

Channel Equalization with Cellular Neural Networks

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Abstract—In this paper, a dynamic neural network structure called Cellular Neural Network (CNN) is employed for the equalization in digital communication. It is shown that, this nonlinear system is capable of suppressing the effect of intersymbol interference (ISI) and the noise at the channel. The architecture is a small-scaled, simple CNN containing 9 neurons, thus having only 19 weight coefficients. Proposed system is compared with linear transversal filters as well as with a Multilayer Perceptron (MLP) based equalizer.

I. INTRODUCTION

Zero-Forcing and Minimum Mean Square Error (MMSE) are commonly used linear transversal filters in channel equalization [1], however their Bit-Error-Rates (BERs) are not satisfactory, especially at lower signal-to-noise-ratios (SNRs). For this reason, alternative methods were developed in literature including Neural Network based architectures [2], [3], [4]. Although their BERs are better than the conventional techniques, because of the complex interconnected structures, they require too much computational power. At this point, CNN can be a good alternative to them with its simple topology. Furthermore, since the outputs of a CNN can take $\{-1,+1\}$ values, it is logical to use it in the reconstruction of Binary Phase Shift Keying (BPSK) signals.

Formerly, CNN was employed to compute the coefficients of the linear transversal filters [5], somehow in our work, we directly used it as an equalizer itself.

II. CHANNEL EQUALIZATION

At a digital communication system, the transmitted signal is affected by the disturbances, ie. Additive White Gaussian Noise (AWGN) and multipath channel which causes ISI that are shown in Fig. 1.

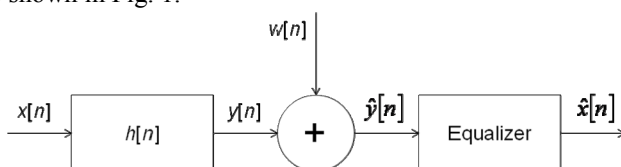


Fig. 1. Model of a communication channel.

The observation model of the system in Fig. 1 can be given as follows

$$\hat{y}[n] = x[n] * h[n] + w[n], \quad (1)$$

where n represents the time index, $x[n]$ is the transmitted BPSK signal, $w[n]$ is a zero mean, real valued AWGN, $\hat{y}[n]$ is the received signal and “*” denotes the linear convolution.

BER is a measure of the exactness of the output signal which can be expressed as follows:

$$\text{BER} = \frac{N_e}{N_t} \quad (2)$$

Here, N_e and N_t stand for number bit errors and transmitted bits respectively.

Channel equalization must be carried out in order to reconstruct the transmitted signal at the receiver. In ideal case $\hat{x}[n] = x[n]$. Although linear transversal filters as well as some special neural network structures, such as Multilayer Perceptron (MLP) can be used; in this paper, a system based on a different neural network CNN, is proposed for this purpose.

III. CNNs

CNNs, introduced by Chua and Yang in 1988 [6], are a class of dynamic neural networks. Generally they are two-dimensional which makes them very suitable for image processing applications [7]. However one-dimensional CNNs are also available in literature for oscillator circuit design [8] and chaos generation [9]. As a dynamic neural network CNN neurons (cells) include an integration unit, however unlike the Hopfield nets, here cells only interact with each other by the r neighbourhood definition given below:

$$N_{ij} = \{C_{kl} \mid \max\{|k-i|, |l-j|\} \leq r; 1 \leq k \leq M, 1 \leq l \leq N\} \quad (3)$$

The constraint between the cells C_{ij} and C_{kl} at an $M \times N$ -cell system dramatically decreases the number of weight

coefficients between the neurons, therefore providing an easy implementation. The nonlinear differential equation for a CNN cell shown in Fig. 2 is given by,

$$\dot{x} = -x + \mathbf{A}f(\mathbf{x}) + \mathbf{B}\mathbf{u} + I \quad (4)$$

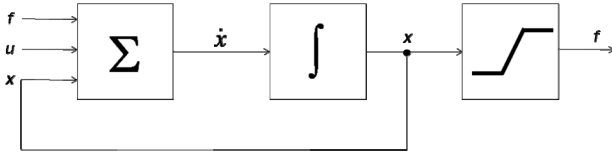


Fig. 2. Block diagram of a CNN cell.

Here, the x is called the “State” of the cell, \dot{x} is its derivative, $f(x)$ is the “Activation function”, \mathbf{u} is the “Input”, \mathbf{A} and \mathbf{B} are matrices that contain the weight coefficients between the outputs and inputs of the neighbouring cells and called “Cloning Template” and “Control Template” respectively, I is a constant threshold value, common for all cells.

The Piecewise Linear (PWL) Activation function given in Fig. 3 with (5) enables the outputs approach to either $\{-1\}$ or $\{+1\}$ under stable operation.

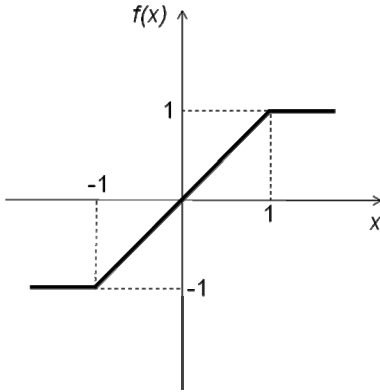


Fig. 3. The PWL Activation function of a cell in CNN.

$$f(x) = \frac{1}{2} \{ |x+1| - |x-1| \} \quad (5)$$

IV. CHANNEL EQUALIZATION WITH CNN

A two-dimensional 3×3 CNN with 9 cells and with a neighbourhood of $r = 1$, shown in Fig. 4 is employed for the equalization process. Therefore, two 3×3 Cloning and Control Template matrices \mathbf{A} , \mathbf{B} and an I scalar, totally 19 parameters have to be computed.

Training process is carried out as follows: The 19000 samples of unequalized data with SNR values varying between 0 and 18dB are applied as the input $\hat{y}[n]$, and the desired uniformly distributed BPSK signals are used as the corresponding outputs $\hat{x}[n]$ for a chosen channel. In order to reorganize the one-dimensional distorted data in two-dimension, we generated three copies of the distorted data and

performed a 2-D convolution with the 3×3 CNN templates as shown in Fig. 5, where all state matrix elements have an initial value of 1. The unknown 19 parameters are found after the training with the Genetic Algorithm [10], [11].

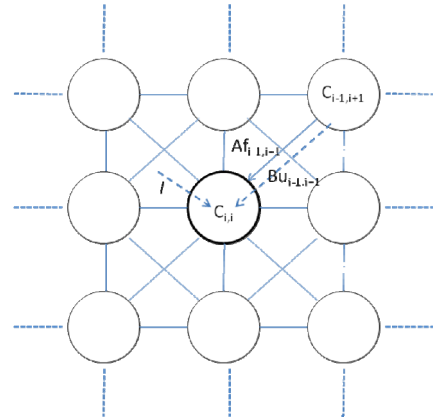


Fig. 4. The 3×3 CNN for the equalization.

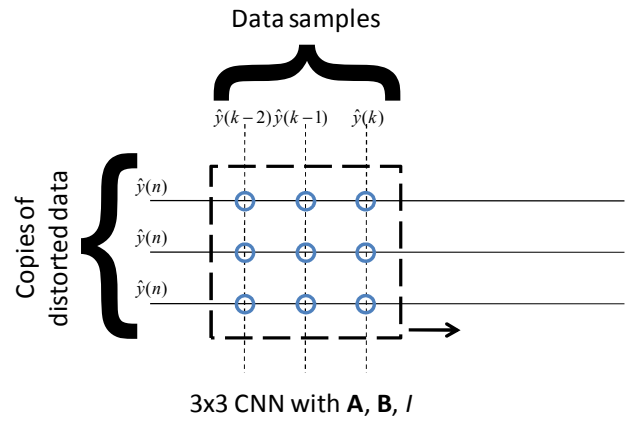


Fig. 5. The training process.

V. SIMULATIONS

Simulations are carried out for the following minimum and linear phase channel models [4].

$$H_{min}(z) = 0.6963 + 0.6964z^{-1} + 0.1741z^{-2} \quad (6a)$$

$$H_{linear}(z) = 0.3482 + 0.8704z^{-1} + 0.3482z^{-2} \quad (6b)$$

The \mathbf{A} , \mathbf{B} matrices and I scalar are trained for both channels and the following numerical values are found:

$$A_{min} = \begin{bmatrix} -1.4527 & 0.6990 & -2.8990 \\ -2.8023 & 1.0193 & 0.8341 \\ 0.1728 & 1.6659 & -2.4458 \end{bmatrix} \quad (7a)$$

$$B_{min} = \begin{bmatrix} 0.3017 & 1.2925 & 4.3744 \\ -0.4973 & 3.3251 & 0.2050 \\ -0.4445 & 1.3226 & 1.4320 \end{bmatrix} \quad (7b)$$

$$I_{min} = 0.0659 \quad (7c)$$

$$A_{linear} = \begin{bmatrix} -0.667 & 0.6638 & -1.3039 \\ -1.5377 & -0.2633 & -0.1592 \\ -0.8225 & 1.4036 & -1.0696 \end{bmatrix} \quad (8a)$$

$$B_{linear} = \begin{bmatrix} -1.8775 & 1.2696 & 1.5824 \\ 1.7204 & 0.0199 & 3.9182 \\ -1.5100 & 0.6271 & 0.2116 \end{bmatrix} \quad (8b)$$

$$I_{linear} = -0.1365 \quad (8c)$$

The SNR vs. BER performance of the proposed CNN system is compared with the conventional linear transversal filters; zero-forcing, MMSE and the neural network structure MLP (with 3 input, 10 hidden, 1 output layers) at both channels for uniformly distributed random data, which are sketched in Fig. 6a and b.

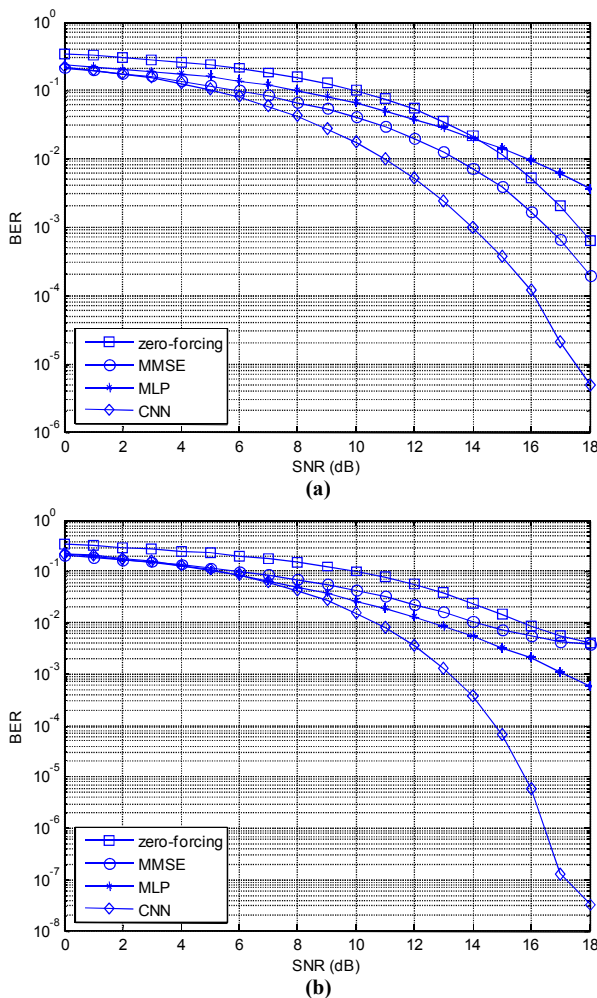


Fig. 6. Performances of the methods:
(a) Minimum, (b) Linear Phase Channels.

VI. CONCLUSION

In this paper, a novel channel equalizer based on a CNN is proposed. The BER performance of the system is better than the classical zero-forcing and MMSE equalizers, as well as than the neural network structure MLP. Moreover, because of the less number of weight coefficients, simpler design is possible as seen from table 1.

Table 1. Comparison of the proposed model with the MLP equalizer.

NN	# of neurons	# of weight coefficients
MLP	10	51
CNN	9	19

One drawback is that, CNN here is not adaptive and only tested for uniformly distributed data and new templates and threshold values have to be assigned if either channel coefficients or probability density function (PDF) are changed. This problem can be overcome by finding very fast learning algorithms for the CNN.

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