SOM Training Approach for OFDM Receiver

Shubhangi Rathkanthiwar, Chandrashekhar Dethe, and Kishore Kulat

Abstract—This paper presents a novel approach for performance improvement in WLAN receiver employing Orthogonal frequency division multiplexing (OFDM) technology. As an effective technology for wireless communications, OFDM is an important multicarrier modulation method that offers high spectral efficiency, multipath delay spread tolerance, and immunity to frequency selective fading. However, some challenging issues still remain unresolved in OFDM based system design, such as its high peak to average power ratio (PAPR). Methods used to reduce PAPR factor carry several disadvantages. Neural approach presented in this paper is the new method which provides function approximation method. WLAN receiver under consideration is Hiperlan/2. Modulation method is 16QAM with code rate $\frac{3}{4}$ and AWGN channel model is used. Self organizing map (SOM) and parameterless self organizing map (PLSOM) structures are used to improve bit error rate (BER) performance, which was degraded because of nonlinear distortions due to high PAPR factor.

Index Terms—High power amplifiers, neural networks, self organizing map, orthogonal frequency division multiplexing.

I. INTRODUCTION (OFDM SYSTEMS PAPR FACTOR)

Most of the radio systems employ the HPA in the transmitter to obtain sufficient transmission power. To provide maximum output power efficiency, the HPA is usually operated at or near the saturation region. Nonlinear characteristics of the HPA are very sensitive to the variation in signal amplitudes. Variations of OFDM signal amplitudes are very wide with high PAPR. Therefore, HPA will introduce inter-modulation between the different subcarriers and introduce additional interference into the systems due to high PAPR of OFDM signals. This additional interference leads to an increase in BER [1]-[4].

An OFDM symbol is a sum of N independent symbols mapped on N different sub-channels with $1/T$ frequency separation. T is the OFDM symbol period. Discrete time domain samples $b^i = (b_0^i, b_1^i, \dots, b_{N-1}^i)$ to be transmitted are obtained via N point IFFT from complex 16 QAM symbols in this case. A block of QAM symbols is given by [5]-[8], $a^i = (a_0^i, a_2^i, \dots, a_{N-1}^i)$.

Mathematically an OFDM symbol can be represented by equation (1)

$$b_n^i = \frac{1}{\sqrt{N}} \sum_{m=0}^{N-1} a_m^i e^{j2\pi mn/N} \quad (1)$$

where a_m^i is the QAM data symbol sent on m^{th} subcarrier of i^{th} OFDM symbol. For large number of subcarriers, time domain samples b_m^i have a zero mean Gaussian distribution, as they are weighted sum of independent, identically distributed random variables. Some of these time domain samples, which lie at the tail of the distribution curve, gain high magnitudes and cause high PAPR of the system. Mathematically, PAPR of OFDM block of digital samples $b = (b_0, b_1, \dots, b_{N-1})$ is given by equation (2).

$$PAPR(b) = \frac{\max_{0 \leq n \leq N-1} |b_n^2|}{E\{|b_n^2|\} / N} \quad (2)$$

II. SOM ALGORITHM

SOM variant is the Gaussian neighborhood, Euclidean distance and neighborhood size [9].

An input $x(t)$ is presented at time t . Winning node $c(t)$, i.e. the weight vector that most closely matches the input at time t , is selected using (3) [10].

$$c(t) = \arg \min_i \left(\|x(t) - w_i(t)\|_2 \right) \quad (3)$$

where $w_i(t)$ is the weight vector of node i at time t . $\| \cdot \|_2$ denotes L^2 norm or n dimensional Euclidean distance. Weights of all nodes are then updated using equation (4)

$$w_i(t+1) = w_i(t) + \Delta w_i(t) \quad (4)$$

$$\Delta w_i(t) = \alpha(t) h_{c,i}(t) [x(t) - w_i(t)] \quad (5)$$

$$h_{c,i}(t) = e^{\frac{-d(i,c)^2}{\beta(t)^2}} \quad (6)$$

where $h_{c,i}(t)$ is the neighborhood function and is a scaling function centered on the winning node c decreasing in all directions from it. $d(i,c)$ is the Euclidean distance from node i to the winning node c in the node grid. $\alpha(t)$ is the learning rate at time t and $\beta(t)$ is the neighborhood size at time t

Learning rate α and neighborhood size β are decreased in accordance with the annealing scheme.

One possible annealing scheme for the decrease of learning rate and neighborhood size is given by (7) and (8).

$$\alpha(t+1) = \alpha(t) \delta_\alpha \quad (7)$$

And

$$\beta(t+1) = \beta(t) \delta_\beta \quad (8)$$

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where $0 < \delta_\alpha < 1$ and $0 < \delta_\beta < 1$.

Here δ_α and δ_β are the scaling constants.

These steps are repeated until some preset condition is met, after some iterations or when measurement error reaches certain level. Density of the nodes is proportional to input samples.

Unfortunately, this unsupervised learning is dependent on two annealing schemes, one for the learning rate and one for the neighborhood size. There is no firm theoretical basis for determining the correct type and parameters for these annealing schemes, so they must be determined empirically. Furthermore, since these annealing schemes are time dependent, they prevent the SOM from assimilating new information, once the training is complete. It is not in tune with adaptive capabilities of SOM we expect.

Parameterless self organizing map is a neural network, based on SOM that eliminates need for a learning rate and neighborhood size. Fundamental difference between SOM and PLSOM is that, while a SOM depends on learning rate and neighborhood size to decrease over time, as a function of number of iterations of the learning algorithm, PLSOM calculates these values based on the local quadratic fitting error of the map to the input space. This allows the map to make large adjustments in response to the unfamiliar inputs i.e. the inputs, that are not well mapped while not making large changes in response to the inputs it is well adjusted to. Fitting error is based on the normalized distance from input to the weight vector of the winning node in the input space. This value is computed in any case, hence this mechanism can be implemented without inducing noteworthy increases in the computational load of the map or hindering parallelized implementation.

III. PLSOM ALGORITHM

Fundamental idea of PLSOM is that the amplitude and extent of weight updates are not dependent on iteration number, but how good the fit is, we calculate a scaling variable $\mathcal{E}$ which is then used to scale the weight update, which can be defined through following equations (9) and (10).

$$\mathcal{E}(t) = \frac{\|x(t) - w_c(t)\|_2}{r(t)} \quad (9)$$

where $r(t) = \max(\|x(t) - w_c(t)\|, r(t-1))$

$$r(0) = \|x(0) - w_c(t)\|_2 \quad (10)$$

$\mathcal{E}(t)$ is best understood as the normalized Euclidean distance from the input vector at time t to the closest weight vector. If this variable is large, network fits the input data poorly and needs a large adjustment. Conversely, if $\mathcal{E}$ is small, the fit is likely to already be satisfactory for that input and no large update is necessary.

Algorithm for PLSOM uses a neighborhood size determined by $\mathcal{E}$ thus replacing the equation governing the annealing of neighborhood with $\beta(t) = \text{constant} \forall t$.

β is scaled by $\mathcal{E}(t)$ in the manner of equation (11), giving $\Theta(\mathcal{E}(t))$ the scaling variable for neighborhood function (12)

$$\Theta(\mathcal{E}(t)) = \beta(t) \quad (11)$$

where

$$\Theta(\mathcal{E}(t)) \geq \theta_{\min} \quad (12)$$

IV. SIMULATIONS

Simulations are carried out using MATLAB SIMULINK model 16 QAM modulation schemes for $\frac{3}{4}$ code rate for AWGN channel. Hiperlan/2 Simulink model with TWTA (Saleh model) and SSPA (Rapp's model) has been simulated for four cases.

- 1) Hiperlan/2 without neural block with AWGN channel
- 2) Hiperlan/2 without neural block with Rayleigh fading channel
- 3) Hiperlan/2 with SOM block
- 4) Hiperlan/2 with PLSOM block

Self organizing map recognize groups of similar input vectors in such a way that neurons physically close to each other respond to similar input vectors. It classifies input vectors according to how they are grouped in the input space. Neurons are arranged originally in physical positions according to topological functions. The function newsom creates a self organizing map with the following parameters.

- 1) PR: The matrix of min and max values
- 2) Di: The size of i th layer dimensions
- 3) TFCN: The topology function
- 4) DFCN: The distance function
- 5) OLR: Ordering phase learning rate
- 6) OSTEPS: Ordering phase steps
- 7) TLR: Tuning phase learning rate
- 8) TND: Tuning phase neighborhood distance

This returns a new SOM. For this paper, SOM is trained with 1000 epochs and the input vectors are plotted with the map that formed the SOM weights. SOM consists of a single layer with 'negdist' weight function, 'netsum' net input function and 'compet' transfer function. The layer has a weight from the input but no bias. The weight was initialized with 'midpoint'. Adaptation was done with the function 'train' and the weights were updated with the algorithm 'learnsom'. The distance function used is 'dist' which calculates the Euclidean distance from home neuron to any other neuron. All the neighborhoods for a S neuron layer map are represented by $S \times S$ matrix of distances. 'Gridtop' topology starts with the neuron in the rectangular grid. Weights of winning neurons are adjusted using Kohonen's rule. The rule allows the weights of neurons to learn an input vector. Thus the neuron, whose weight vector was closest to the input vector was updated to be even closer.

PLSOM completely eliminates selection of learning rate, the annealing rate and the annealing scheme of learning rate and the neighborhood size. It also decreases the number of iterations required to get a stable and ordered map. It has been proved that in 600 epochs we are getting the desired result.

TABLE I: SIMULATION PARAMETERS FOR HIPERLAN/2 WITH SALEH MODEL

Parameter	Value/ Description
WLAN Model for simulation	Hiperlan/2
Modulation scheme	16 QAM
Code rate	3/4
Puncture vector	
Number of sub carriers	52
FFT size	64
GI length	16
Channel model	AWGN/ Rayleigh fading
AM/AM parameter alpha	2.1587
AM/AM parameter beta	1.1517
AM/PM parameter alpha	4.0033
AM/PM parameter beta	9.1040

Fig. 6. BER plot for Hiperlan/2 with saleh model

Simulation setting for getting BER plot for Hiperlan/2 with Rapp's model is given in table 2 and the BER plot is shown in figure 7.

TABLE II: SIMULATION PARAMETERS FOR HIPERLAN/2 WITH RAPP'S MODEL

Parameter	Value/ Description
WLAN Model for simulation	Hiperlan/2
Modulation scheme	16 QAM
Code rate	3/4
Puncture vector	
Number of sub carriers	52
FFT size	64
GI length	16
Channel model	AWGN/ Rayleigh fading
Smoothness factor	2

Fig. 7. BER plot for Hiperlan/2 with Rapp's model

For our case, we have trained MATLAB SOM variants, SOM and PLSOM with identical input data. We have taken pseudorandom two dimensional input data eliminating the need to store training data. Since the training data is uniformly distributed in the input space, perfect distribution

of weight vectors would be an evenly spaced grid with a narrow margin along the edges of the input space. Each weight vector would map an evenly sized area of the input space.

Simulation setting for getting BER plot for Hiperlan/2 with Saleh model is given in table 1 and the BER plot is shown in Fig. 6.

V. CONCLUSION

This paper presents results of simulations run on neural network based Hiperlan/2 WLAN receiver structure in fading multipath environment. Hiperlan/2 uses OFDM as multiplexing scheme, which has a main drawback of having high peak to average power ratio. Most of the signal components are amplified in saturation region of the high power amplifiers used at the transmitter end causing nonlinear distortions. For this paper, simulations are run for Hiperlan/2 with HPA models like Saleh model (TWTA) and Rapp's model (SSPA). Modulation method is 16 QAM, and code rate is $\frac{3}{4}$. Channel models are AWGN and Rayleigh fading. SOM and PLSOM blocks act as adaptive decision devices that not only compensate for nonlinear distortions but also follow up error signals. BER vs SNR plots clearly indicate the better performance of new neural based Hiperlan/2 WLAN receiver structure.

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