Convolutional Self-Attention-Based Multi-User MIMO Demapper

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Abstract—In orthogonal frequency division multiplexing (OFDM)-based wireless communication systems, the bit error rate (BER) performance is heavily dependent on the accuracy of channel estimation. It is important for a good channel estimator to be capable of handling the changes in the wireless channel conditions that occur due to the mobility of the users. In recent years, the focus has been on developing complex neural network (NN)-based channel estimators that enable an error performance close to that of a genie-aided channel estimator. This work considers the other alternative which is to have a simple channel estimator but a more complex NN-based demapper for the generation of soft information for each transmitted bit. In particular, the problem of reversing the adverse effects of an imperfect channel estimator is addressed, and a convolutional self-attention-based neural demapper that significantly outperforms the baseline is proposed.

I. INTRODUCTION

With an ever-growing demand for data rate in wireless communications, machine-learning-based alternatives to the various classical functional blocks in the physical layer have been under consideration in recent times. The recent advances in machine learning in several fields (image recognition, natural language processing, etc.) have aroused an interest for the same in the field of wireless communications. It is a common practice nowadays to replace the functional blocks of a transceiver chain like channel estimation, equalization, log-likelihood ratio (LLR) generation, etc., by deep neural networks (DNNs) [1]–[3]. More recent techniques propose to jointly replace a group of functional blocks by DNNs. An example is [4], which proposes to jointly learn channel estimation, equalization, and LLR generation (demapping) using a DNN. There have also been several proposals to perform end-to-end learning – the joint optimization of the transceiver using an auto-encoder [5].

In many instances, it might not be feasible to have a very complex neural network (NN) in a product due to the large number of trainable parameters. For example, the NN of [4] has around 1.2 million parameters for uplink MIMO reception and detection, and this scales with the number of users. So, it might be more practical in some cases to use a simple channel estimator like the linear minimum mean square error (LMMSE) channel estimator at pilot locations, and employ a more robust demapper to alleviate the adverse impact of the imperfect channel estimator. A very simple multi-user MIMO (MU-MIMO) receiver would perform channel estimation on the resource elements (REs) at the pilot locations, use the nearest-pilot-location estimate for other data-carrying REs, perform equalization using the LMMSE detector, and then use a Gaussian demapper to generate the LLR for each transmitted bit of each user. However, this would entail a significant drop in the bit error rate (BER) performance.

In this paper, we focus on replacing only the Gaussian demapper with a learned NN demapper with the goal of reversing the effects of imperfect channel estimation. The idea is to capture the time-frequency correlation between the equalization errors in an orthogonal frequency division multiplexing (OFDM) grid, and for this purpose, we make use of a convolutional neural network (CNN). Since there is an interdependency between the equalization errors of all users due to inter-user interference, we propose to deal with it by making use of self-attention mechanism [6]. The most significant difference between this work and [7] is that the latter considers a more complex LMMSE channel estimator which requires the spatial, temporal, and frequency correlation matrices (see [7, Sec. II-B]) of the channel for each user, and this has a lot of practical limitations.

The rest of the paper is organized as follows. Section II describes the system model and the set-up while Section III presents the proposed neural demapper. Simulation results are provided in Section IV and the concluding remarks constitute Section V.

Notation: The field of complex numbers and real numbers are respectively denoted by ℂ and ℍ. Throughout the rest of the paper, boldface uppercase (lowercase) letters denote matrices (vectors). The Frobenius norm of a matrix is denoted by ∥X∥. The complex conjugate of x is denoted by x∗, and the transpose and Hermitian transpose of a matrix X by XT and XH, respectively. The identity matrix is denoted by I with its size understood from the context.

II. PRELIMINARIES

A. System Model

In this paper, we consider multiple single-antenna users transmitting on the uplink, but a similar treatment holds for MU-MIMO transmission on the uplink/downlink as well. The
transceiver model is based on the 3rd Generation Partnership Project (3GPP) recommendations for 5G physical uplink shared channel (PUSCH), and the receiver architecture is illustrated in Fig. 1.

We assume that there are \(N_u\) single-antenna users transmitting to a base station equipped with \(N_r\) receive antennas. At the transmitter of each user, message bits are encoded using low-density parity-check (LDPC) coding and then independently mapped to constellation symbols from a unit-energy constellation denoted by \(\mathbb{Q}\) (for simplicity, we assume the same constellation for all users, but these can be different in practice). These data symbols are then mapped to the data-carrying REs and pilot symbols are mapped to pilot-carrying REs in the OFDM grid [8, Sec. 6.4] before being transmitted over the channel. In this paper, we assume that an OFDM grid refers to the grid of REs associated with a transmission slot as defined by 3GPP [8], and has \(N_f\) subcarriers and \(N_t\) symbols (typical value being 14 in 5G NR). The frequency domain signal model for any index pair \((m, n)\) that denotes the \(m\)th subcarrier and the \(n\)th symbol in the grid is given as

\[
y_{m,n} = \mathbf{H}_{m,n}x_{m,n} + n_{m,n}\tag{1}
\]

where \(y_{m,n} \in \mathbb{C}^{N_r \times 1}\) is the received signal vector, \(\mathbf{H}_{m,n} \triangleq [h_{m,n}^{(1)}, \ldots, h_{m,n}^{(N_u)}] \in \mathbb{C}^{N_r \times N_u}\) is the composite channel matrix with \(h_{m,n}^{(i)} \in \mathbb{C}^{N_r \times 1}\) representing the channel from User \(i\) to the base station, where \(w_{m,n} \in \mathbb{C}^{N_r \times 1}\) is the transmitted composite signal from the \(N_u\) users, and \(n_{m,n} \in \mathbb{C}^{N_r \times 1}\) represents the zero mean additive white Gaussian noise (AWGN) with variance \(\sigma^2\). Following the definition in [9, Sec. II-A], the instantaneous signal-to-noise ratio (SNR) at the receiver for the resource grid in context is defined as

\[
\text{SNR} = \frac{\sum_{m,n} ||\mathbf{H}_{m,n}||^2}{N_f N_t N_r N_u \sigma^2}.	ag{2}
\]

At the base station receiver, after cyclic prefix (CP) removal and fast Fourier transform (FFT) of the received signal, LMMSE channel estimation is performed on the signals received at the pilot REs. We assume that the pilots of users are transmitted on mutually non-overlapping REs, as shown in Fig. 2. Therefore, the LMMSE channel estimate at any pilot RE with index pair \((m, n)\) for User \(i\) is given as

\[
\hat{\mathbf{h}}_{m,n}^{(i)} = \left(\mathbf{x}_p^{(i)}\right)^* \mathbf{R}_s^{(i)} \left[\mathbf{R}_s^{(i)} + \sigma^2 \mathbf{I}\right]^{-1} y_{m,n},
\]

where \(x_p^{(i)}\) is the unit-energy pilot signal transmitted by the \(i\)th user, and we assume that the spatial correlation covariance \(\mathbf{R}_s^{(i)} \triangleq \mathbb{E} \left[\mathbf{h}_{m,n}^{(i)} \left(\mathbf{h}_{m,n}^{(i)}\right)^H\right]\) (expectation is over the RE indices) and the noise variance are known at the receiver. For the remaining data-carrying REs, nearest-pilot (NP) channel estimation is performed, i.e., the channel is estimated to be the same as that of the nearest pilot RE in the resource grid.

The composite channel estimate for all users is denoted by \(\hat{\mathbf{H}}_{m,n} \in \mathbb{C}^{N_r \times N_u}\). The covariance of the channel estimation error at the pilot locations for the \(i\)th user is given by the well-known formula as

\[
\mathbf{R}_{e}^{(i)} \triangleq \mathbb{E} \left[\left(\mathbf{h}^{(i)} - \hat{\mathbf{h}}^{(i)}\right)\left(\mathbf{h}^{(i)} - \hat{\mathbf{h}}^{(i)}\right)^H\right] = \mathbf{R}_s^{(i)} - \mathbf{R}_s^{(i)} \left[\mathbf{R}_s^{(i)} + \sigma^2 \mathbf{I}\right]^{-1} \mathbf{R}_s^{(i)}.	ag{4}
\]

Therefore, the error covariance for the composite channel estimate is \(\mathbf{R}_e \triangleq \mathbb{E} \left[\left(\mathbf{H} - \hat{\mathbf{H}}\right)\left(\mathbf{H} - \hat{\mathbf{H}}\right)^H\right] = \sum_{i=1}^{N_u} \mathbf{R}_{e}^{(i)}\).

With \(\hat{\mathbf{H}}\) and \(\mathbf{R}_e\) thus obtained, we have

\[
y_{m,n} = \tilde{\mathbf{H}}_{m,n}x_{m,n} + \left(\mathbf{H}_{m,n} - \tilde{\mathbf{H}}_{m,n}\right)x_{m,n} + n_{m,n}
= \tilde{\mathbf{H}}_{m,n}x_{m,n} + w_{m,n}\tag{5}
\]

where \(w_{m,n} \triangleq \left(\mathbf{H}_{m,n} - \tilde{\mathbf{H}}_{m,n}\right)x_{m,n} + n_{m,n}\) has covariance \(\mathbf{R}_{w} \triangleq \mathbf{R}_e + \sigma^2 \mathbf{I}\) and is uncorrelated with \(\tilde{\mathbf{H}}_{m,n}\) (due to LMMSE estimation). Next, noise-whitening is performed as follows.

\[
\tilde{y}_{m,n} \triangleq \mathbf{R}_w^{-\frac{1}{2}} y_{m,n} = \mathbf{R}_w^{-\frac{1}{2}} \tilde{\mathbf{H}}_{m,n}x_{m,n} + \mathbf{R}_w^{-\frac{1}{2}} w_{m,n}.	ag{6}
\]

The result of this operation is that the covariance of \(\mathbf{R}_w^{-\frac{1}{2}} w_{m,n}\) is the identity matrix. With \(\tilde{\mathbf{H}}_{m,n} \triangleq \mathbf{R}_w^{-\frac{1}{2}} \tilde{\mathbf{H}}_{m,n}\), we perform LMMSE equalization to obtain

\[
\hat{x}_{m,n} = \tilde{\mathbf{H}}_{m,n}^H (\tilde{\mathbf{H}}_{m,n} \tilde{\mathbf{H}}_{m,n}^H + \mathbf{I})^{-1} \tilde{y}_{m,n}.	ag{7}
\]

The post-equalization error is given by

\[
z_{m,n} \triangleq \hat{x}_{m,n} - \hat{x}_{m,n}\tag{8}
\]

with covariance \(\mathbf{R}_{z,m,n} \triangleq \mathbf{I} - \tilde{\mathbf{H}}_{m,n}^H (\tilde{\mathbf{H}}_{m,n} \tilde{\mathbf{H}}_{m,n}^H + \mathbf{I})^{-1} \tilde{\mathbf{H}}_{m,n}\).
we have plotted samples of the equalized signals across time and frequency, as illustrated in Fig. 3. In the figure, the equalization errors are correlated. Moreover, the equalization errors are correlated. Let the Gaussian assumption on \( z \) be true. With the nearest-pilot channel estimator, the assumption that the error \( z_{m,n} \) is Gaussian distributed is no longer a reasonable one. The Gaussian demapper acts on each constellation symbol with bit \( z \), being the equalization error. Let the size of all constellation symbols with bit \( z \), \( Q_{m,n} \), \( \forall m,n \leq N_u \) be \( 2 \). From this figure and from (7)–(8), the errors of each user are independently processed, and it is unlikely that there is a relationship between the errors of adjacent REs for the same user, as shown in Fig. 3. The errors of each user are dependent on the amount of correlation between the user’s channel and the channels of other users (inter-user interference).

Let \( X_i \in \mathbb{C}^{N_f \times N_t} \) denote the grid of equalized signals for User \( i \) so that the \((m,n)^{th}\) entry of \( X_i \) is \( \hat{x}_{m,n,i} \) (given by (9)). Similarly, let \( R_{X,i} \in \mathbb{R}^{N_f \times N_t} \) denote the matrix whose \((m,n)^{th}\) entry is \( r_{m,n}^{(i)} \), which is the \((i,i)^{th}\) element of \( R_{2,m,n} \). Let \( X \in [X_1, \ldots, X_{N_f}] \in \mathbb{C}^{N_u \times N_f \times N_t} \), and \( R_X \in [R_{X,1}, \ldots, R_{X,N_f}] \in \mathbb{R}^{N_u \times N_f \times N_t} \). So, we are interested in finding a suitable function

\[
f : \mathbb{C}^{N_u \times N_f \times N_t} \times \mathbb{R}^{N_u \times N_f \times N_t} \rightarrow \mathbb{R}^{N_u \times N_f \times N_t \times K}
\]

where \( L \in [L_1, \ldots, L_{N_f}] \) with \( L_i \) being the 3-dimensional array of LLRs for each bit of User \( i \) in each RE of the grid. Since \( f \) is not straightforward to obtain, we make use of techniques from machine learning to approximate it, and this is detailed in the following section.

III. CONVOLUTIONAL ATTENTION-BASED NEURAL DEMAPPER

In order to approximate the function given in (12), we need a neural network that is capable of capturing the relationship between the errors of a user within the OFDM grid. A natural choice for this would be a CNN. In recent years, CNN-based architectures have shown great results for the physical layer (see [4], [10]), and these use ResNet blocks [11]. As corroborated by simulation results in Section IV, ResNet-based demappers are performance-limited for our task since the correlation between users is not captured. Indeed, each user’s inputs are independently processed, and it is unlikely that there is a relationship between the errors of adjacent REs for the same user, as shown in Fig. 3. The errors of each user are dependent on the amount of correlation between the user’s channel and the channels of other users (inter-user interference).
that the NN learns to deal with this correlation. We need to capture the effects of the inter-user interference (caused by the correlation between the channels of the users). This is the main motivation for using self-attention that was originally proposed in [6] in the context of natural language processing.

We draw inspiration from RE-MIMO [12], which uses self-attention for MU-MIMO detection. In RE-MIMO, the encoder-decoder-based multi-head-attention (MHA) mechanism that was proposed in [6] is adapted to the physical layer. An inherent issue with using attention is that because it has its roots in natural language processing, the inputs need to be vectorized. If we wish to adapt it to a grid like in the case of OFDM-based signal processing or image processing, we end up with a very large amount of trainable parameters. There have been a few noteworthy efforts that address this issue for the task of image-classification. Some examples are [13] and [14] which implement a fully attention-based image classifier with a performance similar to that of CNN-based models. More recently, jointly using convolution and attention (convolutional-attention) [15], [16] has shown great results, and we use these concepts for our purpose.

**Algorithm 1:** The sequence of operations for the NN of Table I

\[
\begin{align*}
\text{Input: } & X \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times d_m}, \\
& R_X \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times 1}, \quad d_m = 64 \\
\text{Output: } & L \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times K}, \\
Z & \leftarrow \text{Concatenate} \left( \hat{X}, R_X \right) \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times 3}; \\
Z & \leftarrow \text{Reshape} \left( Z \right) \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times d_{m}}; \\
Z & \leftarrow \text{Conv2D} \left( Z \right) \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times d_{m}}; \\
Z & \leftarrow \text{CvT} \left( Z \right) \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times d_{m}}; \\
Z & \leftarrow \text{CvT} \left( Z \right) \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times K}; \\
L & \leftarrow \text{Reshape} \left( Z \right) \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times K};
\end{align*}
\]

**Algorithm 2:** The sequence of operations for the CvT block of Fig. 4

\[
\begin{align*}
\text{Input: } & Z \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times d_{m}}; \\
\text{Output: } & Z \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times d_{m}}; \\
Q & \leftarrow \text{SeparableConv2D} \left( Z \right) \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times d_{m}}; \\
Q & \leftarrow \text{BatchNorm} \left( Q \right) \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times d_{m}}; \\
Q & \leftarrow \text{Rearrange} \left( Q \right) \in \mathbb{R}^{B \times N_f \times N_u \times N_t \times d_{m}}; \\
K & \leftarrow \text{SeparableConv2D} \left( Z \right) \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times d_{m}}; \\
K & \leftarrow \text{BatchNorm} \left( K \right) \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times d_{m}}; \\
K & \leftarrow \text{Rearrange} \left( K \right) \in \mathbb{R}^{B \times N_f \times N_u \times N_t \times d_{m}}; \\
V & \leftarrow \text{SeparableConv2D} \left( Z \right) \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times d_{m}}; \\
V & \leftarrow \text{BatchNorm} \left( V \right) \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times d_{m}}; \\
V & \leftarrow \text{Rearrange} \left( V \right) \in \mathbb{R}^{B \times N_f \times N_u \times N_t \times d_{m}}; \\
A & \leftarrow \text{MHA} \left( Q, K, V \right) \in \mathbb{R}^{B \times N_f \times N_u \times N_t \times d_{m}}; \\
A & \leftarrow \text{Rearrange} \left( A \right) \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times d_{m}}; \\
Z & \leftarrow Z + A \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times d_{m}}; \\
W & \leftarrow \text{BatchNorm} \left( Z \right) \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times d_{m}}; \\
W & \leftarrow \text{SeparableConv2D} \left( \text{ReLU} \left( W \right) \right) \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times d_{m}}; \\
W & \leftarrow \text{SeparableConv2D} \left( \text{ReLU} \left( W \right) \right) \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times d_{m}}; \\
Z & \leftarrow Z + W \in \mathbb{R}^{B \times N_u \times N_f \times N_t \times d_{m}};
\end{align*}
\]

The architecture of the proposed convolutional attention-based NN is depicted in Table I. The sequence of operations...
of the proposed NN is shown in Algorithm 1. The sequence of operations specific to the CvT block is shown in Algorithm 2 while that of the MHA block is shown in Algorithm 3. In these algorithms, B refers to the batch size, and "Rearrange" refers to multiple transpose and reshape operations rather than just a simple reshape.

**B. Training**

Let \( \mathcal{G} \) denote the set of all RE index pairs so that \(|\mathcal{G}| = N_f N_t\), and let \( b_{m,n,i,j} \in \{0,1\} \) denote the \( j \)-th bit transmitted by the \( i \)-th user on the \((m,n)\)-th RE. Then, following the notation used in the previous section, the training aims to maximize the rate

\[
R = \frac{1}{N_u|\mathcal{G}|} \sum_{i=1}^{N_u} \sum_{(m,n)\in \mathcal{G}} \sum_{j=1}^{K} I(b_{m,n,i,j}; \hat{X}, R_X) - \frac{1}{N_u|\mathcal{G}|} \sum_{i=1}^{N_u} \sum_{(m,n)\in \mathcal{G}} \sum_{j=1}^{K} KL(\hat{X}; R_X) + D_{KL}[q(b_{m,n,i,j}|\hat{X}, R_X)||p(b_{m,n,i,j}|\hat{X}, R_X)]
\]

where \( R \) is an achievable information rate \([17]\), \( I(X;Y) \) the mutual information between random variables \( X \) and \( Y \), \( D_{KL}(q||p) \) the Kullback–Leibler divergence between distributions \( q \) and \( p \), \( q(b_{m,n,i,j}|X,R_X) \) the conditional posterior distribution of \( b_{m,n,i,j} \) generated by the demapper, and \( p(b_{m,n,i,j}|\hat{X}, R_X) \) corresponds to the true posterior distribution. It is straightforward to calculate \( q(b_{m,n,i,j}|X,R_X) \) from the LLR generated by the demapper. The first term in (13) corresponds to the rate achieved by an optimal demapper (\( q = p \)) while the second term can be viewed as the rate-loss caused by an imperfect demapper.

Let \( \Theta \) denote the set of trainable parameters of our learned demapper. We use stochastic gradient descent (SGD) to optimize it, and it has been shown in [10] that maximizing \( R \) in (13) is equivalent to minimizing the binary cross-entropy (BCE) between \( q \) and \( p \). Therefore, we generate a batch (of size \( B \)) of independent and identically distributed (i.i.d.) equiprobable bits \( \{b_{m,n,i,j}^{(s)}\}_{s=1}^{D} \), \( i = 1, \cdots, N_u, j = 1, \cdots, K, (m,n) \in \mathcal{G} \) in each training epoch. Let \( q_{\Theta}(i_{m,n,i,j}^{(s)}|\hat{X}, R_X) \), the conditional distribution of \( b_{m,n,i,j}^{(s)} \) generated from the output LLR of the demapper. Using the system model in Section II, we train the NN by using the following loss function on this batch.

\[
L(\Theta) \triangleq \frac{1}{BN_f N_t |\mathcal{G}|} \sum_{s=1}^{D} \sum_{i=1}^{N_u} \sum_{(m,n)\in \mathcal{G}} \sum_{j=1}^{K} \log_2 \left( q_{\Theta}(i_{m,n,i,j}^{(s)}|\hat{X}, R_X) \right)
\]

(14)

The channel is generated using QuaDRiGa [18] in order to obtain the equalized signals in the above equation.

**IV. Simulation Results**

Two sets of channel realizations were generated using QuaDRiGa channel generation tool according to the 3GPP UMi LOS/NLOS model. We used 50,000 realizations for training and 10,000 realizations for evaluation. Since we evaluate the performances for an SNR in the range 10–31 dB, the training was done in the range 7–34 dB. Also, during the training the randomly generated bits were not LDPC-encoded, the reason being that the randomness of the samples can be beneficial and can potentially speed up the training. Table II summarizes the main parameters of the simulation. It

| Layer | Type | # Filters | Filter size | Dilation | Output dimension |
|-------|------|-----------|-------------|----------|-----------------|
| Input 1: \( X \) | Equalized symbols | N/A | N/A | N/A | \((B, N_u, N_f, N_t, 2)\) |
| Input 2: \( R_X \) | Error Covariance | N/A | N/A | N/A | \((B, N_u, N_f, N_t, 1)\) |
| Concat: \( Z \) | Concatenation of Inputs 1 and 2 | N/A | N/A | N/A | \((B, N_u, N_f, N_t, 3)\) |
| Reshape \( Z \) | Reshape | N/A | N/A | N/A | \((B N_u, N_f, N_t, 3)\) |
| \( Conv_{in} \) | Conv2D | 64 | \((3, 3)\) | \((1, 1)\) | \((B N_u, N_f, N_t, 3)\) |
| Three CvT blocks | CvT | 64 | \((3, 3)\) | \((1, 1)\) | \((B N_u, N_f, N_t, 64)\) |
| \( Conv_{out} \) | Conv2D | \( K \) | \((1, 1)\) | \((1, 1)\) | \((B N_u, N_f, N_t, K)\) |

**TABLE I: Convolutional attention-based demapper architecture**
took 200,000 iterations for the training loss to satisfactorily converge for the proposed NN. We also used a ResNet-based demapper (the 3 CvT blocks replaced by 5 ResNet blocks) for comparison in order to highlight the significance of the attention mechanism. This ResNet-based demapper converged within 30,000 iterations.

| Parameter                  | Value |
|----------------------------|-------|
| $N_f$                      | 14    |
| $N_f'$                     | 72    |
| $N_u$                      | 4     |
| $N_r'$                     | 16    |
| Sub-carrier spacing $\Delta f$ (kHz) | 15 |
| Cyclic prefix duration $\Delta C^P$ (µs) | 6 |
| $(d_{mi}, d_{ki}, N_h)$     | (64, 8, 8) |
| Batch size $B$             | 2     |
| LDPC code-rate $r$         | 1/2   |
| User Speed (kmph)          | 3.6   |
| Modulation                 | QPSK  |

**TABLE II: Simulation Parameters**

Figure 5 presents the BER for the following receivers – a genie-aided receiver with perfect channel state information (CSI) and Gaussian demapping (optimal in this case), the nearest-pilot channel estimator with a Gaussian demapper (baseline), the ResNet-based demapper, and our proposed CvT-based demapper. Compared to the baseline, the ResNet-based demapper doesn’t provide any significant gain. On the other hand, the CvT-based demapper provides gains of around 10 dB compared to the baseline and is much closer to the perfect CSI scheme.

![Graph comparing BER for different receivers](image)

**Fig. 5: BER comparison**

V. CONCLUDING REMARKS

In this paper, we presented a convolutional attention-based demapper for MU-MIMO detection in the presence of a very simple channel estimator. This demapper was shown to be capable of significantly reversing the adverse effects of imperfect channel estimation. The gains provided by the proposed NN over the baseline are very promising, and it could be interesting to study the usage of attention in other physical layer applications for MU-MIMO systems. Optimizing the number of trainable parameters of this proposed NN in order to make it more practical could be another direction of research.

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