

# Neuro-Fuzzy System for Equalization Channel Distortion

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**Abstract**— In this paper the application of neuro-fuzzy system for equalization of channel distortion is considered. The structure and operation algorithm of neuro-fuzzy equalizer are described. The use of neuro-fuzzy equalizer in digital signal transmission allows to decrease training time of parameters and decrease the complexity of the network. The simulation of neuro-fuzzy equalizer is performed. The obtained result satisfies the efficiency of application of neuro-fuzzy technology in channel equalization.

**Keywords**— neuro-fuzzy system, noise equalization, neuro-fuzzy equalizer, neural system

## I. INTRODUCTION

SIGNAL transmitted through a channel suffers from linear, nonlinear and additive distortion. The conventional method for compensation of channel distortion is based on introducing of the linear equalizer (linear inverse filter to the channel frequency response) to the output of the channel. This design methodology is appropriate when the channel model is precisely known and characteristics of the channel are not changed with time. When channel has time-varying characteristics the adaptive equalizers [1] are used. A various approaches have been used for nonlinear channel equalization. Classical approaches based on knowledge of the parametric channel model [2]. Next type is decision feedback equalizer that improves the performance of equalizer. Nowadays neural networks are widely used for channel equalization [3-9]. One of the class nonlinear adaptive equalizer is based on multiplayer perceptions (MLP) and radial basis functions (RBF). The MLP equalizers require long training and are sensitive to the initial choice of network parameters. RBF equalizers are simple and require less time for training, but usually require a large number of centers, which increase the complexity of computation.

One of effective way for development of adaptive equalizers for nonlinear channels is the use of fuzzy technology in their development. In [10] for adaptive equalization of channel distortion the fuzzy equalizer is proposed. Human experts determine the fuzzy rules using input-output data pairs of the channel. These rules are used to construct the filter for nonlinear channel. The RLS and LMS algorithms are applied to change parameters of the membership functions of rules and develop equalizers. Using linguistic

and numerical information the fuzzy adaptive filters are developed. The use of such approach improves the adaptation speed.

In some case the construction of fuzzy rules for equalizers is difficult. In this case one of the effective technologies for construction of equalizer's knowledge base is the use of neural network. In this paper the channel equalization by using neuro-fuzzy network is considered. The use of neuro-fuzzy technology allows to use small number of parameters, fast and easy train equalizer. The equalizer based on neural networks doesn't need appropriate knowledge about channel dynamics. These equalizers give better results in bit error rate (BNR), at the cost of computational strength.

## II. NEURO-FUZZY INFERENCE SYSTEM

The structure of neuro-fuzzy inference system is given in figure 1. The input signals applied to the network at time  $k$  are  $x_i(k)$  ( $i=1..N$ ) and output signal of the network are  $u(k)$ .  $N$  is number of neurons in the input layer.

In first layer the number of nodes is equal to the number of external inputs. In second layer each node corresponds to one linguistic term. For each input signal entering the system the membership degree to which input value belongs to a fuzzy set is calculated. To describe linguistic terms the Gaussian membership function is used.

$$\mu_{1j}(x_i) = e^{-\frac{(x_i - c_{1j})^2}{\sigma_{1j}^2}} \quad i=1..n, j=1..J \quad (1)$$

$c_{1j}$  and  $\sigma_{1j}$  are the center and width of the Gaussian membership function of the  $j$ th term of  $i$ th input variable, respectively.  $\mu_{1j}(x_i)$  is membership function of  $i$ -th input variable for  $j$ -th term.  $n$  is number of external input signals.  $J$  is number of linguistic terms assigned for external input signals  $x_i$ ,  $P$  is number of linguistic terms assigned for one-, two-, ...,  $D$ - delayed output signal of network.

In the third layer the number of nodes corresponds to the number of rules. Each node represents one fuzzy logic rule. Here to calculate the values of output signals of the layer AND (min) operation is used.

$$\mu_l = \prod_j \mu_{1j}(x_i), \quad l=1..L, j=1..J+P, i=1,..,n \quad (2)$$

Here  $\Pi$  is min operation.  $\mu_l$  signals are input signals for the next layer. This layer is a consequent layer. In this fourth

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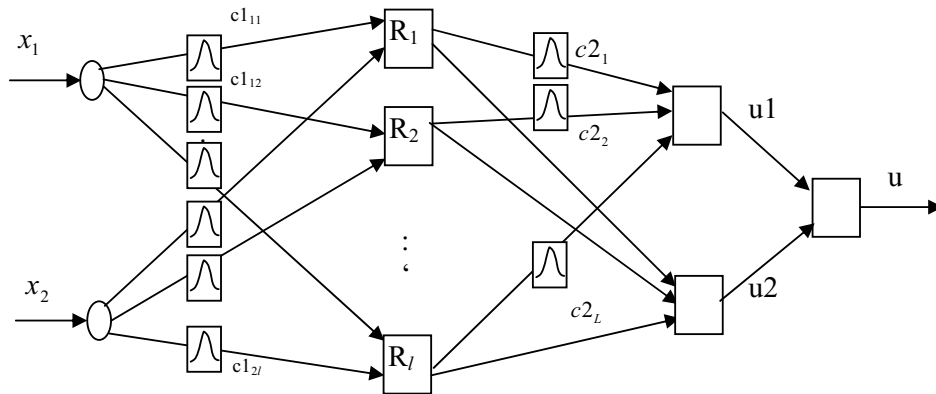


Figure 1. Structure of neuro-fuzzy inference system

layer the output signals of previous layer are multiplied to the weight coefficients of network and in the next layer sum of these products is calculated. Weight coefficients of neuro-fuzzy system are represented by fuzzy set of output variables. They are described by Gaussian function. If as a defuzzification operation we use “center of average” then only the center of Gaussian function is used in the next layer for defuzzification. In this case during development of control system the width of Gaussian function is not used. In formula (3) the parameters  $c2_1$  will represent the center of fuzzy coefficients. Outputs of fifth layer are calculated as

$$u1 = \sum_{l=1}^L \mu_l * c2_l, \quad l=1..L \quad (3)$$

and  $u2 = \sum_{l=1}^L \mu_l$

Using the values of calculated variables the output of the fuzzy system is determined.

$$u = \frac{u1}{u2} = \frac{\sum_{l=1}^L \mu_l * c2_l}{\sum_{l=1}^L \mu_l} \quad (4)$$

After calculating output signal of neuro-fuzzy network the value of error is determined. Using value of error the learning of the parameters of network start.

$$E = \frac{1}{2} \sum_{i=1}^m (u_i(t) - u_i^d(t))^2 \quad (5)$$

where  $u_i(t)$  and  $u_i^d$  are current and desired outputs of the system, m is number of outputs.

For learning network parameters the gradient and least square methods are iteratively used. As a result of learning the

proper values of parameters of neuro-fuzzy system are determined.

The unknown parameters of neuro-fuzzy system are  $c2_1$  parameters of last layer and membership functions of the first layer. Using gradient method the values of unknown parameters of last layer are corrected as

$$c2_l(t+1) = c2_l(t) + \gamma \frac{\partial E}{\partial c2_l} \quad (6)$$

here  $\gamma$  is learning rate.  $\frac{\partial E}{\partial c2_l}$  is determined as

$$\frac{\partial E}{\partial c2} = \frac{\partial E}{\partial u} \frac{\partial u}{\partial c2} = (u(t) - u^d(t)) \quad (7)$$

The adjusting of the membership functions of input layer is carried out by correction unknown coefficients  $c1_{ij}$  and  $\sigma1_{ij}$ . The following formulas can be used for learning these coefficients.

$$c1_{ij}(t) = c1_{ij}(t) + \gamma \frac{\partial E}{\partial c1_{ij}}, \quad (8)$$

$$\sigma1_{ij}(t) = \sigma1_{ij}(t) + \gamma \frac{\partial E}{\partial \sigma1_{ij}}$$

where

$$\frac{\partial E}{\partial c1_{ij}} = \sum_j \frac{\partial E}{\partial u} \frac{\partial u}{\partial \mu_l} \frac{\partial \mu_l}{\partial c1_{ij}}, \quad (9)$$

$$\frac{\partial E}{\partial \sigma1_{ij}} = \sum_j \frac{\partial E}{\partial u} \frac{\partial u}{\partial \mu_l} \frac{\partial \mu_l}{\partial \sigma1_{ij}}$$

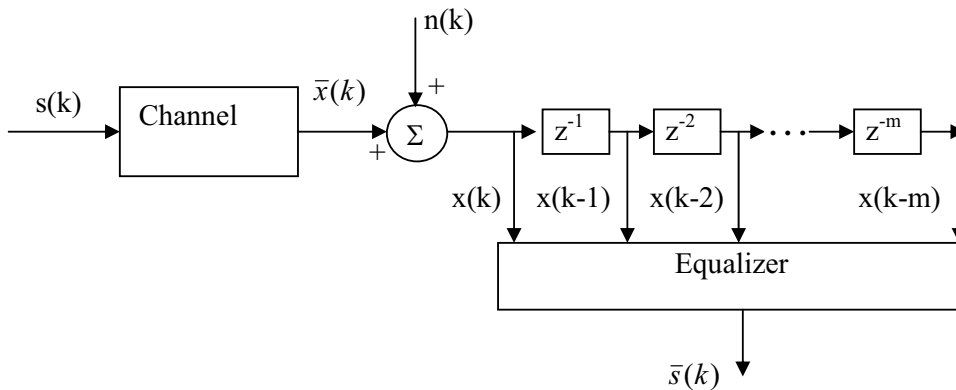


Figure.1. Signal transmitting scheme

Here

$$\frac{\partial E}{\partial u} = u(t) - u^d(t), \quad \frac{\partial u}{\partial \mu_l} = \frac{\sum_{l=1}^L c_{2l} - u}{\sum_{l=1}^L \mu_l} \quad (10)$$

$$\frac{\partial \mu_l(x_j)}{\partial c_{ji}} = \begin{cases} \mu_l(x_j) \frac{2(x_j - c_{ji})}{\sigma_{ji}^2} & \text{if } j \text{ node} \\ & \text{is connected to rule node } l \\ 0, & \text{otherwise} \end{cases}$$

$$\frac{\partial \mu_l(x_j)}{\partial \sigma_{ji}} = \begin{cases} \mu_l(x_j) \frac{2(x_j - c_{ji})^2}{\sigma_{ji}^3} & \text{if } j \text{ node} \\ & \text{is connected to rule node } l \\ 0, & \text{otherwise} \end{cases} \quad (11)$$

Using (6) - (11) the corrections of the parameters of neuro-fuzzy system are carried out.

### III. SIMULATION

Structure of digital signal transmission system is shown in figure 1. The random binary input signals  $s(k)$  are transmitted through communication channel.  $s(k)$  are input known samples with an equal probability of being  $-1$  and  $1$ . These signals are corrupted by additive noise  $n(k)$ . The corrupted signals are given to the equalizer. The problem of the channel equalization is to estimate the input signals using the sequence of  $\{x(k), x(k-1), x(k-2), \dots, x(k-m)\}$ .

The neuro-fuzzy network structure and its training algorithm is used to design equalizer for equalization of noise. The inputs of neuro-fuzzy equalizer are channel output signals. The output of neural network is the recovered transmitted sequence of signal. During equalizer design the sequence of

transmitted signals are given to the channel input. The additive noise is added to the transmitted signal. In the equalizer-using target transmitted signal the deviation from the current network output is determined. This error is used to adjust equalizer parameter. Training is continued until the value of error for all training sequence of signals would be minimum.

During simulation we use the following channel model.

$$x(k) = 0.3482y(k) + 0.8704y(k-1) + 0.3482y(k-2) + n(k) \quad (12)$$

A channel input, the transmitted data sequence  $s(k)$  is assumed to be independent sequence taking values from  $\{-1, 1\}$  with equal probability. In the channel we add additive distortion as white Gaussian noise.

During simulation the four inputs of neural equalizer are  $x(k), x(k-1), x(k-2), x(k-3)$ . The three layer neuro-fuzzy network structure is taken. In the hidden layer number of neurons are 27. The training of neuro-fuzzy network equalizer (NFNE) have been carried out. In figure 2 the error plot of training result of NFNE is given. The figure 3 illustrates the curve that describes the performance (Bit error rate versus signal-noise ratio) analysis of neuro-fuzzy network equalizer (NFNE) for channel (12). The obtained result satisfies the efficiency of application of neuro-fuzzy technology in channel equalization.

### IV. CONCLUSION

The development of neural-fuzzy equalizer for equalization channel distortion is carried out. The operation principle and learning algorithm of neuro-fuzzy network are represented. The construction of neuro-fuzzy equalizer is carried out for the channel in presence of additive distortion. The obtained results of simulation of neuro-fuzzy equalizer are given.

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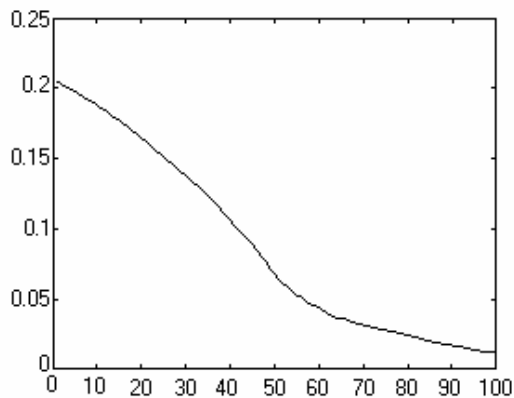


Figure 2. Error plot

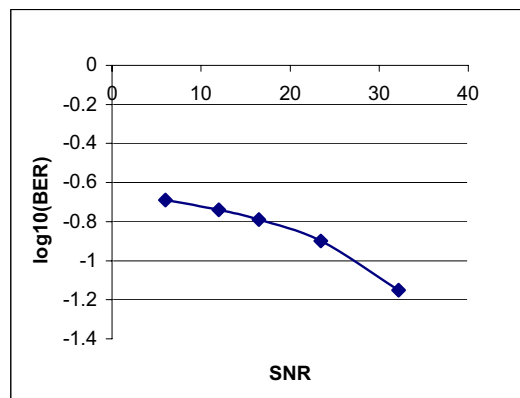


Figure 3. Performance of NFNE equalizer

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