Neural-Network-Enabled Multivariate Symbol Decision in a 100-Gb/s Complex Direct Modulation System

Di Che
Nokia Bell Labs, Holmdel, NJ 07733, United States
di.che@nokia-bell-labs.com

Abstract: We reveal a neural network can be exploited for multivariate symbol decision simply by feeding multiple signal features as its inputs. The concept is verified in a digital coherent receiver which detects dual-polarization 25-GBaud directly-modulated PAM-4 signals.

1. Introduction

Modern digital optical receivers usually exploit multivariate symbol decision (MSD) to squeeze out the system margin, namely, decision based on more than one feature of the received signal. The multiple features can be obtained directly from multi-dimension signal detections. For instance, when using a coherent receiver to detect an intensity-modulation signal from directly-modulated lasers (DML) [1-2], the optical phase can assist the intensity symbol decision via the laser diodes chirp model to enhance the system sensitivity, namely, the complex direct modulation (CDM) [2] scheme. Alternatively, the extra feature can be artificially generated from the received signal, commonly seen in nonlinear equalizations. For example, Volterra equalization [3] takes as its inputs the second and even higher order signal terms generated by the linear term; digital fiber nonlinearity compensation algorithms usually calculate nonlinear noises like intra-channel cross-phase modulation (IXPM) and intra-channel four-wave mixing (IFWM) as extra features which are then fed into special nonlinearity model [4]. In general, these MSD schemes rely on deterministic models, like the laser diode chirp equation [5] for CDM and the perturbation model of the nonlinear Schrödinger equation (NLSE) [6] for fiber nonlinearity mitigation. However, the deterministic-model-based MSD comes with some shortcomings: (i) it may not be easy to derive a deterministic model considering the relation among multiple features is usually nonlinear; (ii) it may be computationally complicated to use the model; (iii) the model may not be accurate enough to approach the optimum MSD, especially when a simplified model is preferred to reduce the complexity.

Recent advances of deep learning shed light on the issue. It is known that a neural network (NN) can serve as a universal function approximator, which could be a potential MSD solution. A simple NN was proposed to compensate the fiber nonlinearity, taking the received dual-polarization linear optical field together with the nonlinear triplets like IFWM and IXPM as the network inputs [4]. In this paper, we choose CDM, namely, a DML coherent system, to study NN's capability of MSD. As the DML frequency chirp is determined by the modulation intensity, the phase detection of the coherent receiver that was commonly regarded as redundant offers extra information of the intensity. Concretely, CDM performs the joint demodulation of both intensity and differential phase (i.e. the digital approximation of chirp) for MSD. Previously CDM-MSD relies either on a deterministic laser diode chirp model [5] or a statistical model [2] combined with the maximum likelihood sequence estimation (MLSE). This paper shows NN can achieve a similar or even better performance simply by feeding both the intensity and the differential phase the as multivariate inputs. The performance is verified in a 100-Gb/s dual-polarization DML coherent system with 25-GBaud PAM-4 modulation [2].

2. Multivariate symbol decision for complex direct modulation (CDM)

As CDM requires the differential phase calculated by 2 adjacent symbols, we use MLSE with 2-tap memory for MSD. We define 2 sets: (i) the state $\{S_t\}$ (each state corresponds to an intensity level); (ii) the transition $\{\chi_t | \chi_t \triangleq (S_t, S_{t-1})\}$. A crucial task of MLSE is to calculate transition probability $P(I_t, \Delta\varphi_t | S_t, S_{t-1})$, namely, the conditional probability of observing $(I_t, \Delta\varphi_t)$ when the transition (S_t, S_{t-1}) is sent, in order to determine the survival path. To simplify the calculation, we regard I_t and $\Delta\varphi_t$ as 2 independent random variables and decompose the 2-D joint distribution into 2 1-D distributions: $P(I_t, \Delta\varphi_t | S_t, S_{t-1}) = P(I_t|S_t) \cdot P(\Delta\varphi_t | S_t, S_{t-1})$, despite I_t and $\Delta\varphi_t$ are correlated with each other. $P(\Delta\varphi_t | S_t, S_{t-1})$, in other words, the chirp model, can either be estimated by a digital approximation of chirp derived from the laser diode rate equation [5], or be acquired statistically by training sequences [2]. In this paper, we use the statistical model (which was shown to outperform the rate equation model) as the comparison baseline. In terms of the NN-based MSD, state-of-the-art deep learning offers a variety of sophisticated NN architectures like convolutional NN and recurrent NN [7]. However, to keep the computational complexity within a practical region for digital optical receivers, we use a simple fully-connected NN which only contains one hidden layer with 16 neurons as shown in Fig. 1, commonly known as a shallow NN. The output layer has the same number of neurons as the constellation size, with the softmax activation for classification. The remaining neurons in the network use the ReLU function as activations.

We reprocessed the experiment data published in [2] to verify the NN-based MSD. Fig. 1 redraw the experiment setup. Two 1549.44-nm distributed feedback (DFB) lasers generated a polarization-multiplexed 25-GBaud PAM-4 signal which was launched into a fiber recirculating loop with 1-span of 80-km standard single mode fiber (SSMF). The signal was detected by a dual-polarization coherent receiver. Intensity-only decision was immediately made after the multi-modulus-algorithm based polarization demultiplexing. Combining the differential phase, MSD was achieved by both MLSE and NN. The MLSE had 2-symbol memory under 1 sample per symbol (sps). For the NN inputs, a sliding window was applied on the received data streams to select adjacent symbols with either 1 or 4 sps for both intensity and phase that led to an input layer size of: memory length (symbols) × oversampling rate (sps) × 2 (intensity and phase). The network was trained by the well-established stochastic gradient descent with momentum [7]. For each OSNR value or transmission distance, the total batch size was around 0.2 million with a mini-batch size of 32 to train the network coefficients. Totally 2 million bits were counted for the BER calculation of each channel condition.

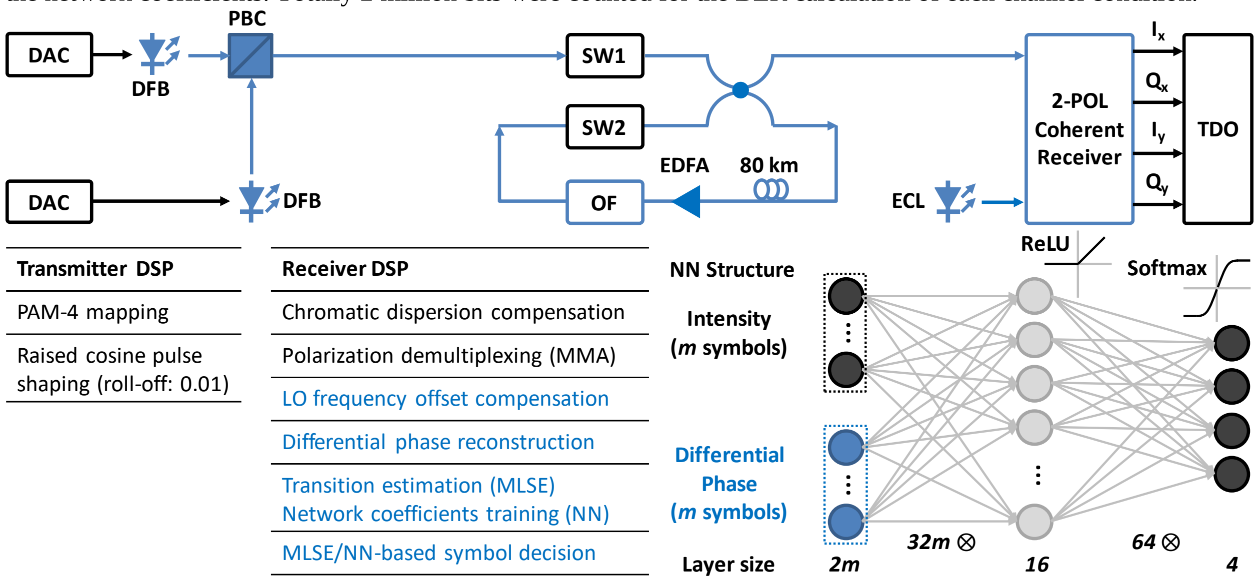

Fig.1. Experiment setup. DAC: digital-to-analog converter; DFB: distributed feedback laser; PBC: polarization beam combiner; SW: optical switch; OF: optical filter; ECL: external cavity laser; TDO: time-domain oscilloscope; MMA: multi-modulus algorithm; ⊗: number of multiplications.

3. Experiment results

We illustrate the system OSNR sensitivity using intensity-only symbol decision and MLSE-based MSD as the baseline in Fig. 2(a). As expected, MSD outperforms the intensity decision with around 7-dB sensitivity advantage at the BER of 1e-2 owing to the extra feature of phase. For NN, we first maintain its input identical to that of MLSE, namely, 2 symbols with 1 sps. NN successfully realizes the MSD with an OSNR sensitivity only slightly worse than MLSE. For MLSE, it is usually sophisticated to acquire an accurate statistic model that includes oversampling information, and its computational complexity increases exponentially with the memory length. In contrast, NN can accommodate such issues easily by adding more neurons on the input layer. We feed both the 2-symbol 4-sps inputs and the 3-symbol 1-sps inputs to the NN, with the OSNR sensitivity shown in Fig. 2(b). With more received signal characteristics, both cases learn more about the DML behavior and outperform the MLSE, while the amount of computation only increases linearly between the input and the hidden layers. Combining longer memory length and oversampling points, the 3-symbol 4-sps inputs provide >2 dB OSNR sensitivity advantage at the BER of 1e-2. We also show in Fig. 2(b) the theoretical OSNR sensitivity for differential-QPSK (DQPSK) modulation, a performance reference of the 4-ary signal that uses differential phase for symbol decision. The curve is not parallel with the NN-MSD ones, and the OSNR gap becomes wider with higher OSNR. This indicates the network has not been suffered from overestimation and there is still room for improvement, either by expanding NN inputs or using more sophisticated NN architectures. We did not investigate further these advanced options in order to keep the computational complexity within a practical region for digital receivers. It is noted that though MLSE is the theoretical optimum detection scheme for a channel with memory, it is not optimum in our comparison because (i) its memory length is limited to 2 symbols and (ii) transition probability is not ideally accurate due to the 1-sps operation and the decomposition of the 2-D distribution of 2 correlated variables into 2 1-D distributions. To address the second issue and perform better channel estimation for MLSE, an NN-based transition probability estimation named ViterbiNet [8] was proposed to replace the conventional one used in this paper.

Although involving NN, ViterbiNet is different from the NN-MSD concept as it still relies on MLSE. While ViterbiNet may further enhance MSD, its computational complexity inevitably increases exponentially with the channel memory.

To illustrate the superiority of MSD over univariate symbol decision, we feed either the intensity or the differential phase (3-symbol 4-sps) into the NN. Although NN can be regarded as a nonlinear equalizer, it cannot improve the OSNR sensitivity in a significant manner for intensity-only decision, as shown in Fig. 2(c). The phase plays a more important role in demodulation. It is well known that in the laser diode rate equation, chirp (i.e. differential phase in digital domain) has a nonlinear relation with the laser output intensity [5]. By simply feeding the differential phase, NN interprets it successfully to the intensity information. What's more, NN automatically combine both intensity and phase information for MSD without resorting to any analytical or statistical models, which outperforms both univariate symbol decision cases. We apply the 3-symbol 4-sps NN-MSD to the transmission, with the results shown in Fig. 2(d). As expected, both NN and MLSE achieve much better MSD performance than the univariate intensity decision. Furthermore, NN remains its advantage over MLSE, indicating it could support even longer transmission distance.

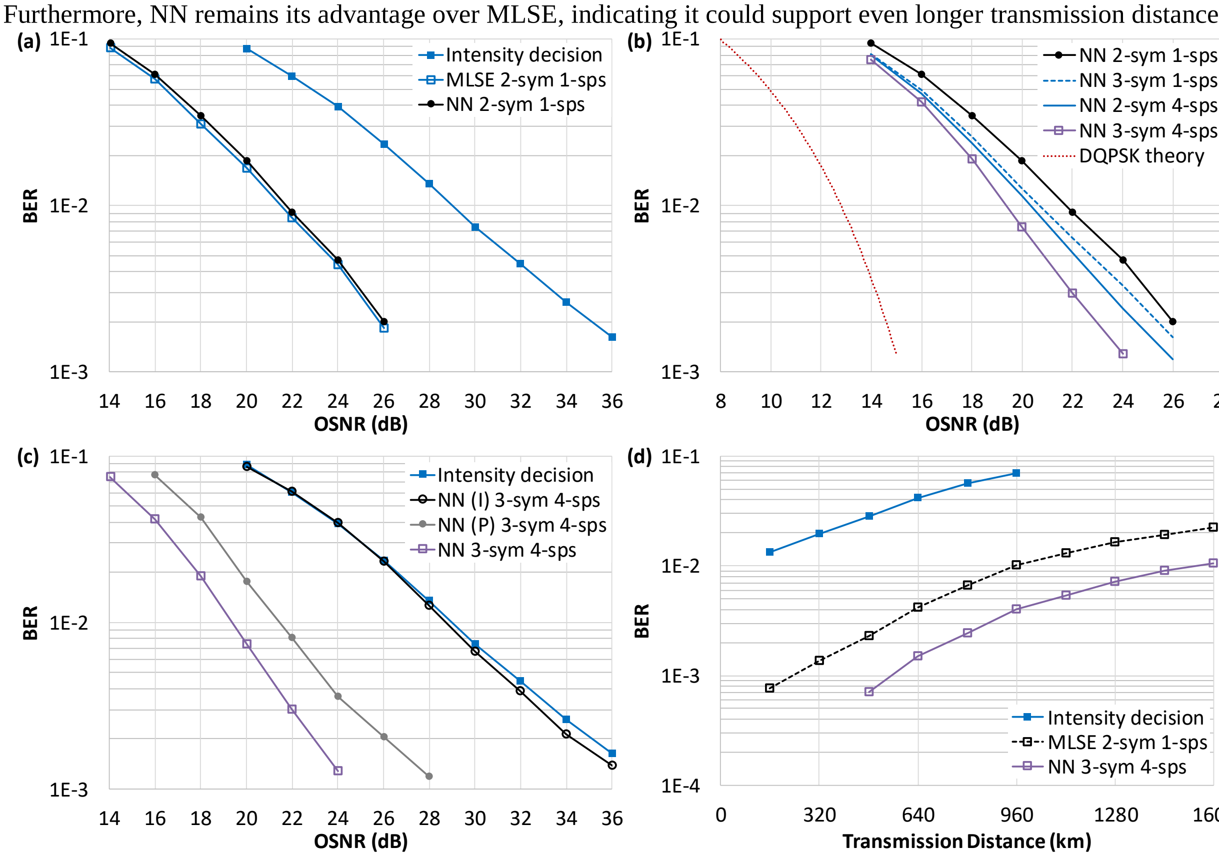

Fig. 2. Performance comparisons among various CDM symbol decision schemes: (a-c) back-to-back OSNR sensitivity; (d) transmissions. NN (I/P) in the legend of Fig. 2(c): neural network with only intensity/phase input; sym: symbol (i.e. channel memory length); sps: samples per symbol.

4. Conclusion

A fully-connected shallow network successfully achieves multivariate symbol decision (MSD) with both intensity and differential phase in a 100-Gb/s direct modulation and coherent detection system, which shows significant sensitivity improvement over the univariate intensity-only decision and outperforms the previous maximum likelihood sequence estimation scheme. The concept can be potentially generalized to other MSD applications, especially when the extra signal feature is generated artificially like in Volterra series, to offer better nonlinear equalization performance.

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