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A Low-Complexity Sliding-Window Turbo Equalizer for Nonlinearity Compensation

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Abstract: We propose a low-complexity turbo equalizer consisting of a sliding window MAP estimator, and a low overhead LDPC decoder. By utilizing 2^{nd} order statistics, we obtain $2.5 \sim 4$dB gain with additional improvement with turbo loop.

OCIS codes: (060.1660) Coherent communication; (060.4370) Nonlinear optics, fibers

1. Introduction

Nonlinear effects have become a major limiting factor for high-rate data transmission in long-haul optical fiber links [1]. A large amount of research effort has been dedicated to mitigating the nonlinear impairments. Digital Back-Propagation (DBP) inverts the channel linear and nonlinear effects using a technique very similar to the standard split-step Fourier method (SSFM) developed for optical fiber modeling. However, the scheme suffers from high complexity; has reduced effectiveness in the presence of Amplified Spontaneous Emission (ASE); and parameters generally need to be manually adjusted to obtain optimal performance. Simplified DBP-based schemes have been reported [7], as well as compensators based on Perturbation techniques [8] and Volterra series expansion [9]. Nevertheless performance and implementation complexity remain a challenge.

Forward Error Correction (FEC) coding is an effective way of improving bit error rate (BER) performance in channels with impairments. Recently, soft-input Low-Density Parity-Check (LDPC) codes have been adopted for high-rate optical communications. In [5] a 2-bit soft input LDPC which achieves over 9dB net coding gain with 20% overhead was reported.

Turbo Equalization (TEQ) was originally developed to deal with inter-symbol interference (ISI) in wireless channels and has been shown to be very effective and can approach channel capacity. A "turbo loop" is formed between a Maximum *A Posteriori* (MAP) equalizer and a Soft-Input Soft-Output (SISO) decoder that exchanges extrinsic information. TEQ for noncoherent fiber-optic nonlinear transmission has been investigated in [3] using a Bahl-Cocke-Jelinek-Raviv (BCJR) MAP equalizer with probability functions obtained using training sequences. Significant performance improvement was obtained in simulations, but the complexity is too high to be realistically implemented in high-rate applications.

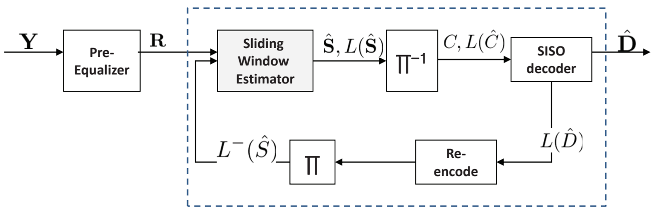
The reduced-complexity symbol detector proposed in [2] uses a training sequence to generate the mean levels at the receiver for each of the M^L possible patterns of L-symbols, where M is the alphabet size. After training, each symbol is decoded by finding the minimum Euclidean distance of an L-symbol received sequence to each of the possible transmitted patterns. An increase in nonlinear tolerance of 2dB was reported.

In this paper we investigate a low-complexity turbo equalization scheme using a sliding window MAP equalizer which significantly reduces the impact of intra-channel nonlinearity. A performance improvement of 4dB or higher was achieved in 40Gbps non-return-to-zero (NRZ) quadrature phase-shift keying (QPSK) transmissions.

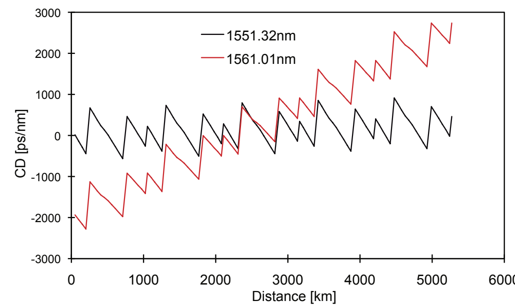
2. Sliding Window-based Turbo Equalizer

Figure 1(a) shows a section of a coherent optical receiver. The turbo equalizer, marked by the dashed-line box Figure 1(a), consists of two major components: a MAP equalizer and a SISO decoder. The soft outputs of one component are fed into the other to form a "turbo loop". For such a turbo process to work properly, it is also necessary to de-correlate the adjacent bits in the feedback stream such that they are considered independent of each other. This is carried out using (de)interleavers (Π and Π^{-1}). Turbo equalization can deliver near capacity performance. However, the complexity of a typical implementation is too high to be used for practical consideration.

The low-complexity turbo equalizer structure we propose employs a sliding window MAP (SW-MAP) estimator that can significantly reduce the overall complexity. Similar to the estimator reported in [2], the SW-MAP estimator uses a symbol sequence with $\ell = 2K+1$ received symbols to estimate the likelihood information of the center symbol.



(a) Turbo equalizer structure



(b) Fiber Channel dispersion maps

Fig. 1. Receiver structure and dispersion map

(The center symbol is chosen due to the symmetrical nature of the fiber chromatic dispersion). The likelihood of the received length-ℓ sequence at time n, $\mathbf{R}_n = (r_{n-K}, \ldots, r_n, \ldots r_{n+K})$ against M^ℓ possible length-ℓ patterns $\mathbf{S}_n$ is given as

$$\Pr(\mathbf{S}_n|\mathbf{R}_n) = \frac{\Pr(\mathbf{R}_n|\mathbf{S}_n)\Pr(\mathbf{S}_n)}{\Pr(\mathbf{R}_n)}, \tag{1}$$

where the likelihood term, $\Pr(\mathbf{R}_n|\mathbf{S}_n)$, can be computed as

$$\Pr(\mathbf{R}_n|\mathbf{S}_n) = \frac{1}{\sqrt{\det[2\pi\boldsymbol{\Sigma}(\mathbf{S}_n)]}} \exp\left(-\frac{1}{2}\begin{bmatrix}\Re[\mathbf{R}_n - \boldsymbol{\mu}(\mathbf{S}_n)]\\ \Im[\mathbf{R}_n - \boldsymbol{\mu}(\mathbf{S}_n)]\end{bmatrix}^{\mathrm{T}} \boldsymbol{\Sigma}^{-1}(\mathbf{S}_n) \begin{bmatrix}\Re[\mathbf{R}_n - \boldsymbol{\mu}(\mathbf{S}_n)]\\ \Im[\mathbf{R}_n - \boldsymbol{\mu}(\mathbf{S}_n)]\end{bmatrix}\right) \tag{2}$$

where $\Re(\cdot)$ and $\Im(\cdot)$ represent element-wise real and imaginary parts, respectively. Here, $\boldsymbol{\mu}(\mathbf{S}_n)$ and $\boldsymbol{\Sigma}(\mathbf{S}_n)$ are mean and covariance dependent on the data-pattern $\mathbf{S}_n$. These mean vectors and covariance matrices can be obtained via an off-line training process (with predetermined training sequence), or an on-line learning process.

Note that the minimum distance detector described in [2] is based on the Euclidean distance between received sequence and the mean patterns, which indicates that all symbols in the sequence are treated equally. Our simulations have shown that the covariances vary with the symbol position in a sequence. Therefore, such a Maximum Likelihood (ML) estimator, or detector is expected to provide enhanced performance.

To turn the sliding window estimator into a MAP estimator, the *a priori* likelihood, $\Pr(\mathbf{S}_n)$, is required. This is provided by the FEC decoder. It can be derived from (1) that the log likelihood of the symbol sequence, denoted as $L(\mathbf{S}_n)$, is simply

$$L(\mathbf{S}_n = \mathbf{s}^k|\mathbf{R}_n) = L(\mathbf{R}_n|\mathbf{s}^k) + L^{-}(\hat{\mathbf{S}}_n) + C, \tag{3}$$

where $L(\mathbf{R}_n|\mathbf{s}^k)$ is derived from (2), $L^{-}(\hat{\mathbf{S}}_n)$ is the extrinsic information, calculated based on the difference between the soft outputs and soft inputs of the decoder. C corresponds to $\Pr(\mathbf{R}_n)$, is a constant and will be eliminated in the log likelihood ratio (LLR) computation.

To further simply the estimator design, the Max Log-MAP approximation is employed in our design, i.e., for each constellation point, only the pattern with the maximum likelihood is used in computing the bit LLR of the center symbol. In each iteration, the best pattern of a constellation s is selected based on the following criterion

$$\underset{\mathbf{S}\in\mathbf{S}^s}{\arg\max}\ L(\mathbf{R}_n|\mathbf{S}) + L^{-}(\hat{\mathbf{S}}_n) \tag{4}$$

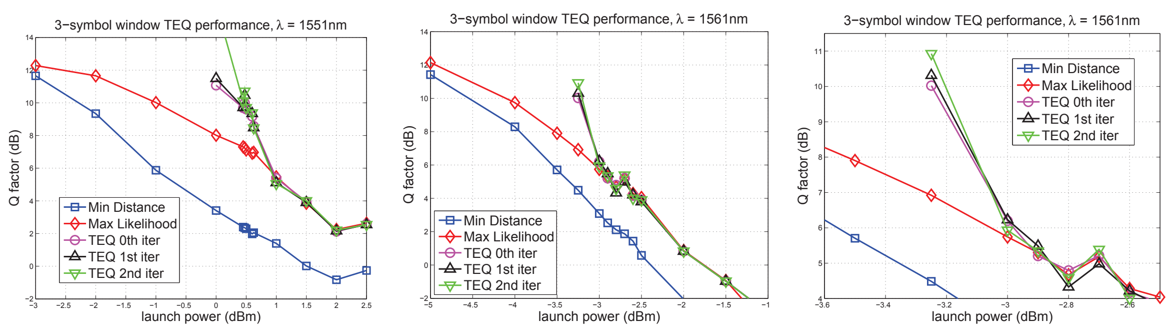
where $\mathbf{S}^s$ denotes the set of sequences with the center symbol being s. In the initial iteration, the *a priori* information is not available and $L^{-}(\hat{\mathbf{S}}_n) = 0$. In each additional interation, $L^{-}(\hat{\mathbf{S}}_n)$ from the previous iteration is used.

3. Performance Evaluations

The simulated fiber link is configured based on the experimental setup used in [6]. The channel under test is a 10GBaud NRZ QPSK single polarization signal with a center wavelength of 1551.32nm or 1561.01nm. After pre-dispersion compensation the signal was propagated through 5 loops of 18 spans of NZ-DSF and 3 spans of SSMF with compensating EDFAs (5dB NF), post-dispersion compensation and an optical filter (4th order Gaussian filter with a bandwidth of 2.5 × 10 GHz). Coherent detection was performed using a hybrid mixer and balanced photo-detectors. The electric transmit filter used is a 25ps rise-time Gaussian filter, and receive filter used a 4th order Bessel filter with a cutoff of 75% of the symbol rate. After digitizing to 2 samples per symbol any residual dispersion was removed using a linear equalizer and the signal decimated to T-spaced symbols before being passed to the turbo equalizer. The loop length was 1046km and the total transmission distance was 5230km. Fig. 1(b) gives the dispersion maps of both channels.

The performance of the proposed turbo equalization scheme is evaluated via simulation. To maintain low complexity, a (1024, 922) LDPC code is chosen for its low overhead (10%) and small block size. We also limit the number of turbo iteration to be 3 for complexity consideration. The window sizes of 1, 3 and 5 are evaluated for the SW-MAP estimator. For comparison, a sliding window minimum distance (SW-MD) detector based on that described in [2] was also implemented. We also simulate the hard decision sliding window maximum likelihood (SW-ML) detector, which is essentially the SW-MAP estimator with hard decision output symbols and without *a priori* information. During the simulation, errors at the detector/decoder outputs are counted and corresponding Q-factors are calculated based on the BER. Figure 2 shows the results with window size of 3 symbols. Performance are evaluated for both the low local dispersion channel (1551.32nm wavelength) and the high local dispersion channel (1561.01nm wavelength). Results are shown in Figure 2(a) for the 1551nm channel, Figure 2(b) and 2(c)for the 1561nm channel. We first note that over the entire range of launch power simulated, the SW-ML detector out-performs the SW-MD detector by as much as 5dB for the 1551nm channel and $2 \sim 3.5$dB for the 1561nm channel. We note that for an equalized linear channel, where symbols are considered independent and have equal variance, the SW-ML and SW-MD detectors have identical performance. This further confirms our analysis that using the 2nd order statistics provides performance gain in non-linear channels.

If Figure 2, we plot Q values after each iterations. The 'turbo' effect is clearly demonstrated. For example, in high dispersion channel with 3.25dBm launch power, the Q at the SW-MAP estimator is 6.92dB, the decoder output is 10.02dB after the initial iteration and improves to 10.31dB and 10.93dB after the 1^{st} and 2^{nd} iteration. The overall gain is greater than 7dB at 0.5dBm launch power for the low dispersion channel and 6.5dB at 3.25dBm launch power for the high dispersion channel.



(a) Q-factor, low local dispersion channel

(b) Q-factor, high local dispersion channel

(c) Q-factor of @3.25dBm, high local dispersion

Fig. 2. TEQ performance

4. Summary

In this paper, we describe a turbo equalizer structure that employs an SW-MAP estimator and an LDPC decoder with short block size. We first design a SW-MAP estimator that utilizes multi-symbol sequence and second-order statistics to produce reliable likelihood information for the following SISO LDPC decoder. The complexity of the proposed turbo equalizer is sufficiently low and can be potentially implemented in hardware. Simulation results have shown significant BER performance and Q-factor improvement over existing techniques.

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