Equalization of the non-linear 60 GHz channel: Comparison of reservoir computing to traditional approach

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Abstract

The non linearities in a communication channel can severely affect the communication quality. These problems are encountered in many communication systems. Because of the high complexity of their power amplifiers, which have a severe non-linear behaviour, combined with an important pathloss, which imposes an important output power, the 60 GHz communications are strongly affected by these non-linearities. Taking these non-linearities into account in channel equalization can increase the communication performances and enable us to work near the saturation point of the amplifier. This paper presents the reservoir computer as a new approach for the equalization of a non-linear communication channels in the case of the 60 GHz communications. We compare the performances and the complexity of the reservoir computer algorithm with an iterative maximum likelihood (ML) equalizer. We find that the reservoir computer is an interesting low complexity solution for this task.

I. Introduction

The capacity requirement in wireless communications is constantly evolving and we reach the performance limits of the present wireless systems. Communications at 60 GHz are an interesting solution because there exists, at this frequency, a large unlicensed available bandwidth [1] which enables communications with important bit rate. Because of the important pathloss, these communications are limited to short distances which enables an important frequency reuse. This high bit rate technology limited to one room can have a lot of applications like high definition uncompressed video streaming, wireless gaming, wireless gigabit Ethernet, data transfer or equipment synchronisation.

This new communication system has a lot of interesting technology challenges, including the channel equalization. Indeed, because of the high bandwidth, the memory of the channel is important and we cannot consider a narrowband channel for the equalization [2]. The conception of 60 GHz amplifiers is also complex due to the high frequency, making the 60 GHz channel non-linear. These non-linearities introduce an additional distortion of the signal which is very penalizing for high order modulations, like the 16-QAM modulation which is the modulation considered in this paper.

This work proposes a new approach for the non-linear channel equalization which consists in using a machine learning algorithm. Specifically we use a bio-inspired algorithm:

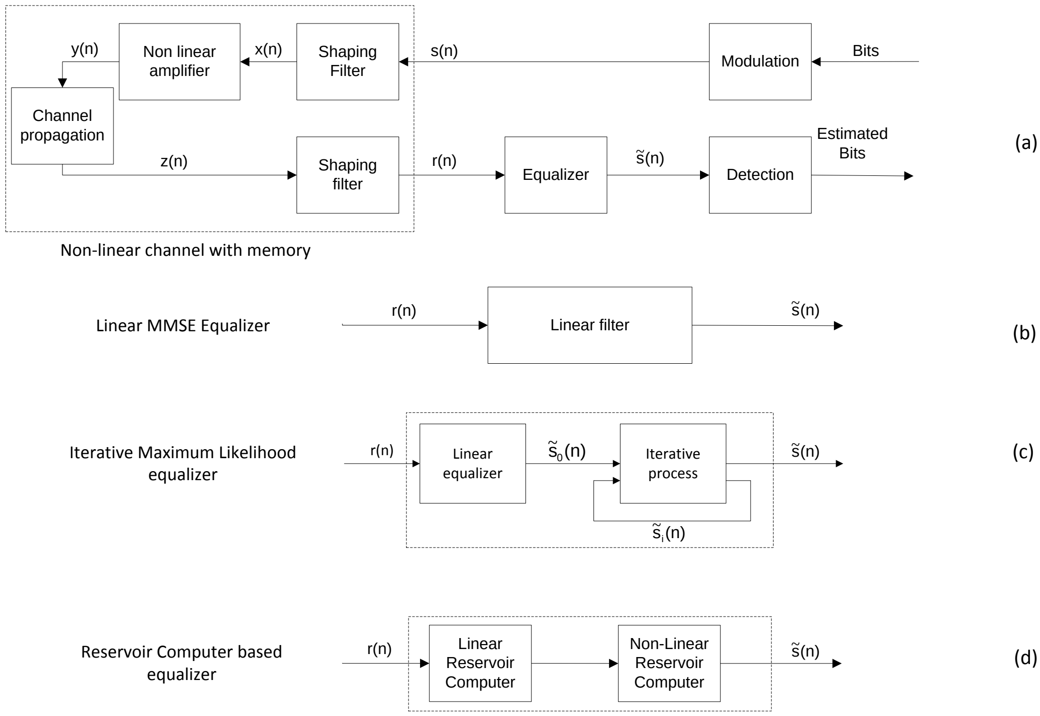

Fig. 1. Baseband bloc diagram of the 60 GHz communication channel (a) with the three considered equalizer structures: linear MMSE described in section III(b), iterative ML described in section IV (c) and Reservoir Computer described in section V (d)

the reservoir computing which is derived from the neural networks [3] [4] [5] [6] which can be trained to minimize the mean square error on the estimated symbol sequence. Because of the memory of the reservoir computer and its non-linear characteristic [7], this structure is a good candidate for non-linear channel equalization . Preliminary results on reservoir computing applied to channel equalization were reported in [8] but with a non-realistic channel model. To evaluate the performances of the reservoir computer, we compare it with an iterative algorithm based on the ML criterion.

The outline of this paper is the following. In section 2, we present the channel communication model. In section 3, we consider a linear MMSE (Minimum Mean Square Error) equalizer which can only attenuate the linear interferences. In section 4, we propose an iterative ML equalizer which will be used as a benchmark. The reservoir computer will be presented in section 5. The comparison in performance and complexity of these algorithms will be done in section 6.

II. 60 GHz COMMUNICATION CHANNEL

The baseband communication channel is described in figure 1(a). We consider half-root Nyquist shaping filters. The propagation channel is obtained with a stochastic model proposed in [2]. Here, we will only consider a Line Of Sight (LOS) communication channel. This channel represents an important challenge for the equalization because of the important sampling frequency, imposed by the standards, which results in an important memory. This specificity implies the use of equalizers which must also have an important memory.

The power amplifier, which is the main source of non-linearities in most of the communication systems, is given by a non-linear baseband model which characterises the AM-AM and AM-PM characteristic of the power amplifier [9]. If the input is defined as $x(n) = a(n)e^{j\phi(n)}$, we have the following signal, $y(n)$, at the output of the amplifier:

$$y(n) = f(a(n))e^{j(\phi(n)+g(a(n)))} \quad (1)$$

where $f(.)$ represents the AM-AM relation and $g(.)$ represents the AM-PM relation.

The amplifier we will use is the GaAs pHEMT 60GHz HPA by NEC. We can characterise this amplifier with a Rapp model [10]:

$$f(x(n)) = \frac{G|x(n)|}{(1+(\frac{G|x(n)|}{V_{sat}})^{2p})^{\frac{1}{2p}}} \quad (2)$$

$$g(x(n)) = \frac{A|x(n)|^q}{1+(\frac{|x(n)|}{B})^q} \quad (3)$$

with the following parameters: G = 19, V_{sat} = 1.4, p = 0.81, A = -48000, B = 0.123, q = 3.7.

The AM-AM and AM-PM characteristics of the amplifier are represented in figure 2. The operating point is defined by the OBO (Output Back Off) which is defined by the following equation:

$$OBO = 20log_{10}\frac{V_{out}}{V_{sat}} \quad (4)$$

where V_{out} is the mean amplitude of the output signal and V_{sat} is the saturation amplitude of the amplifier.

III. Impact of the non linearities

To evaluate the impact of the non-linearities, we will first equalize the channel with a linear minimum mean square error (MMSE) equalizer (figure 1(b)). We make the hypothesis that the channel is perfectly known by the receiver. But in order to characterise this equalizer, a linear approximation of the channel around an operating point must be done. So the non-linear characteristic of the channel are not considered by the equalizer. The impact of these negligences can be observed in figure 3.

A linear approximation of the channel has its limits and we need equalizers which consider more parameters of the channel. The two equalizers proposed in the next sections will take into account these non linearities, thereby improving the performance of the equalization.

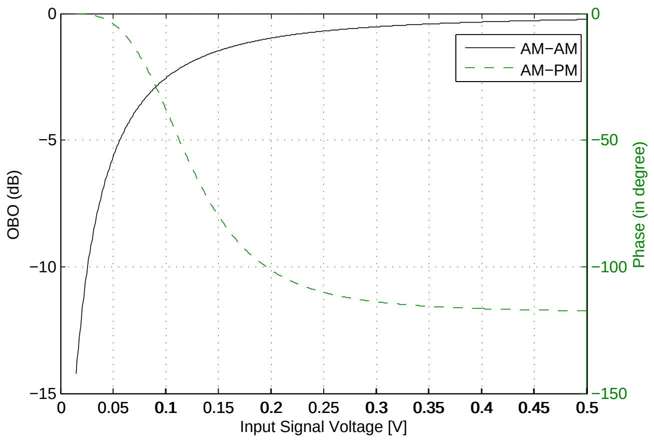

Fig. 2. AM-AM (characterized with the OBO) and AM-PM (characterized with the phase) relation of the power amplifier in function of the amplitude of the input signal

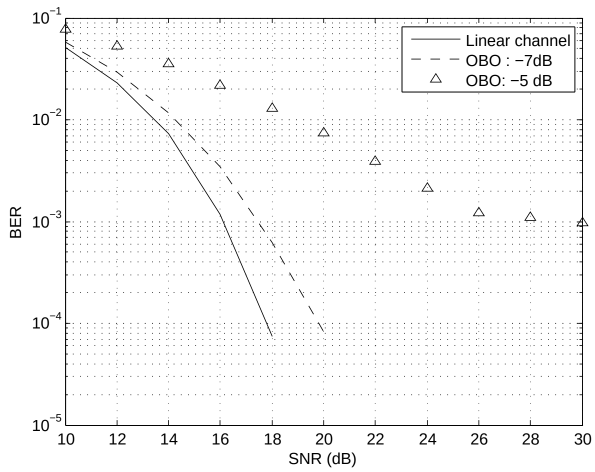

Fig. 3. Linear MMSE equalization of a non linear 16-QAM channel communication with different level of OBO

IV. ML ITERATIVE EQUALIZER

This algorithm is based on the modified order P compensation algorithm [11] adapted for the equalization. The first step of the equalizer consists in a linear equalization to make a first estimation of the transmitted signal ($\tilde{s}_0(n)$ in figure 1(c)). We will use the linear MMSE equalizer for this step. After this first estimation, the algorithm will use an iterative process to estimate the transmitted signal $\tilde{s}_i(n)$ which produced the received one, $r(n)$. This implies that the receiver has a perfect knowledge of the non-linear channel to be able to evaluate which signal $\tilde{r}_i(n)$ the channel will produce with a input $\tilde{(s)}_i(n)$. The objective is to find a sequence $\tilde{s}_i(n)$ which produces an output $\tilde{r}_i(n)$ close to $r(n)$.

At each step i, we will modify each symbol, one by one, in the estimated sequence $\tilde{s}_{i-1}(n)$ by adding a Δ to each symbol. By this way, we move, at each iteration, each symbol from its initial estimation to a value $\tilde{s}_i(n)$ which meets the ML criterion

$$\tilde{s}_i(n) = \tilde{s}_{i-1}(n) + \Delta \tag{5}$$

where $\tilde{s}_i(n)$ is the estimated symbol for the step i and Δ is the modification.

The objective is to find the distance Δ between the actual estimated symbol and its effective position in the emitted constellation. This value of Δ is the one which creates a $\tilde{r}_i(n+l)$ close to $r(n+l)$ for each $l \epsilon [-L_c'; L_c - 1]$ where $L = L_c + L_c'$ is the channel memory. The impact of Δ on the sequence $\tilde{r}_{i-1}(n)$ is evaluated with:

$$\tilde{r}_i(n+l) = \tilde{r}_{i-1}(n+l) + F_{NL}(\Delta) \tag{6}$$

where F_{NL} characterizes the non-linear comportment of the channel.

It is very complicated to derive the optimal value of Δ from this expression. So we use a linear approximation of the channel to reduce the complexity of the evaluation of Δ. If Δ is defined to minimize the euclidean distance between the sequences $\tilde{r}_i(n)$ and $r(n)$, we obtain the following expression:

$$\Delta = \frac{\sum_{l=-L_c'}^{L_c-1} a_l^*(r(n+l) - \tilde{r}_{i-1}(n+l))}{\sum_{l=-L_c'}^{L_c-1} (a_l a_l^*)} \tag{7}$$

where a_l is the linear approximation of the channel.

As the channel is known by the receiver, we can estimate the coefficients a_l by adding a known ε to the actual symbol $\tilde{s}_{i-1}(m)$

$$\tilde{s}_{test}(m) = \tilde{s}_{i-1}(m) + \varepsilon \tag{8}$$

This will produce the signal $\tilde{r}_{test}(n)$.

$$\tilde{r}_{test}(m) = \tilde{r}_{i-1}(m) + F_{NL}(\varepsilon) \tag{9}$$

The linear approximation of the channel can be done with the following equation:

$$a_l = \frac{\tilde{r}_{test}(m+l) - \tilde{r}_{i-1}(m+l)}{\varepsilon} \tag{10}$$

We may not forget that the optimal Δ is obtained by a linear approximation of the channel. A too high value of Δ would not have the desired impact. This is why the Δ can be multiplied by a weight factor $\mu \epsilon [0; 1]$. With a little value of μ, the convergence speed is reduced but the linear approximation is more reliable. An important value of μ can accelerate the convergence speed but the linear approximation is less reliable. At each iteration, the algorithm will modify each sample of the emitted sequence to find the one which optimizes the ML criterion.

The iterative bloc uses the following schema:

1) Estimate the received sequence $\tilde{r}_i(n)$ which corresponds to the estimated sequence $\tilde{s}_i(n)$
2) Evaluate the coefficients a_l
3) Evaluate the optimal Δ

4) Add the optimal Δ and return to point 1)

The complexity of this equalizer is $O(M.K.O_{channel})$ where K is the number of iterations, M is the number of symbols and $O_{channel}$ is the complexity of the channel evaluation. This last operation is an important source of complexity. For this task, we used 100 iterations and a coefficient μ of 0.2.

V. The reservoir computer

A. Presentation of the reservoir computer

The reservoir computer is an algorithm derived from the neural networks which are automatic learning methods. The memory of this structure is defined by its neurons. The evolution of this system is defined by the following equations [4].

$$a_i(n) = A\sum_j \alpha_{ij} b_j(n-1) + Bu_i r(n) \tag{11}$$

$$b_i(n) = f(a_i(n)) \tag{12}$$

$$\tilde{s}(n) = \sum_j w_j b_j(n) \tag{13}$$

where $r(n)$ is the input signal (observed at the channel output), $\tilde{s}(n)$ is the output signal, $b_i(n)$ is the value of the neuron i, α is the interconnection matrix, u is the input mask, w is the output mask, $f(.)$ is the connexion function between neurons, $a_i(n)$ is the activation sent to the neuron i at the time step n.

The scalars A (feedback gain) and B (input gain) are arbitrary weights which can modify the evolution of the system. The values of A and B will define if the entire system is more influenced by the new input value or its previous state. With an important value of B, the system is immediately excited. An important value of A will create a reservoir which stays activated during a long time without excitation. We see that each neuron receives an activation a through a function f(.). In general this function is a sigmoid function [3]. The output mask is obtained with an off-line training. A training sequence is sent in the channel and the coefficients of the output mask are evaluated to minimise the mean square error between the estimation of the training sequence and the effective sequence [4].

B. Equalization with a reservoir computing structure

We will use a reservoir computer with the following interconnection matrix:

$$\alpha = \begin{pmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \\ 1 & 0 & 0 & \cdots & 0 \end{pmatrix} \tag{14}$$

Each neuron is connected to its neighbours in a ring like in figure 4 [12].

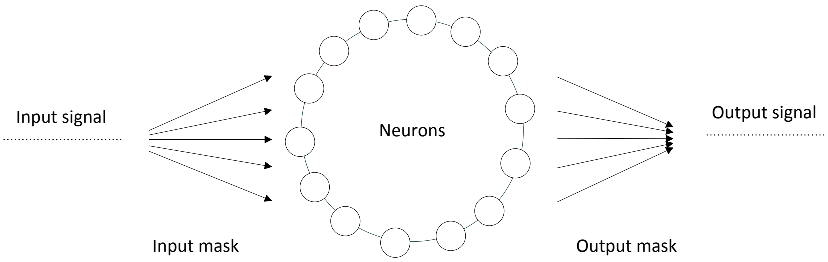

Fig. 4. Structure of the considered reservoir computer

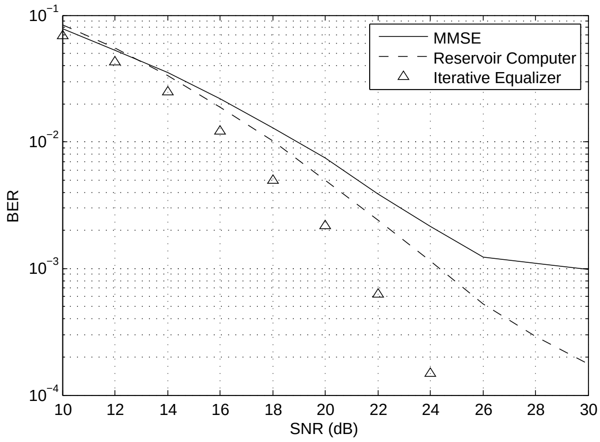

Fig. 5. Comparison of the different equalizer structure for a 16-QAM non linear communication with an OBO of -5 dB

Because of the important memory of the channel propagation (around 50 time steps) combined with the non-linearities, the reservoir computer will need too many neurons to compensate all the interferences. To reduce the complexity of a such equalizer, an alternative structure composed by two reservoir computers is proposed (figure 1(d)). The first one will equalize the linear part of the signal. The second one will work in a non-linear regime to equalize the non-linear part.

The first equalizer will work in a linear regime. So its feedback gain will be important (to improve the memory of the reservoir) but to conserve the echo state property of the reservoir computer, this gain must be lower than 1 [4]. In other case, the reservoir can become unstable because the signal sent by each neuron is amplified. The connexions between neurons will be linear. The second one will use an hyperbolic tangent as inter-connexion function. To work in a non linear regime, we will use an important input gain and a very low feedback gain. Each reservoir has a complexity of $O(MNO_f)$ where O_f is the complexity of the connexion function $f(.)$. For this task, 300 neurons were used. The output mask has been evaluated with the help of a training sequence made of 10,000 symbols.

VI. Conclusion

An equalizer algorithm based on a reservoir computer structure has been presented to equalize the 60 GHz channel. Because of the important channel memory (which comes from the high frequency sampling) combined with the added non-linearities from the power amplifier, the equalizer should be divided into two parts. The first reservoir computer is configured to work in a linear mode to compensate the important memory of the channel. The second reservoir computer is configured to work in a non-linear regime to compensate the non-linearities. Its performance is compared with the other equalizers on figure 5. This equalizer offers better performances than a simple linear equalizer like the MMSE because the second structure can take into account the constellation mismatching and the non-linear interferences.

This paper was also the opportunity to present an iterative ML equalizer which has the advantage of being able to work with a long channel memory (which is not the case of trellis based equalizer like Viterbi [13]). This structure meets the ML criterion with an iterative process but it requires a perfect knowledge of the channel which is not the case of the two previous algorithms which are working with an approximation of this channel. The simulations show that the iterative ML equalizer offers better performances than the double reservoir computer but this latter has the advantage of keeping a low complexity because the evaluation of an hyperbolic tangent is less complex than the evaluation of the non-linear channel.

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