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Machine Learning Methods for Optical Communication Systems

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Abstract: We review application of machine learning methods to tackle fiber linear/nonlinear impairments as well as to estimate crucial signal parameters in optical networks. Recent works involving hierarchical learning approaches are also discussed.
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1. Introduction

High spectral efficiency modulation formats and digital signal processing (DSP) are the cornerstones of current optical transceivers for long-haul global fiber-optic communication networks. DSP algorithms allow complete and adaptive compensation of linear transmission impairments such as chromatic dispersion (CD), polarization-mode dispersion (PMD) and laser phase noise effects [1]. Telecommunication service providers, content providers and researchers worldwide are trying desperately to increase transmission capacities of fiber-optic networks (up to 1 Tbps and beyond per carrier) so as to support emerging data center, cloud computing, 5G wireless, and Internet of Things (IoT) applications. Unfortunately, transmission performance of optical networks is still severely limited by fiber Kerr nonlinearity despite years of advanced DSP research to address the problem. The state-of-the-art DSP algorithms such as digital back-propagation (DBP) can only partially combat fiber nonlinearities as interactions between noise, CD, PMD and nonlinearity are extremely hard to analyze [2]. Consequently, fiber nonlinearity is still not appropriately compensated and continues to be a fundamental capacity-limiting factor.

Apart from adopting advanced multi-level modulation formats and high-speed DSP-based coherent receivers, the network architectures in fiber-optic communication systems are also undergoing major changes and are increasingly becoming more complex, transparent and dynamic in nature. Real-time estimation of various channel impairments ubiquitously across the network, also called optical performance monitoring (OPM), is indispensable for reliable operation and efficient management of such complex optical networks [3]. OPM is also a key enabling technology for elastic optical networks (EONs) which have received considerable attention recently. EONs strongly rely on OPM to become aware of the network conditions and then adaptively adjust various transceiver and network elements parameters such as modulation formats, data rates, spectrum assignment, forward error correction (FEC) codes etc. in order to optimize the transmission performance [4]. Unfortunately, simultaneous and independent monitoring of multiple channel impairments using low-cost (and hence low-quality) components is a difficult task since the effects of various impairments are often intermixed and nearly physically inseparable [5]. Another critical requirement for proper functioning of EONs is the capability to autonomously identify modulation formats of optical signals at the receiver as well as in OPM units deployed at the intermediate network nodes since the algorithms employed in these devices may be modulation format dependent.

A drastically new signal processing philosophy may be necessary for efficient mitigation of nonlinear distortions as well as for accurate estimation of various critical parameters in optical networks. To this end, machine learning techniques have appeared as a new direction of innovation to cope with many emerging challenges in fiber-optic communications. Machine learning is a branch of computer science in which computers/machines are trained to 'learn' from the data without being explicitly programmed and act according to the information learnt. Over the last decade, machine learning has been applied successfully in a myriad of tasks for e.g. prediction, classification, pattern recognition, data mining etc. and has shown tremendous power in application areas such as computer vision, speech recognition, bioinformatics, and telecommunications [6]. Machine learning algorithms are well known to perform unexpectedly and exceptionally well when the underlying physics and mathematics of the problem are too difficult to analyze or impossible to describe explicitly. Recently, we are beginning to see preliminary attempts of applying machine learning methods to optical communication systems with quite promising results. Moreover, with the advent of deep learning, a machine learning approach based on the concept of hierarchical representation of data, the researchers are further motivated to exploit real potential of this emerging field in fiber-optic communications.

2. Machine learning concepts in optical communications

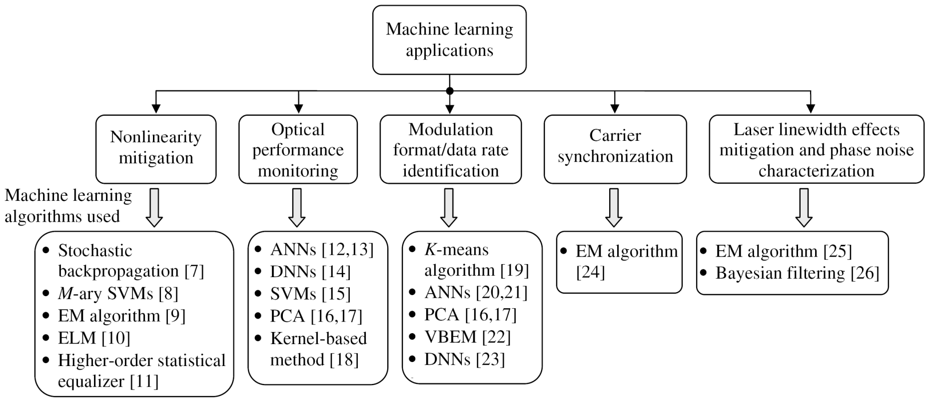

Fig. 1. Some key applications of machine learning in optical communications.

Figure 1 depicts some important applications of machine learning algorithms in optical networks. A brief discussion on these applications is provided below.

Nonlinearity mitigation: Recently, there have been several researches focusing on the use of machine learning techniques for combating nonlinear distortions in fiber-optic networks. These techniques learn the characteristics of various nonlinear impairments from the observed data and then synthesize probabilistic models of these impairments which can later be employed for either compensating these impairments or to quantify the amount of distortions introduced. In [7], stochastic backpropagation has been proposed which is shown to outperform conventional DBP in scenarios where nonlinear phase noise (NLPN) is the dominant impairment. Similarly, in [8], mitigation of NLPN is demonstrated by creating optimal decision boundaries through the use of *M*-ary support vector machines (SVMs). Other machine learning approaches for tackling fiber nonlinearities include the use of expectation maximization (EM) algorithm [9], extreme learning machine (ELM) [10], and higher-order statistical equalizer [11]. Despite the performance improvements shown by these algorithms in single-channel environments, multi-channel fiber nonlinearity compensation remains to be the most challenging goal in long-haul wavelength-division multiplexed (WDM) transmissions. In addition, individual WDM channels can be added or dropped mid-link in a terrestrial optical network which further adds a level of complexity for machine learning methods to address.

OPM: Machine learning algorithms have been applied successfully for cost-effective multi-impairment monitoring in optical networks. These include artificial neural networks (ANNs) [12,13], deep neural networks (DNNs) [14], SVMs [15], principal component analysis (PCA) [16,17], and kernel-based methods [18]. However, the demonstrated works are mostly concerned with dispersion-managed systems only. Machine learning-based OPM techniques for dispersion-uncompensated systems employing low-speed/low-bandwidth components are currently under investigation. Furthermore, as EON paradigm is becoming a major area of research focus recently, there is ample interest in the development of OPM techniques for such heterogeneous optical networks supporting channels with multiple data rates, modulation formats and bandwidths.

Modulation format identification (MFI): Knowledge of the signal's modulation format in digital coherent receivers might be useful for choosing an appropriate carrier recovery module with superior performance as compared to

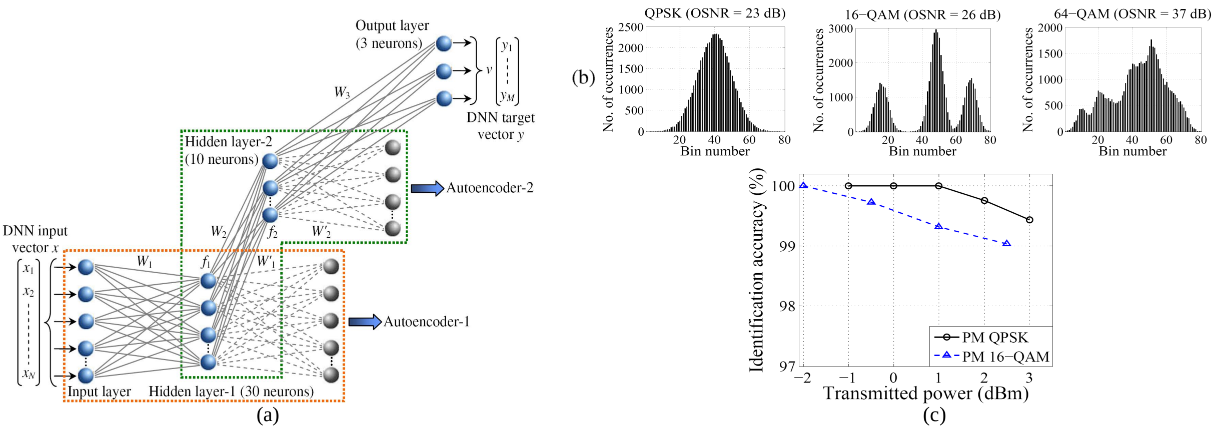

Fig. 2. (a) Structure of DNN used. (b) Unique amplitude histograms for three modulation formats. (c) Identification accuracy of MFI technique [23].

blind equalization approaches. Also, the availability of modulation format information in OPM devices (installed at the intermediate network nodes) can help determine most suitable optical signal-to-noise ratio (OSNR)/CD/PMD monitoring technique for that specific format [3]. Conventional machine learning methods such as K-means algorithm [19], ANNs [20,21], PCA [16,17], variational Bayesian expectation maximization (VBEM) [22] etc. have been used for MFI task. In [23], a hierarchical machine learning approach employing DNNs in combination with signals' amplitude histograms is demonstrated for accurate MFI in digital coherent receivers as shown in Fig. 2.

Other applications: Machine learning has also been applied for carrier synchronization [24] and laser linewidth effects mitigation [25] using EM algorithm and for laser phase noise characterization via Bayesian filtering [26].

We have discussed how the rich body of machine learning techniques can be effectively used as a unique and powerful set of signal processing tools in optical communications. However, much more remains to be investigated to unleash true potential of machine learning field and to incorporate it into much wider areas of optics research.

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4. References

[1] E. Ip *et al.*, "Coherent detection in optical fiber systems," *Opt. Exp.*, vol. 16, no. 2, pp. 753–791, 2008.
[2] E. Ip, and J. M. Kahn, "Compensation of dispersion and nonlinear effects using digital backpropagation," *J. Lightwave Technol.*, vol. 26, no. 20, pp. 3416–3425, 2008.
[3] F. N. Khan, Z. Dong, C. Lu, and A. P. T. Lau, "Optical performance monitoring for fiber-optic communication networks," in *Enabling Technologies for High Spectral-Efficiency Coherent Optical Communication Networks*, X. Zhou and C. Xie, eds. (Wiley, 2016), Chap. 14.
[4] Z. Dong, F. N. Khan, Q. Sui, K. Zhong, C. Lu, and A. P. T. Lau, "Optical performance monitoring: a review of current and future technologies," *J. Lightwave Technol.*, vol. 34, no. 2, pp. 525–543, 2016.
[5] C. Lu *et al.*, "Optical performance monitoring techniques for high capacity optical networks," in *Int. Symp. on Commun. Systems Networks and Digital Signal Processing*, Newcastle upon Tyne, 2010, pp. 678–681.
[6] C. M. Bishop, *Pattern recognition and machine learning*, (Springer, New York, 2006).
[7] N. Jiang *et al.*, "Stochastic backpropagation for coherent optical communications," in *Proc. European Conf. on Optical Commun.*, Geneva, 2011, Paper We.10.P1.81.
[8] M. Li, S. Yu, J. Yang, Z. Chen, Y. Han, and W. Gu, "Nonparameter nonlinear phase noise mitigation by using *M*-ary support vector machine for coherent optical systems," *IEEE Photonics Journal*, vol. 5, no. 6, 2013.
[9] D. Zibar *et al.*, "Nonlinear impairment compensation using expectation maximization for dispersion managed and unmanaged PDM 16-QAM transmission," *Opt. Exp.*, vol. 20, no. 26, pp.B181–B196, 2012.
[10] T. S. R. Shen, and A. P. T. Lau, "Fiber nonlinearity compensation using extreme learning machine for DSP-based coherent communication systems," in *Proc OptoElectronics and Communications Conference*, Kaohsiung, 2011, pp. 816–817.
[11] T. K. Akino *et al.*, "High-order statistical equalizer for nonlinearity compensation in dispersion-managed coherent optical communications," *Opt. Exp.*, vol. 20, no. 14, pp. 15769–15780, 2012.
[12] F. N. Khan, T. S. R. Shen, Y. Zhou, A. P. T. Lau, and C. Lu, "Optical performance monitoring using artificial neural networks trained with empirical moments of asynchronously sampled signal amplitudes," *IEEE Photon. Technol. Lett.*, vol. 24, no. 12, pp. 1041–1135, 2012.
[13] F. N. Khan, Y. Yu, M. C. Tan, C. Yu, A. P. T. Lau, and C. Lu, "Simultaneous OSNR monitoring and modulation format identification using asynchronous single channel sampling," in *Proc. Asia Communications and Photonics Conf.*, Hong Kong, 2015, Paper AS4F.6.
[14] T. Tanimura, T. Hoshida, J. C. Rasmussen, M. Suzuki, and H. Morikawa, "OSNR monitoring by deep neural networks trained with asynchronously sampled data," in *Proc. OptoElectronics and Communications Conference*, Niigata, 2016, Paper TuB3-5.
[15] R. A. Skoog *et al.*, "Automatic identification of impairments using support vector machine pattern classification on eye diagrams," *IEEE Photon. Technol. Lett.*, vol. 18, no. 22, pp. 2398–400, 2006.
[16] M. C. Tan *et al.*, "Simultaneous optical performance monitoring and modulation format/bit-rate identification using principal component analysis," *J. Optical Communications and Networking*, vol. 6, no. 5, pp. 441–448, 2014.
[17] F. N. Khan, Y. Yu, M. C. Tan, W.H. Al-Arashi, C. Yu, A. P. T. Lau, and C. Lu, "Experimental demonstration of joint OSNR monitoring and modulation format identification using asynchronous single channel sampling," *Opt. Exp.*, vol. 23, no. 23, pp. 30337–30346, 2015.
[18] T. B. Anderson *et al.*, "Multi impairment monitoring for optical networks," *J. Lightwave Technol.*, vol. 27, no. 16, pp. 3729–3736, 2009.
[19] N. G. Gonzalez, D. Zibar, and I. T. Monroy, "Cognitive digital receiver for burst mode phase modulated radio over fiber links," in *Proc. European Conf. on Optical Commun.*, Torino, 2010, Paper P6.11.
[20] F. N. Khan, Y. Zhou, A. P. T. Lau, and C. Lu, "Modulation format identification in heterogeneous fiber-optic networks using artificial neural networks," *Opt. Exp.*, vol. 20, no. 11, pp. 12422–12431, 2012.
[21] F. N. Khan, Y. Zhou, Q. Sui, and A. P. T. Lau, "Non-data-aided joint bit-rate and modulation format identification for next-generation heterogeneous optical networks," *Optical Fiber Technology*, vol. 20, no. 2, pp. 68–74, 2014.
[22] R. Borkowski, D. Zibar, A. Caballero *et al.*, "Stokes space-based optical modulation format recognition in digital coherent receivers," *IEEE Photon. Technol. Lett.*, vol. 25, no. 21, pp. 2129–2132, 2013.
[23] F. N. Khan, K. Zhong, W. H. Al-Arashi, C. Yu, C. Lu, and A. P. T. Lau, "Modulation format identification in coherent receivers using deep machine learning," *IEEE Photon. Technol. Lett.*, vol. 28, no. 17, pp. 1886–1889, 2016.
[24] D. Zibar *et al.*, "Joint iterative carrier synchronization and signal detection employing expectation maximization," *J. Lightwave Technol.*, vol. 32, no. 8, pp. 1608–1615, 2014.
[25] D. Zibar *et al.*, "Nonlinear impairment compensation using expectation maximization for dispersion managed and unmanaged PDM 16-QAM transmission," *Opt. Exp.*, vol. 20, no. 26, pp.B181–B196, 2012.
[26] D. Zibar *et al.*, "Bayesian filtering for phase noise characterization and carrier synchronization of up to 192 Gb/s PDM 64-QAM," in *Proc. European Conf. on Optical Commun.*, Cannes, 2014, Paper Tu.1.3.1.