Performance Evaluation of the Clustering Based Sequence Equalizer in Direct Detection Optical Communication Links

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Abstract: In this paper the performance of the Clustering Based Sequence Equalizer is investigated in the context of Intensity Modulated Direct Detection optical communications links operating at 10Gb/s, when non-return to zero on-off keyed and optical differential encoded phase shift keyed transmission is employed. The aforementioned equalizer provides an attractive implementation of the Maximum Likelihood Sequence Estimation, comprising of two successive steps, namely a) nonparametric estimation of the channel response using a cluster based approach and b) sequence estimation using the Viterbi algorithm. The performance of the cluster based equalizer in fiber links is investigated my means of computer simulation.

1 INTRODUCTION

The Intensity Modulated Direct Detection set up (IM/DD) has been extensively used for 10Gb/s up to 40Gb/s commercial optical communication links (Stavdas, 2010). In the IM/DD systems the optical to electrical conversion is directly realized via a nonlinear device, the photodetector, which acts as a square-law function (Agrawal, 2012). Chromatic dispersion (CD) is perhaps the dominant linear impairment which is liable of electronic equalization. When a train of pulses is transmitted, excessive dispersion can force successive pulses to overlap resulting in Intersymbol Interference (ISI). Electronic equalization, applied in the receiver part, is used to mitigate either the residual CD resulting from the incomplete optical compensation or the accumulated CD resulting from uncompensated optical transmission (Singer et al., 2008).

Equalization methods based on the Maximum Likelihood Sequence Estimation (MLSE) have been proposed as a powerful tool for mitigating the effect of the ISI in wireless as well as in wireline communication systems (Proakis, 2001). The MLSE approach has been successfully applied in the context of electronic equalization of optical communication links (Agazzi et al., 2005; Foggi et al., 2006a; Foggi et al., 2006b; Bosco and Poggiolini, 2006; Hueda et al., 2007; Poggiolini et al., 2008; Bosco et al., 2009; Alfiad et al., 2009; Bosco et al., 2010; Maggio et al., 2014), for IM/DD non-return to zero on-off keyed (NRZ-OOK) and for optical differential encoded phase shift keyed (NRZ-DPSK) transmission set up. The MLSE electronic equalizer has been implemented using the Viterbi algorithm (VA) (Proakis, 2001). The histogram method, as well as, parametric closed form approximations of the received signal probability density function (PDF) have been utilized for the computation of the branch metrics associated to the VA implementation (Agazzi et al., 2005; Hueda et al., 2007), requiring however a huge amount of data in order to obtain reliable results. Alternatively, the VA branch metrics can be computed at a much lower cost, adopting a Gaussian approximation for the pertinent PDFs, either directly from the received data (Alfiad et al., 2009), or by means of channel identification using a second order Volterra model (Chung, 2010).

The Clustering Based Sequence Equalizer (CBSE) provides an attractive alternative to the implementation of the MLSE method (Theodoridis et al., 1995; Georgoulakis and Theodoridis, 1997; Georgoulakis and Theodoridis, 2000). The implementation of the MLSE equalizer requires the estimation of the response of the transmission channel. According to the CBSE appoach, the design of the equalizer is treated as a classification task (Theodoridis and Koutroumbas, 2008), thus freeing itself from the need of an explicit adoption of specific models for the channel as well as for the

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interference. The CBSE approach comprises of two successive steps, namely a) estimation of the channel response to the transmitted data using a cluster based approach and b) the estimation of the transmitted sequence using the Viterbi algorithm. The main advantage of the cluster based approach that specific modeling of the channel or the interference is no longer required. Moreover, the CBSE is able to cope with either one-dimensional (1D) or two-dimensional (2D) formulations of the received data, providing in the later case, the advantage of using, apart from the Euclidean, the Mahalanobis distance. One dimensional CBSE implementations of the MLSE have been proposed in the context electronic equalization of IM/DD optical links, either implicitly (Foggi et al., 2006b), or explicitly (Lisnanski and Weiss, 2006; Yang et al., 2008). The application of the 2D CBSE approach in the case of IM/DD NRZ-OOK signaling has been discussed in (Georgoulakis et al., 2010).

In this paper, the performance of the CBSE equalizers is evaluated in the context of IM/DD optical communication links, when NRZ-OOK or NRZ-DPSK transmission is employed. The performance of the CBSE equalizers is investigated by means of computer simulation, both for 1D as well as for 2D formulation of the received data. In the later case, both the Euclidean and the Mahalanobis distance are considered for the computation of the branch metrics of the VA. The required Optical Signal to Noise Ratio (OSNR) for an achieved Bit Error Rate (BER) lower that 10^{-3} is used as a performance index. Moreover, the performance of each method in a typical metro optical link that consists of short or medium long haul optical transmission system hence comprising multiple fiber spans, each of length equal to 100 Km, is investigated in terms of the achieved BER. The computational complexity of each approach is also discussed. Finally, design guidelines for the selection of the appropriate modulation format and the electronic equalization method are drawn, based on the overall performance of each approach, in terms of the achieved BER and the complexity of each method.

2 MLSE AND CBSE CONCEPTS

Consider the discrete time system described by the following equation

$$y(n) = c(n) + w(n) \tag{1}$$

where

$$c(n) = f\left(I(n), I(n-1), ..., I(n-M+1)\right) \tag{2}$$

is the noiseless channel output sequence, $f(.)$ is the function representing the channel action, $I(n)$ is an equiprobable sequence of the transmitted data taken from a binary alphabet, i.e. $I(n) \in \{0,1\}$, and $w(n)$ is the disturbance or the noise signal. The channel memory is represented by M while the channel length is given by $L = M+1$. The MLSE selects, among all possible transmitted sequences, the one that minimizes the cost

$$\min_{\{I_n\}} \left[\sum_n (e(n))^2\right] \tag{3}$$

where

$$e(n) = y(n) - c(n) \tag{4}$$

The minimization of (4) is performed efficiently using the Viterbi algorithm (Proakis, 2001).

The implementation of the MLSE equalizer requires the estimation of the channel response, $c(n)$ in (2), for a given input sequence $I(n), I(n-1), ..., I(n-M+1)$. This in turn requires either the a priori knowledge of the channel, or the identification of the channel, usually employing a parametric model, based on the available data set. Alternatively, the channel response to the input sequence can be estimated using a non parametric technique known as *clustering*, due to the fact the input is taken from a finite alphabet (binary in our case) (Georgoulakis and Theodoridis, 1997). The clustering based concept focuses on the clusters, which the received data form. The received data $y(n)$ form a set of $B = 2^{M+1}$ clusters in the 1D space. Each cluster is represented by a suitably chosen representative which corresponds to an estimate of the noiseless channel response, i.e. $\hat{c}(n) \in \{c_m, m = 0,1,...,B-1\}$. The clusters are usually estimated using a training sequence, although blind cluster estimation may be applied (Georgoulakis and Theodoridis, 2000). Subsequently, the transmitted sequence is estimated using (3), by means of the VA. The resulting MLSE implementation is known as the 1D CBSE approach.

The number of the states of the VA, in the 1D CBSE case, is given by $S = 2^M$. The number of the branches associated to the states of the VA coincides to the number of clusters. Given a set of training data $\{I(n), y(n)\}$, $n = 1,2,\ldots,N$, the cluster representatives are estimated by averaging those values of the received data that belong to a certain cluster. Let $\mathbf{I}(n) = [I(n), I(n-1), \ldots, I(n-M+1)]^T$ be a vector that carries the transmitted bits upon which the output signals $y(n)$ are constructed. Clearly, $\mathbf{I}(n) \in \{\mathbf{I}_0, \mathbf{I}_1, \ldots \mathbf{I}_{B-1}\}$, where $\mathbf{I}_m$ denotes the binary representation of the integer m, with $m = 0,1,\ldots,B-1$. The cluster representatives are computed as

$$c_m = \frac{1}{N_m} \sum_n \left(y(n) | \mathbf{I}(n) = \mathbf{I}_m\right) \tag{5}$$

with N_m denoting the cardinality of the set $\{\mathbf{I}(n) = \mathbf{I}_m\}$, $n = 1,2,\ldots,N$. During the decision mode, the branch metrics associated to each cluster of the VA are estimated as

$$V_m = (y(n) - c_m)^2, \quad m = 0,1,\ldots,B-1. \tag{6}$$

The branch metrics are subsequently utilized to update of the metrics associated to each state of the VA using a compare add select unit. The detection of the transmitted symbol $\hat{I}(n-D)$ is performed by means of the trace back search unit, with $D \approx 5M$ representing the depth of the search (Proakis, 2001).

The 2D CBSE is formulated in a similar way; the new input is the pair of data at consequent time instances n and $n-1$, Thus a received signal of a higher dimension is constructed as

$$\mathbf{y}(n) = \begin{bmatrix} y(n) \\ y(n-1) \end{bmatrix}. \tag{7}$$

The advantages of this approach over the 1D counterpart are a) better cluster classification, and b) the ability to cope with nonwhite interference. (Georgoulakis and Theodoridis, 1997).

The 2D CBSE minimizes the cost function

$$\min_{\{I_n\}} \left[\sum_n \left(\mathbf{e}^T(n) \mathbf{W} \mathbf{e}(n) \right) \right] \tag{8}$$

where

$$\mathbf{e}(n) = \mathbf{y}(n) - \begin{bmatrix} f\left(I(n),\ldots,I(n-M+1)\right) \\ f\left(I(n-1),\ldots,I(n-M)\right) \end{bmatrix} \tag{9}$$

is the error between the received 2D data and the corresponding channel response. $\mathbf{W}$ is an appropriately chosen weighting matrix of dimensions equal to 2×2. The number of the states of the 2D VA is given by $S^+ = 2^{M+1}$ and the number of the associated branches is given by $B^+ = 2^{M+2}$.

Let $\mathbf{I}^+(n) = [I(n), I(n-1), \ldots, I(n-M+1) I(n-M)]^T$ be a vector that carries the transmitted bits upon which the output signal vector $\mathbf{y}(n)$ depends upon at the time instant n. It holds $\mathbf{I}^+(n) \in \{\mathbf{I}_0, \mathbf{I}_1, \ldots \mathbf{I}_{B^+-1}\}$, where $\mathbf{I}_m$ denotes the binary representation of the integer m, with $m = 0,1,\ldots,B^+$. During the training mode the cluster representatives are computed as

$$\mathbf{c}_m = \frac{1}{N_m^+} \sum \left(\mathbf{y}(n) | \mathbf{I}^+(n) = \mathbf{I}_m^+ \right) \tag{10}$$

with N_m^+ denoting the cardinality of the set $\{\mathbf{I}^+(n) = \mathbf{I}_m^+\}$, $n = 1,2,\ldots,N$. The choice of $\mathbf{W} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ results to the standard Euclidean distance. In this case, the branch metrics associated to the 2D VA are estimated as

$$V_m^E = (\mathbf{y}(n) - \mathbf{c}_m)^T (\mathbf{y}(n) - \mathbf{c}_m) \tag{11}$$

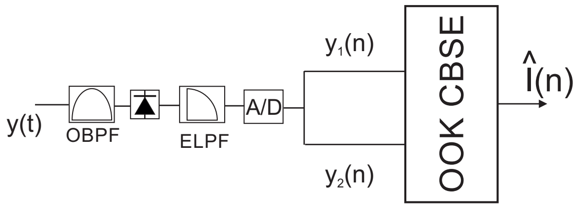

Figure 1: The NRZ-OOK receiver.

with $m = 0,1,\ldots,B^+-1$. Alternatively, the weighting matrix in (8) may be set equal to the inverse of the estimated error covariance matrix corresponding to each one 2D data cluster, i.e.,

$$\mathbf{W}_m = \Sigma_m^{-1}, \quad m = 0,1,\ldots,B^+-1, \tag{12}$$

where

$$\Sigma_m = \frac{1}{N_m^+} \sum \left((\mathbf{y}(n) - \mathbf{c}_m)(\mathbf{y}(n) - \mathbf{c}_m)^T | \mathbf{I}^+(n) = \mathbf{I}_m^+ \right). \tag{13}$$

This particular choice of the weighting matrix results to the so called Mahalanobis metric, where the branch metrics of the 2D VA are computed as

$$V_m^M = (\mathbf{y}(n) - \mathbf{c}_m) \Sigma_m^{-1} (\mathbf{y}(n) - \mathbf{c}_m)^T. \tag{14}$$

3 CBSE IN OOK SIGNALING

The schematic diagram of the NRZ-OOK receiver is depicted in Figure 1. After optical band pass filtering, the optical signal is converted to an electrical signal by means of a photodetector. The electrical signal is subsequently passed through an electrical low pass filter and sampled by an Analog to Digital (A/D) device. Fractionally spaced sampling is employed, as in this case the performance of the electronic equalizers becomes less sensitive to the sampling phase of the receiver (Singer et al., 2008).

Let T_s being the symbol period and let $y(t)$ be the electrical signal that is produced at the receiver. Let $y_1(n) \in \Re$ and $y_2(n) \in \Re$ denote the received signal sampled at time instances nT_s and $nT_s + T_2/2$ respectively (fractionally spaced at $T_s/2$ is assumed). The receiver diversity, due to the fractionally spaced sampling, is incorporated into the MLSE cost as

$$\min_{\{I_n\}} \left[\sum_n \left(\sum_{i=1}^{2} (y(n) - c_i(n))^2 \right) \right]. \tag{15}$$

Here, $c_i(n) \triangleq f_i\left(I(n), I(n-1), \ldots, I(n-M+1)\right)$, $i = 1,2$ denote the channel response to the input sequence $I(n), I(n-1), \ldots, I(n-M+1)$.

When the 1D CBSE is considered, two set of clusters $c_{m,1}$ and $c_{m,2}$, $m = 0,1,\ldots,B-1$, are estimated

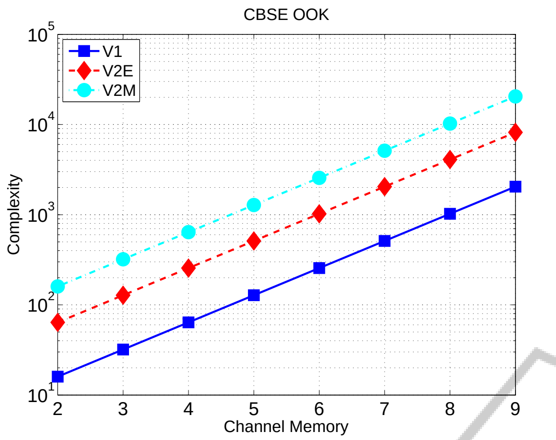

Figure 2: Computational complexity of the CBSE equalizer in the case of NRZ-OOK signaling, for the 1D implementation (V1), the 2D implementation using the Euclidean metric (V2E) and for the 2D implementation using the Mahalanobis metric (V2M).

during the training mode using (5). Each one of them corresponds to the fractionally spaced received signals $y_1(n)$ and $y_2(n)$. During the decision mode, the computation of the branch metrics associated to the 1D VA are computed using (6) as

$$V_m = \sum_{i=1}^{2} \left(y_i(n) - c_{m,i}\right)^2, \quad m = 0,\ldots,B-1. \tag{16}$$

In the case of the 2D CBSE, the cluster representatives $\mathbf{c}_{m,1}$ and $\mathbf{c}_{m,2}$, $m = 0,1,\ldots,B^+ - 1$ are estimated using (10). When the Euclidean metric is considered, the branch metrics of the 2D VA are computed as

$$V_m^E = \sum_{i=1}^{2} \left(\mathbf{y}_i(n) - \mathbf{c}_{m,i}\right)^T \left(\mathbf{y}(n) - \mathbf{c}_m\right) \tag{17}$$

with $m = 0,1,\ldots,B^+ - 1$. In the case when the Mahalanobis metric is adopted, the branch metrics are

$$V_m^M = \sum_{i=1}^{2} \left(\mathbf{y}_1(n) - \mathbf{c}_{m,i}\right) \Sigma_{m,i}^{-1} \left(\mathbf{y}_i(n) - \mathbf{c}_{m,i}\right)^T. \tag{18}$$

$\Sigma_{m,1}$ and $\Sigma_{m,2}$ are the covariance matrices computed using (13) for each one of the received signals $y_1(n)$ and $y_2(n)$.

The computational complexity of the CBSE equalizer in the case of NRZ-OOK signaling, measured in terms of the required multiplications, is given by $C_{OOK}^{1D} = 2^{M+2}$, $C_{OOK}^{2DE} = 2^{M+4}$ and $C_{OOK}^{2DM} = 5 \times 2^{M+3}$, for the 1D implementation, the 2D implementation using the Euclidean metric and for the 2D implementation using the Mahalanobis metric, respectively. The computational complexity of the NRZ-OOK CBSE equalizers is illustrated in Figure 2, for various values of the assumed channel memory M.

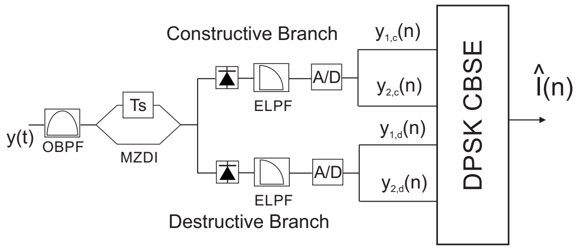

Figure 3: The NRZ-DPSK receiver.

4 CBSE IN DPSK SIGNALING

The NRZ-DPSK transmission has received increased attention as, compared to the NRZ-OOK counterpart, a 3dB improvement is achieved at the back-to-back operation, (Wang and Kahn, 2004; Alfiad et al., 2009; Bosco et al., 2010). The electronic equalization of optical NRZ-DPSK transmission is treated in a similar way, noting however that in this case the equalizer is designed using jointly the constructive and the destructive signals available at the receiver, at the output of a pair of balanced photo-detectors used for the demodulation of the optical DPSK signal (Alfiad et al., 2009). The schematic diagram of the NRZ-DPSK receiver when joint MLSE equalization is employed is depicted in Figure 3. At the receiver side the signal is processed by a Mach-Zahnder delay interferometer which extracts the information from the optical phase between two adjacent symbols, producing the constructive (upper branch) and the destructive (lower branch) output signals. These signals are subsequently fed into two photodetectors and after being filtered by the corresponding electrical filters and fractionally sampled, are both used as input to the MLSE equalizer (Alfiad et al., 2009; Bosco et al., 2010).

As in the case of OOK signaling, fractionally spaced sampling is considered. Thus, at each time instant, four signals are available at the receiver. Let $y_{1,c}(n) \in \Re$ and $y_{2,c}(n) \in \Re$ denote the received signals at the constructive branch of the DPSK receiver sampled at time instances nT_s and $nT_s + T_2/2$. Moreover, let $y_{1,d}(n) \in \Re$ and $y_{2,d}(n) \in \Re$ be the corresponding received signals at the destructive branch of the DPSK receiver. The DPSK receiver diversity implies the following MLSE cost

$$\min_{\{I_n\}} \left[\sum_n \left(\sum_{i=1}^{2} \left(y_{i,c}(n) - c_{i,c}(n)\right)^2 \right) + \sum_n \left(\sum_{i=1}^{2} \left(y_{i,d}(n) - c_{i,d}(n)\right)^2 \right) \right] \tag{19}$$

where $c_{1,c}(n)$, $c_{2,c}$, $c_{1,d}$ and $c_{2,d}$ denote the channel re-

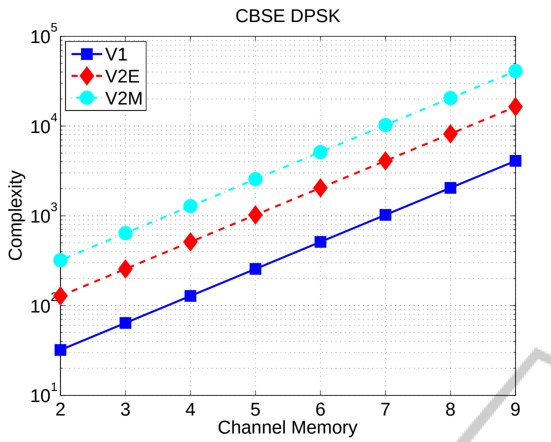

Figure 4: Computational complexity of the CBSE equalizer in the case of NRZ-DPSK signaling, for the 1D implementation (V1), the 2D implementation using the Euclidean metric (V2E) and for the 2D implementation using the Mahalanobis metric (V2M).

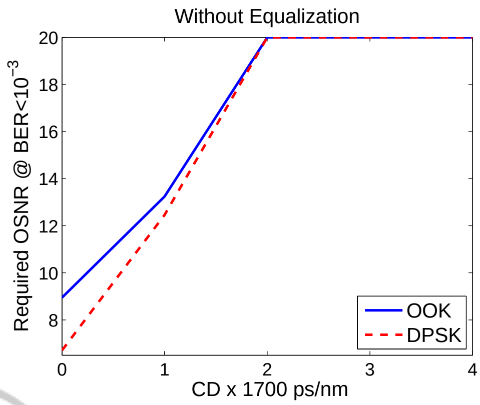

Figure 5: Required OSNR for BER=10^{-3} without electronic equalization, for OOK as well as for DPSK signaling at 10Gb/s.

sponse to the input sequence $I(n), I(n-1), \ldots, I(n-M+1)$.

The 1D CBSE in the case of DPSK signaling involves the computation of four sets of clusters, namely the $c_{m,1,c}$ and $c_{m,2,c}$ that correspond to the constructive branch of the receiver, as well as the $c_{m,1,d}$ and $c_{m,2,d}$ which correspond to the destructive branch of the receiver, $m = 0, 1, \ldots, B$, using (5) applied on the received signals $y_{1,c}(n)$, $y_{2,c}(n)$, $y_{1,d}(n)$ and $y_{2,d}(n)$. During the decision mode, the computation of the branch metrics associated to the 1D VA, are computed using (6), tailored to the DPSK diversity as

$$V = \sum_{i=1}^{2} \left(y_{i,c}(n) - c_{m,i,c}\right)^2 + \sum_{i=1}^{2} \left(y_{i,d}(n) - c_{m,i,d}\right)^2 .$$

The 2D CBSE can be derived following the approach applied in the OOK case, noting however that the receiver diversity includes apart from the fractionally spaced signaling, the diversity due to the constructive and the destructive branches of the DPSK receiver.

The computational complexity of the CBSE equalizer in the case of NRZ-DPSK signaling, is given by $C_{DPSK}^{1D} = 2^{M+3}$, $C_{DPSK}^{2DE} = 2^{M+5}$ and $C_{DPSK}^{2DM} = 5 \times 2^{M+4}$, for the 1D implementation, the 2D implementation using the Euclidean metric and for the 2D implementation using the Mahalanobis metric, respectively. The computational complexity of the NRZ-DPSK CBSE equalizers is illustrated in Figure 4, for various values of the assumed channel memory M. Clearly, the computational complexity of the CBSE equalization methods in the case of DPSK signaling is twice of that required in the case of OOK signaling.

5 PERFORMANCE EVALUATION

The electronic equalization schemes are used to mitigate either the residual dispersion resulting from incomplete optical compensation or the total dispersion resulting from uncompensated optical transmission. Here we focus on the later case, when uncompensated optical transmission is considered. The performance of the MLSE electronic equalizers has been investigated in the past, for the IM/DD NRZ-OOK as well as for the NRZ-DPSK signaling at 10Gb/s, using the 1D VA method (Bosco and Poggiolini, 2006; Rosenkranz and Xia, 2007; Chen et al., 2007; Poggiolini et al., 2008; **?**; Bosco et al., 2009). We extend the performance analysis of the aforementioned methods, considering the 1D CBSE as well as the 2D CBSE approach described in the preceding Section. The required OSNR for an achieved BER $< 10^{-3}$ is used as a performance index. Moreover, the performance of each method in a typical metro optical link comprising multiple fiber spans, each of length equal to 100 Km, is investigated in terms of the achieved BER.

The numerically simulated optical link operating at 10Gb/s consists of a transmitter comprising a 1mW CW laser at 1550 nm with an external modulator having extinction ratio of 25 dB and a Standard Single Mode Fiber with dispersion coefficient 17 ps/nm/km. When NRZ-OOK transmission is considered, on the receiver side, there is an optical filter with 20GHz bandwidth with a 3rd order Gaussian frequency response representing the corresponding demultiplexer output. The photodetector is a PIN diode with a sensitivity of 0.83 A/W and the receiver includes an electrical filter with 4th order Bessel frequency response with a cut-off frequency of 7GHz. The output is fractionally sampled and is fed as input to the CBSE

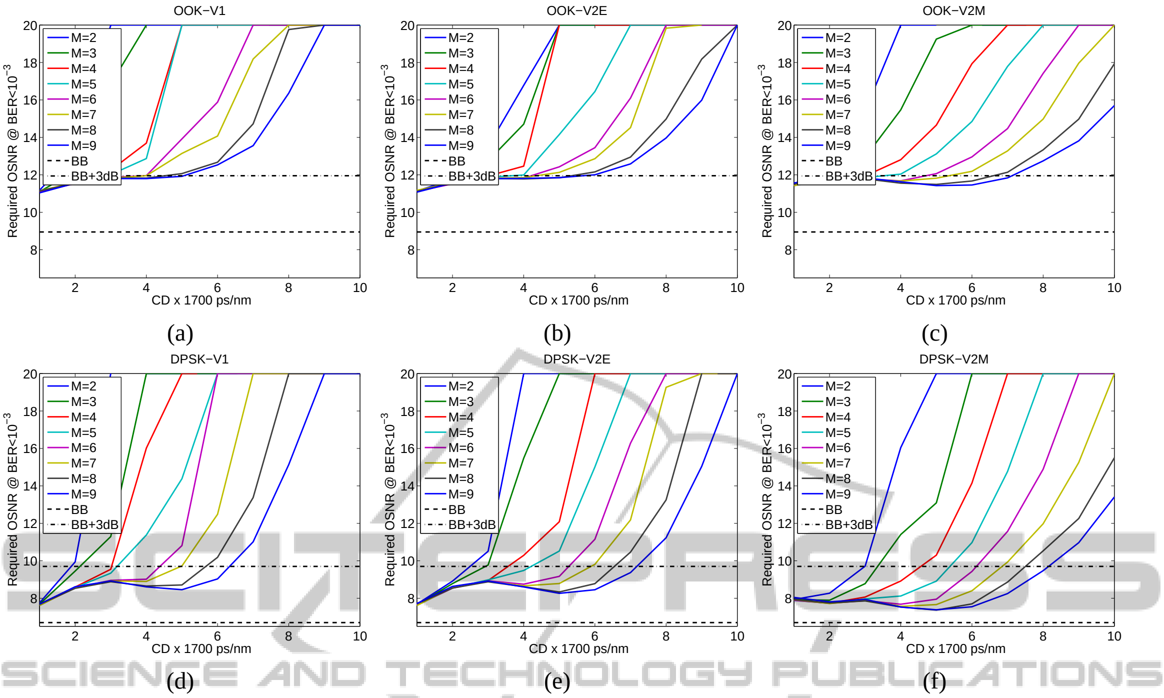

Figure 6: Required OSNR for OOK and DPSK signaling with CBSE equalization, for the the 1D implementation (V1), the 2D implementation using the Euclidean metric (V2E) and for the 2D implementation using the Mahalanobis metric (V2M), for various sizes of the assumed channel memory M, 10Gb/s.

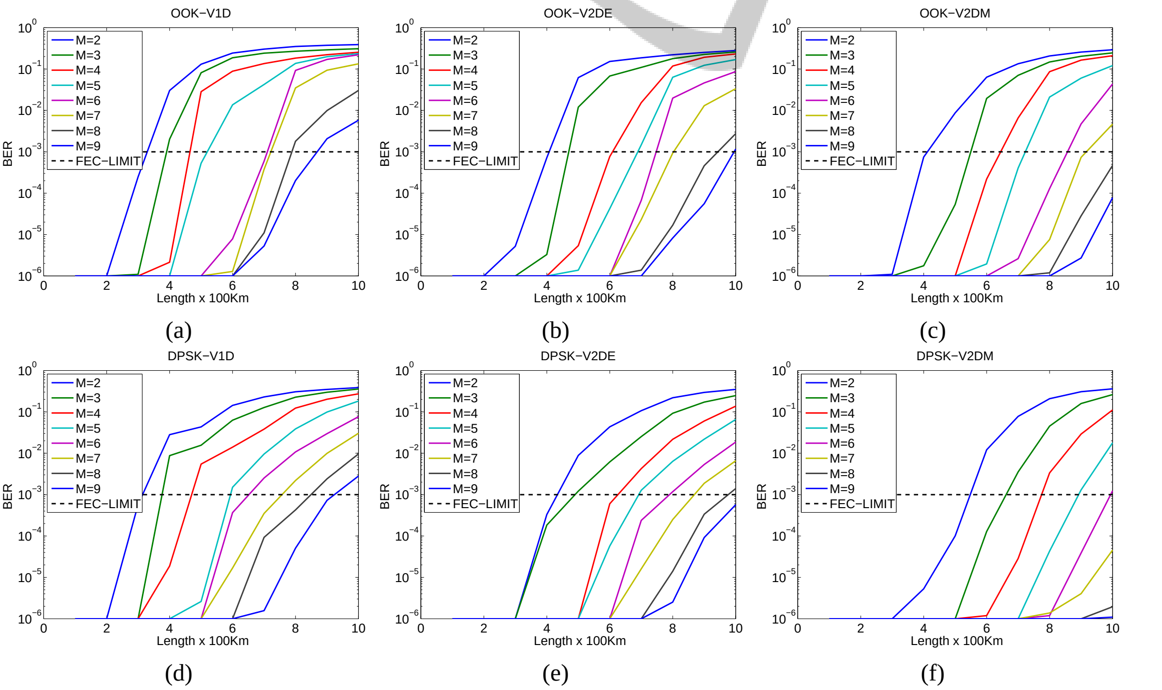

Figure 7: Achieve BER for electronically equalized transmission over a typical optical communication link, comprising of multiple spans, of length equal to $L = 100$Km, 10Gb/s.

equalizers. In the case of NRZ-DPSK transmission, the DPSK modulator is implemented using a standard Mach-Zehnder modulator. At the receiver side the signal is processed by a Mach-Zahnder delay interferometer. These signals are subsequently fed into two photodetectors and after being filtered by the corre-

Table 1: Selected signaling and CBSE approach for particular values of the target BER. Notation V1, V2E and V2M is used to indicate the CBSE approach, i.e. the 1D implementation, the 2D implementation using the Euclidean metric and the 2D implementation using the Mahalanobis metric, respectively. The assumed channel length and the required computational complexity of each method are indicated as $[M/C]$.

L Km	BER$< 10^{-3}$	BER$< 10^{-5}$
100	OOK V1 [2/16]	OOK V1 [2/16]
200	OOK V1 [2/16]	OOK V1 [2/16]
300	OOK V1 [2/16]	OOK V1 [3/32]
400	OOK V2E [2/32]	OOK V2E [3/64]
500	OOK V2E [4/128]	OOK V2E [4/128]
600	OOK V2E [4/128]	OOK V1 [6/256]
700	OOK V2E [6/256]	OOK V2E [8/2048]
800	OOK V2E [7/1024]	OOK V2E [9/4096]
900	OOK V2E [8/2048]	DPSK V2M [7/10240]
1000	DPSK V2E [9/8192]	DPSK V2M [8/20480]

sponding electrical filters and being fractionally sampled. In both cases, the system is optically amplified using a single polarization Erbium Doped Fibre Amplifier such that the power at the receiver input is equal to the transmitted power, which is set equal to 0dBm.

The input signal $I(n)$ is a binary sequence of length equal to $N = 2^{20}$. In all cases, the given results are obtained by averaging the output of ten independent computer experiments. The experimental conditions impose a lower bound on the estimated BER, given by BER $> 10^{-6}$. The required OSNR versus the accumulated CD for uncompensated NRZ-OOK as well as for NRZ-DPSK transmission is depicted in Figure 5. The performance of the CBSE equalizers is illustrated in Figure 6, where it is shown the required OSNR versus the accumulated CD for the 1D and the 2D CBSE approaches, for various values of the assumed channel memory, varying from $M = 2$ and going up to $M = 9$. The attained performance is compared against the the back-to-back performance corresponding to the OOK and to the DPSK signaling. For both modulation formats, the 2D CBSE using the Mahalanobis metric demonstrates the better performance within the margin of the 3dB penalty, followed by the 2D CBSE using the Euclidean metric. The 1D CBSE has the worst performance, noting however that it requires the least amount of computation. In all cases, the DPSK signaling performs better than the OOK counterpart, at the expense of an increase in the complexity of the transponder circuitry and the amount of computations required by the electronic equalization modules.

The achieved BER for each modulation format, when the CBSE approach is used for the implementation of the MLSE, is illustrated in Figure 7, for uncompensated optical transmission over a distance of up to 1000 Km, with the optical link comprising of multiple fiber spans, each of length equal to 100 Km. Once again, the DPSK signaling outperforms the OOK counterpart, however at an expense of complexity. Subsequently, the performance of each method in terms of the required computational complexity is investigated, for two different target BER, specificaly for BER $< 10^{-3}$ and for BER $< 10^{-5}$. The results are tabulated in Table 1, where the selected method, as well as the computational complexity of each CBSE approach is presented. In the case when the target BER is achieved by more than one methods, that which corresponds to the minimum assumed channel lenght M is selected.

6 CONCLUSIONS

The performance of the electronic equalization using the CBSE approach has been investigated by means of computer simulation, in the context of IM/DD optical communications links operating at 10Gb/s, for NRZ-OOK as well as for NRZ-DPSK signaling. The 1D CBSE, as well as the 2D CBSE using the Euclidean or the Mahalanobis distance for the computation of the branch metrics of the VA, provide an attractive approach for the implementation of the MLSE, bypassing the need of explicit estimation of the optical channel response. In principle, the electronically equalized DPSK signaling outperforms the OOK counterpart. Finally, the application of the CBSE method is considered in a simulated typical metro optical transmission link. For a given value of the target BER, the required computational complexity is investigated for different modulation formats and for the various discussed CBSE approaches.

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