Improved Fast Anti-fluctuation Adaptive Digital Back-Propagation for Kerr-nonlinearity Compensation

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Abstract—**Improved fast anti-fluctuation adaptive digital back-propagation (ADBP) is proposed for blind Kerr-nonlinearity compensation. 85% reduction of convergence steps is achieved in the simulation transmission of 69 Gbaud DP-16QAM over 2000 km compared with conventional ADBP.**

Keywords—Coherent optical transmission system; nonlinear damage compensation; digital back-propagation (DBP)

I. Introduction

With the explosive growth in demand for modern communication services, optical transmission capacity has been driven to increase exponentially and been pushed towards nonlinear Shannon limit [1]. To break the capacity bottleneck in long-haul coherent optical communication systems, different nonlinear compensation techniques have been proposed to compensate the nonlinear distortions induced by Kerr nonlinearity [2]. Among them, digital back-propagation (DBP) is a commonly utilized technique for joint compensation of linear and nonlinear effects with high effectiveness and simple structures, which is implemented by solving an inverse nonlinear Schrödinger equation (NLSE) [3].

For compensating the nonlinearity by DBP, an effective nonlinear parameter defined as $\tilde{\gamma} = \xi\times\gamma$ is needed in split-step Fourier method for solving the inverse NLSE, in which ξ is the compensation factor and γ is the nonlinear parameter of the transmission link [3]. However, the optimal value of ξ is difficult to be determined by a precise analytical method, and γ might be time-varying under dynamic optical networks and might be unavailable in reconfigurable systems, both of which cause that we should be capable of adaptively estimating the optimal $\tilde{\gamma}$ to approach the best nonlinearity compensation performance. In recent years, adaptive DBP (ADBP) has been presented as the solution [4]. One obvious drawback in ADBP is the low speed of convergence caused by the gradient descent algorithm (GDA) as the search algorithm. Later, ADBP based on GDA with momentum (GDAM) has been presented to improve convergence speed [5]. The limitation of ADBP based on GDAM is that fluctuations intensified by the momentum item leads to divergence of searching $\tilde{\gamma}$ when the convergence rate is set too fast, which limits the convergence speed in turn. Therefore, it requires a scheme to achieve both fast convergence and low fluctuation for decreasing calculation in digital signal processing (DSP) module so as to imply cost-effective hardware.

In this paper, we propose an improved ADBP technique based on adaptive Nesterov's accelerated gradient descent algorithm (ANAGDA) to improve the convergence speed of estimating the optimal $\tilde{\gamma}$, which contains two key technical parts. Firstly, the fluctuations of $\tilde{\gamma}$ during iterations are suppressed by reducing step sizes in advance to approach the optimal solution once the prediction of next step is so large that the next iteration skips the optimal solution, so as to adapt to faster convergence factors (i.e. rate and momentum parameter) in ANAGDA. Then, based on the prediction of next step, ANAGDA further accelerates the gradient descent speed and decrease fluctuations by adaptively adjusting convergence factors. These two aspects improve the convergence speed together. In order to evaluate the effectiveness of the proposed scheme, simulation transmission of 69 Gbaud DP-16QAM over 2000 km is set up. Results indicate that ADBP based on ANAGDA can reduce 69% and 85% convergence steps compared to GDA-based and GDAM-based. Moreover, our scheme outperforms the traditional DBP both in the conditions of inaccurate γ and fewer steps per span.

II. Principle of the Proposed Scheme

In order to address the problem of slow convergence of GDA, GDAM adds the momentum item which represents the memory of the last change of $\tilde{\gamma}$. But blind accelerations in the direction of the previous change will make updating steps too large to converge in GDAM, especially with large adaptive convergence rate μ_{adap} and momentum parameter m, which limits the convergence speed. Based on this problem, the prediction item of next gradient change of cost function (CF) is employed in our proposed scheme at first to neutralize the momentum item. The update formula is defined as:

$$\tilde{\gamma}(i+1) = \tilde{\gamma}(i) - \mu_{adap}\partial\widehat{\mathrm{CF}}(i+1) + m\Delta\tilde{\gamma}(i-1) \tag{1}$$

where $\tilde{\gamma}(i+1)$ and $\tilde{\gamma}(i)$ represents the effective nonlinear parameter at the iteration i+1 and i respectively, μ_{adap} is the adaptive convergence rate, m is the momentum parameter for controlling the memory degree of the last $\tilde{\gamma}$ change which is defined by $\Delta\tilde{\gamma}(i-1)=\tilde{\gamma}(\mathrm{i})-\tilde{\gamma}(i-1)$, CF is Godard's error calculated in the cascaded multi-module algorithm (CMMA) process [6], $\partial\widehat{\mathrm{CF}}(i+1)$ predicts the CF's gradient of the next iteration i+1 using an approximation of $\tilde{\gamma}(i)+m\Delta\tilde{\gamma}(i-1)$.

Then, on the basis of the prediction item $\partial\widehat{\mathrm{CF}}(i+1)$, multiplying factor $p(i)$ is added in Eq.(1) for further updating μ_{adap} and m adaptively at every different iteration with higher speed and lower fluctuations. The final update formula of ANAGDA is defined as:

$$\tilde{\gamma}(i+1) = \tilde{\gamma}(i) - [\mu_{adap}\partial\widehat{\mathrm{CF}}(i+1) + m\Delta\tilde{\gamma}(i-1)]\times p(i) \tag{2}$$

The prediction item $\partial\widehat{\mathrm{CF}}(i+1)$ allows the iterative process to react in advance of the next step. CF is used to indicate the influence of nonlinear effects, and the more adequately DBP compensates for nonlinear damage, the smaller the CF is. If the predicted $\tilde{\gamma}$ makes CF of the next step smaller, the change

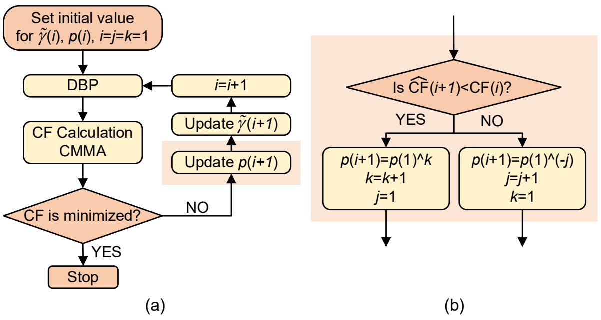

Fig. 1. (a) Flow chart of parameter adaptation for the improved ADBP. (b) The principle of adjusting $p(i+1)$.

in the current direction can be further strengthened by the prediction item to improve the convergence speed in ANAGDA. On the contrast, the update step can be reduced in advance by the prediction item to prevent fluctuations so as to adapt to larger μ_{adap} and m for improving convergence speed as well.

Multiplying factor $p(i)$ derives from the predicted $\partial\widehat{\mathrm{CF}}(i+1)$ in ANAGDA. If the prediction of the next step's CF is lower, μ_{adap} and m increase exponentially to the next predicted step where CF no longer decreases for further accelerating convergence speed. On the contrary, μ_{adap} and m decrease exponentially to the next predicted step where CF no longer increases for further reducing fluctuations to adapt to larger μ_{adap} and m which lead to high convergence speed. The prediction item and multiplying factor increase the convergence speed and reduce the fluctuations jointly in ANAGDA.

Fig.1(a) depicts the flow chart of our improved ADBP. The compensation loop begins with the parameter $\tilde{\gamma}(i)$ and $p(i)$,which are the initial effective nonlinear parameter and the initial multiplying factor. The iteration index i and the multiplying index j, k are set to 1 at the outset. Then, the input signal is processed by DBP and CF is calculated in the next CMMA process. Update of $\tilde{\gamma}(i+1)$ and $p(i+1)$ is iteratively repeated till the CF is minimized (i.e. $\partial\widehat{\mathrm{CF}}(i)=0$), which means DBP can maximize the compensation of nonlinearity by using the $\tilde{\gamma}$ iterated in the last time. The value of $\tilde{\gamma}$ is updated according to ANAGDA to perform a new loop aiming for the descent of CF. As shown in Fig.1(b), $p(i+1)$ is updated to determine whether $\widehat{\mathrm{CF}}(i+1)$ is less than $\mathrm{CF}(i)$. If it is, $p(i+1)$ is updated to $p(1)^k$ and k=k+1, j=1. If it is not, $p(i+1)$ is updated to $p(1)^{-j}$ and j=j+1 , k=1 . Then update $\tilde{\gamma}(i+1)$ according to the Eq.(2) for the iteration loop of $\tilde{\gamma}$.

III. Simulation System and Results

Fig. 2 shows the simulation system built by VPIphotonics for evaluating the performance of the improved ADBP based on ANAGDA. At the transmitter, binary signal undergoes the quadrature modulation and the digital-to-analog conversion (DAC) to obtain 69 Gbaud DP-16QAM electrical signal. The light source at 1550 nm with 200 kHz linewidth is then modulated by the I/Q modulator to achieve electro-optic conversion. The transmission link consists of 20 spans of 100 km (2000 km) single mode fibers (SMFs) with an erbium-doped fiber amplifier (EDFA) for amplification, whose dispersion parameter, attenuation, and nonlinearity factor are D=16.75 ps/nm/km, α=0.2 dB/km, γ=1.31 /W/km respectively.

After transmission, the optical signal passes through an optical band-pass filter (OBPF) and is combined with a local oscillator (LO) at the polarization diversity hybrid to obtain the I and Q optical signals of two polarizations. Then the photodetectors (PDs) achieve photoelectric conversion and the electrical signal is processed in the DSP module implemented by MATLAB software. The DSP module includes analog to digital converter (ADC), Gram-Schmidt orthogonalization procedure (GSOP), ADBP, CMMA, frequency offset estimation (FOE), carrier phase estimation (CPE) and the BER calculation.

Fig. 3. (a) shows the convergence analysis for the ADBP using GDA, GDAM and ANAGDA in terms of the normalized CF value for each iteration. Different convergence rate μ and momentum parameter m were applied to these schemes. Under large μ (μ=3e-4) and m (m=1), neither GDA-based ADBP and GDAM-based ADBP can converge, so these two schemes can only employ lower μ (μ=1e-5) and m (m=0.5) for convergence with 13 and 27 iterations respectively. But ANAGDA-based ADBP converges with only 4 iterations on the condition of large μ (μ=3e-4) and m (m=1). Fluctuations in the convergence process are mitigated in ANAGDA-based ADBP, so our proposed scheme is more flexible to adapt to larger convergence factors. Therefore, faster convergence speed is achieved with larger μ and m, which follows from the result that the ANAGDA-based ADBP reduces 69% and 85% iterations compared with GDAM-based ADBP and GDA-based ADBP. Fig. 3. (b) compares the power-dependent performance of linear equalizer (LE) vs. DBP and ANAGDA-based ADBP. Standard DBP with biased value of γ (0.6, 2 /W/km) causes considerable system degradation, which the performance becomes even worse than LE at some launching powers. The performance of ANAGDA-based ADBP with correct or biased γ employed to count the initial value of $\tilde{\gamma}$ is equal to the standard DBP with correct value of γ (1.31 /W/km), which indicates the good performance of ANAGDA-

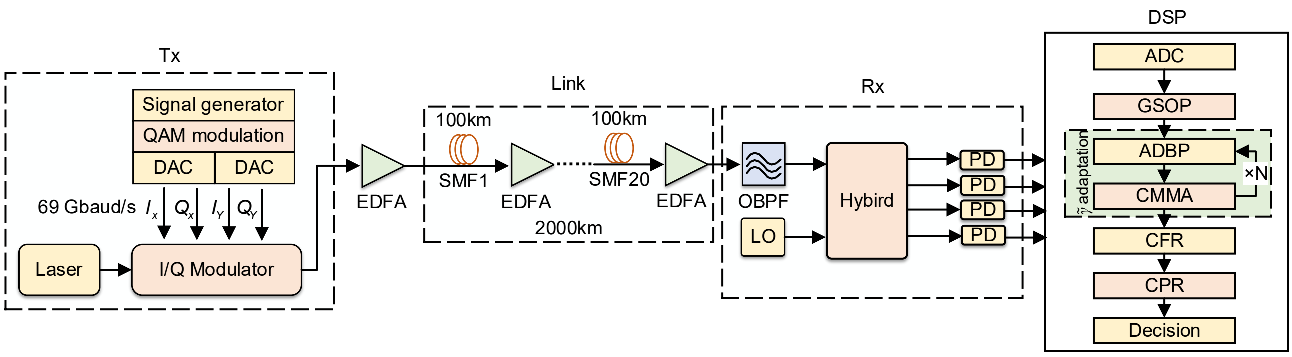

Fig. 2. The simulation system for 69 Gbaud DP-16QAM signal over 2000 km transmission.

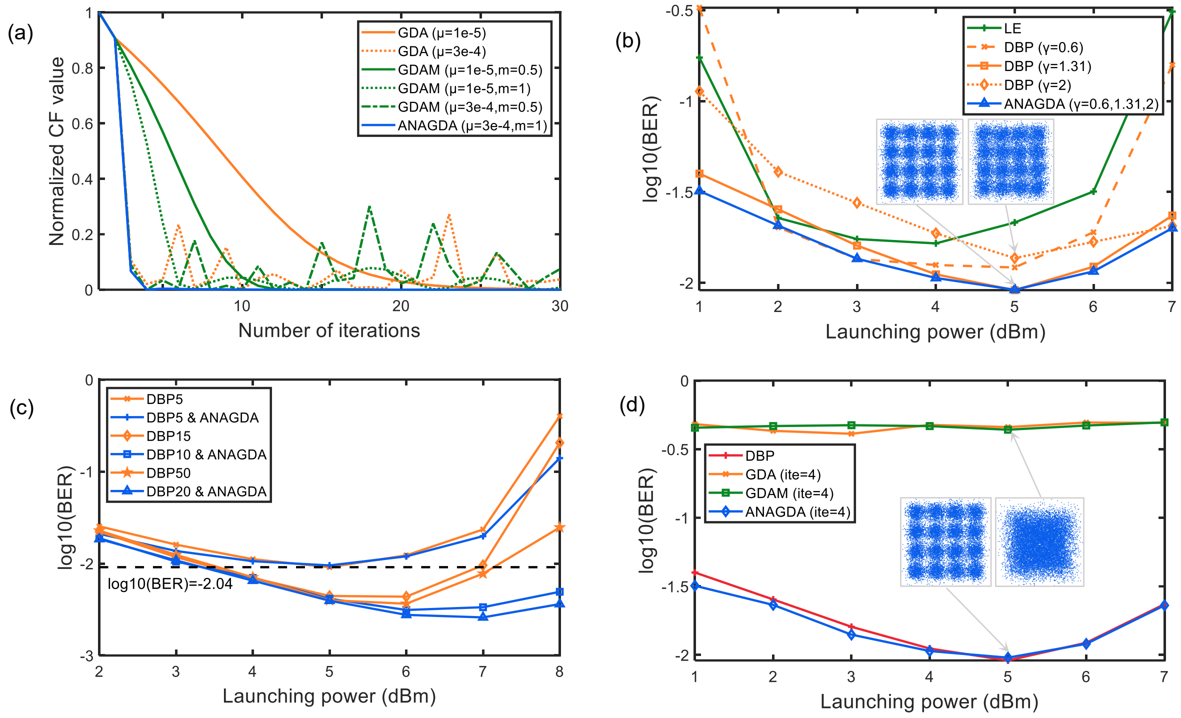

Fig. 3. (a) Normalized CF value versus number of iterations for 5-step DBP with different ADBP at 5 dBm launching power. (b) $\log_{10}$(BER) results as a function of the launching power for LE, standard DBP and ADBP based on ANAGDA with different γ values. (c) $\log_{10}$(BER) results as a function of the launching power for different number of steps per span. (d) $\log_{10}$(BER) results as a function of the launching power for standard DBP and different ADBP at the same iteration of 4.

based ADBP under conditions of incorrect γ. In Fig. 3. (c), $\log_{10}$(BER) results as a function of the launching power for different number of steps per span. Set the $\log_{10}$(BER) limit as -2.04 by optimal BER of standard DBP using 5 steps. Better performance is obtained in ANAGDA-based ADBP using 10 steps compared with DBP using 15 steps and 50 steps, which reduces 50% and 90% steps respectively. This reduction can have a considerable impact on the overall algorithm complexity. Fig. 3. (d) depicts the performance with swept powers for standard DBP and different ADBP at the same iteration of 4. There is little compensation effect of GDA-based ADBP and GDAM-based ADBP, while good performance is achieved by ANAGDA-based ADBP, which is equal to the standard DBP's. Ideal compensation performance is accessible for ANAGDA-based ADBP with low complexity.

IV. Conclusion

The improved ADBP based on ANAGDA is proposed to mitigate fluctuations and achieve faster convergence speed for estimating the optimal effective nonlinear parameter $\tilde{\gamma}$. Considering a 69 Gbaud DP-16QAM simulation system over 2000 km, the proposed scheme has strong adaptability for the conditions with larger convergence factors and reduces 69% and 85% convergence steps compared with ADBP based on GDA and GDAM. Meanwhile, DBP with at least 50% reduction of steps are employed in the proposed scheme to obtain equal or better performance in comparison with the standard DBP. The obtained results indicate that the ANAGDA-based ADBP is a promising approach to reduce the complexity of ADBP-based techniques with strong robustness towards parameters.

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