CNN-Based Inter-Band Interference Cancellation for 100Gbit/s/λ Non-Orthogonal m-CAP in Fronthaul

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***Abstract*—To improve the spectral efficiency (SE) of next-generation-fronthaul-interface-based (NGFI) mobile fronthaul (FH) network, we present a novel inter-band interference (IBI) cancellation method based on convolutional neural network (CNN) in non-orthogonal multiband CAP (NO-m-CAP) system. As a proof of concept demonstration, a NO-4-CAP 100Gb/s/λ NGFI-II data transmission experiment is carried out, which shows 15% SE improvement with the proposed CNN-based IBI canceller assuming a 7% HD-FEC limit. Being more straightforward and practical, the proposed CNN-based IBI canceller with lower complexity could offer more power budget and promise more compression ratio compared to our previously proposed ICA-based (Independent Component Analysis) method.**

***Index Terms*—Next generation mobile Fronthaul, convolutional neural network, non-orthogonal multiband-CAP.**

I. Introduction

The rapid growth on enhanced Mobile Broadband (eMBB) service, ultra-Reliable and Low Latency Communications (uRLLCs) etc. requires the next generation radio access networks (NG-RAN) to meet the trend in terms of growing bandwidth, lower latency and omnipresent access [1]. The next generation fronthaul interface (NGFI, or xHaul), which introduces the distributed unit (DU) between the central unit (CU) and the radio unit (RU), was proposed [2] to support the future fronthaul (FH) with a higher rate and lower delay. NGFI-I refers to the segment between RU and DU (NGFI-II: between DU and CU). NGFI-I segment carries the time-critical traffic while NGFI-II is expected to perform better with broadband services. This letter features the improvement of spectral efficiency (SE) in NGFI-II transmission segment. Many studies are carried out to improve the SE of conventional FH [3], [4] that has become inefficient due to the adoption of new 5G technologies and the increase of wireless throughput. There are reports about spectral aggregation based on multi-band carrierless amplitude and phase (m-CAP) for the optical link with a high capacity [5]–[7]. m-CAP is easier to realize frequency multiplexing and suitable for NGFI-II aggregation. However, the m-CAP system suffers from SE reduction due to the guard bands between sub-bands. In our previous works, we propose a non-orthogonal m-CAP (NO-m-CAP) scheme to further improve the SE [8] and a novel inter-band interference (IBI) cancellation method based on independent component analysis (ICA) is proposed to realize error-free transmission assuming 7% HD-FEC limit. Non-orthogonality in m-CAP means intentionally introduce frequency overlapping between adjacent sub-bands. In addition, transmitting non-orthogonal signal such as spectrally efficient frequency division multiplexing (SEFDM) signal is reported in many studies [9]–[11], confirming the feasibility of non-orthogonal transmission in optical links. Besides, the introduction of mobile-edge-computing (MEC) enhanced DU could provide us new inspiration in mobile FH [12], [13]. The rapid development of parallel computing hardware, such as graphics processing unit (GPU), enables us to implement the computational-consuming neural network (NN) in more practical scenarios like deploying cloud-GPU-enabled DU in FH [13]. Many works are reported on utilizing machine-learning-based methods in FH, including deep NN (DNN) [13], [14], reinforcement learning [15], convolutional NN (CNN) [16] and ICA [8]. And hardware implementation of NN-based equalizer for 100Gbps optical link is also reported [17]. These machine learning techniques have shown impressive performance. And among them, deep-learning based techniques are considered as promising solutions for mitigating interference in non-orthogonal signals [18].

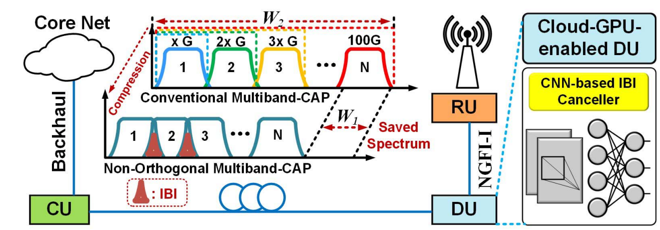

Fig. 1. Architecture of NGFI-based 5G mobile fronthaul. NO-m-CAP modulation and CNN-based IBI canceller is adopted to obtain higher SE. The compression factor α is defined by $\alpha = W_1/W_2$.

In this letter, we propose a novel IBI cancellation method based on convolutional neural network (CNN) in the NO-m-CAP system as shown in Fig.1. Purposely overlapping

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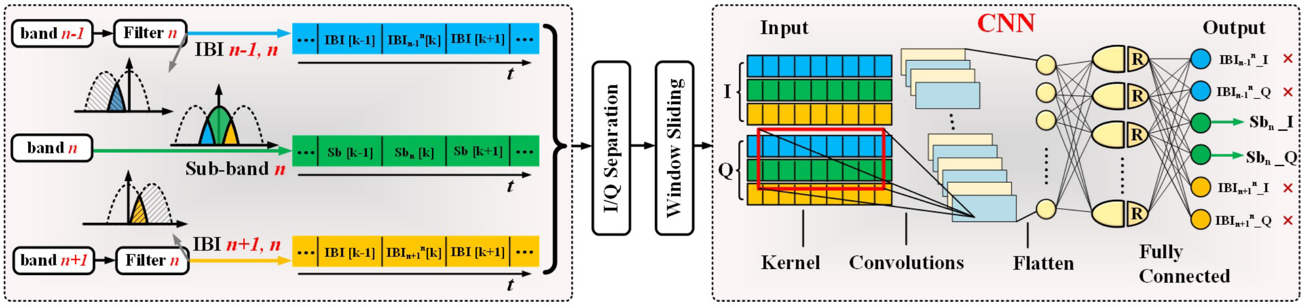

Fig. 2. The principle of the proposed CNN-based IBI cancellation method for NO-m-CAP system.

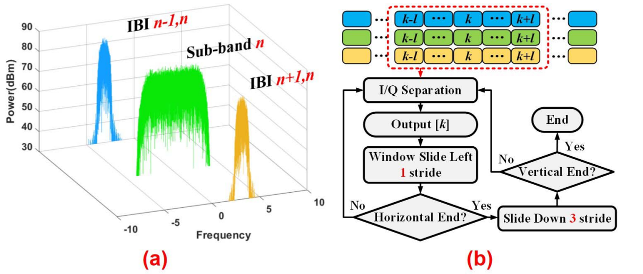

Fig. 3. (a) The frequency spectrums of the IBIs and the current band signals. (b) Details of data pre-processing module before the CNN module.

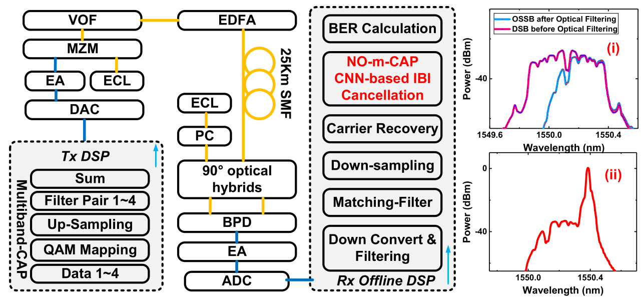

Fig. 4. Experimental setup of 100Gb/s/λ NO-m-CAP16 heterodyne coherent NGFI-II data transmission; inset (i): optical spectrum of DSB and OSSB at Tx; inset (ii): spectrum at Rx with heterodyne coherent detection.

the sub-bands leads to IBIs which cause the performance degradation of each band. The CNN-based IBI canceller could be deployed at the DU side and consequently leads to a SE improvement. As an extension of our previous work in [8], the newly proposed CNN-based IBI canceller could offer more power budget (over 3dB) and promise more compression ratio than the previous ICA-based method. In addition, the proposed CNN-based method is more straightforward and practical with lower complexity.

II. Principle of Operation

The principle of the proposed CNN-based IBI cancellation method is illustrated in Fig.2. The proposed method mainly consists of three modules: (1) IBI extraction, (2) data pre-processing and (3) CNN module. The IBIs extracted in the first module could be theoretically expressed as the Eq. (8-9) in [8], where the recovered signals in adjacent sub-bands (e.g. $s_{n\pm 1}\ (t)$) are m-CAP-modulated and filtered by the current matching filter (e.g. $m_n\ (t)$). The frequency spectrums of the IBIs and the current band signals are shown in Fig. 3(a). Then the signals in current sub-band and the extracted IBIs are fed into the data pre-processing module, which refers to the ‘I/Q separation’ and ‘Window Sliding’ in Fig. 2. The details of the data pre-processing are shown in Fig. 3(b). The ‘Output [k]’ is the kth input of the CNN module. The window’s length is (2l-1), and the window’s width is 3. In this letter, we set the l to be 7 after a proper optimization. Since the signals and IBIs are complex symbols, we conduct a I/Q separation and feed these two components into two different channels of the CNN. This operation is reasonable because our recovered signals barely have interference or distortion between I and Q components, which means I/Qs are well-balanced. It should be noted that there are no $\mathrm{IBI}_{0,1}$ and $\mathrm{IBI}_{5,4}$ for the 4-CAP case in this work. To take Inter-Symbol-Interference (ISI) and IBI into consideration simultaneously, we set the kernel size of the CNN same as the window size in the previous data pre-processing module. The optimized parameters of the CNN used in this study are shown in Table I. The total number of parameters is 1562 and the size is only 0.01 MB according to the summary of torch. The number of nodes in output layer could be $1*2$ (output the I/Q of the desired signal only) or $1*6$ (output both the desired signal and the IBIs). We choose it to be $1*6$ for output layer nodes according to the observation in Fig 5. Although there are 6 outputs, the desired two outputs are reserved, and the rest 4 outputs are abandoned. We observe that only 1 convolutional layer and 1 fully-connected layer are needed for our CNN-based IBI canceller, which indicates the little of complexity. The labels that CNN requires could always be obtained by manipulating the transmitting data in the first place. We transmit 2^{14} symbols in each band and use 40% of them as the training sets while using the rest of them as the validation set. The training part is only required at the initialization stage. More symbols using the same amount of training are tested and the result confirms that the network has good generalization and large amount of training symbols leads to overfitting.

TABLE I
Parameters of CNN in This Letter

Parameters	Values	Parameters	Values
Input size	[2, 3, 13]	FC activation	ReLU
Conv2D out	[-1,12,1,1]	Output layer	1 * 6
Kernel Size	[3, 13]	Optimizer	Adam
Leaky ReLU out	[-1,12,1,1]	learn rate (lr)[a]	0.001
FC layer nodes	32	batch size	256

[a] Lr is adapted based on torch.optim.lr_scheduler.ReduceLROnPlateau.

III. Experimental Setup

Fig. 4 shows the experimental setup to verify the proposed scheme. An external cavity laser (ECL-1, 1550.116 nm, 16dBm) is used as signal light source at CU side. A

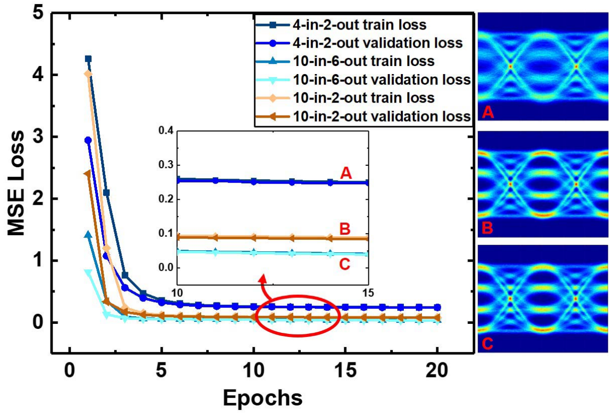

Fig. 5. MSE loss curves of the CNN for different schemes of input and output components. Insets: a, b, c refer to the eye diagrams of in-phase part of recovered signals with 4-in-2-out, 10-in-2-out and 10-in-6-out.

25GBaud 4-CAP-16QAM electrical baseband signal, which is up-sampled by 14 times, is generated by an 87.5GSa/s DAC and amplified by a linear electrical driver (EA). Then the electrical signal externally-intensity-modulates an MZM. The MZM operates at null point. Optical single-sideband (OSSB) transmission is adopted. Then an erbium doped fiber application amplifier (EDFA) is used to boost the optical signal. A balanced-PD (BPD) is used for detection. The LO is generated by another ECL-2 (1549.852 nm, 16dBm). Then the electrical signal obtained from BPD is amplified by an EA and digitalized by an 80GSa/s ADC. The CNN-based IBI cancellation is conducted after the received signal being down-converted and filtered, matching-filtered, down-sampled and carrier-recovered during the receiver offline DSP. As for the carrier and phase recovery, we use a closed-loop frequency and phase offset compensator which adopts the phase-locked-loop-based algorithm. The spectrum of received signal with heterodyne coherent detection is shown in inset(ii) of Fig. 4. Detailed experimental setup is presented elsewhere [8].

IV. Experimental Results and Discussion

To give a better clarification for the proposed method and understand Fig.5 better, we firstly explain the components that are fed into CNN module. As mentioned in [8], since there is an auxiliary extraction module for ICA-based method, the total number of components that are fed into the complex ICA module is given by N_b=3m-2, where m is the number of sub-bands. Similarly, we extract IBIs before the CNN module by filtering method as demonstrated in Fig.2 here. Therefore, there will be 6 IBI components for $m = 4$ in this work.

Fig. 5 shows the MSE loss curves for different schemes of input and output. "4-in-2-out" means the 4 sub-band signals are fed into CNN module only, where the IBIs are not included. And the output of CNN module is the serial I/Q part of 1 sub-band signals only. "10-in-2-out" means the 4 sub-band signals and extracted 6 IBIs are fed into CNN module together. "10-in-6-out" means the output of CNN module is the serial I/Q part of 1 sub-band signals and serial I/Q part of 2 IBIs.

We observe that the train/validation loss converges to a rather higher value (about 2.6e-1) for 4-in-2-out case, and there is no performance improvement according to the eye-diagram of in-phase part of signal in inset(A). However, the train/validation loss converges to smaller values in 10-in cases (about 8e-2 for 2-out case and 4e-2 for 6-out case). And the eye-diagrams confirms the improvement for BERs. This indicates that we must carry out the IBI extraction module before we conduct CNN module so that the CNN-based IBI canceller could perform better. And it does not constitute a convex problem without the information provided by IBIs, resulting in converging to a local optimum during gradient descent. In addition, only around 10 epochs are needed to achieve a satisfactory IBI-free performance with the proposed method.

There are two important parameters affect the SE of the system in this work, which are β and α. Term β is the roll-off factor, which is the excess bandwidth factor of the square-root raised cosine (SRRC) that forms the basis of the pulse shaping filters for m-CAP. Term α is the compression factor which represents how much the bandwidth is narrowed. If we assume that the bandwidth of the entire m-CAP signal as W_2, and the bandwidth of the saved spectrum as W_1, as shown in Fig.1 above, then we define the compression factor α as: $\alpha = W_1/W_2$.

We test many possible different combinations of β and α in this work firstly. But the result is not shown here due to the space limitation. Then we chose two typical value for β (0.15, 0.25) and find out that the corresponding maximum α is 0.1 and 0.15, respectively.

To compare the performance of the proposed CNN-based method with the ICA-based method [8], we presented the receive optical power (ROP) versus average BER for back-to-back and 25km-fiber transmission in Fig. 6(a), (b) where two sets of parameters are chosen: $\beta = 0.15/0.25$, $\alpha = 0.1/0.15$. We observe that the required ROP at 7% FEC limit is -29dBm for $\beta = 0.15$, $\alpha = 0.1$ case and -25dBm for $\beta = 0.25$, $\alpha = 0.15$, respectively. 3dB more power budget could be additionally obtained comparing to the ICA-based IBI cancellation in [8] under the 7% HD-FEC limit, for both B2B and 25km cases. Similarly, larger α and β lead to a larger overlapping and performance degradation consequently. Smaller α and β offer a higher SE. This work did not achieve faster-than-Nyquist. The best SE achieved by the proposed method is 3.865 bit/s/Hz ($\beta = 0.15$, $\alpha = 10\%$). Although same SE may be realized by reducing the β to a very small value, it leads to a higher PAPR and a larger number of taps, which often leads to nonlinearity and increasement of complexity. And too small β is not suitable for realistic implementation. Fig.6(c) presents the BER performance of each sub-band under -22dBm ROP. Each sub-band's BER is below the 7% HD-FEC threshold with the IBI canceller, confirming the effectiveness of the proposed method. The 1st and the last sub-band have better BER performance because the in-band overlapping only comes from one nearby band.

Yet, the 2nd and the 3rd sub-band perform worse because the overlapping comes from adjacent 2 bands. The larger β and α (0.25, 0.15) offer more SE improvement (ΔSE) but the BER performance is worse under the same ROP comparing to the smaller β and α (0.15, 0.1).

The average BER performance versus compression factor α under B2B case with different methods is shown in Fig. 7, where the LMS, ICA-based method in [8] and the proposed CNN-based method are compared fairly. We observe that the proposed CNN-based IBI canceller outperforms the ICA-based and the LMS methods. Specifically, CNN-based IBI canceller can improve the BER performance of the system when there

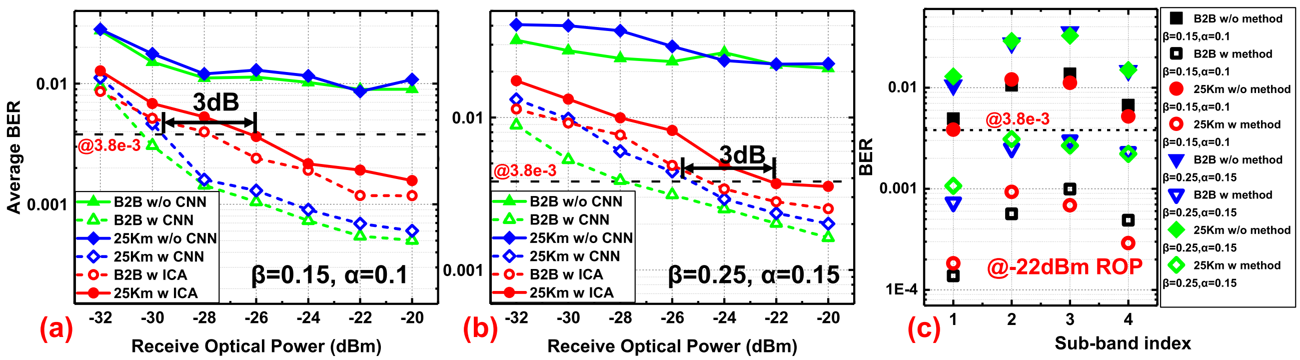

Fig. 6. Average BER vs ROP for B2B case and 25km SSMF transmission when (a): $\beta = 0.15$, $\alpha = 0.1$ and (b): $\beta = 0.25$, $\alpha = 0.15$. (c) The BER performance of each sub-band for B2B case and 25km transmission when $\beta = 0.15$, $\alpha = 0.1$ and $\beta = 0.25$, $\alpha = 0.15$.

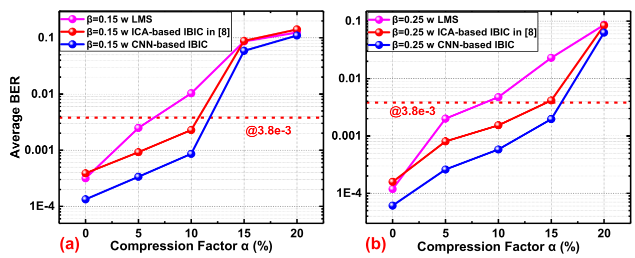

Fig. 7. The BER performance versus α under B2B case (@−22dBm) with different methods for (a) $\beta = 0.15$, and (b) $\beta = 0.25$.

is no overlapping between adjacent bands ($\alpha = 0$), while the ICA-based method has no BER improvement when $\alpha = 0$. This is because the ICA can only solve the linear spectrum aliasing problem, however, the CNN-based technique can deal with channel impairment like residual dispersion when $\alpha = 0$. Nevertheless, the CNN-based method could enhance the signal SNR, which is measured by EVM, by about 1dB even when $\alpha = 0$, indicating the excellence of the proposed method. The CNN-based IBI canceller could promise more compression and more ΔSE improvement consequently, as the Fig. 8 indicates. However, the IBI canceller based on CNN, as well as the ICA-based method in [8], can achieve quasi-Nyquist transmission at most. Although the compression increasement is moderate, the complexity of the newly proposed method is much lower than the complexity of previous work.

In conclusion, we propose and experimentally verify an emerging IBI cancellation method based on CNN in this letter. A 25km NO-4-CAP 100Gb/s/λ NGFI-II data transmission is demonstrated. The necessity of IBI extraction module is verified for our proposed CNN-based IBI canceller, confirming that the model-driven deep learning techniques are more promising for the proposed system. At least 15% SE improvement is guaranteed with the proposed method assuming a 7% HD-FEC limit. More compression ratio and more power budget can be promised with the newly proposed CNN-based method compared to the previous ICA-based work which is unsupervised and requires phase rotation step, while the CNN-based method is more straightforward and practical with lower complexity.

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