A Compensating Method Based on SOM for Nonlinear Distortion in 16-QAM-OFDM System

Xiaqiu WANG†a), Member, Hua LIN††, Nonmember, Jianming LU†, Hiroo SEKIYA†, and Takashi YAHAGI†, Members

SUMMARY This paper presents a compensating method based on Self-Organizing Map (SOM) for nonlinear distortion, which is caused by high-power amplifier (HPA) in 16-QAM-OFDM system. OFDM signals are sensitive to nonlinear distortions and different methods are studied to solve them. In the proposed scheme, the correction is done at the receiver by a SOM algorithm. Simulations are carried out considering an additive white Gaussian (AWG) transmission channel. Simulation results show that the SOM algorithm brings perceptible gains in a complete 16-QAM-OFDM system.

key words: OFDM, self-organizing map, nonlinear distortion

1. Introduction

Due to its robustness in environments affected by high interference and multipath and to its spectral efficiency, orthogonal frequency-division multiplexing (OFDM) is considered as an effective modulation technique for high-speed digital transmission of many services such as messages, facsimile, cordless telephone and image to mobile receivers.

OFDM is a multicarrier transmission scheme, which uses frequency-division multiplexing efficiently implemented through inverse fast Fourier transform (IFFT) to transport an input data stream on $N$ orthogonal subcarriers within the usable frequency band of the channel. This technique is effective in a multipath environment since each subchannel carries a low bit rate, thus, resulting in a symbol period much longer than typical echo delays. In addition, owing to the use of a guard interval (inserted before each modulation period), echo equalization simply reduces to a scalar multiplication of the detected decision variables by a corrective coefficient [1], [2].

The major drawback of the OFDM technique is its large signal dynamics caused by the high (several hundreds) number of subcarriers with random phase and amplitude, which are summed in the modulator. It results in that OFDM signals are sensitive to nonlinear distortions caused by high power amplifier (HPA) [3]. The first obvious solution is to use a very linear HPA, but this solution is expensive and consumes too much power for portable systems.

Several methods are studied to solve this problem. The peak to average power ratio (PAPR) can be reduced with special coding techniques [4], or the signal can be pre- or post-distorted to compensate for its nonlinearity. A post-distortion system uses a compensator in the receiver that corrects the received signal [5].

In this paper, we propose a novel compensator that uses a neural network (SOM algorithm) to correct the nonlinearity introduced by the HPA. Self-organizing maps (SOM) created a vector quantizer by adjusting weights from different methods are studied to solve

2. The OFDM Modulation

The complex envelope of the OFDM signal can be written as [1], [2]

$$x(t) = \sum_{n=-N/2}^{N/2-1} \sum_{l=-\infty}^{\infty} a_n(l)s_n(t - NT')$$

where $T' = T + T_g$ is the OFDM symbol period, $N$ is the number of subcarriers, and

$$s_n(t) = \begin{cases} \sqrt{2\epsilon/NT'}e^{j2\pi f_{nt}}, & \text{for } -T_g \leq t < T \\ 0, & \text{elsewhere} \end{cases}$$

where $\epsilon$ is the transmitted pulse energy, $T_g$ is the guard interval, and $a_n(l) = a_{n0}(l) + ja_{n1}(l)$ is the emitted symbol in the $l$th time slot on the $n$th subcarrier with subcarrier frequency $f_n = n\Delta f$ ($\Delta f = 1/T$ is the subcarrier distance). For sake of clarity, the temporal index $l$ in the emitted symbols will be omitted in the following equation. In the case of a 16-QAM constellation

$$a_{n0}, a_{n1} \in A, \quad A = \{2u - 5, u = 1, 2, \cdots, 4\}$$
It is well known that the OFDM signal can be digitally obtained through IFFT. A baseband scheme of the FFT-based OFDM system is illustrated in Fig. 1. The binary information is first grouped and mapped according to the modulation scheme. In this figure, the samples of the OFDM signal are generated at the output of the parallel to serial (P/S) converter at the emission-end. The signal is then amplified and corrupted by additive white Gaussian noise. In the following analysis, an additive white Gaussian (AWG) transmission channel is assumed since attention is focused on the effects on the nonlinearity. And we also assume that carrier recovery and symbol synchronization are considered ideal in the following analysis.

3. HPA Models

Analog-to-digital (A/D) converters, mixers, and power amplifiers are usually the major sources of nonlinear distortions. It is possible to distinguish between two different classes of nonlinear distortions: the first, hereafter named Cartesian, acts separately on the baseband components of the complex signal, while the second acts on the envelope of the complex signal. A/D distortion, called Cartesian clipping, belonging to the first class, while AM/AM (amplitude distortion which depends on the amplitude of the input) and AM/PM (phase distortion which depends on the envelope of the input) introduced by power amplifiers belong to the second class.

In this section, the memoryless model for the nonlinear HPA is briefly recalled. The complex envelope of the input signal to the HPA is

\[ x(t) = \rho(t)e^{j\phi(t)} \]

and the complex envelope of the output signal can be expressed by

\[ \hat{x}(t) = A[\rho(t)]e^{j[\phi(t)+\Phi[\rho(t)]]} \]

where \( A[\rho] \) and \( \Phi[\rho] \) represent the AM/AM and AM/PM conversion characteristics of the nonlinear amplifier. In this paper, we consider a solid-state power amplifier (SSPA) without AM/PM conversion.

The AM/AM and AM/PM conversion characteristics for SSPA amplifier [13] can be approximated by

\[ A[\rho(t)] = \frac{\rho(t)}{1 + \left(\frac{\rho(t)}{\rho_0}\right)^{2p}} \]

\[ \Phi[\rho(t)] = 0 \]

where \( \rho_0 \) is the maximum output amplitude and the parameter \( p \) controls the smoothness of the transition from the linear region to the limiting region. In this paper, we select \( p = 3 \).

The operating point of the amplifier is usually identified by the “backoff.” In the remainder of this paper, the following definition for the input backoff (IBO) is adopted:

\[ IBO = 10 \log_{10} \frac{P_s}{P_{IN}} \]

where \( P_{IN} \) is the mean power of the signal at the input of the HPA, and \( P_s \) is the input power corresponding to the maximum output power. The effects of the nonlinearities can be reduced by working with high backoff, which corresponds to moving the operating point of the amplifier to the linear region. Unfortunately, this leads to a loss in power efficiency of the HPA.

4. The Proposed Scheme

To compensate for the nonlinearities at the receiver, the proposed scheme uses a SOM algorithm before the Demap. Since the nonlinearity from the HPA is in the time domain, whereas the SOM algorithm is in the frequency domain. The SOM algorithm cannot be moved before FFT because in this case it would have to do the channel equalizing, which is much more complicated in the time domain, although in the frequency domain the nonlinearity is slightly complicated.

Some analyses have been done on the effect of the HPA on the received signal constellation (output of the receiver P/S converter, in frequency domain) [14]. Reference [14] deduced that the HPA determines the following effects on the received constellation at the output of receiver P/S converter: cloud-like shape, rotation, attenuation, and for low IBO, warping. The proposed SOM algorithm is used to adapt to nonlinearity in frequency domain, i.e., to compensate for above effects of the HPA on the received signal constellation in frequency domain.

The principal goal of the SOM is to transform an incoming signal pattern of arbitrary dimension into a one- or two-dimensional discrete map, and to perform this transformation adaptively in a topologically ordered fashion. Figure 2 shows the Kohonen’s model [8], [9] of a two-dimensional self-organized feature map. Each neuron in the lattice is fully connected to all the source nodes in the input layer. This network represents a feedforward structure with a single computational layer consisting of neurons arranged in rows and columns.

The SOM algorithm is introduced in the following steps.

Step 1: Initialize the values of the nodes \( \omega_k \) by using the values of ideal 16 QAM signal constellations. We design the
SOM neurons in the same way as the constellation of ideal 16 QAM. That is, there are 16 neurons in the proposed SOM algorithm, and the two-dimensional weight coefficients of the neuron equal to in-phase and quadrature components of the point in the 16 QAM constellations.

Step 2: Locate the winning node $i$ for the input signal $\hat{I}(k)$ by

$$||\hat{I}(k) - \omega_i|| = \min_j ||\hat{I}(k) - \omega_j||$$

(8)

After locating the winning node $i$, we use the Euclidean distance as neighborhood radius to define neighborhoods of the winning node $i$.

Step 3: Modify the values of the winning node to the direction of the input data and modify the values of the neighbors of the winning node in the same way. The neighborhood function $h_{ji}$ is defined by

$$h_{ji} = \exp\left(-\frac{d_{ji}^2}{2\sigma^2}\right)$$

(9)

where $d_{ji}$ is the neighborhood radius and the parameter $\sigma$ is the effective width of the topological neighborhood. To satisfy the requirement that the size of the topological neighborhood shrinks with time, let the width $\sigma$ of the topological neighborhood function $h_{ji}$ decrease with time.

$$\sigma(k) = \sigma_0 \exp\left(-\frac{k}{\varphi_1}\right) \quad k = 1, 2, \cdots$$

(10)

where $\sigma_0$ is the value of $\sigma$ at the initiation of the SOM algorithm, and $\varphi_1$ is a time constant. Correspondingly, the topological neighborhood assumes a time-varying form of its own, as shown by

$$h_{ji}(k) = \exp\left(-\frac{d_{ji}^2}{2\sigma(k)^2}\right) \quad k = 1, 2, \cdots$$

(11)

Thus, as time (i.e. the number of iterations) increases, the width $\sigma(k)$ decreases at an exponential rate, and the topological neighborhood shrinks in a corresponding manner. Because 2 is the minimum radius for 16-QAM system, we set

$$\sigma_0 = 2$$

(12)

$$\varphi_1 = \frac{1000}{\log \sigma_0}$$

(13)

For the network to be self-organizing, the synaptic weight vector $\omega_j$ of neuron $j$ in the network is required to vary in relation to the input $\hat{I}(k)$. From [8], [9], we may then express the increment of the weight vector of neuron $j$ as

$$\Delta \omega_j = \eta h_{ji} (\hat{I}(k) - \omega_i)$$

(14)

where $\eta$ is a scalar-valued "adaptation gain" ($0 < \eta < 1$), and $\eta$ should be decreased with time, shown as

$$\eta(k) = \eta_0 \exp\left(-\frac{k}{\varphi_2}\right), \quad k = 1, 2, \cdots,$$

(15)

where $\varphi_2$ is another time constant of the SOM algorithm, we assume $\varphi_2 = 1000$ in this paper. Even though the neighborhood function and the learning-rate parameter may not be optimal, they are usually adequate for the formation of the feature map in a self-organized manner.

Step 4: For the input signal $\hat{I}(k)$, the output is defined by the modified weight of the winning neuron $i$, $\omega_i(k + 1)$. And reset the signal constellation by the weight vector $\omega_j(k + 1)$.

Step 2 through Step 4 are repeated once for each input sample, which means that each sample is used once and only once for teaching the map.

5. Simulation and Results Analysis

This architecture has been tested successfully on a 128-carrier OFDM system. We evaluate the bit error rate (BER) for $10^8$ bits in an AWGN channel.

Figure 3 shows the BER performance against SNR (dB) at different IBO values. The solid line represents the traditional receiver (without SOM algorithm), whereas dashed line represents the proposed scheme. The upward pointing triangle, cross, and diamond mean the simulation results at $\text{IBO}=0\text{dB}$, $\text{IBO}=2\text{dB}$, and $\text{IBO}=4\text{dB}$, respectively. When the nonlinear distortion is severe (when $\text{IBO}=0\text{dB}$), without the proposed SOM algorithm, system cannot recover nonlinear distortion even increasing SNR. The performance with the proposed scheme at $\text{IBO}=0\text{dB}$,
is almost the same as the performance without SOM algorithm at IBO=2 dB (when $SNR > 20$ dB). This means the SOM algorithm manages to correct some nonlinear distortion introduced by the HPA and the whole system acts as if it had a higher quality amplifier.

It is useful to look at the necessary SNR to obtain a given BER. If we want a BER of $10^{-3}$ at IBO=4 dB, we need a SNR of 23 dB without the SOM algorithm, whereas 20 dB with the SOM algorithm. This means that with the SOM algorithm we can divide the power of the emitted signal and amplifier saturation by 2 (3 dB) and still have the same performance. The emitter will consume less power and it is very interesting for portable systems.

6. Conclusion

We have proposed a nonlinear compensator for 16-QAM-OFDM signals based on SOM algorithm. The neural network is placed in the receiver, and corrects the nonlinearities introduced by the transmitter’s high power amplifier. The SOM algorithm showed good results in simulations and can improve the performance of OFDM systems, or keep the same performance with a lower power consumption. The adaptation of the proposed scheme is based on the topology-preserving characteristic of the map algorithm, i.e. the map is able to trace the nonlinear distortions tightly.

Acknowledgement

This research is supported by The JSPS Postdoctoral Fellowship for Foreign Researchers of Japan Society for the Promotion of Science.

References