Digital-Optical Hybrid Computation for Deep Unfolding-Aided MIMO Signal Detection

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***Abstract*—In this paper, we propose a digital-optical hybrid computation framework that combines error-prone optical circuits with precise digital computation for projected gradient MIMO signal detection. Our approach strategically alternates between fast but imperfect optical matrix-vector operations and accurate digital computations throughout the iterative process. We optimize algorithm parameters through deep unfolding to mitigate performance degradation caused by optical computation errors. Numerical results demonstrate that our method achieves the speed and energy efficiency benefits of optical computing while maintaining robust detection performance comparable to digital-only approaches.**

I. Introduction

Currently, various research efforts are underway for the 6th generation mobile communication system (6G). Multiple-input multiple-output (MIMO) is one of the key technologies for 6G and emerging wireless systems [1]. In MIMO, base stations (BSs) receive multiple transmitted signals and perform signal detection to recover the original signals, requiring processing a large volume of signals. This extensive signal processing at BS demands high throughput and energy efficiency. To address these processing demands, general-purpose graphics processing unit (GPGPU) has been seriously considered for signal detection due to its parallel processing capabilities [2], [3]. Given these circumstances, there is a growing need for *fast and energy-efficient* signal processing technologies.

Meanwhile, *silicon photonics* has emerged as an active research field, with optical circuits gaining attention for computational applications [4]. Optical circuits can perform computations *faster and more energy-efficiently* than conventional digital computing. This ability to combine high processing performance and low power consumption has led to research in various applications, particularly in neural networks and quantum computing [5]. Within silicon photonics, on optical circuits based on *Mach-Zehnder Interferometers (MZI)* [6] have received strong attention. MZI-based optical matrix-vector multiplication circuits provide broad applicability, supporting extensive research in neural networks, where matrix-vector multiplication operations are frequently performed [7]. Furthermore, MZI-based optical computing is being considered as an important future solution for wireless communication signal processing [8].

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However, it is well-known that MZIs *do not perform ideally* in practical applications due to manufacturing errors in beam splitters that are fundamental components of an MZI, and parameter errors in other components [9], [10]. When MZI parameters contain errors, the output may deviate from the intended computational results. These computational errors affect optical circuit computation and can lead to severely degraded signal processing performance. To prevent performance degradation caused by optical computing errors, a promising approach is to develop a *digital-optical hybrid computation* that combines the high accuracy of digital computing with the high-speed, energy-efficient characteristics of optical circuits. Such a hybrid computation approach leverages the advantages of both computing methods to create an effective signal processing system.

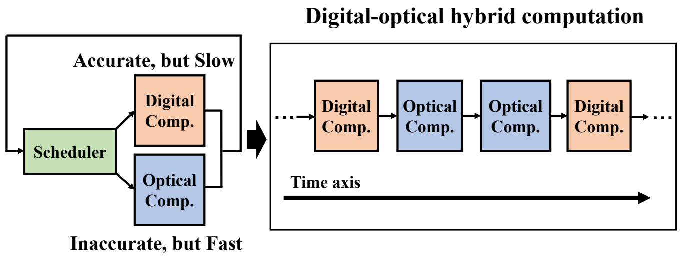

Fig. 1. Concept of digital-optical hybrid computation in iterative algorithms. A scheduler switches digital or optical computation according to the predefined schedule.

This paper aims to develop a *digital-optical hybrid computation* (Fig. 1) for iterative MIMO signal processing that involves matrix-vector product operations. By employing this hybrid approach in signal detection, we seek to achieve high-speed and energy-efficient signal processing through optical circuits while preventing performance degradation that might occur due to computational errors in optical circuits. The signal detection method we consider is an iterative MIMO signal detection method, specifically the projected gradient method [11].

Previous research has demonstrated that *deep unfolding* methodology enhances iterative MIMO signal detection performance [12], [14]. Given the accuracy differences between optical and digital computing, optimizing the scheduling of these computing methods is crucial for performance. Our proposed method combines deep unfolding optimization with strategic optical circuit scheduling to prevent detection performance degradation.

The main contributions of this work can be summarized as follows.

- Proposing the concept of digital-optical hybrid iterative computation for MIMO signal processing. To the best of the authors' knowledge, this is the first attempt to explore iterative algorithms using hybrid digital-optical computation.
- Developing a projected gradient MIMO signal detection method based on digital-optical hybrid computation that strategically alternates between optical and digital matrix-vector operations.
- Demonstrating the effectiveness of deep unfolding in improving the proposed algorithm's performance through comprehensive numerical experiments.

Through numerical experiments, we show that our proposed method, despite utilizing optical circuits with computational errors, can effectively mitigate the impact of these errors. The proposed method can gain the benefit of optical computation such as fast and power efficient computation.

The organization of the paper is as follows. Section II presents the notation, definitions, and fundamental concepts necessary for the subsequent sections. Section III introduces the parameter error model for optical circuits and describes the proposed algorithm employing digital-optical hybrid computation. Section IV reports the results of the numerical experiments. Section V summarizes the findings and concludes the discussion.

II. Preliminaries

A. MIMO Channel Model

We consider an $M \times N$ MIMO system with the received signal

$$\boldsymbol{y} = \boldsymbol{H}\boldsymbol{x} + \boldsymbol{w}, \tag{1}$$

where $\boldsymbol{x} \in \mathbb{C}^N$ is the transmitted signal, $\boldsymbol{H} \in \mathbb{C}^{M\times N}$ is the channel matrix, and $\boldsymbol{w} \in \mathbb{C}^M$ is complex Gaussian noise where each component follows $\mathcal{CN}(0, \sigma^2)$. The signal-to-noise ratio (SNR) is defined as $10\log_{10}(N/\sigma^2)$ dB. We employ quadrature phase shift keying (QPSK) modulation and assume perfect channel state information is available at the BS.

B. MIMO Detection Algorithms

1) Minimum Mean Square Error (MMSE) Detection: MMSE detection is one of the signal detection methods practically used in MIMO communications. Let $\hat{\boldsymbol{x}} \in \mathbb{C}^N$ denote the estimated signal. Linear estimation refers to a method where the estimated signal is calculated as

$$\hat{\boldsymbol{x}} = \boldsymbol{W}\boldsymbol{y}, \tag{2}$$

using a matrix $\boldsymbol{W} \in \mathbb{C}^{N\times M}$. In MMSE detection, the matrix $\boldsymbol{W}$ is determined by minimizing the mean square error (MSE)

$$\mathbb{E}\left[\|\boldsymbol{x} - \boldsymbol{W}\boldsymbol{y}\|^2\right], \tag{3}$$

where $\mathbb{E}[\cdot]$ denotes the mathematical expectation. It is known that the matrix $\boldsymbol{Q}$ that minimizes the MSE is given by

$$\boldsymbol{Q} \equiv (\boldsymbol{H}^H\boldsymbol{H} + \sigma^2\boldsymbol{I})^{-1}\boldsymbol{H}^H. \tag{4}$$

2) Projected Gradient Descent (PGD) Method: PGD [11] is an iterative algorithm that alternately executes *gradient descent steps* and *projection steps*.

The gradient descent step updates the estimated transmitted signal by computing the negative gradient of an objective function. For an objective function $f(\boldsymbol{x})$, the gradient descent step at iteration k is given by

$$\boldsymbol{x}^{[k+1]} = \boldsymbol{x}^{[k]} - \delta^{[k]}\nabla f(\boldsymbol{x}^{[k]}), \tag{5}$$

where $\delta^{[k]}$ denotes the step size. The least squares objective function to be minimized in the gradient descent step is defined as

$$f(\boldsymbol{x}) \equiv \frac{1}{2}\left(\|\boldsymbol{y} - \boldsymbol{H}\boldsymbol{x}\|^2 + \sigma^2\|\boldsymbol{x}\|^2\right). \tag{6}$$

The gradient of this objective function is given by

$$\nabla f(\boldsymbol{x}) = (\boldsymbol{H}^H\boldsymbol{H} + \sigma^2\boldsymbol{I})\boldsymbol{x} - \boldsymbol{H}^H\boldsymbol{y}. \tag{7}$$

Therefore, the updated equation for the gradient descent step becomes

$$\boldsymbol{x}^{[k+1]} = \boldsymbol{x}^{[k]} - \delta^{[k]}(\boldsymbol{H}^H\boldsymbol{H} + \sigma^2\boldsymbol{I})\boldsymbol{x}^{[k]} + \delta^{[k]}\boldsymbol{H}^H\boldsymbol{y}. \tag{8}$$

Following the gradient descent, the projection step maps the result onto the constraint region defined by the signal constellation. Since we assume QPSK modulation, we define the projection function as

$$S_{\lambda^{[k]}}(u) \equiv \mathrm{hardtanh}(\lambda^{[k]}\Re(u)) + \mathrm{hardtanh}(\lambda^{[k]}\Im(u))i, \tag{9}$$

where i is the imaginary unit, $\Re(u)$ and $\Im(u)$ represent the real and imaginary parts of u, respectively, $\lambda^{[k]}$ is a parameter that determines the projection intensity, and $\mathrm{hardtanh}(\cdot)$ denotes the hard hyperbolic tangent function, which is defined as

$$\mathrm{hardtanh}(x) \equiv \begin{cases} 1 & (x \geq 1), \\ x & (-1 < x < 1), \\ 0 & (x \leq -1). \end{cases} \tag{10}$$

C. Optical Matrix-Vector Product Circuit

We now explain the details of optical circuits for matrix-vector product (MVP) operations. These circuits consist of Mach-Zehnder Interferometers (MZI) as basic components and use Reck's decomposition method [15] for implementation.

1) Mach-Zehnder Interferometer: MZI is an optical component with beam splitters, mirrors, and phase shifters that alters the phase of two input light beams and modifies the output light intensity based on the resulting phase difference [15]. An MZI features adjustable phase rotation parameters ϕ and θ that control their operation, and it can be mathematically represented by rotation matrices [16]. For an optical circuit with

N input ports, the rotation matrix $T_{mn} \in \mathbb{C}^{N\times N}$, $(m < n)$ corresponds to an MZI connecting ports m and n, defined as

$$\boldsymbol{T}_{mn}(\phi,\theta) \equiv$$
$$\begin{array}{c} \\ \\ m \\ \\ n \\ \\ \\ \end{array}\begin{pmatrix} 1 & \cdots & 0 & \cdots & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \cdots & \vdots & \cdots & \vdots \\ 0 & \cdots & e^{j\phi}\cos\theta & \cdots & -\sin\theta & \cdots & 0 \\ \vdots & \cdots & \vdots & \ddots & \vdots & \cdots & \vdots \\ 0 & \cdots & e^{j\phi}\sin\theta & \cdots & \cos\theta & \cdots & 0 \\ \vdots & \cdots & \vdots & \cdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & \cdots & 0 & \cdots & 1 \end{pmatrix}. \tag{11}$$

When an input signal passes through this MZI, the rotation corresponding to this rotation matrix acts on the complex input light signal vector, i.e., if $\boldsymbol{x} \in \mathbb{C}^N$ is the input vector to the MZI, the output becomes $\boldsymbol{T}_{mn}\boldsymbol{x}$.

The MZI described above represents an ideally operating MZI. In practice, manufacturing errors such as beam splitter spectral ratio errors [9] and *parameter errors* on MZI-parameters [10] affect computational accuracy. To address these errors, various approaches have been proposed, including optimizing MZI placement in optical circuits [17] and modifying MZI configurations [18]. The present paper assumes conventional MZIs and we aim to mitigate the parameter errors by using digital-optical hybrid computation.

2) Reck's Decomposition Method: To implement arbitrary matrix-vector products using the MZI components, we employ Reck's method [15] . It is known that any unitary matrix $\boldsymbol{U} \in \mathbb{C}^{N\times N}$ can be decomposed into the product of rotation matrices as

$$\boldsymbol{U} = \boldsymbol{D}\prod_{n=2}^{N}\left[\prod_{m=1}^{n-1}\boldsymbol{T}_{mn}(\phi_{mn},\theta_{mn})\right], \tag{12}$$

where $\boldsymbol{D}^{N\times N}$ is a diagonal matrix [15]. Based on this matrix decomposition, an optical MVP circuit can be constructed by arranging MZIs with appropriate phase parameters [15] derived during decomposition. A configuration of the MZI-based MVP circuit is illustrated in Fig. 2.

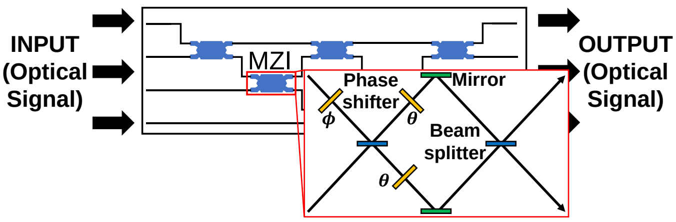

Fig. 2. Configuration of MZI-based optical MVP circuit.

Building on the unitary matrix operations, we can explain an optical circuit for computing the product of an arbitrary matrix $\boldsymbol{A} \in \mathbb{C}^{N\times M}$ (not necessarily unitary) and an input vector. This is achieved through singular value decomposition (SVD), expressing $\boldsymbol{A}$ as $\boldsymbol{U}_A\boldsymbol{\Sigma}_A\boldsymbol{V}_A^H$, where $\boldsymbol{U}_A \in \mathbb{C}^{N\times N}$ and $\boldsymbol{V}_A^H \in \mathbb{C}^{M\times M}$ are unitary matrices implemented using the optical circuits described earlier, and $\boldsymbol{\Sigma}_A \in \mathbb{C}^{N\times M}$ is implemented using phase shifters. This approach enables the implementation of arbitrary MVP in the optical domain.

D. Deep Unfolding

Deep Unfolding (DU) [13] is a type of deep learning technique that effectively enhances the performance of iterative algorithms. It is known to achieve improved convergence rates when applied to iterative algorithms [14]. The method involves unfolding the iterative process along the time dimension and embedding learnable parameters and learnable substructures within the model. Subsequently, training is performed to optimize these learnable parameters contained within the iterative algorithm.

III. Proposed Method

A. Parameter Error Model for Optical Circuits

In this subsection, we explain the parameter error model for optical circuits assumed in this work. As mentioned earlier, MZIs cannot be expected to operate ideally in practice, and parameter errors may occur due to various reasons. Therefore, in this research, we employ a simple model that assumes phase errors as the dominant source of non-ideal operation of an MZI according to [10].

For any unitary matrix $\boldsymbol{U}$, let Φ and Θ denote the sets containing all ideal phase rotation parameters ϕ_{mn} and θ_{mn} respectively, as defined in Reck's decomposition. In practical implementations, however, the actual optical circuit implements a matrix $\boldsymbol{U}'$ that differs from $\boldsymbol{U}$ due to manufacturing imperfections and parameter errors.

To model these imperfections, we represent each implemented parameter as

$$\phi'_{mn} = \phi_{mn} + n^{\phi}_{mn},\ \ \forall\phi_{mn} \in \Phi, \tag{13}$$
$$\theta'_{mn} = \theta_{mn} + n^{\theta}_{mn},\ \ \forall\theta_{mn} \in \Theta, \tag{14}$$

where n^{ϕ}_{mn} and n^{θ}_{mn} are error terms following independent normal distributions $\mathcal{N}(0,\sigma_n^2)$.

Consequently, an optical MVP circuit based on MZIs with Gaussian parameter errors outputs $\boldsymbol{U}'\boldsymbol{x}$ instead of ideal $\boldsymbol{U}\boldsymbol{x}$. Generally, since matrix $\boldsymbol{U}'$ differs from the target matrix $\boldsymbol{U}$, the output from the error-containing circuit includes computational errors. Preliminary experiments have shown that these computational errors cause significant degradation in detection performance in the MIMO signal detection circuit.

B. Digital-Optical Hybrid Computation

As seen in Section II-B2, the gradient descent step in the projected gradient method involves MVP operations and these operations dominate the computational complexity of the algorithm. In this subsection, we propose a projected gradient MIMO signal detection method based on digital-optical hybrid computation, which employs both digital computation and optical computation for the MVP operation.

The proposed method is constructed on the hypothesis that *by appropriately switching* between digital and optical computation for the MVP operations within the iterative process, we can leverage both the accuracy of digital computation and the high-speed, energy-efficient characteristics of optical computation while mitigating the impact of computational errors from optical calculations.

In our proposed method, we select either optical or digital computation for the MVP operations in the gradient descent step. The iterative equations of the proposed method are defined by

$$\boldsymbol{r}^{[k]} = \boldsymbol{x}^{[k]} + \delta^{[k]} \boldsymbol{H}^H \boldsymbol{y} - \delta^{[k]} (\alpha^{[k]} \boldsymbol{Q} + (1 - \alpha^{[k]}) \boldsymbol{R}) \boldsymbol{x}^{[k]}, \quad (15)$$

$$\boldsymbol{x}^{[k+1]} = S_{\lambda^{[k]}}(\boldsymbol{r}^{[k]}), \quad k = 1, 2, 3, \ldots, \quad (16)$$

where $\alpha^{[k]} \in \{0, 1\}$ denotes the *switch parameter* for selecting between digital computation and optical circuit computation, $\boldsymbol{Q} \equiv \boldsymbol{H}^H \boldsymbol{H} + \sigma^2 \boldsymbol{I}$ corresponds to the matrix for digital computation, and $\boldsymbol{R}$ represents the optical circuit implementation of $\boldsymbol{Q}$.

The optical realization is achieved by decomposing $\boldsymbol{Q}$ into unitary components, i.e., through SVD, which are then implemented using MZI-based circuits via Reck's method. Due to manufacturing imperfections and parameter errors, which are described in Section III-A, the resulting optical matrix $\boldsymbol{R}$ deviates from the ideal $\boldsymbol{Q}$, introducing computational errors.

When $\alpha^{[k]} = 1$, the k-th iteration performs accurate digital computation, and when $\alpha^{[k]} = 0$, computation is performed using optical circuits. Since users need to determine the selection between digital computation and optical circuit operations in advance, we assume that the *scheduling of digital and optical circuit computation is predetermined* before the execution of the algorithm.

Figure 3 shows the structure of our proposed projected gradient MIMO signal detection method based on digital-optical hybrid computation. As the projected gradient method is an iterative algorithm, signals circulate within the circuit. In the figure, $\boldsymbol{x}^{[0]}$ represents the initial value, and $\hat{\boldsymbol{x}}$ represents the estimated signal. For MVP operations, either digital computation or optical circuits can be selected. The switch operation is performed by a *scheduler* according to a given switching schedule. When using optical circuits, signals are converted from electrical to optical (E/O) signals through an E/O conversion device, and after computation, the output is converted back to electrical signals through an O/E conversion device. In this research, we assume that the conversion of signals between optical and electrical signals uses efficient devices and incurs *no computational time overhead*.

C. Application of Deep Unfolding

The convergence and error-resilience of our method depend critically on parameters $\delta^{[k]}$ and $\lambda^{[k]}$. In this work, we utilize DU to optimize these parameters by treating them as learnable parameters. In our training procedure, we generate the training data following the MIMO transmission model in Section II-A and optimize the parameters using gradient descent to minimize the MSE between the transmitted signal $\boldsymbol{x}$ and estimated signal $\hat{\boldsymbol{x}}$.

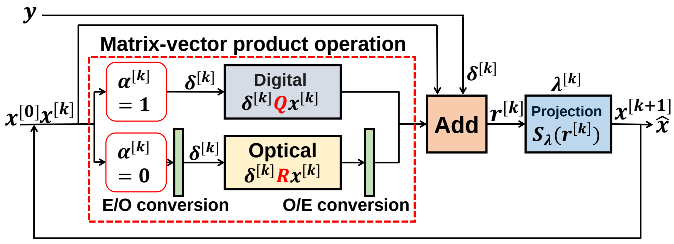

Fig. 3. Digital-optical hybrid computation for proposed projected gradient MIMO signal detection.

From a stochastic optimization perspective, optical computation errors can be viewed as gradient noise. DU learns optimal step size $\delta^{[k]}$ and projection parameters $\lambda^{[k]}$ that compensate for this noise, similar to optimal strategies in stochastic gradient descent [19] that adapt to noise characteristics.

IV. Numerical Experiments

A. Experimental Setting

We conducted experiments with a 16×16 MIMO system. Each element of the channel matrix $\boldsymbol{H}$ was drawn from a complex normal distribution with zero mean and unit variance. For DU training, we used 100 samples per batch and ran $30,000$ training loops. Parameters were updated using Adam optimization with a learning rate of 1.0×10^{-3}. The gradient descent step parameter $\delta^{[k]}$ was initialized to $1/\lambda_{\max}$, where $\lambda_{\max}$ is the maximum eigenvalue of $\boldsymbol{H}^H \boldsymbol{H}$, and the projection parameter $\lambda^{[k]}$ was initialized to 1.0. Without DU, these parameters remained fixed at their initial values.

The MZI parameter errors n^{ϕ}_{mn} and n^{θ}_{mn} followed a normal distribution with zero mean and variance $\sigma_n^2 = 0.001$ (unless otherwise specified). During training, we generated different error matrices for each iteration, while for performance evaluation, we used a fixed matrix across $100,000$ trials and measured performance using symbol error rate (SER).

We evaluated three scheduling patterns for the digital-optical hybrid computation, each comprising 25 optical and 5 digital computations over 30 total iterations, as illustrated in Fig. 4:

- First: Optical computation initially, followed by digital computation for the final 5 iterations
- Repeat: Alternating pattern of 5 optical computations followed by 1 digital computation
- Last: Beginning with 5 digital computations followed by 25 optical computations

B. SER Performance of Digital-Only/Optical-Only Computation

Figure 5 presents the SER performance of the proposed MIMO detector with *digital-only/optical-only computation*. For this experiment, we fixed $\alpha^{[k]} = 1$ for digital-only and $\alpha^{[k]} = 0$ for optical-only computation across all 30 iterations. DU was applied to optimize the trainable parameters $\delta^{[k]}$ and

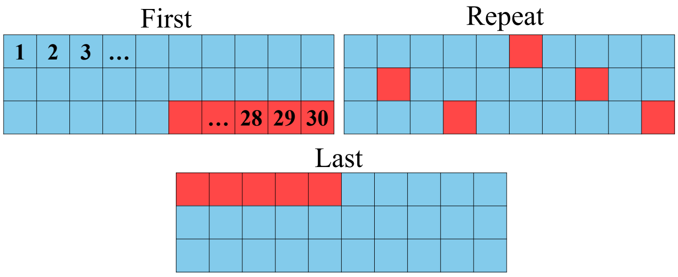

Fig. 4. Visualization of the three scheduling patterns for digital-optical hybrid computation. Each block represents one iteration, arranged from top left to bottom right. Red blocks indicate digital computation ($\alpha^{[k]} = 1$), while blue blocks indicate optical computation ($\alpha^{[k]} = 0$). All patterns maintain the same computational budget: 5 digital and 25 optical computations.

$\lambda^{[k]}$. Results show that optical-only computation exhibits the worst SER performance due to computational inaccuracies, while digital-only computation significantly outperforms the MMSE detector. This indicates that even with DU optimization, optical-only computation cannot achieve detection performance comparable to digital-only approaches.

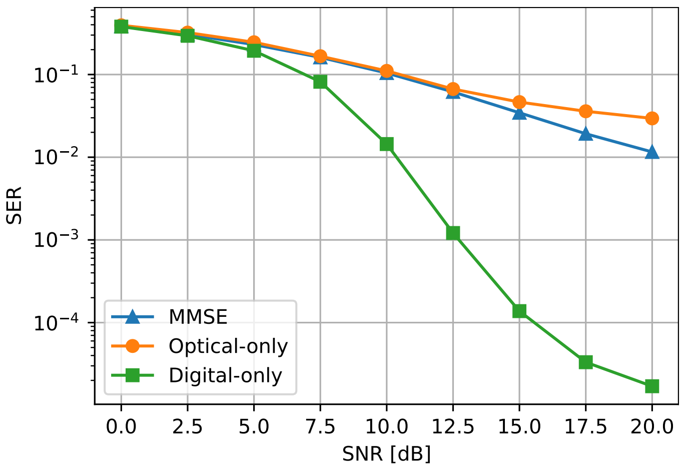

Fig. 5. Comparisons of SER performance of digital-only/optical-only computation with DU. The number of iterations is set to 30.

C. SER Performance of Proposed Method

In the following numerical experiments, the total number of iterations was set to 30, comprising 25 iterations using optical circuits and 5 iterations using digital computation for hybrid computation.

Figure 6 shows a comparison of signal detection performance between cases with and without DU for our proposed method using the "Repeat" scheduling pattern. We include as baselines the SER of the MMSE method (*Baseline 1*) and a projected gradient method with DU that uses only digital computation with 5 iterations (*Baseline 2*).

The dashed line showing the SER without DU exhibits higher values than the MMSE method (Baseline 1) in regions where SNR exceeds 7.5dB, indicating the poorest performance among all detection methods. Conversely, the proposed method with DU indicates significantly lower SER values. This result demonstrates the effectiveness of learning parameters $\delta^{[k]}$ and $\lambda^{[k]}$ through DU.

Comparing with Baseline 2, which uses the same number of digital computations (5 iterations), we confirmed that the use of optical circuits, despite containing computation errors, leads to improved signal detection performance. If the computation-time of optical computation is negligible compared to that of digital computation, our hybrid approach achieves superior SER without additional computational overhead.

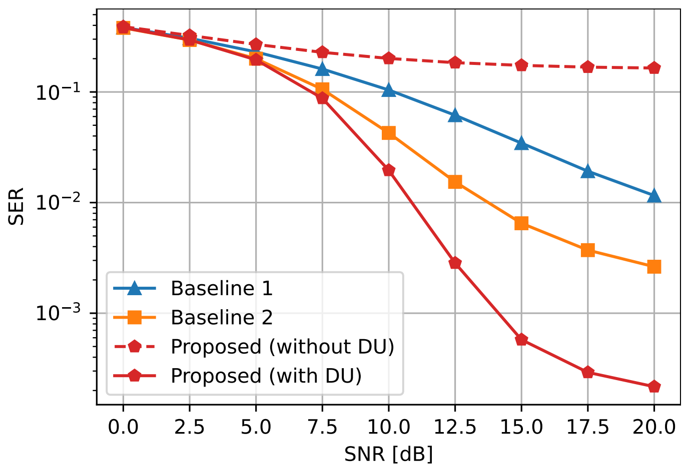

Fig. 6. Comparisons of SER performance with/without DU (scheduling pattern: Repeat). Baseline 1: MMSE method; Baseline 2: only digital computation with 5 iterations with DU.

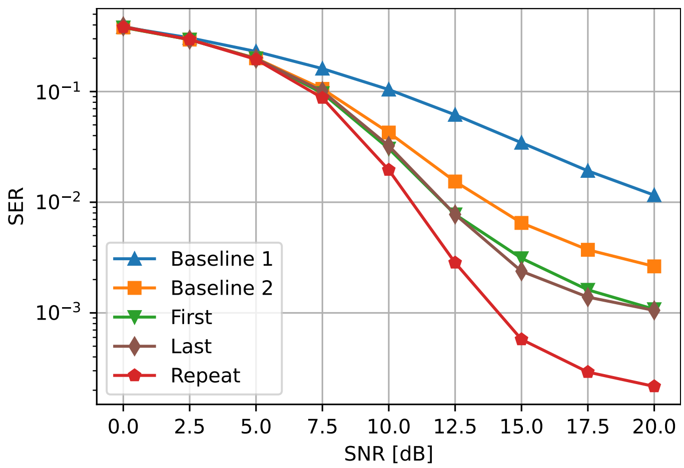

Fig. 7. Comparisons of SER performance across different scheduling patterns. Baseline 1: MMSE method; Baseline 2: only digital computation with 5 iterations with DU.

Figure 7 shows a comparison of signal detection performance across different scheduling patterns. The baselines are the same as in Fig. 6. When SNR is greater than 10dB, all scheduling patterns achieve lower SER than the projected gradient method using only digital computation. Furthermore, there are differences in SER among the three scheduling patterns. The Repeat pattern shows the lowest SER among the proposed methods, followed by Last and then First. These results indicate that scheduling optimization is crucial for performance, with the Repeat pattern offering the best error performance.

In the above simulations, DU improves performance by optimizing parameters to counteract optical computation noise patterns. The 'Repeat' pattern's superior performance can be explained through error accumulation and correction, where periodic digital computation serves as error correction for accumulated optical computation errors, similar to variance reduction techniques in stochastic optimization.

D. Dependency on MZI Parameter Error Variance

Figure 8 compares the SER performance of the proposed method under different MZI parameter error variances, with $\sigma_n^2 \in \{0.1, 0.01, 0.001\}$. As expected, larger parameter errors degrade detection performance, yet the hybrid scheme consistently outperforms the digital-only projected gradient method with the same number of digital iterations. This demonstrates that the corrective role of periodic digital computations effectively mitigates the accumulation of optical errors and enhances robustness.

Moreover, no error floor was observed within the simulated SNR range even at low parameter error levels, confirming the stable error performance of the proposed scheme. Under high error variances, the hybrid method still provides a clear advantage over the digital-only baseline, highlighting its practical applicability across a wide range of hardware imperfections.

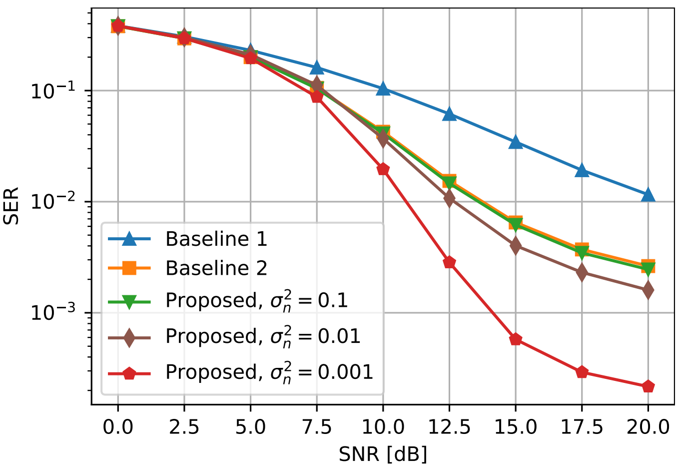

Fig. 8. SER performance of proposal: dependency on MZI parameter error variance (scheduling pattern: Repeat). Baseline 1: MMSE method; Baseline 2: only digital computation with 5 iterations with DU.

V. Summary

In this paper, we introduced a digital-optical hybrid computation framework for MIMO signal detection using the projected gradient method that strategically combines accurate digital computation with efficient but imperfect optical circuits. By optimizing algorithm parameters through deep unfolding, our approach effectively mitigates optical circuit errors while maintaining the speed and energy efficiency benefits of optical computing. However, our results demonstrate that DU alone cannot fully compensate for errors in pure optical computation, making the hybrid approach essential. Numerical results confirm performance improvements over digital-only approaches despite using imperfect optical components. Future work could explore optimization of scheduling patterns through *structural learning techniques* [20], and further theoretical analysis of error correction mechanisms in hybrid computation.

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