2012 International Conference on Networks and Information (ICNI 2012)
IPCSIT vol. 57 (2012) © (2012) IACSIT Press, Singapore
DOI: 10.7763/IPCSIT.2012.V57.01

A Novel WLAN Receiver Performance in Highly Dispersive and Nonlinear Environment

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Abstract: An efficient, adaptive and intelligent transmission–reception system, which will take care of challenging fading multipath problems in real case scenario, is always needed in digital communications. This paper presents a novel, neural based method to improve performance of WLAN receiver in presence of nonlinear distortions introduced by high power amplifiers, Doppler effect, delay spread and many other fading multipath problems.

Keywords: BER, HPA, OFDM, SOM, PAPR, WLAN

1. Introduction

There is still a gap between previous research conducted on performance improvement in receiver structure in fading multipath environment and use of neural networks as learning systems which can incorporate constraints on their capability to handle several problems coming in upcoming technologies in the wireless communications [1]. Main gap is exponentially growing demand for great quality services at high data rates and implementation of structures using computational intelligence to take care of many complex cases arising in multicarrier communications [2,3].

As OFDM is the most promising candidate in present as well as future generation wireless communications, we have selected wireless local area network model Hiperlan2 for constructing this paper, as it uses OFDM as multiplexing/ modulation technique. One of the most challenging issues in OFDM based system that has still remained unresolved is the problem of nonlinear distortion. It has been taken into consideration along with multipath fading problems.

Main idea behind use of neural networks in OFDM based systems is the signal classification. If the classification is done properly in presence of environment harshly deteriorating the signal, we say that there is an improvement in the performance of the system. Neural networks are the learning systems that allow the people to specify what the systems should do for each case. It can decide in a reasonable way what to do in a particular situation from previous experiences and/or provided examples of appropriate behaviors even though the situation may not be experienced by the system before. Review of research work clearly indicated limitations of the supervised network approaches like MLP and RBF in handling migratory signals whose stochastic properties such as average values of signals in each cluster are varying continuously.

We have identified the self-organizing map (SOM) method as a powerful software tool for the visualization of high-dimensional data. It converts complex, nonlinear statistical relationships between high dimensional data into simple geometric relationships on a low dimensional display. It thereby compresses information while preserving the most important topological relationships of the primary data elements. Visualization and abstraction are the two aspects that occur in a number of complex engineering tasks such as process analysis, machine perception, control, and communication[4].

Purpose of selecting an algorithm based on self organizing learning is to discover significant patterns in the input data in absence of supervision. This is specially and specifically required feature in our case, i.e. the receiver structure which is expected to provide reliable reception of the signal at high data rate coming through harsh environment. In addition to multipath problems, nonlinear distortions and Doppler spread, multicarrier communication system face several challenges. Intuitive principles of self organizing networks clearly indicate that this approach is useful in an adaptive vector quantization of migratory signals like OFDM signals, whose stochastic properties such as average values of signals in each cluster are varying continuously. All the weights self-organize to predict appropriate future reference vectors. The prediction in such networks enables the separation of continuously varying components form random noise components, resulting in a better performance of the adaptive vector quantization.

2. Our proposed model

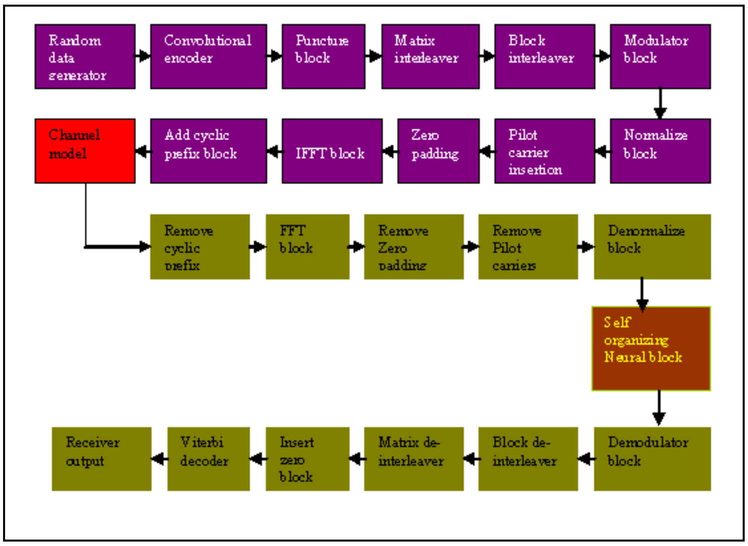

Fig. 1: Proposed Intelligent WLAN model.

The PHY layer of this WLAN system provides transportation mechanisms of bits between transmitter and receiver. The standard defines seven functions in the transmitter section.

- Scrambling of the binary input stream
- Forward Error Correction (FEC) coding
- Interleaving
- Mapping
- Modulation using OFDM
- Physical burst generation
- Transmitting of the burst

The data is generated with Random Binary Generator block. Frame size, i.e. number of samples per frame depends on PHY layer bit ate, which in turn depends on modulation type and code rate. Frame size of 24, 36, 48, 72, 96, 144, and 216 is provided for data rates 6, 9, 12, 18, 27, 36 and 54MBPS respectively. Binary data is created and stored in a buffer. The output of that buffer depends on the number of OFDM symbols per frame chosen in the simulation parameters.

The Multipath Rayleigh Fading Channel block implements a baseband simulation of a multipath Rayleigh fading propagation channel. This block models outdoor channel conditions for mobile wireless communication systems. Relative motion between the transmitter and receiver causes Doppler shifts in the signal frequency. We can specify the Doppler spectrum of the Rayleigh process using the Doppler spectrum type parameter. For channels with multiple paths, each path a different Doppler spectrum can be assigned by entering a vector of Doppler objects in the Doppler spectrum field. As a multipath channel reflects signals at multiple places, a transmitted signal travels to the receiver along several paths, each of which may have differing lengths and associated time delays. In the block's parameter dialog box, the discrete path delay vector specifies the time delay for each path. The number of paths indicates the length of discrete path delay vector or Average path gain vector, whichever is larger. If both of these parameters are vectors, then they must have the same length; if exactly one of these parameters contains a scalar value, then the block expands it into a vector whose size matches that of the other vector parameter. The block multiplies the input signal by samples of a Rayleigh-distributed complex random process. We have used self organizing learning to adapt discrete signal levels. The topology of the learning network in the algorithm is a planar array of adaptive cells; each cell corresponding to a particular grid point in the ideal discrete signal constellation. The learning network is a group of adaptive vectors, which have a beforehand adjusted neighborhood. To each node of the map, which has a time varying weight vector the map defines a best matching label. That kind of a group of labels covers all the possible classification results. When the map is used in a classification, the distance between the sample vector and all the weight vectors consisting the nodes of the map is calculated. The classification result is the corresponding label of the node, with the best response that is to say with the nearest weight vector.

The distances between the vectors can be calculated using different kinds of vector norms. The most generally used is the Euclidean distance, where the Euclidean norm between the sample vector and the weight vectors of the nodes is calculated.

We have simulated all subsystems with and without Rapp's model and with and without SOM block. It has already been observed from table: that although frame size differs as per selected modulation scheme and data rate, so does the output bits of various blocks like convolutional encoder/ Viterbi decoder, Matrix and block interleavers/deinterleavers, but in all cases output of the modulator blocks is same i.e. 48, since number of subcarriers is 48. This observation was very important in designing of the neural block of self organizing type. Secondly, we were interested in adding the neural block in frequency domain as time domain analysis of neural structure is extremely difficult.

Self Organizing Maps are neural networks that produce localized responses to input signals and represent the topology of the input signal space over the network. In the adaptive detection method based on the SOM the learning framework in the algorithm is a planar array of adaptive cells, each cell corresponding to a particular grid point in the ideal discrete signal constellation. Each cell of the SOM is characterized by an adaptive parameter. Before transmission, the adaptive parameter vectors of each cell are initialized to the ideal signal values. During the transmission, the learning framework of the receiver receives a replica of the transmitted discrete signal, which in general contains the original signal and possibly some noise and distortion. The adaptation is designed to maintain the two dimensional parameters as close as possible to the current levels of the corresponding signal values, even when distortions are present. Even in the case of random input signal the SOM is able to follow up corresponding signal distribution [5].

For all simulations with self organizing neural block, we have trained the network by corresponding target data (aimed for particular modulation scheme) after modulator block in the transmitter chain and utilized this knowledge in receiver chain after demodulator block.

Let a block of N symbols $X = \left\{ X_k, k = 0,1,2.........N-1 \right\}$ is formed with each symbol modulating one of a set of subcarriers $\left\{ f_k, k = 0,1,2........N-1 \right\}$, where N is the number of subcarriers. The N subcarriers are chosen to be orthogonal, where $f_k = k\Delta f$, $\Delta f = \frac{1}{NT}$ and T is the original symbol period. Therefore, the complex envelope of the transmitted OFDM signals can be written as,

$$X(t) = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} X_k e^{j2\pi f_k t} \quad 0 \le t \le NT \tag{1}$$

Suppose that the input data stream is statistically independent and identically distributed i.e. the real part $\mathrm{Re}\left\{x(t)\right\}$ and imaginary parts $\mathrm{Im}\left\{x(t)\right\}$ are uncorrelated and orthogonal. Therefore, based on the central limit theorem, when N is considerably large, the distribution of both $\mathrm{Re}\left\{x(t)\right\}$ and $\mathrm{Im}\left\{x(t)\right\}$ approaches Gaussian distribution with zero mean and variance,

$$\sigma^2 = E\frac{\left[\left|\operatorname{Re}\{x(t)\}\right|^2 + \left|\operatorname{Im}\{x(t)\}\right|^2\right]}{2} \tag{2}$$

Where $E[x]$ is the expected value of x. In other words, OFDM signals with large N become Gaussian distributed with Probability Density Function (PDF) as

$$P_r\{x(t)\} = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-[x(t)]^2}{2\sigma^2}} \tag{3}$$

Where σ is variance of $x(t)$.

Most radio systems employ the HPA in the transmitter to obtain sufficient transmission power. To achieve the maximum output power efficiency, the HPA is usually operated at or near the saturation region. Moreover, the nonlinear characteristic of the HPA is very sensitive to the variation in signal amplitudes. However, the variation of OFDM signal amplitudes is 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.

In general, the PAPR of OFDM signals $x(t)$ is defined as the ratio between the maximum instantaneous power and its average power

$$PAPR[x(t)] = \max_{0\le t\le NT} \frac{\left[\left|x(t)\right|^2\right]}{P_{av}} \tag{4}$$

Where P_{av} is the average power of $x(t)$ and it can be computed in the frequency domain because Inverse Fast Fourier Transform (IFFT) is a (scaled) unitary transformation.
Weight structure of SOM is shown in figure 2, followed by algorithm.

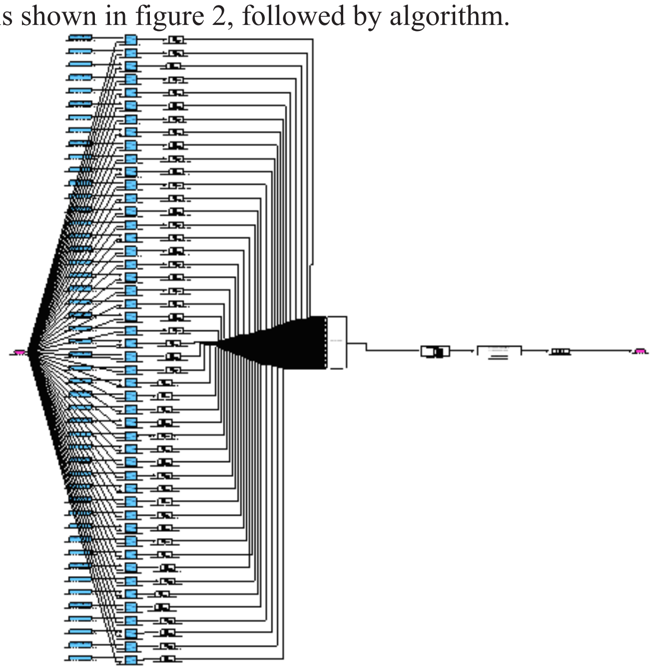

Fig. 2: Weight structure of SOM

SOM variant is the Gaussian $h_{c,i}(t) = e^{\frac{-d(i,c)^2}{\Theta(\varepsilon(t))^2}}$ neighborhood, Euclidean distance and neighborhood size.
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.

$$c(t) = \arg\min_t(\|x(t) - w_i(t)_2 \tag{5}$$

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

$$w_i(t+1) = w_i(t) + \Delta w_i(t) \tag{6}$$

$$\Delta w_i(t) = \alpha(t) h_{c,i}(t) \left[x(t) - w_i \right](t) \tag{7}$$

$$h_{c,i}(t) = e \frac{-d(i,c)^2}{\beta(t)^2} \tag{8}$$

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 (4.3.24) and (4.3.25).

$$\alpha(t+1) = \alpha(t)\delta_\alpha \tag{9}$$

And

$$\beta(t+1) = \beta(t)\delta_\beta \tag{10}$$

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.

3. Simulation results

Figures 3(a) and 3(b) show comparison of BER performances of all subsystem models with ½ and ¾ code rates respectively.

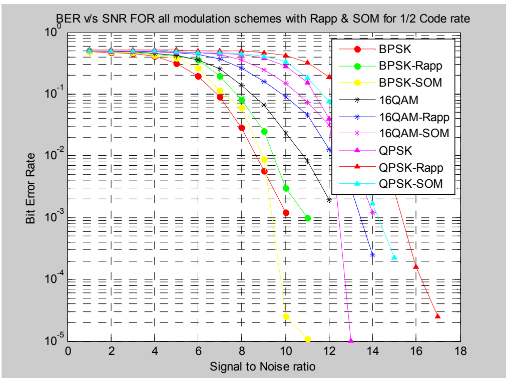

Fig. 3[a] BER Vs SNR plot of all subsystem models with and without neural block for ½ code rate

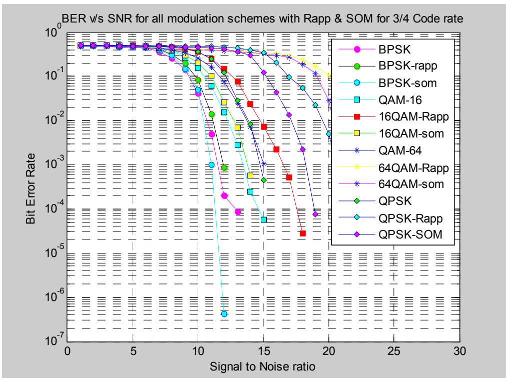

Fig. 3[b] BER Vs SNR plot of all subsystem models with and without neural block for ¾ code rate

Figure 3 Comparative plots for all modulation schemes with and without neural block

Through simulations carried out in this section clearly indicates that receiver structure based on the SOM algorithm is able to follow up the distortions, if the distortions are such that the local order of the signal constellation is preserved. In particular, it should be pointed out that the nonlinear distortions can be compensated along with noises and interference effects, provided that all mutually neighboring signal levels remain in the same topological order as in the initial signal constellation. Even when absolute signal levels change drastically, they can be effectively and steadily followed.

Nonlinear distortions effects on OFDM based system are studied through BER plots for all modulation schemes available with Hiperlan2. In all these simulations we have taken Rapp's model, which accounts for AM/AM distortions, which can be treated as a Gaussian nonlinear noise. It is observed through simulations that in case of detection of BPSK signal, our SOM based neural performs extremely well in presence of noise signals of additive type, especially when SNR is above 10dB, and for remaining modulation techniques, i.e. QPSK, 16QAM and 64QAM also neural network provides compensation for nonlinear distortions.

4. Conclusions

A new adaptive system based on self organizing map for dynamic discrete signal detection in wireless LAN receiver employing OFDM has been proposed and results for different modulation schemes under different fading conditions are presented. Different parameter effects have been studied by simulations using a system model based on Hiperlan2. Sub-system models are developed for all modulation schemes and for all code rates available for Hiperlan2 standard. Simulations are run for all subsystem models for AWGN channel model. To add multipath effects, multipath fading channel model has been added in all subsystems and simulations are run for no fading, flat fading and dispersive fading conditions. To add the effects of nonlinearity, SSPA (Rapp's model) and TWTA (Saleh model) HPA blocks are inserted in the subsystems and then simulations are run for all subsystem models. To model indoor and outdoor channel conditions, Rician and Rayleigh fading channels have been added to all subsystems and simulations are run.

In general, the results have shown that our proposed system adapts very well to changing channel conditions, including nonlinear distortion. SOM learn to recognize groups of similar input vectors in such a way that neurons physically close to each other in the neuron layer 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 a topology function. The adaptation of the proposed combined systems is based on the topology preserving property of the Map algorithm and the map is able to follow up signal distortions as long as the local order of the peaks of the pdf is preserved. SOM performs nonlinear adaptive vector quantization of migratory signals like OFDM signals. It predicts future position of the reference vectors by using the self-organizing signal-equivalent weights. In difficult channels, consisting of both multipath and nonlinear distortions, the new scheme outperforms the conventional WLAN receiver structures with these effects. distortions effects on OFDM based system are studied through BER plots for all modulation schemes available with Hiperlan2. In all these simulations we have taken Rapp's model, which accounts for AM/AM distortions, which can be treated as a Gaussian nonlinear noise. It is observed through simulations that in case of detection of BPSK signal, our SOM based neural performs extremely well in presence of noise signals of additive type, especially when SNR is above 10dB, and for remaining modulation techniques, i.e. QPSK, 16QAM and 64QAM also neural network provides compensation for nonlinear distortions.

5. Future scope

While dealing with the signals in wireless communication, we have to come across harsh environment. For multicarrier signals such as OFDM signals, stochastic properties, such as average value of the signal in each cluster vary. There are some phase rotations due to Doppler effects. If we train the self organizing map in such a way, that stationary noise components are captured by ordinary weights and migratory components are captured by time derivative weights, then it can bring further improvement in the suggested system.

New directions of the detection problem include effects of interference are still open for further research.

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