Nonlinear Distortion Cancellation using Particle Swarm Optimization (PSO) based Predistortion in OFDM systems

Pedro Luis Carro, Paloma García Dúcar, Jesús de Mingo, Antonio Valdovinos Department of Electronic Engineering and Communications Aragon Institute Engineering Research (I3A) University of Zaragoza Zaragoza, 50018 Spain Email: plcarro@unizar.es, paloma@unizar.es, mingo@unizar.es, toni@unizar.es

Abstract— A new adaptive digital predistorter based on the use of PSO (Particle Swarm Optimization) algorithm is developed and applied in an orthogonal frequency-division multiplexing (OFDM) transmission scheme, such as a WiMAX system. OFDM transmission is an efficient way to deal with multipath, being its implementation less complex than traditional equalizers, however, it is also very sensitive to nonlinear distortions due to its greatly variable envelope. The perfomance of this method has been verified by means of simulation and has been compared to the well-known LMS (Least Mean Squares) algorithm. In both cases, a reduction in out-of-band distortion around 20 dB is obtained when the power amplifier woks with a 6 dB Output Backoff (OBO). Both estimation algorithms are presented and discussed.

I. INTRODUCTION

WiMAX is a short name for Worldwide Interoperability of Microwave Access. WiMAX is described in IEEE 802.16 Wireless Metropolitan Area Network (MAN) standard. It is expected that WiMAX compliant systems will provide fixed wireless alternative to conventional DSL and Cable Internet. WiMax promises to deliver high data rates over large areas to a large number of users in the near future. On the whole, the base characteristic of 802.16 standard provide a coverage as far as 50 km, with the possible operation outside the direct visibility zone, which in prospect will give a peak data exchange rate up to 70 Mbit/s per sector, with the typical base station having up to coverage sectors. The recently approved IEEE 802.16e amendment will expand the standard to address mobile applications thus enabling broadband access directly to WiMAX-enabled portable devices, such as smartphones or PDAs [1]. This standard is based on a multi-carrier modulation as the OFDM scheme (Orthogonal Frequency Division Multiplexing). OFDM is a multi-carrier transmission technique which has recently become popular thanks to the advance of the integrated circuits technology regarding high-speed and economical prices. Today, OFDM is also used in a variety of systems such as asymmetric digital subscriber line (ADSL), as well as wireless systems such as IEEE 802.11a/g and wireless digital audio and video broadcasting. An OFDM signal consists of a sum of subcarriers that are modulated

by using phase shift keying (PSK) or quadrature amplitude modulation (QAM) [2]. The OFDM transmission is an efficient way to deal with multipath, being its implementation less complex than traditional equalizers. It is also robust against narrowband interferences, because such interferences affect only a small percentage of the subcarriers. This has made it not only ideal for such new technology like WiMax, but also one of the prime technologies being currently considered for use in future fourth generation (4G) networks. Another advantage of the OFDM system is that the digital transmitter and receiver can be efficiently implemented using the Fast Fourier Transform (FFT) algorithm. However, one of its drawbacks is its sensitivity to nonlinear distortions due to its greatly variable envelope and high peak to mean envelope power ratio values [3-4]. Wideband digital modulation requires a high degree of linearity. Linearity implies higher power consumption. The tradeoff between efficiency and linearity is a constant battle. For WiMAX, a class A power amplifier can work at 4 to 5% efficiency for about a 6 dB backoff from output P1 dB. Such a backoff results in about a 2.5% Error Vector Magnitude (EVM) or 32 dBc of Signal to Noise plus Distortion (SNDR). High power efficiency can be obtained with class AB power amplifiers, but they show more non-linear characteristics. In order to achieve both spectrum and power efficiency, several classical linearizing techniques for power amplifiers have been proposed in the technical literature. These techniques are usually categorized as Feed-forward, Feedback, Predistortion and LINC transmitter. Several techniques in order to reduce the effects of nonlinear distortion on the performance of OFDM systems have been proposed in the recent literature [5-10], being the predistortion method the most promising scheme to be implemented in both base stations and portable terminals.

In this work a predistortion method, based on the estimation of an inverse predistortion function corrrespondign to an amplifier model for compensating the nonlinear distortion, is used. Fig.1 shows the proposed scheme. There are several proposals in the literature for modelling and estimating the predistorter and power amplifier coefficients [11-13]. Authors propose an algorithm based on Particle swarm optimization (PSO) and it is compared to the classical LMS algorithm.

II. ESTIMATION ALGORITHMS

Gradient based optimization techniques attempt to estimate the gradient of the error surface and proceed to an optimum solution by following the negative direction of this estimated gradient. These algorithms are well known, widely used, and proven simple, effective, and convergent local optimization techniques. The most notable of these algorithms is the least mean squares (LMS) algorithm [14]. The problem is that gradient descent is a local optimization technique, which is limited because it is unable to converge to the global optimum on a multimodal error surface if the algorithm is not initialized in the basin of attraction of the global optimum.

A. Particle Swarm Optimization (PSO)

Particle Swarm Optimization was first developed in 1995 by Eberhart and Kennedy [15,16], rooted on the notion of swarm intelligence of insects, birds, etc. The algorithm attempts to mimic the natural process of communication of individual knowledge inside a group, that occurs when such swarms flock, migrate, forage, etc... in order to achieve some optimum property such as configuration or location. Since its invention, PSO has received substantial attention in the optimization and evolutionary algorithm communities, but this is the first time the algorithm is applied in power amplifier linearization methods. In this context, PSO has several advantages that make it competitive with the conventional optimization techniques such as LMS, RLS

Conventional PSO begins with a random population of individuals; here termed a swarm of particles. Each particle in the swarm is a different possible set of the unknown parameters to be optimized. According to predistortion, particles will model the polynomial coefficients used to compute the output predistorted signal, where each particle represents a point in the solution space that has a relative fitness determined by evaluating the parameters with respect to a predetermined function, called J, having an extremum at the desired optimal solution. The particles' parameters can be real-valued or encoded depending on the particular circumstances. The premise is to search efficiently the solution space by swarming the particles toward the best fit solution encountered in previous iterations with the aim of finding better solutions through the course of the process and eventually converge to a single minimum error solution.

B. PSO algorithm in predistorter design

Let w_i such that $i = 1..k, w_i \in \mathbb{C}$ the coefficients corresponding to the predistorter model where 2k is the problem dimension. The steps in figuring out the optimal solution will comprise:

Initialize a random swarm of M particles (i.e. M predistorter possible solutions), compute J, the error fitness (see eq.8) and evaluate pbest, gbest (as eq.2), where pbest, gbest are the best solution in each iteration and thorough the whole iteration process, respectively.

2) Update velocity, v, and particle position, w, according to the following equations:

$$w_{n+1} = w_n + v_n \tag{1}$$

$$v_{n+1} = \mu v_n + c_1 rand() \cdot (p_{best} - w_n) + c_2 rand() \cdot (g_{best} - w_n)$$
(2)

where μ is the inertial weight and c_1, c_2 are the cognitive and social rates. Rand() denotes a random variable uniformly distributed between 0 and 1.

- 3) Evaluate the fitness function and update pbest, gbest.
- 4) Repeat steps (2) and (3) until a desired fitness value is achieved.

Unless there is prior knowledge about the parameter space, the initial particles are typically distributed uniformly about the presumed parameter space to facilitate a global search. Therefore, the number of iterations will depend on required fitness value, the number of dimensions and search parameter size.

III. LEARNING ARCHITECTURE

A schematic diagram of the simulation model is depicted in Fig. 1. The presented method consists of a predistorter scheme based on the estimation of an inverse predistortion function corresponding to an amplifier model for compensating the nonlinear distortion.



Fig. 1. Schematic diagram of the simulation model

The source signal $\psi[n]$ used in simulations is an OFDM signal (with a QPSK, 16-QAM and 64-QAM modulation) with a 20 MHz bandwidth defined in the WiMAX standard. The modulated OFDM signal during a symbol can be expressed as follows

$$\psi[n] = e^{j2\pi f_c n} \sum_{k=K_{min}}^{K_{max}} c_{0,0,k} e^{j2\pi k'(n-\Delta)/Tu}$$
(3)

where

$$k' = k - \frac{K_{max} + K_{min}}{2}$$

 T_u is the inverse of the carrier spacing, Δ is the duration of the guard interval, k denotes the carrier number, f_c is the central frequency of the RF signal and $c_{0,0,k}$ is a complex symbol for carrier k. These parameters have been chosen to accomplish the Wimax standard with the required bandwith. The predistorter is modeled as a memoryless polynomial (up to order six) given by:

$$\zeta(\psi)[n] = \sum_{i=1}^{k} w_i \psi[n] |\psi[n]|^{i-1}, w_i \in \mathbf{C}$$
(4)

The power amplifier is characterized by a complex gain which depends on the input signal level and it is extracted from AM-AM and AM-PM characteristics. A sixth order polynomial regression is used to model the amplifier complex gain.

$$A(|\zeta[n]|) = M(|\zeta[n]|) \cdot e^{j\phi(\zeta[n])}$$
(5)

where

$$M(|\zeta[n]|) = 192.3 + 91.83|\zeta(n)| - 736.8|\zeta[n]|^{2} + 907.01|\zeta[n]|^{3} - 490.95|\zeta[n]|^{4} + 124.72|\zeta[n]|^{5} - 12.11|\zeta[n]|^{6}$$
(6)

$$\phi(|\zeta[n]|) = -1.9758 + 0.9187|\zeta[n]| - 2.0892|\zeta[n]|^{2} +$$

$$+1.7987|\zeta[n]|^{3} - 0.7584|\zeta[n]|^{4} +$$

$$+0.1157|\zeta[n]|^{5} - 0.0124|\zeta[n]|^{6}$$
(7)

Figs. 2,3 show the behaviour of the power amplifier represented by the equations above.

G represents the amplifier complex gain when operating in linear zone and BL is a parameter involved in the fitness function. The mean square error will be used in this paper so that LMS and PSO can be compared, although it is important to point out that the algorithm may use other type functions, in contrast to gradient algorithms. Thus, the fitness function, supposing a perfect estimation in the loop delay, is defined as:

$$J[n] = \frac{1}{BL} \sum \left| \frac{\psi}{-\frac{\xi}{G}} \right|^2 \tag{8}$$

where $\underline{\psi}, \underline{\xi}$ are de vector signals of size BL corresponding to the learning architecture, that is:

$$\underline{\psi} = \{\psi[n] \ \psi[n-1] \dots \psi[n-BL+1]\}$$
(9)

$$\underline{\xi} = \{\xi[n] \ \xi[n-1] \dots \xi[n-BL+1]\}$$
(10)

In the case of the LMS-architecture, BL will be set to 1 (i.e. a non-block algorithm) whereas in the PSO-architecture this parameter plays a key role to achieve convergence and will depend on the input signal statistics. A suggested value of BL=100, which has been tried, provides good results, although it is necessary to study more carefully the performance.



Fig. 3. Power Amplifier Phase model

IV. RESULTS

Two different estimation algorithms in the predistorter identification were tried: Non linear LMS and PSO. As mentioned, these algorithms are based in totally opposed philosophies. However, provided similar fitness function, they should lead to identical predistorsion performances.

Regarding the PSO parameters as the inertial weight, social and cognitive rates, they have been selected according to typical non-linear PSO problems. The inertial weight was started in 0.5 and finished in 0.2 changing linearly with the iteration number. Acceration rates (both social and cognitive) were selected to be 2, as in typical implementations.

Fig. 4 compares the normalized output power spectral density with and without the proposed predistortion method, using the coefficients obtained by means of the LMS algorithm and PSO algorithm with a 6 dB output backoff. The improvement regarding out-off band spurious emission is around 18-20 dB.

Fig. 5 shows the temporal evolution of the predistorter coefficients, in real and imaginary part, using the LMS estimation algorithm. It can be seen the algorithm converges in a short time (4-5 symbols).

Fig 6 introduces fitness function evolution showing the convergence in the case of PSO algorithm. As seen, the con-



Fig. 4. Normalized Power Spectral Density of simulated output signal with and without the LMS and PSO predistortion methods (16-QAM input signal modulation and 20 MHz bandwidth). OBO=6 dB.



Fig. 5. Mean Square Error showing the PSO convergence.

vergence is faster in the first iterations because the algorithm identifies the linear coefficient in fewer iterations than the other non-linear coefficients.

One of the advantages of the Non-Linear LMS implementation is its computational cost when compared to PSO, due to the fact that PSO needs a block computation. Without it, the particles would not be able to identify properly the best solution as the fitness function is dependent upon the input signal, changing the value that the particle explores in the search space. However, the block makes this space statistically stable, allowing the particles to find the right optimum. On the other hand, LMS has several drawbacks such as convergence speed and several parameters that have to be adjusted if stability is required. This process is quite complex, if not possible, especially when high peak to mean envelope power ratio signals are introduced in the architecture. In contrast, PSO is found to be more stable dealing with those signals.

Besides, LMS or other similar algorithms are not able to identify memory polynomial predistorters like Wiener-



Fig. 6. Evolution of predistorter coefficients (real and imaginary part) estimated by a LMS algorithm.

Hammerstein models [17] where the identification cannot be reduced to a linear problem. The limitation comes from the Wiener model (fig 7), which obeys:

$$\zeta(n) = \sum_{k=1}^{K} a_k \left[\sum_{m=0}^{M-1} h(m)\psi(n-m) \right]^k$$
(11)

This equation states that the filter coefficients, h(m), cannot be identified in a linear way. PSO offers a new method in order to focus this problem, since a simple modification in the definition of particles could identify the best solution, and even other more non linear complex model predistorters.



Fig. 7. Wiener Model of predistorter.

V. CONCLUSION

A global optimization technique, Particle Swarm Optimization (PSO), is proposed and evaluated in predistorter design for high power amplifiers in WiMAX applications. It is compared to classical algorithms showing similar performances in nonlinearity corrections (around 18-20 dB), and better stability dealing with high peak to mean envelope power ratio signals. Besides, due to its inherent global approach, PSO offers a new way of identifying predistorters modeled with functions where coefficients are not linear.

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