A Novel GRU-CNN Model for Self-Interference Cancellation in IBFD Underwater Communication Systems

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Abstract: *The in-band full-duplex (IBFD) scheme has attracted immense attention in the underwater communication society due to its ability to improve communication throughput. However, self-interference (SI) remains a major problem for the performance and efficiency of IBFD systems, as the transmitted signal from a device leaks into its own receiver, necessitating advanced cancellation techniques to enable effective communication. Recently, machine learning (ML), particularly deep learning (DL), has presented promising techniques for self-interference cancellation. In this work, we propose a deep learning-based hybrid model, termed GCCN, which synergistically integrates Gated Recurrent Units (GRU) with Convolutional Neural Networks (CNN) specially designed to enhance self-interference cancellation (SIC) in IBFD underwater communication systems. Our proposed model leverages the temporal processing skills of GRUs for sequential data, along with the spatial feature extraction strengths of CNNs for collecting complex patterns in data, to effectively mitigate SI. Experimental results demonstrate that the GCCN model outperforms traditional methods and standalone deep learning models in terms of interference cancellation performance and improves the bit error rate (BER), achieving significant improvements in signal quality and system throughput.*

Keywords: *in-band full-duplex, self-interference, GRU, CNN.*

1. INTRODUCTION

IBFD communication systems have received much attention recently due to the possibility of improving the spectral efficiency effectively through enabling sending and receiving simultaneously at the same frequency band [1][2]. However, a crucial barrier for the implementation of IBFD systems is self-interference. SI arises when the transmitted signal leaks into the receiver at the same location, and the leaked signal can swamp the receiver signal with noise, making it difficult to distinguish between the desired incoming signals and the SI signal generated by the transmission itself [3]. In order to eliminate or reduce SI, several interference cancellation techniques have been proposed [4]. Conventional SIC approaches achieved different degrees of success, but they frequently struggled with complicated and nonlinear interference. The advancements of recent years in the areas of ML and DL have generated better opportunities for addressing these difficulties.

In this paper, we propose a novel hybrid GRU-CNN model specifically designed for SI cancellation in IBFD underwater systems, combining the temporal processing capabilities of GRUs with the spatial feature extraction capabilities of CNNs. A proposed hybrid DL model shows promise to improve both the mean squared error (MSE) and efficiency of SI cancellation.

1.1. RELATED WORK

IBFD transmission is the main emphasis of modern wireless communication systems, as it improves spectrum efficiency. Different methods exist to tackle the problem of SI signals in IBFD systems. This segment surveys some of the existing literature on SIC methods while discussing traditional approaches and recent advances in ML.

Reference [5] demonstrates how SIC schemes enhance system performance in IBFD transmission systems. The two main categories of traditional SIC approaches are passive and active (analog and digital) SI cancellation. For instance, passive SIC employs a secondary transformer to reduce SI in the received signal, as reported in [6]. In contrast, active cancellation methods use the transmitter chain to produce duplicate signals that are then subtracted from the signals that are received. The authors in [7] introduce an adaptive SIC technique for underwater acoustic systems, utilizing the normalized least mean squares (NLMS) algorithm. In [8], the researchers suggested an SIC model based on separating the SI channel from the far channel by orthogonal pilots for improved performance in IBFD-UWA. A digitally assisted analog SIC (DAA-SIC) system for a complicated SI propagation channel was presented by researchers in [9], highlighting the significance of addressing hardware parameters to improve system performance. Conventional SIC technologies struggle in dynamic environments since they rely on static characteristics, which might result in lower communication efficiency [10].

Recent SIC methods have started to rely more heavily on ML techniques. Neural networks have been successfully applied to non-linear SIC in (FD) radios [11]. Advanced ML approaches including recurrent and complex value neural networks, has achieved remarkable success in eliminating SI signals [12]. Furthermore, researchers in [13] introduced a long short-term memory (LSTM) to cancel SI signals in co-frequency co-time FD systems.

Nowadays, studies combine several neural network architectures in order to take advantage of the special advantages of each to achieve the best performance. For example, researchers in [14] suggested a hybrid network that combines multi-head self-attention with a mix of 1D CNN and bidirectional LSTM to relieve inter-symbol interference in MIMO-FTN-OWC systems,

achieving a BER increase of up to 7 dB while lowering computational complexity by 31.15%. An integrated model that combines CNN, GRU, ResNet, and self-attention to reconstruct SI signals was proposed in [15]. The model increases its nonlinear SIC capacity by up to 28% relative to current neural network-based eliminators and polynomial eliminators.
Our proposed GCCN model capitalizes on these advancements by fusing temporal and spatial feature extraction to create solutions to the SI challenge in IBFD systems.

1.2. CONTRIBUTIONS

The paper's contributions are summarized as follows:

- Design a GCCN model that integrates the temporal abilities of GRUs with the feature learning capacity of CNNs to effectively SIC in IBFD underwater systems.
- Performance analysis of the GCCN model and evaluation of its effectiveness in removing self-interference.
- A comparison of the proposed GCCN model with standalone machine learning methods and traditional SIC techniques to prove the efficiency of the model.

1.3. ARRANGEMENT OF THE PAPER

The rest of the paper is arranged as follows: In Section 2, we present the system model, detailing the architecture of the IBFD system and the proposed model. Section 3 presents the simulation results of the proposed model. Finally, a conclusion and suggestions for potential avenues for future research are presented in Section 4.

2. SYSTEM MODEL

2.1. IBFD ARCHITECTURE

The IBFD system utilizes the orthogonal frequency division multiplexing (OFDM) technique. The block diagram architecture of an IBFD transceiver is illustrated in Fig. 1.

At the transmitter system, the information bits $d(m)$ are modulated to obtain X_t using quadrature amplitude modulation (QAM). After modulation, applying the Inverse Fast Fourier Transform (IFFT) to convert the signal to the time domain and adding a cyclic prefix (CP) to mitigate inter-symbol interference (ISI), can be expressed as

$$x_t(n) = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} X_t(k) e^{j\frac{2\pi}{N}kn} \tag{1}$$

$$x_{tcp}(n) = \begin{cases} x_t(N-L+n), & \text{for } n = 0, 1, \ldots, L-1 \\ x_t(n-L), & \text{for } n = L, L+1, \ldots, N+L-1 \end{cases} \tag{2}$$

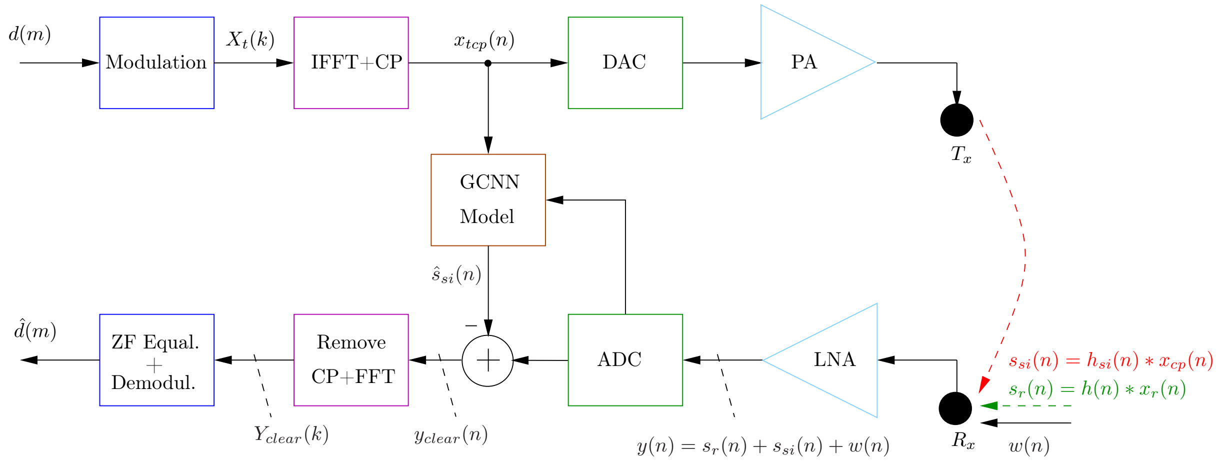

Figure 1: Architectural of IBFD system.

where L denotes the length of the CP. Next, the signal is converted to an analog format through a digital-to-analog converter (DAC) and amplified by a power amplifier (PA). Finally, the signal is transmitted by the transmitting antenna and transferred between nodes over a channel. The channel used is based on scientific measurements taken underwater, as described in [16].

Concurrently, at the receiver system, the system receives a signal that can be expressed as

$$y(n) = s_r(n) + s_{si}(n) + w(n), \tag{3}$$

where $w(n)$ denotes the additive white Gaussian noise (AWGN), and $s_r(n)$ denotes the signal received from the distant node given as

$$s_r(n) = \sum_{p=0}^{P-1} h(n-p)x_r(p), \tag{4}$$

and $s_{si}(n)$ denotes the SI signal given as

$$s_{si}(n) = \sum_{m=0}^{M-1} h_{si}(n-m)x_t(m). \tag{5}$$

After receiving the signal, it is amplified by a low-noise amplifier (LNA) to enhance the signal quality and is digitized using an analog-to-digital converter (ADC). Next, the predicted interference from the GCCN model $\hat{s}_{si}(n)$ is subtracted from the signal, which can be represented after subtracting as

$$y_{clear}(n) = s_r(n) + r_{si}(n) + w(n), \tag{6}$$

where r_{si} denotes the residual SI after cancellation, and can be written as

$$r_{si}(n) = s_{si}(n) - \hat{s}_{si}(n), \tag{7}$$

Subsequently, remove the CP from the clear signal and apply the Fast Fourier Transform (FFT) to convert the signal to the frequency domain, which can be expressed as

$$Y_{clear}(k) = S_r(k) + R_{si}(k) + W(k), \tag{8}$$

where $S_r(k)$ denotes the signal of interest, $R_{si}(k)$ denotes the residual SI, and $W(k)$ denotes the ambient noise in the frequency domain. Finally, the demodulation is applied to the signal using the same modulation scheme (QAM) to extract the received information.
The next subsection will cover a discussion on the GCCN model.

2.2. PROPOSED MODEL

In this part, we discuss the architecture of the suggested model, comprising the GRU and CNN architectures.

2.2.1. GRU

GRU networks are the most recent networks of RNN [17], which has a simpler architecture and lower computational demands than LSTM, where the input and the forget gates have been merged into one gate (update gate) [18]. Such simplification leads to a reduction in the parameters, meaning shorter training time durations are achieved while the temporal dependence is maintained in the long run.

The structure of the GRU is illustrated in Fig. 2. The GRU architecture has a two-gate [19]. The first gate is the reset gate $\mathbf{r}_t$, determining how much of the past it should forget, while the second gate is the update gate $\mathbf{z}_t$, determining how much of the previous information to retain and how much of the next information to incorporate. The GRU is computed by the following equations. Initially the reset gate is updated using

$$\mathbf{z}_t = \sigma(\mathbf{W}_z \cdot [\mathbf{h}_{t-1}, x_t] + \mathbf{b}_z) \tag{9}$$

Then, the update gate is computed as

$$\mathbf{z}_t = \sigma(\mathbf{W}_z \cdot [\mathbf{h}_{t-1}, x_t] + \mathbf{b}_z) \tag{10}$$

Finally, the hidden state candidate is selected as

$$\begin{aligned}\tilde{\mathbf{h}}_t &= \tanh(\mathbf{W}_{\tilde{h}} \cdot [\mathbf{r}_t \odot \mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_h) \\ \mathbf{h}_t &= (1 - \mathbf{z}_t) \odot \mathbf{h}_{t-1} + \mathbf{z}_t \odot \tilde{\mathbf{h}}_t\end{aligned}$$

where σ and tanh are the activation functions, $\odot$ is the Hadamard product, $\mathbf{h}_{t-1}$ is the prior hidden state, x_t is the input data at time t, $\mathbf{h}_t$ is the new hidden state, $\tilde{\mathbf{h}}_t$ is the candidate hidden state, $\mathbf{W}_{\tilde{h}}$ and $\mathbf{W}_z$ are the weight matrices, and $\mathbf{b}_z$ and $\mathbf{b}_h$i are the bias vectors. In this study, we employed a one-layer GRU network with 40 hidden neurons to learn temporal aspects of the data.

2.2.2. CNN

Convolutional neural networks enhance the ML capabilities of neural networks by incorporating convolutional layers into the architecture [21]. CNN is particularly suitable for processing network-like data, such as images [22] or sequential data [23], due to its ability to automatically

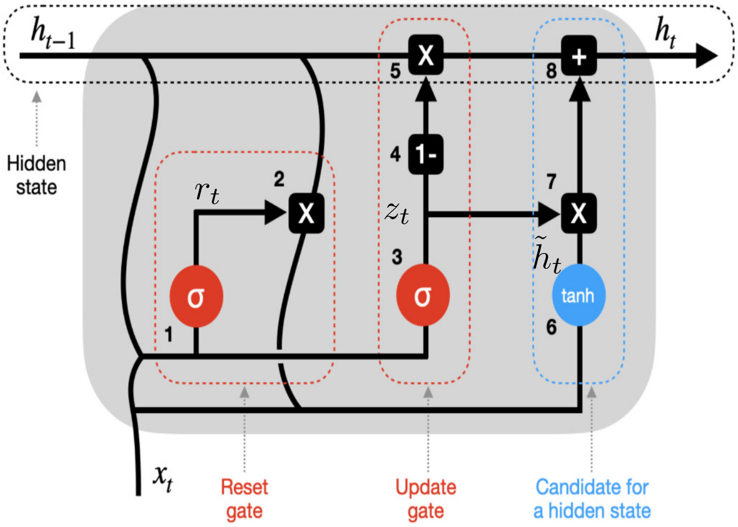

Figure 2: GRU structure [20].

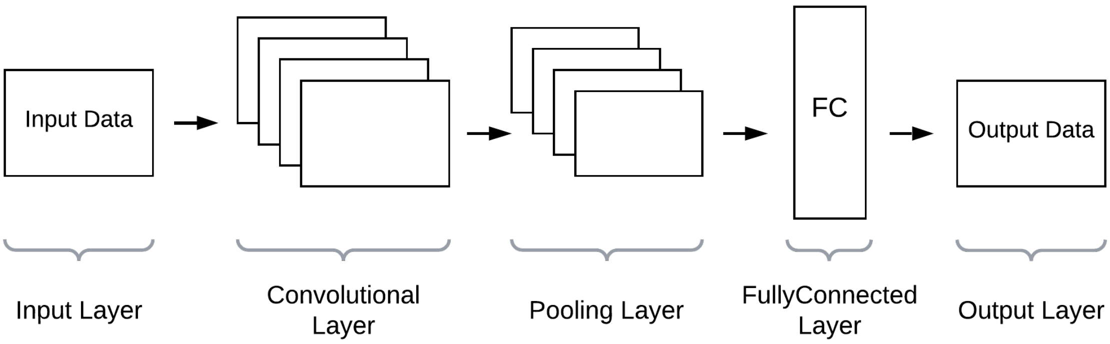

Figure 3: Simple CNN architecture.

learn the spatial hierarchy of features through convolutional layers. CNNs are composed of several layers, including input, convolution, pooling, and fully connected layers. Fig. 3 illustrates a minimal CNN architecture.

In this work, we employed 1D CNN, which contains a convolution layer, a batch normalization layer, and a ReLU activation, operates in conjunction with the GRU component. The CNN is used to extract spatial features from the GRU output.

2.2.3. GCCN MODEL

In this part, we present the architecture of the GCCN model, which integrates GRU and CNN algorithms.

The GCCN structure is initiated with an input layer that takes data. This data then passed through a GRU layer, which deals with the sequential information. Following the GRU layer, a 1D CNN with a kernel size of (3, 128) is employed to extract spatial features from the sequential data. The result from the CNN is passed through fully connected layers, which are responsible for the predictions. Lastly, the results are obtained from the output layer. Fig. 4 shows the structure of the GCCN network.

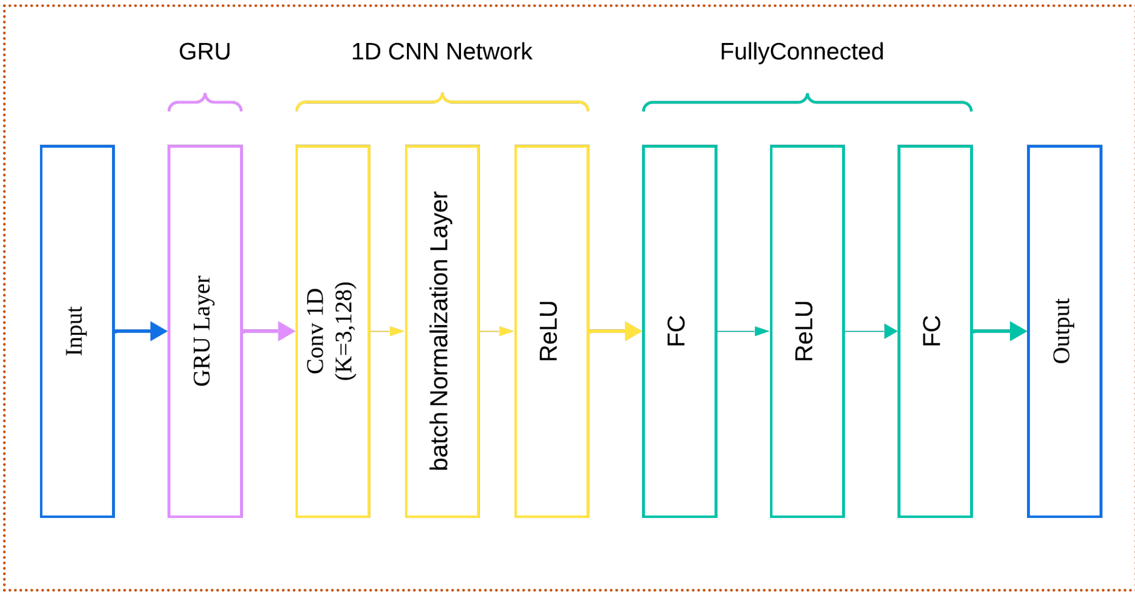

Figure 4: GCCN structure.

The GCCN model leverages the temporal processing capabilities of GRUs for sequential data, alongside the spatial feature extraction strengths of CNNs for collecting complex patterns in data to achieve reduced SI.

3. RESULTS

This section summarizes the results of MATLAB simulations of the suggested SI cancellation model. Table 1 displays the simulation parameters used in this work. The performance of the proposed model is evaluated using MSE, which measures the average squared difference between the estimated and actual signals, and cancellation rate in decibels (C_{dB}), which measures the reduction in SI achieved by the model, calculated as

$$MSE = \frac{1}{N}\sum_{i=1}^{N} |r_{si}(i)|^2, \tag{11}$$

$$C_{dB} = 10\log_{10}\left(\frac{P_{SI}}{P_{RSI}}\right) \tag{12}$$

where N is the number of samples, P_{SI} is the power of the SI signal, and P_{RSI} is the power of the residual SI signal. The outcomes for the two metrics are summarized in Table 2.

Fig. 5 illustrates the performance of BER under various conditions, including theoretical performance, performance with interference, and performance after applying the SI cancellation using our model.

Parameter	Value
Optimizer	sgdm
Training SNR	30 dB
Loss Function	MSE
Input Features	2(1 real,1 imaginary)
GRU Hidden Size	40
Number of Epochs	500
Batch Size	200
InitialLearnRate	0.1
LearnRateDropFactor	0.1
LearnRateDropPeriod	150
Modulation Type	16-QAM
CP	$16, 32, 64, 128$

Table 1: Simulation parameters.

Metrics	MSE	C_{dB}
SNR=0	3.302e-04	44.865
SNR=5	1.801e-04	47.373
SNR=10	8.07e-05	50.94
SNR=15	4.672e-05	53.344
SNR=20	2.371e-05	56.245
SNR=25	1.083e-05	59.688
SNR=30	6.149e-06	62.135

Table 2: Performance of GCCN model.

Performance without interference is represented by the BER curve theory of the system. This curve is used as the base to compare with that of the performance of the proposed model. The orange curve illustrates poor BER performance when SI is present in the system. Furthermore, Fig. 5 displays the BER curves after cancelling SI using the GCCN model at various CP. The BER decreases significantly, putting it close to the theoretical performance. Fig. 6 illustrates the spectrum of the SI signal, alongside the residual signal spectrum after cancellations achieved with traditional methods (LMS and NLMS), as well as with individual ML methods (CNN and GRU). In addition, it presents the residual signal spectrum after cancellations using the proposed method. The ability of the GCCN model to model complex interference patterns and adapt to communication channels makes it the most efficient solution for SI cancellation.

4. CONCLUSION

In this paper, we proposed a GCCN model to eliminate SI caused by signal leakage to the receiver in IBFD underwater systems. Our approach leverages the strengths of GRUs and CNNs to further enhance performance in the SIC effectively. The GRU maintains temporal connectivity to analyze interference signals while the CNN performs spatial feature extraction from the signal. The results demonstrate the GCCN model outperforms individual machine learning approaches (GRU and CNN), and significantly outperforms traditional SIC methods (LMS and

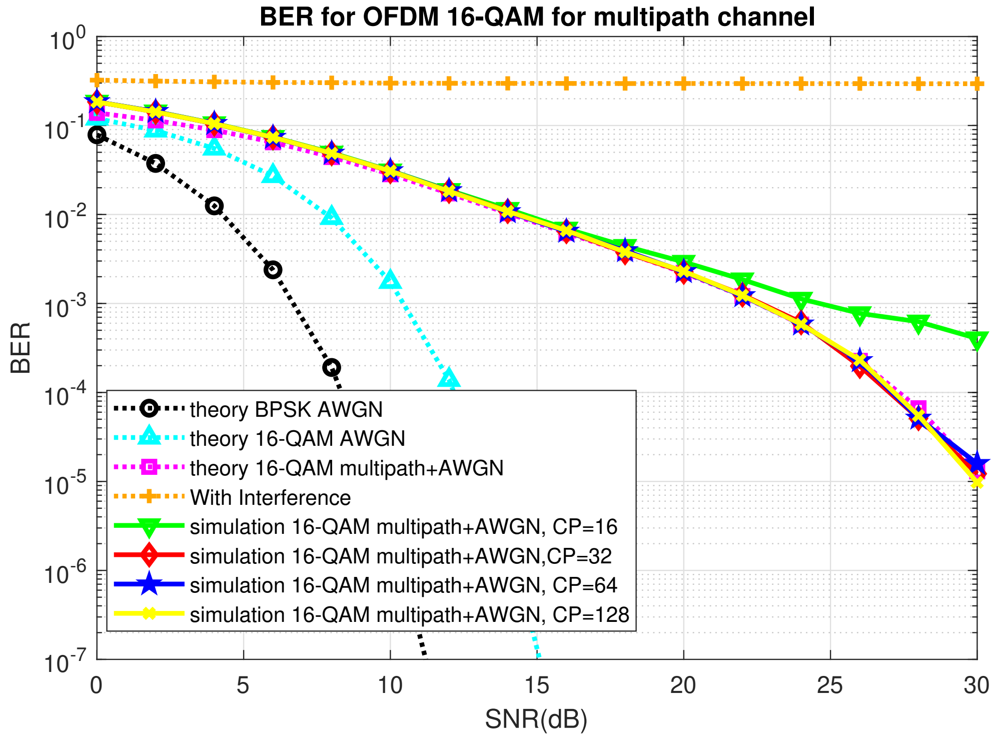

Figure 5: BER performance comparison of different conditions: theoretical performance, performance with interference, and performance after applying the proposed GCCN model for SI cancellation.

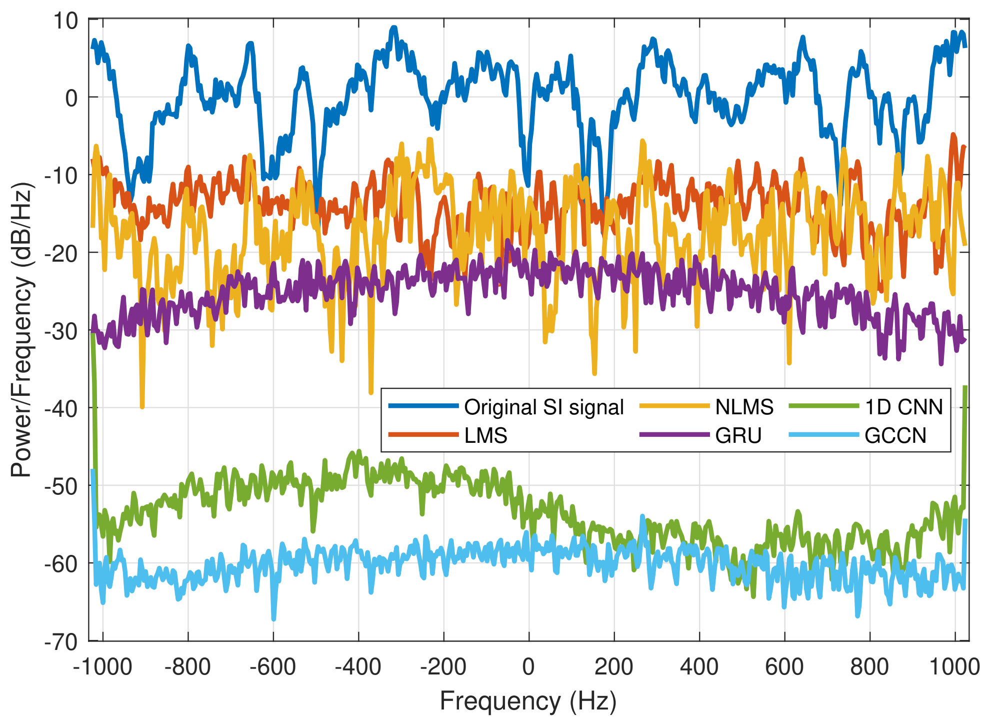

Figure 6: Signal spectrum after cancellation.

NLMS). Future work will focus on further optimizing the model architecture.

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