On the optimum signal constellation design for high-speed optical transport networks

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Abstract: In this paper, we first describe an optimum signal constellation design algorithm, which is optimum in MMSE-sense, called MMSE-OSCD, for channel capacity achieving source distribution. Secondly, we introduce a feedback channel capacity inspired optimum signal constellation design (FCC-OSCD) to further improve the performance of MMSE-OSCD, inspired by the fact that feedback channel capacity is higher than that of systems without feedback. The constellations obtained by FCC-OSCD are, however, OSNR dependent. The optimization is jointly performed together with regular quasi-cyclic low-density parity-check (LDPC) code design. Such obtained coded-modulation scheme, in combination with polarization-multiplexing, is suitable as both 400 Gb/s and multi-Tb/s optical transport enabling technology. Using large girth LDPC code, we demonstrate by Monte Carlo simulations that a 32-ary signal constellation, obtained by FCC-OSCD, outperforms previously proposed optimized 32-ary CIPQ signal constellation by 0.8 dB at BER of 10^{-7}. On the other hand, the LDPC-coded 16-ary FCC-OSCD outperforms 16-QAM by 1.15 dB at the same BER.

OCIS codes: (060.0060) Fiber optics and optical communications; (060.4080) Modulation; (999.9999) Optimum signal constellation design; (999.9999) Forward error correction (FEC); (999.9999) Low-density parity-check (LDPC) codes.

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1. Introduction

Approaching channel capacity has been one of the major topics of interest for many researchers for decades [1]. With the rapid growth in carrier-grade data-centric applications and services, and the general deployment of broadband wireless and wire line access network, there has been a strong impetus for the DWDM network to upgrade from 10 Gb/s per channel to more spectrally-efficient 40 Gb/s or 100 Gb/s per channel transmission and optical transmission at 100 Gb/s Ethernet data rate has been standardized by ITU-T and IEEE forums [2]. According to industry experts [3,4], 400 GbE and 1 Tb/s Ethernet (TbE) should be standardized in the near future. To support beyond 400 Gb/s serial transmission, a better modulation format would be needed to get closer to the channel capacity. In this paper, we describe two algorithms to design the nonuniform signal constellations that are applicable to fiber-optics communication channels with/without inline chromatic dispersion compensation. The first algorithm is optimum in the minimum mean-square error (MMSE) sense, and it is called MMSE optimum signal constellation design (OSCD) algorithm. This algorithm is quite straightforward for use as it does not require the employment of constrained optimization software. Instead, simple Monte Carlo simulation can be used in signal constellation design. It is well known fact from information theory [5] that feedback channel capacity is higher than the channel capacity of systems without feedback. Inspired by this fact, we proposed another algorithm that performs optimization for different OSNR values. Given the fact OSNR estimate can be obtained from monitoring channels, this information can be used on transmitter side to adapt the signal constellation according to the channel conditions. Since this algorithm has roots in channel capacity of feedback systems, it is called here feedback channel capacity inspired (FCC) OSCD. The key advantage of this algorithm is that the signal constellation design can be matched to regular quasi-cyclic (QC) low-density parity-check (LDPC) code of large girth, to facilitate implementation of nonuniform coded-modulation schemes at ultra-high speeds. Both algorithms require the knowledge of optimum source distribution that can be obtained by transmitted the training sequence to determine conditional probability density functions and then run Arimoto-Blahut algorithm [5] to determine the optimum source distribution. Once the optimum source distribution is known, we generate samples from the optimum source distribution and run the proposed algorithms, with details provided in Sections 2 and 3, respectively. The MMS-OSCD is OSNR independent, while FCC-OSCD is OSNR dependent. The signal constellations obtained by FCC-OSCD when combined with QC LDPC codes of large girth in coded modulation fashion together with polarization-division multiplexing (PDM) can be used in beyond Tb/s optical transport. Monte Carlo simulations indicate that 32-ary signal constellation obtained by FCC-OSCD, when used in combination with large girth LDPC codes, outperforms previously optimized 32-ary CIPQ by about 0.8 dB. The Monte Carlo simulations also show that the LDPC-coded 16-ary FCC-OSCD outperforms the LDPC-coded 16-QAM by 1.15 dB.

The signal constellation optimization is a well known research topic [5–12], which dates back to 60s. Although a number of different constellations have been proposed not many have been used in practice, except from conventional QAM constellations, in particular in optical communications. There are different criteria used in design including BER [12], MSE [6–8], and mutual information [10]. All these algorithms require the use of optimization software and theory of nonlinear optimization. On the other hand, the proposed algorithms do not require any optimization software; instead simple Monte Carlo simulations are used in signal

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constellation design. Another advantage is that the proposed algorithms are quite general, they are applicable to any channel, including Gaussian-like channels, such as fiber-optics channel upon compensation of chromatic dispersion, PMD and nonlinearities (by digital backpropagation method for instance). Further, the proposed algorithms can easily be used in multidimensional signal constellation design, which is of high importance for few-mode fiber applications. The use of channel capacity approach in multidimensional signal constellation design is numerically extensive, in particular when the number of dimensions is larger than three.

This paper is organized as follows. Section 2 describes the MMSE-OSCD algorithm, while the Section 3 describes the FCC-OSCD algorithm. In Sec. 4, we describe how to combine the signal constellations obtained in Sections 2 and 3, with PDM and LDPC coding. In Sec. 5, we evaluate performance of developed signal constellations against conventional QAM and previously optimized signal constellations. The final section concludes the paper.

2. The MMSE-OSCD algorithm

The first stage in proposed algorithm is to use the conventional Arimoto-Blahut algorithm in order determine the optimum source distribution, in channel capacity sense, for a given optical channel. In the second stage, we first initialize the algorithm with a set of initial constellation points, for example QAM constellations can be used for initialization. After initialization, we generate the training sequences from optimum source distribution and split them into clusters of points according Euclidean distance squared from constellation obtained in previous iteration. New constellation points are obtained as the center of mass of such obtained clusters. This procedure is repeated until convergence or until a predetermined number of iterations has been reached. It can be shown that this algorithm is optimum in MMSE sense.

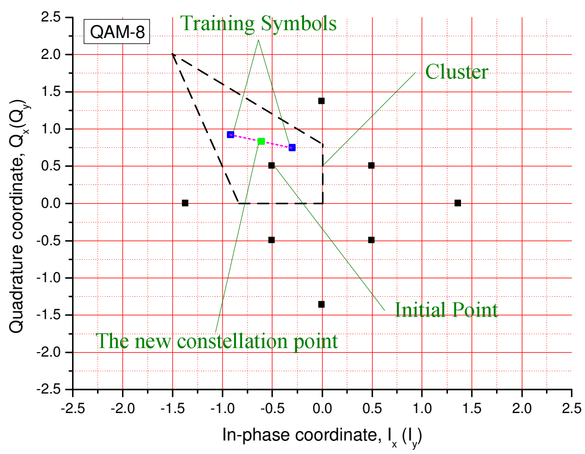

Fig. 1. MMSE-OSCD algorithm illustration.

The MMSE-OSCD algorithm can be formulated as follow:

0) Initialization: Choose an arbitrary auxiliary input distribution. Choose an arbitrary signal constellation as initial constellation and set the size of this constellation to M.

1) Apply the Arimoto-Blahut algorithm to determine optimum source distribution.

2) Generate long training sequences $\{x_j; j = 0,\ldots,n-1\}$ from optimum source distribution, where n denotes the length of the training sequence used for signal constellation

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design. Let $\boldsymbol{A_0}$ be the initial M-level signal constellation set of subsets of constellation points.

3) Group the samples from this sequence into M clusters. The membership to the cluster is decided by Euclidean distance squared of sample point and signal constellation points from previous iteration. Each sample point is assigned to the cluster with smallest distance squared. Given the mth subset (cluster) with N candidate constellation points, denoted as $\hat{A}_m = \{y_i; i = 1, \cdots, N\}$, find the minimum mean square error of partition $P(\hat{A}_m) = \{S_i; i = 1, \cdots, N\}$, as follows

$$D_m = D\left(\left\{\hat{A}_m, P\left(\hat{A}_m\right)\right\}\right) = n^{-1} \sum_{j=0}^{n-1} \min_{y \in \hat{A}_m} d\left(x_j, y\right),$$

where d is Euclidean distance squared between jth training symbol and symbol y being already in the subset (cluster). With $D(\cdot)$, we denoted the distance function.

4) If the relative error $|D_{m-1}-D_m|/D_m \leq e$, where e is the desired accuracy, the final constellation is described by $\{\hat{A}_m\}$. Otherwise continue.

5) Determine the new constellation points as center of mass for each cluster. With the mean square-error criterion, $x(S_i)$ is the Euclidean center of gravity or centroid given by

$$x\left(S_i\right) = \left\|S_i\right\|^{-1} \sum_{j: x_j \in S_i} x_j,$$

where $\|S_i\|$ denotes the number of training symbols in the region S_i, as illustrated in Fig. 1. If there is no training symbol in the region, set $x(S_i) = y_i$, the old constellation point. Define $\hat{A}_{\mathrm{m+1}} = \mathrm{x}(P(\hat{\mathrm{A}}_{\mathrm{m}}))$, replace m by $m+1$, and go to step 3).

Repeat the steps 2)-5) until convergence. For non-Gaussian channels, we will need to iterate the steps 1)-5) instead. In addition, instead of minimization of Euclidean distance we need to maximize the log-likelihood function. Since we are concerned with fundamental limits, we observe ASE noise dominated scenario. Given the fact that the ASE noise is a Gaussian process, from information theory we know that optimum information source is Gaussian, so there is no need to repeat the step 1) as well. Moreover, from digital communications [13], we know that correlation, matched, log-likelihood and Euclidean receivers are equivalent to each other for Gaussian channels. Therefore, maximization in log-likelihood function or minimization in Euclidean distance leads to the same result.

As an illustration, in Fig. 2 we provide the signal constellations obtained for following signal constellation sizes: (a) 8, (b) 16, (c) 32, and (d) 64. The results are obtained for ASE noise dominated scenario. Notice that these signal constellations remind to that of IPQ-signal constellations we introduced in [6], except for the center point. Alternatively, someone may use IPQ-approach by placing first the central point in the origin and then apply the IPQ-procedure, as we described in [7]. Notice, however, that IPQ-procedure uses some approximations to come up with closed-form solutions [7], which are valid assumptions for reasonable large signal constellation sizes. Therefore, it is a suboptimum solution for medium signal constellations' sizes. The proposed MMSE-OSCD method can easily be expanded to the higher-dimensional space and other design criteria. Notice that the optimum solution is not the unique one, in particular for medium size constellations. Namely, the algorithm is based on a training sequence generated from optimum source. The solution is also dependent on initial constellation. However, even though that several solutions might appear different,

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very often they are just rotations of each other. Moreover, they perform exactly the same in terms of information capacity and BER.

During the generation of training sequences in signal constellation design, we have found that 50000 training symbols for 16-ary constellation and 100000 for 32-ary constellation are sufficient. When the IPQ constellation is used as an initial constellation, the algorithm converges faster, compared to QAM as initial constellation. However, the constellations obtained after optimization for either initial case are almost identical.

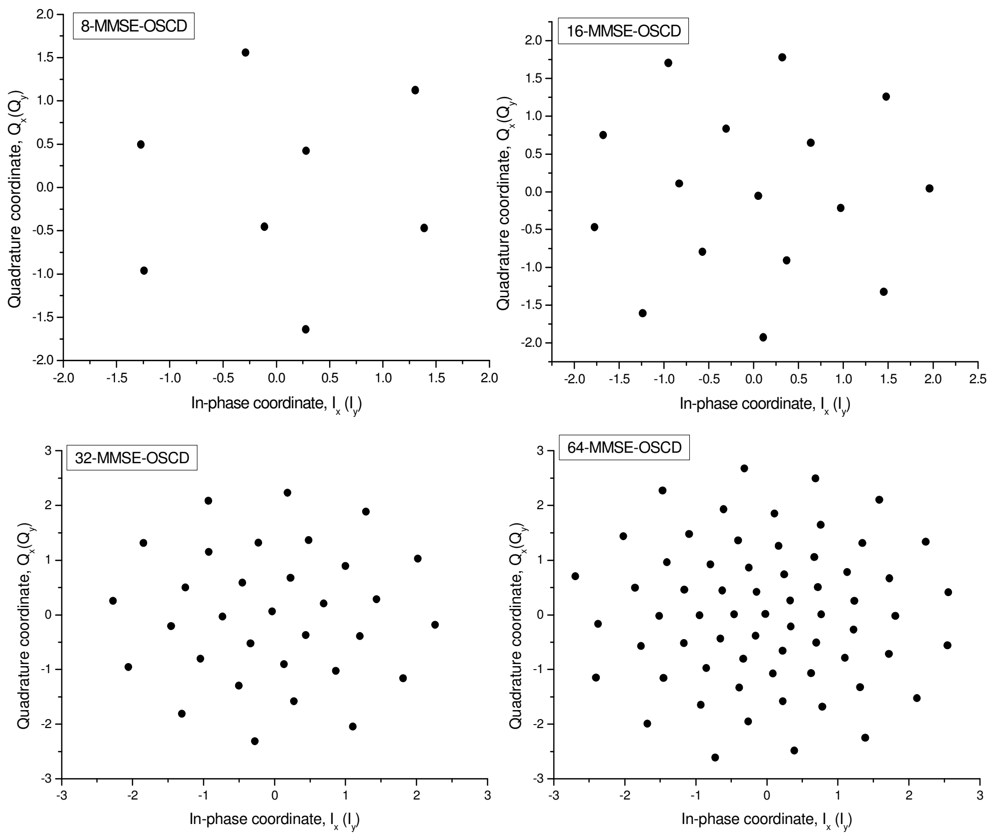

Fig. 2. MMSE-OSCD algorithm based signal constellations.

3. The FCC-OSCD algorithm

The proposed FCC-OSCD algorithm, which is an upgrade of MMSE-OSCD, can be formulated as follows. In the first stage, we determine the optimum source distribution by using Arimoto-Blahut algorithm, based on conditional probability density functions obtained by sufficiently long training sequence. In the second stage, in initial phase we set the desired signal constellation size to M, and chose an arbitrary signal constellation as the initial constellation. The following two steps are iterated until MSE of optimum source representation falls below target MSE.

Step 1: Generate a long training sequence from optimum source distribution, for a given OSNR, and split the generated samples into M clusters based on minimum Euclidean distance (maximum log-likelihood function for non-Gaussian channels) from signal constellation points obtained in previous iteration.

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Step 2: The signal constellation points in current iteration are obtained as center of mass of cluster points.

This procedure needs to be repeated for different OSNR values, which is the main difference with the MMSE-OSCD algorithm.

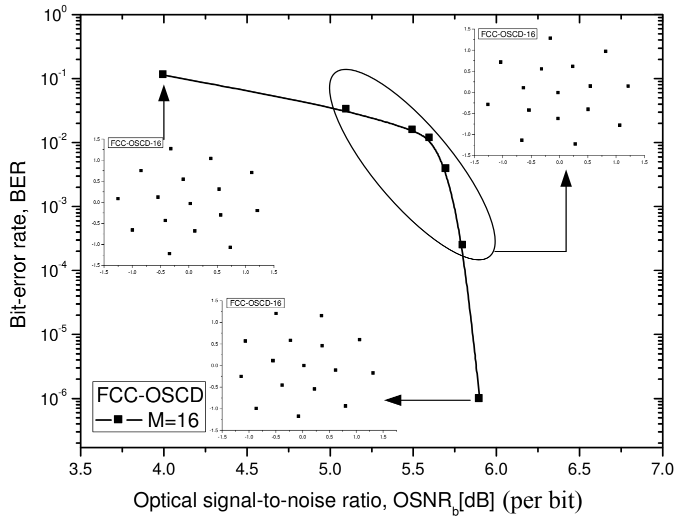

Fig. 3. BER performance of 16-FCC-OSCD constellations for different OSNRs. Insets show how the optimized constellations look like for different OSNR ranges.

By estimating the OSNR by the monitoring channels at the receiver side, we can use this information on transmitter side to select the signal constellation that represents the best match to the current channel conditions, which is illustrated in Fig. 3 when LDPC (16935, 13550) code is used. For different OSNR, we use different constellations in the simulation in order to improve the OSNR sensitivity and lower the bit error rate. Clearly, the 16-FCC-OSCD constellations with different OSNRs are distinct. The number of constellation points in inner circle changes with OSNR: for ONSRs below 5 dB the number of points is six, for OSNRs in the range 5-5.5 dB it is seven, and for OSNRS ≥5.75 dB it is six. Form Fig. 3 is evident that the coordinates of optimum constellations change slow as the OSNR increases so that three optimum constellations are sufficient to cover whole OSNR range.

In fiber optics communications, it is a common practice to use optical SNR (OSNR) instead of electrical SNR. If we want to compare various signal constellation sizes, we need to use OSNR per bit and per single polarization, denoted as $OSNR_b$, and defined as

$$OSNR_b = \frac{OSNR}{\log_2 M} = \frac{R_{s,\text{info}}}{2B_{\text{ref}}} SNR_b, \tag{1}$$

where M is signal constellation size, $R_{\text{s,info}}$ is information symbol rate, and B_{ref} is referent bandwidth (12.5 GHz, which corresponds to a 0.1 nm resolution bandwidth of optical spectrum analyzers at 1550 nm). In Eq. (1) SNR_{b} denotes signal-to-noise ratio per information bit defined by E_b/N_0, where E_b is the bit energy and N_0 is a power spectral density (PSD) originating from ASE noise (it is assumed that photodiode responsivity is 1 A/W so that $N_0 = N_{\text{ASE}}$, where N_{ASE} is PSD of ASE noise in one polarization). The OSNR per single polarization is defined conventionally as $OSNR = ER_s/(2N_{\text{ASE}}B_{\text{ref}})$, where E is symbol energy and R_s is symbol rate related to symbol information rate $R_{\text{s,info}}$ as follows $R_s = R_{\text{s,info}}/R_c$, where R_c is the code rate. On the other hand, in order to show the results in OSNR [dB / 0.1nm] per single polarization instead, someone needs to shift corresponding curves by $10\log_{10}(\log_2 M)$ dBs to the right. Notice that this definition is consistent with that used in [11].

The LDPC code used in simulations requires four bits for representation of LLRs, without degradation, see ref [14]. For representation of constellation points obtained by OSCD algorithm, additional two bits are required, which is comparable to the number of bits required for QAM.

4. MMSE- and FCC-OSCDs in Polarization-Division Multiplexed (PDM) LDPC-Coded Optical Communication Systems

In this section, we describe how to use the signal constellations obtained by optimization algorithms described in Sections 2 and 3 in combination with PDM and LDPC coding. The proposed polarization-multiplexed LDPC-coded scheme based on FCC-OSCD signal constellations is depicted in Fig. 4. There are $m_x + m_y$ independent sources, where subscripts x and y correspond to x- and y- polarizations, respectively. Since the configurations of LDPC-coded FCC-OSCD transmitter (*Tx*) are identical for both polarizations, we provide full details only for x-polarization. The independent streams in x-polarization are encoded using $[N,K_x]$ binary LDPC codes of code rate $R_x = K_x/N$; and outputs of encoders are written row-wise into block-interleaver. The m_x bits are taken from interleaver column-wise and used to select a point from MMSE-OSCD 2^{mx} -ary signal constellation implemented as a look-up-table (LUT). The LUT coordinates are after pulse shaping used as inputs to I/Q modulator (I/Q MOD). The independent polarization streams are combined by polarization beam combiner and transmitted over the system of interest. At the receiver side, conventional course digital back-propagation is used, with small number of coefficients just to reduce the channel memory so that the complexity of sliding-window MAP equalizer that follows is not too high (see ref [8]. for additional details). The sliding-MAP equalizer provides soft symbol log-likelihood ratios (LLRs), which are used to calculate bit LLRs, which are further passed to the LDPC decoders. Further, the turbo equalization principle is used as explained in [8]. The aggregate date rate of this scheme is $(m_x R_x + m_y R_y) R_s$, where R_s is the symbol rate.

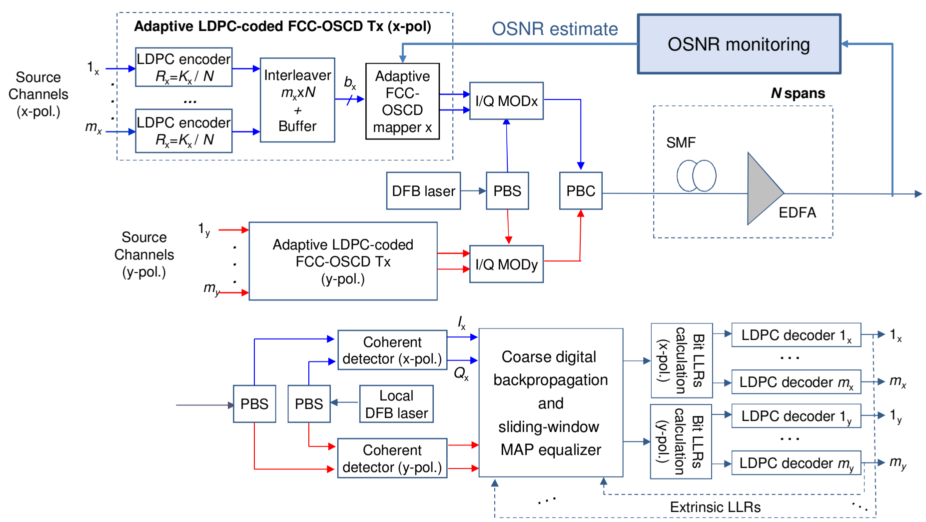

Fig. 4. Polarization-division multiplexed LDPC-coded modulation scheme based on FCC-OSCD signal constellations.

In the proposed PDM LDPC-coded scheme based on FCC-OSCD signal constellations, we use the OSNR monitoring circuit to estimate the channel OSNR and feedback this information back to transmitter, as shown in the Fig. 4. The transmitter changes the signal constellation based on the OSNR estimate. From Fig. 3 is evident that typically three different signal constellations are sufficient, which suggests that system complexity is not that high. Alternatively, someone can use the signal constellation obtained for moderate values of OSNR all the times.

5. Performance analysis

To demonstrate the high-potential of the proposed schemes, we perform Monte Carlo simulations. The result of the Monte Carlo simulations for different signal constellations obtained by MMSE-OSCD and FCC-OSCD algorithms are summarized in Figs. 5-9. The Fig. 5 shows the information capacities for signal constellations obtained by using the FCC-OSCD algorithm for various signal constellation sizes. In the same figure we provide information capacity results for conventional QAM and CIPQ scheme, obtained by placing one point in the origin while determining the remaining M-1 points by IPQ-procedure [6]. Clearly, the constellations derived by FCC-OSCD algorithm, outperform both QAM and CIPQ constellations. Moreover, for medium SNRs, FCC-OSCD-based constellations of lower size outperform QAM of larger constellation size.

The result of Monte Carlo simulations for different signal constellation sizes of proposed MMSE-OSCD-algorithm-based constellations are summarized in Fig. 6. All result of simulations are obtained for 25 LDPC decoder (inner) iterations and 3 MAP-LDPC (outer) iterations. It is clear to see that the largest improvement is obtained for 16-ary MMSE-OSCD, and at BER of 10^{-8} it is almost 1 dB over 16-QAM. The Fig. 7 shows the result of simulations for different FCC-OSCD signal constellation sizes. All the result are obtained for 20 LDPC decoder iterations and 5 MAP-LDPC iterations. The LDPC-coded 16-ary FCC-OSCD scheme outperforms the corresponding 16-QAM scheme by 1.15 dB at BER of 10^{-7}. On the other hand, the LDPC-coded 32-ary FCC-OSCD outperforms the corresponding 16-ary CIPQ scheme by 0.8 dB at the same BER. The BER performance of MMSE-OSCD and FCC-OSCD are compared in the Fig. 8. The results are obtained with 20 inner iterations and 5 outer iterations. Notice that the first three points in low OSNR regime are almost the same. Clearly, the FCC-OSCD outperforms MMSE-OSCD by more than 0.2 dB at BER of 10^{-7}. The Fig. 9 shows the result of 16-ary FCC-OSCD signal constellation with different number of inner iterations and outer iterations in iterative APP demapper-LDPC decoding. It is evident that the case with 25 inner iterations and four outer iterations performs the best. Notice that in all simulations above we use a natural bit-to-symbol mapping rule. The design of optimum mapping rule is out of scope of this paper. Since the FCC-OSCD is performed for natural mapping rule we do not expect mach improvement for the optimum mapping rule. For optimum mapping rules an interested reader is referred to [15].

We evaluate the performance of the proposed constellations from fundamental point of view, in a back to-back configuration, which represents the worst case scenario for comparison with LDPC-coded QAM. In the presence of imperfect PMD compensation and nonlinearity compensation, the optimum constellations perform much better than QAM, as shown in [9] for related iterative polar modulation [6].

The information symbol rate (channel symbol rate) used in simulations above is set to 25GS/s (32.25GS/s). The channel code is based on QC LDPC (16935, 13550) code of rate 0.8, column-weight 3 and girth g≥8.

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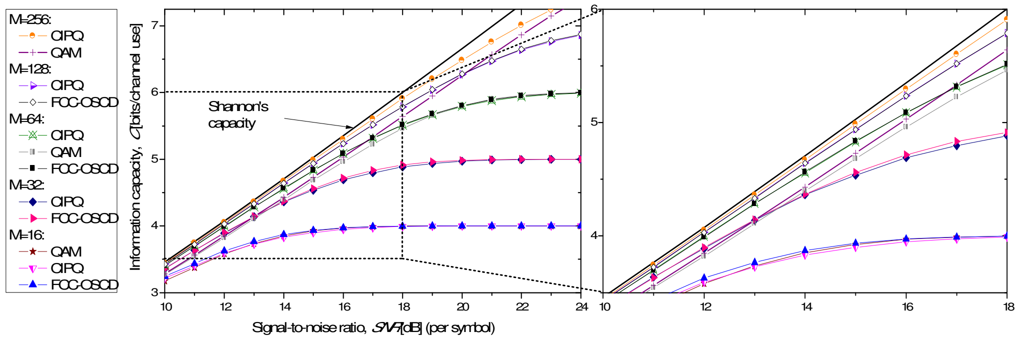

Fig. 5. Information capacities of FCC-OSCD-based signal constellation against QAM and CIPQ.

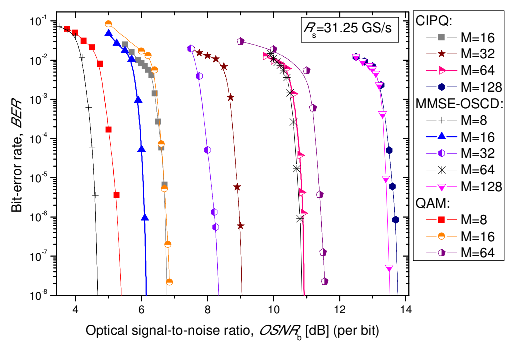

Fig. 6. BER performance of MMSE-OSCD constellations.

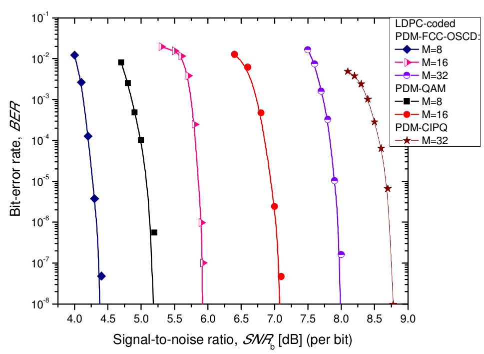

Fig. 7. BER performance of FCC-OSCD constellations.

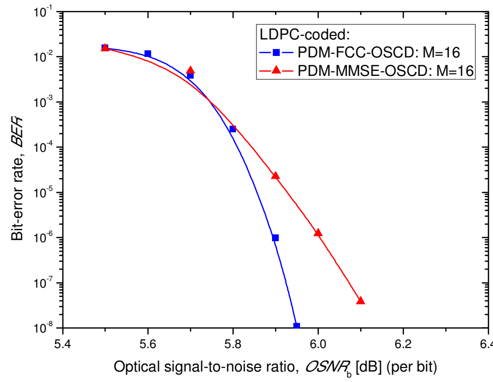

Fig. 8. BER performance for FCC and MMSE-OSCDs.

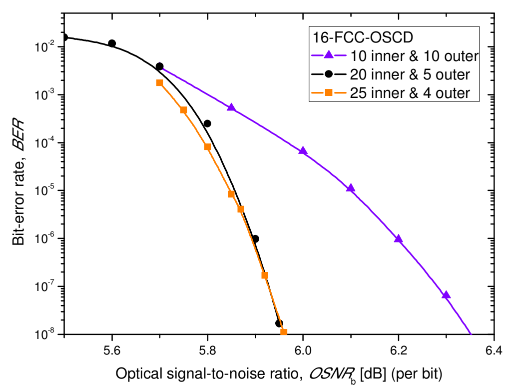

Fig. 9. BER performance for different number of inner and outer iterations.

6. Conclusion

In this paper, we described two signal constellation design algorithms: MMSE-OSCD and FCC-OSCD. The first algorithm is optimum in MMSE sense. The second algorithm provides the optimum signal constellations for different OSNR values. Both algorithms require the knowledge of optimum source distribution, obtained by using Arimoto-Blahut algorithm. The signal constellations obtained by these algorithms have been used in combination with polarization-multiplexing and LDPC coding to evaluate high potential of developed signal constellations. The key idea in our pragmatic coded-modulation approach is to optimize signal constellation given the limitations in LDPC code design: practical codeword length, practical code rates, and quasi-cyclic structure of parity-check matrices to facilitate decoder hardware implementation. This is particularly important for optical communications, as we are concerned with symbol rates in the range 25 Gs/s - 33 Gs/s, and the implementation of highly irregular LDPC decodes at these speeds is practically impossible given the current state of the art FPGA technology. The Monte Carlo simulations have shown that a 32-ary signal constellation, obtained by FCC-OSCD, outperforms previously proposed CIPQ algorithm based 32-ary signal constellation by 0.8 dB at BER of 10^{-7}. On the other hand, the LDPC-coded 16-ary FCC-OSCD outperforms the LDPC-coded 16-QAM by 1.15 dB. Given the recent experimental evaluation of LDPC-coded 256-IPM by Liu *at al* [9], which have shown excellent nonlinearity tolerance compared to LDPC-coded QAM; it is expected the signal constellations developed by FCC-OSCD will significantly extend the transmission distance of conventional PDM-QAM schemes. In addition, given the fact that FCC-OSCD is

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OSNR dependent, the constellations obtained by FCC-OSCD are suitable for adaptive modulation and coding applications, as the signal constellation size and LDPC error correction capability can be simultaneously adapted based on channel condition information obtained from monitoring channels.

The proposed signal constellation design algorithms do not require the use of any optimization software; instead simple Monte Carlo simulations are used in signal constellation design. Another advantage is that the proposed algorithms are quite general, they are applicable to any channel, including Gaussian-like channels, such as fiber-optics channel upon compensation of chromatic dispersion, PMD and nonlinearities (by digital back-propagation method for instance). The OSCD algorithms can also be used in development of multidimensional signal constellations, which are of high importance for few-mode fiber applications. Finally, given the improvements in OSNR sensitivity, the OSCD-based signal constellations should be used in future multi-Tb/s optical transport networks.

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