Nonlinear Decision Boundary Created by a Machine Learning-based Classifier to Mitigate Nonlinear Phase Noise

Danshi Wang(1), Min Zhang(1), Ze Li(1), Yue Cui(1), Jingdan Liu(1), Yang Yang(1), Hongxiang Wang(1)

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

Abstract *A machine learning-based classifier, namely SVM, is introduced to create the nonlinear decision boundary in M-ary PSK-based coherent optical system to mitigate NLPN. The maximum transmission distance and LPRD tolerance are improved by 480 km and 3.3 dBm for 8PSK.*

Introduction

Machine learning as a powerful interdisciplinary tool has been widely applied to solve various problems in different areas, such as data mining, pattern recognition, medical imaging, and artificial intelligence, etc[1]. Recently, techniques from machine learning have been equally well applied to nonlinear optical fiber communication channel[2]. Among various algorithms, we find that support vector machine (SVM)[3] as one of the most popular machine learning algorithms has the potential to be applied to digital signal processing (DSP) for the nonliearity mitigation.

The fiber nonlinearities have been identified as the limiting factors for enhancing the capacity and transmission length of coherent optical system. Nonlinear phase noise (NLPN) is one of the dominating factors, especially for the *M*-ary phase-shit keying (*M*-PSK) modulation formats, such as BPSK, QPSK, and 8PSK. The NLPN is induced by the interaction of the amplified spontaneous emission (ASE) noise from the inline optical amplifier and fiber Kerr effect, known as self-phase modulation (SPM)[4].

In order to mitigate NLPN, various schemes have been proposed. Based on DSP technique, the NLPN could be supressed by the maximum likehood estimation (MLE)[5] and digital back-propagation (DBP) algorithms[6]. However, all these electronic methods rely on the deterministic information of the fixed fiber link, implying that they are not suitable for dynamic and reconfigurable optical network link.

In this paper, we introduce SVM algorithm into the *M*-PSK based coherent optical transmission system to mitigate the NPLN. Without any prior information, SVM can learn and capture the link properties from the training data. As a nonlinear classifier, SVM creats the decision boundary to classify the different constellations from each other to avoid the crosstalk and mistake caused by NPLN. The numerical results show that SVM outperforms MEL algorithm[5], especially for the high order formats. The launch power dynamic range (LPDR) is increased by 3.3 dBm for 8PSK, 1.2 dBm for QPSK, but not significant for BPSK.

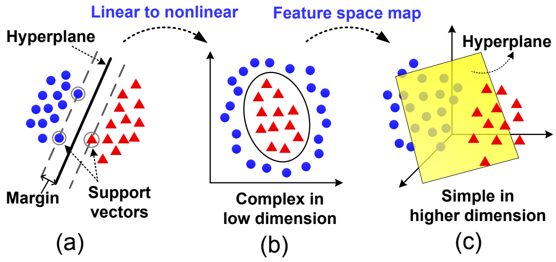


Fig. 1: SVM schematic diagram

The maximum transmission distance for 8PSK is improved by 480 km and the reason is also analyzed. As a result, NPLN is effectively mitigated by SVM, so that the longer distance and larger launch power range are achieved.

Operation principle of SVM for *M*-ary PSK

The SVM as a binary classifier could generate one separating boundary to classify two groups of data (represented by red triangles and blue circles), as shown in Fig. 1(a). Based on the statistical learning theory, SVM aims at finding the point closest to the separating hyperplane and making sure it is as far away from the separating line as possible, namely maximizing the margin[1]. The points closest to the separating hyperplane are known as support vectors. However, the above situation is under one assumption: the data is linearly separable. But it is clear that the data cannot always be separated linearly, as shown in Fig. 1(b). Hence the kernel function, such as Gaussian radial bias function, is adopted to map linearly inseparable data from one lower-dimensional feature space to another higher-dimensional feature space[1]. After making the substitution, we can solve this linear problem in higher-dimensional space, which is equivalent to solving a nonlinear problem in lower-dimensional space in Fig .1(c).

If we regard the different constellations of *M*-PSK signals as different classes of data, SVM may be applied to creat the decision boundary to avoid the errors induced by nonlinear impairment. We design three classification strategies for three corrsponding PSK signals. For example in Fig. 2(a), BPSK with two

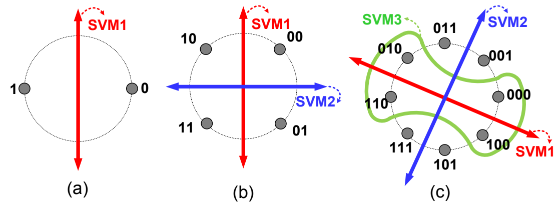


Fig. 2: Classification strategy based on SVM for *M*-ary PSK signals: (a) BPSK, (b) QPSK, and (c) 8PSK

constellations (standing for 0 and 1) could be classified by one hyperplane to identify the different data. For QPSK and 8PSK, inspired by the idea of multicalss classifier[3], only $\log_2(M)$ SVMs are needed for *M*-classes problem. In this method, each signal's category is labeled in binary format with each bit modeled by a two-class SVM, namely bit "1" labeled as "+1" and "0" labeled as "-1". The constellations using the Gray code are shown in Fig. 2. Here we take one constellation (011) of 8PSK as example. If the test data (011) is detected by SVM1, the first bit "0" is classified with the label "-1", then detected by SVM2, the second bit "1" labeled as "+1", finally detected by SVM3, the third bit "1" labeled as "+1". As a result, all the constellations of 8PSK can be decisided correctly.

Numerical model and results

The numerical model based on coherent optical transmission system is set up, as shown in Fig. 3. Three kinds of Gray coded *M*-PSK signals operating at 40 Gbaud (i.e. BPSK at 40 Gbps, QPSK at 80 Gbps, and 8PSK at 120 Gbps) are generated by the IQ modulator, which is driven by the NRZ pulse shaping filter to transmit the PRBS with the length of 2^{15}-1. The transmission link consists of *N*×80 km dispersion-shifted fiber (DSF) spans. The fiber nonlinear coefficient is $\gamma = 1.3\text{W}^{-1}\text{km}^{-1}$ and the loss efficient is $\alpha = 0.2$ dB/km. Following the referenced model[5], in this paper, we mainly focus on NLPN dominant single-channel system neglecting chromatic dispersion and multichannel effects. The EDFA with the noise figure of 6 dB is placed at the end of each span to compensate the fiber's loss. Next, the received signal is detected by a coherent receiver and the sampled signal is detected by the SVM-based digital detector. Different modulation formats need different amounts of SVM: one required by BPSK, two by QPSK, and three by 8PSK. The number of training symbol is 1000. If the training course is finished, then the test data could be labeled as "+1" or "-1" by the trained SVMs. According to the output labels, the data will be mapped to the corresponding symbol, as dsigned in Fig. 2.

The detection examples of SVM-based decision boundaries for BPSK, QPSK, 8PSK

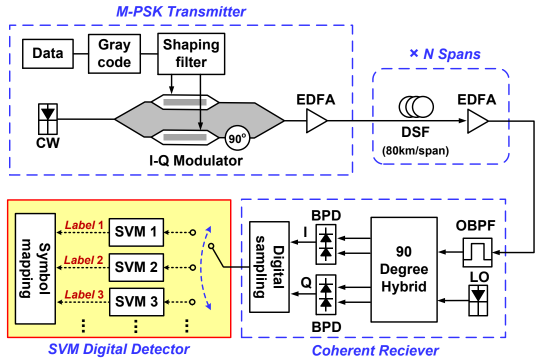


Fig. 3: Numerical model: CW: continuous wave; EDAF: erbium-doped fiber amplifier; LO: local oscillator; OBPF: optical band-pass filter; BPD: balanced photodiode.

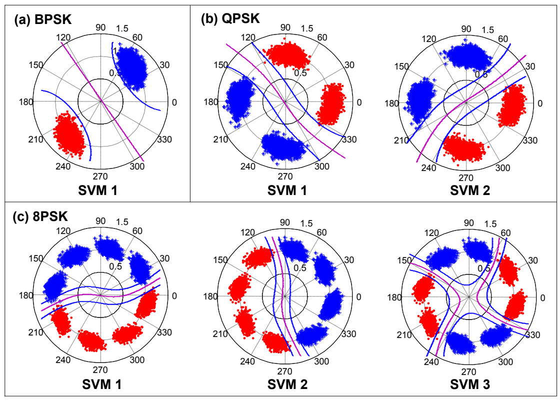


Fig. 4: The nonlinear decision boundaries created by SVM-based classifiers: (a) BPSK by one SVM; (b) QPSK by two SVMs; (c) 8PSK by three SVMs.

systems over 1600 km with the launch power of 0 dBm are presented in Fig. 4. Suffering from the ASE noise and NLPN, the constellations of *M*-PSK have rotated large angles and deflected significantly which may result in the crosstalk, decision errors, as well as high bit-error rate (BER). If without the effective decision boundary, we can hardly identify the original signals properly. With the help of SVM, the nonlinear decision boundary is successfully created, as shown in Fig. 4.

In order to demonstrate the feasibility of SVM, the widely-used MLE algorithm[5] is selected as a comparison. The BER performances of the received signals as a function of launch power are separately measured for BPSK, QPSK, and 8PSK, and as a reference, the direct decision without any mitigation is also tested, as shown in Fig. 5(a)-(c). The launch powers for the all three formats range from -15 dBm to 15 dBm. However, different PSK formats have different resistances to nonlinear impaiment. In order to obtain the appropriate BER values, we set different formats to transmit through different fiber lengths: 50 spans (4000 km) for BPSK, 35 spans (2800 km) for QPSK, and 20 spans (1600 km) for 8PSK.

From Fig. 5, it is seen that the BER performances of three formats are very poor when without NLPN mitigation (in green line). For the other two mitigation methods (MLE in red line and SVM in

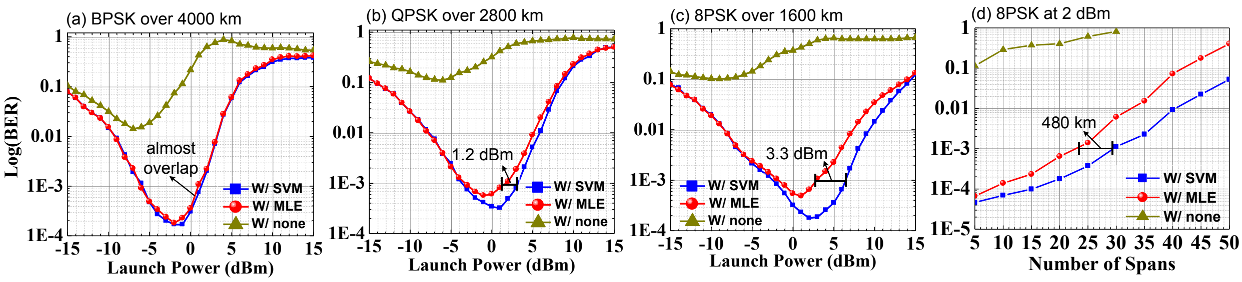
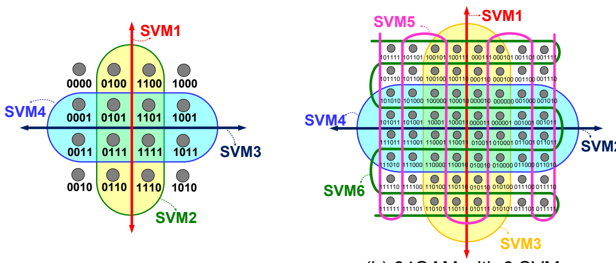


Fig. 5: BER as a function of optical launch power for (a) BPSK over 4000 km, (b) QPSK over 2800 km, and (c) 8PSK over 1600km; (d) BER as a function of transmission distance for 8PSK at the launch power of 2 dBm.

blue line), with the increase of the launch power, the OSNR of the received signal grows higher, contributing to the better BER performance. When the launch power exceeds the optimal values, the received signal suffers from the remarkable nonlinear effect, which deteriorates the BER performance again. Here, the LPDR, which denotes the difference between the two power values corresponding to the points at BER of 1×10^{-3}, is employed to evaluate the effect of SVM and MLE. However, compared with MLE method, it can also be observed that SVM scheme displays different superior performances for different formats. For BPSK, the BER curves of SVM and MLE almost overlap, and the LDPRs of them are similar. For QPSK, the LDPR of SVM has 1.2 dBm larger than that of MLE, while for 8PSK, the improvement expands to 3.3 dBm. Moreover, the maximum transmission distance corresponding to BER of 1×10^{-3} at a given launch power of 2 dBm is also investigated for 8PSK. From Fig. 5(d), it is seen that the maximum distance is improved by SVM to 480 km longer than MLE. As a result, SVM achieves longer distance and larger launch power range, especially for high order formats.

This is mainly because that high order formats are more sensitive to NLPN due to the closer Euclidean distance and more number of constellations. Therefore, the decision boundary for high order format needs to be precisely designed according to the shape of adjacent constellations to reduce the error probability. While the decision boundary of MLE based on Rice distribution and relying on the transmission link is more fixed and difficult to be adjusted flexibly. On the other hand, for SVM, by modifying the hyperplane parameters and selecting the appropriate kernel function, the shape of nonlinear decision boundary can be flexibly adjusted to create any irregular nonlinear shape and satisfy the more precise classification. Therefore, the SVM performs a relatively larger improvement in nonlinear system tolerance.



(a) 16QAM with 4 SVMs (b) 64QAM with 6 SVMs

Fig. 6: (a) 16QAM can be classified by 4 SVMs and (b) 64QAM can be classified by 6 SVMs.

Conclusions

We have shown that SVM is a powerful tool to mitigate the nonlinear phase noise. For *M*-PSK-based coherent optical transmission systems, SVM achieves longer distance transmission and larger LPRD tolerance, more significant for high order formats: 480 km and 3.3 dBm improvement for 8PSK. In addition, we believe that SVM can also be applied in other formats, and may better exert its advantages in the higher order and more complex formats, such as 16QAM or 64QAM. We design the classification strategies for 16QAM with four SVMs and 64QAM with six SVMs, respectively. Therefore, SVM may have the great potential to combat other nonlieanr problems for other complex formats. Meanwhile, inspired by SVM method, other machine learning algorithms are also valuable to be investigated for the coherent optical transmission system in the future.

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