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Digital Self-Interference Cancellation Using Convolutional Neural Networks in In-Band Full-Duplex Systems

Manar T. Alhamnday[1*], Bilal A. Jebur[1]
[1]*Computer and Information Engineering Department, College of Electronics Engineering, Ninevah University, Mosul, Iraq*

Abstract

In-band full-duplex (IBFD) communication systems represent a major breakthrough in wireless communication, allowing transmission and reception of signals on the same channel simultaneously. However, a critical challenge in IBFD systems is mitigating Self-Interference (SI), which results from the leakage of the transmitted signal into the receiver, potentially overwhelming the received signal and degrading overall system performance. This paper investigates the application of Convolutional Neural Networks (CNNs) for digital Self-Interference Cancellation (SIC) in IBFD systems. We propose a CNN architecture consisting of three convolutional layers, designed to learn and suppress the nonlinear characteristics of self-interference effectively. Simulation results demonstrate that the proposed CNN-based SIC method achieves 52.492 dB interference suppression at an SNR of 30 dB, significantly improving the bit error rate performance compared to conventional methods.

Keywords: In-Band Full-Duplex, Self-Interference, Convolutional Neural Networks.

إلغاء التداخل الذاتي الرقمي باستخدام الشبكات العصبية التلافيفية في أنظمة الدوبلكس الكامل داخل النطاق

منار طلال[1]*, بلال علاء الدين جبر
[1]قسم هندسة الحاسوب والمعلوماتية, كلية هندسة الإلكترونيات, جامعة نينوى, الموصل, العراق

الخلاصة

تمثل أنظمة الاتصالات ذات النطاق الكامل المزدوج (IBFD) تقدمًا كبيرًا في مجال الاتصالات اللاسلكية، حيث تسمح بإرسال واستقبال الإشارات على نفس القناة في وقت واحد. ومع ذلك، فإن التحدي الحاسم في أنظمة IBFD هو التخفيف من التداخل الذاتي (SI)، والذي ينتج عن تسرب الإشارة المرسلة إلى المستقبل، مما قد يؤدي إلى إغراق الإشارة المستقبلة وتدهور الأداء العام للنظام. يبحث هذا البحث في تطبيق الشبكات العصبية التلافيفية (CNNs) لإلغاء التداخل الذاتي الرقمي (SIC) في أنظمة IBFD. نقترح بنية CNN تتكون من ثلاث طبقات تلافيفية، مصممة لتعلم وقمع الخصائص غير الخطية للتداخل الذاتي بشكل فعال. توضح نتائج المحاكاة أن طريقة SIC القائمة على CNN المقترحة تحقق قمعًا للتداخل بمقدار 52.492 ديسيبل عند نسبة إشارة إلى ضوضاء تبلغ 30 ديسيبل، مما يحسن بشكل كبير من أداء معدل خطأ البت مقارنة بالطرق التقليدية.

1. Introduction

In recent years, the demand for higher data rates in wireless communication has accelerated the development of IBFD systems, which allow devices to transmit and receive data simultaneously over the same frequency [1, 2]. Unlike traditional half-duplex systems, which can either transmit or receive signals at a time. However, one of the key challenges in IBFD systems is the presence of strong SI, where the transmitted signal interferes with the reception of the incoming signal. The SI degrades system performance significantly[3]. Therefore, the efficient SIC techniques play a critical role in realizing the potential of IBFD systems.

Conventional SIC methods use a variety of strategies, including passive, analog, and digital cancellation [4-6], to lessen SI. Even though these techniques have demonstrated some efficacy, however, these methods may not be sufficient to address the non-linear effects introduced by transceiver impairments [7], in addition to the inability to adapt to changing circumstances. These shortcomings show that in order to improve the performance of IBFD systems, more reliable and adaptable solutions are required.

In order to overcome the limitations and challenges associated with conventional cancellation methods, recent studies have focused on applying Neural Networks (NNs) for SIC in IBFD systems [7-9]. Reference [7] investigated the use of neural networks as an alternative to traditional non-linear cancellation methods based on polynomial basis functions, and in [8, 9], hardware architectures for NN-based SI cancellers were presented, and their performance was compared with conventional polynomial-based cancellers. Furthermore, in [10], Machine Learning (ML) methods such as recurrent and complex-valued NNs for SIC in Full-Duplex (FD) radios have been investigated. Additionally, the authors in [11] achieved a suppression capacity of 47.19 dB using the long short-term memory.
Moreover, convolutional neural networks have achieved remarkable success in various applications such as image processing [12], speech recognition [13], and recently in wireless communication, where they have been used for SIC in full-duplex millimeter-wave systems [14]. These capabilities illustrate the possibility of CNNs in refining signal processing.

In this paper, we propose the implementation of CNNs for digital SIC in IBFD systems, with the goal of demonstrating their usefulness in reducing SI and enhancing system performance. The paper is organized as follows: Section 2 describes the methodology, including the system model and the architecture of the proposed CNN. In Section 3, we present the results. Finally, Section 4 provides a conclusion of the paper.

2. Methodology

In this section, we describe the architecture of the IBFD system that serves as the foundation for our research.

2.1 System Model

The IBFD system comprises a transmitter and a receiver that are both operating on the same frequency channel. The transmitter sends signals while the receiver receives signals. During this simultaneous operation, a part of the signal that is transmitted by the transmitter is reflected back into the receiver, resulting in SI as illustrated in Figure 1.

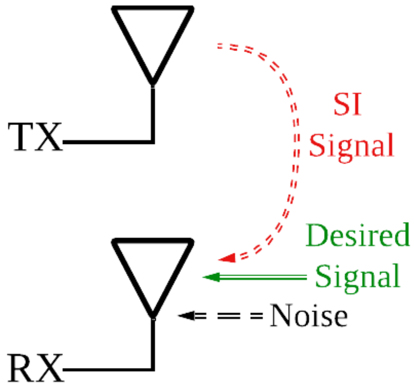


Figure -1 Received signal model.

The received signal can be written as

$$y(t) = s(t) + s_i(t) + n(t), \tag{1}$$

where $s(t)$ denotes the desired signal received from the far node and $s_i(t)$ denotes the SI signal, can be modeleds as

$$s(t) = h * x_f(t), \tag{2}$$

$$s_i(t) = h_{si} * x_n(t), \tag{3}$$

where * represents the convolution operator, h and h_{si} represents the transmission channel and the SI channel, respectively. Moreover, $n(t)$,represents the additive white Gaussian noise (AWGN). To mitigate the impact of $s_i(t)$ on the received signal, we employ SIC-based CNNs. The architecture of the CNNs will be discussed in the following subsection.

2.2 CNN Architecture

CNNs are a type of deep neural network which have recently attracted considerable interest in multiple ML applications [15]. They are especially useful when applied to the structured grid patterns like images in two dimensional (2D) [16] and sequence data in one dimensional (1D) [17]. The CNNs make use of the spatial hierarchies through convolutional layers, to efficiently extract patterns of the input data.

In this study, we present a CNN architecture made up of three convolutional modules (each consisting of a convolution one-dimensional layer, a batch normalization layer, and a ReLU), as seen in Figure 2. Subsequently, a fully connected layer was used to accurately learn the properties of the SI signal and suppress it from the received signal. The CNN model was trained with the parameters shown in Table 1.

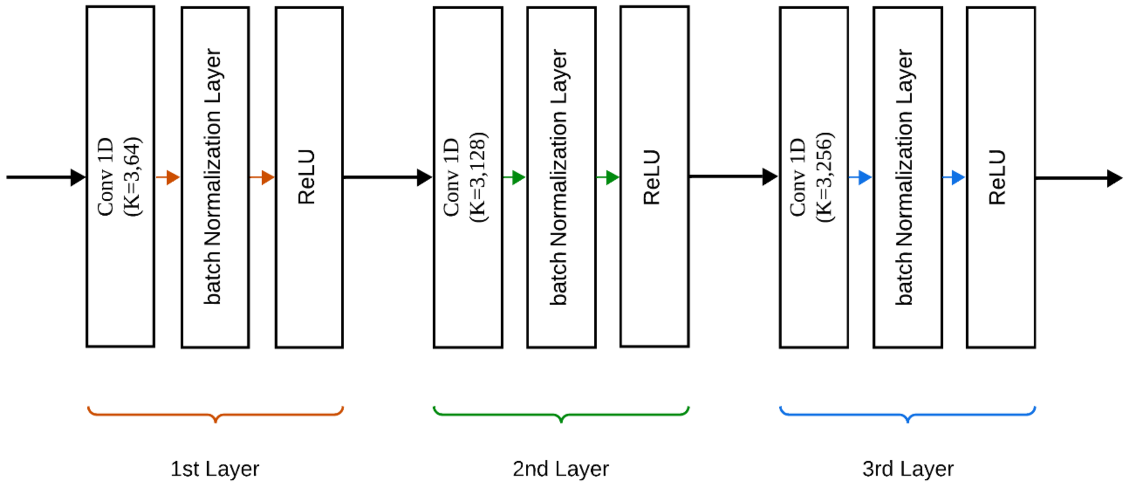


Figure -2 CNN structure.

Table 1- Parameters for the proposed systems.

Parameter	**Value**
Input features	2(1 real,1 imaginary)
Activation function	ReLU
Optimizer	sgdm
Number of epochs	300
Batch size	300
InitialLearnRate	0.1
LearnRateDropFactor	0.1
LearnRateDropPeriod	100
Modulation type	QAM
Cyclic Prefix (CP)	2^(4:7)
Training SNR	30 dB
Loss Function	MSE

The anticipated interference from the output of the suggested model is stated as

$$\hat{s}_i(t) = \hat{h}_{si} * \hat{x}_n(t), \tag{4}$$

2.3 Interference Cancellation

After forecasting the $s_i(t)$ signal with the proposed model, we subtract it from the received signal y(t), which may be expressed as

$$y_c(t) = s(t) + \underbrace{s_i(t) - \hat{s}_i(t)}_{Residual\ SI} + n(t). \tag{5}$$

where $y_c(t)$ represents the signal after cancellation.

3. Results and Discussion

In this section, we present the results of the proposed SIC technique, which was obtained through a simulation process conducted in MATLAB R2022b, based on the system model illustrated in Figure 3. The simulations utilized 16 QAM modulation with N=2048. The performance evaluation includes the criteria presented in Table 2.

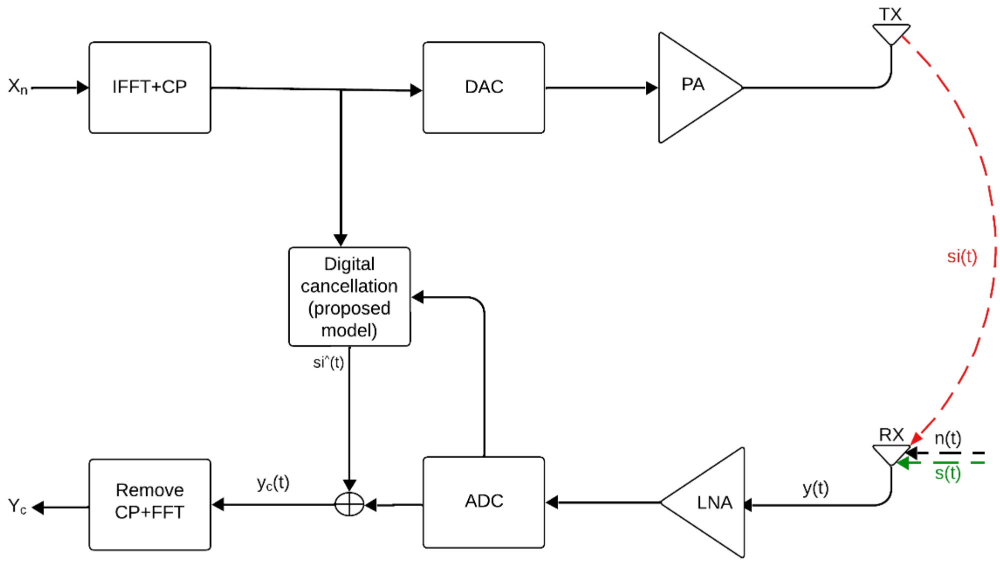


Figure -3 Architectural model of IBFD system.

Table 2- Evaluation Metrics.

Name	Formula
SI suppression capability	$C_{dB} = 10log_{10}\left(\frac{P_{SI}}{P_{RSI}}\right),$
MSE	$MSE = \frac{1}{N}\sum_{i=1}^{N}(\mathrm{y_i} - \hat{\mathrm{y}}_\mathrm{i}),$
RMSE	$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\mathrm{y_i} - \hat{\mathrm{y}}_\mathrm{i}),}$
Accuracy	$Accuracy = \frac{N_c}{N_t},$

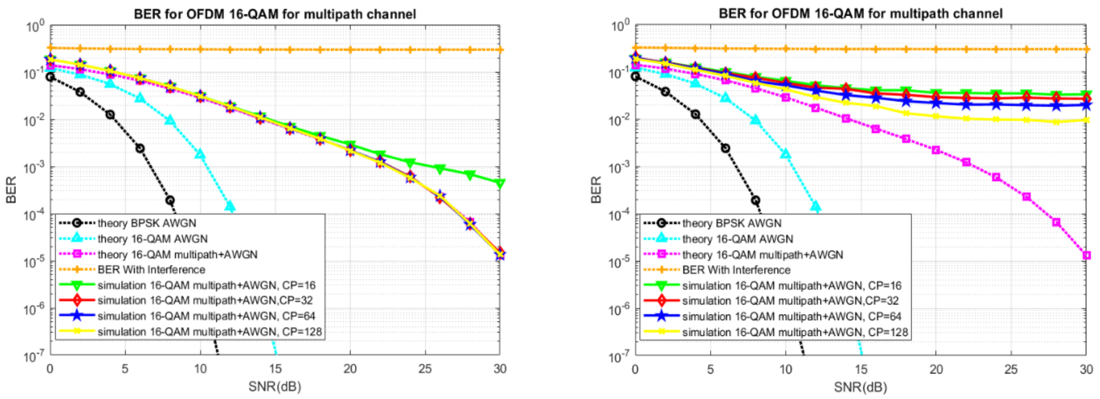
where P_{SI} stands the power of SI signal, P_{RSI} stands the power of residual SI signal, N stands the number of samples, $\mathrm{y_i}$ stands the actual value, $\hat{\mathrm{y}}_\mathrm{i}$ stands the predicted value, N_c stands the number of correct predictions, and N_t stands the total number of predictions. Table 3 compares the results of the suggested method (CNN) with the traditional Normalized Least Mean Squares (NLMS) algorithm. The NLMS was configured with a filter order = 50 and a step size = 0.3, evaluated across various Signal-to-Noise Ratio (SNR) levels. A closer look at Table 3 shows that the suggested technique outperforms the traditional method significantly.

Table 3- Performance propose vs. traditional methods.

SNR	C_{dB}	MSE	RMSE	Accuracy
		Propose Method		
SNR=0	46.267	2.398e-04	0.0155	99.976
SNR=5	47.303	1.856e-04	0.0136	99.981
SNR=10	48.851	1.3e-04	0.0114	99.987
SNR=15	49.815	1.064e-04	0.0103	99.989
SNR=20	50.994	7.887e-05	0.0089	99.992
SNR=25	51.868	6.408e-05	0.008	99.993
SNR=30	52.492	5.556e-05	0.0075	99.994
		Traditional Method		

SNR=0	16.128	0.246	0.496	75.424
SNR=5	16.212	0.239	0.489	76.064
SNR=10	16.317	0.226	0.476	77.399
SNR=15	16.415	0.224	0.473	77.643
SNR=20	16.506	0.222	0.471	77.821
SNR=25	16.616	0.217	0.465	78.277
SNR=30	16.749	0.214	0.462	78.563

Furthermore, Figure 4 illustrates the BER curves for the proposal and traditional methods. With interference, the BER stays high and stable as the SNR raises. Additionally, as shown in Figure 4a, the proposed CNN has a much lower BER compared to the standard cancellation techniques illustrated in Figure 4b. For instance, at an SNR = 20 dB and when CP = 64, the BER of the proposed CNN model was 0.002, while the BER of conventional methods equals 0.028. This demonstrates the CNN's capability to enhance signal integrity in IBFD systems.



(a) **(b)**

Figure -4 BER efficiency for our proposal and traditional method (a) CNN (b) NLMS.

Lastly, Figure 5 displays the SI signal's power spectral density (PSD), the residual signal's spectrum after cancellations using the traditional method, and the residual signal's spectrum after cancellations using the suggested method, it is important to note that the spectrum of the residual SI signal obtained from the proposed method is lower than that of conventional methods.

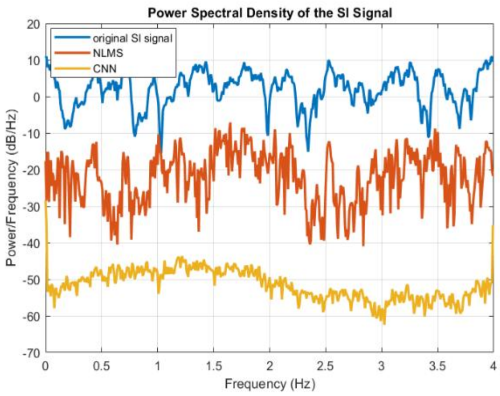


Figure -5 PSD after SI cancellation.

4. Conclusions

In this paper, we presented a digital SIC method that utilizes CNNs in the IBFD system to effectively diminish the SI signal. The proposed method takes advantage of the capability of CNNs to learn complex nonlinear patterns in interference data to realize improved signal quality compared to traditional SIC techniques. The obtained results have shown the proposed CNN-based SIC technique achieves an interference suppression of 52.492 dB, which is superior to the traditional NLMS algorithm's 16.749 dB at an SNR of 30 dB. Future research will concentrate on exploring new types of neural network architectures for SIC and investigating how CNNs are integrated with other techniques to achieve higher levels of performance of SIC.

References

[1] S. Li and R. D. Murch, "An investigation into baseband techniques for single-channel full-duplex wireless communication systems," *IEEE Transactions on Wireless Communications*, vol. 13, no. 9, pp. 4794-4806, 2014.

[2] K. E. Kolodziej, B. T. Perry, and J. S. Herd, "In-band full-duplex technology: Techniques and systems survey," *IEEE Transactions on Microwave Theory and Techniques*, vol. 67, no. 7, pp. 3025-3041, 2019.

[3] M. Duarte *et al.*, "Design and characterization of a full-duplex multiantenna system for WiFi networks," *IEEE Transactions on Vehicular Technology*, vol. 63, no. 3, pp. 1160-1177, 2013.

[4] Y. Chen, C. Ding, Y. Jia, and Y. Liu, "Antenna/propagation domain self-interference cancellation (SIC) for in-band full-duplex wireless communication systems," *Sensors*, vol. 22, no. 5, p. 1699, 2022.

[5] G. Özkul and C. Toker, "Analog self-interference cancellation for full duplex communication systems," in *2022 30th Signal Processing and Communications Applications Conference (SIU)*, 2022: IEEE, pp. 1-4.

[6] E. Ahmed and A. M. Eltawil, "All-digital self-interference cancellation technique for full-duplex systems," *IEEE Transactions on Wireless Communications*, vol. 14, no. 7, pp. 3519-3532, 2015.

[7] A. Balatsoukas-Stimming, "Non-linear digital self-interference cancellation for in-band full-duplex radios using neural networks," in *2018 IEEE 19th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*, 2018: IEEE, pp. 1-5.

[8] Y. Kurzo, A. Burg, and A. Balatsoukas-Stimming, "Design and implementation of a neural network aided self-interference cancellation scheme for full-duplex radios," in *2018 52nd Asilomar Conference on Signals, Systems, and Computers*, 2018: IEEE, pp. 589-593.
[9] Y. Kurzo, A. T. Kristensen, A. Burg, and A. Balatsoukas-Stimming, "Hardware implementation of neural self-interference cancellation," *IEEE Journal on Emerging and Selected Topics in Circuits and Systems,* vol. 10, no. 2, pp. 204-216, 2020.
[10] A. T. Kristensen, A. Burg, and A. Balatsoukas-Stimming, "Advanced machine learning techniques for self-interference cancellation in full-duplex radios," in *2019 53rd Asilomar conference on signals, systems, and computers*, 2019: IEEE, pp. 1149-1153.
[11] Y. Wang *et al.*, "Digital SI Cancellation Based on LSTM for Co-frequency Co-time Full Duplex Communication Systems," in *Journal of Physics: Conference Series*, 2022, vol. 2405, no. 1: IOP Publishing, p. 012020.
[12] M. Browne and S. S. Ghidary, "Convolutional neural networks for image processing: an application in robot vision," in *Australasian Joint Conference on Artificial Intelligence*, 2003: Springer, pp. 641-652.
[13] R. A. Ramadan and K. Yadav, "RETRACTED ARTICLE: Nonlinear acoustic noise cancellation based automatic speech recognition system (NANC-ASR) with convolutional neural networks," *International Journal of Speech Technology,* vol. 25, no. 3, pp. 605-613, 2022.
[14] S. Huang, Y. Ye, and M. Xiao, "Learning-based hybrid beamforming design for full-duplex millimeter wave systems," *IEEE Transactions on Cognitive Communications and Networking,* vol. 7, no. 1, pp. 120-132, 2020.
[15] A. Chen, J. Demmel, G. Dinh, M. Haberle, and O. Holtz, "Communication bounds for convolutional neural networks," in *Proceedings of the Platform for Advanced Scientific Computing Conference*, 2022, pp. 1-10.
[16] J. Koushik, "Understanding convolutional neural networks," *arXiv preprint arXiv:1605.09081,* 2016.
[17] T. O. Omotehinwa, M. O. Lawrence, D. O. Oyewola, and E. G. Dada, "Bayesian optimization of one-dimensional convolutional neural networks (1D CNN) for early diagnosis of Autistic Spectrum Disorder," *Journal of Computational Mathematics and Data Science,* vol. 13, p. 100105, 2024.