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## FACULTY OF COMPUTER SCIENCE AND AUTOMATION

# COMPUTER SCIENCE MEETS AUTOMATION

## VOLUME I

Session 1 - Systems Engineering and Intelligent Systems

Session 2 - Advances in Control Theory and Control Engineering

Session 3 - Optimisation and Management of Complex Systems and Networked Systems

Session 4 - Intelligent Vehicles and Mobile Systems

Session 5 - Robotics and Motion Systems

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## Preface

Dear Participants,

Confronted with the ever-increasing complexity of technical processes and the growing demands on their efficiency, security and flexibility, the scientific world needs to establish new methods of engineering design and new methods of systems operation. The factors likely to affect the design of the smart systems of the future will doubtless include the following:

- As computational costs decrease, it will be possible to apply more complex algorithms, even in real time. These algorithms will take into account system nonlinearities or provide online optimisation of the system's performance.
- New fields of application will be addressed. Interest is now being expressed, beyond that in "classical" technical systems and processes, in environmental systems or medical and bioengineering applications.
- The boundaries between software and hardware design are being eroded. New design methods will include co-design of software and hardware and even of sensor and actuator components.
- Automation will not only replace human operators but will assist, support and supervise humans so that their work is safe and even more effective.
- Networked systems or swarms will be crucial, requiring improvement of the communication within them and study of how their behaviour can be made globally consistent.
- The issues of security and safety, not only during the operation of systems but also in the course of their design, will continue to increase in importance.

The title "Computer Science meets Automation", borne by the 52nd International Scientific Colloquium (IWK) at the Technische Universität Ilmenau, Germany, expresses the desire of scientists and engineers to rise to these challenges, cooperating closely on innovative methods in the two disciplines of computer science and automation.

The IWK has a long tradition going back as far as 1953. In the years before 1989, a major function of the colloquium was to bring together scientists from both sides of the Iron Curtain. Naturally, bonds were also deepened between the countries from the East. Today, the objective of the colloquium is still to bring researchers together. They come from the eastern and western member states of the European Union, and, indeed, from all over the world. All who wish to share their ideas on the points where "Computer Science meets Automation" are addressed by this colloquium at the Technische Universität Ilmenau.

All the University's Faculties have joined forces to ensure that nothing is left out. Control engineering, information science, cybernetics, communication technology and systems engineering – for all of these and their applications (ranging from biological systems to heavy engineering), the issues are being covered.

Together with all the organizers I should like to thank you for your contributions to the conference, ensuring, as they do, a most interesting colloquium programme of an interdisciplinary nature.
I am looking forward to an inspiring colloquium. It promises to be a fine platform for you to present your research, to address new concepts and to meet colleagues in Ilmenau.

Professor Peter Scharff
Rector, TU Ilmenau

Professor Christoph Ament
Head of Organisation

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Ye. Bodyanskiy / Ye. Gorshkov / V .Kolodyazhniy / P. Otto

# Evolving Network Based on Double Neo-Fuzzy Neurons

## INTRODUCTION

Hybrid computational intelligence systems, and mainly adaptive neuro-fuzzy systems, are widely used in the problems of analysis and processing of non-stationary signals of arbitrary nature under the uncertainty conditions. In most cases these systems have comparatively complex architecture (e.g. 5-layer ANFIS and the like) [1] which results in a complication and deceleration of the learning process in the problems that need to be solved in real-time.

To overcome these difficulties, a new approach called neo-fuzzy neuron (NFN) was proposed in [2–4]. The NFN architecture is quite similar to a conventional $n$-input formal neuron. However, instead of regular synaptic weights it contains nonlinear synapses $\mathrm{NS}_i$, $i = 1, 2, \ldots, n$, which are formed by a set of membership functions $\mu_{ji}$, $j = 1, 2, \ldots, h_i$ with tunable weight $w_{ji}$ on each function.

The response of the NFN to the input signal vector $x(k) = (x_1(k), x_2(k), \ldots, x_n(k))^T$ (here $k = 1, 2, \ldots$ is the discrete time) is

$$y(k) = \sum_{i=1}^{n} f_i(x_i(k)) = \sum_{i=1}^{n}\sum_{j=1}^{h_i} \mu_{ji}(x_i(k)) w_{ji}(k), \tag{1}$$

where $w_{ji}(k)$ is the current value of the tunable weights at the time step $k$ on a $j$-th membership function of $i$-th input signal component. As the error criterion for the learning of NFN a local quadratic error function is usually used

$$E(k) = \frac{1}{2}(d(k) - y(k))^2 = \frac{1}{2}e^2(k) = \frac{1}{2}\left(d(k) - \sum_{i=1}^{n}\sum_{j=1}^{h_i} \mu_{ji}(x_i(k)) w_{ji}\right)^2 \tag{2}$$

and the learning process itself is the minimization of this criterion using the gradient-based procedure

$$w_{ji}(k+1) = w_{ji}(k) + \eta e(k) \mu_{ji}(x_i(k)), \tag{3}$$

where $d(k)$ is the reference learning value, and $\eta$ is the learning rate parameter which is usually chosen empirically and fully determines the speed of the learning process.

The membership functions of the NFN are formed as an array of triangular functions satisfying the following criterion

$$\sum_{j=1}^{h_i} \mu_{ji}(x_i(k)) = 1, \quad i = 1, 2, \ldots, n \tag{4}$$

(the so called Ruspini partitioning). Thus, the network does not require a normalization layer.

The goal of this paper is to improve the approximating capabilities of the NFN by modification of its architecture and speed-up the learning procedure by a special selection of the learning rate parameter.

## DOUBLE NEO-FUZZY NEURON

Consider the architecture of the double neo-fuzzy neuron (DNFN). Its architecture in a compact form is presented in Fig. 1.

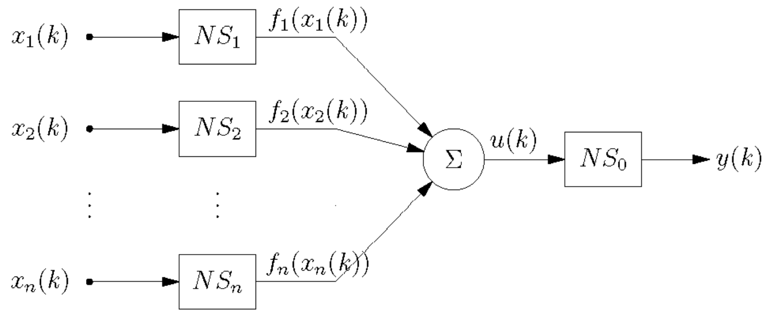


Fig. 1: Double neo-fuzzy neuron

Thus, the DNFN consists of two layers: the input layer of $n$ nonlinear synapses $\mathrm{NS}_i$ with $h_i$ membership functions and synaptic weights each, and the output layer formed by a nonlinear synapse $\mathrm{NS}_0$ with $h_0$ membership functions $\mu_{l0}$, $l = 1, 2, \ldots, h_0$ and synaptic weights $w_{l0}$.

When the vector $x(k) = (x_1(k), x_2(k), \ldots, x_n(k))^T$ is fed to the input of the DNFN, it produces the response in the form

$$y(k) = f_0(u(k)) = f_0\left(\sum_{i=1}^{n} f_i(x_i(k))\right) = \sum_{l=1}^{h_0} \mu_{l0}(u(k)) w_{l0} = \sum_{l=1}^{h_0} \mu_{l0}\left(\sum_{i=1}^{n}\sum_{j=1}^{h_i} \mu_{ji}(x_i(k)) w_{ji}\right) w_{l0}. \tag{5}$$

The output value of the DNFN is determined by the input vector and the values of $\sum_{i=1}^{n} h_i + h_0$ membership functions and corresponding tunable synaptic weights.

As we have already mentioned, the membership functions are of triangular form providing the Ruspini partitioning:

$$\mu_{ji}(x_i) = \begin{cases} (x_i - c_{j-1,i})/(c_{ji} - c_{j-1,i}), & x_i \in [c_{j-1,i}, c_{ji}], \\ (c_{j+1,i} - x_i)/(c_{j+1,i} - c_{ji}), & x_i \in [c_{ji}, c_{j+1,i}], \\ 0 \quad otherwise, \end{cases} \tag{6}$$

$$\mu_{l0}(u) = \begin{cases} (u - c_{l-1,0})/(c_{l0} - c_{l-1,0}), & x_i \in [c_{l-1,0}, c_{l0}], \\ (c_{l+1,0} - u)/(c_{l+1,0} - c_{l0}), & x_i \in [c_{l0}, c_{l+1,0}], \\ 0 \quad otherwise, \end{cases} \tag{7}$$

where $c_{ji}$, $c_{l0}$ are the centers of the corresponding membership functions.

According to this partitioning, at each time step only two neighbouring membership functions of each nonlinear synapse are fired. Denote these functions by $\mu_{pi}$ and $\mu_{p+1,i}$ respectively. Then we can write

$$\begin{aligned} f_i(x_i(k)) &= \sum_{j=1}^{h_i} \mu_{ji}(x_i(k)) w_{ji} = \mu_{pi}(x_i(k)) w_{pi} + \mu_{p+1,i}(x_i(k)) w_{p+1,i} \\ &= \frac{c_{p+1,i} - x_i(k)}{c_{p+1,i} - c_{pi}} w_{pi} + \frac{x_i(k) - c_{pi}}{c_{p+1,i} - c_{pi}} w_{p+1,i} = a_i x_i(k) + b_i, \end{aligned} \tag{8}$$

where $a_i = \dfrac{w_{p+1,i} - w_{pi}}{c_{p+1,i} - c_{pi}}$, $\quad b_i = \dfrac{c_{p+1,i} w_{pi} - c_{pi} w_{p+1,i}}{c_{p+1,i} - c_{pi}}$, and

$$u(k) = \sum_{i=1}^{n} a_i x_i(k) + b_i, \tag{9}$$

$$\begin{aligned} y(k) &= \sum_{l=1}^{h_0} \mu_{l0}(u(k)) w_{l0} = \mu_{l0}(u(k)) w_{p0} + \mu_{p+1,0}(u(k)) w_{p+1,0} \\ &= \frac{c_{p+1,0} - u(k)}{c_{p+1,0} - c_{p0}} w_{p0} + \frac{u(k) - c_{p0}}{c_{p+1,0} - c_{p0}} w_{p+1,0} = a_0 u(k) + b_0, \end{aligned} \tag{10}$$

where $a_0 = \dfrac{w_{p+1,0} - w_{p0}}{c_{p+1,0} - c_{p0}}$, $\quad b_0 = \dfrac{c_{p+1,0} w_{p0} - c_{p0} w_{p+1,0}}{c_{p+1,0} - c_{p0}}$.

Hence, the DNFN provides a piecewise linear approximation of the unknown nonlinear function $d(k) = F(x(k))$ in the form

$$y(k) = a_0 \left( \sum_{i=1}^{n} a_i x_i(k) + b_i \right) + b_0. \tag{11}$$

The approximation is determined by the given set of membership functions and corresponding synaptic weights.

## LEARNING ALGORITHM OF THE DNFN

To develop a learning algorithm for the DNFN parameters, consider the criterion (2) and the gradient-based optimization procedure with a variable learning rate $\eta_i(k)$. Then we can write a simple algorithm for learning in the output synapse $\mathrm{NS}_0$:

$$\begin{cases} w_{l0}(k+1) = w_{l0}(k) + \eta_0(k)e(k)\mu_{l0}(u(k)), \quad l = p, p+1, \\ w_{l0}(k+1) = w_{l0}(k), \quad \forall l \neq p, l \neq p+1. \end{cases} \tag{12}$$

Thus, at each time step only two of the synaptic weights corresponding to the fired membership functions can be tuned.

In order to optimize the speed of the learning procedure, we propose using a one-step modification of the Levenberg-Marquardt algorithm with the Sherman-Morrison formula for inverse matrix computation as proposed in [5, 6]. This approach leads to the following procedure:

$$\begin{cases} w_{l0}(k+1) = w_{l0}(k) + r_0^{-1}(k)e(k)\mu_{l0}(u(k)), \quad l = p, p+1, \\ r_0(k+1) = \alpha r_0(k) + \mu_{p0}^2(u(k+1)) + \mu_{p+1,0}^2(u(k+1)), \quad 0 \le \alpha \le 1, \\ w_{l0}(k+1) = w_{l0}(k), \quad \forall l \neq p, l \neq p+1. \end{cases} \tag{13}$$

For a zero value of the forgetting factor $\alpha$ this procedure coincides with the optimal Kaczmarz-Widrow-Hoff algorithm, and with the Goodwin-Ramadge-Caines nonlinear identification algorithm possessing expressed smoothing properties for $\alpha = 1$. Varying of the parameter $\alpha$ provides tracking or filtering properties to the learning process.

It should be noted that if the learning data set $x(k)$, $d(k)$ is given *a priori*, the learning of the output nonlinear synapse $\mathrm{NS}_0$ can be performed in a batch mode with the standard least squares method. In this case the learning process will be reduced to a single procedure. To learn the weights in the input layer nonlinear synapses, consider the criterion in the form:

$$E(k) = \frac{1}{2}(d(k) - f_0(u(k)))^2 = \frac{1}{2}\left(d(k) - f_0\left(\sum_{i=1}^{n}\sum_{i=1}^{h_i}\mu_{ji}(x(k))w_{ji}\right)\right)^2. \tag{14}$$

Whence,

$$\frac{\partial E(k)}{\partial w_{ji}} = -e(k)\frac{\partial f_0(u(k))}{\partial u(k)}\frac{\partial u(k)}{\partial w_{ji}} = -e(k)a_0(k)\frac{\partial u(k)}{\partial w_{ji}}. \tag{15}$$

Taking into account (15) we can write to the following simple algorithm, which is a gradient-based optimization of the criterion (14):

$$\begin{cases} w_{ji}(k+1) = w_{ji}(k) + \eta_i(k)e(k)a_0(k)\mu_{ji}(x_i(k)), \quad j = p, p+1, i = 1, 2, \ldots, n, \\ w_{ji}(k+1) = w_{ji}(k), \quad \forall j \neq p, j \neq p+1. \end{cases} \tag{16}$$

Denote

$$a_0(k)\mu_{ji}(x_i(k)) = \mu_{ji0}(x_i(k)). \tag{17}$$

Applying the technique described above, we can write the algorithm for learning of the input layer synaptic weights:

$$\begin{cases} w_{ji}(k+1) = w_{ji}(k) + r_i^{-1}(k)e(k)\mu_{ji0}(x_i(k)), \quad j = p, p+1, i = 1,2,\ldots,n, \\ r_i(k+1) = \alpha r_i(k) + \mu_{pi0}^2(x_i(k+1)) + \mu_{p+1,i0}^2(x_i(k+1)), \quad 0 \le \alpha \le 1, \\ w_{ji}(k+1) = w_{ji}(k), \quad \forall j \ne p, j \ne p+1, \end{cases} \tag{18}$$

which fully coincides with the procedure (13) by its structure. Thus, in fact, all the synaptic weights of the DNFN are learned using only a single algorithm.

## NETWORK BASED ON DNFNs

The proposed DNFN is a basic building block of the evolving network shown in Fig. 2.

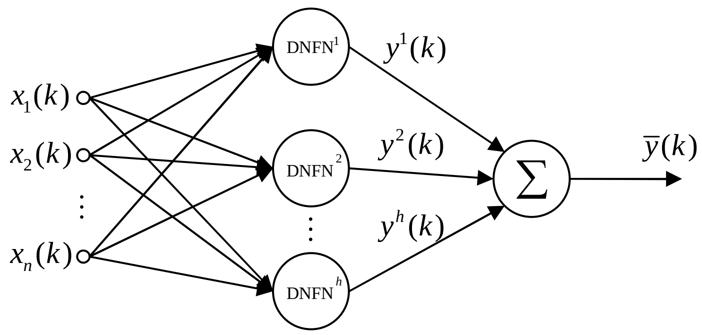


Fig. 2: Evolving network based on DNFNs

This network consists of a set of double neo-fuzzy neurons $DNFN^g$, $g = 1,2,\ldots,h$ combined into a layer. The network contains $(\sum_{i=1}^{n} h_i + h_0)h$ tunable weights and performs the following mapping:

$$\bar{y}(k) = \sum_{g=1}^{h} y^g(k) = \sum_{g=1}^{h}\sum_{l=1}^{h_0} \mu_{l_0}^g \left( \sum_{i=1}^{n}\sum_{j=1}^{h_i} \mu_{ji}^g(x_i(k)) w_{ji}^g \right) w_{l0}^g \tag{19}$$

where $g = 1,2,\ldots,h$; $l = 1,2,\ldots,h_0$; $i = 1,2,\ldots,n$; $j = 1,2,\ldots,h_i$.

An essential feature of such network is the absence of the tunable weights in the output summation element synapses. This allows changing of the number of neurons by adding or removing neurons without the impact on the learning of the existing or newly added neurons. Each neuron learns independently from another according to the algorithm (18).

It can be easily seen that (19) corresponds, in fact, to the Kolmogorov's approximation scheme of a nonlinear function [7–9]. However, in contrast to the other neuro-fuzzy Kolmogorov's networks [5, 10, 11], the proposed approach possesses more flexibility, since it allows modification of the network structure directly during the learning process.

## CONCLUSION

In the paper, an evolving network architecture based on double neo-fuzzy neurons is proposed. The proposed network performs Kolmogorov's approximation of an arbitrary nonlinear function, and possesses greater flexibility for network structure modification during the learning process in comparison to the other Kolmogorov's neuro-fuzzy systems. The learning algorithm is computationally simple and possesses filtering and tracking properties, which become significant in the processing of noisy non-stationary signals.

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