Signal Detection by Using M-ary Support Vector Machine for 16-QAM Coherent Optical Systems with Nonlinear Phase Noise

Minliang Li, Song Yu, Zhixiao Chen, Jie Yang, Yi Han, Wanyi Gu

State Key Laboratory of Information Photonics and Optical Communications,
Beijing University of Posts and Telecommunications, Beijing, 100876, China.
minliangli@bupt.edu.cn

Abstract: We introduce a nonlinear phase noise (NLPN) mitigation scheme based on the M-ary support vector machine (SVM) for 16-QAM coherent optical systems. This scheme can perform better than existing methods while no information of the link is required.

OCIS codes: (060.1660) Coherent communications; (060.4370) Nonlinear optics, fibers

1. Introduction

As one of the major distortion factors in the fiber communication systems, nonlinear phase noise (NLPN) [1] has attracted much attention in recent years. Various electronic processing methods have been proposed to mitigate the effect of NLPN, such as the various phase rotations [2] at the transmitter and the receiver, close-form suboptimal detector [3], stochastic back propagation [4], etc. Because of the stochastic nature and nonlinear properties of the NLPN, so far, there is little approach to combat it without the knowledge of various parameters of the link. When the signal propagates through dynamic optical network link instead of fixed point-to-point link, the variation of link parameters would lead these existing methods become invalid [5]. Hence, it is meaningful to investigate techniques which are independent of the parameters of the link to mitigate the NLPN.

In this paper, we introduce the M-ary support vector machine (SVM) [6] to mitigate the NLPN in the 16-QAM coherent optical systems for the first time. As a hypothesis test problem, the decision for the received signal is conducted by the M-ay SVM through a series of binary classification in this work. Moreover, because the model of each SVM of the M-ary SVM is obtained by a number of training data, this scheme don't need any information about the transmission link. By numerical simulation, the results show that the M-ary SVM scheme can achieve better performance than the method proposed by Lau and Kahn [2].

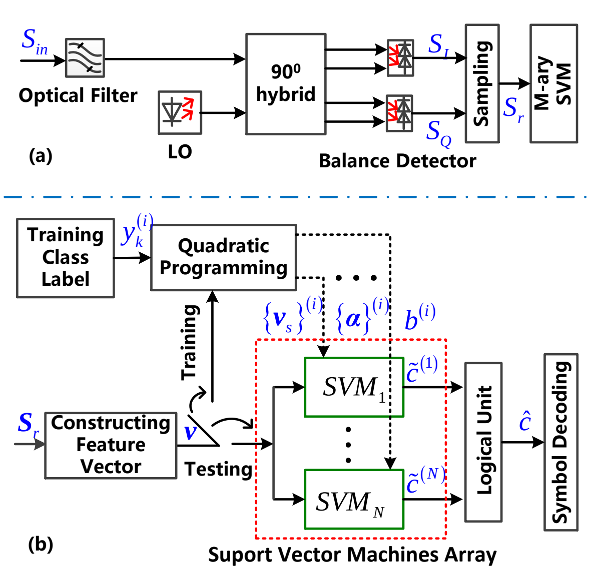

Fig. 1: (a) The receiving end structure of the 16-QAM optical coherent systems. (b) The structure of the M-ary SVM used to mitigate the NLPN.

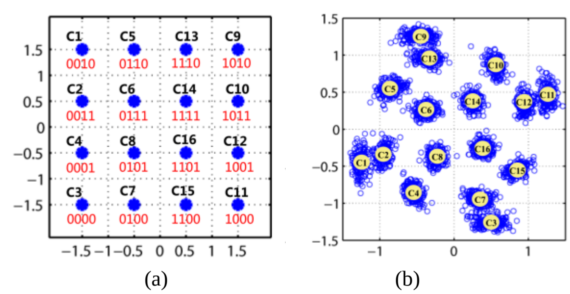

Fig. 2 (a) Class assignment and coding for signal constellations for 16-QAM system, (b) and received constellation diagram for 1600km with 0dBm launch power.

Tab. 1: Parameters of numerical simulation system

Parameter	Value
Fiber length per span	$80\ km$
Symbol rate	$28\ GBaud$
Fiber loss coefficient	$0.2\ dB/km$
Nonlinear coefficient	$1.3\ W^{-1}\cdot km^{-1}$
Noise figure of EDFA	$6\ dB$
Training length of SVM	$1000\ symbols$
Penalty factor of SVM (C)	3
Gaussian kernel σ^2	2

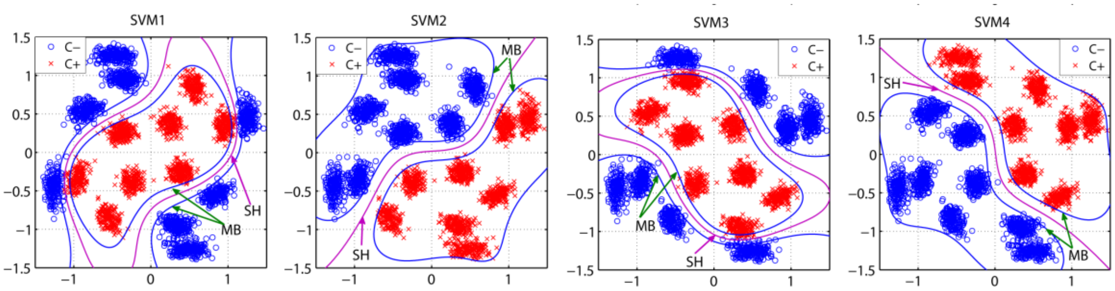

Fig. 3: The results of binary classification of each SVM of the M-ary SVM for 16-QAM system with 1600km transmission link and 0dBm power

2. NLPN mitigation by the M-ary SVM

For a 16-QAM coherent optical receiver, the inphase and quadrature electrical signal are obtained by two balance detectors after the optical signal mixed with the local oscillator via a 90 degree hybrid, which is illustrated in Fig 1 (a). Then, the received signal with NPLN impairment is detected by the M-ary SVM which is cascaded behind the sampling module, and its structure is showed in Fig 1 (b). This scheme regards each modulation constellation as a specific class (16-QAM modulation corresponds to 16 different classes). In the receiving end, the M-ary SVM decides the received signal by judging which class it belongs to. The core unit of the M-ary SVM detector is the support vector machines array. According to the theory of the M-ary SVM [6], the SVMs array contains $\lceil \log_2 K \rceil$ parallel SVMs, where K is the number of classes of the modulation signal can be considered ($K = 16$ for the 16-QAM system). Each SVM conducts binary classification [7] with soft margin under a given classification strategy for the received signal. The classification strategy for the i^{th} SVM in the array in Fig 1 (b) is [6]

$$C_i^+ = \left\{ n \in S \,|\, \mathrm{mod}\left(\left\lfloor (n-1) \cdot 2^{-(i-1)} \right\rfloor, 2 \right) = 0 \right\}, \tag{1a}$$

$$C_i^- = \left\{ n \in S \,|\, \mathrm{mod}\left(\left\lfloor (n-1) \cdot 2^{-(i-1)} \right\rfloor, 2 \right) \neq 0 \right\}, \tag{1b}$$

where, $S = \{1, 2, \cdots, 16\}$ is the set of classes assigned to modulation symbols, n is the class label of the training data, C_i^+ and C_i^- are the positive and negative class sets of the i^{th} SVM, respectively. When the separating hyperplane (SH) of each SVM is established, the i^{th} SVM classifies the unknown symbol according to the following function

$$\tilde{c}^{(i)} = \mathrm{sign}\left[f_i(\vec{v}) \right] = \mathrm{sign}\left\{ \sum_{k \in V} \alpha_k^{(i)} \cdot y_k^{(i)} \cdot < \vec{v}, \vec{v}_k^{(i)} > + b_i \right\}. \tag{2}$$

where, $f_i(\vec{v})$ is the separating hyperplane of the i^{th} SVM, and its variable $\vec{v}$ is the feature vector of the signal which is discriminated. In order to make the hyperplane of each SVM as simple as possible, we assign the class for each constellation point according Fig. 2 (a). The Fig.2 (b) shows the position of constellation points after propagating through 1600km with 0dBm launch power. When the signal is classified by each SVM according to (2), the specific category for the symbol can be calculated by the logical unit [6]

$$\hat{c} = 1 + \sum_{i=1}^{N} \left(\tilde{c}^{(i)} + 1 \right) \cdot 2^{i-2} \ . \tag{3}$$

The result of $\hat{c}$ is the element of S , so the symbol is decoded based on the coding mapping of Fig. 2 (a).

3. Numerical simulation and results

In order to investigate the NLPN mitigation performance of the M-ary SVM, we have conducted a numerical simulation for 16-QAM single channel optical coherent system. The parameters of the simulation system are given in Tab. 1. As in the previous study [2], [4], we also consider the dominant impairment is the NLPN and neglect the effect of chromatic dispersion. Moreover, we compare the M-ary SVM scheme with the various phase rotations (VPR) [2] and the maximum likelihood back-rotation (MLB). Note that the MLB is also introduced as reference scheme by [3], [4] in which the signal symbols are determined by

$$\hat{a}_n = \underset{a \in \Omega^2}{\arg\min} \left\| \vec{r}_n - \vec{a}_n \cdot \exp\left(i\gamma L_{eff} N_{span} \left\| \vec{a}_n \right\|^2 \right) \right\|^2 \tag{4}$$

Fig. 3 illustrates the binary classification result of each SVM for the 16-QAM signal with 0dBm launch power after propagating through 1600km fiber link. The separating hyperplane (SH) and margin boundaries (MB) are

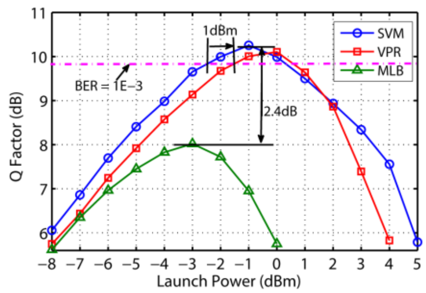

Fig. 4: Q factor versus launch power for 16-QAM systems with a 1600km transmission fiber link.

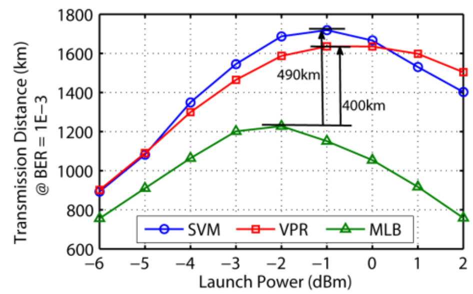

Fig. 5: Transmission distance versus optical launch power at a BER of 10^{-3}.

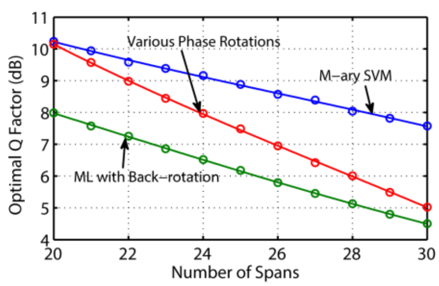

Fig. 6: Optimal Q factor versus the number of fiber spans

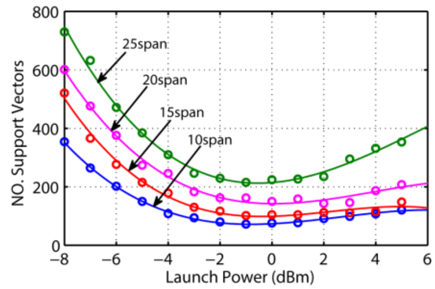

Fig. 7: Number of support vectors of the M-ary SVM versus the launch power.

obtained by the training data under the given classification strategy for each SVM. Fig. 4 shows the Q factor as a function of optical launch power for 1600km 16-QAM coherent system. Compared with the MLB, the M-ary SVM can achieve 2.4dB improvement. When the Q factor equals 9.8dB (i.e. the BER is 1×10^{-3}), the M-ary SVM can obtain 1dBm power margin compared with the VPR. The maximum transmission distance corresponds to a BER of 1×10^{-3} is determined for a given launch power, and the results for above three methods are depicted in Fig. 5. The achievable maximum transmission distances of the M-ary and VPR are 490km and 400km longer than that of the MLB, respectively. The changes of the optimal Q factors for different mitigation approaches with the increasing of the number of fiber spans are shown in Fig. 6. We can find that the gap of the optimal Q factors between the M-ary SVM and the MLB is approximately equals to 2dB, while that for the M-ary SVM and VPR is gradually increased. Because the computational complexity of the M-ary SVM is relay on the number of the support vectors (SV), in Fig. 7, we illustrate the number of the support vectors (SV) versus the launch power. At the optimal power point of the Fig. 5, the number of SV is the least.

4. Conclusions

We have presented a fiber nonlinear phase noise mitigation scheme for the 16-QAM coherent optical systems by employing the M-ary SVM. The M-ary SVM can achieve notable performance without having to care about the specific characteristics of the fiber link compared with other existing techniques.

5. Acknowledgements

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