1.6.

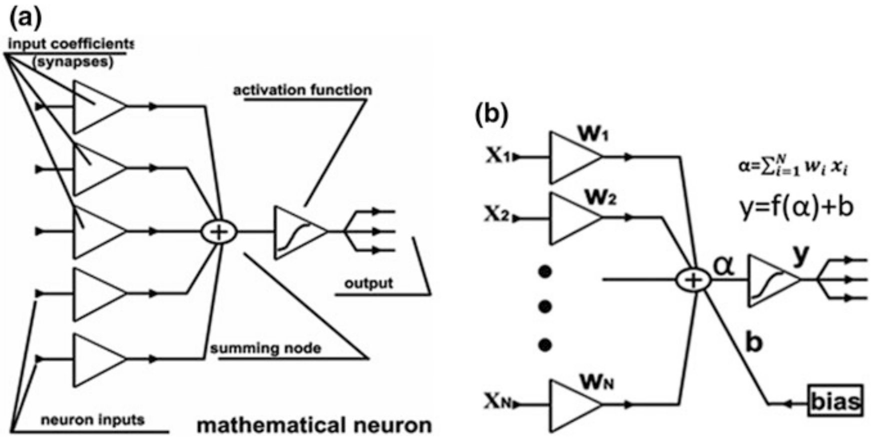


Fig. 1.6 **a** Mathematical model of a 'perception' or 'neuron' **b** the weighted sum of the inputs is rescaled by an activation function. Redrawn from Van der Baan and Jutten (2000)

As shown in Fig. 1.6 the neuron consists of a set of inputs:

$$X = [x(1),\ x(2), \ldots,\ x(n)]$$

and one output. Functionally each input x(i) is weighted or multiplied by a weight function W(i) and summed in a process equivalent to the mathematical process known as Convolution. This is called net input of the neuron:

$$net = \sum_{i=1}^{N} [x(i)w(i)]$$

Then an activation function is computed. This simulates the firing of the nerve cells by inputs from other never cells. The Full diagram of steps from a biological neuron to its mathematical model is shown in Fig. 1.7.

The activation function can be a: step function (hard-limiter), arc-tangent sigmoidal function, hyperbolic tangent sigmoid etc. (see Fig. 1.8). The various kind of activation functions or transfer functions are listed in Table 1.1 with their related MATLAB commands.

The 'sigmoid' activation function is very commonly used for geophysical applications because many applications require a continuous valued output rather than the binary output produced by the hard-limit. In addition, it is particularly well-suited to pattern recognition problems because it produces an output between 0 and 1 that can often be interpreted as a probability estimate (Richard and Lippmann 1991).

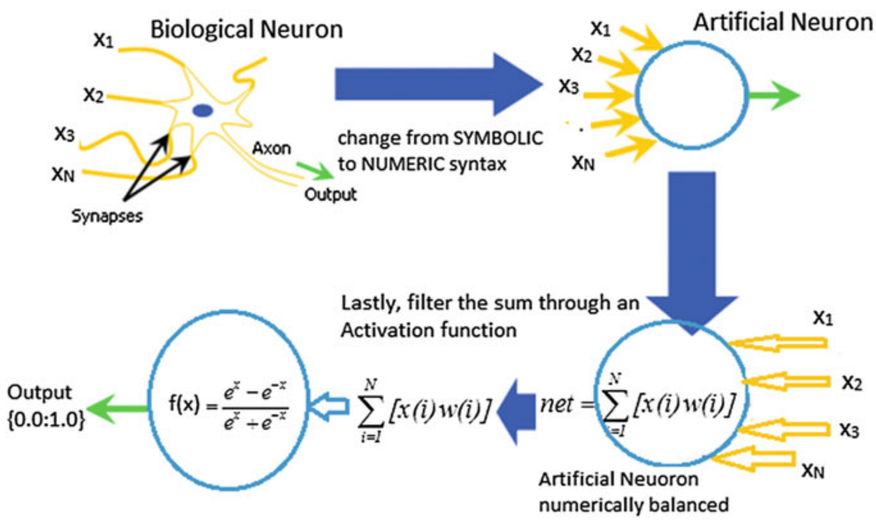


Fig. 1.7 Full diagram of steps from a biological neuron to its mathematical model (here, the activation function is a tangent sigmoid, see Table 1.1)

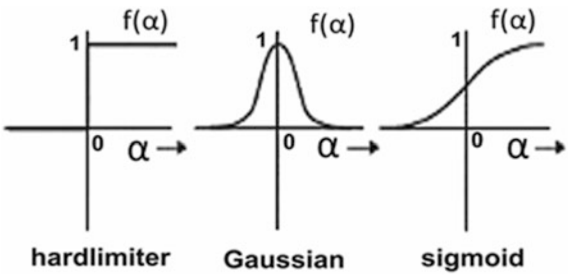


Fig. 1.8 Some of common activation functions

Table 1.1 Some of activation functions with related relations and Matlab commands

Function	Equation		Matlab command
Hard limit	$y = \begin{cases} 0 \\ 1 \end{cases}$	$x<0$ $x\geq 0$	Hardlim
Symmetrical hard limit	$y = \begin{cases} -1 \\ 1 \end{cases}$	$x<0$ $x\geq 0$	hardlims
Saturating linear	$y = \begin{cases} 0 \\ x \\ 1 \end{cases}$	$x<0$ $0<x<1$ $x\geq 1$	–
Symmetrical saturating linear	$y = \begin{cases} -1 \\ x \\ 1 \end{cases}$	$x<-1$ $-1<x\leq 1$ $x>1$	elliotsig
Log-sigmoid	$y = \frac{1}{1+e^{-x}}$		logsig
Hyperbolic tangent sigmoid	$y = \frac{e^x-e^{-x}}{e^x+e^{-x}}$		tansig
Linear	$y = x$		purelin
Positive linear	$y = \begin{cases} 0 \\ x \end{cases}$	$x<0$ $x\geq 0$	–
Competitive	$y = \begin{cases} 1 \\ 0 \end{cases}$	Neuron with Max X other neurons	–

Before the activation function is computed, a bias value (v) is added which serves as a threshold for the activation function. For example if the activation function is a sigmoidal function the output of the neuron will be:

$$b(j) = \frac{1}{\left\{1 + exp\left[-\frac{net+v}{d}\right]\right\}} \tag{1.1}$$

where “d” is a sigmoid shaping factor, “v” is the bias factor and net is the weighted average of neuron inputs. If “d” is a high number then the sigmoid will be a gently

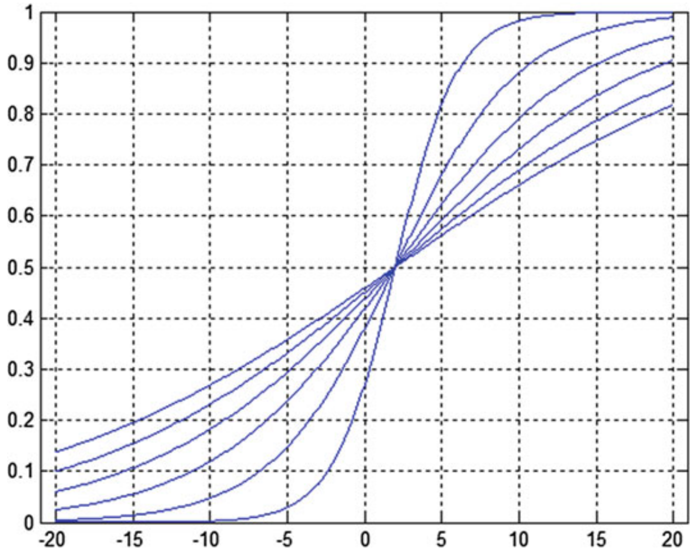


Fig. 1.9 Sigmoid activation functions for different values of shaping factor (as it can be seen the bias factor is fixed at 2)

varying function. For lower values of the shape factor the sigmoid will take a steeper form. To plot the neuron output in MATLAB run below codes the results are illustrated in Fig. 1.9.

```
*****Matlab codes to generate sigmoid activation functions with different
shape factors****************************************


x=[-20:0.1:20];
bias=2;
for j=1:6
   d=[2 4 6 8 10 12];
         f=-(x-bias)/(d(j));
ff=exp(f)+1;
      b=ff.^(-1);
axis([-21 21 0 1])
      plot(x,b)
   hold on
end
grid
```