CNN Based Polarization Rotation Rate Estimation Using TIA Gain Monitoring in Integrated Coherent Receiver

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Abstract *We propose a hardware efficient machine learning based polarization rotation rate estimation scheme by monitoring TIA gain in the standard integrated coherent receiver. The proposed method was experimentally verified with various signal formats and conditions, estimated up to 200 kHz within 2.45 kHz error.*

Introduction

Monitoring fast polarization rotation, also known as state of polarization (SOP) change, has been investigated for optical fibre transmission systems to prevent the signal degradation caused by Polarization Mode Dispersion (PMD) before the advent of digital coherent technologies, since PMD compensation was challenging at the optical domain [1]. Digital coherent technologies have enabled polarization multiplexing (PM) and also PMD compensation in digital domain. Still, it is important to monitor fast polarization rotation since polarization demultiplexing is realized by Multiple-input-multiple-output (MIMO) equalizer and its tracking performance for fast polarization rotation is limited. Notably, fibre squeezing, mechanical vibration, temperature fluctuation, and even lighting strike result in fast polarization rotation [2]; therefore, it is important to monitor SOP changes not only to maintain the transmission performance but also to detect failure of optical transmission link.

Obviously, additional measurement equipment would enable to monitor polarization rotation; however, it requires extra cost and footprint. Polarization state monitor by optical supervisory channel with polarization beam splitter (PBS) and two photodiodes (PD) has been proposed [2], but it still requires additional hardware components and it is restricted to single span links. Alternatively, relying on digital signal processing (DSP), applying Finite Impulse Response filter coefficients of MIMO equalizer to derive SOP in the Stokes coordinates [4, 5] is an attractive method since it does not require the extra hardware. However, as it uses the equalized signal, thus it is intrinsically limited by the polarization tracking performance of MIMO equalizer, which is not ideal due to circuit implementation constraints. Therefore fast SOP transients may possibly yield loss-of-signal, unable to calculate the polarization rotation rate. Here, we aim to propose a polarization rotation monitoring method without additional hardware and which is efficient even if the signal can no longer be demodulated. Therefore we focus on an essential hardware part of transceivers.

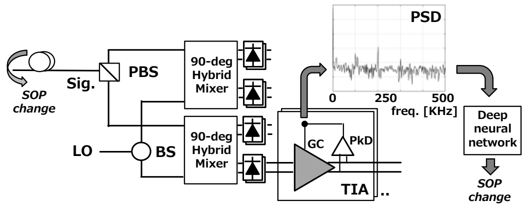


Fig. 1: Concept of CNN based polarization rotation estimation using TIA gain monitoring

To demodulate PM signal, Integrated Dual Polarization Intradyne Coherent Receiver (ICR) [6] is firstly used, it incorporates four sets of PDs and Trans-Impedance Amplifiers (TIA), and noticeably it features polarization and phase diversities. To maintain the signal quality, commercially available ICRs support auto gain control (AGC) mode for TIA, where it keeps constant output signal level regardless of the received signal condition. Therefore, it may be possible to estimate the polarization rotation rate from the information of TIA gain variation.

In this paper, we propose a hardware efficient machine learning based polarization rotation rate estimation scheme by monitoring TIA gain variation. Compared with the other methods, the proposed method neither rely on the received signal format and condition nor require extra hardware. The proposed method was experimentally verified with various signal formats and conditions, and enabled the polarization rotation rate estimation up to 200 kHz within a precision of 2.45 kHz.

CNN based polarization rotation rate estimation using TIA gain monitoring

The concept of CNN based polarization rotation rate estimation using TIA gain monitoring is shown in Fig. 1. The received PM signal is separated via PBS to recover two orthogonal polarizations that are steered to two 90°hybrid mixers. The hybrid mixer combines the received signal with the local oscillator (LO) to obtain baseband signal, outputs In-phase and Quadrature signal for both polarization. Each of outputs is connected with PD, interconnected to TIA that perform optical-to-electrical conversion for following DSP section. In this concept, we use TIA with AGC mode, where the amplifier gain is controlled by peak detector feedback loop. Assuming a PM signal, the hybrid mixer output has both polarization elements, which are then de-multiplexed by DSP. The mixing ratio of other polarization elements change when polarization dependent loss (PDL) exists, notably in optical components or in the transmission fibre. Thus, the output level of each hybrid mixer fluctuates with the polarization rotation. It is worth noting that fluctuation level depends on PDL, but even small amounts of PDL, like the ones in commercial systems, still introduce some detectable fluctuation. Typical gain feedback loop bandwidth of TIA is of MHz order, whereas fastest polarization rotations in WDM systems are a few hundred krad/s for lighting strikes; it is therefore possible to track SOP change in this manner, using the gain variation as a sensor for the polarization rotation rate.

Concerning our proposed method, it does not require signal demodulation and therefore nor depend on conditions (power, OSNR) since gain feedback loop only uses peak level of the received signal. As it works on analog control loops, it is independent on modulation format and symbol-rate, which we demonstrate in the following parts. No additional hardware is used as we rely on ICR manual gain control (GC) pins which are also used for monitoring point of GC voltage variation in AGC mode; the control unit of digital coherent transceiver easily digitize GC variation by the low speed peripheral ADC.

To estimate the polarization rotation rate from GC variation, we propose a deep learning based method using the logarithmic power spectrum density (PSD). The inset of Fig. 1 shows the measured PSD with the polarization rotation rate of 200 kHz. It clearly showed several high frequency peaks around 200 kHz. Then, we specifically selected a convolutional neural network (CNN) for deep learning as has been shown in use radio identification with PSD [7]. CNN is a kind of supervised learning, which not only has fully connected layers, but also has convolutional layers. We assume that CNN is advantageous under the limited frequency resolution of PSD since CNN effectively converge filters with the dataset which has time series correlation. In contrast, we observed that non-machine learning methods, such as the peak detection from PSD may suffer from insufficient frequency resolution and from contamination by the frequency response of gain feedback loop.

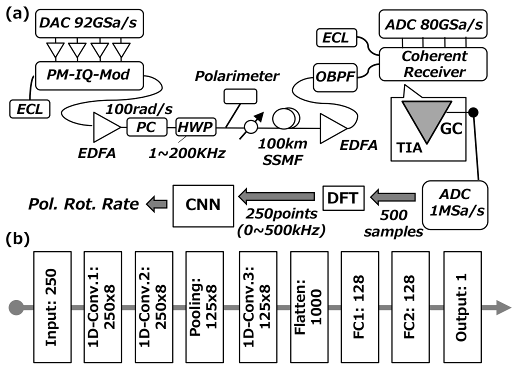


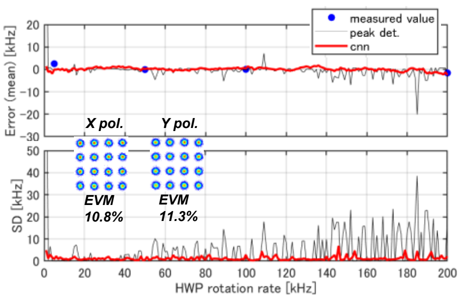
Fig. 2: (a) Experimental setup for the validation, (b) Structure of CNN

Experimental setup and parameter settings for the validation

Fig. 2 (a) shows the experimental setup and data analysis block for the validation of CNN based polarization rotation rate estimation using TIA gain monitoring. The Nyquist shaped 32- and 64-GBaud PM-QPSK, 16QAM, and 64QAM signal were generated with 100 kHz linewidth External cavity laser (ECL). The generated optical signal was fed into the polarization rotation stage, consisted of the polarization controller (PC), half-wave plate (HWP) rotator, and polarimeter. PC set fixed 100 rad/s with Rayleigh distribution, it sufficiently rotated SOP trace on all of Poincare sphere under the data acquisition period. HWP was dominant for the polarization rotation, the rotation frequency was set from 1 kHz to 200 kHz with 1 kHz resolution. The polarimeter was used for polarization rotation rate measurement as a reference of the validation. For back-to-back evaluations, ASE was loaded on the signal before the optical bandpass filter (OBPF) to adjust OSNR. For transmission experiments, we used 100 km SSMF, the fibre launch power was set to 0 dBm, resulting in a received OSNR of 28.6 dB/0.1nm. The optical signal was captured by the standard ICR and digitized by 80-GSa/s ADCs which were used for verifying the signal reception only. For collecting TIA gain variation dataset, 1-MSa/s ADC was connected to GC-XI pin of ICR.

On the data analysis part, PSD datasets were generated from measured TIA gain variation by Discrete Fourier Transform (DFT), where each 500 samples of time variant data was converted to 250 points of PSD datasets over 0 to 500 kHz. CNN is implemented by Keras [8] with Tensorflow [9]. The HWP rotation frequencies were provided to the CNN for training. As shown in Fig. 2 (b), our network has five hidden layers, consisting of

(a)



(b)

Test dataset	Error	SD
64G, 64QAM, 41dB	0.56	1.24
64G, 16QAM, 41dB	0.56	1.22
64G, 16QAM, 20dB	0.63	1.44
64G, 16QAM, 10dB	1.47	4.94
64G, QPSK, 20dB	0.66	1.67
32G, 64QAM, 41dB	0.73	1.94
32G, 16QAM, 20dB	0.84	2.77
32G, QPSK, 10dB	2.45	8.02

unit: kHz

(c)

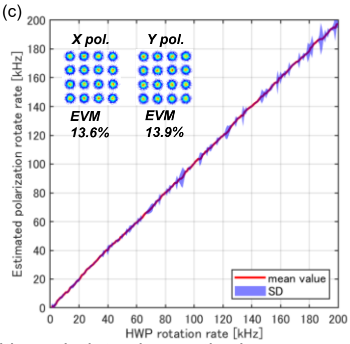


Fig. 3: Polarization rotation rate estimation results, (a) compared CNN with peak detection method, (b) verified trained CNN with each signal format and condition (c) verified trained CNN with 100km SSMF transmission

three one dimensional convolutional layers and two fully connected layers (FC). In addition, we use a drop-out rate of 0.2 after FCs to avoid over-fitting. The rectified linear unit activation function is used except for the output layer where linear regression is used. Mean squared error is used to compute the loss, and Adam is used as optimization of the weight coefficients of NN. To train CNN, 64-GBaud-16QAM with 41 dB/0.1nm was selected, the number of training datasets was 160,000.

Results and Discussion

First, we verified the proposed polarization rotation rate estimation with 64-GBaud-16QAM with 41dB/0.1nm. Note that we used 40,000 test datasets which were different from that of used for training CNN. In Fig.3 (a), the mean error and standard deviation (SD) of the estimated polarization rotation rate were plotted as a function of pre-set HWP rotation rate. The insets in Fig. 3 (a) show PM-16QAM constellation with 1 kHz rotation rate. The error vector magnitude (EVM) for both polarization were similar value, indicated negligible PDL existed. First, measured polarization rotation rates by polarimeter were plotted, HWP rotation rates were almost identical with measured value, so we used HWP rotation rate as a reference afterwards.

For comparison, we also applied non-machine learning based peak detection to the same dataset. To verify the effect of peak detection, each 2,000 DFT points was used with moving average filtering, and applied simple calibration which subtracted frequency response of GC loop filter, otherwise, relevant peaks could not be detected, causing wrong monitored values.

Even though, peak detection method suffered from high estimated error and SD, up to 67 kHz and 139 kHz, respectively. Comparatively, CNN was successfully trained to estimate the polarization rotation rate, it showed high estimation accuracy, errors were less than 2.49 kHz, and SD were less than 6.68 kHz.

Next, we verified the trained CNN with various different test datasets contained each OSNR, modulation format, and symbol rate. Fig. 3 (b) shows the mean value of mean error and SD of each 40,000 dataset over HWP rotation rate from 1 kHz to 200 kHz. Overall, the trained CNN showed the ability to estimate the polarization rotate rate with different signal formats and conditions. Note that relatively high SD were observed with 10dB OSNR cases where the signal could no longer be demodulated; although excessive noise components affected PSD of GC voltage variation, we showed sufficient estimation accuracy, less than 2.45 kHz error and 8.02 kHz standard deviation.

Finally, the trained CNN was applied for 64-GBaud-PM-16QAM signal after 100km SSMF transmission. In Fig. 3 (c), the estimated polarization rotation rate and SD were plotted as a function of HWP rotation rate. The proposed method showed the robustness with chromatic dispersion of 1700ps/nm from SMF transmission, mean estimation error and SD were 0.63 kHz and 1.69 kHz, maximum values were less than 3.55 kHz and 11.22 kHz, respectively.

Conclusions

We propose a hardware efficient CNN based polarization rotation rate estimation scheme by monitoring TIA gain in the standard ICR. We experimentally demonstrated the proposed method. The CNN was trained with Nyquist shaped 64-Gbaud-PM-16QAM and showed high estimation accuracy and the robustness when it was applied to different signal formats and conditions even after 100km SSMF transmission. The estimation errors were less than 2.45 kHz over polarization rotation rate up to 200 kHz with 1 kHz resolution.

Acknowledgements

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