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Reducing Training Time of Deep Learning Based Digital Backpropagation by Stacking

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***Abstract*— A method for reducing the training time of a deep learning based digital backpropagation (DL-DBP) is presented. The method is based on dividing a link into smaller sections. A smaller section is then compensated by the DL-DBP algorithm and the same trained model is then reapplied to the subsequent sections. We show in a 32 GBd 16QAM 2400 km 5-channel wavelength division multiplexing transmission link experiment that the proposed stacked DL-DBPs provides a 0.41 dB gain with respect to linear compensation scheme. This needs to be compared with a 0.56 dB gain achieved by a non-stacked DL-DBPs compensated scheme for the price of a 203% increase in total training time. Furthermore, it is shown that by only training the last section of the stacked DL-DBP, one can increase the compensation performance to 0.48 dB.**

***Index Terms*— Coherent communication, deep learning, digital backpropagation, digital signal processing, nonlinearity compensation, optical fiber communication.**

I. Introduction

FUTURE long haul and high-capacity coherent fiber optic link will likely include a nonlinear compensation (NLC) scheme that ideally has high performance and low complexity. NLC is needed to counteract the capacity-limiting fiber nonlinearity [1]. A trained neural network (NN) is a promising candidate for such a scheme. It has been shown that an NN based NLC outperforms the well-known and well-studied digital backpropagation (DBP) [2], both in terms of gain and inference complexity [3]–[8].

In [3], an NN was used as an equalizer while in [4], it was used to approximate the signal perturbation. Although they perform well, for practical applications, clear guidelines for choosing the network architecture are necessary, i.e., number of hidden layers, number of neurons within the hidden layers, and the activation function. To address this, reference [8] mimicked the DBP by using the coupled fiber Kerr nonlinearity as the activation function. Yet, the method is rather cumbersome since a synthetic received signal that requires an application of the chromatic dispersion filter twice is needed at the input of the network.

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Interestingly, it has been shown that the DBP and a NN are mathematically similar [9]. This similarity simplifies the design process since one could start from a well-known DBP and proceed with an NN, i.e., a deep learning based digital backpropagation (DL-DBP). Leveraging this similarity, it has been shown in laboratory setting that DL-DBP performs better than DBP [6], [7]. This improvement is partially because the trained DL-DBP has a low-pass characteristic [7] similar to that of the filtered version of DBP [10]. However, the DL-DBP method has also its limitations: The numbers of hidden layers in DL-DBP linearly scale with the transmitted distance. Consequently, the required training time also scales with the transmitted distance.

In this letter, we propose a new method for reducing the training time of a DL-DBP dividing a link into shorter sections. A shorter section is then trained and reused for the subsequent sections. This method is also known as a transfer learning method, similar to what has been shown in [11]. By stacking of sections, we show in a proof-of concept experiment a total training time reduction of about 67% with a SNR gain that is close to what one would find for a fully trained network. More precisely, we show in a 32 GBd 16QAM 2400 km 5-channel wavelength division multiplexing (WDM) link that our proposed method offers a 0.41 dB gain with respect to linear compensation. This gain is similar to what one would win by applying a 1 step per span (SpS) DBP on the full distance–yet at about half the inference complexity [7]. If training of a network is done in two steps, i.e., first fully training a short first section and then training only the second section of the DL-DBP intended for the longer distance then one finds an SNR gain of 0.48 dB. This is beneficial for a scenario where the model for the first section have already been obtained, e.g., from an earlier fiber deployment. For a gain of 0.56 dB, the whole stacked DL-DBP needs to be trained.

II. Stacking Trained DL-DBPs

To demonstrate the nonlinear fiber compensation concept and how it can be simplified by dividing the link into sections, we use an exemplary fiber link with L spans and total length of L_{tot}. The fiber link with its subdivision into sections, spans and mathematical DBP steps or DL-DBP layers is shown in Fig. 1. Since, it has been shown that DBP and NN are mathematically similar [9], the two structures can be organized similarly when applying either the conventional DBP or the DL-DBP.

The nonlinear compensation relying on conventional DBP is shown in Fig. 1(a). The whole link with L spans is subdivided into M_{s} steps per span with total steps $M = M_{\text{s}}L$.

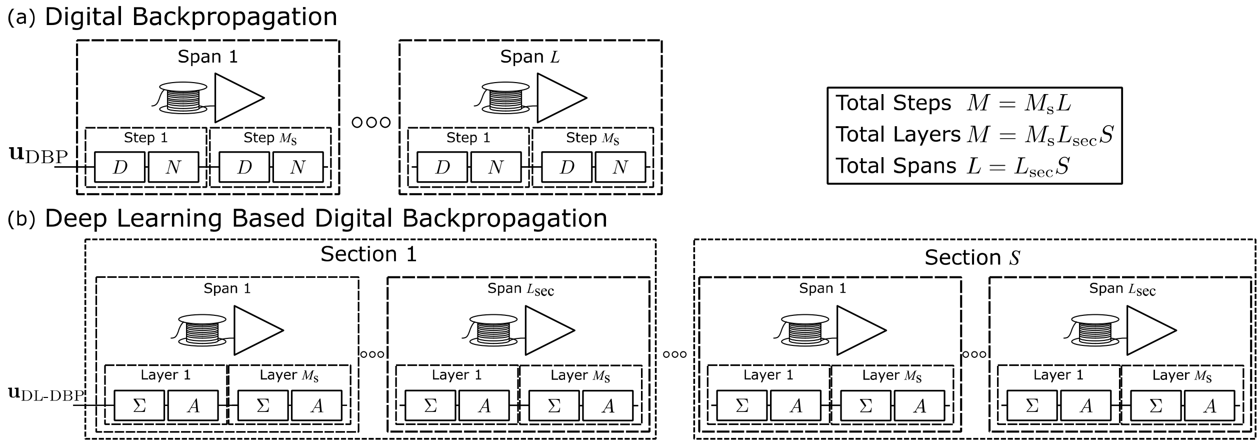

Fig. 1. Block diagram of the structure of (a) a digital backpropagation and (b) a deep learning based digital backpropagation (DL-DBP) for a fiber link with L spans. D and N are the dispersion operator and the nonlinear Kerr operator for the m^{th} step of the fiber respectively. Σ and A are the linear operator and nonlinear operator for the m^{th} hidden layer, respectively. We propose to divide the link into S sections and then train a DL-DBP for the fiber impairment within the shorter section only. The same trained DL-DBP model is then reapplied to all subsequent sections of the link.

Each step compensates for a distance of $\Delta = L_{\mathrm{tot}}/M$. The DBP alternates in every step between a linear operator applying dispersion D and a nonlinear Kerr operator N onto the dual-polarization input signal $\mathbf{u}(t) = [u_{\mathrm{X}}(t), u_{\mathrm{Y}}(t)]^{\mathrm{T}}$. D is the time-domain FIR implementation of the dispersion filter [12]. The $N-$ operator—in case of dual polarization—is defined as

$$f_{\mathrm{X}}(\gamma, x, y) = x \cdot \exp\left(\mathrm{j}\frac{8}{9}\gamma\left(|x|^2 + |y|^2\right)\right),$$
$$f_{\mathrm{Y}}(\gamma, y, x) = y \cdot \exp\left(\mathrm{j}\frac{8}{9}\gamma\left(|x|^2 + |y|^2\right)\right),$$

where x, y are the signals in the x- and y-polarization, respectively and γ is the nonlinear Kerr coefficient. Here, we use the simpler Manakov definition of the DBP so that there is a factor $8/9$ in the nonlinear Kerr operator definition [2].

In the NN, see Fig. 1(b), we alternate—within each layer—between a linear operator Σ and a nonlinear operator A that is defined by an activation function $g(x)$. By equating the linear operator as the convolutional dispersion operator and the nonlinear operator as the nonlinear Kerr operator, an M-step DBP can be realized as an M-layered NN, i.e., a deep learning based digital backpropagation (DL-DBP). The DL-DBP then can be trained using a gradient descend optimization. Here, training means to update the complex weights within the linear operator and the complex γ_{NN} within $g(x)$. Experimental results show that by using the trained DL-DBP, not only could one produce an improved gain over one can obtain with a conventional DBP, but also with less inference complexity [6], [7].

For longer distances, the number of required layers within the DL-DBP increases since the spatial resolution of the DL-DBP should be kept constant. Yet, this comes at the expense of an increased training time. To reduce training time, we propose to divide the link into S sections with L_{sec} spans per section and then train a DL-DBP for nonlinear fiber impairment on the smaller section. The same trained DL-DBP model is then reapplied to all subsequent sections of the link, see Fig. 1(b). For this work, we limit ourselves to $S = 2$ with the same L_{sec}. Lastly, we compare the performance of the stacked DL-DBP with that of a sectionally trained stacked DL-DBP (we only train the last section of the stacked DL-DBP that has not seen the new link yet) and a fully trained DL-DBP.

III. Experimental Setup

Fig. 2 (a) shows the experimental setup for this work. A dual-polarization IQ modulator with a 64 GSa/s arbitrary waveform generator (AWG) combined with external drivers is used to generate a 32 GBd 16QAM signal with a square-root-raised-cosine shape and a roll-off-factor of 0.1. The AWG produces a single randomly generated waveform of size 2^{18} samples. Then, we use spectrally shaped amplified spontaneous emission (ASE) noise to simulate a transmission of 5 WDM channels as proposed in [13]. The inset in Fig. 2 shows the transmitted WDM spectrum. The channel under test (CUT) with a bandwidth of around 35.2 GHz is placed within a 68 GHz notch of the spectrally shaped noise. This is the same as placing 16.4 GHz guard bands on either side of the CUT. We then use a recirculating loop to simulate 1200 km and 2400 km transmission distance. The loop consists of three 100 km fiber spans, four Erbium doped fiber amplifiers (EDFAs), two variable optical attenuators (VOAs) and a wave shaper. The fiber spools have a dispersion parameter of 17 ps/(km nm), 0.183 dB/km of attenuation (α) and an effective area of 83.3 $\mu\mathrm{m}^2$. At the receiver, we demultiplex the signal using a Gaussian shaped bandpass filter (BPF) with a 3 dB bandwidth of 0.6 nm. Prior to receiving, we bring our CUT to the optimal power level of the coherent receiver using an EDFA and a 0.6 nm BPF. We then receive the signal using a coherent receiver that consists of a 90 deg hybrid, 4 balanced photodiodes and 80 GSa/s digital storage oscilloscope (DSO). The digitized signals are then processed further using offline digital signal processing (DSP) in MATLAB.

For offline signal processing, we first resample to 2 samples per symbol and normalized the signal to the CUT power level. We then apply linear compensation only (chromatic dispersion), conventional Manakov DBP, conventional DL-DBP or the new stacked DL-DBP technique. Afterwards, a matched

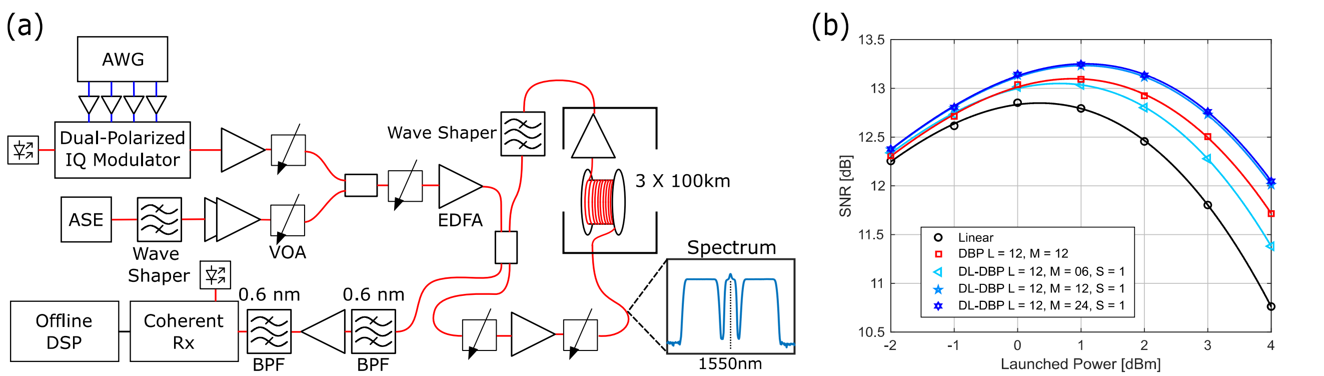

Fig. 2. (a) Experimental setup for the wavelength division multiplexing (WDM) using spectrally shaped amplified spontaneous emission (ASE) source WDM emulator and received with dual polarization coherent receiver (Rx) and offline DSP. AWG is arbitrary waveform generator and VOA is variable optical attenuator. Inset shows the spectrum of the transmission of the channel under test and the emulated WDM channels. (b) Average estimated SNR (markers) and interpolated (solid lines) SNR at transmission distance of 1200 km (L=12) as a function of launched power for linear compensation, DBP, and fully trained DL-DBPs. L is the total number of spans, M is either the total number of steps for DBP or total number hidden layers for DL-DBP, S is the number of DL-DBP sections.

filter, a timing recovery, polarization demultiplexing filter, carrier recovery and additional linear equalizations are applied to the signal. For the DL-DBPs, the total number of hidden layers within the stacked and conventional DL-DBP is chosen such that it is equal to the number of SpS of the DBP. Unless stated otherwise, we initialize the DL-DBP using the impulse response of the chromatic dispersion filter, and zero rotational strength during the training state. We train using the static hidden layer method [7], complex number compatible ADAM optimizer and 1.5 million iterations. The framework for training the DL-DBP is developed in-house in MATLAB. The training set comprises a set of 10 different measurements, each consisting of 150’000 symbols. It should be noted that at the current version, the timing recovery static hidden layer cannot do minibatch training. Using minibatch could reduce the total training time for all considered schemes while still preserving the relative reduction between the schemes. Prior to training, we shuffle the order of the measurement set. Following [14], for the conventional DBP, the loss α and the Kerr-nonlinearity γ are optimized until the SNRs at the end of receiver DSP chain plateau.

IV. Compensation Performance at 1200 km

Fig. 2 (b) shows the average estimated SNR and interpolated SNR at 1200 km at 1200 km ($L = 12$) for linear compensation only, DBP and DL-DBPs with $S = 1$ and $L_{\text{sec}} = 12$. The launched power refers to the power at the begin of the link. The DL-DBP with total hidden layers of 12 ($M = 12$) provides a gain of 0.38 dB with respect to linear compensation and a 0.13 dB gain with respect to DBP with 1 step per span ($M = 12$). The gain of DL-DBP with respect to the linear compensation increases to 0.37 dB when we increase to $M = 24$ and decreases to 0.17 dB when we reduce to $M = 6$. The gains are calculated using the interpolated SNR. Further, the DL-DBP is the fully trained version, and the training is done at the launched power of 4 dBm, i.e., the DL-DBP is trained for a launch power of 4 dBm and then is used for other launched powers, and the DL-DBPs use 149, 93, and 65 taps per hidden layer for DL-DBP with M equal to 6, 12, and 24 respectively. The number of taps is optimized by first using the minimum number of taps of 55, described in [12] and then increasing the number of taps until the gain is maximized.

TABLE I
Comparison of the Total Training Time for Stacked DL-DBP, Sectionally Trained DL-DBP and Fully Trained DL-DBP

	Initial [minutes]	Additional [minutes]	Total [minutes]
Stacked DL-DBP (L=24, M=12, S=2)	495.6	0	495.6
Sectionally Trained (L=24, M=24, S=2)	495.6	748.4	1244
Fully Trained (L=24, M=24, S=2)	495.6	1004.3	1500

V. Compensation Performance at 2400 km

For the 2400 km ($L = 24$) experiment, we stack two 1200 km-trained DL-DBP as introduced in Fig. 2 (b) and use the stacked DL-DBP ($S = 2$) to compensate the 2400 km link. This is done by simply using the trained 1200 km model two times in succession. Prior to entering the second trained DL-DBP, we renormalize the signal power. Fig. 3 (a) and (b) show that a stacked DL-DBP with $M = 6$ and $S = 2$ outperforms the linear compensation scheme by 0.2 dB, albeit still below the DBP with a total step of $M = 24$. Fig. 3(a) and (b) also show that the stacked DL-DBP with $M = 12$ and $S = 2$ and conventional DBP with $M = 24$ deliver a similar gain in the order of 0.41 dB with respect to the linear compensation scheme while both the stacked DL-DBP with $M = 24$ and $S = 2$ and conventional DBP with $M = 48$ also deliver similar gains of 0.45 dB with respect to a linear compensation scheme. This shows that for longer distances, we could have 67% reduction on the total training time by reusing DL-DBPs that have been trained for a shorter distance, see Table I. Further, the stacked method could be extended to more than 2 sections provided that the shorter section has enough accumulated fiber nonlinearity.

In a next experiment, we do a sectional training where we only train the second section. Here we assume that we already have the model for the first section, and we initialize the new

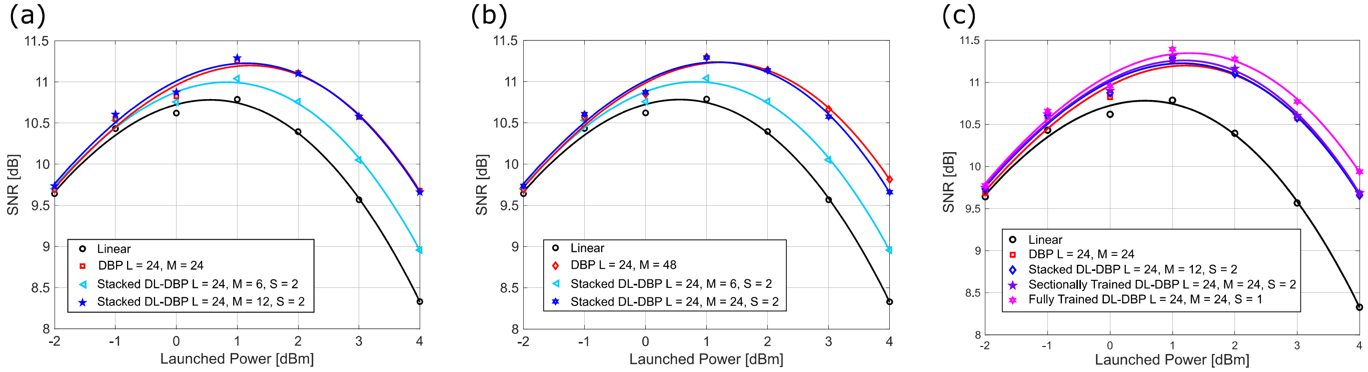

Fig. 3. Average estimated SNR (markers) and interpolated (solid lines) SNR at transmission distance of 2400 km (L = 24) as a function of launched power for: a) and b) linear compensation scheme, DBP, stacked DL-DBP. c) Linear compensation scheme, DBP, stacked DL-DBP, sectionally trained DL-DBP, and fully trained DL-DBP. L is the number of spans, M is either the number of steps or hidden layers, S is the number of DL-DBP sections.

model with a stacked DL-DBP with M = 12 and S = 2. The model could be obtained from the earlier fiber deployment of the shorter section. Training only the later shorter-section increases the gain with respect to stacked DL-DBP. For this result, we first initialize the new DL-DBP by using a stacked DL-DBP with M = 12 and S = 2 and only train the 2nd section of the link, i.e., from the 13th layer onward. Fig. 3 (c) shows that the gain of the sectionally trained DL-DBP improves to 0.48 dB with respect to linear compensation.

Further, we fully train the DL-DBP with M = 24 and S = 1. Following the previous paragraph, we initialize also with a stacked DL-DBP with M = 12 and S = 2. Fig. 3(c) shows that the fully trained DL-DBP produces a 0.56 dB gain with respect to linear compensation while it produces around 0.15 dB gain with respect to DBP with M = 24. This shows that for the best performance of the DL-DBP, a fully trained DL-DBP is needed albeit with 203% (Table I) increase in total training time with respect to the 2-section stacked DL-DBP. Lastly, for each scheme, we list in Table I the training time to reach the performance of Fig. 3 (c) (as needed with our algorithm on our machine). The initial time refers to the training time of the DL-DBP for 1200 km. For fully trained DL-DBP one could remove the initial training time entirely. The total training time for the sectionally trained and fully trained scheme can be reduced since the retraining of the two schemes over the longer distance, i.e., new domain, requires less training data [11].

VI. Conclusion

We introduce a method to reduce the training time of a deep learning based digital backpropagation (DL-DBP) by stacking two trained DL-DBPs. In a 32 GBd 16QAM 2400 km 5-channel WDM transmission, we show that stacking DL-DBP sections provides a similar 0.41 dB gain as by applying a conventional 1 step per span (SpS) DBP algorithm – yet at about half of the inference complexity and 67% decrease in training time. Further, we show that by only training the second section of the stacked DL-DBP (assuming the model for the first section has already been obtained earlier), the gain improves to 0.48 dB with respect to linear compensation scheme. Training the whole stack of the DL-DBP provides a 0.56 dB gain with respect to a linear compensation scheme, yet at the price of higher training time.

The results indicate that DL-DBP training can be simplified using sections. While these results have been experimentally verified in the lab, the results need to be confirmed in a field experiment where fiber spans are not looped.

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