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Citation for published version (APA):

Amari, A., Lin, X., Dobre, O. A., Venkatesan, R., & Alvarado, A. (2019). A machine learning-based detection technique for optical fiber nonlinearity mitigation. *IEEE Photonics Technology Letters*, 31(8), 627-630. [8660506]. <https://doi.org/10.1109/LPT.2019.2902973>

DOI:

[10.1109/LPT.2019.2902973](https://doi.org/10.1109/LPT.2019.2902973)

Document status and date:

Published: 15/04/2019

Document Version:

Accepted manuscript including changes made at the peer-review stage

Please check the document version of this publication:

- A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher's website.
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A Machine Learning-Based Detection Technique for Optical Fiber Nonlinearity Mitigation

Abdelkerim Amari, Xiang Lin, Octavia A. Dobre, Ramachandran Venkatesan, Alex Alvarado

Abstract—We investigate the performance of a machine learning classification technique, called the Parzen window, to mitigate the fiber nonlinearity in the context of dispersion managed and dispersion unmanaged systems. The technique is applied for detection at the receiver side, and deals with the non-Gaussian nonlinear effects by designing improved decision boundaries. We also propose a two-stage mitigation technique using digital back propagation and Parzen window for dispersion unmanaged systems. In this case, digital back propagation compensates for the deterministic nonlinearity and the Parzen window deals with the stochastic nonlinear signal-noise interactions, which are not taken into account by digital back propagation. A performance improvement up to 0.4 dB in terms of Q factor is observed.

Index Terms—digital back propagation, fiber nonlinearity mitigation, machine learning, optical communication systems, Parzen window.

I. INTRODUCTION

FIBER nonlinearity mitigation has been considered as a key technology to increase the optical system capacity. Several digital signal processing (DSP) techniques have been proposed to compensate for the nonlinear distortions in the optical link, as reviewed in [3]–[2]. Machine learning techniques have recently received significant attention as promising approaches to deal with such effects. These techniques have been applied as detectors at the receiver side [4]–[7], and also as channel model-based compensation algorithms [8]–[10].

Machine learning-based detectors provide two main advantages. Firstly, they can partially mitigate both deterministic fiber nonlinearities and stochastic nonlinear signal-amplified spontaneous emission (ASE) noise interactions. Secondly, they do not require the knowledge of the optical link parameters, which makes them well-suited for dynamic optical networks.

Multiple machine learning-based detectors have been proposed in the context of dispersion unmanaged (DUM) and dispersion managed (DM) systems, such as support vector

machines (SVM) [4], K-means clustering [5], and the K-nearest neighbors algorithm [6]. The main idea of machine learning-based detectors is to design improved nonlinear decision boundaries more adapted to the nonlinear fiber channel. Thus, the nonlinear distortions such as nonlinear non-Gaussian noise can be mitigated.

In this letter, we propose a machine learning-based classification technique, known as the Parzen window (PW) classifier [11], [12], to mitigate the non-Gaussian nonlinear effects. The PW classifier is applied as a detector at the receiver side. We show that a performance improvement in terms of the Q factor is observed when applying the PW classifier to both DUM and DM systems. Another advantage of the PW-based detector is the non-requirement of carrier phase estimation (CPE) because the detection is based on the training data.

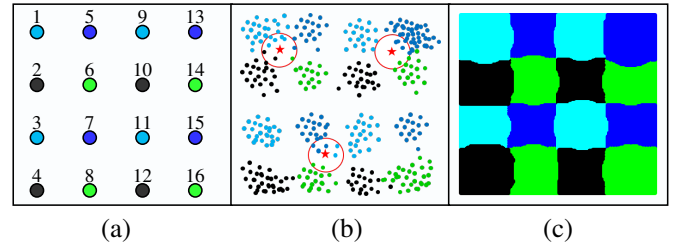


Fig. 1. PW principle: (a) Tx training symbols; (b) Rx detection based on training symbols; (c) Rx decision regions.

Furthermore, we complement the PW classifier with digital back propagation (DBP) [13], and propose a two-stage fiber nonlinearity mitigation. DBP is used to compensate for the deterministic nonlinear effects. Then, the PW-based detector is applied to deal with the nonlinear non-Gaussian signal-ASE noise interactions. In DUM systems, the two-stage nonlinearity mitigation using DBP and the PW classifier increases the performance in comparison with DBP, used with the classic minimum distance(MD)-based detector.

II. PARZEN WINDOW PRINCIPLE

Machine learning techniques are widely investigated in the context of optical communication systems, as discussed in [14]–[16]. In particular, machine learning-based classification techniques have been proposed as detectors to deal with the nonlinear effects. In this context, we propose the PW, which is a machine learning nonparametric classification technique based on supervised learning. It is inherently a multi-class technique and can be applied for multi-level modulation formats without adaptation. This is unlike other proposed

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This work was supported by Atlantic Canada Opportunities Agency (ACOA) and Research Development Corporation (RDC) Canada, and by the Netherlands Organisation for Scientific Research (NWO) via the VIDI Grant ICONIC (project number 15685).

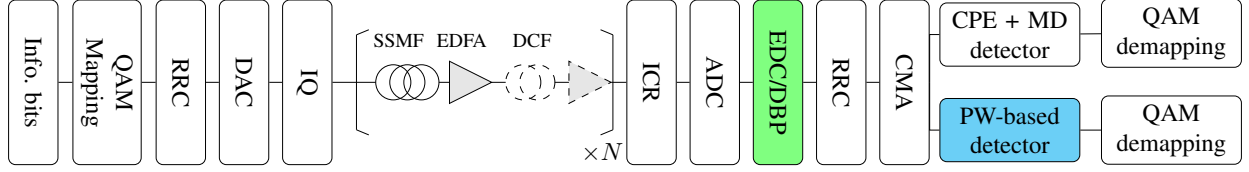


Fig. 2. Transmission diagram: IQ: In-phase and quadrature modulator, ICR: Integrated coherent receiver. Dashed lines represent the partly-considered components.

machine learning techniques, such as SVM [6], which is a binary classifier; multiple SVMs are required for the detection of high-order modulations. In addition, PW does not require an offline training process, like SVM and artificial neural networks.

The main idea of PW is to associate a label to each symbol, and then classify it at the receiver based on labeled training data. The principle of the PW-based detection is depicted in Fig. 1, where 16-QAM is used as example, and the closest neighboring constellation points are represented using different colors. Fig. 1 (a) shows the transmitter side where the M -QAM constellation points $\{s_1, s_2, \dots, s_M\}$ are labeled to M clusters. We denote the label of each cluster s_m by $m \in \{1, 2, \dots, M\}$. At the beginning of the transmission, T training symbols x_k (and their corresponding labels m_k) with $k = 1, 2, \dots, T$ are generated. This training data is followed by $N - T$ testing data symbols $x_k, k = T + 1, T + 2, \dots, N$. The N symbols $[x_1, x_2, \dots, x_N]$ are transmitted over the optical channel. At the receiver side, for each received testing symbol y_k , one Euclidean distance between y_k and each received training symbol is calculated. Thus, for each $k = T + 1, \dots, N$, T Euclidean distances denoted by $D_{k,t} = |y_k - y_t|$, where $t = T + 1, \dots, N$ are calculated.

The decision rule of the PW technique depends on two parameters: a window size R and a window function $f_{k,t}$. Both parameters should be optimized and adapted to the classification problem. Since the data is distributed in a 2-dimensional plane, a circle with a radius R centered around the testing symbol is employed as the window shape. This process is schematically shown in Fig. 1 (b), where three testing symbols (stars) are shown together with the labeled training symbols (colored dots). Furthermore, we use a kernelized window function, in which the closest training points to the testing data have the highest significance, namely,

$$f_{k,t} = \begin{cases} \frac{1}{D_{k,t}} & \text{if } D_{k,t} \leq R \\ 0 & \text{otherwise} \end{cases}, \quad (1)$$

where $t = 1, \dots, T$.

The last step in the classification process is to compute a metric $L_{k,m}$ for each possible transmitted symbol (cluster) m . This metric is calculated by adding up all the contributions of $f_{k,t}$ in (1) for each training cluster, i.e.,

$$L_{k,m} = \sum_{\substack{t=1 \\ x_t=s_m}}^T f_{k,t}, \quad m = 1, \dots, M. \quad (2)$$

The estimated cluster is then the one with the largest metric, i.e., $\hat{m}_k = \operatorname{argmax}_{m \in \{1, \dots, M\}} L_{k,m}$, and thus, the estimated

symbol is $\hat{x}_k = s_{\hat{m}_k}$, with $k = T + 1, \dots, N$. An example of decision regions generated by the PW-based detection is depicted in Fig. 1 (c).

The use of the inverse of the Euclidean distance as a weight for the window function f improves the performance of the PW technique. It also avoids the particular case of having two clusters with the exact same metric L_m . A similar idea was considered in [6], by using square Euclidean distances.

III. SIMULATION SETUP AND RESULTS

The performance of the PW classifier is investigated by numerical simulation. In this simulation, we consider a single-channel dual-polarization configuration and focus on the intra-channel fiber nonlinearity. The simulation setup is shown in Fig. 2. We evaluate the performance of the PW classifier in combating the fiber nonlinearity in both DM and DUM transmission systems and for 16-QAM and 64-QAM modulations. The symbol rate per polarization is 28 Gbaud and the total bit rate is 224 Gbps. For the DUM system, the transmission link consists of multi-span standard single mode fiber (SSMF) with an attenuation coefficient $\alpha = 0.2 \text{ dB} \cdot \text{km}^{-1}$, a dispersion parameter $D = 16 \text{ ps} \cdot \text{nm}^{-1} \cdot \text{km}^{-1}$, and a nonlinear coefficient $\gamma = 1.4 \text{ W}^{-1} \cdot \text{km}^{-1}$. The polarization mode dispersion (PMD) is $0.1 \text{ ps} \cdot \text{km}^{-1/2}$. An erbium-doped fiber amplifier (EDFA) with a 5.5 dB noise figure and 16 dB gain is used at each span of 80 km. When a DM system is considered, an additional EDFA and a dispersion-compensated fiber, with full chromatic dispersion (CD) compensation, are deployed at each span. A root-raised cosine (RRC) filter with a roll-off factor $\rho = 0.1$ is employed for spectrum shaping and the analog-to-digital converter (ADC) works at twice the symbol rate. 1000 symbols are used as training symbols for 16-QAM modulation and 2000 symbols in case of 64-QAM modulation. 2^{14} symbols are used as testing data.

The DSP at the receiver consists in CD compensation, and deterministic fiber nonlinearity mitigation via DBP (if used). After that, an RRC matched filter is applied and an adaptive constant modulus algorithm (CMA) is employed to handle the PMD and the residual dispersion. Finally, PW-based detection is performed before QAM demapping and error counting. When applying the PW classifier, CPE is not required because the signal detection is based on the labeled training symbols. However, CPE is carried out by using training sequence for the minimum distance-based detection, which is used for comparison with the proposed PW-based detector.

The performance of the PW depends on the window size R , which should be optimized. In Fig. 3, we plot the Q factor versus the PW size R for 16-QAM at 800 km transmission

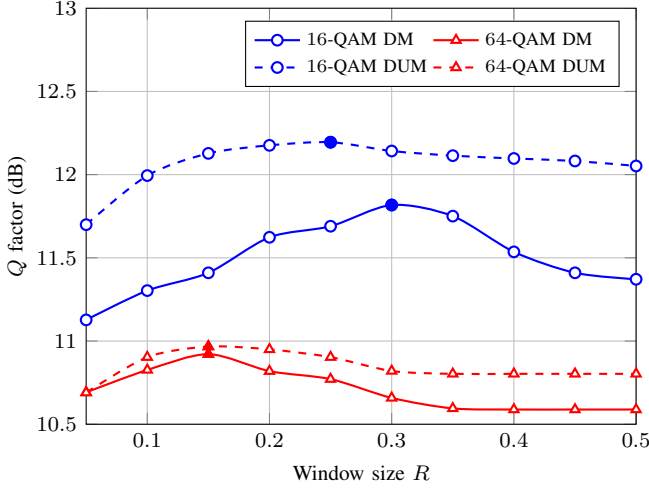


Fig. 3. Q factor vs. window size R for DM and DUM systems.

distance, and 64-QAM at 240 km, at optimal input power and for both DM and DUM systems. The optimal window sizes are $R = 0.3$ and $R = 0.15$ for 16-QAM and 64-QAM DM system, and $R = 0.25$ and $R = 0.15$ for 16-QAM and 64-QAM DUM system, respectively. These optimal values of R are used for the evaluation of the PW-based detector.

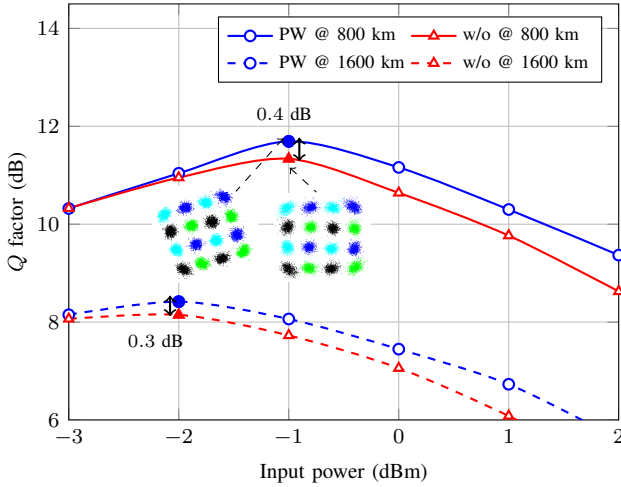


Fig. 4. Q factor vs. input power for DM 16-QAM.

We firstly focus on the performance evaluation of the PW-based detector in the DM system. Fig. 4 shows the Q factor versus the input power for 16-QAM at 800 km and 1600 km, with and without the PW classifier. Without PW means that the detection is performed using MD after CPE, as shown in Fig. 2. At optimal input powers, the PW technique improves the performance by about 0.4 dB and 0.3 dB, in terms of the Q factor for 800 km and 1600 km, respectively. We also show the constellation diagrams of the detected symbols at optimum input power -1 dBm for 800 km. These constellation plots emphasize the first advantage of the PW classifier, which consists in detecting the signal without the need of CPE. This is due to the design of new decision boundaries depending

only on the training symbols.

In Fig. 5, we plot the Q factor performances for 64-QAM at 240 km and 480 km. At optimal input power, the PW-based detector increases the performance in comparison with the MD-based detector, by about 0.35 dB and 0.3 dB for 240 km and 480 km, respectively. In the linear regime, PW-based detector provides similar performance to MD-based detector, while a significant improvement is observed in the nonlinear regime, due to the increased nonlinear non-Gaussian noise.

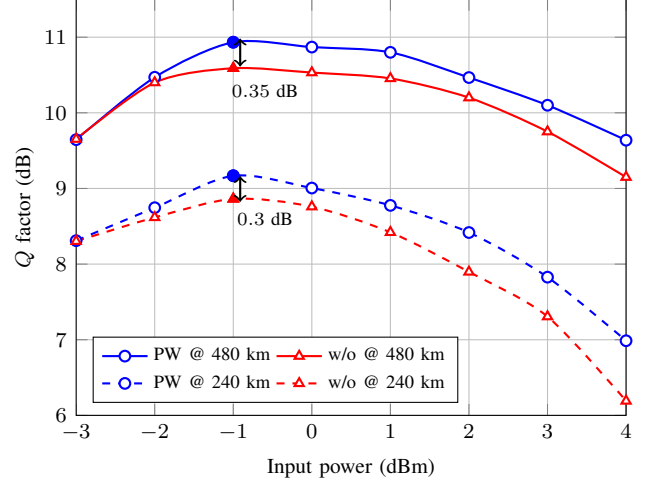


Fig. 5. Q factor vs. input power for DM 64-QAM.

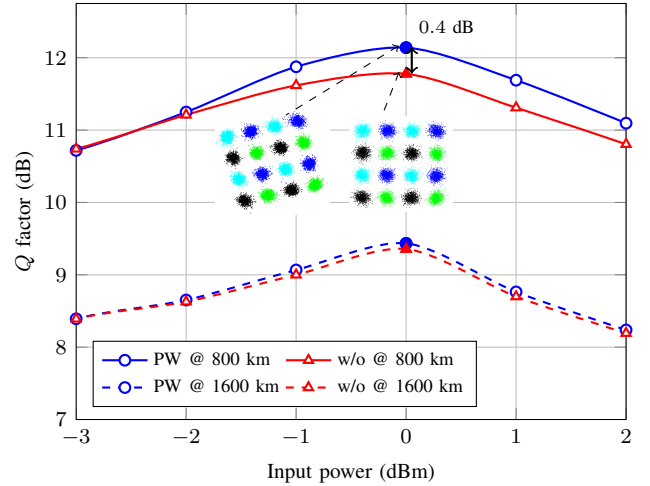


Fig. 6. Q factor vs. input power for DUM 16-QAM.

We now turn our attention to the DUM system. In Fig. 6 and Fig. 7, an increase of about 0.4 dB and 0.2 dB in terms of Q factor is observed when applying the PW for 16-QAM at 800 km and 64-QAM at 240 km, respectively. At high transmission distance, the PW-based detector exhibits limited improvement when compared to the MD-based detector. This is because PW efficiently mitigates the nonlinear non-Gaussian noise by designing new decision boundaries more adapted to the nonlinear fiber channel. However, for uncompensated DUM system and at high transmission distance, the fiber nonlinearities behave

like Gaussian noise, and are effectively modeled by the so-called Gaussian noise and enhanced Gaussian noise models [17], [18]. In this case, PW, and in general machine learning-based detectors, show limited performance improvement in comparison with the classic MD-based detector, which is the optimal detection technique for a channel with Gaussian noise.

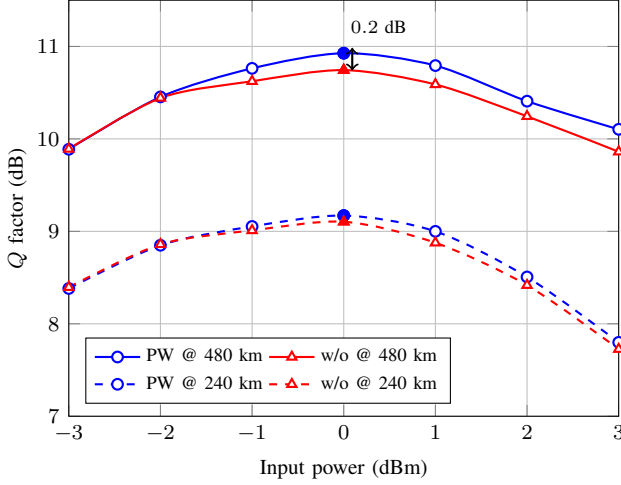


Fig. 7. Q factor vs. input power for DUM 64-QAM.

In the following, we propose two-stage fiber nonlinearity mitigation. Firstly, DBP is applied to compensate for the deterministic nonlinear effects. Then, PW-based detection is performed to deal with the stochastic nonlinearity due to signal-ASE noise interactions. As shown in Fig. 8, for 16-QAM at 1600 km and 64-QAM at 240 km, the two-stage compensation scheme using DBP and PW increases the performance with about 0.35 dB and 0.2 dB, respectively, when compared to DBP with MD detection. This confirms that the proposed PW technique also mitigates the nondeterministic nonlinear effects due to signal-noise interactions.

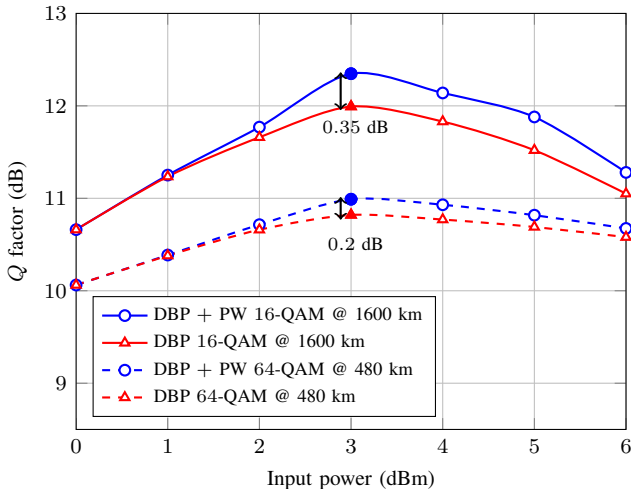


Fig. 8. Q factor vs. input power for DUM with DBP.

IV. CONCLUSION

We have proposed to use the Parzen window (PW) classifier as a detection technique to deal with the nonlinear non-Gaussian noise in both DM and DUM systems for different QAM modulations. Performance improvement in terms of the Q factor is observed in DM systems and short reach DUM systems when applying the PW classifier. This increase in performance is obtained without the need of carrier phase estimation because the detection relies on only the training data. We have also introduced a two-stage compensation using DBP and PW, which shows that PW can mitigate the stochastic nonlinear signal-ASE noise interactions, as well. An experimental validation of PW-based detector and comparison with other machine learning techniques is left for future work.

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