JOINT BLIND EQUALIZATION AND BLIND ESTIMATION OF EQUALIZER PERFORMANCE

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ABSTRACT

This paper proposes a new method for the estimation of the bit-error-rate (BER) in the output of blind equalizers, which could be applied for telecommunication system fault management. Trends in radio communications are discussed, which motivate the focus on blind adaptation, and a simple test for assessing decision errors in the output of the decision device is derived. Simulations validate theoretical results, and point out the main features of the proposition: low computational burden and accurate BER estimation.

INTRODUCTION

The Universal Mobile Telecommunication System (UMTS) norm is the major trend in mobile communications. Three main characteristics of the UMTS are discussed in the following [1].

(C1) Transmission rates present currently an increasingly growing demand.

(C2) The communication channel is a time-variant system of difficult characterization.

(C3) The management of a global communication system as UMTS is complex, since it may be divided in several local subsystems. Recent work [2] pointed out that, for assuring competitive quality, reliability and availability, UMTS wireless fault management should employ an overlay system that continuously evaluates the signal quality at the level of local subsystems. The key issue is to enable the detection and location of signal degradation, which could be achieved by assessing the local bit-error-rate (BER).

Blind equalization techniques play an important role in UMTS, since they may keep up the transmission rates by avoiding the training period of the equalizer, and since they do not impose the accurate synchronization between transmitter and receiver. These advantages comply with UMTS characteristics (C1)-(C3). Particularly, this work focus on Bussgang algorithms [3]. Although they present several interesting features, such as simple implementation, low computational burden and well-established theoretical results; Bussgang algorithms present drawbacks connected to the minimized cost functions. In fact, it was demonstrated that [3], for practical purposes, at least one of the local minima of all Bussgang cost functions may be associated with a poor steady-state equalization or even no equalization at all. This means that Bussgang blind techniques can not assure all the time that equalization will take place.

Of course, if Bussgang equalizers are to be used in an UMTS, then it is of paramount importance to develop methods to assess the equalizer performance, for example, the estimation of the BER in the output of the blind equalizer. Such procedure is motivated by two major reasons. Firstly, it enables to monitor, detect and provide solutions for local minima problems associated with the problematic learning of Bussgang equalizers. Secondly, in view of UMTS characteristic (C3), the BER in the output of a Bussgang equalizer could be considered as a kind of signal quality measure at the level of a local subsystem.

There are few works of literature devoted to the analysis and development of estimators for the BER in the output of blind equalizers. In [4], the authors propose a binary hypothesis test in order to detect errors due to an incorrect decision of the equalizer. Although such technique is quite effective and general, since it may be applied to both FIR and DFE equalizers, it presents high computational complexity and it does not work "on-line". In [5], the authors estimate the bit-error-rate (BER) at the equalizer output by means of a neural network, which computes the probability of wrong decisions. Although this method may be applied to non-linear channels, the authors did not discuss the transient performance of the BER estimates, which may be affected by local minima problems connected with the neural network learning.

In the most recent work of the author [6], a simple recursive method is developed in order to estimate the BER at the output of an adaptive equalizer. This paper ellaborates on the previous work [6] to derive a more efficient BER estimator.

THEORETICAL FRAMEWORK

Fig.1 depicts the classical mathematical model used for the analysis of adaptive equalizers.

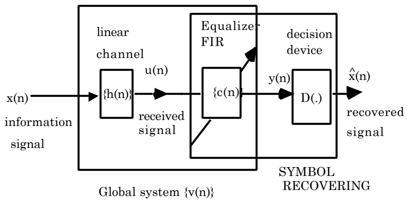

Figure 1 – Communication system model

Where {h(n)}, {c(n)} and {v(n)} are respectively the impulsive response of the channel, the linear equalizer and of the global system (channel plus linear equalizer). Besides, the global system is given by the following convolution:

$$\{v(n)\} = \{h(n)\}*\{c(n)\} \tag{1}$$

where the operator "*" is the discrete convolution. Suppose that:

(H1) The communication system model is baseband.

(H2) The signal-to-noise ratio is high, such that the additive noise may be neglected.

(H3) The information signal x(n) is zero-mean, iid and M-PAM (where M is the number of modulation levels).

(H4) The communication system is linear and stable.

It may be demonstrated that the output of the linear equalizer is given by:

$$y(n) = x(n-d) \pm dist(n); \quad dist(n) = \left| \sum_{\substack{j=0 \\ j\neq d}}^{N+L-2} v(j).x(n-j) \right| \Big/ \left| v(d) \right| \tag{2}$$

Where d is the equalization delay, dist(n) the distortion or intersymbol interference, N the channel model length, L the equalizer length and v(j) the j-th coefficient of the global system {v(n)}. The main goal of the linear equalizer is to recover the information signal, such that at the output of the decision device the "open-eye" condition is verified:

$$\hat{x}(n) \cong x(n-d) \Leftrightarrow \left|dist(n)\right| < Q/2 \tag{3}$$

$$e(n) \overset{?}{=} \begin{cases} 0; & \text{if } x(n-d) \cong \hat{x}(n) \Leftrightarrow \left|dist(n)\right| < Q/2 \\ 1; & \text{if } x(n-d) \neq \hat{x}(n) \Leftrightarrow \left|dist(n)\right| \geq Q/2 \end{cases} \tag{4}$$

Where Q is the distance between two adjacent levels of the M-ary PAM signal and e(n) is the equalization error or decision error.

NEW THEORETICAL RESULTS FOR THE OPEN-EYE CONDITION AND A NEW BER ESTIMATOR

Since the distortion (2) is a function of the global system coefficients v(j), and since each coefficient v(j) is bounded due to the stable character of {v(n)}, one may define an upper bound for the distortion dist(n), which will be represented by the symbol Sup{dist(n)}. (The operator Sup{(.)} represents the maximum value of (.)).Suppose that:

(H5) The bound Sup{dist(n)} is derived by assuming the worst case, where the distortion is maximum.

(H6) The bound is defined by taking into account just the effects of the transmitted signal x(n), such that Sup{dist(n)} is a function of {v(n)}.

Hypothesis (H5) and (H6) define a particular bound of the distortion and they were proposed in [3,7] in order to analyse the open-eye condition (3)-(4). In both references, the authors study the worst case of maximum distortion, which enables to cope with the general situation where the distortion may take any value lower than Sup{dist(n)}. The following theorem establishes further relations between the equalizer coefficients and the open-eye condition. Due to space limitations and the mathematical complexity involved, the demonstration of theorem 1 is not shown here, and the reader is addressed to [8] for further details.

Theorem 1 (MAIN RESULT): "Suppose that (H1)-(H6) hold, and that 0 < d < L-1. Label $\underset{m}{Sup}\{|h(m)|\}$ (m = 1, ..., N-1) as the maximum absolute value of the set of coefficients $\{|h(1)|, |h(2)|, ..., |h(N-1)|\}$. Define $\underset{q}{Sup}\{|c(q)|\}$ as the maximum absolute value of the set of filter coefficients c(q); where q = 0,1,...,L-1 and $q \neq d$. Then,

$$IF\ |c(d)| > B.\left(\underset{q}{Sup}\{|c(q)|\}\right) \Rightarrow x(n-d) \cong \hat{x}(n) \Rightarrow e(n)=0 \quad ;\ q = 0,1,...,L-1,\ q \neq d \tag{5}$$

$$\text{Otherwise } e(n) = 1 \tag{6}$$

where B is a real constant depending on the channel model:

$$B = \frac{S}{S - \underset{m}{Sup}\{|h(m)|\}}\ ;\ m = 1,..., N-1\ ;\ S = \sum_{k=0}^{N-1} |h(k)| \tag{7}$$"

Theorem 2 may be used to propose a method for carrying out joint blind equalization and blind BER estimation

PROCEDURE 1 (Given d, L, M and N)

for n = 1 to the total number of iterations

Step 1: Equalize the input signal and calculate the recovered signal $\hat{x}(n)$.

Step 2: Estimate the channel model { $\hat{h}$ (n)} by means of the the "C(Q,k)" algorithm [9].

Step 3: From { $\hat{h}$ (n)}, select $\underset{m}{Sup}\{|h(m)|\}$ and calculate B according to (7).

Step 5: Compare $|c(d)|$ with $B.\left(\underset{q}{Sup}\{|c(q)|\}\right)$ according to (5) and calculate e(n).

Step 6: Update the following estimator of the BER (expressed in percentage):

$$BER(n) = \left(\frac{n-1}{n}\right) BER(n-1) + \left(\frac{100}{n}\right) e^2(n) \tag{8}$$

SIMULATIONS AND RESULTS

A comparison between procedure 1, the blind estimatiors described in [4,6] and the classical BER estimator was carried out. These four estimators are respectively labeled as P1, P2, NN, SP. The last one (classical estimator) is defined as the average of decision errors obtained by comparing the pilot signal x(n) to the recovered signal $\hat{x}(n)$ .A linear filter of L = 33 taps was used as equalizer in all simulations, whereas the radial-basis function network of method SP has 13 centers in all situations.The transmitted signal x(n) is 2-PAM and the channel model impulse response is given by H(z) = $0.319+0.62z^{-1} + 0.634z^{-2} + 0.323z^{-3} + 0.087z^{-4}$ [4].

For all results, the step-sizes of all BER estimators were set in order to achieve the same steady-state BER as fastest as possible. Extensive simulation pointed out that equalization takes place as the steady-state BER is lower than 5%. Besides, all results are the average among 60 Monte Carlo runs.

Fig. 2 presents the convergence of the BER estimators and it defines the three performance criteria. The first criterium is the convergence time T (iterations), the second criterium is the difference (D) between the steady-state value of the estimated BER and the steady-state amplitude of the classical BER estimator (method SP). The third criterium is the quadratic error (QE), which evaluates the average difference between the value of the classical BER estimator and the amplitude of the other BER estimator considering all iterations of the convergence procedure.

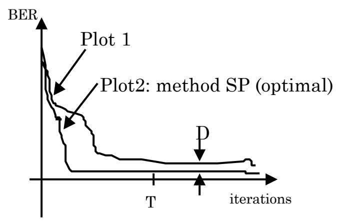

Fig. 2 – Performance criteria

Notice that criteria convergence time (T) and quadratic error (QE) characterize the transient performance of BER estimators, whereas the difference (D) characterizes the steady-state performance. Table II present the results.

Table II – Results for channel H(z)

Criteria	SNR	SP (optimal)	P2	P1	NN
Convergence time T (iterations)	SNR = 40 dB	1200	1700	1210	1200
	SNR = 20 dB	1300	2200	1400	2300
	SNR = 10 dB	2600	7200	5000	8000
Quadratic error QE (adimensional)	SNR = 40 dB	-	600	200	190
	SNR = 20 dB	-	700	300	350
	SNR = 10 dB	-	978	700	1200
Difference D (%)	SNR = 40 dB	-	23	7	9
	SNR = 20 dB	-	30	9	33
	SNR = 10 dB	-	35	39	57

Careful analysis of table II point out that:
- Concerning convergence (criterium T), P2 presents a slow convergence, whereas NN is disturbed by noise.
- Concerning tracking capability (criterium QE), the neural network NN and P1 follow closely the optimal estimator for high SNR values. For low SNR scenarios, all methods fail, with exception of P1.
- Concerning the accuracy of estimators (criterium D), procedure P1 is the most accurate one for all situations.

CONCLUSIONS

In this paper, a new theoretical relationship concerning the open-eye condition was derived and applied to blind equalizer performance estimation, leading to a simple procedure which presents an interesting trade-off between tracking capability and accurate BER estimation. A comparative simulation study pointed out that the estimation of BER for low SNR scenarios represents an interesting challenge, particularly when the SNR is under 10 dB. Current work addresses the extension of theory to complex modulations and to low SNR situations.

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