9 NEUROFUZZY SYSTEMS

Witold Pedrycz\(^1\), Abraham Kandel\(^2\), Yan-Qing Zhang\(^3\)

\(^1\)Department of Electrical and Computer Engineering
University of Manitoba
Winnipeg, Canada R3T 2N2
pedrycz@ee.umanitoba.ca

\(^2\)Department of Computer Science and Engineering
University of South Florida
Tampa, FL 33620
U.S.A.
kandel@csee.usf.edu

\(^3\)School of Computer and Applied Sciences
Georgia Southwestern State University
Americus, GA 31709
U.S.A.
yqz@canes.gsw.peachnet.edu

9.1. INTRODUCTION
A neurofuzzy system is a hybrid system with integration of fuzzy logic and neural networks, which is capable of performing high-level fuzzy reasoning by using trained fuzzy neural networks which are constructed by learning from sample data. Such a neurofuzzy integration brings high-level fuzzy IF-THEN rules into neural networks, and provides low-level numerical learning mechanisms for fuzzy logic systems. In general, the neurofuzzy system is much more powerful than either neural networks or fuzzy logic systems since it can incorporate the advantages of both, shown in Table 9.1 [86][200].

The current wave of fuzzy neural systems, fuzzy neural controllers or neurofuzzy classifiers, etc. is spectacular. What makes this research so vital and fruitful? The main reason behind this successful fusion of fuzzy sets and neurocomputing is that these technologies are highly complementary. As often emphasized in the literature, fuzzy sets are focused on knowledge representation
issues including the way in which various factors of vagueness are taken care of. As primarily normative in their essence, fuzzy sets cannot cope with the prescriptive aspects of phenomena to be modeled (Pedrycz, 1992; Yamakawa, 1989) and accommodate efficacies implied by the underlying data. Hence the superiority of neurocomputing is overwhelming. Neural networks tend to be more efficient when it comes to learning (Rumelhart and McLelland, 1986) and therefore are naturally inclined to address the descriptive factors of the problem at hand. The two technologies are ideally geared into the handling of the evident duality in the perspective - descriptive duality accompanying any problem statement. The agenda of this study is twofold:

-first, we propose a general taxonomy of hybrid neuro fuzzy topologies by studying various temporal and architectural aspects of this symbiosis.

**Table 9.1: Comparison Between Neural Networks and Fuzzy Logic Systems**

<table>
<thead>
<tr>
<th>No.</th>
<th>Features</th>
<th>Neural Networks</th>
<th>Fuzzy Logic Systems</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>High-level Knowledge</td>
<td>Implicit representation by weights</td>
<td>Explicit representation by fuzzy rules</td>
</tr>
<tr>
<td>2</td>
<td>Model-Free Estimator</td>
<td>Trainable dynamical systems</td>
<td>Structured numerical systems</td>
</tr>
<tr>
<td>3</td>
<td>Knowledge Acquisition</td>
<td>From sample data</td>
<td>From experts</td>
</tr>
<tr>
<td>4</td>
<td>Uncertain Information</td>
<td>Quantitative</td>
<td>Quantitative and qualitative</td>
</tr>
<tr>
<td>5</td>
<td>Uncertain Cognition</td>
<td>Perception</td>
<td>Decision making</td>
</tr>
<tr>
<td>6</td>
<td>Reasoning Mechanism</td>
<td>parallel computations</td>
<td>Heuristic search</td>
</tr>
<tr>
<td>7</td>
<td>Reasoning Speed</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>8</td>
<td>Fault-tolerance</td>
<td>Very high</td>
<td>Low</td>
</tr>
<tr>
<td>9</td>
<td>Adaptive Learning</td>
<td>Adjusting weights</td>
<td>Induction</td>
</tr>
<tr>
<td>10</td>
<td>Knowledge Storage</td>
<td>In neurons and links</td>
<td>In fuzzy rule base</td>
</tr>
<tr>
<td>11</td>
<td>Natural Language</td>
<td>Implicit</td>
<td>Explicit</td>
</tr>
</tbody>
</table>
Neurofuzzy systems have been around for over 25 years. The history is reviewed decade by decade and the main works on neurofuzzy systems and their applications are shown in Table 9.2.

(1) In 1970s
Lee and Lee were the first to study the concept fuzzy neurons in 1970 [187]. Kandel, Lee and Lee then introduced the theory of fuzzy sets to the conventional McCulloch-Pitts model, and finally analyzed fuzzy neural networks based on the principle of neural networks and the mechanism of fuzzy automata [150,188-190]. However, the development of research in neurofuzzy systems was very slow since (1) there were few researchers who did work on either neural networks or fuzzy logic systems and (2) the researchers didn’t find the powerful learning algorithms for neural networks and didn’t have the real applications of fuzzy logic systems.

(2) In 1980s
After a relatively difficult period with neural networks and fuzzy logic in the1970’s, neural networks and fuzzy logic systems attracted a resurgence of attention from a lot of researchers in a variety of scientific and engineering areas in the 1980’s. The first reason for this resurgence was that Hopfield and Tank designed a neural network to solve constraint satisfaction problems such as the "Traveling Salesman Problem", and Rumelhart, Hinton and Williams [235] refined and publicized an effective Backpropagation algorithm for multilayer neural networks which had been first investigated by Werbos[289]. The second reason was that some companies, most in Japan, had successfully made a lot of fuzzy logic products such as fuzzy washing machines, fuzzy air conditioners, and fuzzy subway trains [6,267,268]. With the rapid development of techniques of neural networks and fuzzy logic systems, neurofuzzy systems were attracting more and more interest since they would be more efficient and powerful than either neural networks or fuzzy logic systems. Keller and Hunt studied how to incorporate fuzzy membership functions into the perceptron in 1985[163]. Shiue and Grondin [249] studied fuzzy learning neural-automata in 1987. Takagi and Hayashi [263] analyzed artificial-neural-network driven fuzzy reasoning in 1988. Furuya et al. [72] proposed a neurofuzzy inference system in 1988. Amano et al. [3] used neural nets and fuzzy logic in speech recognition in 1989. Hayashi et al. [93] studied the artificial-neural-network-driven fuzzy control and its application to the inverted pendulum problem in 1989. Kuncicky and Kandel [181] studied a fuzzy neuron model in which the output of one neuron is represented by a fuzzy level of confidence in 1989. Yamakawa and Tomoda discussed the fuzzy neuron and its application to pattern recognition in...
Table 9.2: History of Neurofuzzy Systems

<table>
<thead>
<tr>
<th>Year</th>
<th>Main Works on Neurofuzzy Systems</th>
</tr>
</thead>
<tbody>
<tr>
<td>1970</td>
<td>Fuzzy neurons.</td>
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<tr>
<td>1990-95</td>
<td>(1) Learning algorithms for fuzzy neural networks; (2) Learning algorithms for neural fuzzy networks; (3) Genetic Algorithms for Neurofuzzy Systems; (4) Consumer Products (neurofuzzy washing machine, neurofuzzy fan heater, etc.) (5) Fusion of fuzzy logic, neural networks and chaos; (6) Softcomputing; (7) Applications of Neurofuzzy systems (Fuzzy Control, Fuzzy ARTMAP, Petri Net, Generating Fuzzy Rules, Decision System, Pattern Recognition, Adjusting Membership Functions, Systems Engineering, Medicine, Game theory, Fuzzy Mathematics, Expert systems, etc.).</td>
</tr>
</tbody>
</table>

(3) In 1990s

Important progress with neurofuzzy systems has been made in recent years. Most research papers and applications dealing with neurofuzzy systems appeared in the early 1990's.

In the theoretical realm, many effective learning algorithms for neurofuzzy systems have been developed and a lot of structures of neurofuzzy systems have been proposed. For example, Jang's adaptive-network-based fuzzy inference systems [145], Lin's neural-network-based fuzzy logic control and decision system [197], Wang's several adaptive fuzzy systems [287], the fuzzy ARTMAP by Carpenter et al. [36], the fuzzy Kohonen clustering networks by Bezdek et al. [13], the fuzzy neural network with fuzzy signals and weights by Hayashi et al. [106], the fuzzy
neural net with fuzzy inputs and fuzzy targets by Ishibuchi et al. [137], the fuzzy neural network learning fuzzy control rules and membership functions by fuzzy error backpropagation by Nauck and Kruse [217], etc.

In application, neurofuzzy systems have been widely used in control systems, pattern recognition, consumer products, medicine, expert systems, fuzzy mathematics, game theory, etc. The details are in section 6.

In the interdisciplinary aspect, more and more other techniques such as genetic algorithms, chaos, probability, and AI are being applied to improve neurofuzzy systems [33, 68, 141, 155-160, 178, 221, 310-312]. Therefore, the neurofuzzy system, an important research area of softcomputing, will become more and more powerful and efficient over the future.

9.2 SYNERGY OF NEURAL NETWORKS AND FUZZY LOGIC

Since Lee and Lee [187] first defined the fuzzy neuron in 1970, various definitions of fuzzy neurons have arisen. We start off with a brief summary of a generic type of neuron and then embark on a diversity of logic-driven neurons. It will be emphasized that their functional variety helps design system more efficiently by encapsulating domain knowledge.

A biological neuron is a simple processing element that combines signals from 1000 to 10000 other neurons through dendrites. If the combined signal exceeds a threshold, the neuron excites, and generates an output signal to other neurons through the axon which connects to dendrites of the other neurons. Based on the properties of the biological neuron, an artificial neuron can be constructed as in Fig.9.1. First, the aggregation function $S$ combines the input signals $x_i$ ($i = 1, 2, \ldots, n$) with respective weights $w_i$ ($i = 1, 2, \ldots, n$). Second, the activation function $F$ generates the output signal $y$ of the neuron based on the value of $S$. Commonly used aggregation function $S$ and activation function $F$ are given below,

$$S = \sum_{i=1}^{n} w_i x_i - \theta$$  \hspace{1cm} (9.2.1)

$$y = F(S) = \frac{1}{1 + e^{-\alpha S}}$$  \hspace{1cm} (9.2.2)

where $\theta$ is the threshold (or bias) while $\alpha$ stands for the activation gain.
combining the ideas stemming from fuzzy sets and neural networks. We have investigated various levels of symbiosis and proposed a consistent classification of the systems emerging as an outcome of the symbiosis of these two technologies.

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(Note: cited references are marked by * at their reference numbers' superscripts.)


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