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Abstract

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Perspective of Statistical Learning for Nonlinear Equalization in Coherent Optical Communications

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Abstract: Modern statistical learning technologies such as deep learning have a great potential to deal with linear/nonlinear fiber impairments for future coherent optical communications. We introduce various learning techniques suited for nonlinear equalizations.

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1. Nonlinear Fiber-Optic Communications

In fiber-optic communications, we encounter various linear/nonlinear impairments, such as laser linewidth, amplified spontaneous emission (ASE) noise, chromatic dispersion (CD), polarization mode dispersion (PMD), self-phase modulation (SPM), cross-phase modulation (XPM), four-wave mixing (FWM), and cross-polarization modulation (XPolM). In particular, mitigating nonlinear distortions has been of great importance to realize ultra-high-speed, reliable, and long-haul transmissions [1, 2]. The linear/nonlinear fiber impairments can be governed by nonlinear Schrödinger equation (NLSE), which may need split-step Fourier method (SSFM) to solve lightwave propagation numerically. From a natural implication, the fiber nonlinearity necessitates nonlinear signal processing to deal with the nonlinear distortions. A number of different nonlinear equalizations have been studied, e.g., decision-feedback equalizer (DFE), maximum-likelihood sequence equalizer (MLSE), statistical sequence equalizer (SSE) [3–5], turbo equalizer (TEQ) [6–8], Volterra series transfer function (VSTF) [9, 10], and digital back-propagation (DBP) [11, 12]. Recently, some variants of DBP methods [13, 14] exhibit an outstanding performance by solving inverse NLSE with SSFM, which considers logarithmic perturbation or particle representation of stochastic noise. However, it is still difficult to compensate for inter-channel nonlinearity and PMD especially for dispersion un-managed systems. To advance further, we may need to comprehend overall channel statistics, which are particularly important for communications because the mutual information derived from the statistics determines the maximum possible data rates.

2. Statistical Learning Techniques

Here, we introduce some learning techniques to analyze nonlinear statistics. Classical method includes histogram estimator, which is simple but sensitive to bin-width parameter, and does not work well for high-dimensional data. We envision that modern machine learning techniques [15, 16] would provide novel insights to optical communications as shown in Fig. 1. For example, density estimation trees (DET), kernel density estimation (KDE) and Gaussian mixture model (GMM) can be direct alternatives of histograms. In particular, GMM provides robust and generic models by expectation-maximization (EM) algorithms. Principal component analysis (PCA) and independent component analysis (ICA) are also useful to analyze important factors of data. For high-dimensional data sets, we may use Monte-Carlo inference, including importance sampling (IS) and Markov-chain Monte-Carlo (MCMC). To analyze probabilistic models for stochastic sequence data, extended Kalman filter (EKF), unscented Kalman filter (UKF), particle filter (PF), and those smoother versions based on hidden Markov model (HMM) may be useful.

Since backpropagation algorithm (i.e., stochastic gradient) gained recognition in mid-70's, artificial neural networks (ANN) have lead machine learning researches. Various graphical topology including multi-layer perceptron (MLP), Hopfield neural networks (HNN), restricted Boltzmann machines (RBM), convolutional neural networks (CNN), and recurrent neural networks (RNN) have been investigated. Since mid-90's, support vector machine (SVM) has taken over the lead for machine learning. One of important techniques to analyze nonlinear statistics is kernel trick, in which we can analyze higher-dimensional linearlized feature spaces (or reproducing kernel Hilbert space: RKHS) by the inner products with kernel functions. Most common kernels include polynomial kernel, Gaussian kernel (a.k.a. radial basis function: RBF), and sigmoid kernel. Kernel-PCA and kernel-SVM work well for nonlinear statistics analysis.

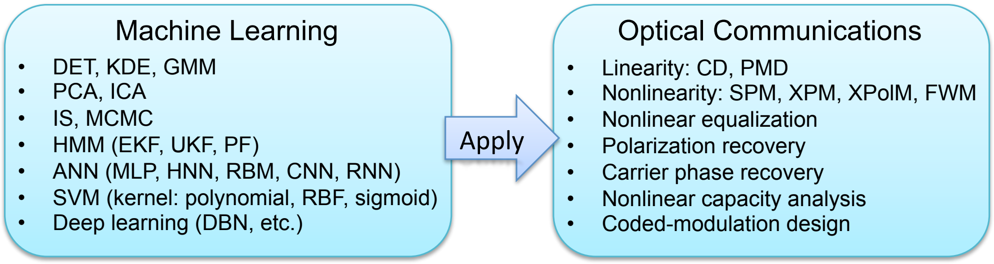

Fig. 1. Statistical machine learning approaches applied to optical communications technologies.

Since 2006, deep learning [17] based on ANN have been rediscovered as a breakthrough technique for statistical learning in speech and image processing societies. In deep learning, layer-wise training in many-layer deep belief networks (DBN) is taken place with a massively large number of data sets. Note that big data are available in optical communications, where we can obtain gigabits or terabits class data in a second. Such DBN has another advantage in massively parallel computations, which may be suited for high-speed optical communications transceivers.

3. Machine Learning for Optical Communications

Now, we show some examples of machine learning approaches applied to nonlinear fiber-optic communications. Xie *et al.* proposed the use of ICA for polarization recovery [18] as an alternative to constant-modulus adaptation (CMA). We have proposed HNN-based nonlinear equalization [19], which showed close-to MLSE performance. Other ANN-based nonlinear equalizers have been studied in literature [20, 21]. It was shown that RNN-based nonlinear equalization [20] outperforms DFE and VSTF. We have investigated GMM-based sliding MLSE or TEQ receivers [5], where up-to 2dB performance improvement was achieved compared to DBP. SVM has been also studied as another nonlinear equalizer [22, 23], in which a complicated decision rule like Yin-Yang spiral decision [24] can be learned by kernel-SVM. RBF kernels have been studied in other literature, e.g., [25,26]. We have shown that HMM-based turbo cycle-slip recovery [27] offers more than 2dB gains in presence of frequent cycle slips.

4. Summary

We have discussed various potentials behind statistical machine learning for fiber-optic communications to deal with nonlinear distortion. Through literature survey, we been seen that nonlinear signal processing based on machine learning can be of great use for many applications, such as nonlinear equalization, polarization recovery, carrier phase recovery, cycle slip recovery, *etc*. There remain a lot of interesting research topics in nonlinear optical communications exploiting modern machine learning techniques.

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