# Investigation of Back Propagation Algorithm Implementation in Analog Neural Networks

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*Abstract*—**Intriguing point of analog neural network implementation is the influence of network parameters over analog neural network behaviour. While such a simulation ignores the parallelism issues inherent in neural networks, it nevertheless provides us to investigate an analog neural network behaviour in relation to network parameters variation. In this paper, an investigation of an analog neural network by means of Matlab simulation is made.**

*Keywords*— **Neural network, Analogue methods, Analogue models**

## I. INTRODUCTION

A popular method for study of neural networks is network simulation using computers. It is appropriate approach from a theoretical and illustrative standpoint, but their applicability to practical implementations of analogue neural network is doubtful. The analysis of the circuits assumed that all the components were ideal. In this paper a simulation using Matlab is presented, but in equations take part the parameters of real components. The variation of some of them reflects to learning and recognition properties of the neural network. In such a way an influence of parameter variation to the learning and recognition properties of the neural network can be examine.

## II. ANALOG NEURAL CELL MATHEMATICAL MODEL

In last years many researchers investigated different an analog neural network implementation. In [6] neural network implementation by means of analog amplifiers is presented. Equation 1 depicts activation function of an implemented on this way neuron.

$$\mathrm{h}_{\mathrm{k}}^{1} = \frac{g_{mk}}{W_0 / L_0 U_c} \sum_j W_j / L_j U_{W_{kj}} u_{zj} \tag{1}$$

Equation \ref{u} depicts neuron output voltage.

$$y_k^l = g(h_k^l) = \frac{1}{\beta_{OR} U_{OR}} \alpha_{FC} I_\beta \tanh\left(\frac{h_k^l}{2\beta_{is} U_{is} U_t}\right) \tag{2}$$

where W/L are the MOS resistive circuit multiplier width/length ratios, $U_C$ controls the total transconductance $g_{mk}$, $\alpha_{FC}$ is the emitter-collector current gain, $I_B$ is the bias current, $\beta$ is MOSFET tranconductance parameter, $U_{OR}$, $U_{IS}$ are control voltage and $U_t$ is thermal voltage.

A Matlab model, which includes parameters of real components is made on basis of these equations.

Assuming:

$$\frac{\alpha_{FC} I_\beta}{\beta_{OR} U_{OR}} = A \tag{3}$$

and

$$\frac{g_{mk} W_j / L}{2.W_0 / L_0 \beta_{IS} U_{IS} U_t U_c} = B \tag{4}$$

the equation 2 simplifies to:

$$y_k^l = A^L \tanh\left(B^L \sum_j U_{wkj} u_{yi}^{\,l-1}\right) \tag{5}$$

The parameter variation leads to A and B variation.

$$\frac{(\alpha_{FC} + \Delta\alpha_{FC})(I_B + \Delta I_B)}{(\beta_{OR} + \Delta\beta_{OR})U_{OR}} = A + \Delta A \tag{6}$$

$$\frac{(g_{mk} + \Delta g_{mk}) W_j / L_j}{2.W_0 / L_0 .(\beta_{is} + \Delta\beta_{is}) U_{is} (U_t + \Delta U_t) U_c} = B + \Delta B \tag{7}$$

Then from equations 6 and 7 the output neuron voltage cell be written as

$$y_k^L = (A + A^L) \tanh((B + B^L).\sum U_{W_{kj}} .u_{y_i}^{l-1}) \tag{8}$$

## III. MATLAB SIMULATION RESULTS

In the discussed paper a two-layer neural network with four neurons in the input layer, three neurons in the hidden layer and one neuron in the output layer is presented

Simulation was performed with neural network showed to igure 1. On this way it is showen that most appropriate results are obtained at A=1. Figure 2 shows that at $\eta$ =0.1 and A=1 the characteristic has least steepness of all.

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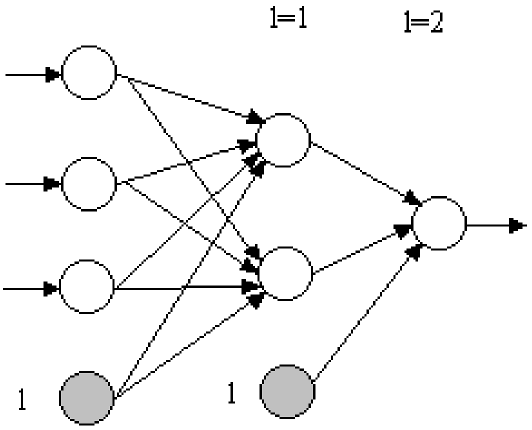


Fig. 1. A two-layer neural network

The learning patterns are:

$$x_1 = \begin{bmatrix} -1 \\ -1 \\ -1 \end{bmatrix} \quad x_2 = \begin{bmatrix} 0 \\ -1 \\ -1 \end{bmatrix} \quad x_3 = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$$

$$x_4 = \begin{bmatrix} -1 \\ -1 \\ 0 \end{bmatrix} \quad x_5 = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} \quad x_6 = \begin{bmatrix} 1 \\ 1 \\ -1 \end{bmatrix}$$

$$x_7 = \begin{bmatrix} -1 \\ 0 \\ 0 \end{bmatrix} \quad x_8 = \begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix} \quad x_9 = \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix}$$

$$x_{10} = \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} \quad x_{11} = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} \quad x_{12} = \begin{bmatrix} 0 \\ -1 \\ 1 \end{bmatrix}$$

$$x_{13} = \begin{bmatrix} -1 \\ 1 \\ -1 \end{bmatrix}$$

$d_1$=-1, $d_2$=0, $d_3$=1, $d_4$=-1, $d_5$=0, $d_6$=1, $d_7$=-1, $d_8$=0, $d_9$=1, $d_{10}$=-1, $d_{11}$=1, $d_{12}$=0, $d_{13}$=-1

The recognition patterns are:

$$x_1 = \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix} \quad x_2 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \quad x_3 = \begin{bmatrix} -1 \\ 1 \\ 1 \end{bmatrix}$$

$$x_4 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \quad x_5 = \begin{bmatrix} 1 \\ -1 \\ -1 \end{bmatrix} \quad x_6 = \begin{bmatrix} -1 \\ -1 \\ 1 \end{bmatrix}$$

$$x_7 = \begin{bmatrix} 0 \\ -1 \\ 0 \end{bmatrix} \quad x_8 = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \quad x_9 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$

$$x_{10} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \quad x_{11} = \begin{bmatrix} -1 \\ 0 \\ -1 \end{bmatrix} \quad x_{12} = \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix}$$

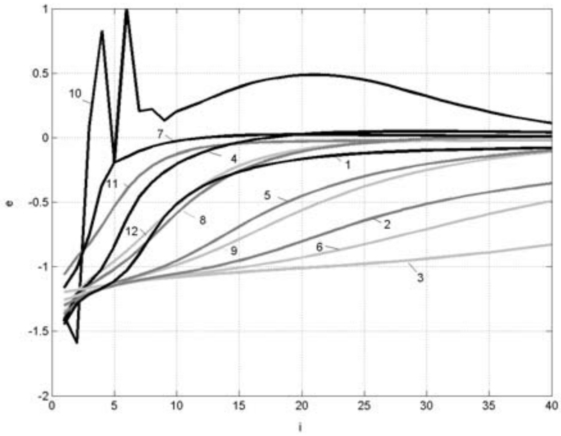


Fig. 2. Variation of A and B reflects to recognition capability of neural network.

TABLE I
NOTATION OF FIGURE 2

| A | B | notation |
|---|---|---|
| 1 | 0.77 | 1 |
| 1 | 0.4 | 2 |
| 1 | o.26 | 3 |
| 1.25 | 0.77 | 4 |
| 1.25 | 0.4 | 5 |
| 1.25 | 0.26 | 6 |
| 1.66 | 0.77 | 7 |
| 1.66 | 0.4 | 8 |
| 1.66 | 0.26 | 9 |
| 2.5 | 0.77 | 10 |
| 2.5 | 0.4 | 11 |
| 2.5 | 0.26 | 12 |

With $\eta$ increasing the characteristic steepness increasing too. When A increase, learning rate decrease. $A_t$=2.5 the neural network is capable only for value $\eta$=0.1. Figures 3, 4, 5 depict these dependences. The values of the parameters of a neuron are: $I_B$=50mA, $U_{OR}$=5V, $\alpha_{FC}$=0.5, $\beta_{is}$=1mA/V$^2$, $U_t$=26mV, $g_{mk}$=1mA/V, $U_{IS}$=5V, $W_j/L_j$=1, $U_C$=5V, $W_0/L_0$=1, 2 or 3, $\beta_{OR}$=2,3,4 or 5mA/V$^2$. For $\beta_{OR}$=2mA/V$^2$, the value of A is A=2.5, for $\beta_{OR}$=3mA/V$^2$, the value of A is A=1.66, $\beta_{OR}$=4mA/V$^2$, A=1.25 and for $\beta_{OR}$=5mA/V$^2$, the value of A is A=1. Respectivly for $W_0/L_0$=1, the value of B is B=0.77, for $W_0/L_0$=2, the value of B is B=0.4, and for $W_0/L_0$=3, the value of B is B=0.26.

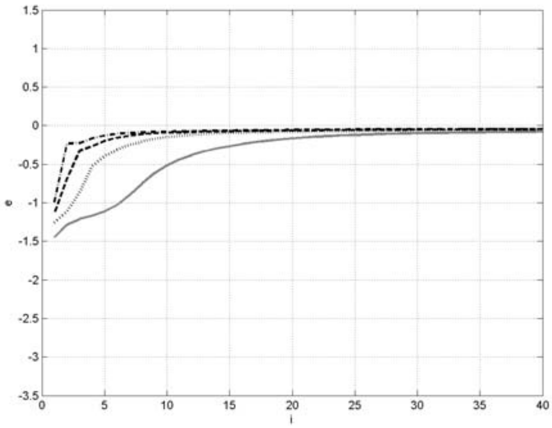


Fig. 3. Influence of $\eta$ to recognition capability of neural network, A=1, B=0.77.

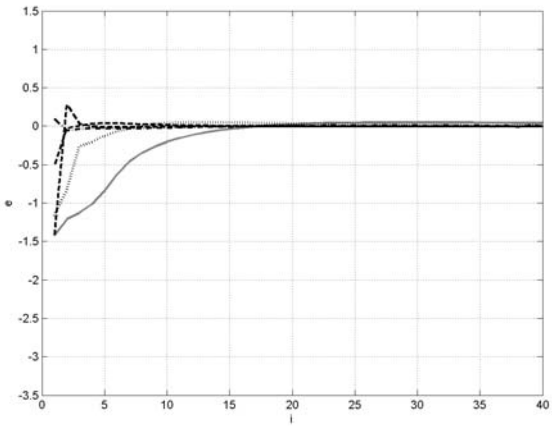


Fig. 4. Influence of to recognition capability of neural network, A=1.25, B=0.77.

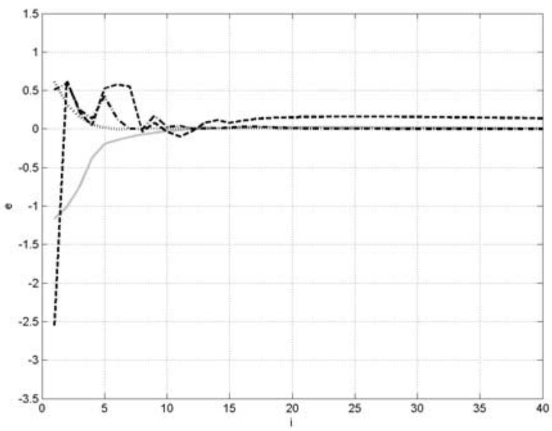


Fig. 5. Influence of $\eta$ to recognition capability of neural network, A=1.66, B=0.77.

TABLE II
FIGURE 3,4,5 - NOTATION VALUE OF B IS B=1

| A | $\eta$ | notation | Figure N: |
|---|---|---|---|
| 1 | 0.5 | - - | 3 |
| 1 | 0.4 | -.- | 3 |
| 1 | 0.3 | . . | 3 |
| 1 | 0.2 | gray | 3 |
| 1.25 | 0.5 | - - | 4 |
| 1.25 | 0.4 | -.- | 4 |
| 1.25 | 0.3 | . . | 4 |
| 1.25 | 0.2 | gray | 4 |
| 1.66 | 0.5 | - - | 5 |
| 1.66 | 0.4 | -.- | 5 |
| 1.66 | 0.3 | . . | 5 |
| 1.66 | 0.2 | gray | 5 |

## IV. CONCLUSION

In this paper a computer simulation using Matlab is presented. In neural network equations take part the parameters of real components. The variation of some of them reflects to learning and recognition properties of the neural network. In such a way an influence of parameter variation to the learning and recognition properties of the neural network can be examine. The simulation results shows that neural network has adequate behaviour for values for A=1 and for B=0.77.

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