A NEURAL NETWORK APPROACH TO DATA PREDISTORTION WITH MEMORY IN DIGITAL RADIO SISTEMS

N. Benvenuto, F. Piazza and A. Uncini*

* Dip. di Elettronica e Informatica - Università di Padova, Italy
Via Gradenigo 6/A - 35131 Padova, Italy
Dip. di Elettronica e Automatica - Università di Ancona, Italy
Via Brecce Bianche - 60100 Ancona, Italy

ABSTRACT This paper presents an algorithm to determine the coefficients of a general data-predistorter with memory for compensation of high-power amplifier (HPA) nonlinearities in digital microwave radio system. That technique is based on modeling the predistorter-modulator-HPA system as a neural network with memory. It is shown that by extending the optimization algorithm of back-propagation to complex signals and with neurons modeled as FIR filters, the proposed algorithm determines automatically the predistorter with the objective that the overall transmitter behaves as a linear system with a prescribed pulse shape. The novelty with respect to previous techniques is that in our scheme a control on the spectrum of the signal after the HPA is exercised. This minimizes the interference between adjacent channels. The algorithm as been tested successfully in several radio system employing QAM signal formats and some examples of application will be reported.

I. INTRODUCTION

In many digital radio systems, there are typically several sources of nonlinear distortion, but the major one is the high-power amplifier (HPA) used at the transmitter. In fact, when it operates near the maximum output power, its characteristic is very far from linearity. The effect can be decreased by backing off the HPA from its saturation point, but this reduces the output signal level and, therefore, the channel flat-fade margin. The operating point of the HPA is fixed in practice by trading off between an high signal-to-noise ratio (SNR) and a small nonlinear distortion.

The nonlinearity of a typical HPA, a traveling-wave tube (TWT) or a GaAs FET amplifier, affects both amplitude (AM/AM conversion) and phase (AM/PM conversion) of the amplified signal, and can be considered as memoryless, i.e. the HPA is a nonlinear system without memory under a wide range of operational conditions [1]. However, in practice, the transmitter contains a pulse shaping circuit (modulator) at the baseband or at the intermediate frequency (IF) stage virtually in all digital radio systems. Therefore, the overall baseband-equivalent system (the cascade of transmitter, HPA nonlinearity and receiver) is a nonlinear system with memory.

The presence of this nonlinear distortion can pose serious problems to the use of high-capacity modulation formats, such as multi-level quadrature amplitude modulation (QAM). It is well known that the 64 and 256-QAM links are very sensitive to nonlinear distortion, although they can exhibit better bit-error rate (BER) performance than equivalent phase-shift keying (PSK) systems on additive white noise Gaussian channels. The effects of the nonlinear channel with memory on the QAM signal are manifold, but three of them have particular importance:

Spectral spreading. The spectrum of the amplified signal after the HPA is much wider than that of the signal before the HPA, due to the presence of the nonlinearity. The output signal may not comply with the design limit on the transmitted power spectral density, as the FCC mask for common carrier radio channels. This may cause intolerable inter-channel interference, which must be removed by a radio frequency (RF) filter with the consequent loss in signal level and increased distortion.

Intersymbol interference (ISI). Since the overall system has memory, each symbol of the QAM alphabet, usually referred to as a constellation point, becomes at the receiver a cluster of points due to the interference among symbols at the sampling instants.

Constellation warping. The respective centres of gravity of the clusters caused by the ISI are no longer on a rectangular grid as in the original constellation.

Two different approaches have been followed to cope with the nonlinearity of the link.

The first is based on the idea of accepting the nonlinear channel as is, without trying to do anything to modify its behaviour, and designing a receiver which minimizes the effects of ISI, nonlinearities and noise. An optimum technique based on this approach is the Maximum Likelihood Sequence Estimation by the Viterbi algorithm [2]. However, its processing complexity has suggested several less-demanding suboptimum equalization schemes [3], whose major limitation is the high sensitivity to noise. In fact the channel noise tends to be enhanced by any nonlinear inverse filter used to compensate for the channel distortion [4],[5].

The second approach is based on the idea of compen-

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sating the nonlinearity before the noise addition, i.e. at the transmitter side of the channel. The techniques based on this approach, generally referred to as predistortion techniques, try to linearize the HPA characteristic by predistorting the input signal in such a way that the cascade predistorter-amplifier-receiver resembles as close as possible a ISI-free channel. They can be divided in two categories: analog signal predistortion and data predistortion. The analog signal predistortion consists of nonlinearly transforming the continuos-time IF or RF signal waveform. Usually the third-order distortion is cancelled using a fixed structure [6], however it is not able to cope with possible drifts of the HPA characteristic and does not support automatic transmitted power control. The data predistortion instead exploits the possibility of recovering the HPA nonlinearity by a nonlinear filtering of the symbol sequence before entering the modulator. It is more suitable for a digital implementation and sometimes it is easier to make adaptive.

Two techniques have been proposed. One is based on a finite-order p-th inverse of nonlinear systems [4]. Based on a model of the HPA, a Volterra series representation of the overall discrete time system is easily derived. A nonlinear filter of order p (represented by another Volterra series) is used to pre-equalize the overall system. The other technique [7], denoted global compensation, instead considers the error sequence between the signal at the decision point and the desired symbol sequence (training sequence). By means of a LMS algorithm (similar to that presented in [8]), these errors are used to derive the non linear filter coefficients. Actually, since this filter is realized by a RAM, the adaptation is used to derive the output of the nonlinear filter directly (this is the classical distributed arithmetic implementation of a filter). The global compensation technique yields better performance than the p-th order inverse [7]. Furthermore, it does not need to model the nonlinearity. Thus there is no need to identify the nonlinear system. This identification is quite a difficult operation because it is signal dependent, it must be accurate, and repeated once in a while in order to track the HPA variations in time.

As far as the implementation of the global compensation technique is concerned, we see some practical difficulties. It is not simple to feedback the errors from the receiver to the transmitter site. Consider that they are located very far away from each other. We can envision a scheme where the channel is bypassed and the transmitter and receiver are in back-to-back configuration. A training sequence is then transmitted and the adaptation algorithm can be used to find nonlinear compensator of the HPA nonlinearities.

The purpose of this paper is to present a new data predistortion technique which is based on a neural network (NN) approach. The major difference with respect to previous techniques is that now a control on the spectral shaping at the output of the HPA is introduced. This is obtained by optimizing the NN with the objective that the system formed of predistorter, modulator and HPA behaves as a linear system with a prescribed pulse shape. The adaptation algorithm relays only on signals at the transmitter site and no feedback is needed from the receiver. Furthermore, no special training sequence is used.

The paper is organized as follows. Section II describes the structure of the proposed data distortion scheme and reports the adaptation algorithm, while Section III reports the simulation results and does a short performance analysis.

II. NEURAL NETWORK DATA PREDISTORTION

It is known that some models of artificial neural networks have had a wide variety of applications in digital signal processing [9]. In particular the MultiLayer Perceptron (MLP) structure has been extensively used in nonlinear processing of real-valued signals. For this structure the most common technique for determining the real-valued coefficients is the BackPropagation (BP) algorithm [10], [11].

The classical baseband-equivalent transmitter with data predistortion and global compensation is reported in Fig. 1. For simplicity, the channel after the HPA has been considered ideal and thus omitted in Fig. 1, $\{a(kT_0)\}$ is the data stream (T_0 is the symbol period), $\{b(kT_0)\}$ is the predistorted data stream and $\{c(kT_0)\}$ is the signal at the decision point. $g_T(t)$ and $g_R(t)$ are respectively the impulse response of the modulator and demodulator pulse shaping filter. Usually, both are square-root raised-cosine filters with a given roll-off factor α. The difference between the input symbol $a(kT_0)$ and the signal $c(kT_0)$ is used to update the predistorter in order to minimize a MSE criterion [7].

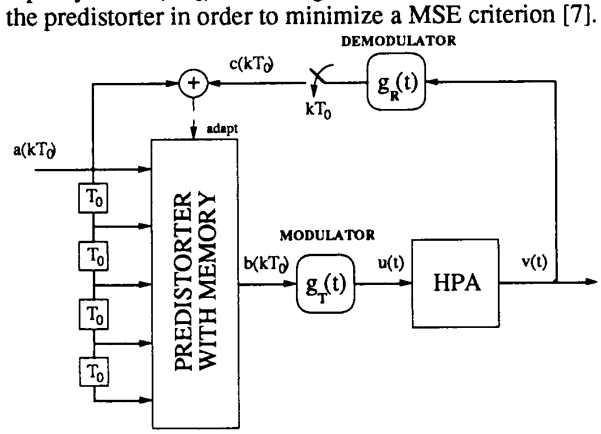

Fig. 1 Baseband equivalent of the radio system with global compensation.

In any case, only by designing a predistorter which minimizes the error between the HPA output and the ideal undistorted signal at all instances, it is possible to build a system which can effectively reduce the unwanted nonlinear effects and at the same time minimize the cross-channel interference. In practice, if the bandwitdh of v(t) is within

$1/(2T_S)$ Hz where $T_S = T_0/Q$, the adaptation can be made at instances pT_S. Fig. 2 shows such a scheme where a NN is used as predistorter.

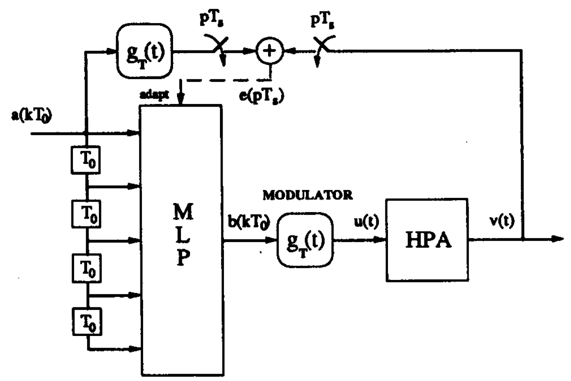

Fig. 2 Baseband equivalent of the radio system with the proposed predistortion technique.

Based on error $e(pT_S)$, the general adaptive scheme to determine the NN weights is illustrated in Fig. 3. Note that a general model of both modulator and HPA is required (indicated by g' and HPA' respectively). This model is simply used to speed-up the convergence process. In effect, the estimate does not need to be very accurate because the scheme of Fig. 3 is only used in the feedback mode, i.e. to backpropagate the error $e(pT_S)$ to the MLP. Only scheme of Fig. 2 is used in the forward mode.

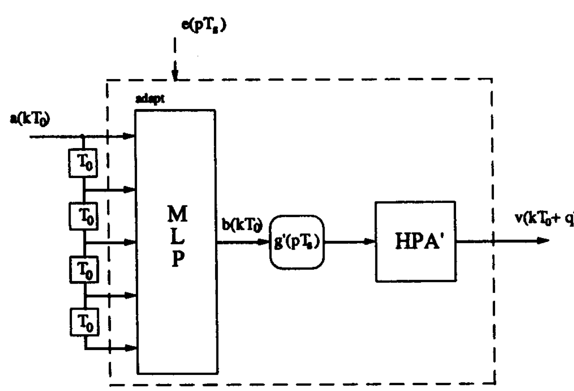

Fig. 3 Block diagram of the adaptation of the MLP.

Assume $g'(pT_S)$ is a FIR filter with $(2L+1)Q$ taps and let $\{g_q'(mT_0)\}$ be its polyphase representation, i.e.

$$g_q'(mT_0) = g'(mT_0 + qT_S), \qquad q = 0, 1, \ldots, Q-1; \quad m = -L, \ldots, 0, \ldots, L.$$

Noting that the MLP works at a much slower rate than the modulator filter, an efficient realization of the adaptation scheme is shown in Fig. 4. Now all filters work at the slowest rate $(1/T_0)$. The actual output is derived by cyclically taking the value of each polyphase path output. In the figure, also the internal layers of the original MLP has been drawn, from layer 1 to layer (M-1). The last layer (index M) is then the layer comprising the HPA characteristic and filtering. In the figure, SMG denotes a complex nonlinear function, the analogous of the real-valued sigmoidal function [14], [15].

There is no space here to enter into the formulation of the adaptation algorithm. We just mention that from the signal $e(pT_S)$ a general complex-valued back-propagation algorithm has been used to find the coefficients of the predistorter [15]. In particular, a modification was introduced due to the fact that the NN has memory (each polyphase filter comprises a delay line). A novel algorithm has been used which is more efficient than those found in the literature [16]-[18].

III. SIMULATIONS RESULTS

A computer simulation study was carried out in order to evaluate the performance of this approach. The channel used in the simulation comprises a HPA characterized by the following input-output relationship [1]:

$$v(t) = \frac{2u(t)}{1+|u(t)|^2} \exp\left(j\Phi_0 \frac{2|u(t)|^2}{1+|u(t)|^2}\right)$$

where $\Phi_0 = \pi/6$. The modulator and demodulator filters (square-root of a raised-cosine) have a roll-off factor α equal to 0.5 and are composed by 5Q taps. The oversampling factor Q is chosen equal to 3. Last, estimated models of g_T and HPA in Fig. 4 were assumed to be correct, i.e. $g'(t) = g_T(t)$ and HPA' = HPA.

The transmission of QAM complex signals has been considered. For the sake of brevity, only two different cases are reported here:

- in the first, 16 QAM signals have been transmitted with the maximum input power P_{IN} (max) to the HPA equal to -2 dB;
- in the second, 64 QAM signals have been transmitted with the maximum input power P_{IN} (max) to the HPA equal to -2 dB.

In both cases, 4 different predistorters have been tested:

1 - "none" predistorter, consisting simply of a complex adaptive gain factor;
2 - "C3_1" predistorter, consisting of a complex adaptive linear combiner with 3 taps;
3 - "C3_3_1" predistorter, consisting of a complex MLP neural network with 3 inputs, 3 nonlinear hidden neurons and one linear output neuron;
4 - "C3_5_1" predistorter, consisting of a complex MLP neural network with 3 inputs, 5 nonlinear hidden neurons and one linear output neuron.

Table 1 reports, for any combination of input signals and predistorter type, the Mean Square Error MSE_{HPA} com-

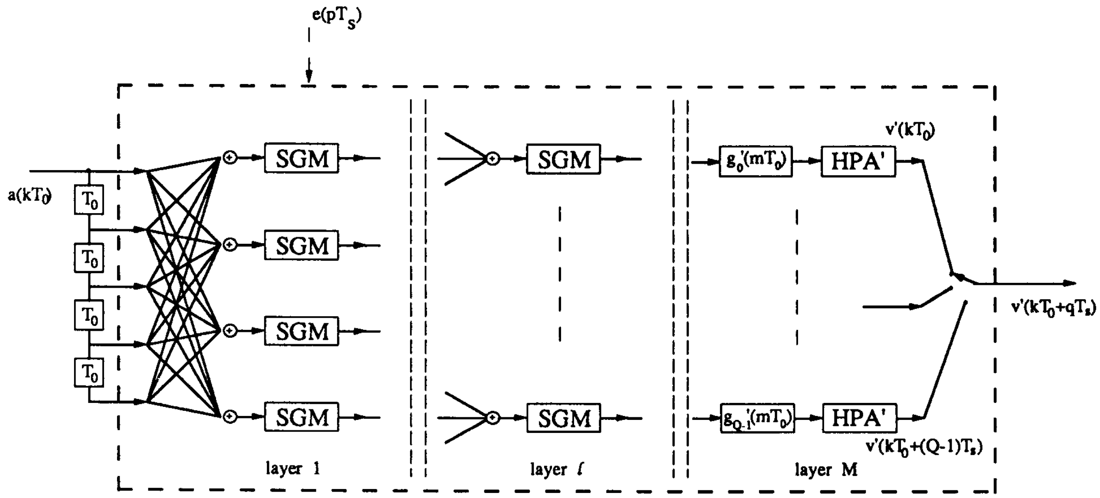

Fig. 4 An efficient realization of the adaptation scheme of Fig. 3.

puted between the HPA output signal v(t) and the desired signal as well as the Mean Square Error MSE_{SYM} computed between the received symbol stream $c(kT_0)$ and the input simbol stream $a(kT_0)$. It is clear that the introduction of a neural, i.e. nonlinear, predistorter allows to reduce the MSE either at the HPA ouput, letting the output spectrum to be better controlled, as well as at the received symbol level.

The performance of the proposed scheme is well illustrated by the graphical representation of the transmitted and received 64 QAM symbols when P_{IN}(max)=-2 dB. Without any compensation, the received constellation is shown in Fig. 5a. The estimated MSE between the received signal and actual data is -21.08 dB. If a neural predistorter with only three inputs, one hidden layer with five neurons and one linear output (C3_5_1) is used, the MSE decreases to -29.53 dB and the corresponding constellation is reported in Fig. 5b, showing much less distortion with respect to the original, undistorted, symbol constellation. In both cases, the maximum symbol amplitude has been normalized to 1.

IV. CONCLUSIONS

Although a complete performance evaluation is still in progress (e.g. we are evaluating the total degradation versus HPA back-off [7]), the proposed scheme seems very promising as digital compensator for nonlinear channels with memory. The major advantage with respect to other schemes is that it allows to control the power spectral density of the signal at the output of the HPA. Furthermore, this scheme does not suffer of memory requirements as that in [7].

Table 1 The Mean Square Error computed on the HPA output signal (MSE_{HPA}) and on the received symbols (MSE_{SYM}) with different predistorters and different HPA inputs. All values are in dB.

predist.	P_{IN} (avg)	P_{IN} (max)	MSE_{HPA}	MSE_{SYM}
16-QAM				
none	-7.01	-2.0	-13.40	-20.98
C3_1	-7.01	-2.0	-18.95	-22.97
C3_3_1	-7.01	-2.0	-20.36	-26.80
C3_5_1	-7.01	-2.0	-21.60	-28.58
64-QAM				
none	-8.46	-2.0	-17.40	-21.08
C3_1	-8.46	-2.0	-20.03	-25.01
C3_3_1	-8.46	-2.0	-21.85	-28.61
C3_5_1	-8.46	-2.0	-22.67	-29.53

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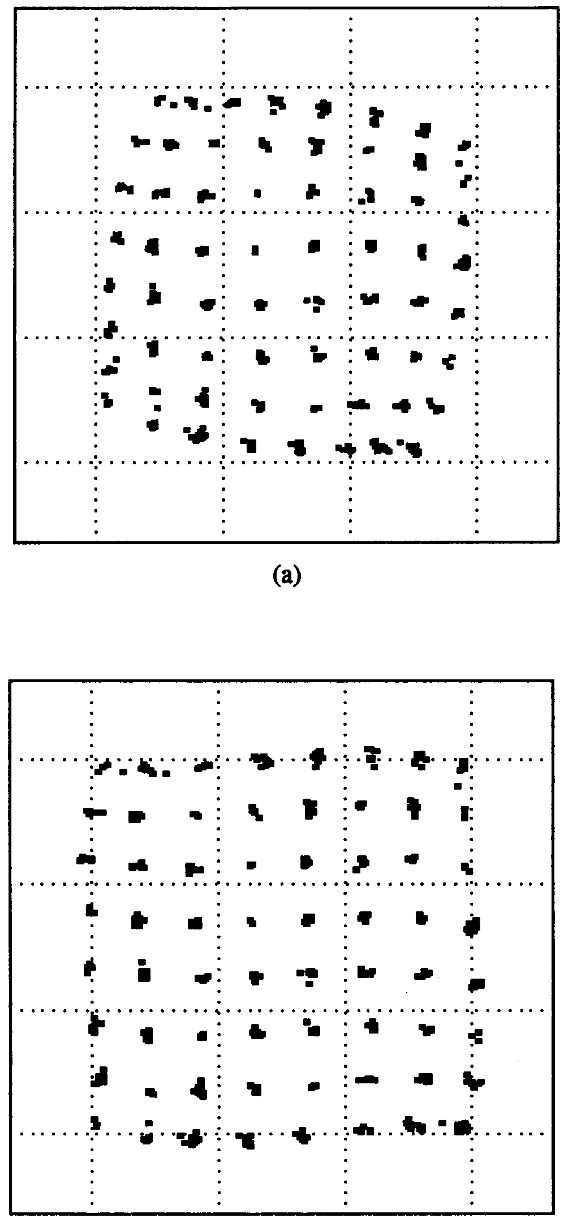

(a)

(b)

Fig 5. (a) The undistorted 64 QAM symbol constellation input and the corresponding distorted output obtained when P_{IN} (max)=-2 dB and the "none" predistorter is used; (b) output obtained when P_{IN} (max)=-2 dB and the proposed C3_5_1 predistorter is used.