GCMAC-BASED EQUALIZER FOR NONLINEAR CHANNELS

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ABSTRACT

This paper deals with the compensation for the nonlinear distortion introduced by power-efficient amplifiers on linear modulations by means of equalization. We propose a new equalizer based on a reduced-complexity network called GCMAC. The GCMAC-based equalizer is compared with other well-known structures such as the Volterra filter and the Multi-layer Perceptron. Extensive computer simulations have been carried out. The obtained results show the effectiveness of the proposed structure to compensate for strong nonlinearities.

1. INTRODUCTION

The available spectrum for the new communications networks will soon be at a premium as the user population increases, and employing multilevel Pulse Amplitude Modulation (PAM), one kind of bandwidth efficient transmission method for digital signals, may significantly ease the problem. Nevertheless, practical digital communication systems employing PAM, require a compromise between power efficiency and linearity of the transmitter amplifiers. If the amplifiers are working near its saturation point, a better use of the available power is achieved, but the PAM signal is severely distorted due to its envelope fluctuation. It is possible to diminish the nonlinear distortion by reducing the level of input signals, operating the amplifier in a quasi-linear region far from its saturation point (the reduction of output power is used to be called input back-off). However, this strategy reduces the transmitted signal power and, therefore, the noise margin.

The need of some compensation technique has been recognized long time ago, and some early proposed solutions are described in [1], [2] and [3]. Nonlinear compensators consist of controlling either the signal before it is sent (TX-techniques) or the noisy received signal (RX-techniques). In this paper we consider the compensation problem from the receiver perspective. The optimal solution is the Maximum Likelihood Sequence Detector (MLSD) using the Viterbi Algorithm [4], however its large complexity makes this method useless for practical channels.

In this paper, a new approach for the Decision-Feedback Equalizer (DFE) using the Generalized Cerebellar Model Arithmetic Computer (GMAC) [5, 6] is presented. The GCMAC network possesses nonlinear decision making capabilities and yet has a linear-in-the-parameters structure. The former property is essential for realizing the optimal equalization solution and the latter characteristic is beneficial in practical implementation. In this paper, that extends the earlier work reported in [7] where the GCMAC was employed for nonlinear channel predistortion, the GCMAC-based DFE (GCMAC-DFE) is compared with the conventional Linear DFE (L-DFE), the Volterra (V-DFE) and the MLP-based DFE (MLP-DFE) in terms of their convergence rates and Signal-to-Noise Ratio (SNR) degradation. The simulation results show that the GCMAC improves the performance of previous networks when strong nonlinearities are present.

The paper is organized as follows. The effects of nonlinear amplification of PAM signals are analyzed in Section 2. The structure of the GCMAC network is discussed in Section 3. Simulation results and performance comparisons are explained in Section 4. Finally, conclusions are given in Section 5.

2. PROBLEM STATEMENT

Figure 1 depicts the block diagram of a PAM sys-

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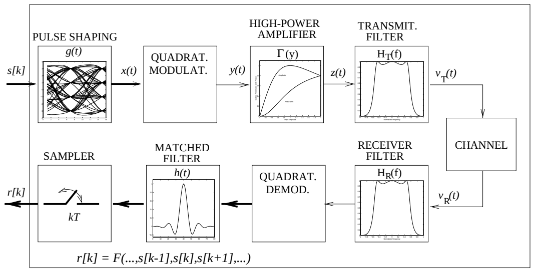

Figure 1: Block diagram of the PAM communication system.

tem. The transmitter input consists of complex symbols belonging to a M-ary discrete-amplitude set. For the purposes of this paper, we will assume that the PAM symbols are independent and identically distributed, forming a white discrete-time random process. Driving the PAM communication system with this process, the baseband complex signal at the output of the symbol-rate sampler can be written as :

$$r[k] = F(\dots, s[k-1], s[k], s[k+1], \dots) \qquad (1)$$

where $r[k]$ is the received symbol, $\{s[k]\}$ are the original PAM symbols, and $F(\bullet)$ is the nonlinear mapping which describes the behavior of the channel[1].

Channel Equalization

The general Decision-Feedback Equalizer (DFE) transforms a finite sequence of P correlative received and detected PAM symbols and produces the estimated symbol $\hat{s}[k]$:

$$\begin{aligned} \hat{s}[k] &= H(\hat{s}[k-N_b], \dots, \hat{s}[k-1], \\ &\quad r[k], r[k+1], \dots, r[k+M_f]) \\ &= H(\boldsymbol{r}_P[k]) \end{aligned} \qquad (2)$$

where N_b is the order of the feedback part, M_f is the order of the feedforward part and $P = N_b + M_f + 1$ is the order of the equalizer (it is assumed that the channel does not introduces additional delay). The optimum decision making function $H(\bullet)$ has to be designed in such a way that minimizes the BER.

Equalization can be formulated as an approximation problem and, for this reason, many structures for approximating are essentially valid to be applied to this problem. We have selected the GCMAC network [6] due to its fast and simple learning algorithm which provides a powerful capability for approximating discrete-domain functions; it is important to remark that part of the input space of the function $H(\bullet)$ has a discrete-amplitude nature (it should be noticed that the feedback part is driven by the previous M-ary PAM symbol decisions).

[1] We consider the channel including all the elements and devices between the modulator and the detector.

3. NETWORK STRUCTURE

The GCMAC network has its roots in a model proposed by Albus in the mid seventies for control applications [5]. The GCMAC network approximates the desired nonlinear function (the optimal decision function) using a set of overlapped local basis functions distributed across the input domain. The GCMAC allows the local basis functions to be defined on hyper-parallelepipedic regions; the size of these regions is specified by the vector $\boldsymbol{\rho} = [\rho_1, \dots, \rho_P]^T$, where $1 \le \rho_i < M$, and M is the number of levels of the discretized input variables. To provide the network with generalization abilities, $\rho_{max} = \max(\boldsymbol{\rho})$ basis functions cover every cell of input space. In this way, the generalization is influenced by the geometry of the local domains, and, for this reason, the vector $\boldsymbol{\rho}$ is called generalization vector[2].

The GCMAC input/output function can be decomposed into two consecutive mappings. The first one produces an N-dimensional addressing vector $\boldsymbol{a}$ given by:

$$\boldsymbol{x} \to \boldsymbol{a}(\boldsymbol{x}) = [\Phi_1(\boldsymbol{x}), \dots, \Phi_N(\boldsymbol{x})]^T \ , \qquad (3)$$

where $\{\Phi_1(\boldsymbol{x}), \dots, \Phi_N(\boldsymbol{x})\}$ is the set of basis functions [3]. The addressing vector $\boldsymbol{a}$ only has ρ_{max} non-zero elements and, generally, the relationship $P < \rho_{max} \ll N$ holds. The addressing vector lies in a higher-dimensional space where the desired function can be approximately linear. For this reason, the second map consists of the projection of the transformed input vectors $\boldsymbol{a}$ onto a vector of weights $\boldsymbol{w}$, which produces the output of the network :

$$y = H(\boldsymbol{x}) = \boldsymbol{w}^T \boldsymbol{a}(\boldsymbol{x}) = \sum_{j=1}^{N} \boldsymbol{w}_j \Phi_j(\boldsymbol{x}) \ . \qquad (4)$$

Hence, the approximation used by the GCMAC network is linear in the unknown coefficients $\boldsymbol{w}$ and, therefore, simple instantaneous learning laws can be used, for which convergence can be established subject to well-understood restrictions [8]. Moreover, the number of weights that are used to update or construct the output, ρ_{max} is independent of the dimension of input

[2] When $\rho_i = 1, \forall i$, the GCMAC becomes a LUT (no generalization); the larger ρ_i is, the more generalization is obtained.

[3] In order to remain consistent with the notation developed for the CMAC network, the input vector is represented by $\boldsymbol{x}$.

space; for this reason, the GCMAC network is capable of managing high-dimensional input spaces, useful property when the nonlinear channel has a large memory.

3.1. Computational requirements

The number of available basis functions (weights), N, can be bounded by :

$$\rho_{max} \min_i \left(\frac{M}{\rho_i}\right)^P \leq N \leq \rho_{max} \max_i \left(\frac{M}{\rho_i}+1\right)^P . \tag{5}$$

The GCMAC network is trained by using a modified version of the Albus' rule [5, 9]. Our algorithm requires one float point complex subtraction to compute the actual error, ρ_{max} complex additions and one float-point inversion to compute the gains of the weights, and ρ_{max} scaling operations and ρ_{max} additions to update the weights. The network's output is computed after $2\rho_{max} - 1$ complex multiplications and accumulations.

4. PERFORMANCE ANALYSIS

To illustrate the behavior of the analyzed equalizers, we have simulated a typical 16-QAM system with root-raised cosine pulse shaping filter ($\alpha = 0.5$) and a High Power Amplifier (HPA) operating at 2 dB of input back-off. The channel is assumed to have a flat frequency response with additive, white, circularly symmetric, Gaussian noise. The chosen order of the feedforward and feedback parts of the compared equalizers are $M_d = 1$, $N_r = 1$, respectively.

The networks used for approximating the ideal equalization function are a fifth-order Volterra Filter (with 57 adjustable parameters), a MLP with two-hidden layers (10 nodes in the first hidden layer and 6 in the second one, giving 150 adjustable parameters), and a GCMAC network whose configuration is explained as follows. The inputs coming into the feedforward part are quantized using 32 nonuniform-spaced levels; the corresponding generalization vector is $\boldsymbol{\rho}_d = [16, 16, 16, 16]^T$ (it should be noticed that the dimension of input space is doubled to process complex inputs). Since, the previous decisions are already discrete in amplitude, no quantization is needed, and the selected generalization vector is $\boldsymbol{\rho}_r = [3, 3]^T$. For simplicity, simulations were carried out with constant basis functions.

The Volterra and the GCMAC equalizers have been trained using the LMS algorithm. The MLP was trained using the Back-Propagation (BP) algorithm modified with a momentum term that increases the convergence rate and produces smooth weight changes [10]. The

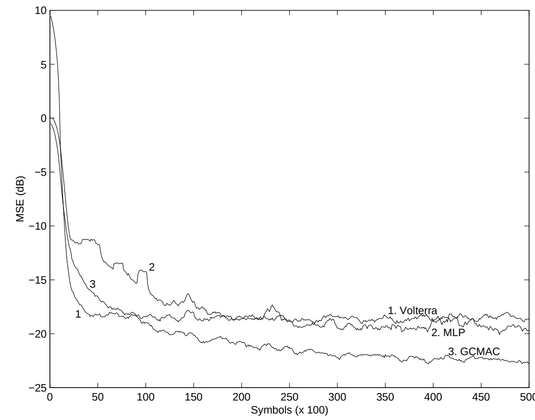

Figure 2: Convergence curves. Curve 1: Fifth-order Volterra equalizer; curve 2: Multi-Layer Perceptron (6-10-6-2); curve 3: GCMAC ($\boldsymbol{\rho}_d = [16, 16, 16, 16]^T$, $\boldsymbol{\rho}_r = [3, 3]^T$). Traces are ensembled average of 15 convergence curves.

Mean Square Error (MSE) curves achieved by the analyzed equalizers are represented in Figure 2. It is observed that the Volterra equalizer presents the fastest convergence (curve 1). The learning curve of the MLP (curve 2) reveals the irregular behavior of the BP algorithm; in spite of this, the MLP outperforms the Volterra, although at the expense of a larger training time. Finally, the GCMAC network achieves the least final MSE outperforming both the MLP and the Volterra equalizers in 3 dB and 4 dB, respectively.

Other way to quantify the validity of the analyzed equalizers is to compute the equivalent SNR degradation caused by the residual nonlinear distortion at a specified Bit-Error Rate (BER). The Total Degradation, expressed in dB, is defined as the difference between the required SNR by the equalized system to reach the specified BER at a given output back-off, and the required SNR to obtain the same BER on the Gaussian flat channel. The total degradation results in a convex function of the input back-off, taking the minimum value at the optimum input back-off (BO_{in}^{opt}). We have obtained this function after using the quasi-analytical procedure described in [11]. Results for a target BER of 10^{-4} are shown in Figure 3 and Table 1.

Again, it is confirmed that the GCMAC-based equalizer performs clearly better than the other equalizers for low input back-off, i.e. when strong nonlinearities are present in the received sequence. The gain[4] achieved by the GCMAC equalizer is 6 dB with re-

[4]The gain is defined as the difference between the values of the Total Degradation evaluated at the optimum input back-off.

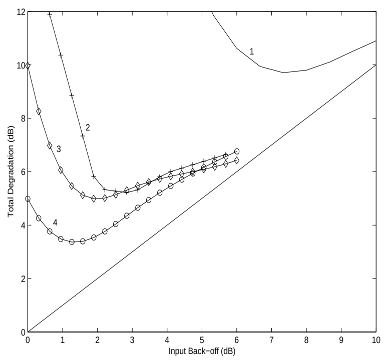

Figure 3: Total degradation for the analyzed equalizers. Curve 1: Linear DFE; curve 2: Fifth-order Volterra equalizer; curve 3: Multi-Layer Perceptron equalizer; curve 4: GCMAC equalizer.

	[Gain]	$[BO_{in}^{opt}]$	Weights	It. (x100)
1. L-DFE	0	7.35	3	2
2. Volterra	4.44	2.79	57	60
3. MLP	4.67	1.98	150	500
4. GCMAC	6.28	1.28	4924	250

Table 1: Gain and optimum input back-off for the simulated equalizers.

spect to the linear DFE. Furthermore, the optimum input back-off is only 1.28 dB, which means in practice a better use of the available power.

5. CONCLUSIONS

In this paper we have proposed a new structure to equalize nonlinear channels. In particular, we have focused the compensation for nonlinear distortion caused by power efficient amplifiers on Pulse Amplitude Modulation systems. By means of a GCMAC-based equalizer, it is possible to obtain effective compensation even for strong nonlinearities. The proposed equalizer provides better performance in steady state MSE, BER and SNR degradation over other nonlinear structures, namely the Volterra and the MLP-based equalizers.

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