Channel monitoring for optical WDM networks

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**CHANNEL MONITORING FOR OPTICAL WDM
NETWORKS**

YE DAN

**SCHOOL OF ELECTRICAL & ELECTRONIC
ENGINEERING**

2007

Channel Monitoring for Optical WDM Networks

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School of Electrical & Electronic Engineering

A thesis submitted to the Nanyang Technological University
in fulfillment of the requirement for the degree of
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Summary

As in any other transmission systems, signals transported in optical WDM networks suffer from various kinds of distortions and impairments. Optical amplifiers give rise to amplified spontaneous emission (ASE) noise. Network components such as optical cross-connects (OXC) and optical add-drop multiplexers (OADM) introduce both interband and intraband crosstalk. Different kinds of dispersion including chromatic dispersion, polarization mode dispersion (PMD) are limiting factors in today's long-haul transmission networks. In addition, fiber nonlinearities including self-phase modulation (SPM), cross-phase modulation (XPM) and four wave mixing (FWM) are harmful to the desired optical signals, since the signal transmission power is highly increased in today's high-speed optical transmission networks. In order to efficiently operate, manage and maintain optical networks, efficient optical monitoring techniques are highly desired.

Bit error rate (BER) is a fundamental performance parameter for digital transmission systems. The conventional method uses error codes that are appended to the data frame to facilitate the measurement of BER. However, this method requires prior knowledge of the bit rate and coding format of the signal and it is not suitable for transparent optical networks because transparent optical network is capable to carry arbitrary data rates and protocols simultaneously. One promising solution for BER estimation in optical networks is to make use of optical signal's amplitude histograms.

The amplitude histogram reflects the distribution properties of signal spaces (data “0”) and marks (data “1”). The amplitude histogram can be collected by sampling the signal eye diagram at the most widely opened position. Conventionally, a single Gaussian function is used to approximate the amplitude histogram in estimating BER. This works well only if the dominant noise is of Gaussian noise. However, in real optical networks, various impairments will distort the signal waveform and deviate the histogram from Gaussian distribution.

One possible approach to the above problem is to reconstruct the distorted probability density function (PDF) using multiple Gaussian functions to fit the distorted amplitude histogram. In this thesis, we propose an improved multi-Gaussian curve fitting method for estimating the BER of optical signals. Comparing with previous works, the fitting process is conducted purely mathematically without the knowledge of physical parameters of the receiver and extra instruments. The number of Gaussian functions used for fitting is not predefined but depends on the actual shape of the histogram. The new fitting technique is validated using a commercial optical system design simulation tool, *VPI transmissionmakerTM* and the results show that the estimated BER is much closer to the BER measured by BER tester (BERT) compared with single Gaussian approximation, particularly when the optical channel is severely distorted by the impairments.

Identifying and discriminating sources of signal degradation is another critical issue in

monitoring the optical network performance. Based on the observation that different impairments impose different types of distortion on the histogram, we propose a new impairments identification scheme using the X^2 distance metric and asymmetry property of the histogram. The X^2 distance is a measurement of histogram difference between the distorted histogram and the undistorted histogram. The distorted histograms also exhibit different asymmetry properties for both the space and the mark. It is shown that our technique can successfully identify three major impairments namely, ASE noise, chromatic dispersion and inband crosstalk.

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List of Acronyms

Acronyms	Expansion
ASE	Amplified spontaneous emission
BER	Bit error rate
CRC	Cyclic redundancy check
DWDM	Dense wavelength division multiplexing
EDFA	Erbium-doped fiber amplifier
FEC	Forward error correction
FWM	Four-wave mixing
GVD	Group velocity dispersion
ISI	Intersymbol interference
NRZ	Non-return-to-zero
OADM	Optical add/drop multiplexer
O/E/O	Optical-to-electrical-to-optical
OXC	Optical crossconnect
PMD	Polarization-mode dispersion
QOS	Quality of service
RF	Radio frequency
RIN	Relative intensity noise
RZ	Return-to-zero
SBS	Simulated Brillouin scattering
SDH	Synchronous digital hierarchy
SMF	Single-mode fiber
SNR	Signal-to-noise ratio

SONET	Synchronous optical network
SOP	State of polarization
SPM	Self-phase modulation
SRS	Stimulated Raman scattering
XPM	Cross-phase modulation
WDM	Wavelength division multiplexing
VSF	Vestigial sideband

Chapter 1 Introduction

1.1 Background and Motivation

In recent years, the long-distance, high-capacity transmission of digital signals is mainly dominated by fiber optic transmission. Compared with the conventional electrical transmission systems that use copper-based co-axial cables, the carrier frequency of optical light is several orders higher than that of electrical signals, and accordingly the transmission bandwidth of optical systems is dramatically increased. The optical fiber developed in the early stage suffers from high signal attenuation of 20dB/km, and the data rate could only reach 45Mb/s with a single wavelength over a single fiber. After two decades of development, the signal attenuation is reduced to 0.2dB/km in today's optical fibers and systems operating at data rates of 10Gb/s, 40Gb/s and even higher over a single wavelength have been commercially available [1-5].

In 1990s, fueled by the fast growth of Internet, the demand for higher bandwidth was expanding dramatically. Optical networks based on wavelength division multiplexing technology (WDM) offer a further boost in fiber transmission system [4]. WDM allows many different data channels to be transmitted over a single optical fiber by allocating each channel to a different optical wavelength. The great advantage offered by WDM is that each wavelength channel can operate independently with the other channels in the fiber, so that different bit-rates, protocols and even modulation schemes can be transmitted concurrently over a single optical fiber.

The first generation optical networks such as the synchronous optical network (SONET) and the synchronous digital hierarchy (SDH) use optical fibers as transmission media simply to provide more capacity [3]. All the switching, routing and signal amplification are conducted in the electronic domain. Optical-to-electrical-to-optical (O-E-O) conversions have to be performed at each network node. As the data rate goes increasingly higher, it becomes more difficult for electronics to perform data processing.

The second generation optical networks - all-optical transparent photonic networks - are already under developing, which will allow the data signals to be routed and transmitted purely in the optical domain without undergoing O-E-O conversions. One key feature of the second-generation optical networks is the service transparency [5]. This implies that a network operator can provide a variety of services using a single network infrastructure. This infrastructure is robust to protocol and data rate changes. New services can be added efficiently and rapidly to the existing network.

Although optical transmission technology offers superior advantages, there are always limiting factors that considerably affect the operation and system performance of the network [7-10]. Erbium-doped fiber amplifiers (EDFAs) play an imperatively important role in optical networks by compensating the signal power loss in the optical domain. However, besides providing gains, EDFAs introduce amplified spontaneous emission noise (ASE) that would accumulate along the transmission path. As a consequence, both signal levels '0' and '1' are scattered from their original position and become difficult to be detected. As the transmission distance and data rate increase, chromatic dispersion and other types of dispersion become a serious

problem, they broaden the signal pulses and cause inter-symbol interference (ISI) that prohibits the data rate from going higher and shorten the transmission distance. Almost all WDM components like optical line terminals (OLT), optical add/drop multiplexers (OADM), and optical crossconnects (OXC) introduce interband and intraband crosstalk. Crosstalk affects the desired signal and results in power penalty to the system. As the transmitted power is vastly increased in today's high speed long haul optical transmission networks, nonlinear effects like four wave mixing (FWM), self-phase modulation (SPM) and cross-phase modulation (XPM) may cause severe distortions to the desired optical signals.

In order to efficiently operate, manage and maintain optical networks, cost-effective optical signal quality monitoring techniques are highly desired [7-9]. Several optical channel monitoring schemes have been reported [9-17]. Most of these techniques are focused on monitoring a single performance parameter, such as optical signal to noise ratio (OSNR) [17-19], or chromatic dispersion [20-23], or channel crosstalk [24-25]. However, the most fundamental performance parameter that can tell the goodness of a digital transmission channel is the bit error rate (BER). The problem with transparent optical channels is that it is difficult to determine the BER directly from the data frame structure such as evaluation of overhead bytes because of the coexistence of multiple frame formats and transmission rates. One promising approach is to make use of distribution properties of binary signals. The distribution properties can be obtained from the optical amplitude histogram. The optical amplitude histograms of data 0's and data 1's can be collected by sampling the received signal synchronously or asynchronously [26-41]. From the histogram, the probability density functions (PDF) of both signal levels can be constructed using single Gaussian approximation

and the BER can be calculated from the overlapping area of the two PDFs. The amplitude histogram approach for estimation of BER is attractive due to its simplicity and transparency. Unfortunately, the accuracy of estimation may not be satisfactory as the single Gaussian assumption is not always valid because it has been observed that different impairments tend to distort the histogram away from Gaussian distribution. Therefore, there is a need to develop a more accurate and robust method to monitor the BER of optical channels.

Since different impairments can cause different distortions on the histogram, such phenomena may also be used for identifying the sources of degradation [29-34], [36-43]. So far there is no standard metric to quantitatively describe how histogram is deformed and hence to distinguish different impairments. An effective approach for identifying various sources of impairments is also desired.

1.2 Objectives

In this work, we aim to develop a novel optical performance monitoring technique that can accurately estimate BER of optical signals especially when they are distorted by various impairments and also to develop a novel methodology for identifying various sources of impairments. Our objectives are as follows:

- To study the impacts from various impairments to the signal waveform, and subsequently analyze their effects on the resulted optical amplitude histogram.
- To compare various existing BER estimation techniques that are based on the amplitude histogram and study their advantages and drawbacks.
- To propose a more accurate and efficient multiple Gaussian curve fitting technique to reconstruct the PDF from the distorted amplitude histogram.

Based on the fitting result, to calculate the BER and to compare it with the result from the conventional single Gaussian approximation method.

- To quantitatively describe the impacts from various types of and different levels of impairments on the amplitude histogram and hence to propose a novel impairment identification technique from the histogram difference and asymmetry property.
- To conduct computer simulations to verify the feasibility and effectiveness of the proposed methods under different network conditions.

1.3 Main Contributions of the Thesis

The main contributions of the thesis are listed as follows:

- A detailed study of the generation of synchronous amplitude histogram is first carried out. Various situations of optical channels distorted by ASE noise, chromatic dispersion, inband crosstalk and fiber nonlinear effects are analyzed individually. From a theoretical point of view, we explain why different impairments deform the histogram in a different way and give the reasons why the conventional single Gaussian approximation method induces a large error in the calculation of BER.
- An improved BER estimation method based on multiple Gaussian curve fitting is proposed. Compared with previous works, the improved BER estimation method does not require the knowledge of the physical parameters of the optical receiver and the frequency spectrum analyzer. The number of Gaussian functions used for fitting is not predefined but is automatically determined based on the distortion level and shape of the histogram. Therefore the

improved method is easier to be implemented and more computationally efficient. This method is verified under different network conditions by simulation experiments. Comparison between the new method and the conventional single Gaussian approximation method has been carried out and the results show that the new method can provide more reliable and accurate BER measurement.

- A novel method based on the histogram difference has been proposed to identify various optical impairments. X^2 distance that is used for color matching in digital image processing is introduced as histogram difference measurement. The relationship between the X^2 distance and the levels of impairments is studied. The histogram asymmetry property is also introduced as an additional parameter to further distinguish the histogram difference. Simulation results show that this method is effective in distinguishing three common types of dominant impairments even under different levels of receiving power.
- Computer simulations using a commercial optical system design software are conducted to validate the proposed techniques. The simulation results show a good agreement with real experimental results that have been acquired by other researchers.

1.4 Organization of the Thesis

The rest of this thesis is organized as follows:

Chapter 2 gives a literature review of current optical channel monitoring techniques. Among them, the amplitude histogram method is of most interest and is discussed in detail. The drawbacks of current optical channel monitoring methods are also discussed.

Chapter 3 discusses how an amplitude histogram is deformed by different impairments. By summarizing some existing analytical results that are available in literature, we study the effects of inter-symbol interference from dispersion, phase noise from inband crosstalk and FWM, ASE-to-ASE and signal-to-ASE beating noise.

Chapter 4 proposes an improved BER estimation method based on multiple Gaussian curve fitting on amplitude histogram. An example is used to illustrate the fitting process. The effectiveness of the proposed method is verified by computer simulation using a commercial optical design simulation tool – *VPI TransmissionmakerTM*.

Chapter 5 proposes a novel impairment identification technique based on the histogram difference. X^2 distance together with histogram asymmetry properties of signal space and mark is used for identifying different impairments. Computer simulations are also carried out for verification.

Chapter 6 concludes this thesis and briefly discusses the possible future works.

Chapter 2 Review of Current Optical Channel Monitoring Techniques

In this chapter, we first discuss the major sources of impairments that may be present in optical transmission systems. We then review the current channel monitoring techniques, including specialized and general-purpose techniques. We put our focus on reviewing the optical amplitude histogram method.

2.1 Major Sources of Signal Degradation in Optical Channels

2.1.1 Amplifier Noise

Optical amplifier is an essential component in optical networks to compensate power losses. The most common optical amplifier today is the erbium-doped fiber amplifier (EDFA) [6]. The great advantage of EDFAs is that they are able to amplify many WDM channels simultaneously in optical domain regardless of their bit rates. However, an EDFA is not a perfect device, in addition to providing gain, it also introduces noise. The dominant noise generated by an optical amplifier is the amplified spontaneous emission (ASE) noise. It comes from the spontaneous recombination of electrons and holes in the amplifier medium. This recombination gives rise to a broad spectral background of photons that get amplified along with the optical signal. Normally it can be treated as Gaussian-distributed optical white noise. It causes fluctuation of the signal level and hence reduces the optical signal to noise ratio (OSNR). At the optical receiver, ASE noise beats with the desired signal and

ASE noise itself. These ASE-to-ASE and signal-to-ASE beating noises may severely distort the distribution property of signal spaces and marks [52-53].

2.1.2 Crosstalk

Crosstalk is the effect of other signals interfering with the desired signal [1-3]. Crosstalk may be generated from almost every component in the optical transmission system. There are two types of crosstalk: interband crosstalk and intraband crosstalk. Interband crosstalk (also known as out-of-band crosstalk) is the interference from adjacent channels with different wavelengths, which is mostly due to the imperfection of optical devices such as filters, demultiplexers, and space switches. Intraband (also known as inband crosstalk) crosstalk comes from the signal with the same wavelength as the desired signal or sufficiently close to it. Interband crosstalk can be suppressed by providing additional optical filtering. However, the intraband crosstalk is at the same wavelength as the desired signal, once present, it cannot be filtered out. In most cases, intraband crosstalk is much more detrimental than interband crosstalk [44-49].

Intraband crosstalk can be further classified into two categories: incoherent crosstalk and coherent crosstalk [46]. Incoherent crosstalk occurs when the relative optical phases of the desired and crosstalk signals vary randomly on a time scale that is comparable to the coherence time of the optical source of the desired signal. Coherent crosstalk occurs when the relative phases of the desired and crosstalk signals are fixed, or drift on a time-scale that is much smaller than the coherence time of the optical source.

2.1.3 Dispersion

Dispersion is the effect that different spectral components of the transmitted signal travel at different velocities in the fiber, arriving at different times at the receiver [1-5] [11]. In a multi-mode fiber (MMF), inter-modal dispersion dominates. In an MMF fiber, the energy in pulse travels in different modes, each with a different speed. At the end of the fiber, the different modes arrive at slightly different times, resulting in a broaden pulse. In a single-mode fiber (SMF), inter-mode dispersion is absent and hence fiber transmission length can be greatly increased. However, even in an SMF fiber, pulse spread still occurs. This is due to another form of dispersion, namely, intra-modal dispersion or chromatic dispersion. There are two contributions of chromatic dispersion: the material dispersion and waveguide dispersion. Material dispersion arises because the refractive index of the core material (silica) is a function of frequency. Thus different frequency components travel at different speed in the silica fiber, even different wavelengths follow the same path, signal pulses will still become spreading. Waveguide dispersion arises because the power distribution of a mode between the core and cladding of the fiber is a function of the wavelength. Even in the absence of material dispersion, if wavelength changes, the power distribution changes, causing the effective index or propagation constant of the mode to change. Chromatic dispersion is a cumulative process, the longer the link, the greater amount of the dispersion. Hence it is an important limiting factor in today's long haul transmission networks.

Another type of dispersion is the polarization-mode dispersion (PMD) [12]. The origin of PMD is that the light energy of a pulse propagating in a fiber is usually split between two orthogonally polarized modes. Because of the ellipticity of the fiber

core, light with different polarizations travels with different group velocities. But unlike the two kinds of dispersion we discussed above, PMD does not change linearly with the length of the fiber because the fiber birefringence changes randomly over the length of the fiber and is sensitive to environmental changes like temperature variation. The difference in group velocity gives rise to pulse spreading.

All the above dispersions cause inter-symbol interference (ISI), which is an effect that the neighboring pulses overlap with each other and cause misinterpretation of transmitted data signals at the receiver [13].

2.1.4 Fiber Non-Linearity

Fiber non-linear effect is an important issue when the optical power within the fiber is high [1-3], [14-16]. This is because, in reality, both the loss and refractive index depend on the optical power in the fiber, when the optical power is low, the fiber can be treated as a linear medium. However, high bit rates such as 10 Gb/s and above require higher transmission power, the effect of fiber non-linearity has to be taken into account. Generally speaking, there are two categories of non-linear effects. The first category is due to the interaction of light waves with photons in the silica medium. Two main effects in this category are stimulated Brillouin scattering (SBS) and stimulated Raman scattering (SRS). The second type of nonlinear effect is due to the dependence of the refractive index on the intensity of the applied field, which in turn is proportional to the square of the field amplitude. Self-phase modulation (SPM), cross-phase modulation (XPM) and four wave mixing (FWM) are the three main effects in the second category.

SPM and XPM make the signal phase change and result in spectral broadening, which have similar effects as chromatic dispersion [14]. FWM occurs when two or more frequencies of light propagate through an optical fiber together [15,50]. Providing a condition known as phase matching is satisfied, light at a new frequency is generated using optical power from the original frequencies. The new frequency may fall into the same bandwidth as the desired signal and its effect may be similar to inband crosstalk.

2.2 Optical Signal to Noise Ratio (OSNR) Monitoring

OSNR is an important parameter for evaluating the performance of a system comprised of optical amplifiers. Several techniques focused on optical spectrum analysis were reported in [16-18]. The signal power can be measured at the desired wavelength and the noise power can be measured at the wavelength that is adjacent to the desired one (Figure 2-1).

Figure 2-1 OSNR monitoring using spectrum analysis

However, this approach is not effective in the presence of multi-path interference effects, amplifier pump laser relative intensity noise (RIN) and four-wave mixing

(FWM) because the power level adjacent to signal channel is not stable. Further more, in dense WDM (DWDM) systems, the actual noise level is difficult to be monitored, because the signal spectrum is too narrow. Figure 2-2 illustrates the difficulty with dense channel packing. The actual noise level is shown near 1566 nm, where a channel has been turned off whereas noise levels derived from other adjacent channels are much higher than the actual one.

Figure 2-2 Errors in ASE noise measurement from dense packed spectrum [7]

Other than optical spectrum analysis, optical polarization-nulling method was proposed in [18-19]. This is based on the assumption that optical signal has a well-defined polarization whereas optical noise is unpolarized. With such a method, an optical polarizer is used to separate the desired signal and noise signal as shown in Figure 2-3. An arbitrary polarized signal with ASE noise is firstly changed to a linearly polarized signal by adjusting a polarization controller, then the linearly polarized signal and ASE noise are split into two polarization components (in which one polarization component consists of signal and ASE noise, while the other contains ASE noise only). The signal power together with the polarized ASE noise can be measured using a linear polarizer, which is aligned to the signal's polarization, the

polarized ASE noise can be measured using the second linear polarizer, which is in the orthogonal state to the signal's polarization. However, optical signals do not always behave well with respect to polarization, especially in long haul transmission systems, polarization fluctuations are impractical to track.

Figure 2-3 Polarization nulling for OSNR monitoring [17]

In a practical optical channel monitoring system, OSNR itself is not sufficient to tell how the network condition is. For example, in a dispersive environment, the OSNR may be very high whereas the BER is actually high as a result of ISI.

2.3 Dispersion Monitoring

One effective method for monitoring chromatic dispersion is to make use of subcarrier (pilot tone) multiplexing [21-23]. This is based on the fact that chromatic dispersion causes periodic power fading of an RF subcarrier tone after detection by a square law detector. The reason is that the frequency-dependent dispersion produces a harmful time delay between the two transmitted sidebands, thereby causing serious

RF power fading. As shown in Figure 2-5, a subcarrier is inserted at the transmitter, the upper and lower bands of the subcarrier is initially in phase with each other. During the transmission in the fiber, a phase difference accumulates between the two sidebands as a result of the frequency dependent fiber chromatic dispersion. The degree of phase mismatching is related to the amount of accumulated dispersion. Therefore it can be used for dispersion measurement.

Figure 2-4 Subcarrier multiplexing technique for chromatic dispersion monitoring [21]

This method could achieve a good accuracy in measuring chromatic dispersion, but it requires modification of the transmitter.

An improved method is to detect the relative group delay between the upper and lower vestigial-sideband (VSB) signals in the transmitted data [22]. As shown in Figure 2-4, the lower and upper vestigial sidebands are obtained by tuning an optical filter away from the optical spectrum center of the double-sideband data. Since the two optical sidebands occupy different wavelength ranges, fiber chromatic dispersion

induces a relative group velocity between the lower and upper VSB signals. The group delay can be used to evaluate the chromatic dispersion without modification at the transmitter.

Figure 2-5 Chromatic dispersion monitoring using vestigial sideband (VSB) filtering [22]

2.3.1 Crosstalk Monitoring

Pilot tone can also be used for crosstalk monitoring especially in a dynamic WDM network, because the pilot tones are bound to follow their corresponding optical signals anywhere in the network [24,25]. Pilot tones with unique tone frequency can be applied to each laser transmitter by adding a distinct sinusoidal current to the injection current. Thus each optical path in this network could be monitored easily by tracking the relevant tone frequency since every channel is assigned with a unique tone frequency. In Figure 2-6, 4 WDM signals $\lambda_1 - \lambda_4$ in the range of 1550.92-1555.75nm are transmitted at 8 different nodes, at each node a unique tone frequency is bounded to the signal. At the outputs of the optical switch, Fast Fourier Transform

(FFT) is applied to monitor the signal spectrum, from the spectrum, crosstalk from different nodes can be identified by the corresponding tone frequency.

Figure 2-6 Optical path and crosstalk monitoring using pilot tone [24]

Pilot tone technique also has its limitations. Firstly, unwanted amplitude modulation on the data signal may be induced, which will degrade the receiver sensitivity. Secondly, ghost tones generated by crosstalk-gain modulation and stimulated Raman scattering may deteriorate the desired signal.

2.4 Bit Error Rate Estimation Using Amplitude Histogram

The most direct and general way to evaluate the performance of digital transmission system is to estimate the Bit Error Rate (BER). But in transparent transmission environment with multiple services and data rates, it is difficult to monitor the BER directly from the protocol layer. One promising way is to use signal amplitude

histograms and signal Q -factor measurements. Q -factor has strong relationship with BER and it can be obtained from the signal amplitude histogram [26-36].

The eye diagram has been used to determine the goodness of digital signal. The eye diagram can be obtained by supposition of bit patterns. The vertical opening of eye implies the degree of bit errors due to impairments. A widely opened eye shows a better quality of a digital signal over a narrowly opened eye. However, the eye diagram is only a qualitative description. In order to evaluate the digital signal more precisely and to obtain more information from eye diagram, amplitude histogram is used. Amplitude histogram can be obtained by sampling the eye diagram at the most widely opened position as shown in Figure 2-7. In binary digital communication systems, there are only two possible signal levels: data “1” and “0” or mark and space. The amplitude histogram describes the signal distribution characteristics of mark and space. If the signal is undistorted, the signal levels are concentrated at their initial positions and the resulting histogram will display two distinct humps corresponding to the mark and space levels. However, if the signal is degraded by impairments in the network as we mentioned in the previous section 2.1, both the mark and space levels will be scattered and the histogram will appear to be a flat bell shape. To decide whether ‘1’ or ‘0’ has been transmitted, a threshold decision level needs to be determined. When a bit ‘1’ (or ‘0’) is transmitted, if it goes below (or above) the decision threshold level at the receiver, a bit error occurs. An optimized threshold level can be chosen by varying the decision threshold until the minimum BER is reached.

Figure 2-7 Generation of amplitude histogram

Generally speaking, there are two types of sampling methods: synchronous sampling and asynchronous sampling [26,28,29]. Synchronous sampling requires the precise system timing information of the signal. In other word, signal clock has to be recovered. With synchronous sampling, the data samples can be collected at exactly the most widely opened position of the synchronous eye. Therefore, the synchronous histogram can accurately capture the signal distribution properties. In contrast, asynchronous sampling does not require system timing and the sample is collected randomly throughout the bit stream, and hence the equipment set up can be greatly simplified. However, the histogram includes samples across the entire bit period, a large amount of undesired samples in the transient region between the mark and space are also collected to form the histogram. This hides the exact distribution properties of the mark and space. Although some researchers have reported different methods to remove the undesired samples in the transient portion to reconstruct the synchronous histogram [32-33], the accuracy is always not as satisfactory as synchronous sampling method, which will be discussed in the next section.

If the composite optical noise at the input of the decision circuit is assumed to be a Gaussian noise, and the mark and the space of the signal are of equal probabilities, the BER can be calculated by [1-3], [26]

$$BER = \frac{1}{2\sqrt{2\pi}\sigma_0} \int_{I_{th}}^{\infty} \exp\left[\frac{-(I_{th} - \mu_0)^2}{2\sigma_0^2}\right] di + \frac{1}{2\sqrt{2\pi}\sigma_1} \int_{-\infty}^{I_{th}} \exp\left[\frac{-(\mu_1 - I_{th})^2}{2\sigma_1^2}\right] di \quad (2.1)$$

where σ_0 and σ_1 are the standard deviation of the signal space and the signal mark, respectively; μ_0 and μ_1 are the mean of the signal space and the signal mark, respectively; I_{th} is the decision threshold.

With such a Gaussian assumption, we only need to know the means μ_0 and μ_1 and standard deviations σ_0 and σ_1 of the signal mark and space. The error probability can be calculated accordingly. Generally, the BER performance is evaluated at the optimum decision level I_{th} that minimizes the BER. The minimum BER (BER_{min}) can be calculated by:

$$BER_{min} = \frac{1}{2} \operatorname{erfc}\left(\frac{Q}{\sqrt{2}}\right) \quad (2.2)$$

where $\operatorname{erfc}(x)$ is the complementary error function given by:

$$\operatorname{erfc}(x) = \frac{2}{\sqrt{\pi}} \int_x^{\infty} e^{-y^2} dy \quad (2.3)$$

and the Q factor is given by:

$$Q = \frac{\mu_1 - \mu_0}{\sigma_1 - \sigma_0} \quad (2.4)$$

The BER calculation in (2.1) and (2.2) is valid only when the noise distribution can be approximated as Gaussian distribution. However, in practical systems, optical signal

distortions resulting from various sources such as dispersion, crosstalk, and fiber nonlinear effects are not Gaussian noises. Therefore, a better method is needed for evaluating BER of optical signals that are distorted by non-Gaussian noises. In the next section, some of the existing amplitude histogram monitoring methods are reviewed.

2.5 Review of Amplitude Histogram Monitoring Methods

2.5.1 Asynchronous Sampling Method

Current optical transmission system has reached the data rate as high as 320Gbit/s in the laboratory [35]. To get synchronous sampling, electrical equipment with such a high clock rate recovery will be very costly. As discussed in the previous section, asynchronous sampling can greatly reduce the complexity of the equipment setup in acquiring the amplitude histogram of an optical signal. However, the main difficulty is how to remove the undesired samples from the transient region. Several possible solutions have been proposed to reconstruct the acquired histogram.

The cut and flip method reported in [32] is based on the assumption that the histogram's edges are only influenced by the noise distributions, and not by the transient. The histogram is therefore symmetric with respect to its peak. With this assumption, the outer edges representing the noise distribution are flipped inside to construct an approximate model of the PDF (Figure 2-8). This method is more appropriate for systems influenced by low ASE noise only because a small amount of amplifier noise could be treated as Gaussian approximately. However, it can be seen

in the next chapter that impairs like dispersion, crosstalk and high ASE noise tend to cause asymmetry of the histogram. Thus this method has limited application.

Figure 2-8 Cut and flip method for reconstruction of PDF from asynchronous histograms

Another method is called average Q factor [27, 31]. As discussed in the previous section, Q factor is an essential parameter to evaluate BER. In case of asynchronous sampling method, the Q factor cannot be obtained directly using the standard deviation and mean because sufficient amount of undesired samples are collected in the transient region. In order to collect the effective sampled points that constitute the histogram and reject the unwanted ones, Shake *et al* [27, 31] used two threshold levels (Figure 2-9).

Figure 2-9 Definition of average Q factor [27]

As shown in Figure 2-9, they determined the set of points higher than a predetermined threshold level, μ_{th1} , belonging to mark, and the set of points lower than a predetermined threshold level, μ_{th0} , belonging to space. The average Q (Q_{avg}) is then defined as:

$$Q_{avg} = \frac{|\mu_{1,avg} - \mu_{0,avg}|}{\sigma_{1,avg} + \sigma_{0,avg}} \quad (2.5)$$

The threshold level for the mark is

$$\mu_{th1} = \mu_{1,avg} - \alpha |\mu_{1,avg} - \mu_{0,avg}| \quad (2.6)$$

and the threshold level for the space is

$$\mu_{th0} = \mu_{0,avg} + \alpha |\mu_{1,avg} - \mu_{0,avg}| \quad (2.7)$$

where the coefficient α lies between 0 to 0.5.

In order to choose an appropriate value of α , they studied the linear relationship between the real Q and the average Q_{avg} using the least squared method. Shake *et al.* showed that when α was chosen to be 0.3, the real Q and the average Q_{avg} agreed quite well.

2.5.2 Sub-harmonic Sampling Method

The synchronous sampling method can provide a much higher accuracy than the asynchronous sampling method. However, ultra-high speed electronic clock recovery is very complex and expensive. A compromise solution is to use sub-harmonic sampling method [37]. The sampling rate is set to be 1/8 or 1/16 of the bit rate. In such a way, the histogram obtained is very similar to the synchronous histogram.

However, because the sampling rate is reduced, a longer time is required to get enough number of samples and the original data rate still needs to be known.

2.5.3 Eye Diagram Reconstruction from Asynchronous Sampling

Shake *et al.* further proposed a method for reconstructing the synchronous eye diagram using asynchronous sampling [33]. They suggested that a synchronous eye diagram could still be reconstructed even when the sampling frequency did not exactly follow the system timing as long as the local sampling frequency (f_c), the number of required samples (N_{sam}) and the system bit rate (f_s) follow the following relationship

$$f_c \geq \sqrt{2f_s N_{sam} |\delta f|} \quad (2.8)$$

where δf is the frequency detuning between the sampling clock frequency and signal bit rate frequency. For example, if f_s is 10 Gb/s, f_c is at 1 GHz and N_{sam} is limited to 250, it allows an inaccuracy in the setting of f_c (δf) to the level of ± 200 kHz.

Such a relationship shows that a certain level of variation between the sampling frequency and the signal bit rate is acceptable when constructing synchronous eye diagram and hence obtaining the synchronous amplitude histogram. However, we should also notice that the frequency variation is inversely proportional to the number of samples. To capture the distribution properties of the received signal, a large number of samples are always expected. Consequently, the sampling frequency

variation is very limited. This method is also non-effective to the Return-to-Zero (RZ) signal as the signal period is too short.

2.5.4 Histogram and Impairment Identification

Besides BER estimation, it has been reported that the amplitude histogram can also be used for impairment identification [27], [29-32], [34], [38-41]. Weiner *et al.* [34] have shown that a small number of inband crosstalk signals tend to cause a prong shape at the mark level due to phase mismatching, and the width of the mark is proportional to the level of the crosstalk signal. However when the crosstalk level is low, it is difficult to figure out the multiple peaks of the histogram. This is due to the receiver noise imposed on each rail, which hides the actual distribution property. They further proposed a method using Gaussian deconvolution to remove the effect of the receiver noise [34]. Numerical approach using Fast Fourier Transform (FFT) was conducted to find a proper Gaussian function to represent the receiver noise. After the deconvolution, the resultant histogram shows multiple peaks more clearly. They also pointed out that this approach is effective for identifying inter-symbol interference (ISI) because ISI also incur multiple peaks on the histograms of both space and mark. Similar experiment has also been carried out by Y. Benlachtar *et al.* [41]. However, their work still remains a qualitative description. Shake *et al.* [30] attempted to describe the changing of histogram quantitatively. They analyzed the amplitude histogram property directly from the mean and standard deviation and indicated that the accumulation of chromatic dispersion caused the standard deviation of mark (σ_1) to increase and also caused the difference between the average mean of space and mark $|\mu_{1,avg} - \mu_{0,avg}|$ to decrease when the received power is kept constant (the definition of average mean and standard deviation can be found in Figure 2-9). They

normalized the $\sigma_{l,avg}$ and $|\mu_{1,avg} - \mu_{0,avg}|$ of the undistorted histogram to be 1 and plotted the normalized $\sigma_{l,avg}$ and $|\mu_{1,avg} - \mu_{0,avg}|$ versus the dispersion value. The vertical distance from $\sigma_{l,avg}$ to 1 is denoted as $X_{\sigma l}$, which represents the changing of the $\sigma_{l,avg}$, similarly, X_{μ} represents the changing of the $|\mu_{1,avg} - \mu_{0,avg}|$, (Figure 2-10).

Figure 2-10 Definition of $X_{\sigma l}$ and X_{μ} [30]

Subsequently, he plotted $|X_{\sigma l} + X_{\mu}|$ against chromatic dispersion. As the dispersion increases linearly, the value $|X_{\sigma l} + X_{\mu}|$ also increases but in a non-linearly way, as can be seen in Figure 2-11.

Figure2-11 $|X_{\sigma l} + X_{\mu}|$ versus chromatic dispersion [30]

The drawbacks of this method are that the parameters used are still based on the assumption of Gaussian distribution and the authors did not give us convincing evidence showing that their method is also effective in determining or differentiating other impairments such as crosstalk and non-linear effects.

2.6 Summary

In this chapter we reviewed various channel monitoring techniques including spectrum analysis and polarization nulling for OSNR measurement, the use of a pilot tone for dispersion and crosstalk monitoring, and the amplitude histogram method for BER estimation and impairments identification. Among them, the amplitude histogram technique is very attractive. The amplitude histogram method makes use of the distribution properties of signal mark and space. When we only consider the optical receiver noise, the signal PDF can be well modeled as a Gaussian distribution. The BER estimation can be easily evaluated from the means and variances of the space and the mark. However, when the optical signal is distorted by various impairments, the histogram may no longer follow Gaussian distribution. Therefore, directly applying single Gaussian approximation may induce large error in estimating the BER. We also compared synchronous sampling with asynchronous sampling method. Although asynchronous sampling is simpler and more economical, its accuracy can hardly be satisfactory. Hence, in the following chapters, our studies will be based on synchronous sampling method. Besides BER estimation, the amplitude histogram can also be used for channel impairments identification. These techniques are based on the fact that different impairments cause different deformation to the histogram. However, the main challenge is how to effectively quantify the impacts

from different impairments on the histogram in order to identify and distinguish them.

In the following chapters, we intend to address these problems.

Chapter 3 Analysis of the Causes of Amplitude Histogram Distortion

It has been observed that different impairments cause the amplitude histogram to deform differently [29], [34], [38-41]. For this reason, the conventional single Gaussian approximation fails to estimate BER accurately. In this chapter, we discuss and summarize the impacts from several common types of impairments on signal's amplitude histogram. By reviewing some existing research results, we illustrate how different impairments affect the amplitude histogram so as to get a better understanding of the effects of different impairments on the amplitude histogram.

3.1 Inter-Symbol Interference (ISI)

It is well known that chromatic dispersion, polarization mode dispersion and narrow filtering all cause signal pulse broadening [42]. The broadened signal pulse interferes with its neighboring pulses and finally makes the signal undistinguishable at the receiver. Such a phenomenon is known as inter-symbol interference (ISI). Due to the effect of ISI, the resulted amplitude histogram is also distorted. To simplify the analysis, the input signal pulse at the transmitter is assumed to be Gaussian, which can be represented as:

$$A(0, t) = A_0 \exp \left[-\frac{1}{2} \left(\frac{t}{T_0} \right)^2 \right] \quad (3.1)$$

where A_0 is the peak amplitude and T_0 is the half width at $1/e$ intensity point.

The propagation equation that governs pulse evolution inside a single-mode fiber is given by [1]:

$$\frac{\partial A}{\partial z} + \frac{i}{2} \beta_2 \frac{\partial^2 A}{\partial t^2} - \frac{1}{6} \beta_3 \frac{\partial^3 A}{\partial t^3} = 0 \quad (3.2)$$

where A is the amplitude of input signal, β_2 is a parameter related to the dispersion parameter D by $D = -\frac{2\pi c}{\lambda^2} \beta_2$, and β_3 is related to the second-order dispersion parameter S by $S = (2\pi c / \lambda^2)^2 \beta_3 + (4\pi c / \lambda^3) \beta_2$.

To solve the above equation in the Fourier domain, and we get:

$$A(z, t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \tilde{A}(0, \omega) \exp\left(\frac{i}{2} \beta_2 z \omega^2 + \frac{i}{6} \beta_3 z \omega^3 - i\omega t\right) d\omega \quad (3.3)$$

where $\tilde{A}(0, \omega)$ is the Fourier transform of equation (3.1).

Assuming the carrier wavelength is far from zero-dispersion wavelength so that the contribution from β_3 is negligible, after traveling a distance Z , due to chromatic dispersion the pulse becomes:

$$A(Z, t) = \left(\frac{A_0 T_0}{\sqrt{T_0^2 - i\beta_2 Z}} \right) \exp\left(-\frac{t^2}{2[T_0^2 - i\beta_2 Z]}\right) \quad (3.4)$$

The above equation shows that a Gaussian pulse remains Gaussian after the propagation, while the pulse width is increased as a function of distance Z :

$$T_1 = T_0 \left[\left(1 + \frac{C\beta_2 Z}{T_0^2} \right)^2 + \left(\frac{\beta_2 Z}{T_0^2} \right)^2 \right]^{1/2} \quad (3.5)$$

where T_1 is the half-width at $1/e$ of the signal after it transmits a distance Z and the pulse amplitude A_1 is reduced to:

$$A_1 = A_0 \frac{\sqrt{T_0^2 - i\beta_2 Z}}{T_0} \quad (3.6)$$

where A_0 is the peak amplitude of the signal at the transmitter.

Considering the patterning effect of the neighboring 3 digits, there are eight possible combinations which are (1,1,1), (1,1,0), (1,0,1), (1,0,0), (0,1,1), (0,1,0), (0,0,1) and (0,0,0). The eye diagram is a superposition of the above eight bit patterns.

Figure 3-1 Eye diagram comprised of 8 rails, (a) without receiver noise. (b) with receiver noise imposed

Figure 3-1 (a) shows the eye diagram comprised of 8 rails without considering receiver's noise and (b) shows the eye diagram after the receiver noise is imposed [41-43]. Sampling the eye-diagram at the most opened position, we can obtain the amplitude histogram that contains 6 possible signal levels and we may mark them as h_1 , h_2 , h_3 , h_4 , h_5 and h_6 . Table 1 illustrates the relationship between these 6 signal levels and their corresponding data patterns.

	h_1	h_2	h_3	h_4	h_5	h_6
Data patterns	(0,0,0)	(0,0,1) and (1,0,0)	(1,0,1)	(0,1,0)	(0,1,1) and (1,1,0)	(1,1,1)

Table 1 Rails in an eye diagram formed by data patterns comprised of 3 bits

Since h_2 is the cross-section point of functions $A(Z, t)$ and $A(Z, t-2T_0)$, h_2 is the height of the pulse at time T_0 , and hence

$$h_2 = \left(\frac{A_0 T_0}{\sqrt{T_0^2 - i\beta_2 z}} \right) \exp\left(-\frac{(t-T_0)^2}{2[T_0^2 - i\beta Z]}\right) \quad (3.7)$$

h_3 is approximately twice of h_2 ,

$$h_3 = 2 \times \left(\frac{A_0 T_0}{\sqrt{T_0^2 - i\beta_2 z}} \right) \exp\left(-\frac{(t-T_0)^2}{2[T_0^2 - i\beta Z]}\right) \quad (3.8)$$

h_4 is the peak value of single Gaussian pulse after transmission

$$h_4 = \frac{A_0 T_0}{\sqrt{T_0^2 - i\beta_2 z}} \quad (3.9)$$

h_6 is the signal level of continuous '1', therefore it follows the original signal level.

$$h_6 = A_0 \quad (1.10)$$

Assuming that h_5 lies approximately in the middle of h_4 and h_6 , then

$$h_5 = \frac{1}{2} \left(A_0 + \frac{A_0 T_0}{\sqrt{T_0^2 - i\beta_2 z}} \right) \quad (3.11)$$

From the above derivation, we may see that ISI causes at least 6 possible rails.

Assuming the occurrence of each bit sequence is the same, and then the occurrence of h_2 and h_5 should be double of the others rails, as shown in Figure 3-2.

Figure 3-2 Occurrence of difference signal levels

Considering the effect of the optical receiver noise and assuming that the optical receiver imposes the Gaussian noise equally on each rail. The overall histogram of space and mark is a superposition of 6 Gaussian curves, as illustrated in Figure 3-3.

Figure 3-3 Amplitude histogram consisting of 6 Gaussian curves each corresponding to a rail.

It should be noted that the above analysis is based on a simplified model. Firstly, the signal pulse at the transmitter is assumed to be Gaussian. In a real system, the signal pulse may not be an exact Gaussian pulse. Secondly the rails may not exactly follow the described position, for example, h_2 and h_5 may not lie exactly in the middle of the neighboring rails. Thirdly, optical receiver may impose different noise levels on different rails, higher signal levels (h_4 , h_5 , h_6) may have a larger variance due to signal-to-noise beating and therefore the mark may have a larger variance. Fourthly, we only considered a 3-bit sequence that form the six rails, in fact, other rails formed by other bit sequences may also affect the resulted histogram.

Although the above analysis is greatly simplified, we still can clearly see that the amplitude histogram of a signal distorted by ISI cannot be approximated as a single

Gaussian, but may be considered as a superposition of multiple Gaussian functions with different means and variances.

3.2 Phase Noise of Interacting Signals

Intraband crosstalk (also known as inband crosstalk) and four wave mixing (FWM) can introduce severe signal interference [44-49]. The interference can be either constructive or destructive depending on the phase difference. For the simplicity of analysis, we first study the impact of a single inband crosstalk signal on the amplitude histogram.

The effect of crosstalk can be analyzed by examining the field equation. If we consider the interaction between a main field E_0 and an interfering field E_1 , each field can be written as:

$$\tilde{E}_k(t) = E_k \exp\{j[\omega_k t + \phi_k(t)]\} \quad (3.12)$$

where E_k is the field magnitude, ω_k is the angular frequency and $\phi_k(t)$ is the phase noise of the field source [46]. The optical power due to interference between these two fields is given by [47]:

$$P_{tot}(t) = |\tilde{E}_0 + \tilde{E}_1|^2 = E_0^2 + E_1^2 + 2E_0E_1 \cos[(\omega_0 - \omega_1)t + \phi_0(t) - \phi_1(t)] \quad (3.13)$$

In the case of interband crosstalk, the beating frequency of the two field, $(\omega_0 - \omega_1)/2\pi$, is outside of the electrical bandwidth of the receiver and its effect can

be removed by a filter. Only the first two terms remain, so the effect of interband crosstalk is simply to give additional power at the receiver. Therefore, the effect of interband crosstalk on BER is very limited. However, when the beat frequency of the two fields fall into the bandwidth of the receiver, which is the case of inband crosstalk, the effect is much more detrimental.

For inband crosstalk, there are two possible conditions about the phase noise $\phi_0(t)$ and $\phi_1(t)$. The first condition is when the phase difference $(\phi_0(t) - \phi_1(t))$ is a constant over the time. This is valid when the signals are generated by the same optical source. The other condition is the phase difference varies rapidly and randomly over $[0, 2\pi]$. This occurs when the interfering fields are generated by either one or multiple optical sources, which is more common in practical systems. For the second condition, the received power fluctuates over the range $|E_0 \pm E_1|^2$. The above equation thus can be simplified to:

$$P_{tot}(t) = E_0^2 + E_1^2 + 2E_0E_1 \cos[\Delta\phi(t)] \quad (3.14)$$

where $\Delta\phi = \phi_0(t) - \phi_1(t)$ is the phase difference between the two interfering fields. The effect is illustrated in Figure 3-4.

Figure 3-4 Interaction of two optical fields at the same wavelength but with different phases.

The maximum value of E_{tot} occurs when E_0 and E_1 are in phase ($\Delta\phi=0$), and the minimum when E_0 and E_1 are out of phase ($\Delta\phi=\pi$). The probability density function (PDF) F_{tol} of the resulting power P_{tol} is given by [45]:

$$F_{tol}(P_{tol}) = \frac{1}{\pi \sqrt{(2E_0E_1)^2 - (P_{tol} - E_0^2 - E_1^2)^2}} \quad (3.15)$$

where $(E_0 - E_1)^2 < P_{tol} < (E_0 + E_1)^2$

The plotted PDF in Figure 3-5 obviously does not follow a Gaussian distribution [38-49].

Figure 3-5 The PDF of an optical signal affected by an inband crosstalk signal [49]

There are four possible data combinations due to signal intraband crosstalk: (0,0), (0,1), (1,0), (1,1), where the first digit in the brackets is the data bit of the main signal and the second is the data bit of the interfering signal, assuming the power ratio of the interfering signal to the main signal is ε . The four combinations at the receiver are shown in Figure 3-6.

Figure 3-6 Crosstalk effect from four different bit combinations [46]

In Figure 3-6, we may observe that the crosstalk has a relative large effect on the distribution of the mark while the effect on space is negligible. If we consider the effect of the receiver noise (approximately Gaussian) that imposed on each rail, the overall PDF of the space and mark will show in Fig. 3-7:

Figure 3-7 Optical amplitude histogram distorted by inband crosstalk

The mark appears to be a well-known prong shape and the space also tends to be slightly unsymmetrical. The level of distortion is proportional to the relative power of interfering signal ε .

Nonlinear effect of FWM also causes similar effect as inband crosstalk. To simplify the analysis, we consider the case of 3 equally-spaced wavelengths: ω_1 , ω_2 and ω_3 . The most detrimental wavelength generated due to FWM follows the formula [50]:

$$\omega_{ijk} = \omega_i + \omega_j - \omega_k, \quad i \neq j \neq k \quad (3.16)$$

If we only consider the wavelength signal in the middle, the generated new wavelengths may impose two inband crosstalk terms on the desired channel as shown in Figure 3-8.

Figure 3-8 FWM induced crosstalk on the middle wavelength

The power of the signal generated at frequency ω_{ijk} due to FWM is governed by [3,14]

$$P_{ijk} = \eta_{ijk} \left(\frac{\omega_{ijk} n d_{ijk}}{3cA_e} \right)^2 P_i P_j P_k L_e^2 \quad (3.17)$$

where n is the nonlinear refractive index, d_{ijk} is the degeneracy factor, P_i , P_j and P_k are the respective power of the mixing waves, L_e is the effective fiber length. A_e is the effective cross-section area of the fiber and η_{ijk} is the efficiency of mixing of the three waves. η_{ijk} can be expressed as equation (3.18) [3,14].

$$\eta_{ijk} = \frac{\alpha^2}{\alpha^2 + (\Delta\beta)^2} \left[1 + \frac{4e^{-\alpha l} \sin^2(\Delta\beta l / 2)}{(1 - e^{-\alpha l})^2} \right] \quad (3.18)$$

where $\Delta\beta$ represents the phase matching between different waves. $\Delta\beta$ is reduced when the channel spacing is reduced or when the dispersion is compensated. η_{ijk} is

inversely related to $\Delta\beta$. Hence in a WDM system, FWM is closely related to the channel spacing and total dispersion of the fiber link.

It should be noted that when the number of crosstalk wavelengths increases, the prong shape of the mark will not be obvious. It has been reported that when there are more than 8 crosstalk wavelengths, the distribution of the mark could be well approximated as Gaussian distribution [51]. Such effect will be discussed in the later chapters.

3.3 ASE-to-ASE and Signal-to-ASE Noise Beating

When the receiver's thermal noise and shot noise are dominant, the PDF of the detected signal can be well approximated as Gaussian distribution. However, in a system that is dominated by ASE noise, the condition becomes complicated. Marcuse gave a detailed analysis on deriving the PDF of signal in presence of ASE noise and the procedure is summarized below [52-53]:

The electrical field of the optical signal can be expressed as a time function $E(t)$ and the ASE noise can be expressed as a corresponding function $e_s(t)$. Their squares are proportional to the corresponding optical power by:

$$P_{Ls} = Q\overline{E_s^2} \quad (3.19)$$

$$P_{Lsp} = Q\overline{e_{sp}^2} \quad (3.20)$$

where P_{Ls} and P_{Lsp} are the optical power of $E(t)$ and $e_s(t)$, Q is a constant, $\overline{E_s}$ and $\overline{e_{sp}}$ are the short-time average values of $E(t)$ and $e_s(t)$, respectively. The optical power is related to the photocurrent by:

$$I_s = \eta \frac{q}{hf} P_{Ls} = K \overline{E_s}^2 \quad (3.21)$$

$$I_{sp} = \eta \frac{q}{hf} P_{Lsp} = K \overline{e_{sp}}^2 \quad (3.22)$$

where η is the quantum efficiency of the detector, h is Planck's constant, q is the magnitude of the charge of the electron, f is the carrier frequency of the pulses, and K is a constant value that is related to Q by $K = \eta \frac{q}{hf} Q$.

$E(t)$ and $e_s(t)$ can be expressed in Fourier series over the bit time interval T .

$$E_s(t) = \sum_{v=-\infty}^{\infty} \varepsilon_v e^{i\omega_v t} \quad (3.23)$$

$$e_{sp}(t) = \sum_{v=-\infty}^{\infty} c_v e^{i\omega_v t} \quad (3.24)$$

where $\omega_v = \frac{2\pi}{T} v$. Assuming the optical filter bandwidth is M and it covers from

$v=v_1$ to $v=v_2$, the corresponding filtering for real quantities can be expressed as

$$\widehat{E(t)} = 2 \sum_{v=v_1}^{v_2} \overline{\varepsilon_v} \cos(\omega_v t + \Psi_v) \quad (3.25)$$

$$\hat{e}_{sp}(t) = 2 \sum_{v=v_1}^{v_2} \bar{c}_v \cos(\omega_v t + \varphi_v) \quad (3.26)$$

with the definitions:

$$\mathcal{E}_v = \bar{\mathcal{E}}_v e^{i\psi_v} \quad (3.27)$$

$$c_v = \bar{c}_v e^{i\varphi_v} = c_{rv} + i c_{iv} \quad (3.28)$$

where c_{rv} and c_{iv} are random variables. The output of the integrated and dump circuit is expressed as

$$y = \frac{K}{T} \int_0^T (\hat{E}_s + \hat{e}_{sp})^2 dt + y_{th} \quad (3.29)$$

and $y_{th} = \frac{1}{T} \int_0^T I_{th}(t) dt$ is the thermal noise contribution from thermal current.

Substituting (3.24) and (3.25) into (3.28), we may obtain the following equation

$$y = I_s + 2K \sum_{v=v_1}^{v_2} [c_{rv}^2 + c_{iv}^2 + 2\bar{\mathcal{E}}(c_{rv} \cos \psi_v + c_{iv} \sin \psi_v)] + y_{th} \quad (3.30)$$

In (3.30), the first order of c_{rv} and c_{iv} ($2\bar{\mathcal{E}}(c_{rv} \cos \psi_v + c_{iv} \sin \psi_v)$) represents the signal-to-ASE noise beating, and the second order of c_{rv} and c_{iv} , ($c_{rv}^2 + c_{iv}^2$), represents the ASE-to-ASE noise beating. Since the signal is not a random variable, the signal-noise beats retain the Gaussian probability distribution. But the noise-noise beats by themselves have a chi square distribution.

The variance of mark can be expressed as a summation of variances of signal-to-ASE beating, ASE-to-ASE beating, signal and thermal noise [55].

$$\sigma_1^2 = \sigma_{sig-sp}^2 + \sigma_{sp-sp}^2 + \sigma_s^2 + \sigma_T^2 \quad (3.31)$$

Assuming the signal power at space is zero, the variance of space only comprises of ASE-to-ASE beating and thermal noise.

$$\sigma_0^2 = \sigma_{sp-sp}^2 + \sigma_T^2 \quad (3.32)$$

According to (3.31) and (3.32), the noise of the space is dominated by ASE-to-ASE beating and the noise of the mark is dominated by signal-to-ASE beating. Therefore the PDF of space does not follow Gaussian distribution.

B. Chan *et al.* experimentally studied the distribution property of signal space and mark in the presence of ASE noise [54]. The results show that the histogram of the space is clearly non-Gaussian and the histogram of the mark is also slightly skewed due to the contribution from ASE-to-ASE beating.

When the received power is fixed, the mark can be treated approximately Gaussian because the dominant signal-to-ASE beating noise is Gaussian. However, when the received power fluctuates, the effect of signal-to-ASE beating should be reconsidered. The variance of signal-to-ASE beating can be expressed as [48]:

$$\sigma_{sig-ASE}^2 = 4R^2GP_{in}n_{sp}(G-1)h\nu B_e \quad (3.33)$$

where R is the responsivity of the photo-detector, G is the gain of the optical preamplifier, P_{in} is the input power, n_{sp} is the spontaneous emission factor, $h\nu$ is photon energy and B_e is the detector electronic bandwidth. It should be noted that the term $\sigma_{sig-ASE}^2$ is proportional to the input signal power P_{in} , which implies that the variance of the mark is varying with the received power. As we have discussed in the

previous sections, due to the presence of impairments, the input power may not always a constant value.

Jiang *et al.* [56] have studied optical systems with a combination of crosstalk and ASE noise, and found that in addition to the prong shape at the mark, the histogram of the mark also becomes asymmetric due to the signal-ASE noise beating (Figure 3-9). As shown in Figure 3-9, a higher signal level induces a larger variance and therefore a broader tail at the right side of the PDF, even when the number of crosstalk terms is increased to 4, such asymmetry is still observable.

Figure 3-9 Asymmetrical PDF caused by signal-ASE beating. (a) Single crosstalk, (b) 4 crosstalk terms [49]

Non-linear effects also cause signal level fluctuation. Lyubomirsky *et al.* studied the effect of ASE-XPM noise beating in [57] and also found that PDF is skewed toward the mark level when taking into account the beating terms. The effect is shown in Figure 3-10. The solid curves show the conventional Gaussian PDF models for both the mark and space levels. The dashed curve shows how PDF for the mark level changes when ASE-XPM beating effects are included.

Figure 3-10 Effect from ASE-XPM beating [57]

3.4 Summary

By analyzing some existing research results, this chapter discussed the impacts of several common types of impairments on the generation of amplitude histogram. Dispersion and narrow filtering cause signal pulse broadening and result in inter-symbol interference (ISI). The resultant amplitude histogram appears to be asymmetric and have multiple peaks on both the space and mark. Inband crosstalk tends to cause a prong shape at the mark due to the signal phase mismatching when the number of crosstalk signals is less than 8. FWM has similar effect as inband

crosstalk if the generated new wavelengths are within the bandwidth of the desired signal. In a system contains optical amplifiers, the ASE-to-ASE and signal-to-ASE noise beating at optical receiver should be taken into account. Both analytical and experimental studies show that ASE-to-ASE beating is naturally non-Gaussian, which results in asymmetry on the histogram of the space and mark. Since the variance of signal-to-ASE beating term is proportional to the received power, the power fluctuation also results in asymmetry PDF of the mark.

All the analyses show that directly applying single Gaussian approximation on the amplitude histogram may induce large error particularly when the signal is severely distorted. It is highly desirable to develop a better technique that can construct the PDFs of both signal levels more accurately and hence can estimate the BER of signal more precisely.

Chapter 4 An Improved BER Estimation Technique Based on Multiple Gaussian Curve Fitting

4.1 Introduction

In Chapter 2, Section 2.5, we reviewed the amplitude histogram method for BER estimation, and in Chapter 3 we studied the histogram distortion due to various channel impairments including crosstalk, chromatic dispersion, ASE noise and FWM. Although the conventional Gaussian approximation for BER estimation is simple and widely employed, the accuracy is not satisfactory when the amplitude histogram is highly distorted.

As discussed in Chapter 3, the amplitude histogram for the space and mark of the optical signal tend to be deviated away from the Gaussian distribution if the signal is distorted by various optical impairments. Statistically, a non-Gaussian PDF can be approximately treated as a superposition of multiple Gaussian functions [58]. The distorted histograms can then be reconstructed by the summation of multiple Gaussian functions in the same way.

In [59], the authors interpreted the discrete amplitude classes as contained in the histogram to represent the different sampled photocurrent values of a distorted signal, and name them $I_{0,n}$ and $I_{1,m}$ ($n=1 \dots N$, and $m=1 \dots M$) for space and mark, respectively

(Figure 4-1). The values of N and M are given by the resolution of the histogram and by the range of amplitude classes with nonzero photocurrent [59].

Figure 4-1 Superposition of Gaussian random processes [59].

Each photocurrent carries Gaussian noise with a variance according to

$$\sigma_{0,n}^2 = 2RI_{0,n}p_N B_e + R^2 p_N^2 B_e (B_0 - (B_e / 2)) \quad (4.1)$$

$$\sigma_{1,n}^2 = 2RI_{1,m}p_N B_e + R^2 p_N^2 B_e (B_0 - (B_e / 2)) \quad (4.2)$$

where R is the photodiode responsivity, B_e is the electrical bandwidth, B_0 is the optical bandwidth, and p_N is the spectral power density due to ASE noise. The authors assumed that all the receiver parameters were known and the value of p_N could be measured with a spectrum analyzer and current values of $I_{0,n}$ and $I_{1,m}$ were taken from the histogram. Assuming the optimized decision threshold is I_{th} , then the BER calculation can be expressed as:

$$BER = \frac{1}{2} \cdot [\sum_n H(I_{0,n}) \cdot \text{erfc}(\frac{I_{th} - I_{0,n}}{\sqrt{2}\sigma_{0,n}}) + \sum_m H(I_{1,m}) \cdot \text{erfc}(\frac{I_{1,m} - I_{th}}{\sqrt{2}\sigma_{1,n}})] \quad (4.3)$$

where $H(I)$ is the relative occurrence of the photocurrent amplitude and $\text{erfc}(x)$ is the complementary error function that is defined in equation (2.3). Assuming equal probability for marks and spaces, $H(I)$ can be normalized as:

$$\sum_n H(I_{0,n}) = \sum_m H(I_{1,m}) = 0.5 \quad (4.4)$$

The experimental results showed that the BER accuracy can be much improved. However, this method has two limitations. Firstly, the parameters of optical receiver have to be predetermined and an optical spectrum analyzer is needed for noise estimation. This makes this technique too complicated to be practical. Secondly, the selection of $I_{0,n}$ and $I_{1,m}$ is critical to the BER estimation and different choices of $I_{0,n}$ and $I_{1,m}$ may affect the accuracy of BER results. The authors did not clearly elaborate how to determine the values of $I_{0,n}$ and $I_{1,m}$.

Recently Ding and Zhong *et al.* [60] proposed another histogram-based BER estimation technique whereby multiple Gaussian functions are determined by curve fitting of the signal's histogram, which eliminates the needs for measuring the noise power spectral density and receiver's parameters. The fitting is conducted purely mathematically, by varying the relative weighting and standard deviation of each Gaussian function, the function group whose summation has the smallest discrepancy with the original histogram is chosen as the fitting function group. The advantage of this method is that the knowledge about the receiver and other information is not required, as long as the amplitude histogram can be obtained, and BER can subsequently be calculated, however, in this work, the curve fitting process is based on the assumption that the mean μ of each Gaussian function is equally spaced. Such

assumption has two limitations. Firstly, the fitting accuracy depends on the number of Gaussian functions used predefined. In general, the more Gaussian functions used, the better of the fitting results, however, the computational time may be excessive and the fitting process cannot guarantee a best fitting result. Secondly, in the calculation of BER, it is reported that the tails for the mark and the space that are close to the decision threshold significantly affect the accuracy of the BER estimation [61]. Hence a better fit nearby the decision threshold is necessary.

In this chapter, we propose an improved BER estimation method based on multiple Gaussian curve fitting. The new method is independent of physical parameters of the optical receiver and no extra equipment is necessary. The number of Gaussian functions to be generated is not predetermined but is determined by the actual shape of the amplitude histogram and hence it is more intelligent and computationally efficient. The fitting process puts the fitting priority on histogram portion that is close to the decision threshold, so that a more accurate fitting result can be guaranteed at this region. The new method is validated by computer simulation using the commercial software - *VPI TransmissionMakerTM* [63].

4.2 Improved Multiple Gaussian Curve Fitting Method

In this section, we present an improved multiple Gaussian curve fitting method for BER estimation. The improved multiple Gaussian curve-fitting method is based on the observation that in the presence of waveform distortion (e.g., inter-symbol interference due to dispersion), the signal's eye diagram appears to have multiple rails, and its amplitude histograms (space and mark) may display multiple peaks each corresponding to a rail in the eye diagram [34, 41-42, 61]. Gaussian noises are

superimposed around the respective rails of mark and space. The new curve fitting method intends to select the positions of these peaks as the mean values of the respective Gaussian functions. With this method, the number of Gaussian functions used for fitting depends on the actual shape of the amplitude histogram. Generally speaking, a severely distorted amplitude histogram requires more Gaussian functions in order to achieve a better fitting result than a less distorted histogram. Therefore the improved fitting program is more computational efficient and intelligent. The previous work only investigated BER caused by inband crosstalk and ASE noise [59]. In this work, the new method is applied to evaluate the BER of optical channels that suffer from various kinds of impairments including chromatic dispersion, ASE noise, single and multiple inband crosstalk and non-linear effect of FWM. Our study has shown that the new method is computationally simpler and more accurate as compared to the previous method.

The curve-fitting program is written in Matlab 6.0. For the ease of data processing, the histogram is normalized initially. Let S be the sum of the bins of the obtained histogram. We divide every bin by S . The resulting bin and histogram is called normalized bin and normalized histogram. In the following, all the bins and the histogram are meant normalized bins and normalized histogram.

The fitting process is conducted on histogram of space and mark separately. The first step is to separate the space and mark. Assuming that data 0's and data 1's (spaces and marks) are transmitted with equal probability, we can sum up the bins from the left to the right until the sum is equal or very close to 0.5. More specifically, suppose all the bins are numbered from the left to the right, if the summation of the first M

bins is slightly smaller than 0.5 and the sum of the first $(M+1)$ bins is slightly greater than or equal to 0.5, then the $(M+1)th$ bin is deemed as the separation point for the space and the mark. The first $(M+1)$ bins constitute the histogram for the space, and the remaining bins forms the histogram of the mark

After the separation of space and mark, the space histogram is fitted with multiple Gaussian functions first, following the three steps below:

Step 1: Divide the histogram into several portions, each of which contains one local peak (If there is only one peak, go to Step 2 directly). For example, the histogram in Figure 4-2 contains 4 troughs whose positions are denoted as $T1$, $T2$, $T3$ and $T4$, and 3 peaks whose positions are denoted as $P1$, $P2$ and $P3$. (In the curve fitting program, both T 's and P 's are integer index that refer to the positions of the bins). This histogram is then separated into 3 portions each of which contains one local peak in the middle and two troughs on both sides (i.e., $T1$ to $T2$, $T2$ to $T3$ and $T3$ to $T4$).

Figure 4-2 Determination of peaks and troughs

Step 2: Perform fitting. It has been reported that the histogram portion which is just next to the decision threshold has greater impact on determination of the BER [61], a better fitting at this portion is necessary. Therefore, the fitting process starts from the portion near the decision threshold. From the right to the left, the histogram portion ($T1$ to $T2$) is separated for fitting. The position of the peak $P1$ is chosen as the mean ($\mu_{0,1}$) of the first Gaussian function $G_1(x)$. By varying the weighting $A_{0,1}$ and the standard deviation $\sigma_{0,1}$, the Gaussian function is compared with this histogram portion only in the region of $T1$ to $T2$. The goodness of fitting in the region of $T1$ to $T2$ is calculated using R square metric [62]. R is defined as

$$R = 1 - \frac{\sum_{i=T1}^{T2} (h_i - g_i)^2}{\sum_{i=T1}^{T2} (h_i - \bar{h})^2} \quad (4.5)$$

where h_i is the bin value at position i of the original histogram; g_i is the bin value at position i of the histogram of the derived Gaussian function $G_I(x)$; $\bar{h}$ is the mean value of the bins of the original histogram in the range from $T2$ to $T1$ ($T1 > T2$) and is

calculated by $\bar{h} = \frac{\sum_{i=T1}^{T2} h_i}{T1 - T2}$. R is in the range from 0 to 1. For a perfect fitting, R

should be 1. In this fitting process, the threshold of R is set to be 0.98. There are 2 possible results:

- 1) If R is greater than or equal to 0.98, the fitting result is acceptable and therefore a Gaussian function can be derived.
- 2) If R is less than 0.98, the fitting result is unacceptable. In that case, a Gaussian function that is closest to the histogram portion in the region of $T1$ to $T2$ will be derived. However, in order not to over fit the histogram and result in residual bins with negative values, the Gaussian function is determined in such

a way that the summation of difference $\sum_{i=T1}^{T2} (h_i - g_i)$ is the smallest but remains positive so as to ensure the majority residual bins are positive.

Step 3: Calculate the residual histogram. Subtract the Gaussian function derived in Step 2 from the overall histogram and obtain a residual histogram (i.e., $h(x) - G_I(x)$). In order not to incur excessive computation, bins with very small and negative value are eliminated by setting their values to be zero. After removing very small and negative bins, the residual histogram is then used as the new histogram to determine the next Gaussian function.

The above three steps are repeated until the summation of the residual is less than 2% of the overall histogram (this is to ensure the goodness of the overall fit statistics is better than 98%).

The flow chart of the curve fitting process is given in Figure 4-3. The above fitting process is also applicable to the mark histogram, but the fitting for the mark should starts from the left to the right of the mark histogram, since the decision threshold D is in between the space and the mark.

Figure 4-3 Flow chart of the curve fitting process

Figures 4-4 (a) and (b) show the fitting results of optical amplitude histograms impaired by chromatic dispersion and inband crosstalk, respectively. For the case of chromatic dispersion (Figure 4-4 (a)), it can be observed that 4 Gaussian functions of

different weightings and variances are derived from the fitting of the space histogram, because the space histogram has multiple peaks ; two Gaussian functions are derived from the fitting of the mark histogram, because the mark is slightly asymmetrical. In contrast, in Figure 4-4 (b), it is shown that 5 Gaussian functions are derived for fitting the mark histogram while only 1 Gaussian function is derived from fitting the space histogram. The proposed method appears to be quite effective in choosing the proper number of Gaussian functions to fit the distorted histogram, at the same time, it can also achieve a good accuracy. As shown in both Figures 4-4 (a) and (b), the overall discrepancy between the original histogram and the fitting result (summation of multiple Gaussian functions) is very small.

Figure 4-4 Multiple Gaussian curve fitting on distorted histograms. (a) Histogram impaired by chromatic dispersion. (b) Histogram impaired by inband crosstalk. Solid curve: original histogram; dashed curve: derived Gaussian functions; dotted curve: discrepancy between the original histogram and summation of the Gaussian functions.

After deriving the respective Gaussian functions for the space and mark histograms, the BER for the signal can be calculated using equation (4.3). In order to find a minimum BER, the threshold level I_{th} is optimized by adjusting its value between the space and the mark.

4.3 Multi-Gaussian Curve Fitting Process

In this section, we use the histogram of an optical signal that is distorted by chromatic dispersion (Figure 4-5) as an example to illustrate the fitting process in detail.

Figure 4-5 Non-smoothed amplitude histogram

The first step that the fitting program does is to convert the raw data into a histogram with 360 bins and normalize it so that the summation of all the bins is equal to 1. We may observe that the histogram contains small peaks and troughs and is not smooth enough; those peaks and troughs should be eliminated because in the fitting process, the peaks and troughs may lead to wrong determinations of the mean of the Gaussian functions. Hence, the original histogram should be smoothed before the fitting process. The smoothing method we choose is the moving average filtering, which is done by averaging the neighboring bins. It is defined as [67]:

$$y_s(i) = \frac{1}{2W+1} \sum_{x=i-W}^{i+W} y(x) \quad (4.6)$$

where $y_s(i)$ is the smoothed value for the i th bin, and W is the number of neighboring bins on either side of $y_s(i)$. Care must be taken when choosing a proper value of W . W is related to the total number of the bins; a large value will over smooth the histogram

and hide the natural distribution properties while a small value of W may not be enough to remove the noises. Figure 4-6 shows the effect of W with different values:

Figure 4-6 Effect of the smoothing factor W on the histogram. (a) Original histogram, (b) $W=1$, (c) $W=2$, and (d) $W=3$

As shown in Figure 4-6, the histogram becomes smoother and flatter as the value of W increases, and also the histogram shape is changed slightly. If W is chosen to be a very large value, the histogram will appear to be much flatter, which may not be able to capture the actual distribution of signal's amplitude, and hence may result in high error in the BER estimation. In our simulation study, we have observed that when the number of bins is smaller than 200, the appropriate value of W is 1 or 2; when the number of bins is above 200 and below 400, W should be 3 or 4. The choice of proper value of W is discussed in Section 4.5.2.

Figure 4-7 shows the histogram after smoothing. We may observe that the small peaks and troughs have been eliminated while the overall shape remains virtually unchanged as compared to the original one.

Figure 4-7 Histogram after smoothing with $W = 4$

The next step is to split the bins for the mark and space and treat them separately. In the example of Figure 4-7, bin 119 is the separation point for the space and the mark.

After separation of the space and mark, the curve fitting is conducted for the space histogram first. The fitting program splits the space histogram into portions each of which contains only one peak. This is done by determining the peaks and troughs. Note that this space histogram has 119 bins. We use h_i to denote the position of the i th bin. In this example (Figure. 4-8), h_5 , h_{27} , h_{50} and h_{58} are the peaks; h_{13} , h_{41} and h_{55} are the troughs. From the right to the left, bins from h_{55} to h_{119} are split out for fitting first.

Figure 4-8 Histogram of the space and the first portion for fitting is from bin 41 to bin 119

The mean of the first Gaussian function is set to be equal to the position of the maximum value in the region of h_{55} to h_{119} . In this example, h_{58} is selected as the mean of the first Gaussian. The weighting of the first Gaussian function is initially chosen to be the value of the original histogram at position h_{58} , that is 0.075 . The standard deviation is varied, which in turn changes the opening of the Gaussian curve. Every time the Gaussian function is compared with this portion of the original histogram, the goodness of fitting is determined using R metric defined by equation (4.5).

However, in this case, the R value is below the preset value of 0.98 during the first fitting, which implies that the Gaussian function cannot be directly derived from the histogram. The fitting program will still ensure that one Gaussian function is generated. It should be noted that it is not correct to choose the Gaussian function corresponding to the largest R , this is because such a Gaussian function may over fit the original histogram and result in residuals bins with negative value. Gaussian

function cannot be derived for bins with negative value. Therefore, with the same mean, apart from varying the variance, the weighting of the Gaussian function is decreased from 0.0075. The step of decrement we used is the 1% of the maximum value of the current histogram set. In the above graph, the maximum value of the current histogram set is 0.0075, therefore the step of decrement is 0.000075. The Gaussian function is then chosen based on two criteria:

- 1) The largest R ; and
- 2) The summation of the residual $\sum_{i=55}^{119} (h_i - g_i)$ is the smallest but remains positive.

The result for the fitting is shown in Figure 4-9. The first Gaussian function is derived just slightly below the original histogram portion.

Figure 4-9 Derivation of the first Gaussian function (space)

After deriving the first Gaussian function, the residual is collected by subtracting the first Gaussian function from the original histogram data, as shown in Figure 4-10.

Figure 4-10 Residual histogram after the first fitting (space)

It can be observed that the residual histogram contains a small number of bins with negative and ultra small values. Since Gaussian functions can only be derived from histogram bins with positive values, the negative bins have to be eliminated by setting them to be zero before further processing. Besides that, bins with very small values, whose amplitude is smaller than 1% of the bin with maximum value in the histogram, should also be removed in order to avoid excessive computation on insignificant values. Figure 4-11 shows the residual histogram after removing those very small (negative or positive) values.

Figure 4-11 Residual histogram after removing bins with negative and ultra small values (space)

Following the same steps as described above, the results of the second to fourth fittings are shown in Figure 4-12 to Figure 4-13, respectively.

Figure 4-12 Derivation of the second Gaussian function (space)

Figure 4-13 Derivation of the third Gaussian function (space)

Figure 4-14 Derivation of the fourth Gaussian function (space)

Figure 4-15 Final residual after the fourth fitting (space)

Every time before carrying out the next fitting, the summation of the residual is calculated. If the summation is smaller than 0.02, indicating that the residual occupies less than 2% of the original histogram, the fitting is fulfilled. However, there may also be such situation that the summation of the residual is still greater than 2%, but no more Gaussian function can be derived. This normally happens when the residual bins are not consecutive (i.e, they cannot form a continuous block). In such case, we can set a maximum number of loops in deriving Gaussian functions. When the maximum number is reached and no more new Gaussian function can be derived, the fitting process is deemed to have been completed.

Figure 4-15 shows the residual after the fourth fitting. After deriving the fourth Gaussian function, the sum of the remaining bins is less than 2% of the overall space portion. This is an indication that the fitting process is accomplished. The final fitting result on the space histogram is illustrated in Figure 4-16.

Figure 4-16 Fitting result of the space histogram

We may observe that the curve-fitting program can accurately capture the property of the original histogram. In this example, 4 Gaussian functions with different mean, variance and weightage are derived from the fitting process. It is also observed that the composite (sum) of the derived Gaussian functions is very close to the original histogram, and the difference between them can be made extremely small.

After successfully fitting the space histogram, the fitting program continues to fit the mark histogram, following the same process described above. Figure 4-17 to Figure 4-19 show the fitting process and result.

Figure 4-17 Derivation of the first Gaussian function (mark)

Figure 4-18 Derivation of the second Gaussian function (mark)

Figure 4-19 Fitting result of the mark histogram

Figure 4-19 depicts that two Gaussian functions are derived from the fitting of the mark histogram. This is due to the asymmetric of the mark histogram.

After all the Gaussian functions are derived from the fitting process. The BER is calculated using equation (4.3). The parameters of each Gaussian function are listed in the table below:

	Space				Mark	
Functions	Gaussian 1	Gaussian 2	Gaussian 3	Gaussian 4	Gaussian 5	Gaussian 6
Mean	78.0000	107.0000	110.0000	123.0000	109.0000	143.0000
Variance	7.7281	3.8880	15.3060	2.0797	21.9572	14.0783
Weighting	0.0700	0.0600	0.3400	0.0400	0.4500	0.0400

Table 1 Parameters of each Gaussian function

To obtain an optimized BER, the threshold level I_{th} is adjusted between the inner side of the space and mark and the BER is calculated using equation (4.3). This step is essential because the optimal threshold is to be changed with different distortions [55]. The minimum BER is selected as the final result. The relationship between BER and I_{th} is illustrated in Figure 4-20.

Figure 4-20 BER versus threshold level I_{th}

From the above graph, we may find that when D is 102, the minimum value of BER is around 10^{-9} .

In the above, we use an example to explain and demonstrate the improved multiple Gaussian fitting process. Further assessment on the effectiveness of this method is presented in the next section.

4.4 Simulation Investigations

The effectiveness of the improved multiple Gaussian curve fitting technique is validated using computer simulation. The simulation is conducted using commercial software *VPI transmissionmaker*TM from VPI system [63]. This software is able to simulate optical systems and networks from single channel TDM systems to several-hundred channel WDM systems and it contains plenty of modules for optical components that meet the industrial standards.

The laser source at the transmitter is externally modulated with a data stream at bit rate of 10 Gb/s via a Mach-Zehnder modulator (MZM). The data stream generated is a non-return-to-zero (NRZ) pseudo random binary sequence (PRBS). The probability for both the marks and spaces is equally set at 0.5. The rise time of the signal is set to be approximately $0.25T$, where T is the pulse duration. The center wavelength of the transmitted signal is 1544.4nm and the average transmitted power is 1mW. The configuration of the transmitter is shown in Figure 4-21.

Figure 4-21 Optical transmitter configuration

The fiber link comprises of a standard single mode fiber, the default attenuation parameter is 0.2dB/km and the dispersion parameter is $16\text{ns} / \text{nm} / \text{km}$.

The receiver comprises of a tunable low noise preamplifier, an optical filter and a PIN detector (Figure 4-22). The bandwidth of the optical filter is $2 \times \text{BitRate}$ and the bandwidth of the electrical filter is set to be $0.7 \times \text{BitRate}$ [65-66], which is able to remove the excessive noise without introducing signal distortion. The PIN diode has a responsivity of 1 A/W with a standard deviation of thermal noise of $10^{-12} \text{ A}/\sqrt{\text{Hz}}$.

Figure 4-22 Optical receiver configuration

The synchronous eye diagram is generated by a time domain scope, and the histogram is collected at the center of the eye where the eye is mostly widely opened.

We have studied various types of impairments including ASE noise, chromatic dispersion, single and multiple inband crosstalk and FWM. In order to make comparison with the conventional single Gaussian approximation method, the exact BER that are obtained by the built-in BER tester in the *VPI transmissionmaker*TM together with the BER from the single Gaussian approximation and the BER from the new multi-Gaussian curve fitting are plotted in the same graph.

4.4.1 ASE Noise

The ASE noise source is generated using a backward-pumped EDFA. The main signal and ASE noise is then coupled into a single fiber using a coupler as shown in Figure

4-23. The levels of ASE noise can be adjusted by a tunable attenuator (A1). The fiber comprised of a 20km of single mode fiber (SMF) and a 4km of dispersion shift fiber (DSF), so that the fiber link has approximately zero dispersion. The received power is set at a fixed level of -30dBm by tuning a tunable attenuator (A2) before the receiver. Optical signal-to-noise ratio (OSNR) is used as a measurement of noise levels.

Figure 4-23 BER measurement setup for optical signal distorted by ASE noise

The OSNR is varied in a range from 15 dB to 20 dB in step of 0.5 dB. Figure 4-24 shows the BER measured by the BER tester, the BER estimated by the method of single Gaussian fitting, and the BER estimated by the new method (multi-Gaussian curve fitting).

Figure 4-24 BER versus optical OSNR

As shown in Figure 4-24, there is little difference between the BER obtained by three different methods when the OSNR is relatively large (the BER is smaller than 10^{-8}). However, the proposed new method can get a more accurate result at low OSNR (i.e., high ASE noise). This can be explained as follows: The ASE noise can be modeled as a Gaussian process, but when ASE level is high, the increment of ASE-ASE beating noise at the receiver causes the histogram to appear to be asymmetrical [52-54]. (that is, the PDFs of the two signal levels are no longer Gaussian)

4.4.2 Chromatic Dispersion

In this simulation, the optical signal is transmitted through a standard SMF with dispersion coefficient of 16ps/km/nm. The amplitude histogram is collected at the fiber distances of 10km, 20km, 30 km, ...100km (Figure 4-25). At the receiver, a

tunable attenuator (A1) is used so that the received signal power is kept constant at -30dBm

Figure 4-25 BER measurement setup for optical signal distorted by chromatic dispersion.

Figure 4-26 BER versus chromatic dispersion

Figure 4-26 shows the BER obtained with three different methods for various amount of chromatic dispersion. Due to the signal pulse broadening induced by chromatic dispersion, inter-symbol interference (ISI) effect causes the amplitude histogram to be asymmetrical with multiple peaks both marks and spaces [42,61]. The single Gaussian

approximation always tends to overestimate the BER. The proposed multi-Gaussian method again shows a much better agreement with the BER measured by the BER tester.

4.4.3 Intraband Crosstalk

We examined the situations for both single and multiple inband crosstalk. The simulation setup is shown in Figure 4-27.

Figure 4-27 BER measurement setup for optical signal distorted by Inband crosstalk

In Figure 4-27, a number of independent signals at the same wavelength but with different random phases are combined using a coupler (C1). The combined signals is used as a source of multi-inband crosstalk signals. After being attenuated by a tunable attenuator (A1), the combined multi-inband crosstalk signals are combined with the main signal by a second coupler (C2). The levels of crosstalk can be adjusted by tuning the value of the tunable attenuator (A1). The combined signal passes through a 20km single mode fiber and a 4km dispersion shift fiber (the dispersion is compensated). Before the receiver, another tunable attenuator (A2) is used so that the power of the received signal is kept at -30dBm.

4.4.3.1 Single Inband Crosstalk

We first studied the effect of single inband crosstalk by setting the number of crosstalk signal to 1. The levels of crosstalk to signal ratio are changed from -22dB to -15dB in step of 1dB by tuning the attenuator (A1). Figure 4-28 shows the BER versus the crosstalk level for the three different methods.

Figure 4-28 BER versus single inband crosstalk.

As shown in the above figure, the new curve fitting method can estimate the BER more accurately, whereas the single Gaussian method gives rise to a big discrepancy with the BER measured by the BER tester, particularly when the crosstalk level is high. Previous study shows that single inband crosstalk tends to cause a obvious prong shape histogram at the mark, which is far from the Gaussian distribution [44-49]. The single Gaussian method always overestimates the BER due to improper

fitting. The new multi-Gaussian curve-fitting method can accurately capture this property and hence provide a better estimation.

4.4.3.2 Multiple Inband Crosstalk

As described in Chapter 3, section 3.2, single inband crosstalk tends to cause a prong shape histogram at the mark due to the phase difference between the main signal and the crosstalk signal, however, when the number of inband crosstalk increases, such effect may not be obvious [48-49,51]. To study the relationship between the BER and the number of inband crosstalk signal, we simulated the situation where the number of inband crosstalk signals was changed from 1 to 8. The crosstalk to signal ratio is fixed at -19dB by adjusting the attenuator (A1).

Figure 4-29 shows the simulation result, as the number of crosstalk signals increases, the BER tend to increase, however, it reaches limit of 10^{-7} . This agreed with the result reported [51]. It is also observed that when the number of crosstalk signal is less than 5, the new multi-Gaussian curve fitting method gives a much better result than the single Gaussian approximation approach.

Figure 4-29 BER versus the number of inband crosstalk signals.

4.4.4 Four-Wave Mixing

Four-wave mixing (FWM) is a common type of fiber non-linear effect in WDM systems, and may cause severe interference to the desired signal, particularly when the signal power is high. Referring to section 3.2, the generated wavelength signals may just lie on or very closed to the desired channels which is the most detrimental. FWM effect has close relationship with the channel spacing. We investigate the relationship between BER and channel spacing. As shown in Figure 4-30, there are 8 channels involved in the simulation. The frequency of each transmitter is $193 \times 10^{12} + i \times \text{channelspacing}$ Hz, ($i = -3, -2, -1, 0, 1, 2, 3, 4$). The BER of the center channel at 193×10^{12} Hz is measured. The parameter *channelspacing* is varied from 50 GHz to 150 GHz with 10GHz per step.

All the channels are multiplexed using a multiplexer and transmitted over a 20km single mode fiber. In order to remove the effect of dispersion, a 4km dispersion shift fiber is used to compensate the dispersion. The targeted channel at 193×10^{12} Hz is selected by an optical bandpass filter (inside the receiver). A tunable attenuator (A1) is inserted before the receiver end to reduce the received power. The tunable attenuator is tuned so that the initial BER is below 10^{-14} when there is no FWM interference (all other channels are turned off).

Figure 4-30 BER measurement setup for optical signal impacted by FWM.

The BER versus channel spacing plotted in Figure 4-31

Figure 4-31 BER versus Channel Spacing

The effect of FWM is similar to multiple inband crosstalk but its impact is strongly related to the channel spacing, Figure 4-31 shows the BER versus channel spacing. As shown in the above figure, the reduction in channel spacing results in an increment of BER. However, when the channel spacing is above 120GHz, the BER remains almost unchanged because FWM effect is negligible. Again the multiple curve-fitting method shows a better result than the single Gaussian fitting especially when the channel spacing becomes narrower.

4.5 Discussion

We have proposed an improved BER estimation technique based on multiple Gaussian curve fitting. The fitting process is more intelligent and computationally efficient as compared to the previous proposed method in [59] and [60]. Simulation

results have shown that this new method can achieve much better accuracy than the conventional single Gaussian fitting method especially when the signal is severely distorted. It is also robust to histogram distortion under different impairments. However, a certain level of inaccuracy is still observable. We will discuss the causes in the following sections.

4.5.1 Choice of Appropriate Number of Histogram Bins

The purpose of collecting signal's amplitude histogram is to find the distribution property of signal space and mark. Therefore, a sufficiently large number of samples need to be collected for histogram construction. The collected points will then be converted into the histogram based on their position and density. The more histogram bins (smaller bin width) used, the more accurate the distribution property is. However, in the curve-fitting program, the derivation of a Gaussian function is based on bin to bin comparison (equation (4.5)), the number of bins cannot be very large as otherwise this will lead to tremendous computation without improving BER accuracy much. On the other hand, the number of bins also cannot be too small. A small number of bins may not represent the distribution property of the signal correctly. Figure 4-32 (a) and (b) depict a same histogram with 360 bins and 80 bins, respectively.

Figure 4-32 Histogram representation (a) Histogram with 360 bins (b) Histogram with 80 bins

From the above figures, we may observe that these two histograms appear significantly dissimilar on the shape, especially the space portion. In addition to that, a small number of bins may not be sufficient for derivation of accurate Gaussian functions.

During the study, we have found that the proper number of bins should be in between 200 and 400. In this range, the histogram can represent the distribution property of a signal with an acceptable accuracy without incurring excessive computation in performing the curve fitting.

4.5.2 Choice of Smoothing Factor

As described in section 4.2, smoothing the histogram data is a very important initial step before the actual fitting is performed. The mean of each Gaussian function is set to be equal to the position of the corresponding peak of the histogram. In the fitting program, the peaks are determined by comparing the bins with their adjacent bins. A bin that is greater than the bins on both its right and left sides is chosen as a peak. If

the histogram is unsmoothed, the program will determine too many inaccurate peaks and hence may result in excessive computation and large errors. We have introduced a histogram-smoothing method using equation (4.6). It should be noted that the smoothing process may change the histogram shape slightly. We have showed such effect in Figure 4-6 when W is chosen as different value.

The question is how to identify an appropriate value of W . Using the histogram in Figure 4-5 as an example, we may plot BER against W in Figure 4-33.

Figure 4-33 BER VS. Smoothing Factor W

It can be seen that when W is in the range of 1 to 4, the BER exhibit a slight increase with the value of W , which implies BER is insensitive to the choice of W in this range, therefore we may conclude that the values of 1,2,3,4 can all be considered as appropriate values for W . However, when W is greater than 5, the BER increases rapidly with the value of W . This is because the histogram is over smoothed and

distorted and does not reflect the actual distortion of signal's amplitude. It should be noted that the value of W also depends on the total number of bins and the actual condition of the histogram.

4.5.3 Other Factors that Affect the Goodness of Fitting

The goodness of fitting is based on bin-to-bin comparison. During the fitting process, when the majority of the bins of a histogram have been split out, the remaining bins may not be sufficient to derive one more Gaussian function. In the fitting program, we define the minimum number of bins that can be used for derivation of a Gaussian function is 5, otherwise the remaining bins will be discarded. This may not be appropriate because the sum of the remaining bins may be still bigger than 0.02. In addition, during the fitting process small and negative bins are eliminated to reduce the computation, and this again may induce a certain level of inaccuracy.

4.6 Summary

We have proposed an improved BER estimation technique that makes use of multiple Gaussian curve fitting on the distorted amplitude histogram. The new technique is independent of physical parameters of the optical receiver and no extra equipment is required. The number of Gaussian functions to be generated is determined by the actual shape of the amplitude histogram and hence it is more intelligent and computationally efficient as compared to the previously proposed method. We also consider the fact that the histogram portion near the decision threshold has more impact on the accuracy of BER estimation, the fitting process is therefore started by fitting the most significant portion that is next to the decision threshold for both the

space and the mark. The newly proposed technique is validated by computer simulation using the commercial software - *VPI Transmissionmaker*TM. Five different types of impairments have been examined to validate the effectiveness of the proposed technique. The simulation results have showed that the proposed technique is robust to various impairments including ASE noise, chromatic dispersion, single and multiple inband crosstalk and FWM. The new technique can achieve a much better accuracy than the conventional signal Gaussian approximation, especially when the distortion level is high. Finally we have also discussed the factors that may affect the fitting accuracy.

Chapter 5 Determination of the Sources of Signal Degradation

5.1 Introduction

Another important aspect of optical channel monitoring is the identification of the sources (causes) of signal degradation. This is extremely desirable for network administrators to take actions effectively against different network conditions. As described in Chapter 2, various techniques have been developed for monitoring specific impairments such as ASE noise, dispersion and crosstalk. However, a versatile method with the ability to identify various impairments simultaneously is yet to be developed.

It has been observed that different impairments may cause the resultant amplitude histogram to deform differently [29-34]. This phenomenon was discussed and analyzed in Chapter 3. However, there has not been a useful and effective approach for quantifying how and in what way the amplitude histogram is changed by a specific impairment. From the review in Chapters 2 and 3, we know that the analysis solely based on the mean and variance of signal's amplitude histogram is not sufficient for determining the sources of degradation [30].

In this chapter, we propose a histogram distance-based approach together with histogram asymmetry property to identify three major types of impairments, namely ASE noise, chromatic dispersion and intraband crosstalk. In conjunction with the

multiple Gaussian curve-fitting method for BER estimation, this method is effective in identifying the above 3 impairments under different receiver power levels.

5.2 Principle of Histogram Difference Measurement

In the field of digital image processing it is well known that color content can be represented by color histogram [68-69]. A color histogram illustrates how pixels in an image are distributed by graphing the number of pixels at each color (Figure 5-1).

Figure 5-1 Color histogram representation

Comparison of image color histogram has been proved to be effective in the field of image retrieval and image database query [68-69]. Histogram distance is used as a metric to describe the histogram difference. If two images have the same or similar color distribution, the distance should be zero or near zero. In contrast, the distance becomes large when two histograms are very different.

In this work, we apply this technique to optical signal monitoring. When an optical signal passes through an optical network, its amplitude histogram will be distorted due to various impairments, as shown in Figure 5-2. A different level of signal distortion will result in a different level of histogram distortion and different kinds of impairments will deform the histogram differently. If we could construct certain

relationship between the histogram distance and the impairment, our objective of identifying the sources of impairment could be achieved.

Figure 5-2 Comparison of undistorted and distorted optical amplitude histograms

5.2.1 Choice of Distance Function

The distance function is based on bin-to-bin comparison. There are two general forms of distance comparison [68-69]. These two forms are described below.

(1) Minkowski -form Distance [68]

The first form is known as Minikowski-form which is given by:

$$d_p(Q, T) = \left(\sum_{i=0}^{N-1} (Q_i - T_i)^p \right)^{\frac{1}{p}} \quad (5.1)$$

where $Q = \{Q_0, Q_1, \dots, Q_{N-1}\}$ and $T = \{T_0, T_1, \dots, T_{N-1}\}$ are the query and target histograms, respectively. When $p=1$, the distance function becomes *city block distance* or *Manhattan distance* in (5.2).

$$d_1(Q, T) = \sum_{i=0}^{N-1} |Q_i - T_i| \quad (5.2)$$

when $p=2$, the distance function becomes *Euclidean distance* in (5.3).

$$d_2(Q, T) = \left(\sum_{i=0}^{N-1} (Q_i - T_i)^2 \right)^{\frac{1}{2}} \quad (5.3)$$

(2) X^2 Distance [69]

The second form is referred to as X^2 distance, which is defined as:

$$d_{\chi^2}(Q, T) = \sum_{i=0}^{N-1} \frac{(Q_i - m_i)^2}{m_i} \quad (5.4)$$

where $m_i = \frac{Q_i + T_i}{2}$.

In this work, the distorted histogram needs to be compared with the undistorted histogram. Here we use the histogram from the back-to-back (BTB) signal with an ultra low BER of 10^{-16} as the reference. The BTB histogram is taken as the target histogram, and the distorted histogram is used as the query histogram. In order to evaluate which distance method is more suitable, a comparison is carried out first.

We studied a transmission system influenced by single crosstalk. The condition is the same as section 4.4.3.1. We use H_{btb} to represent the histogram collected at the transmitter, and $H_{20}, H_{19} \dots H_{10}$ to represent collected histograms with different crosstalk levels. All the bins are normalized so that the summation of a histogram is equal to 1. The resultant distance versus the crosstalk level is shown in Figure. 5-3.

Figure 5-3 Comparison of distance measurement

As shown in Figure 5-3, the X^2 distance curve is much steeper and linear than the other two distances. That is, the X^2 distance is more sensitive to the change of the crosstalk level. Therefore, the X^2 distance method is adopted in our following studies.

5.3 Simulation Investigations

The simulation setup for 3 types of impairments is the same as what was described in Chapter 4. The only difference is that another set of histogram collector is placed just after the transmitter in order to collect the BTB histogram. Without using the BER tester in the VPI software, the BER can be evaluated directly using the multiple Gaussian curve fitting method based on the collected histograms. X^2 distance is a measurement of level of difference between the histogram collected at the transmitter side and the histogram collected at the receiver side. With the increment of the distortion, the distance also increases. In order to be comparable, the BER for all the

three cases is ranged from 10^{-14} to 10^{-5} . Figure 5-4 shows the general simulation setup for the histogram distance comparison.

Figure 5-4 Simulation setup for histogram difference comparison

The power at both two receivers is monitored by optical power meter. The received power is kept at -30dBm for all three cases. For each case (Figure 5-5, 5-7 and 5-9), the amplitude histograms for the BER of 10^{-14} , 10^{-8} and 10^{-5} are plotted in the same graph from which we may observe how the histograms are changed under different levels of impairments. In Figure 5-6, 5-8 and 5-10, X^2 distance against different levels of impairments is also plotted. The x-axis represents both distortion level and the BER accordingly, the y-axis represent the normalized distance.

Figure 5-5 shows the amplitude histogram for an optical signal impacted by different levels of ASE noise. OSNR is used to measure the levels of ASE noise. As shown in Figure 5-5, the histograms for both the space and the mark become flatter as the level of OSNR is increased, and a clear shift towards the decision threshold for the space is observed. This is due to the square law detection of the ASE noise at the receiver. Figure 5-6 shows the X^2 distance versus the OSNR level. The corresponding BER is also indicated in the horizontal axis in Figure 5-6.

Figure 5-5 Amplitude histogram for optical signal distorted by different levels of ASE noise

Figure 5-6 X^2 distance versus ASE noise level

Figure 5-7 shows the amplitude histogram for an optical signal impacted by different levels of chromatic dispersion. Figure 5-8 shows the X^2 distance versus the chromatic dispersion. The corresponding BER is also indicated in the horizontal axis in Fig. 5-8.

Figure 5-7 Amplitude histogram for optical signal impacted by different levels of chromatic dispersion

Figure 5-8 X^2 distance versus the chromatic dispersion

As shown in Figure 5-7, clear asymmetry and multi-peaks at the space and mark are observed when chromatic dispersion increases, which is agreeable with our previous analysis in section 3.1.

Figure 5-9 shows the amplitude histogram for an optical signal impacted by single inband crosstalk, and Figure 5-10 shows the X^2 distance versus the levels of inband crosstalk. The corresponding BER is also plotted in the horizontal axis in Figure 5-10.

Figure 5-9 Histograms of system impacted by different levels of inband crosstalk

Figure 5-10 X^2 distance versus inband crosstalk

In the case of inband crosstalk, the histogram deviation is dominated by the mark, a prong shape can be clearly observed at the mark. When the BER becomes larger another peak beside the space is also observed, which agrees with the previous analysis in section 3.2.

For the purpose of comparison, Figure 5-11 illustrates the X^2 distance versus the BER for three kinds of impairments. As can be observed in the figure, the general trend is: the X^2 distance increases as the BER increases (i.e., the level of impairments increases) for all the three cases.

Figure 5-11 Distance comparison for 3 impairments

Although the value of X^2 distance is different for different kinds of impairments at a given BER, it is still not confident enough to discriminate them because all the distance curves appear to increase linearly in a similar way as the signal degrades.

5.3.1 Local Difference of Space & Mark

The above problem occurs because, during the calculation of the X^2 distance, we did not consider the fact that different impairments distort the distribution of mark and space in a different manner. From Figures 5-5, 5-7 and 5-9, we can observe that ASE noise and chromatic dispersion cause a bigger histogram difference on the space while inband crosstalk causes a larger histogram difference on the mark. In order to reveal the histogram difference for different kinds of impairments, we need to take into account the different influence on the mark and space separately.

To separate the histogram of the mark and space levels, a separation point has to be determined first. As explained in Chapter 4, the normalized bins are added up from the left to the right until the summation is equal to or very close to 0.5, and this point is chosen as the separation point. In the following figures, the X^2 distance for the space and the mark is plotted separately (Figure 5-12 to Figure 5-14).

Figure 5-12 X^2 distance for the mark and the space versus the ASE noise.

Figure 5-13 X^2 distance for the mark and the space versus the chromatic dispersion

Figure 5-14 X^2 distance for the mark and the space versus the inband crosstalk

As can be seen in the above three figures, the X^2 distance for the mark and the space behaves quite dissimilarly for different kinds of impairments. When the ASE noise is increased, the X^2 distance for the space increases rapidly whereas the X^2 distance for the mark increases slowly, and the space always dominates the overall difference.

Chromatic dispersion behaves similarly to the case of ASE noise, but the distance of mark shows a trend of increment and the distance difference between the space and the mark is not that large. However, for the case of inband crosstalk, the X^2 distance for both the mark and the space increases as the inband crosstalk level increases, and the distance for the mark is always greater than that for the space. To illustrate the distance difference between the mark and the space for the above three cases, we plot the distance difference (C_{dif}) between the space and the mark versus the BER in Figure 5-15. We define the distance difference to be: $C_{dif} = Distance_{space} - Distance_{mark}$,

Figure 5-15 X^2 distance difference between the mark and the space versus the BER for the three different kinds of impairments

From Figure 5-15, we may observe that the distance difference (C_{dif}) for inband crosstalk is always negative, indicating that the histogram difference is dominated by the mark. That can be easily distinguished from the other two impairments. The distance differences for both the ASE noise and dispersion are positive, indicating that the histogram differences are dominated by the space. However, the distance difference for the ASE noise is always greater than that for the dispersion, which

implies that the ASE noise affects the space histogram more severely than the dispersion at the same value of BER.

We have also investigated the effectiveness of the X^2 method when the receiver power is varied. By tuning the transmission power or changing the attenuation, four power levels are tested and they are -28dBm, -29dBm, -30dBm and -31dBm, respectively. For a better illustration, the results for the four cases are plotted in a 3-dimensional graph (Figure 5-16). On this graph x-axis stands for the logarithm of BER, y-axis for the received power and z-axis for the X^2 distance.

Figure 5-16 X^2 distance difference versus BER and received power

From the above graph, we may see that each of the impairments occupies one surface. The surface at the top is for the ASE noise, the one at the bottom is for the inband crosstalk, and the one in between is for the chromatic dispersion. For a received signal whose power and BER is determined, the single dominant source of degradation may be concluded from the value of X^2 distance. However, the X^2

distance difference of ASE noise surface and chromatic dispersion surface stay quite closely, some overlapping area is even observable, which may induce ambiguous conclusion. Therefore, further discriminating the X^2 distance of ASE noise and chromatic dispersion is necessary.

5.3.2 Asymmetric Analysis of Space and Mark

We notice that the cause of the histogram difference for ASE noise and chromatic dispersion is different. For the case of ASE noise, besides the broadening of the histogram, the large difference also comes from the misalignment of the space. The signal level of space is shifted towards the center. Considering a worst case when $\text{BER}=10^{-5}$ (Figure 5-17), the space is almost uncorrelated with the BTB histogram, therefore a large difference is resulted when applying bin-to-bin comparison.

Figure 5-17 Space of Signal influenced by amplifier noise when $\text{BER}=10^{-5}$

In the case of chromatic dispersion, the histogram difference mainly resultant from the deformation of the distorted histogram. Considering the same condition when $\text{BER}=10^{-5}$ (Figure 5-18), the space is obviously asymmetric and a long tail towards the decision threshold is observed, and the difference is mainly caused in this region.

Figure 5-18 Space of Signal influenced by dispersion $\text{BER}=10^{-5}$

Based on the above observations, to further distinguish dispersion from ASE noise, the symmetry property of mark and space can also be introduced as an additional metric. Some researchers reported that the statistical moments of the histogram could be used to monitor the chromatic dispersion [70]. In their analysis, the third order statistical moment and higher odd ones reflect the asymmetry of the amplitude histogram and they are increased as the amount of chromatic dispersion increases. As shown in Figure 5-19, the third, fifth and even sixth order of moment is increased when the total amount of dispersion increases.

Figure 5-19 Moments representing the asymmetry of histogram distorted by Chromatic dispersion [70]

The asymmetric property of the histogram of the space and mark can also be evaluated in a simple way. In this work, we propose a cut and flip histogram comparison. For an idea Gaussian histogram (either mark or space), it must be symmetrical along its center. If we fold the outer histogram along its centerline onto the inner histogram, they must be identical so that their difference is zero. On the contrary, if a histogram of mark or space is asymmetrical, there must be a certain level of difference.

In order to separate the right and left side bins for the histogram of space and mark, the folding line has to be first determined. There are several possible ways to determine it. The line may be chosen at the position where the peak of the histogram lies. But this is not applicable when a histogram contains multiple peaks. The separation line may also be chosen as the geometry center of the histogram using

$\frac{1}{2}(x_{right} + x_{left})$, where x_{right} and x_{left} are the right most and left most position of the bins. However, the values for both two parameters cannot be accurately determined because of the long tail of the histogram.

To avoid the above problems, we separate the left and right portions based on the summation of bins. Bins are summarized from left to right until the summarization is equal or very close to 0.25 (assuming equal transmission possibility of space and mark, the summation of normalized bins in space or mark should be 0.5, therefore 0.25 represents the summation of half bins for the space or mark). This group of bins belongs to the left portion and the rest bins belong to the right portion, as shown in Figure 5-20, where m is the position of the folding line, n is the total number of bins, Hl and Hr represent the bins on the left and right sides of the folding line, respectively.

Figure 5-20 Folding the histogram to calculate its degree of asymmetry with respect to the

folding line where $\sum Hl \approx \sum Hr \approx 0.25$

To estimate the asymmetric degree of a histogram, we can still make use of the X^2 distance metric by comparing bins on the left and right sides of the folding line, However, the number of bins on the left and right side may not be the same due to the

histogram asymmetry. In Figure 5-20, the number of bins on the left side is less than the number of bins on the right side. In order to be comparable, we need to force the number of bins on both sides to be the same by inserting the extra bins with zero value. As an example in Figure 5-20, the number of bins on the right side is greater than that on the left side (i.e. $n > 2m$), and hence we set bins $Hl_{2m+1}, Hl_{2m+2}, \dots, Hl_n = 0$. Assuming the number of bins on the right side is greater than that on the left side, the asymmetric degree of a histogram can then be defined as follows

$$d_{asym}(Hl, Hr) = \sum_{i=m}^n \frac{(Hr_i - M_i)^2}{M_i} \quad (5.5)$$

where $M_i = \frac{Hl_i + Hr_i}{2}$, $Hl = \{Hl_1, Hl_2, \dots, Hl_m\}$ and $Hr = \{Hr_{m+1}, \dots, Hr_{2m}\}$ are the bins on the left and right sides of the folding line, respectively.

Figures 5-21, 5-22 and 5-23 show the degree of asymmetry for the space and mark histograms distorted by ASE noise, chromatic dispersion and inband crosstalk. We also measured the asymmetric degree for the space and mark histograms collected from the BTB measurement and found neither of them is ideally symmetrical. The asymmetric degree of the BTB histogram is 0.15 for the space and 0.05 for the mark. The small value of asymmetry is due to ASE noise beating from the preamplifier at the receiver. The asymmetric degree of the BTB histogram is also plotted in the same figure for reference purpose.

Figure 5-21 Asymmetric degree of histogram distorted by ASE noise

Figure 5-22 Asymmetric degree of histogram distorted by chromatic dispersion

Figure 5-23 Asymmetric degree of histogram distorted by inband crosstalk

Comparing Figure 5-21 and Figure 5-22, we may find that there is a large difference in the asymmetric property of the mark and space for the system influenced by chromatic dispersion. The histogram tends to be very asymmetrical as the chromatic dispersion is accumulated, especially for the space histogram. Initially the asymmetric is only 0.165 when the dispersion is 160 ps/nm, which is quite close to the back-to-back condition. Whereas, when the total dispersion is increased to 1040ps/nm, the degree of asymmetric is increased to 0.485. A similar trend of increase in the asymmetric degree for the mark is also observed. The asymmetry is mainly due to the inter-symbol interference from the pulse broadening. In contrast, for the condition of ASE noise, both the space and mark undergo a slight increment when the ASE noise is accumulated. The small asymmetry is mainly due to the ASE-to-ASE beating noise [52-54]. These differences are also agreeable with the observation in Figure 5-7 and Figure 5-9. In Figure 5-23, an increment in the histogram asymmetric degree of the space is also observed for inband crosstalk. In Chapter 3, section 3.2, we have

analytically described the impact from inband crosstalk to the amplitude histogram. The crosstalk to signal ratio (i.e., crosstalk level) is represented by ε . When ε is large enough, it causes a hump at the inner side of the space and the hump in turn induces a large asymmetry and this can be observed in Figure 5-9 too.

Therefore, the histogram asymmetric metric can be used together with the previously discussed distance metric to further discriminate the histogram difference. To remove the effect of the BTB histogram and combine the asymmetry property of the space and mark histogram, we define the average relative asymmetry (A_{ra}) parameter:

$$A_{ra} = \frac{(d_0 - d_{0-bts}) + (d_1 - d_{1-btb})}{2} \quad (5.6)$$

where d_0 and d_1 are the asymmetry degree of the space and mark respectively, d_{0-btb} and d_{1-btb} is the asymmetry degree of the BTB histogram of space and mark respectively.

Figures 5-24, 5-25 and 5-26 show the average relative asymmetry of a histogram influenced by ASE noise, chromatic dispersion and inband crosstalk, respectively.

Figure 5-24 Average relative asymmetry of histogram distorted by ASE noise

Figure 5-25 Average relative asymmetry of histogram distorted by chromatic dispersion

Figure 5-26 Average relative asymmetry of histogram distorted by inband crosstalk

From the above graphs, we may notice that the average relative asymmetry (A_{ra}) of ASE noise falls in the range from 0 to 0.1, while for chromatic dispersion and inband crosstalk it is in the range from 0 to 0.2. For the ease of computation, we can normalize the A_{ra} so that they fall in the range from 0 to 1. This can be done by dividing each individual A_{ra} value by the maximum value of A_{ra} (in the current case, the maximum value is 0.2). Subsequently, we can relate the normalized A_{ra} to the BER. The results are shown in Figure 5-27.

Figure 5-27 Normalized asymmetry of the amplitude histogram versus BER for three different impairments

In order to relate the asymmetric property to the X^2 distance so as to further distinguish different impairments, we assume that an increment in the asymmetry will impose a reduction in the X^2 distance. With such an assumption, we may expect that chromatic dispersion will impose larger reduction in the X^2 distance than the other two impairments. We denote the average relative asymmetry to be A_{ra} , the histogram distance difference between the space and the mark to be C_{dif} and the modified distance metrics to be M_{dif} , their relationship is defined as:

$$M_{dif} = C_{dif} \times (1 - A_{ra}) \quad (5.6)$$

Figure 5-28 shows M_{dif} versus the BER

Figure 5-28 Modified difference (M_{dif}) versus BER for various kinds of impairments

From Figure 5-28, we may observe that the modified distance curve for the chromatic dispersion appears significantly different from that in Figure 5-15 when we include the asymmetry property, in contrast, the distance curve for ASE noise and inband crosstalk remains virtually in their original trend, which implies negligible influence from the asymmetry property. Therefore, we can further distinguish the ASE noise and the chromatic dispersion.

The above procedure can be summarized as the following steps:

- 1) Separate histogram mark and space;
- 2) Calculate the histogram distance of mark and space separately;
- 3) Calculate the asymmetry of histogram mark and space separately;
- 4) Calculate the asymmetry of mark and space of reference histogram (BTB histogram) separately;
- 5) Use Equation (5.6) to calculate the average relative asymmetry (A_{ra});

- 6) Use Equation (5.8) to calculate the modified distance metrics (M_{dif}),
- 7) Plot M_{dif} against BER.

We then apply the modified distance metric under different amount of received power (Figure 5-29). Compared with Figure 5-16, the three surfaces in Figure 5-29 stay at clearly different levels. Especially for the ASE noise (top) and chromatic dispersion (middle), they are much easier to be discriminated.

Figure 5-29 Modified distance versus BER and received power

Therefore if the power of received signal is fixed, from the amplitude histogram we can calculate the BER and M_{dif} . If the M_{dif} falls on or near a certain surface, we may infer the main cause of signal degradation.

5.4 Summary

We have proposed a novel optical impairment identification technique using signal's amplitude histogram. This is based on the fact that different impairments impact the optical signals differently and distort the histogram in a different way. The level of distortion of a histogram can be described using the X^2 distance-based metric by comparing the distorted histogram with the undistorted histogram. Initially we measured the overall histogram distance, but we found that it is difficult to discriminate different impairments since all of the resulted X^2 distances behave quite similarly. Our study shows that different impairments have different impacts on the space and mark. We therefore measured the X^2 distance of the space and mark separately. By calculating the X^2 distance difference between the space and mark, we can successfully determine the inband crosstalk because inband crosstalk distorts the mark more severely than the space, while ASE noise and chromatic dispersion have larger impact on the space. However, the ASE noise and chromatic dispersion are still difficult to be discriminated. We further consider the asymmetric properties of the amplitude histogram. It is observed that chromatic dispersion imposes much more asymmetry on both space and mark than ASE noise. The histogram asymmetry can be measured using the flip and fold method. By combining the X^2 distance and histogram asymmetry, we can successfully determine the ASE noise and chromatic dispersion.

In this work, we have mainly investigated three kinds of impairments. It should be noted that certain types of impairments may result in similar histogram distortion, for example, chromatic dispersion, polarization mode dispersion and nonlinear effects like SPM and XPM all cause signal pulse broadening and result in inter-symbol interference. Inband crosstalk and FWM also have similar impact on signal pulses.

Therefore, the distance based metric studied in this chapter may not be able to identify all types of impairments. This method can only detect an impairment that is dominant in the histogram deformation. If multiple impairments exist simultaneously, this method would not be effective. Further research needs to be carried out

Chapter 6 Conclusions and Future Work

6.1 Conclusions

Optical channel monitoring is essential for network operators to provide guaranteed quality service to their users. The network is evolving towards a transparent optical network. An idea transparent optical network will be capable of carrying digital signals with arbitrary bit rates and protocols. In such a network, network operators or service providers will be allowed to offer a wide range of services without any constraints. Such a network is also future-proofing since new services can be easily added without a significant change of the network infrastructure. However, a transparent network is difficult to be monitored. It is well known that bit error rate (BER) is an essential parameter for evaluating the performance of digital systems. In current optical networks like SONET and SDH, the BER can be directly evaluated from the frame overhead whereas this is not possible for transparent optical networks because both the protocols and bit rates may not be predetermined. Although other system performance parameters such as optical power level and optical signal to noise ratio (OSNR) still can be obtained, they are not always sufficient to tell the network conditions. Therefore, a cost-effective in-service optical channel monitoring method is highly desirable.

BER estimation technique based on optical amplitude histogram is promising due to its simplicity and transparency. The amplitude histogram contains the distribution properties of signal marks and spaces. Conventionally, single Gaussian distribution is assumed for both space and mark histogram, and BER can be evaluated directly

without the knowledge of the signal format. However, the accuracy of histogram method is not always satisfactory especially when BER is high. The reason is that different impairments tend to distort the signal pulse and hence deform the histogram away from Gaussian. In Chapter 3, three types of histogram distortion caused by inter-symbol interference, phase noise and ASE noise have been studied. Inter-symbol interference result from dispersion, narrow filtering, SPM and XPM causes multiple rails in the eye diagram and leads to multiple peaks and asymmetry of the amplitude histogram. Phase noise from inband crosstalk and FWM causes either constructive or destructive gains to the signal mark due to phase matching or mismatching with the original signal. The mark appears to be an obvious prong shape especially when the number of inferring signals is less than 8. The ASE noise not only broadens the space and mark, but also causes asymmetry of histogram when it beats against itself and the main signal.

In order to obtain a more accurate BER, an improved multiple Gaussian curve fitting technique has been proposed in Chapter 4. The concept of this method is to the reconstruct the real probability density function by super-positioning multiple Gaussian functions. In the previous works, either the physical parameters of optical receiver have to be known or the fitting is based on a fixed number of Gaussian functions. In this work, the fitting process is conducted purely mathematically without the detailed information about the optical receiver and no extra equipment is needed. The number of Gaussian functions to be generated depends on the actual shape of the histogram so that the improved method is more computationally efficient. The histogram portion near the decision threshold that affects the BER estimation most significantly has higher priority to be fitted than the other portions, therefore, the

fitting accuracy can be guaranteed. Computer simulations for 5 types of impairments namely, ASE noise, chromatic dispersion, single and multiple inband crosstalk and FWM have been carried out. The results agree well with the values from the software built-in BER tester. Issues that affect the accuracy of the proposed method have also been discussed.

Determination of the sources of signal degradation is another challenging topic of optical channel monitoring. Previous studies show that different impairments tend to deform the histogram in a different way. To describe how the histogram is deformed, we have proposed a novel histogram distance based technique in Chapter 5. The principle is to compare the distorted histogram with the undistorted histogram (BTB) using the X^2 distance metric. However, we have found that directly applying histogram comparison is not sufficient to differentiate the impairments because the X^2 distance for all different impairments behaves quite similarly. It is observed that inband crosstalk distorts the mark more severely than the space, while for chromatic dispersion and ASE, the effect is just opposite. So we evaluate the distance for the space and mark separately and successfully determine the inband crosstalk. To further distinguish chromatic dispersion and ASE noise, the asymmetry property of histogram is considered. ASE noise causes an approximately symmetrical distribution for both the space and mark because the noise can be well approximated to be Gaussian. In contrast, chromatic dispersion induces ISI, which causes the histogram to be clearly asymmetrical. The degree of asymmetry of a histogram (space or mark) can be measured by comparing the histogram portions on the right and left sides with respect to the center folding line. After obtaining the asymmetric degree of histogram for both the space and mark, ASE noise and chromatic dispersion can be further distinguished.

The X^2 distance method in conjunction with asymmetry measurement has also been extended to the conditions of different transmission power. A three dimensional graph with the information of BER, received power and X^2 distance has been plotted for distinguishing different impairments. The graph shows that each impairment occupies a different surface therefore they can be easily discriminated.

6.2 Future work

The amplitude histograms used in this thesis are all collected from synchronous sampling method, synchronous sampling has its advantage in accurately representing the distribution property of the space and mark. However, synchronous sampling requires the knowledge of the data rate which is not always obtainable. Alternatively, asynchronous sampling method is much more general and economical, but the asynchronous amplitude histogram contains unnecessary bins between transmitted marks and spaces which cannot be directly used to construct the PDF. Hence, the major challenge is still on how to reconstruct the synchronous histogram from asynchronous sampling or how to find other alternative technique to obtain the synchronous histogram.

In this work, we focused on BER evaluation and impairment identification from amplitude histogram. Recent research work shows that other useful information such as the signal rise time can also be extracted [71], therefore other applications of amplitude histogram are worth of further exploring.

Non-Return-to-Zero (NRZ) signal format has been used in the simulation. There are also situations where Return-to-Zero (RZ signal) format is used. Due to the difference of the duty circle and pulse shape, the amplitude histogram of RZ signal behaves differently from that of NRZ. Therefore, studying the amplitude histogram property of RZ signal is worth of further research.

This work is all based on computer simulation, although the simulation can greatly reduce the complexity of the system setups and component constraints, it would be necessary to conduct real experiment to verify the results. With real experiment, the results will be more reliable and convincing.

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List of Author's Publication

1. D. Ye, W. D. Zhong and M. Premaratne, "Investigation on Sources of Optical Channels Using Amplitude Histograms," *Proceeding of the 3rd International Conference on Optical Communications and Network (ICO CN2004)*, pp. 237-240, Hong Kong, China, Dec 2004.
2. D. Ye, W.D. Zhong, D. Lei and Y.J. Wen, "Improved BER Monitoring Based on Amplitude Histogram and Multi-Gaussian Curve Fitting," *Proceedings of the 4th International Conference on Optical Communications and Network (ICO CN2005)*, pp.33-35, Bangkok, Thailand, Dec 2005.
3. D. Ye and W. D. Zhong, "An Improved BER Monitoring Technique Based on Amplitude Histogram and Multi-Gaussian Curve Fitting," submitted for publication.
4. D. Ye and W. D. Zhong, "A New Approach for Identifying Various Impairments of Optical Channels," submitted for publication.