A Scheme for High Performance Real-Time BER Measurement

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Abstract—Bit error rate (BER) is a fundamental measure of performance in digital communication systems, since it is a measure of the integrity of received information.

A statistically based method of BER estimation has been devised which does not necessitate the transmission of test patterns or the interruption of data for measurement purposes. It is demonstrated that the method allows accurate estimation of BER several orders of magnitude faster than the Monte Carlo method. Design of an optimal BER estimator based on the maximum-likelihood principle is proposed.

The performance of the technique is presented from simulations for the case of QPSK modulation in AWGN and for a live Rayleigh-fading HF link. The ability of the method to accurately predict BER using relatively few samples means that it is particularly suitable for high-speed BER estimation.

I. INTRODUCTION

The development of the BER monitoring technique we have called EVEREST (Extremely Versatile Error Rate ESTimator) was instigated by the need to measure the performance of low-rate terrestrial digital radio links subject to natural and deliberate degradation. Such links are characterized by Raleigh fading, intersymbol interference, additive and impulsive noise, as well as frequency selective fading from multipath components. Noise distributions are generally non-Gaussian and channel statistics are liable to alter drastically in just a few minutes. It is, therefore, necessary to perform the measurement quickly.

Regardless of channel characteristics, the error rate provides the ultimate measure of performance for a digital communication system. The importance of this measure has been recognized [1] and quite some research effort has been applied to the problems of its measurement. Of the numerous methods proposed [1], [2], few are applicable to rapid measurement and fewer still appear to be applicable to non-Gaussian (e.g., fading) channel statistics.

II. THE EVEREST APPROACH

The EVEREST method requires access to the receiver decision statistic (decision variable) or, if this is not available, the demodulation process must be emulated to derive it. The decision variable is that signal in a digital demodulator/detector, just prior to making data (symbol) decisions. In a demodulator, the decision variable may be represented as \( Y_i \), \( i = 1, 2, \ldots, N \), representing samples taken at time intervals corresponding to the symbol interval.

Fig. 1. A phasor diagram for QPSK showing a possible set of decision regions.

\[ y = \text{Actual decision thresholds} \]

\[ x = \text{Expected phasor positions} \]

We wish to test the hypothesis that a set of decision variable observations correspond to a given prior model \( A_k \) \( (k = 1, 2, \ldots, L) \).

\[ H_k : \{Y_i\} \in A_k. \] (1)

We wish to test this hypothesis against each model \( (k = 1, 2, \ldots, L) \) and choose the best matching \textit{a priori} model (in a maximum likelihood sense) fitting these collective observations. The chosen model \( A_k \) will have a BER value associated with it, so that the actual estimated BER will be taken as the BER of the chosen model. Due to the fact that the decision variable is the sole signal which constitutes the received data (and perturbations), we claim that its distribution directly relates to error occurrences and the error rate.

Each value of \( Y_i \) is recorded by accumulating a count of the number of times \( Y_i \) falls within a region \( R_j \). There are \( M \) such regions spanning the entire range \( Y_i \). Thus, at the end of \( N \) observations, a histogram has been built, representing the distribution of the decision variable. Fig. 1 shows an example of decision regions for a QPSK demodulator, and Fig. 2 illustrates a histogram of counts for the regions shown in Fig. 1 for AWGN and \( E_b/N_0 \geq 3 \) dB.

In one symbol period, one count is recorded in only one of the regions \( R_j \) \( (j = 1, 2, \ldots, M) \). If the observation \( Y_i \) are random variables, then the accumulated histogram counts are also random variables.
Fig. 2. Histogram of counts for regions shown in Fig. 1 for AWGN and $E_b/N_0 \approx 3$ dB.

The BER estimate is, then, the known BER of the library model $A_k$.

This method of BER estimation has proven to be far superior to estimating the BER from the measured data [4], [5]. Equation (6) describes a maximum a posteriori probability (MAP) scheme. If we decide to give equal weighting to priors, this reduces to a maximum likelihood (ML) BER estimator (which may be implemented as a bank of correlators or matched filters).

The library should contain an adequate set of models which cover each type of condition to be expected, with a resolution compatible with the required precision. Each model will contain a histogram of the decision variable and the corresponding error rate for that situation. The library models may be compiled from theory, simulation, and/or from live measurements on links. The latter method would be ideal in situations where it is possible to accurately measure the true error rate (say, by sending a known data sequence and counting errors off-line) and the decision variable distribution over the measurement period. Actual channel measurements would have the advantages of allowing the effects of receiver calibration subtleties and nonlinearities to be incorporated into the models. If the channel is time-varying with a period comparable to the measurement interval, additional models accounting for the different possible initial channel conditions would need to be incorporated.

The performance of the ML EVEREST has been simulated using an arbitrary choice of equal sized regions for a coherent QPSK modulation scheme in an AWGN channel environment. A small number of equally spaced regions has proven to be effective in practice. Fig. 4 shows the performance using four equal-sized regions ($M = 4$) and $L = 400$ and $L = 40$ library models covering a range of BER values from $10^{-1}$ to $10^{-5}$ in equal steps for 1000 and 16000 symbol samples.

The practical performance using $L = 40$ models demonstrates that the accuracy is not significantly compromised by lowering the precision and a coarser, nonetheless accurate, estimation results.

The ML implementation of the previous section used the multinomial distribution to describe the histogram-forming process. This assumes that the region probabilities $P_j$ are
constant over the period of accumulating \( N \) samples. If the channel distribution is nonstationary (e.g., Rayleigh fading) over the sampling interval, samples may be correlated. The effect of correlated samples is to increase the variance of sample counts \( u_j \) in a region. This is effectively the same as reducing the number of independent samples [6]. This will increase the variance in \( \theta_k \) and, thus, the effective sample size of the EVEREST will be reduced.

The EVEREST technique relies on characterizing the error rate from an accumulated distribution of the decision variable(s). If an ambiguity occurs whereby similar distributions correspond to a different error rate, a larger number of samples (\( N \)) and/or regions (\( M \)) would need to be made to make the models as distinguishable from one another as possible. Increasing \( M \) would, of course, imply increased estimator complexity.

The EVEREST has been implemented and trialed over a skywave HF radio link between Darwin and Melbourne, Australia. The results represent about 350 h of measurement in August 1989. The decision variables were extracted directly from a parallel-tone Kineplex\(^\text{®} \) (2400 bps) QPSK MODEM and applied via an A-to-D converter into an IBM AT–PC. The EVEREST was implemented entirely in the PC, using \( M = 4 \) regions and \( N = 3750 \) samples for each of the sixteen parallel tones. A pseudorandom sequence was transmitted over the same MODEM in order to allow the error rate to be measured. The EVEREST measurement time was 50 s, in this time a total of \( 16 \times 3750 = 6 \times 10^4 \) symbols were sent, allowing the error rate to be calculated with reasonable accuracy to as low as \( 10^{-4} \). The EVEREST error rate was taken as the average of the sixteen error rates estimated for each tone. Fig. 5 shows the results. The library contained a total of \( L = 300 \) models, made up of 250 flat Rayleigh fading models for fade rates of 0.2, 0.4, 0.6, 0.8, and 1 Hz and 50 AWGN models covering the range of error rates from 0.5 to \( 10^{-6} \). The accuracy of error rate estimates as low as \( 10^{-6} \) could not be confirmed without extending the error-counting measurement time to around 80 minutes, so the results to \( 10^{-4} \) are shown.

III. CONCLUSION

A method of BER estimation has been proposed which is suitable for applications requiring rapid measurement and where it is undesirable or infeasible to send a known data stream and count actual bit errors. A maximum likelihood implementation of the method has been simulated for the case of QPSK modulation, but it is equally suited to any modulation scheme. The simulated performance of the method shows BER estimation accuracy of within half an order of magnitude for 95% of measurements for BER values as low as \( 10^{-5} \) using only 1000 symbol samples in an AWGN environment. A sample size of 16,000 symbols reduces the estimation error to about 0.1 in log error rate.

Live link results on a HF link using Rayleigh and AWGN channel models showed that 95% of all measurements were within one order of magnitude to as low as BER = \( 10^{-4} \), using only 3750 samples.

The method outlined achieves a previously unattainable standard of speed and accuracy in BER measurement.

REFERENCES