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Supervised learning Laplace transform artificial neural networks and using it for automatic classification of geological structure

P. Szymczyk *, M. Szymczyk

AGH University of Science and Technology, The Faculty of Electrical Engineering, Automatics, Computer Science and Biomedical Engineering, Department of Automatics and Biomedical Engineering, al. A. Mickiewicza 30, 30-059 Kraków, Poland

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ABSTRACT

This paper presents a method of learning novel Laplace transform artificial neural network (LTANN) and shows examples of network learning. It also contains a description of the use of the LTANN for searching anomalies in geological structures (loosened zone of river embankments).

1. Introduction

Learning artificial neural network is one of the most important issues related to the practical use of their capabilities. Having selected the type and structure of the network and the function of the transition we want the network to adequately respond to inputs. An important factor in the learning network is the appropriate choice of learning strategies. Several basic methods of learning can be distinguished:

- Supervised learning [1].
- Unsupervised learning [2].
- Reinforcement learning [3].

In this paper only method of learning with a teacher will be used. In the learning mode with the teacher aside from the input data we are in possession of the output that we want to get (the expected response). The goal of teaching is to minimize the error between the received and the expected response network through adjustment of the network weights.

In Fig. 1 the simple artificial neuron with $n+1$ inputs $x_0, x_1, \ldots, x_n$ is shown. Each input has the corresponding weight $w_0, w_1, \ldots, w_n$. The neuron has a bias $b = w_0 x_0$. It can be written as the following equation:

$$u = \sum_{i=0}^{n} w_i x_i \tag{1}$$

and the formula for the neuron output:

$$y = f(u) \tag{2}$$

where

i the number of given input,
n the number of inputs.

The most known is the algorithm proposed by Widrow and Hoff [4–6]. In this method, the weight is modified as follows:

$$w_i^{k+1} = w_i^k + \beta^k (d^k - y^k) \tag{3}$$

where

w_i^k the value of the weight for the i-th input in the k-th learning step,
β^k a factor in the k-th learning step which satisfies $1 \ge \beta^k > 0$
d^k the expected response in the k-th learning step
y^k the received response in the k-th learning step

2. Supervised learning Laplace transform artificial neuron

The definition of Laplace transform artificial neuron (LTAN) is described in the Appendix and in detail in the article [7] and in the book [8].

* Corresponding author.
E-mail addresses: piotr.szymczyk@agh.edu.pl (P. Szymczyk), magdalena.szymczyk@agh.edu.pl (M. Szymczyk).

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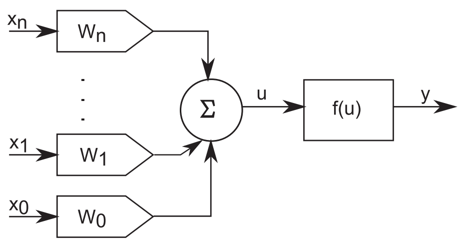

Fig. 1. The simple artificial neuron.

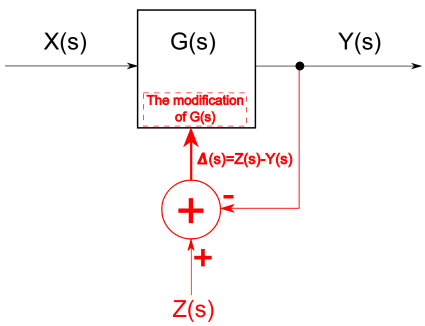

Fig. 2. The supervised learning LTAN. (For interpretation of the references to colour in this figure caption, the reader is referred to the web version of this paper.)

Learning process of LTAN is shown in Fig. 2. It consists of a lot of iteration modifications of $G(s)$ in order to minimize the value of $\Delta(s)$, which is given as

$$\Delta(s) = Z(s) - Y(s) \tag{4}$$

$Z(s)$ is the known learning value of the output signal in response to input signals $X(s)$. $Y(s)$ is a real value of the output signal. The learning algorithm is represented by the feedback (red colour) in Fig. 2.

The following labelling is introduced – superscript in the formulas represents the iterations of the learning process: $k = 0, \ldots, p-1$ where p represents the number of iterations:

$$Y^k(s) = G^k(s) X^k(s) \tag{5}$$

$$\Delta^k(s) = Z^k(s) - Y^k(s) \tag{6}$$

$$G^{k+1}(s) = \frac{k * G^k(s) - \beta(k) * \Delta^k(s)}{k+1} \tag{7}$$

where $\beta(k)$ is a coefficient that satisfies the following condition:

$$\beta(k) = [\beta_0(k) \ \ \beta_1(k) \ \ \ldots \ \ \beta_n(k)] \tag{8}$$

$$1 \geq \beta_i(k) > 0 \tag{9}$$

The value can be set to one: $\beta_i(k) = 1$.

Using the notation from Eqs. (57) and (7) we obtain

$$G_i^{k+1}(s) = G_i^k(s) - \beta_i(k) * \Delta^k(s) \tag{10}$$

The learning process begins with setting the transmittance $G(s)$ on the values:

$$G^0(s) = [0 \ \ 0 \ \ \ldots \ \ 0] \tag{11}$$

and for all i coefficient value is set:

$$\beta_i(0) = 1 \tag{12}$$

As a result of the learning process, we obtain

$$G(s) = G^{p-1}(s) \tag{13}$$

Proposed learning method is similar to the algorithm proposed by Widrow and Hoff [4–6] but in our work the transmittances $G_i(s)$ are determined but not weights of neuron inputs.

3. Supervised learning Laplace transform artificial neural network

The definition of Laplace transform artificial neural network (LTANN) is described in the Appendix and in detail in the article [7] and in the book [8].

The learning process of LTANN is shown in Fig. 3. It consists of a lot of iteration modification $F(s)$ in order to minimize value of $\Theta(s)$, which is given as

$$\Theta(s) = Z(s) - Y(s) \tag{14}$$

where

$$Z(s) = \begin{bmatrix} Z_0(s) \\ Z_1(s) \\ \vdots \\ Z_m(s) \end{bmatrix} \tag{15}$$

and

$$\Theta(s) = \begin{bmatrix} \Theta_0(s) \\ \Theta_1(s) \\ \vdots \\ \Theta_m(s) \end{bmatrix} \tag{16}$$

$Z(s)$ is the known learning value of the output signal in response to input signals $X(s)$. $Y(s)$ is a real value of the output signal. The learning algorithm is represented by the feedback (red colour) in Fig. 3.

As it was done for LTAN the following labelling is introduced – superscript in the following formulas represents the iterations of the learning process: $k = 0, \ldots, p-1$ where p represents the number of iterations:

$$Y^k(s) = F^k(s) X^k(s) \tag{17}$$

$$\Theta^k(s) = Z^k(s) - Y^k(s) \tag{18}$$

$$F^{k+1}(s) = \frac{k * F^k(s) - \Theta^k(s) * \Psi(k)}{k+1} \tag{19}$$

where $\Psi(k)$ is a coefficient that satisfies the following condition:

$$\Psi(k) = [\Psi_0(k) \ \ \Psi_1(k) \ \ \ldots \ \ \Psi_n(k)] \tag{20}$$

$$1 \geq \Psi_i(k) > 0 \tag{21}$$

The value can be set to one: $\Psi_i(k) = 1$.

Using the notation from Eqs. (62) and (19) we can obtain

$$F_{i,j}^{k+1}(s) = \frac{k * F_{i,j}^k(s) - \Psi(k) * \Theta^k(s)}{k+1} \tag{22}$$

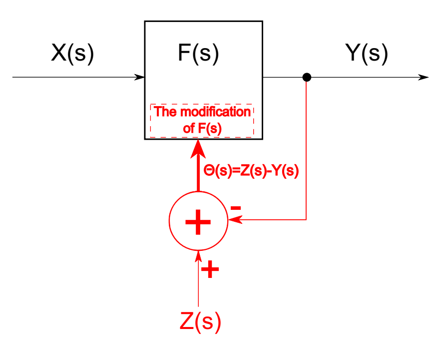

Fig. 3. The supervised learning LTANN. (For interpretation of the references to colour in this figure caption, the reader is referred to the web version of this paper.)