A Fast LUT+CMAC Data Predistorter

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ABSTRACT

The subject of this communication is the compensation of nonlinearities in digital radio links, where the major source of nonlinearity is caused by the High Power Amplifier (HPA), typically working close to its saturation point because of energy constraints. This paper deals with the design of CMAC-based predistorters for application in digital transmission over nonlinear channels with memory. A novel hybrid structure composed of a Look-Up-Table in parallel with a CMAC network is proposed. Finally, a performance analysis for typical radio channels is presented.

1 Introduction

The High Power Amplifier (HPA) of transmission systems is required to operate at or near saturation for cost-effective utilization of the available power. In addition, because of the limited availability of bandwidth, the transmitted signals must be tightly band limited. Modulation schemes such as M-QAM with appropriate pulse shaping comply with this requirement but at the expense of envelope fluctuations which requires that the final RF amplifying stage be linear in order to preserve the narrow-band properties of the modulation. However, when a band-limited linearly modulated carrier with non-constant envelope undergoes non-linear amplification, two unwanted effects arise : i) the widening of the transmitted pulse restores the side-lobes and causes severe adjacent channel interference (ACI), and ii) the inclusion of the HPA between linear transmission and receiving filters leads to the increase of the linear and nonlinear inter-symbol interference (ISI). The ISI has two major consequences on the "constellation" of detected M-QAM samples. Instead of M discrete points arranged in a regular pattern, there are M *clusters* of points, with the averages of the individual clusters forming a possibly *warped* M-point constellation. This kind of distortion can be modelled as a nonlinearity with memory.

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To overcome nonlinear distortion, several linearization approaches has been developed. Predistortion at the transmitter side (TX) and equalization at the receiver side (RX) are two of the best methods of nonlinear compensation [1],[2]. This paper describes a new digital baseband predistortion scheme composed by an adaptive memory (or Look-Up-Table, LUT) in parallel with a neural network called CMAC (Cerebellar Model Articulation Controller)[3].

2 Digital data predistortion

In digital data predistortion the digital data constellation sequence $s[k]$ is transformed in a predistorted sequence, $x[k]$, so that the received sequence $r[k]$ is as close as possible to the original. Therefore, the necessary components for predistorter control are the transmitted signal $s[k]$ and the approximation of the received symbol $\hat{r}[k]$ which is obtained from the High Power Amplifier (HPA) output through a local receiver, as shown in figure 1.

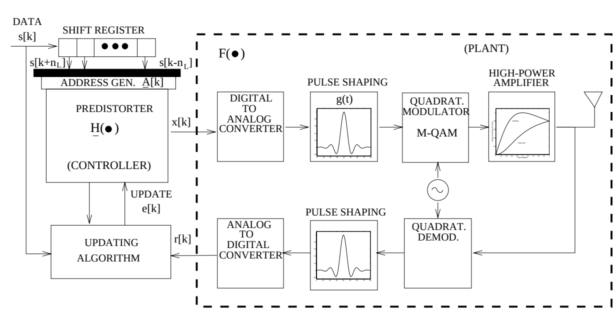

Figure 1: Model of the nonlinear system

Even if the HPA is a memoryless device, the whole transmission chain exhibits a temporal behavior where the output has a finite temporal dependence on the input:

$$r[k] = F(x[k+n_L], \ldots, x[k], \ldots, x[k-n_L]) \qquad (1)$$

where $K = 2n_L + 1$ is the memory of the global channel and $F(\bullet)$ is a nonlinear mapping which describes the behavior of the nonlinear device. The data predistorter, $H(\bullet)$, could be designed in such a way that, after linear filtering and nonlinear processing in the link, the constellation of the average samples at the detector would match (or approximate) the desired squared M-QAM signal constellation. Mathematically, this can be represented by the following equation:

Find $H(\bullet)$ that minimizes

$$E\{|s[k]-F(x[k+n_L],\ldots,x[k],\ldots,x[k-n_L]|^2\} \quad (2)$$

with $x[k]=H(s[k+n_M],\ldots,s[k],\ldots,s[k-n_M])$,

where $P=2n_M+1$ is the order of the predistorter.

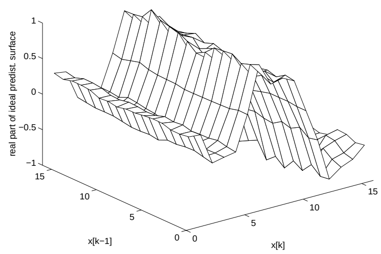

Figure 2: Ideal predistortion surface (real part).

Data predistortion can also be formulated as a discrete surface approximation. Figure 2 shows the real part of the ideal predistortion surface, $H(\bullet)$, required to compensate the nonlinear distortion in a realistic situation (16-QAM modulation, root-raised cosine filters with 0.5 roll-off factor at the transmitter and the receiver, and the HPA modelled by its AM/AM and AM/PM characteristics). In this sense, it is possible to implement the approximation of the hyper-surface directly in the form of a Pth order Look-Up-Table (LUT) [4, 2]. Unfortunately, the memory size increases as M^P, what makes the structure only practical for nonlinearities with short memory. Another drawback arises from the particular shape of the hyper-surface. From figure 2 two major features can be observed:

- The largest contribution to the surface corresponds to the correction of the actual symbol, $s[k]$, that is, the reduction of warping effect. The ripple in the past symbol ($s[k-1]$) direction corresponds to the elimination of nonlinear ISI.

- The value of hyper-surface at one point depends on other values nearby. For this reason it does not make sense to use a Pth order LUT, since it does not extrapole information to nearby memory locations. The smoothness of the ideal predistortion hypersurface guarantees that reduced complexity architectures like the CMAC [3] can obtain good approximations.

3 The CMAC network

The Cerebellar Model Articulation Controller (CMAC) [3, 5] was proposed as a control method based on the principles of the cerebellum's motor behavior. The CMAC can approximate a wide variety of nonlinear functions by local training. In this way, its memory addressing algorithm causes similar inputs to tend to generalize and produce similar outputs; this property is called generalisation. Another feature of the weight addressing scheme is the ability to train the network in one part of the input space without corrupting what has already been learned in more distant regions. Hence, the CMAC generalises locally.

In a previous paper [6], we have applied the CMAC-based predistorter to the digital communication system showed in figure 1. After extensive computer simulations it was confirmed that, even though the reduced complexity (in comparison with the Pth order LUT) of CMAC allows one to speed up the training phase, its performance was not as good as expected due to the effort that the CMAC dedicates to model the influence of the present symbol (warping effect), $s[k]$; therefore, our starting point is to exploit the particular nature of the nonlinear disturbance introduced by the HPA.

4 Proposed scheme

Since most of the energy of error produced by the mismatch between the original and the distorted constellations results from the warping effect, we suggest distributing the nonlinearity identification effort by paying more attention to the warping effect than to the impact of clustering. In this way, a new technique is presented which offers a significant improvement in convergence rates with higher performance levels.

A procedure for improving the performance of CMAC-based predistorters is to remove the influence of the actual symbol on the hyper-surface to be approximated. In this way, we propose to divide the predistortion surface, $H(\bullet)$, in the form:

$$H(s[k+n_M],\ldots,s[k],\ldots,s[k-n_M]) = H_1(s[k]) + H_2(s[k+n_M],\ldots,s[k],\ldots,s[k-n_M]) \quad (3)$$

where $H_1(\bullet)$ models the influence of the actual symbol (warping effect), and $H_2(\bullet)$ the nonlinear ISI (clustering effect).

The LUT+CMAC predistorter, showed in figure 3, initially, ignores the contribution of the nonlinear ISI (clustering effect) and then, after convergence down to an acceptable noise floor has been reached, attempts

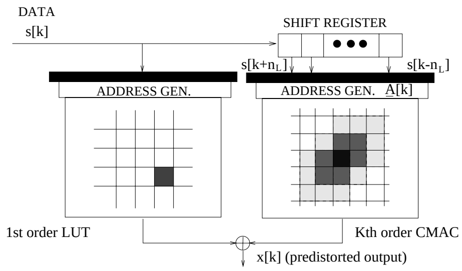

Figure 3: LUT+CMAC predistorter.

to reduce the remaining unknown nonlinearity. In our proposal, the "warping" is compensated by means of a first-order LUT which produces a convergence down to a noise floor directly related to the remaining unidentified nonlinearity (nonlinear ISI). After this noise has been reached, a full CMAC is utilized to compensate the remaining nonlinearity ("clustering"). The CMAC uses information from the LUT and allows subsequent convergence from the nonlinear noise floor to the final compensation depth. The output of the hybrid structure is given by:

$$x[k] = \underline{\mathbf{a}}_{\mathrm{LUT}}[k]^T \; \underline{\mathbf{w}}_{\mathrm{LUT}}[k] + \underline{\mathbf{a}}_{\mathrm{CMAC}}[k]^T \; \underline{\mathbf{w}}_{\mathrm{CMAC}}[k] \qquad (4)$$

where $\underline{\mathbf{a}}_{\bullet}$ and $\underline{\mathbf{w}}_{\bullet}$ are the addressing vectors and the weight vectors of each substructure. Initially, only the vector $\underline{\mathbf{w}}_{\mathrm{LUT}}$ is adapted until the noise floor corresponding to the nonlinear ISI is reached. Further adaption of $\underline{\mathbf{w}}_{\mathrm{LUT}}$ produces no improvement in the error performance. At this point, adaption of $\underline{\mathbf{w}}_{\mathrm{LUT}}$ is halted, and a gradient search algorithm is applied to the CMAC coefficients in order to achieve the desired data predistortion.

5 Optimizing CMAC Speed of Convergence

CMAC weights may be trained using an updating algorithm equivalent to Widrow's LMS rule. The Albus' original training rule assumes a fixed training step in such a way that the error ($e[k] = s[k] - r[k]$) is divided in equal parts (ρ) among the functions participating in the output; this rule is given by:

$$\underline{\mathbf{w}}[k+1] = \underline{\mathbf{w}}[k] + \frac{\mu}{\rho}\left(s[k] - r[k]\right)\underline{\mathbf{a}}[k] \qquad (5)$$

where $s[k]$ is the transmitted symbol, $\underline{\mathbf{a}}[k]$ is the association vector which addresses the CMAC weights activated by the input vector $\underline{\mathbf{s}}[k] = (s[k+n_M], \ldots, s[k], \ldots, s[k-n_M])^T$, $\mu[k]$ is the training step and $r[k] = F(x[k+n_L], \ldots, x[k], \ldots, x[k-n_L])$ is the received sample after nonlinear filtering in the channel. Although CMAC learning using the Albus' rule is faster than its counterpart in other neural networks, this is not the best way to adapt the CMAC weights. An approximated rule to compute the learning step is based on adjusting this value depending on the inverse of the mean power of the association vector $\underline{\mathbf{a}}[k]$; since the mean power of the input vector to the linear combinator is

$$E\left[\underline{\mathbf{a}}[k]^2\right] = \left[v_1^{-1} v_2^{-1} \cdots v_N^{-1}\right]^T \qquad (6)$$

the step value is determined as follows

$$\mu_{c(i)}[k] = \frac{\frac{1}{v_{c(i)}}}{\sum_{j=1}^{\rho} \frac{1}{v_{c(i)}}} \qquad (7)$$

where $c(j)$ denotes the index of the local functions chosen by the input vector $\underline{\mathbf{s}}[k]$. The modified updating algorithm can be rewritten as

$$\underline{\underline{\mathbf{C}}} = \begin{bmatrix} v_1^{-1} & 0 & \cdots & 0 \\ 0 & v_2^{-1} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & v_N^{-1} \end{bmatrix} \qquad (8)$$

$$D = \underline{\mathbf{a}}[k]^T \underline{\underline{\mathbf{C}}}\; \underline{\mathbf{a}}[k] \qquad (9)$$

$$\underline{\mathbf{w}}[k+1] = \underline{\mathbf{w}}[k] + \frac{e[k]}{D} \underline{\underline{\mathbf{C}}}\; \underline{\mathbf{a}}[k] \qquad (10)$$

This method requires a double memory: for each CMAC weight, its associated hypervolume inverse is also stored (in the matrix $\underline{\underline{\mathbf{C}}}$). The increase in the computational load is moderate with respect to Albus' rule: ρ additions, ρ multiplications and one division.

6 Performance analysis

We have used the new nonlinear system (LUT+CMAC) as data predistorter within a digital communications framework (figure 1). We have simulated a 64-QAM with squared root raised cosine roll-off pulse shaping, $g(t)$, with an excess bandwidth factor of 0.5; similar filtering is performed at the local receiver. Since the radio channels of interest are narrow-band, the HPA was modeled as a nonlinear memoryless device according to the AM/AM and AM/PM characteristics given by Saleh [7]. The assumption about the down-conversion/coherent demodulation is that the carrier reference is ideal, i.e., has no phase jitter. The sampling and the detector systems are assumed to be ideal. Within this framework, extensive computer simulations of the proposed predistortion methods have been carried out. The results are summarized in the figures 4 and 5 (traces are ensembled average of 15 convergence curves).

Figure 4 shows the RMS error (difference between the desired response and the actual response) evolution for the LUT+CMAC predistortion technique. Simulations show that the LUT+CMAC clearly outperforms the CMAC predistorter, both in speed of convergence and in final degree of nonlinearity cancellation. We notice that the LUT+CMAC has a performance close to

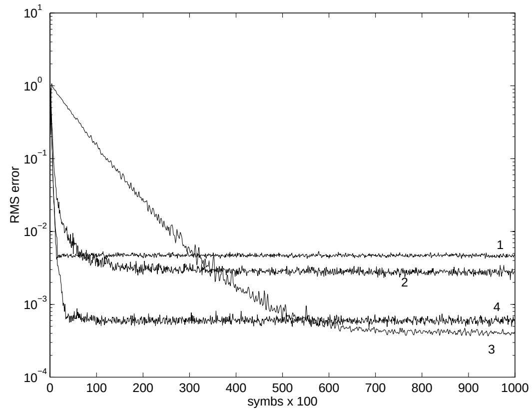

Figure 4: RMS smoothed error evolution for a 64-QAM system. Curve 1: 1st. order LUT; curve 2: 3rd. order CMAC with $\rho = 7$; curve 3: 2nd. order LUT; curve 4: Proposed LUT+CMAC predistorter

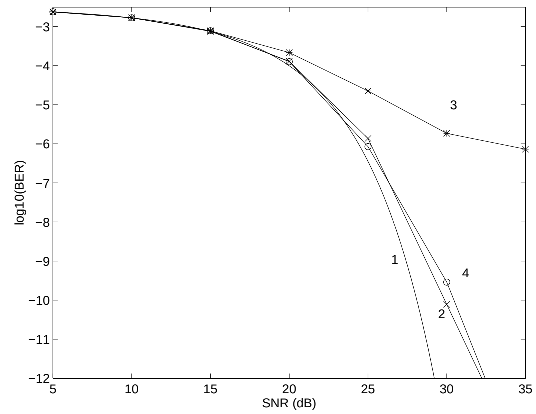

Figure 5: Probability of bit error *vs.* Signal-to-Noise Ratio. Curve 1: Ideal performance (absence of TWT nonlinearity); curve 2: Second order Look-Up-Table; curve 3: Standard CMAC predistorter; ($\rho = 7$); curve 4: Proposed LUT+CMAC predistorter; (CMAC $\rightarrow \rho = 7$)

the 2nd. order LUT with a much lower complexity (512 *vs.* 4096 complex positions).

Finally, we have considered a complete 64-QAM radio system operating over an ideal link with no multipath propagation, i.e., we suppose that the transmission medium is an additive white Gaussian noise (AWGN) channel. Furthermore, the receiver timing and carrier synchronisation systems are assumed to be perfect, so the global system can be represented by a simple baseband-equivalent model. The computer simulations were carried out using the previously described predistorters. Using the rectangular 64-QAM signal constellation, the performance of the presented predistortion technique was evaluated and compared with both standard CMAC predistorter and predistortion based on Look-Up-Tables. The performance measure used was the bit error rate (BER) and the results are reported in the figure 5.

Figure 5 shows the poor performance of standard CMAC predistorter (curve 3) when the system operates under high Signal-to-Noise conditions. This is mainly due to the relatively high noise floor produced by the standard CMAC (-26 dB). The LUT+CMAC-based predistorter (curve 4) produces a noticeable improvement of 3.5 dB of power saving (for a BER of 10^{-5}) with respect to the standard CMAC . The results produced by the second order LUT (curve 2) and the proposed LUT+CMAC-based predistorter are nearly the same.

References

[1] D. Falconer, "Adaptive equalization of channel nonlinearities in QAM data transmission," *Bell Systems Technology Journal*, vol. 57, pp. 2589–2611, Sept. 1978.

[2] G. Karam and H. Sari, "A data predistortion technique with memory for QAM radio systems," *IEEE Transactions on Communications*, vol. 39, pp. 336–344, Feb. 1991.

[3] J. Albus, "A New Approach to Manipulator Control: the Cerebellar Model Articulation Controller," *Journal on Dynamic Systems, Measurements and Control*, pp. 220–227, September 1975.

[4] A. Saleh and J. Salz, "Adaptive linearization of power amplifiers in digital radio systems," *Bell S. Technical Journal*, vol. BSTJ-62, pp. 1019–1033, April 1983.

[5] S. H. Lane, D. A. Handelman, and J. J. Gelfand, "Theory and Development of Higher-Order CMAC Neural Network," *IEEE Control Systems*, pp. 23–30, April 1992.

[6] A. Artés-Rodríguez, F. González-Serrano, A. Figueiras-Vidal, and L. Weruaga-Prieto, "Compensation of Bandpass Nonlinearities by Look-Up-Tables and CMAC," in *Proceedings of the International Workshop on Applied Neural Networks to Telecommunication*, IWANNT, May 1995.

[7] A. A. M. Saleh, "Frequency-Independent and Frequency-Dependent Nonlinear Models of TWT Amplifiers," *IEEE Transactions on Communications*, vol. COM-29, pp. 1715–1720, November 1981.