CHAPTER 7

Hybrid Systems

7.1 Introduction

Fuzzy logic systems and neural networks were inspired by human computational abilities. Thus, they share some common ground. For example, they do not require mathematical models and they work under imprecise, uncertain, and noisy environments. It is also interesting to observe that both are numerical in nature, although this is not a human trait. They also have some complementary characteristics. Fuzzy logic provides inference mechanisms under cognitive uncertainty; it enables computing with words. Fuzzy logic systems require rules set by a human expert; they cannot learn by example or on their own. In contrast, neural networks can learn, adapt, and generalize. In addition, neural networks exhibit fault tolerance due to their distributed structures.

Neural methods can be incorporated into fuzzy systems and fuzzy logic methods can be introduced into neural networks to take advantage of their complementary characteristics. Such combinations lead to what is referred to here as hybrid systems, which are also called fuzzy-neural, neural-fuzzy, or fuzzy-neuro systems. Such systems combine the merits of both fuzzy logic systems and neural networks; namely, the explicit knowledge representation from fuzzy logic methods and the learning ability of neural networks. Using this combination of methods, a more versatile system with a human-like approach can be designed.

7.2 Fuzzy Neuron

There are numerous possible ways to introduce fuzzy logic methods into a neural network. For example, the model of the neuron discussed in Section 6.1 could be generalized to incorporate fuzziness leading to a fuzzy neuron. It is also possible to introduce fuzziness in a network with non-fuzzy neurons by modifying the learning algorithms to allow for membership functions. In this section the concept of fuzzy neurons is illustrated.
A possible model for a fuzzy neuron, FN, that can express and process fuzzy information was put forward by Kwan and Cai. It is illustrated in Figure 7.1. The FN has inputs $x_i$ associated with weights $w_i$ ($i = 1$ to $n$). It also has outputs $y_j$ ($j = 1$ to $m$); all of the outputs have values in the interval $[0, 1]$. These could represent membership values of a given pattern to a particular fuzzy set. The inputs may be thought of as the representation of a linguistic variable and the output expresses the membership values of assigned linguistic descriptions such as TALL, MEDIUM, SMALL, etc. These values could then be propagated to other neurons.

In mathematical terms, the FN operation could be described by

$$y_j = g_i \left[ f \left( h^{w_i}_{i=1} (w_i - x_i) - \theta \right) \right]$$

where $h$ is an aggregation function (such as MIN, MAX, etc.) that replaces the summation operation in a non-fuzzy neuron model, $f$ is an activation function, $\theta$ is the activation threshold, and $\{g_i, j = 1, 2, \ldots, m\}$ are $m$ output functions that represent the membership functions of the input pattern in all the $m$ fuzzy sets.
If $z$ is the aggregated weighted input $h_i^n (w_ix_i)$, then one could define:

- **INPUT-FN** with which an input layer is composed such that $z = x$.
- **MAX-FN** in which the aggregation function is a MAX operation, leading to
  
  $$z = \max_{i=1}^n (w_ix_i)$$
  
  Such a neuron could be referred to also as an or-FN.
- **MIN-FN** in which the aggregation function is a MIN function, leading to
  
  $$z = \min_{i=1}^n (w_ix_i)$$
  
  Such a neuron could be referred to as an AND-FN.
- **COMP-FN** (competitive FN) in which the activation threshold, $\theta$, is a variable and there is only one output such that
  
  $$y = g(s - \theta) = 0, s < \theta$$
  
  $$= 1, s \geq \theta$$
  
  $s = f(z - \theta)$ defines the state of the FN, and
  
  $\theta = t(c_1, c_2, \ldots, c_k), t$ being the threshold function, and
  
  $c_k (k = 1$ to $K)$ are competitive variables of the FN.

All these neurons could appear in one fuzzy neural network, FNN, leading to a heterogeneously structured network as opposed to the homogeneous structures, where all the neurons have similar definitions, as discussed in Chapter 6.

### 7.3 Multilayer FNN Architectures

A multilayer computational structure consisting of fuzzy neurons can be described as a multilayer fuzzy neural network. Numerous architectures have been suggested in the literature. The following two examples are provided to illustrate the concept.

**Example**

**Pedrycz Structures**

A simplified three-layer fuzzy neural network structure is shown in Figure 7.2. Each layer consists of the same type of FNs, but different types are used for each layer. The input layer consists of INPUT-FNs, the hidden layer of MAX-FNs, and the output layer of a single MIN-FN. Figure 7.3 illustrates an alternative structure where the hidden layer is composed of MIN-FNs, and the output layer is a single MAX-FN.
**Example**

**Kwan-Cai Structure**

A four-layer feedforward fuzzy neural network, FNN, for 2-D pattern processing is shown in Figure 7.4. The first layer of the network accepts pixel values of an input pattern and transfers them into normalized values in the interval $[0, 1]$. The second layer fuzzifies the input pattern to an adjustable predetermined degree such that all distinct training patterns can be separated by the network and it produces an acceptable recognition rates. The $m^{th}$ output of this layer can be thought of as expressing a fuzzy concept. The third layer gives similarity of the input pattern to all learned patterns. The fourth layer is a defuzzier stage. It chooses the maximum similarity as the activation threshold of all the COMP-FNs.

![Figure 7.4: Kwan-Cai FNN structure.](image)

**7.4 Fuzzy ART**

Adaptive Resonance Theory neural networks, ART, can be built on prior learning as outlined in Chapter 6. They can create new categories to accommodate inputs that do not belong to any of the categories learned before. Fuzzy ART generalizes ART1 to incorporate fuzzy computations. The generalization to learning both analog and binary input patterns is achieved by replacing the classical intersection operator in ART1 calculations with the fuzzy AND operation—that is, the MIN operation. Fuzzy ART still clusters patterns (vectors) by comparing an input pattern to existing ones, then creating a new category if the need arises. The highlights of the model put forward by Carpenter et al. are as follows:
Chapter 7

Bibliography


Web Resources

1. **First IF/THEN for neural systems**
   
   faculty.washington.edu/chudler/papy.html  
   www.eoa.org.eg/edwintxt.htm#TOP
   
   These two sites provide a description of an ancient Egyptian papyrus that contains a surgery database in the form of an if/then rule. The papyrus has the first use of the neuro words recorded in history.

2. **Neural Fuzzy Systems**
   
   citeseer.nj.nec.com/64350.html
   
   
   Also,
   
   www.abo.fi/~rfuller/nfs.html
   
   Lecture notes on neural fuzzy systems in both Web and PDF formats by the same author.

3. **Neural Networks and Fuzzy Systems**
   
   

4. **Evolving Fuzzy Neural Networks**
   
   divcom.otago.ac.nz/infosci/kel/CBIIS/pubs/pdf/ajiips-si98.pdf
   
   
   citeseer.nj.nec.com/kasabov01evolving.html
   
5. Adaptive Neuro-Fuzzy Inference System, ANFIS
   www.control.hut.fi/Kurssit/AS-74.115/Material/FVAnfis2.pdf

6. Neural Fuzzy Motion Estimation and Compensation
   sipi.usc.edu/~kosko/MotionEstimation.pdf

7. Soft Negotiation
   www.iis.ee.ic.ac.uk/~frank/surp98/report/mgm1/
   A report in Web format by Myles MacRae and Marcus Pickering, the Department of Computing, Imperial College of Science, Technology and Medicine, University of London. The report covers several topics including a simple, short account of soft computing. The account addresses neural networks, fuzzy logic, genetic algorithms and their combinations.

8. Neural Fuzzy Techniques
   scholar.lib.vt.edu/theses/available/etd-5733142539751141/unrestricted/ETD.PDF

9. Neural Fuzzy Inference Network
   A paper by Castellano and Fanelli, Università degli Studi di Bari, Italy. It presents a self-organizing neural fuzzy inference network. It is 6 pages long, with 13 references. It is available in PDF format.

10. Fuzzy ARTMAP vs. MLP
    www cairo.utm.my/publications/yhtay_airtc97.pdf
    A paper available in PDF format: Tay and Kalid, Comparison of fuzzy ARTMAP and MLP Neural Networks for Handwritten Character Recognition, IFAC Symposium on AI in Real-Time Control, Kuala Lumpur, Malaysia, 1997.
The paper presents results of comparisons between Fuzzy ARTMAP and backpropagation based multilayer perceptrons, MLP. Fuzzy ARTMAP outperformed MLP in both learning convergence and recognition accuracy.

11. Fuzzy ARTMAP Applications

Slah et al., Vehicle Licence Plate Recognition by Fuzzy ARTMAP Neural Network, World Engineering Congress, WEC’99, Universiti Putra Malaysia, 1999. It is a six page report with seven references available in PDF format. It reports on the prototype of a system being developed at the Center for Artificial Intelligence and Robotics in Cairo and the Universiti Teknologi Malaysia.

12. Simplified Fuzzy ARTMAP Applications
medusa.sdsu.edu/Robotics/Neuromuscular%20Control/Fuzzy_ARTMAP.pdf


13. Combining Neural Networks and Fuzzy Controllers
citeseer.nj.nec.com/nauck93combining.html

A paper by Nauck, Klawonn, and Kruse that appeared in Fuzzy Logic in Artificial Intelligence, FLAI93; it has 13 pages and 21 references, and is available in PDF format.

14. Modified Fuzzy Neural Network Classifier

This paper discusses neural networks based on modifying the Kwan-Cai Networks.

Authored by Kularni and Sontakke, SGGS College of Engineering and Technology, India.

15. Comparative Study of NN Structures
mecha.ee.boun.edu.tr/~efe/PDF/IMechatronics.pdf

Efe and Kayank of Bogazici University, Turkey present a 16-page report that presents the results of investigating the identification of nonlinear systems by neural networks. Feedforward Neural Networks, Radial Basis Function Neural Networks, Rung-Kutta Neural Networks, and Adaptive Neuro Fuzzy Inference Systems are evaluated and their performance compared.
16. Soft Computing Resources  
www.cs.nthu.edu.tw/~jang/nfsc.htm

A web site maintained by Prof. Jang, Computer Science Department, Tsing Hua University, Taiwan. It provides Web links to numerous resources including FTP sites, newsgroups, neurofuzzy research sites, journals, technical reports, and more.

17. Computational Intelligence Links  

This Web site provides a large number of Web links to mainly introductory information on Computational Intelligence (Neural, Fuzzy, and Genetic). It is maintained by Pacific Northwest National Laboratory, operated by Battelle, an industry located in Ohio, USA.

18. Neuro Fuzzy Resources  
e1vele.ttu.ee/mesel_www_home/R&D/NEUROFUZ/Resourc.htm

A large collection of Web links to resources including tutorials, courses, journals, commercial companies, and much more. It is maintained by Martin Brown, Department of Electronics, Tallinn Technical University, Estonia.

citeseer.nj.nec.com/abraham01neuro.html

A document from Lecture Notes in Computer Science by Ajith Abraham of Monash University, Australia. It is an eight page paper with eleven references that suggest a modeling approach for neuro-fuzzy systems.