Closed-Loop Digital Pre-Distortion for Power Amplifier Linearization using Genetic Algorithms

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Abstract — **This paper continues our investigation of genetic pre-distortion algorithms to power amplifier (PA) linearization. In previous work, we reported simulation results of an adaptive algorithm that requires only a measure of out-of-band emission. Compared to traditional algorithms that require wideband feedback, the proposed algorithm is implemented using narrowband feedback, affording a large cost savings in ADC components. In our current work we apply the genetic algorithm to a laboratory PA and present linearization results in terms of adjacent and alternate channel leakage ratio (ACLR) and efficiency improvement.**

I. Introduction

Power amplifiers are one of the most expensive and power-consuming components in a 3G basestation. They are inherently nonlinear and, when operated near saturation, cause intermodulation products that distort adjacent and alternate channels. This distortion, or ACLR, is strictly limited by FCC and ETSI regulations as specified in [1].

PAs in the field today are predominantly linearized by some form of feed-forward technology. Only in recent years has the interest in digital pre-distortion been substantial. Digital implementations now show higher efficiency at lower cost with greater pre-distortion bandwidths than traditional feed-forward techniques.

In this paper, we revisit the genetic algorithm introduced in [2] to linearize a laboratory PA during transmission of a multi-carrier CDMA2000 waveform centered at 881MHz using narrowband feedback. Linearization is achieved through the adaptation of a look-up table (LUT) in which we use polynomial functions to correct for amplitude and phase, as in [3]. We will show that our low-cost implementation is able to improve ACLR by approximately 15dB, thus meeting the 3GPP specification.

The paper is organized as follows. Section 1 is an introduction. Section 2 presents linearization fundamentals emphasizing a digital pre-distortion technique. Section 3 introduces the genetic algorithm adaptation process. Section 4 describes a hardware architecture and presents laboratory results. A summary is given in section 5.

II. Linearization Fundamentals

In this section, we present some fundamental principles of digital pre-distortion, particularly the methods used to linearize a PA. Current linearization techniques employ feedforward pre-distortion to meet ACLR requirements. Technology advances have made it possible to use digital feedback as an alternate technique providing higher efficiency at a lower cost. Figure 1 shows an example of state-of-the-art digital feedback compensation. This architecture uses Intersil's digital pre-distorter (PD) employing a technique similar to that proposed by Faulkner in [4]. Faulkner's algorithm requires a sample-by-sample comparison between the PD input and PA output, significantly driving up the cost of the ADC located in the feedback path. The algorithm that we propose in this paper requires only a measure of the power in the out-of-band emissions, thereby substantially reducing the ADC requirements.

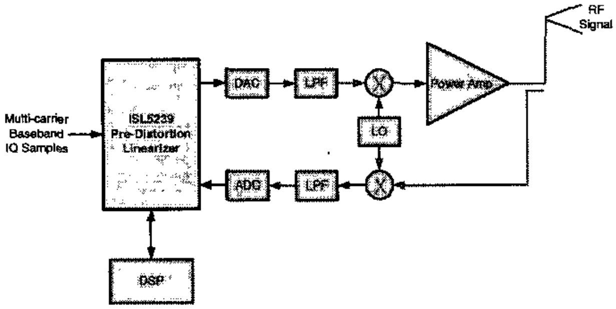

Fig. 1. State-of-the-art digital pre-distortion using ISL5239 wideband feedback architecture.

For our implementation, we will consider the linearization of power amplifiers that can be modeled by a memoryless nonlinearity. The input-output block diagram used to represent a PA is shown in Figure 2, where $v_i(t)$ and $v_o(t)$ represent the input and output signals respectively. The complex baseband model of our PA output is expressed as:

$$v_o(t) = g\left(|v_i(t)|^2\right) v_i(t) = g_a\left(|v_i(t)|^2\right) e^{jg_\phi\left(|v_i(t)|^2\right)} v_i(t) \quad (1)$$

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where g_a ($|v_i(t)|$) and g_ϕ ($|v_i(t)|$) are the amplifier's amplitude and phase characteristics.

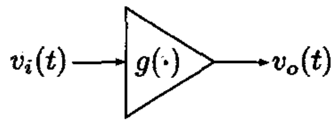


Fig. 2. Power amplifier input-output diagram.

A PD preceding the amplifier is used to apply correction to achieve linear operation, which can be broken down into amplitude and phase correction. When the PA is operating in the linear mode, the PD does not apply correction. In the nonlinear range, the PD applies gain to either amplify or attenuate the input signal and the appropriate phase shift to correct for offsets. Figure 3 shows the PD-PA block diagram where $v_d(t)$ is the PD output. The PA output is now expressed as follows:

$$v_o(t) = g\left(\left|f\left(|v_i(t)|^2\right) v_i(t)\right|^2\right) f\left(|v_i(t)|^2\right) v_i(t) \quad (2)$$

The genetic algorithm described next attempts to identify a function that minimizes spectral regrowth in the adjacent and alternate channels.

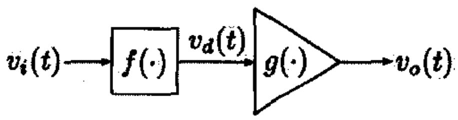


Fig. 3. Pre-distorter and power amplifier input-output diagram.

III. GENETIC ALGORITHMS

The genetic algorithm used for our application creates polynomial PD function of the form:

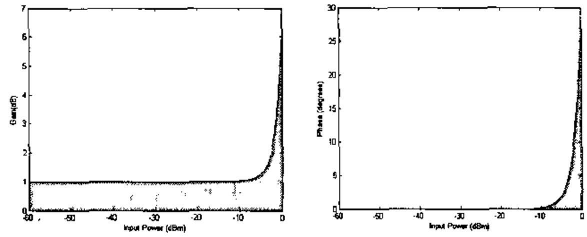
$$\hat{f}(|v_i(t)|^2) = \hat{f}_a(|v_i(t)|^2)e^{j\hat{f}_\phi(|v_i(t)|^2)} \quad (3)$$

Where

$$\begin{aligned}\hat{f}_a(|v_i(t)|^2) &= (\bar{A}_a + \tilde{A}_a) + (\bar{B}_a + \tilde{B}_a)|v_i(t)|^2 + \\ &\quad (\bar{C}_a + \tilde{C}_a)|v_i(t)|^4 + (\bar{D}_a + \tilde{D}_a)|v_i(t)|^6 \quad (4)\end{aligned}$$

$$\begin{aligned}\hat{f}_\phi(|v_i(t)|^2) &= (\bar{B}_\phi + \tilde{B}_\phi)|v_i(t)|^2 + \\ &\quad (\bar{C}_\phi + \tilde{C}_\phi)|v_i(t)|^4 + (\bar{D}_\phi + \tilde{D}_\phi)|v_i(t)|^6 \quad (5)\end{aligned}$$

The GA proposed above uses polynomial functions, however the technique is not limited to polynomials but can be applied using a number of parameterized models. The nominal or bar coefficients $\{\bar{A},\bar{B},\bar{C},\bar{D}\}$ define the center of the search space while the delta or tilde coefficients $\{\tilde{A},\tilde{B},\tilde{C},\tilde{D}\}$ define the range of the search space. The values of the nominal coefficients were defined in [2] as being initialized in the neighborhood of the expected solution. Figure 4 shows the overall search space of the GA. Figures 4(a) and 4(b) show w that the PD solution may have up to 6.5 dB of amplitude expansion and 30 degrees of phase shift respectively.



(a) Search space for $\hat{f}_a$. (b) Search space for $\hat{f}_\phi$.

Fig. 4. AM-AM and AM-PM polynomial search space for the genetic algorithm.

The GA optimization technique is described in four steps that follow and is further illustrated in Figure 5:

1. Generate random population of N members.
2. Evaluate the fitness of each member in the population and sort.
3. Generate new population.
   (a) Elitism. Select best K members of the current population.
   (b) Non-elitism.
      i. Selection. Identify parents by stochastic sampling with replacement.
      ii. Crossover. Apply uniform crossover.
      iii. Mutation.
4. Loop to step 2 and repeat for a new population.

In the first step, the GA initializes a population table of N sets of delta coefficients with values uniformly distributed over the search space. Each element in the table is indexed by an integer $k \in [1,2,\ldots,N]$. The next five steps of the algorithm are repeated iteratively. We index each iteration of the algorithm by the integer i = 0,1,2... Using this notation, the k^{th} member of the population on iteration i is denoted by the following:

$$\{\tilde{A}_a(i,k), \tilde{B}_a(i,k), \tilde{C}_a(i,k), \tilde{D}_a(i,k), \tilde{B}_\phi(i,k), \tilde{C}_\phi(i,k), \tilde{D}_\phi(i,k)\} \quad (6)$$

In step 2 of the process, each member is evaluated to calculate its fitness. Fitness is defined as the inverse of the measured ACLR, thus the desired low ACLR corresponds to a high value of fitness. After the entire population has been evaluated for fitness, the N members of the population are sorted in descending order.

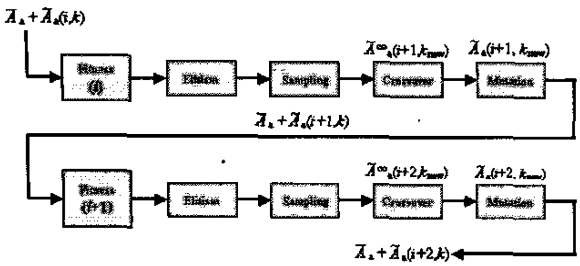


Fig. 5. Genetic algorithm process with two iterations.

In step 3, we generate the new population through elitism, sampling, crossover and mutation [5]; these are called *genetic operators*. The process of elitism selects the best members of the current population and duplicates them into the new population. The number of members duplicated is determined by the rate of elitism as defined by the user. Elitism prevents the algorithm from loosing the optimal solution.

The algorithm now selects two members, k_1 and k_2, of the current population to create a member of the new population. This is done through stochastic sampling with replacement where the probability of selection for a member is determined by its fitness. The process is repeated for each member of the new population. This process can be compared to natural selection in genetic studies.

Following selection of two parents, uniform crossover combines the two sets of delta coefficients to create a new population member. The new member contains elements from both parents which are determined by the crossover rate as defined by the user. A random binary string B_{CO} is generated in which the probability of a 1 in each bit position is equal to the crossover rate. The crossover operator creates a new offspring through the following logic statement. Other forms of crossover are available, but this is the preferred embodiment.

$$\tilde{A}^{co}_a(i+1,k_{new}) = [\tilde{A}^*_a(i,k_1) \text{ AND } B_{CO}] \text{ OR } [\tilde{A}^*_a(i,k_2) \text{ AND } \bar{B}_{CO}] \quad (7)$$

Before the new member can join the population, it is subjected to the mutation operator. Similarly to crossover, the mutation rate creates a binary mutation string which modifies in a limited fashion the new members. Mutation prevents the algorithm from converging in a local minimum solution. The following equation defines the mutation operator.

$$\tilde{A}_a(i+1,k_{new}) = \tilde{A}^{co}_a(i+1,k_{new}) \text{ XOR } B_{MU} \quad (8)$$

Step 4 returns the process to step 2 where the genetic operations are repeated for the N members of the new population and every iteration i to achieve acceptable levels of ACLR reduction. During periods of nonadaptation, the member with the best fitness is used by the PD.

IV. LABORATORY RESULTS

In this section, we present our laboratory setup and results. Figure 6 illustrates our implementation of digital pre-distortion. Our forward path uses direct RF conversion. However, for our test bed, the spectrum analyzer is used to replace the feedback path. The Intersil ISL5217 evaluation board was used to generate a three-carrier CDMA2000 waveform, with each carrier having a signal bandwidth of 1.23MHz for a total bandwidth of 3.75MHz. The CDMA2000 waveform has a PAR of approximately 12.4dB. This waveform was pre-distorted using the Intersil ISL5239 evaluation board. The ISL5239 is a baseband look-up table (LUT) pre-distortion device. The ISL5239 also included gain, phase, and offset correction to improve image rejection and carrier leakage of the direct upconverter. The ISL5239 evaluation board includes the Intersil ISL5929 dual DAC and interfaces with the Sirenza STQ-2016 direct upconverter to generate the 881MHz pre-distorted RF waveform. The waveform was driven by a Mini-Circuits ZHF-1000 amplifier. The waveform was then amplified by a Sirenza SHF-0189 PA. The output was fed back to a computer through an Agilent E4404B Spectrum Analyzer. The data was processed in Matlab to implement a LUT solution in the ISL5239.

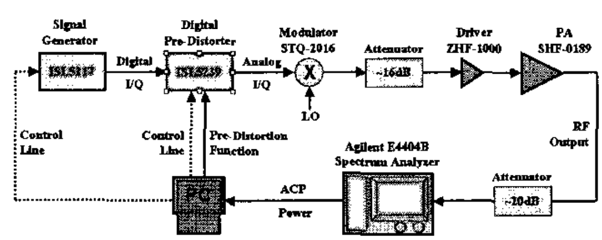


Fig. 6. Laboratory setup of the closed-loop adaptive digital pre-distortion system.

The genetic operators were defined by an elitism rate of 20%, a mutation rate of 3%, and a crossover rate of 50%. Our initial populations were comprised of N=25 members and the simulations were allowed to run over i=20 iterations. Figure 7 shows the AM-AM and AM-

PM characteristic curves of the LUT after the algorithm has converged. The P_{1dB} of the PA is -3.5dB thus both tables remain constant up to an input power of approximately -4dBm after which correction is applied.

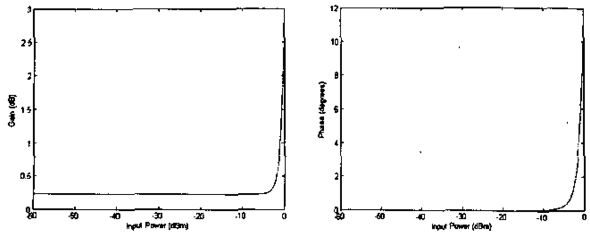


Fig. 7. AM-AM and AM-PM pre-distortion curves for the laboratory PA.

Figure 8 shows the PA output with and without pre-distortion. The PA output power is held constant for both cases. Without linearization the ACLR is measured to be 31dBc. This improves to 46dBc with the pre-distortion defined by the GA.

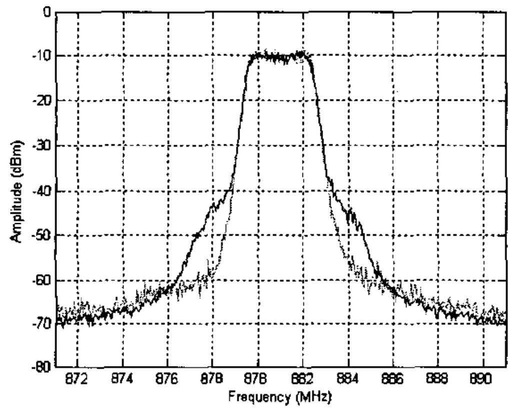


Fig. 8. PA performance with and without digital pre-distortion.

Figure 9 shows the GA adaptation curves demonstrating the progress of the algorithm as a function of the number of iterations. The results shown prior to iteration 0 indicate ACP measurements without pre-distortion. The uppermost line shows the average adjacent channel power for the population. The second line corresponds to the GA optimal solution. Even though the adjacent channel power decreases for each iteration the optimal solution does not remain constant due to varying input power levels. Finally, the lowest line represents the minimum possible adjacent channel power as defined by the noise floor of the system.

As explained in [1], the output noise floor is lower for a PA operating in compression than for a PA operating in its linear region. Our results reflect that optimum ACLR performance is achieved when the PD gain is at its maximum level and the resulting output noise floor is at a minimum. The increase in PD gain also causes the PA to operate with higher efficiency.

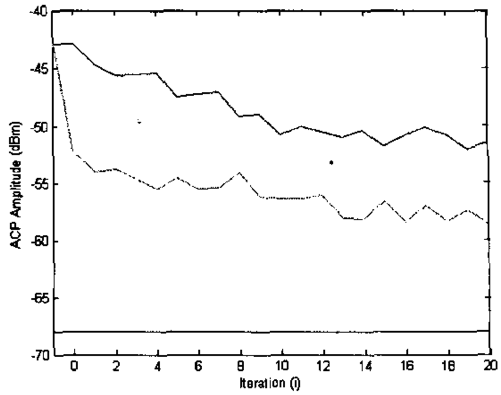


Fig. 9. Average, optimal, and lower limit for adjacent channel power for each iteration.

V. CONCLUSION

In this paper, we used genetic algorithms with digital pre-distortion to linearize a laboratory PA. We presented results showing that a narrow-band feedback technique was able to achieve approximately 15dB of ACLR reduction on a 3.75MHz bandwidth three-channel CDMA2000 waveform. We presented the hardware architecture based on the ISL5239 digital pre-distortion linearizer. This solution offers high performance and is an attractive alternative to the more expensive feed-forward and wide-band feedback techniques.

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