NEW DATA DETECTION AND SYMBOL TIMING RECOVERY APPROACHES FOR BURST OPTICAL SIGNAL TRANSMISSION

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ABSTRACT

Burst mode receivers are key components of optical transmission systems and have received much attention in recent years. We present new efficient methods for burst optical signal detection and blind channel estimation in burst-mode data transmission based on a modified *K*-means clustering technique. A data-aided feedforward symbol timing recovery method is also developed, based on polynomial interpolation and maximum likelihood estimation theory. It can be implemented rapidly and efficiently; therefore, it is suitable for burst mode receivers. A performance criterion of this method has also been derived. We also give some numerical examples to demonstrate the performance of the proposed methods.

1. INTRODUCTION

As high-speed optical communications develop rapidly, the burst-mode data transmission system in passive optical networks (PONs) have been investigated extensively. A very significant feature of this burst-mode data transmission is that due to unequal distances between central office and optical network units (ONUs), optical signal attenuation in PONs is not the same for each ONU. The amplitude of the received signals at the optical line terminal (OLT) will be different for each ONU. Therefore, conventional signal detection methods are not suitable for burst-mode data transmission because they cannot handle the different arriving frames with large difference in optical power level alignment.

Recently, signal detection methods in burst-mode receivers have received much attention [1]. Most of these detection methods are implemented using analog or hybrid analog-digital technologies, for example, peak detection circuites will be used in the receiver. In this paper, we present a new efficient burst-mode signal detection method based on a modified *K*-means data clustering technique. Data clustering plays an important role in pattern recognition and many other fields. Lately, data clustering, especially the *K*-means clustering technique, has also been applied to digital communications. Since the *K*-means clustering method is efficient and has low computation complexity, it is suitable for applications where high processing speed is need.

The task of acquiring timing synchronization is another important problem in burst-mode receiver. In burst-mode data transmission, synchronization of all relevant parameters must be performed very quickly, normally within a limited period of time at the start of each data-burst. However, conventional synchronization methods are usually accomplished using feedback schemes which lead to long acquisition time [2], [8]. Hence, feedforward synchronizers are particularly well suited for burst-mode data transmission systems. But conventional feedforward timing recovery techniques are based on some assumptions of the statistical distribution of received signals and their implementation is very computationally complex [2].

Recently, polynomial interpolation has been introduced as a simple and efficient method to implement symbol timing recoveries. Some interpolation based synchronization methods are presented [3], [4]. However, these methods are either suitable only for the situation where the over-sampling ratio is two, or require high sampling frequency to obtain the acceptable synchronization performance, which is difficult to realize in high-speed optical communication systems. Besides these, theoretical performance analysis of these methods have not been investigated. In this paper, we present a more general interpolation-based feedforward symbol timing recovery method. We also derive a performance criterion for this type of synchronizer, in which the errors caused by the interpolation approximation are considered. The proposed method is efficient, performed quickly and very suitable for burst-mode data transmission.

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2. BURST OPTICAL SIGNAL DETECTION

We present a new signal detection approach and channel estimation in the burst optical signal transmission, based on a modified *K*-means clustering algorithm.

2.1. Modified *K*-means Clustering Detection Method

A typical burst optical signal is in the form of a frame with a number of binary signals. Each binary signal is transmitted in the form of very short pulses with power level A_0 or A_1, corresponding to binary 0 or 1 respectively. However, the power levels A_0 and A_1 may vary slowly from bit to bit with the laser's temperature. Also considering the nonlinear amplification at the receiver, we cannot rely on knowledge of these power levels to design the receiver. Under such situations, we propose the following received signal mode, in which the power levels A_0 and A_1 are modelled as Gaussian random variables with the same variance and different means. Both variance and mean are unknown at the receiver.

First, we assume there is no intersymbol interference and each pulse is sampled at the optimal sampling instant. Then the received signal model is

$$y_n = x_n + w_n, \qquad n = 1, 2, \ldots, N \tag{1}$$

where x_n's are independent distributed Gaussian random variables with mean μ_n and variable σ_A^2. Here μ_n is either μ_0 or μ_1, corresponding to A_0 or A_1 respectively; w_n is a zero mean white Gaussian noise with variance σ_w^2. Therefore, the burst-mode signal detection problem can be considered as the following binary hypothesis test:

$$\begin{array}{ll} \mathrm{H}_0: & y_n \sim \mathcal{N}(\mu_0,\ \sigma_A^2 + \sigma_w^2) \\ \mathrm{H}_1: & y_n \sim \mathcal{N}(\mu_1,\ \sigma_A^2 + \sigma_w^2) \end{array} \tag{2}$$

According to the above received signal model and hypotheses, there will be two clusters centered at μ_0 and μ_1 in the distribution of the received signals. Therefore, we can implement the data clustering method to divide the received signals into two clusters corresponding to the binary values 0 and 1 respectively.

The most commonly used clustering strategy is based on the squared-error criterion. However, this criterion does not coincide with the minimizing bit error rate (BER) criterion in the burst signal detection. The reason is that the squared-error criterion gives equal weight to every within-cluster variation of each cluster. But in the burst-data transmission, in each burst the probabilities of sending binary 0 or 1 are not the same. Hence, the weights of within-cluster variations have to be different. To overcome the performance degradation caused by this problem, in our proposed method we modify the conventional *K*-means clustering to obtain a new clustering algorithm. The essential point of this new method is to give different weights to the within-cluster variations in the squared-error criterion to make it equivalent to the minimizing the BER criterion.

Since the burst signal detection is a one-dimension clustering problem, the *K*-means algorithm can be simplified to find an optimal threshold τ_{opt} to partition the received data into two clusters corresponding to binary 0 and 1. For the binary hypothesis test in (2), the optimal threshold that minimizes the BER is

$$\tau_{\mathrm{opt}} = \frac{\mu_0 + \mu_1}{2} + \frac{\sigma^2}{\mu_1 - \mu_0} \ln \frac{p_0}{p_1} \tag{3}$$

where p_0 and p_1 are the prior probability of transmitting binary 0 and 1, see [5]. Therefore, in our modified algorithm we use this threshold to replace the threshold used in the conventional *K*-means which is just the average of the centers of all clusters. However, the parameters $\{\mu_0, \mu_1, p_0, p_1, \sigma^2\}$ are unknown at the receiver. By considering that the *K*-means clustering algorithm is iterative, we can use the clustering results of the previous iteration to estimate these unknown parameters and use these estimations to update the threshold in the current iteration.

The algorithm is described by the following procedure: let $Y = \{y_1, \ldots, y_N\}$ denote the received data to be clustered. Suppose at the mth iteration we obtain the partition results S_{0m} and S_{1m}, which are the subsets of Y corresponding to the binary 0 and 1. Let the number of data in S_{0m} and S_{1m} be n_{0m} and n_{1m}. Then at the $(m+1)$th iteration, we update the threshold to be

$$\tau_{m+1} = \frac{\hat{\mu}_{0m} + \hat{\mu}_{1m}}{2} + \frac{\hat{\sigma}_m^2}{\hat{\mu}_{1m} - \hat{\mu}_{0m}} \ln \frac{\hat{p}_{0m}}{\hat{p}_{1m}}. \tag{4}$$

In the above updated threshold, the unknown parameters are estimated by applying the partition results in the mth iteration into the following formulas:

$$\hat{p}_{0m} = n_{0m}/N, \qquad \hat{p}_{1m} = n_{1m}/N$$

$$\hat{\mu}_{0m} = \textstyle\sum_{n\in S_{0m}} y_n/n_{0m}, \quad \hat{\mu}_{1m} = \textstyle\sum_{n\in S_{1m}} y_n/n_{1m}$$

$$\hat{\sigma}_m^2 = \frac{\sum_{n\in S_{0m}} (y_n - \hat{\mu}_{0m})^2 + \sum_{n\in S_{1m}} (y_n - \hat{\mu}_{1m})^2}{N-1}$$

This algorithm is terminated when there is no reassignment of any data from one cluster to another or the modified squared-error ceases to decrease significantly after an iteration.

2.2. Blind Channel Estimation in the Presence of ISI

The burst-mode data transmission in PON is often impaired by channel intersymbol interference (ISI). Since in the burst-mode data transmission in PON, the ISI is mainly from the effect of the nearest previous symbol, in this paper we use a first-order ISI channel model. Assume that the characteristics of the channel vary slowly, we have the following ISI channel model for the burst-mode data transmission:

$$y_n = x_n + b x_{n-1} + w_n, \tag{5}$$

where b is the ISI parameter assumed unknown deterministic. In conventional detection methods in the presence of ISI, we need to estimate the channel parameters by using training data and then implement an equalizer to remove the ISI according to the estimated parameters. However, in the burst-mode data transmission the header of the burst is very short in order to increase efficiency. This implies that using a training sequence to estimate the channel is very difficult to realize. In the following, we present a new blind channel estimation method which is based on the above modified *K*-means clustering algorithm

In the ISI channel model (5), when we consider all possible values for the mean of the random variables x_n and x_{n-1}, we can conclude that the detection problem based on this ISI channel model is a four-hypothesis test:

$$\begin{array}{ll} \mathrm{H}_0: y_n \sim \mathcal{N}(\mu_{00},\ \sigma^2) & \mathrm{H}_2: y_n \sim \mathcal{N}(\mu_{10},\ \sigma^2) \\ \mathrm{H}_1: y_n \sim \mathcal{N}(\mu_{01},\ \sigma^2) & \mathrm{H}_3: y_n \sim \mathcal{N}(\mu_{11},\ \sigma^2) \end{array} \tag{6}$$

where $\mu_{ij} = \mu_i + b\mu_j$, $i, j = 0, 1$ and $\sigma^2 = (1 + b^2)\sigma_A^2 + \sigma_w^2$. Therefore, the distribution of the received data contains four clusters with centers μ_{ij}, $i, j = 0, 1$, respectively. However, if we detect the transmitted binary signal by directly using the above proposed modified *K*-means clustering algorithm, the detection performance will be very poor. The reason is the effect of ISI makes the cluster centers μ_{01} and μ_{10} very close with each other. Therefore, its BER will be much larger than the BER when using training sequence and linear equalizer to remove the ISI.

Considering this point, in the proposed blind estimation method, first we still use the modified *K*-means algorithm to partition the received data into four clusters. Then, instead of using a long training sequence to estimate μ_{ij}, $i, j = 0, 1$, we use the centers of each cluster as their estimate. According to the relationships between μ_{ij} and the parameters $\{\mu_i,\ \mu_j,\ b\}$, we have the following equations:

$$\hat{\mu}_{ij} = \mu_i + b\mu_j, \qquad i, j = 0, 1. \tag{7}$$

where $\hat{\mu}_{ij}$ is the estimation of real μ_{ij}. Since b, μ_0 and μ_1 are all unknown parameters, the above equations are nonlinear. We will use numerical methods to solve this nonlinear system in the sense of the least square and obtain the estimation of the ISI parameter b. Using the resulting estimate, we can remove the ISI by implementing a linear equalizer.

3. SYMBOL TIMING RECOVERY

We present a data-aided feedforward symbol timing recovery method based on interpolation, which is implemented efficiently and rapidly and thus suitable for the burst-mode data transmission.

3.1. Interpolation-Based Symbol Timing Recovery

The proposed method for symbol timing recovery is represented in the Fig. 1. The basic idea is as follows. The data, after being sampled by a free-running sampling clock, passes through an interpolator to form a polynomial approximation of the matched filtered signal and then maximum likelihood estimation is applied to this approximated signal. By using this interpolation approximation, we obtain an analytical form of the likelihood function. Hence, numerical methods can be used to calculate the estimation of the synchronization parameters. Therefore, a tracking loop that leads to the long acquisition time is not needed [2], [8].

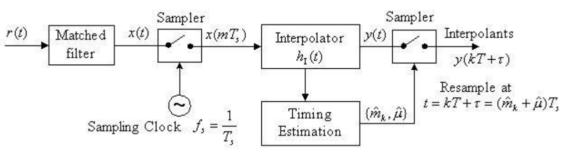

Fig. 1. Receiver with non-synchronized sampling and interpolator.

As shown in Fig. 1, the received baseband signal after passing through the matched filter is sampled using the over-sampling ratio of $\beta = T/T_s$, where T and T_s are the symbol and sampling intervals respectively. In the digital part of the receiver, the synchronization parameters m_k and μ_k is estimated. For convenience, we assume that the sampling rate is an integer multiple of the symbol rate and the sampling rate at the output of the interpolator is equal to the symbol rate. Under these assumptions, the over-sampling ratio β is an integer and the fractional interval μ_k is a constant, i.e., $\mu_k = \mu$.

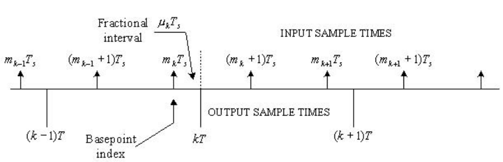

Fig. 2. Sample time relations.

Denote the impulse response of the analog interpolating filter as $h_{\rm I}(t)$. Then the continuous-time output of the filter is

$$y(t) = \sum_m x(m) h_{\rm I}(t - mT_s). \tag{8}$$

Define a filter index $i = \text{int}\left[(kT+\tau)/T_s\right] - m$, where int$[z]$ means the largest integer not exceeding z. Also define a basepoint index $m_k = \text{int}\left[(kT+\tau)/T_s\right]$ and a fractional interval $\mu_k = (kT+\tau)/T_s - m_k$. These time relationships are illustrated in Fig. 2. Now resample the continuous-time output of the filter at the time instants $t = kT + \tau$, where τ is the time delay between this resampling and the original free-running sampling, and apply the above definitions, the interpolants can be computed from

$$y(kT+\tau) = \sum_{i=i_1}^{i_2} x(m_k - i) \sum_{l=0}^{L} b_l(i) \mu_k^l = \sum_{l=0}^{L} \mu_k^l v_l(m_k) \tag{9}$$

where $v_l(m_k) = \sum_{i=i_1}^{i_2} b_l(i) x(m_k - i)$, $b_l(i)$ are the interpolator coefficients which are determined solely by the filter's impulse response $h_{\rm I}(t)$. Here we use the classical Lagrange polynomial interpolating filter.

Therefore, when we vary m_k from $k\beta$ to $(k+1)\beta - 1$ and vary μ_k from 0 to 1 continuously for each m_k, the output of the interpolation filter $y(kT+\tau)$ forms a polynomial approximation for the continuous-time signal $x(t)$, which is the output of matched filter, in the interval $kT \leq t < (k+1)T$.

From [8], we know that in order to estimate the synchronization parameter using maximum-likelihood method, the log-likelihood function is

$$\Lambda(\tau) = C_L \sum_n I_n x_n(\tau) \tag{10}$$

where C_L is a constant, I_n's are the transmitted binary digits and $x_n(\tau)$ is the output of the matched filter. Since in (9) we already use the interpolation to obtain a polynomial approximation of the output signal of the matched filter, by substituting this approximation into (10) we achieve the polynomial approximation of the log-likelihood function as

$$\Lambda((m_k + \mu)T_s) = C_L \sum_{l=0}^{L} \mu^l \sum_n I_n v_l(m_k). \tag{11}$$

Hence, the synchronization parameters can be estimated as:

$$\{\hat{m}_k,\, \hat{\mu}\} = \arg \max_{\{m_k,\, \mu\}} \left\{\Lambda((m_k+\mu)T_s)\right\}, \tag{12}$$

and the value of the output at the desired time instant $kT + \tau$ is determined by equation (9).

3.2. Performance Characteristics

The Cramèr-Rao bound (CRB) for an unbiased estimate of an unknown synchronization parameter τ is defined as

$$\sigma_\tau^2 = E\{[\hat{\tau}(\boldsymbol{y}) - \tau]^2\} \geq \frac{1}{E\left\{\left[\frac{\partial}{\partial \tau} \ln p(\boldsymbol{y}|\tau)\right]^2\right\}}. \tag{13}$$

This lower bound is very useful for analyzing the performance of parameter estimates. However, in the proposed new maximum-likelihood estimator, we use the Lagrange interpolation to form an approximation of the received matched filtered signal. Hence the conventional CRB for the estimate of synchronization parameter τ, as derived in [8], cannot be used as a criterion for the performance analysis. The error caused by the interpolation should be included in the CRB of this new maximum-likelihood method.

The error of the Lagrange interpolation polynomial is studied by Henrici in his book [6]. Some further research results can be found in [7]. The main results for the Lagrange interpolation error is concluded in the following theorem.

Theorem 3.1 *Let the real function f be defined on an interval I, and let $x_0, x_1, \ldots, x_N$ be $N+1$ distinct points of I. Let P represents the Nth order Lagrange interpolation polynomial of f and let f be $N+1$ times continuously differentiable on the interval*

I. Then to each $x \in I$ there exists a point ξ_x located in the smallest interval containing the points $x, x_0, x_1, \ldots, x_N$ such that

$$f(x) - P(x) = \frac{1}{(N+1)!} L(x) f^{(N+1)}(\xi_x) \tag{14}$$

where

$$L(x) = (x - x_0)(x - x_1) \ldots (x - x_N).$$

The quantity $f^{(N+1)}(\xi_x)$ in (14) can be defined as a continuous function of x for $x \in I$.

By applying the above theorem to the new method, we conclude that the proposed method could be considered as a conventional maximum-likelihood estimation under a different signal model such that the output of the matched filter in this new model is the same as the Lagrange interpolation polynomial approximation. Therefore, we can directly replace $x_n(\tau)$ in (10) with the Lagrange interpolation polynomial formula in (14) and obtain the CRB of the proposed new maximum-likelihood estimator as

$$\sigma_\tau^2 \geq \frac{1}{E\left\{\left[\frac{\partial}{\partial \tau} C_L \sum_n \left(I_n x_n(\tau) - I_n \Gamma(\tau)\right)\right]^2\right\}}, \tag{15}$$

where

$$\Gamma(\tau) = \frac{1}{(N+1)!} L(\tau) x_n^{(N+1)}(\xi_\tau).$$

4. NUMERICAL EXAMPLES

In this section, we use some numerical examples to investigate the performance of the proposed methods. In the first experiment, we simulate the optical signal detection method in the presence of ISI in the channel, as we presented in section 2. We compare the BER of the detection method based on the proposed blind channel estimation with the results when using a long training sequence. The above results are also compared with the performance of an alternative blind detection method that uses directly the modified *K*-means clustering to find the detection threshold. The results are shown in Fig. 3. We observe that the performance of the proposed blind estimation method is nearly the same as the method when using a long training sequence and is much better than the method that directly uses the modified *K*-means method. This is so since the proposed method takes full advantage of the information provided by the ISI channel model.

In the next experiment, we analyze the performance of the proposed data-aided interpolation based symbol timing recovery method with a different over-sampling ratio β. As shown in Fig. 4, increasing the over-sampling ratio will increase the detection performance. We also observe that even we use the low over-sampling ratio like $\beta = 2$, the BER is still close to the theoretical results. This point is very important for burst-mode data transmission in PON, where high over-sampling ratio is difficult to implement.

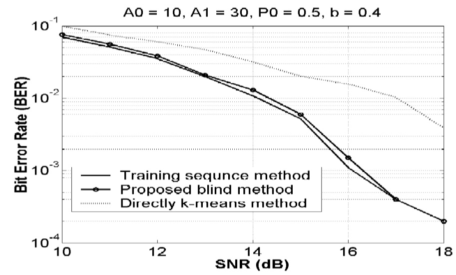

Fig. 3. Performance of the blind channel estimation.

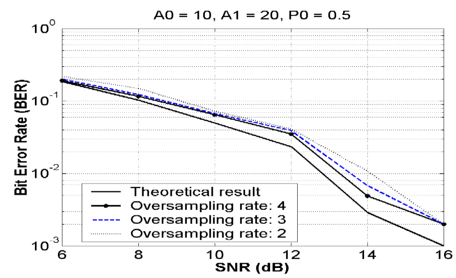

Fig. 4. Performance dependence on over-sampling rate.

5. CONCLUSIONS

We investigated the burst optical signal detection and symbol timing recovery in burst-mode data transmission in passive optical networks. We proposed a new modified *K*-means clustering based detection and a blind channel estimation methods. These methods are implemented efficiently and suitable for the burst transmission in PON. For the symbol timing recovery, we proposed an interpolation based data-aided feedforward timing recovery scheme. By using a feedforward approach instead of the feedback loop, we achieve a very fast synchronizer. This is very important and necessary for burst-mode data transmission in PON. We also derived a performance criterion for the proposed method, in which the errors caused by the interpolation approximation are considered. In the future work, we will study the performance of the proposed optical signal detection method analytically, especially its convergence.

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