Quality monitoring of WDM channels with blind signal separation methods

Yumang Feng, Vicente Zarzoso, and Asoke K. Nandi

Department of Electrical Engineering and Electronics, The University of Liverpool, Brownlow Hill, Liverpool, L69 3GJ, United Kingdom

aknandi@liverpool.ac.uk

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An effective technique to monitor the quality of wavelength-division-multiplexed (WDM) channels is presented. This process uses a blind signal separation (BSS) method based on higher-order-statistics (HOS), and an optical-loop structure to extract the baseband channels from the WDM transmission. From the reconstructed baseband waveforms, a series of WDM transmission quality parameters are evaluated. Relative to previously proposed methods for WDM-channel monitoring, the HOS-based optical-loop procedure shows reduced complexity, improved cost efficiency, and better performance. © 2004 Optical Society of America

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1. Introduction

For the proper management of WDM transmission systems and particularly optical networks that use optical add–drop multiplexing (OADM) and optical cross connect (OXC), it is essential to monitor a variety of channel-performance parameters such as signal-to-noise ratio (SNR), bit-error rate (BER), and Q factor without compromising transparency. Traditional methods for WDM channel monitoring use tunable optical filters, phased-array demultiplexers, or photodiode arrays with diffraction gratings [1].

The disadvantage of these methods is that complex (expensive) optical components are involved.

In an effort to reduce the number of expensive optical components, cost-effective monitoring solutions aim to perform most of the processing electronically. The (spatial) independence between the transmitted WDM channels has been exploited in recent studies [2–4]. The technique presented in Ref. [3] can be used to reconstruct the complete channel waveforms, from which performance parameters can be measured. Along the lines of Ref. [4], wavelength-dependent attenuators (WDAs) are employed to obtain additional observations of the WDM signal, each observation considered as a mixture of the constituent channels. Because the WDA has an adjustable nonlinear relation between the wavelength and the output power, the independent channels contribute with different strengths to each observation, and sufficient spatial diversity is available for a suitable blind signal separation (BSS) method to recover the original transmitted waveforms.

The symmetric adaptive decorrelation (SAD) technique of Ref. [5] was adopted as a separation device. This particular technique, however, has a number of deficiencies. On the one hand, its complexity is of order $O(N!)$ for an N-channel WDM transmission. On the other hand, the method has inherent stability and convergence difficulties—including spurious nonseparating solutions [5]—which may hinder the monitoring process in practical cases. More specifically, the method is based on second-order statistics, which causes problems with identification in the separation of spectrally white sources. In Refs. [6] and

[7], each channel uses a unique set of WDA and photodetector, which makes this technique less efficient with increasing number of channels.

In this paper we overcome these shortcomings with a more cost-effective optical-loop structure to WDM monitoring, but still applying BSS based on higher-order statistics (HOS), and provide a satisfactory solution of WDM quality evaluation through the reconstructed baseband waveforms. In Section 2, the system setup is described in sufficient detail for understanding the computer experiments that follow. Three BSS methods are reviewed in Section 3, and these are subsequently applied in the following experiments. In Section 4 are described quality-monitoring parameters from WDM transmissions. Simulations are described and results are presented in Section 5. Finally, the paper is concluded in Section 6.

2. System Description

Figure 1 shows a system setup of the proposed WDM channel monitoring scheme. A small fraction of each of the N channels' WDM signal is coupled out of the network with an asymmetric power splitter. A predetermined period of time, say, T_1, of this split optical signal is then sent into an optical loop, which contains a delay fiber and an optical pump, to generate a periodic optical signal sequence of repeating signal fraction T_1 for N times, each period of the signal is spaced from the other by a predetermined period of "all-zeros." An adjustable WDA [6] is used to attenuate this sequence. The WDA is synchronized with the optical switch; thus the attenuation factors for each period of signal fraction T_1 are adjusted to be different from one another. This synchronization is implemented by relating the driving voltage of the WDA to the optical switch; the required switching speed of the optical switch and WDA is related to T_1, thus the length of the delay fiber, and the length of the "all-zero" sequences used to space the "T_1" sequences. An optical pump is also applied to compensate the power coupled out of the optical loop. The attenuated optical signal sequence is converted into an electrical signal sequence by a photodetector. The purpose of the loop and WDA structure is to generate several linear mixtures of the WDM channels, which a BSS method can later use for extracting the WDM channels separately. From the reconstructed WDM waveforms, quality parameters such as eye diagrams, Q factor, and BER can be estimated.

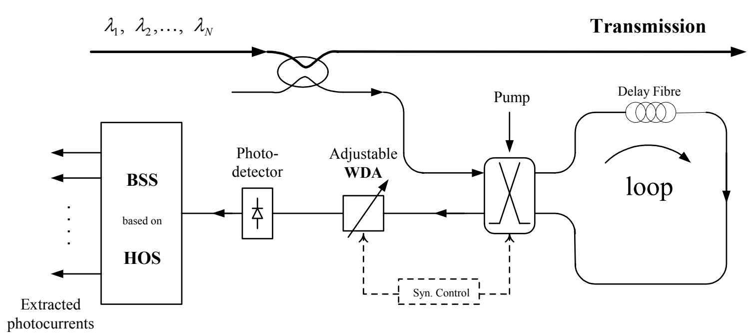

Fig. 1. Experimental setup.

The wavelength-dependent attenuating procedure above is a form of nonlinear optical signal processing, which can compensate the loss of wavelength information caused by the conversion from optical domain to electrical domain [4]. By applying appropriate electrical signal processing methods, up to some extent, we do not need to know the details of this nonlinear optical signal processing (i.e., the WDA). In Section 3 we show that BSS methods based on HOS can be applied to extract the WDM signals.

3. WDM Signal Extraction Using HOS-Based BSS

Let $y_i(k)$, $1 \le i \le M$, denote the M observed photocurrents of the N-channel WDM signal ($M \ge N$), where k represents a discrete time index. Accordingly, let $s_i(k)$, $1 \le i \le N$, represent the channel (or source) baseband data, multiplexed within the WDM signal and thus not directly observable.

Direct photodetection of the WDM transmission causes all wavelength information to be lost. As a result, with additive noise terms neglected, the detected signal appears as a weighted linear combination of the baseband data:

$$y_i(k) = \sum_{j=1}^{N} h_{ij} s_j(k), \qquad 1 \le i \le M. \tag{1}$$

Coefficients h_{ij} represent the WDA effects over channel j in observed photocurrent i. Hence the observation vector $\mathbf{y} = [y_1, \ldots, y_M]^T$ (symbol T denoting the transpose operator) and the channel vector $\mathbf{s} = [s_1, \ldots, s_N]^T$ fulfill at any time instant the linear model:

$$\mathbf{y} = \mathbf{H}\mathbf{s}, \tag{2}$$

where the elements of the $(M \times N)$ mixing matrix $\mathbf{H}$ are given by $(\mathbf{H})_{ij} = h_{ij}$. Equation (2) corresponds to the BSS model of instantaneous linear mixtures [8].

Separation is generally achievable under two main assumptions:

(A1) the source signals are mutually statistically independent;

(A2) the mixing matrix is full column rank.

Otherwise both entities—$\mathbf{H}$ and $\mathbf{s}$—are unknown in model (2). Note that assumption A2 guarantees considerable freedom in the selection of the WDA attenuation patterns.

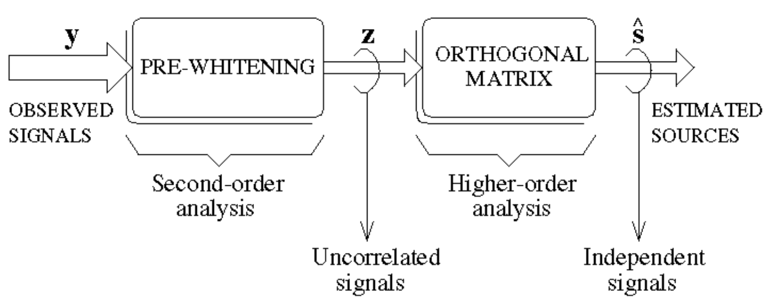

Fig. 2. Two-step approach to BSS.

As in Ref. [4], we aim to perform the monitoring by first extracting the channel waveforms from the photocurrent observations, but here we resort to the BSS methods based on HOS. The use of HOS is restricted to non-Gaussian signals, which is clearly the case in the problem at hand, with sources composed of digital modulations. Most methods operate in two steps (Fig. 2). The first step is so-called (spatial) prewhitening, which seeks to normalize and decorrelate the observations by means of conventional second-order statistical analysis (principal component analysis). This operation results in a signal vector $\mathbf{z}$, which is linked to the channel components through an unknown $(M \times N)$ orthogonal transformation $\mathbf{Q}$:

$$\mathbf{z} = \mathbf{Q}\mathbf{s}. \tag{3}$$

The second step finds an estimate $\hat{\mathbf{Q}}$ of $\mathbf{Q}$, from which the channel signals can be reconstructed as $\hat{\mathbf{s}} = \hat{\mathbf{Q}}^T \mathbf{z}$. Essentially, a linear transformation approximating the inverse of $\mathbf{Q}$ is sought such that it maximizes the statistical independence between the separator output components. This is the purpose of independent component analysis (ICA) techniques. Independence can be measured, directly or indirectly, through a variety of different criteria such as Kullback–Leibler divergence, negentropy, mutual information, maximum likelihood (ML), and so on, leading to an array of different algorithms. The general rationale behind these techniques as well as more details about them can be found in Ref. [9]. Below are described the three HOS-based BSS methods used in the experiments reported later in this paper.

3.A. JADE

Let us denote the fourth-order cumulant of random variables $\{z_i\}_{i=1}^N$ as

$$\kappa_{ikjl}^z = \mathrm{Cum}\left\{z_i, z_j, z_k, z_l\right\}, \tag{4}$$

which is endowed with a tensor structure. The cross cumulants of independent random variables are zero, a property that can be used to measure statistical independence. Gaussian signals have a particular property that all their higher-order (cross and marginal) cumulants are always zero; thus it is impossible to discern whether a set of Gaussian signals is mixed. The cumulant tensor of independent non-Gaussian variables shows a diagonal shape, that is, $\kappa_{ikjl}^s = 0$ unless $i = j = k = l$. Hence the diagonalization of the cumulant tensor would accomplish the source separation. However, as yet no algebraic tools are available to diagonalize a tensor of order higher than two. The JADE (joint approximate diagonalization of eigenmatrices) method [10] tries to circumvent this difficulty by simultaneously diagonalizing a particular set of matrix "slices" of the fourth-order cumulant tensor. This diagonalization can be carried out in a cost-effective manner by means of conventional Jacobi-like iterations [11] based on planar Givens rotations:

$$\mathbf{Q} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}. \tag{5}$$

It has been proven [10] that this joint diagonalization is associated with a particular *contrast* function. Contrast functions [12] are an important concept in BSS / ICA, since they are particularly well suited for signal separation in the presence of noise. The main disadvantage of JADE is its computational complexity. The method requires the calculation of the N^4 elements of the fourth-order cumulant tensor, followed by the diagonalization of N^2 matrices with dimensions $(N \times N)$, each made from such cumulants. This complexity can be restrictive in separation problems with a large number of sources.

3.B. EML

In the two-signal case ($N = 2$), matrix $\mathbf{Q}$ becomes a Givens rotation defined by a single real-valued parameter θ [Eq. (5)]. The estimation of θ can be accomplished in closed form, i.e., without any sort of iterative optimization. Several analytic expressions exist, but the estimator of Ref. [13] presents the advantage that it approximates (using the Gram–Charlier pdf expansion truncated at fourth order) the maximum-likelihood solution when the source signals have the same statistics. This is the case in the WDM monitoring problem, in which all transmitted channels are composed of bit streams, possibly contaminated by noise and interference. This estimator expression reads:

$$\hat{\theta}_{\mathrm{EML}} = \frac{1}{4}\angle\left[\xi \operatorname{sign}(\gamma)\right], \tag{6}$$

with

$$\xi = \left(\kappa^z_{1111} - 6\kappa^z_{1122} + \kappa^z_{2222}\right) + j4\left(\kappa^z_{1112} - \kappa^z_{1222}\right), \tag{7}$$

$$\gamma = \kappa^z_{1111} + 2\kappa^z_{1122} + \kappa^z_{2222}, \tag{8}$$

where $j = \sqrt{-1}$ is the imaginary unit. Notation $\angle a$ denotes the principal value of the argument of complex-valued quantity a. Estimator (6) can be considered as an extension of the approximate ML solution of [14], thus its name "extended ML" (EML).

To achieve the source estimation for $N > 2$ channels, the closed-form expression is applied over each pair of whitened signals until convergence is reached. Since there exist $N(N-1)/2$ signal pairs and approximately $\left(1+\sqrt{N}\right)$ sweeps over the signal pairs are usually necessary for convergence, the method's complexity with respect to the number of channels is of order $O\left(N^{5/2}\right)$. This value is lower than the $O(N!)$ of Ref. [2], especially for a large number of channels.

3.C. MaSSFOC

The ICA contrast function of Ref. [12] results from certain approximations of negentropy. Further simplifications show that such contrast admits, in the two-signal case, a closed-form solution, called the maximum sum of squared fourth-order cumulants (MaSSFOC) estimator [15]. It was later discovered [16] that MaSSFOC belongs to a wider family of so-called weighted closed-form estimators (WEs), whose general expression is given by

$$\hat{\theta}_{\mathrm{WE}} = \frac{1}{4}\angle\xi_{\mathrm{WE}}, \tag{9}$$

with

$$\xi_{\mathrm{WE}} = \omega\gamma\xi + (1-\omega)\,\xi_2^2, \qquad 0 < \omega < 1, \tag{10}$$

where

$$\xi_2 = \left(\kappa^z_{1111} - \kappa^z_{2222}\right) + j2\left(\kappa^z_{1112} + \kappa^z_{1222}\right). \tag{11}$$

The above expression reduces to the EML estimator [Eq. (6)] for $\omega = 1$. Similarly, the MaSSFOC estimator is obtained with $\omega = 1/2$. The approximate ML solution of Ref. [17] (similar to that for MaSSFOC) is also reached for $\omega = 1/3$.

The EML performance degrades when the source kurtosis sum tends to zero [16]. MaSSFOC overcomes this adverse effect, hence proving more robust in the presence of noise and impulsive interference. This method handles more than two signals in the same Jacobi-like fashion as the EML.

Finally, it should be noted that the HOS-based methods described in this section ignore any temporal structure in the processed signals so that spectrally white photocurrents could also be separated. If the data symbols transmitted by a single user are uncorrelated, such spectrally white photocurrents could arise when the photodectector output are sampled at rates as low as the symbol rate. Low sampling frequencies enable us to reduce the speed requirements, and hence the cost, of the digital signal processing used for WDM channel extraction and monitoring without sacrificing performance.

4. Quality Evaluation of WDM Transmissions

Inasmuch as WDM signal waveforms (and thus the eye diagrams) can be reconstructed in electrical domain, it is not always necessary to use optical methods to obtain WDM transmission quality information. Several reports have evaluated amplitude histograms, Q factors, and BER obtained by the electrical technique [18–20]. Reference [18] confirmed that the degradation of an optical signal due to noise, cross talk, and chromatic dispersion can be detected from amplitude histograms. However, it is difficult to evaluate SNR degradation quantitatively because the mark level peak in the histograms is not clear when the chromatic dispersion is large. Reference [19] defined a method to evaluate average Q factor from the eye diagrams and amplitude histograms. This method has sensitivity to both the SNR degradation and pulse distortion of optical signals influenced by chromatic dispersion in transmission fiber. Reference [20] introduced a technique to evaluate BER through the Q factor.

As described in Fig. 3, the average Q factor(Q_{avg}) is expressed by [19]

$$Q_{\text{avg}} = \frac{|\mu_{1,\text{avg}} - \mu_{0,\text{avg}}|}{\sigma_{1,\text{avg}} + \sigma_{0,\text{avg}}}, \qquad (12)$$

where $\mu_{i,\text{avg}}$ and $\sigma_{i,\text{avg}}$ are the mean and standard deviation of the mark ($i = 1$) and space ($i = 0$) levels of all sampled data, respectively. μ is set to the difference of the mean of the mark and the space levels. Two thresholds are defined with coefficient α lying between 0 and 0.5:

$$D_{0,1} = \mu_{0,1} \pm \alpha\mu, \qquad 0 < \alpha < 0.5. \qquad (13)$$

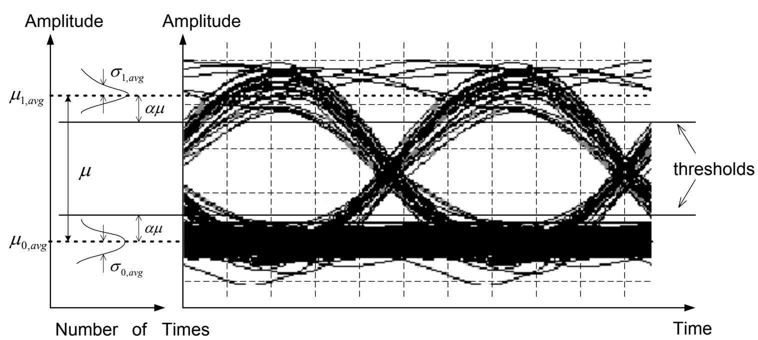

Fig. 3. Definition of averaged Q factor.

Histograms with amplitudes larger than $\mu_1 - \alpha\mu$ are regarded as mark level distributions, whereas histograms with amplitudes smaller than $\mu_0 + \alpha\mu$ are regarded as space level distributions. This masking process removes the cross-point data and improves measurement accuracy [21].

Although the exact probability density function for optical noise is not exactly Gaussian, a Gaussian approximation can lead to good BER estimates [20]:

$$\text{BER}(D) = \frac{1}{2}\left\{\text{erfc}\left(\frac{|\mu_1 - D|}{\sigma_1}\right) + \text{erfc}\left(\frac{|\mu_0 - D|}{\sigma_0}\right)\right\}, \qquad (14)$$

where $\mu_{0,1}$ and $\sigma_{0,1}$ are the mean and standard deviation of the mark and space data rails, D is the decision level, and $\text{erfc}(x)$ is a form of the complementary error function given by

$$\text{erfc}(x) = \frac{1}{\sqrt{2\pi}}\int_x^{\infty} e^{-\beta^2/2}\,\text{d}\beta \approx \frac{1}{x\sqrt{2\pi}} e^{-x^2/2}, \qquad (15)$$

where the approximation is nearly exact for $x > 3$.

In a high-performance optical transmission system, the BER is very low, traditional quality-monitoring methods need very long time to detect errors in transmission. Equations (12) and (14) provide fast and simple evaluations of WDM optical transmission quality with acceptable accuracy, as demonstrated in Section 5.

5. Simulations and Results

Illustrative experiments are carried out with the aid of the VPI simulation software, with the blind separation part implemented in MATLAB code.

First, we demonstrate the technique in a four-channel WDM setup. Four channels at wavelengths 1551.0, 1554.2, 1557.4, and 1560.6 nm (i.e., 3.2-nm separation), respectively, compose the WDM signal. The laser sources are modulated with Mach–Zehnder modulators by NRZ data from a pseudorandom binary sequence at a 10-Gbit/s bit rate.

As explained in Section 2, a small fraction of the transmitted WDM signal is diverted from the optical link into the monitoring system through an asymmetric splitter, and a fiber span of 50 km is included in front of the monitoring point. A block of this WDM signal fraction is then let into an optical loop. The signal block runs in the loop for four circles, and at the end of each circle the signal is coupled out of the optical loop. This means that the output of the optical loop are four blocks of repeated signals, with blocks spaced from one another by 128-bit all-zeros. These four signal blocks are sent to an optical signal processor, i.e., the adjustable WDA, sequentially. The adjustable WDA is synchronized with the optical loop, and is tuned to have different but unknown attenuation on each of the signal blocks. All these attenuated signal blocks are detected by a p-i-n photodetector, which generates the corresponding observed photocurrents shown in Fig. 4.

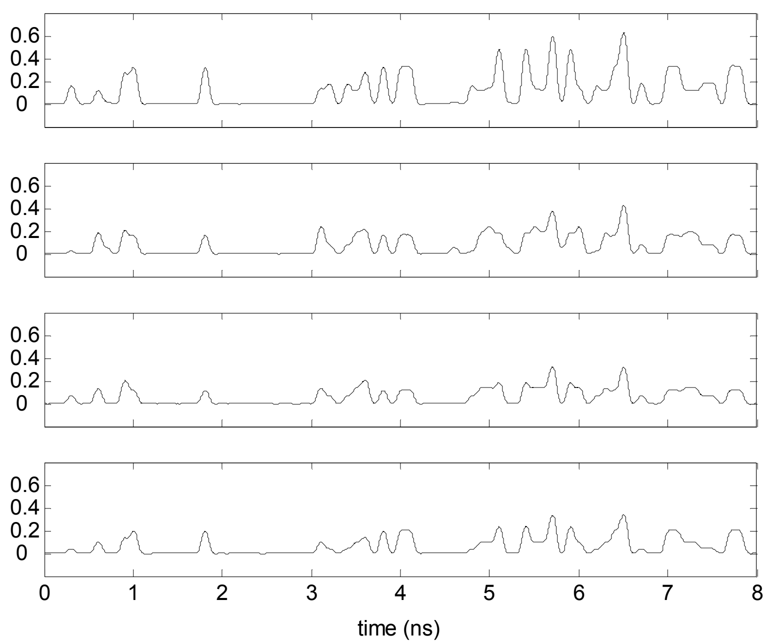

Fig. 4. Observed photocurrents in the four-channel experiment.

These electronic signals are then collected and processed by the HOS-based BSS methods described in Section 3 to obtain the signal separation. The normalized (i.e., zero-mean, unit-power) channel data estimated by EML method are shown by the solid curves of Fig. 5. A block of 256 bits (32,768 samples) was processed, of which only a short portion is displayed in the figure for the sake of clarity. Observe the accuracy with which the estimated sequences approximate the actual transmitted data (dotted curves).

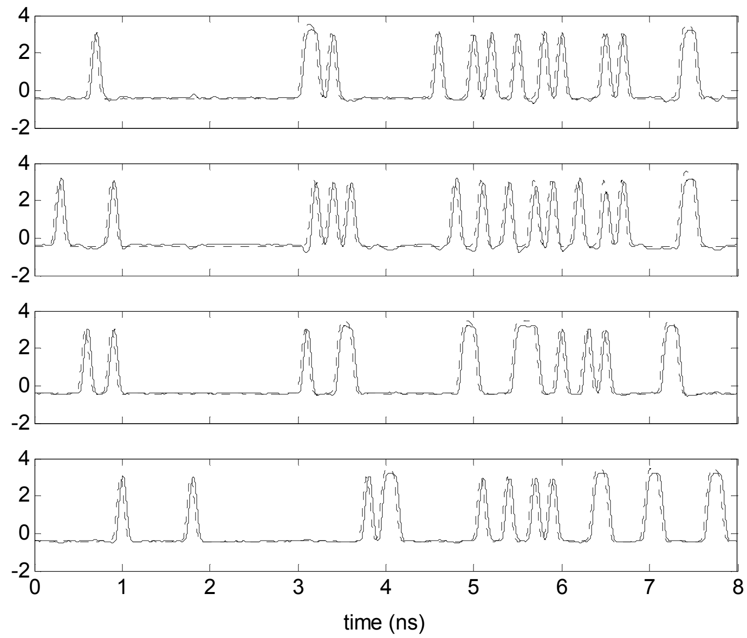

Fig. 5. Normalized data sequences in the four-channel experiment. Dotted curves, transmitted data. Solid curves, channel data estimated by the HOS-based BSS method (EML) from the photocurrents shown in Fig. 4.

Eye diagrams for each channel can be plotted from the separated waveforms, shown in Fig. 6; thus the average Q factors and BERs for each channel can be evaluated with the method introduced in Section 4.

Table 1 gives the average Q factors of all four channels, with the channel waveforms extracted by EML, MaSSFOC, and JADE method, respectively. The input power levels at the Mach–Zehnder modulators are tuned between -38 and -30 dBm, and the coefficient α in Eq. (13) is set to 0.1, 0.2, 0.3, 0.4, respectively. VPI software estimates BER through a Gaussian assumption [22], and the estimated average Q factors are presented in the tables as well. Comparison of the results shows that the EML method provides the best approach of Q_{avg} estimation to the industrial simulation software (VPI) with $\alpha = 0.3$. Figure 7 presents the average BER curves with the channel waveforms extracted by the EML, MaSSFOC, and JADE method, respectively, which shows that the EML method provides the best approach of BER estimation to the industrial simulation software (VPI), with the BER curves for each single channel shown in Fig. 8.

The proposed method is also capable of monitoring a higher number of channels. Figure 9 shows the observed photocurrents and separation results for an eight-channel WDM transmission with 1.6-nm channel spacing, under the general conditions for the four-channel experiment. The estimated BER curves for each channel are shown in Fig. 10(a), with the EML method, compared with the results from VPI software shown in Fig. 10(b).

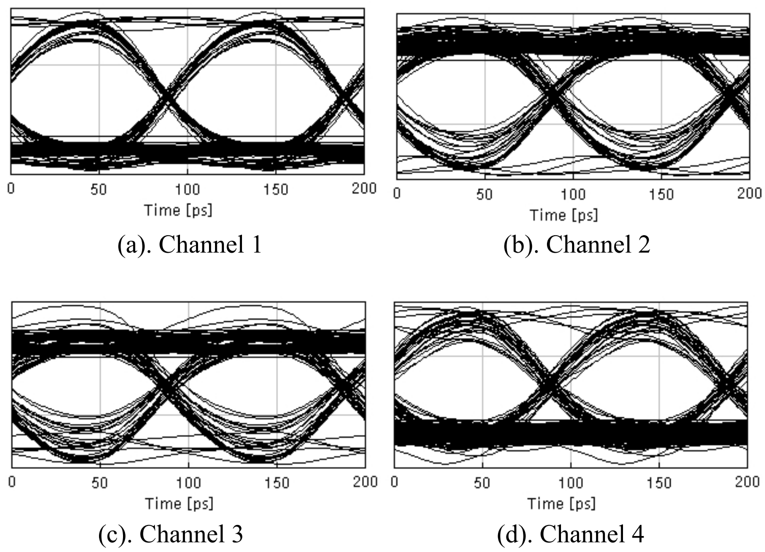

Fig. 6. Eye diagrams for the four-channel experiment.

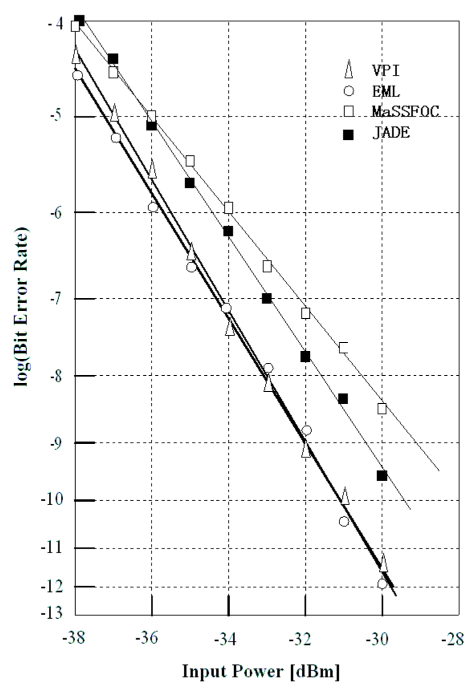

Fig. 7. Comparison of average BER curves from different methods.

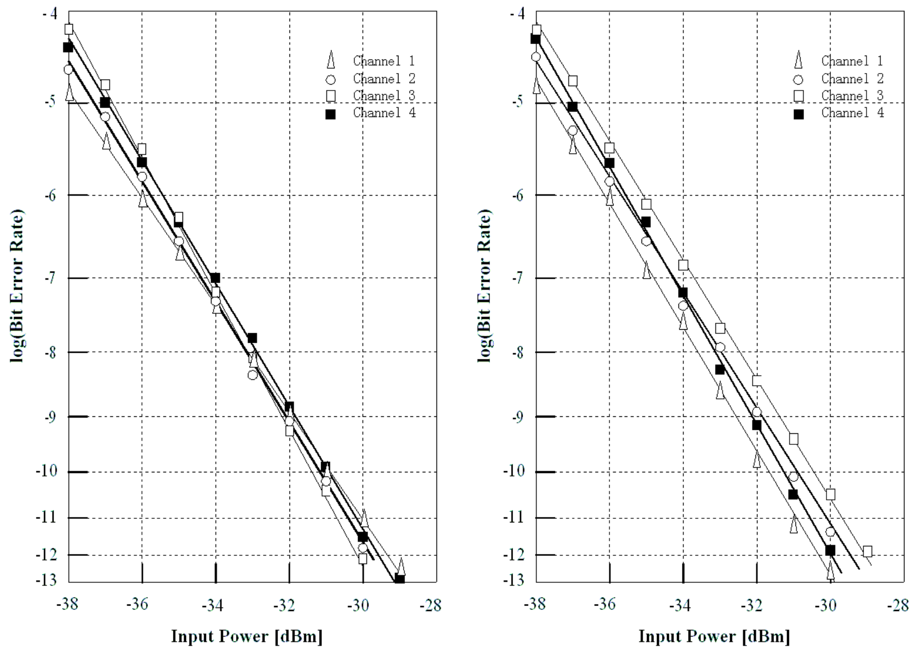

Fig. 8. BER versus input power curves. (a) EML method with the optical loop structure, (b) Gaussian assumption by VPI.

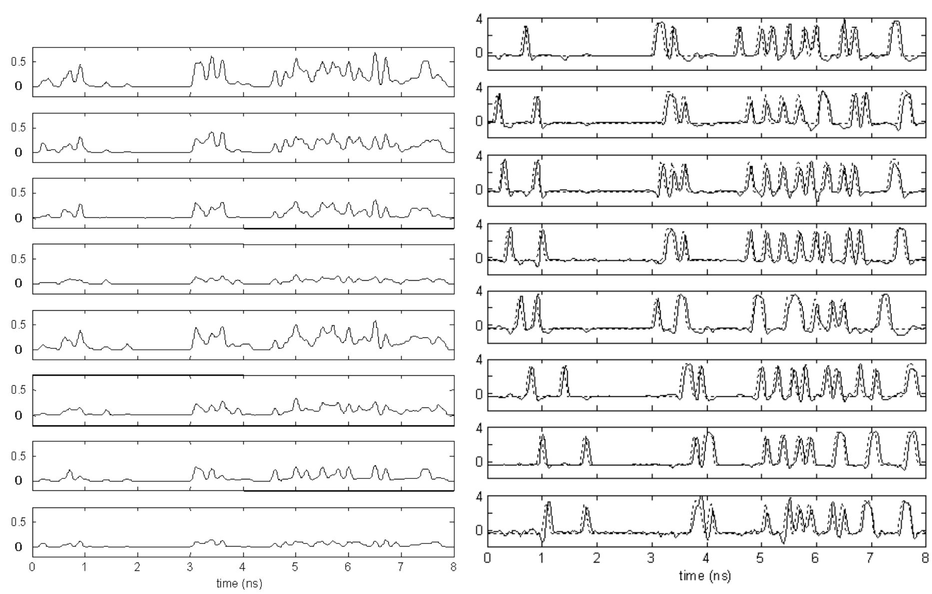

Fig. 9. (a) Observed photocurrents and (b) separation results for an eight-channel WDM transmission.

Table 1. Average *Q* Factors

Input power (dBm)	Average Q-factor			
	VPI	EML	MaSS	JADE
-38	3.7	4.3	4.1	3.4
-37	4.5	5.0	4.6	4.0
-36	5.2	5.6	5.1	4.5
-35	5.8	6.3	5.5	4.9
-34	6.3	6.9	6.0	5.4
-33	6.7	7.4	6.3	6.0
-32	7.3	8.0	6.4	6.4
-31	7.8	8.5	6.7	6.7
-30	8.5	9.2	6.9	7.1

(a). $\alpha = 0.1$

Input power (dBm)	Average Q-factor			
	VPI	EML	MaSS	JADE
-38	3.7	4.1	3.6	3.3
-37	4.5	4.8	4.1	4.0
-36	5.2	5.5	4.8	4.8
-35	5.8	6.0	5.2	5.2
-34	6.3	6.7	5.5	5.5
-33	6.7	7.2	5.7	5.8
-32	7.3	7.9	6.0	6.3
-31	7.8	8.5	6.2	6.7
-30	8.5	8.9	6.6	7.1

(b). $\alpha = 0.2$

Input power (dBm)	Average Q-factor			
	VPI	EML	MaSS	JADE
-38	3.7	3.9	3.4	3.1
-37	4.5	4.6	4.0	3.7
-36	5.2	5.3	4.5	4.2
-35	5.8	5.9	4.9	4.8
-34	6.3	6.3	5.2	5.2
-33	6.7	6.7	5.5	5.7
-32	7.3	7.2	5.8	6.3
-31	7.8	7.8	6.2	6.8
-30	8.5	8.6	6.6	7.5

(c). $\alpha = 0.3$

Input power (dBm)	Average Q-factor			
	VPI	EML	MaSS	JADE
-38	3.7	3.2	2.9	2.6
-37	4.5	3.8	3.4	3.1
-36	5.2	4.5	4.0	3.7
-35	5.8	5.1	4.4	4.2
-34	6.3	5.6	4.7	4.6
-33	6.7	6.0	5.0	5.1
-32	7.3	6.3	5.2	5.7
-31	7.8	6.9	5.3	6.1
-30	8.5	7.7	5.8	6.6

(d). $\alpha = 0.4$

6. Conclusions

We have proposed and demonstrated an optical transmission monitoring technique that uses blind signal separation (BSS) methods based on higher-order statistics (HOS), and an optical-loop structure. This technique shows reduced complexity, reformative cost efficiency, and improved performance.

The EML method provides an approximate optimal solution (in the maximum-likelihood sense) for the case of two channels, and entails a computational cost of $O\left(N^{5/2}L\right)$ when processing L-sample blocks of an N-channel WDM signal. For the signal distributions typically occurring in WDM monitoring, the method presents no undesired solutions. In addition, the case of spectrally white channels can also be handled, thus allowing beneficial reductions in the rates at which the photocurrents are sampled. Although the suggested procedure operates on signal blocks (batch processing), fast adaptive implementations can easily be designed as well [23].

Relative to previously proposed methods [6, 7], the optical-loop structure presented in this paper has cost-effective features, especially when WDM signals are composed of a large number of channels. We have found that a combination of the BSS method and quality measurement methods with associated thresholds that provide average Q-factor and BER estimates, with most of the processing in the electrical domain, to yield results close to those of traditional methods requiring expensive optical components, which simulated in an industrial simulation package (VPI).

It should be noted that the blind separation approach is not only useful in monitoring but also effectively demultiplexes the WDM signal. It appears that this feature has enormous potential for BSS in optical transmission systems.

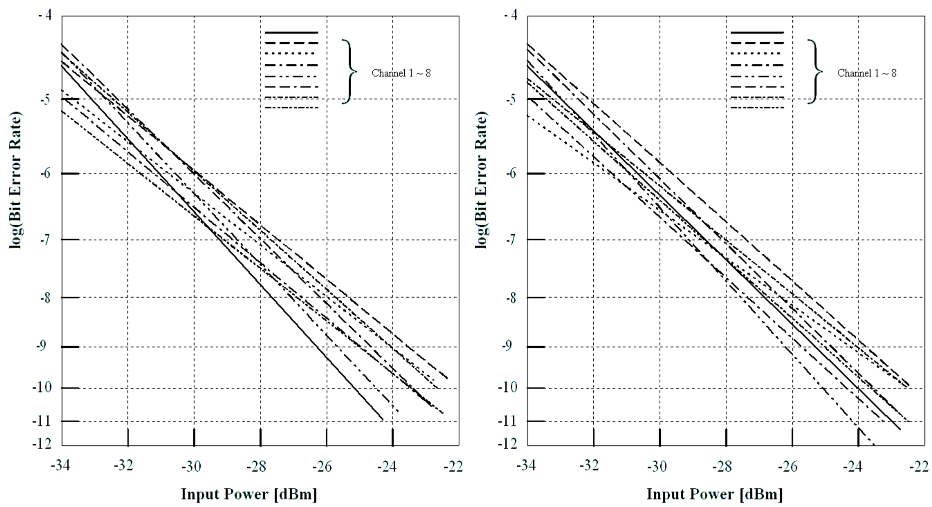

Fig. 10. BER versus input power curves. (a) EML method with the optical loop structure; (b) Gaussian assumption by VPI.

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