Spherical Normalization, Differential Encoding, and Complex-valued Convolutions for Deep Learning in Time-varying MIMO Channel State Estimation

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Contents

1 Introduction

Here is an example of a citation [1]. Citations are included in the `cited_works.bib` file.

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1.1 Introduction Section #1

For an example of a figure with subfigures, see Fig 1a or 1b.

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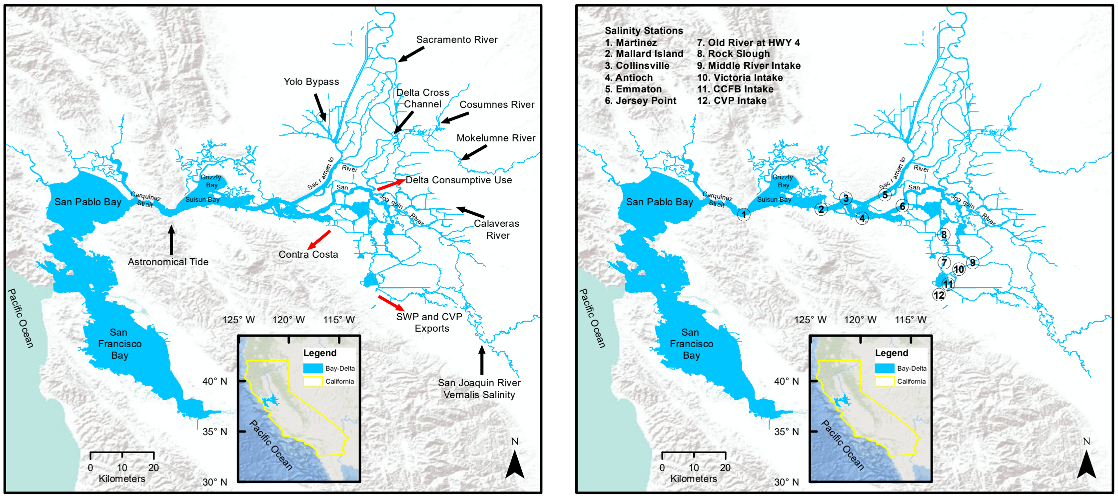

(a) ANN inputs and input locations.

(b) Locations of the 12 Study Salinity Stations.

Figure 1: ANN input and output locations in San Francisco Bay and Sacramento-San Joaquin Delta Estuary (Bay-Delta Estuary).

1.1.1 MIMO Channel Overview

In this work, we consider a MIMO channel with a multiple antennas ($n_B \gg 1$) at the transmitter (gNodeB or gNB) servicing one or more user equipment (UE) with single antennas. The network utilizes orthogonal frequency division multiplexing (OFDM) with N_f subcarriers, the m-th downlink and uplink channels at the receiver are given as

$$y_{d,m} = \mathbf{h}_{d,m}^H \mathbf{w}_{t,m} x_{d,m} + n_{d,m}, \tag{1}$$

$$y_{u,m} = \mathbf{w}_{r,m}^H \mathbf{h}_{u,m} x_{u,m} + \mathbf{w}_{r,m}^H \mathbf{n}_{u,m}. \tag{2}$$

The resulting downlink and uplink CSI matrices are given as

$$\mathbf{H}_d = \begin{bmatrix} \mathbf{h}_{d,1} & \dots & \mathbf{h}_{d,N_f} \end{bmatrix}^H \in \mathbb{C}^{N_f \times N_b},$$
$$\mathbf{H}_u = \begin{bmatrix} \mathbf{h}_{u,1} & \dots & \mathbf{h}_{u,N_f} \end{bmatrix}^H \in \mathbb{C}^{N_f \times N_b}.$$

Table 1: MIMO system parameters and variables considered in this work.

Symbol	**Dimension**	**Description**
$y_{d,m}$	$\mathbb{C}^1$	Received downlink symbol on m-th subcarrier
$\mathbf{h}_{d,m}$	$\mathbb{C}^{N_b \times 1}$	Downlink impulse response on m-th subcarrier
$\mathbf{w}_{t,m}$	$\mathbb{C}^{N_b \times 1}$	Transmitter precoding vector for m-th subcarrier
$x_{d,m}$	$\mathbb{C}^1$	Trasmitted symbol on m-th subcarrier
$n_{d,m}$	$\mathbb{C}^1$	Downlink noise on m-th subcarrier
$y_{u,m}$	$\mathbb{C}^1$	Received uplink symbol on m-th subcarrier
$\mathbf{h}_{u,m}$	$\mathbb{C}^{N_b \times 1}$	Uplink impulse response on m-th subcarrier
$\mathbf{w}_{r,m}$	$\mathbb{C}^{N_b \times 1}$	Received precoding vector for m-th subcarrier
$x_{u,m}$	$\mathbb{C}^1$	Received symbol on m-th subcarrier
$\mathbf{n}_{u,m}$	$\mathbb{C}^1$	Uplink noise on m-th subcarrier

1.2 Introduction Section #2

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1.3 Channel Model

For all CSI tests, we mainly rely on the COST2100 MIMO channel model [2]. We use two datasets with a single base station (gNB) and a single user equipment (UE) in the following scenarios:

Table 2: Parameters used for COST2100 simulations for both Indoor and Outdoor datasets.

Symbol	**Value**	**Description**
N_b	32	Number of antennas at gNB
N_f	1024	Number of subcarriers for OFDM link
R_d	32	Number of delay elements kept after truncation
N	10^6	Total number of samples per dataset
T	10	Number of timeslots
δ	40ms, 80ms	Feedback delay interval between consecutive CSI timeslots

1. **Indoor** channels using a 5.3GHz downlink at 0.001 m/s UE velocity, served by a gNB at center of a 20m×20m coverage area.

2. **Outdoor** channels using a 300MHz downlink at 0.9 m/s UE velocity served by a gNB at center of a 400m×400m coverage area.

In both scenarios, we use the parameters listed in Table 2.

2 Spherical Normalization

Most work in deep learning for CSI estimation focuses on different neural network architectures, training frameworks, or hyperparameter tuning. However, the normalization used in these works is typically the same; the extrema (i.e., the minimum and the maximum) of the dataset are used to perform minmax scaling on the entire dataset,

$$\mathbf{H}_{k,\text{minmax}}(i,j) = \frac{\mathbf{H}_k(i,j) - \mathbf{H}_{\text{min}}}{\mathbf{H}_{\text{max}} - \mathbf{H}_{\text{min}}}$$

for $n \in [1, \dots, N]$ given a dataset of N samples and i, j indexing the rows/columns of the CSI matrices. The resulting samples are cast to the range $[0, 1]$.

For image data, minmax normalization results in each image's color channels scaled to the range $[0, 1]$. The resulting distribution for each color channel is typically satisfactory for image tasks, as the variance is not much smaller than the range of the normalized data (see Fig. 2).

However, for CSI matrices, minmax normalization is applied to the real and imaginary channels of each element. For typical channel models and parameters, the distribution of channel elements (see Fig. 3) tends to have much lower variance than that of ImageNet. This smaller variance can be explained by the difference in the datasets' ranges – while the channels in image data (e.g., ImageNet) assume integer values between $[0, 255]$, the channels in CSI data (e.g., COST2100) assume floating point values smaller than 10^{-3}.

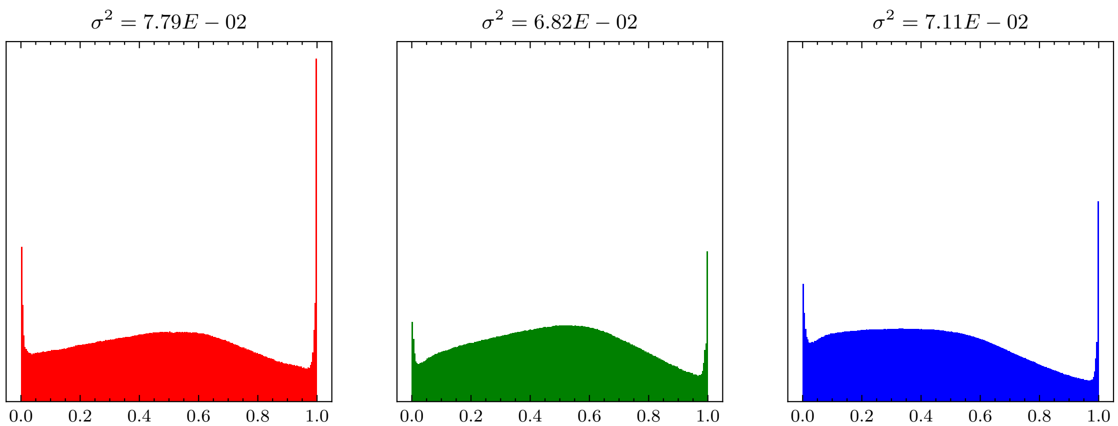

Figure 2: Distribution and variance of minmax-normalized ImageNet color channels ($N = 50000$) images.

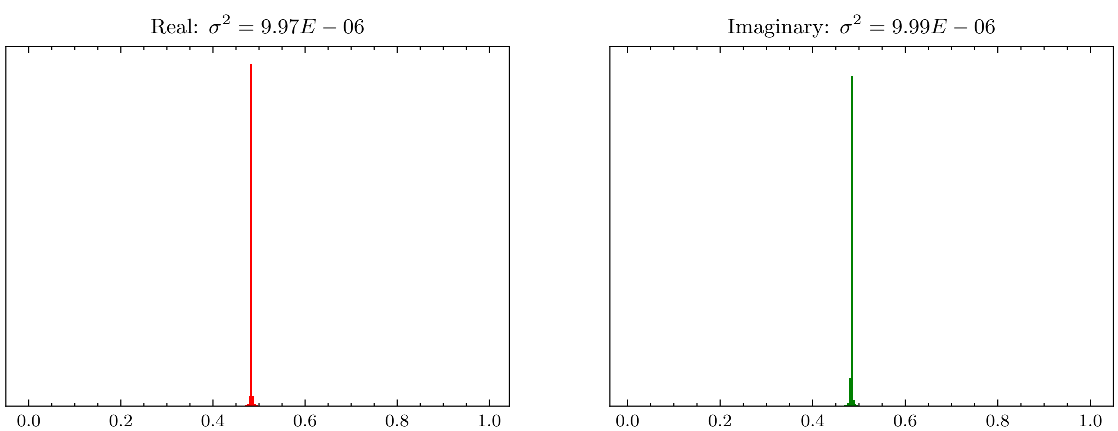

Figure 3: Distribution and variance of minmax-normalized COST2100 real/imaginary channels ($N = 99000$) images.

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2.1 Related Work

Several works have investigated normalization techniques for deep learning such as batch normalization [3], instance normalization [4], layer normalization [5], and group normalization [6]. These normalization techniques scale the outputs of latent layers in neural networks, which helps to solve the problem of covariate shift [3] where the mean and variance of changes between subsequent layers of the network.

Other works have studied normalization of the network's inputs. A number of works have investigated adaptive normalization techniques for time series estimation tasks [7–9]. In [10], the authors proposed a trainable input network which learns to shift, scale, and filter the unnormalized data while training the target network for a time series prediction task.

2.2 Methods

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2.2.1 Notation

For an example of a table, see Table 4.

Table 3: Notations

Variable	Definition
M	Number of input hydrological variables denoted in Fig. 1a
N	Number of data samples, or days, in dataset
T	Number of days' data used for estimation
T_r	Dimension of data after pre-processing
z_n	Time series used for estimating salinity level on day n, size is $\mathbb{R}^{M \times T}$
x_n	Pre-processed time series with size $\mathbb{R}^{M \times T_r}$ for day n
f	A convolutional filter with size $\mathbb{R}^{M \times T \times T_r}$
y_n	ANN-estimated salinity level for one or more locations on day n

2.2.2 Spherical Normalization

Rather than apply minmax normalization, which is adversely impacted by outliers, we propose spherical normalization. Before describing spherical normalization in detail, consider z-score normalization. Given a random variable, x, with mean μx and standard deviation μ.

The z-score normalized version of this random variable is given as

$$z = \frac{x - \mu}{\sigma^2}. \tag{3}$$

Assuming x is normally distributed, the resulting random variable, z, is a standard normal distribution such that $z \sim \mathcal{N}(0, 1)$. Inspired by z-score normalization, we seek a normalization scheme which adjusts the range of each channel sample. Under spherical normalization, each sample in the dataset is scaled by its power. Denote the k-th downlink CSI matrix of the dataset as $\mathbf{H}_d^k$. The spherically normalized version of the downlink CSI is given as

$$\check{\mathbf{H}}_d^k = \frac{\mathbf{H}_d^k}{\|\mathbf{H}_d^k\|_2}. \tag{4}$$

Observe that (4) is similar to (3) without the mean shift in the numerator[1] and with the power term of each CSI sample rather than the variance of the entire distribution. After applying (4) to each sample, minmax scaling is applied to the entire dataset. The resulting dataset under spherical normalization can exhibit a larger variance than the same dataset under minmax scaling (compare Fig. 4 with Fig. 3). Beyond desirable properties in the input

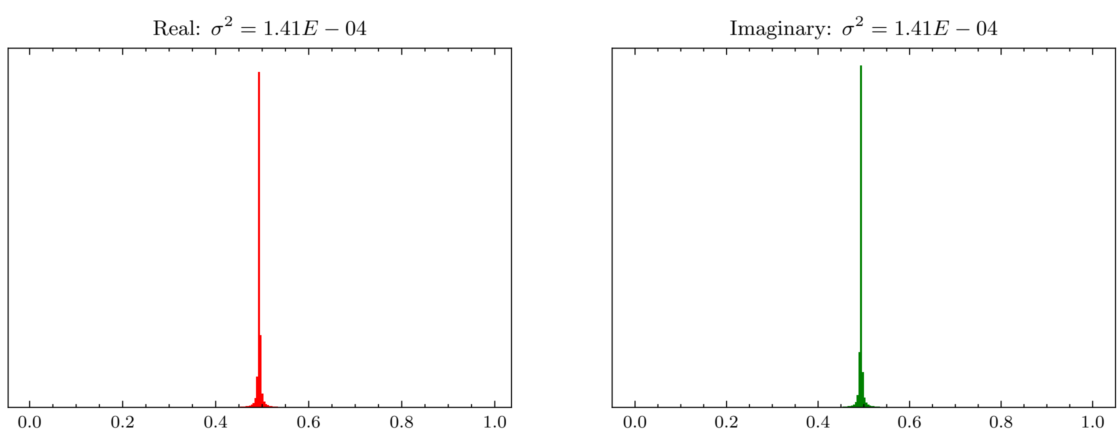


Figure 4: Distribution and variance of COST2100 real/imaginary channels under spherical normalization ($N = 99000$) images.

[1]Since the mean of COST2100 data is $\approx 10^{-10}$, we can safely ignore this mean shift in spherical normalization.

distribution, spherical normalization also results in an objective function which is better matched with the evaluation criterion. Neural networks for CSI estimation are optimized using the mean-squared error loss,

$$\mathrm{MSE} = \frac{1}{N}\sum_{k=1}^{N} \|\mathbf{H}_k - \hat{\mathbf{H}}_k\|^2, \tag{5}$$

while channel state reconstruction accuracy is measured in terms of normalized mean-squared error,

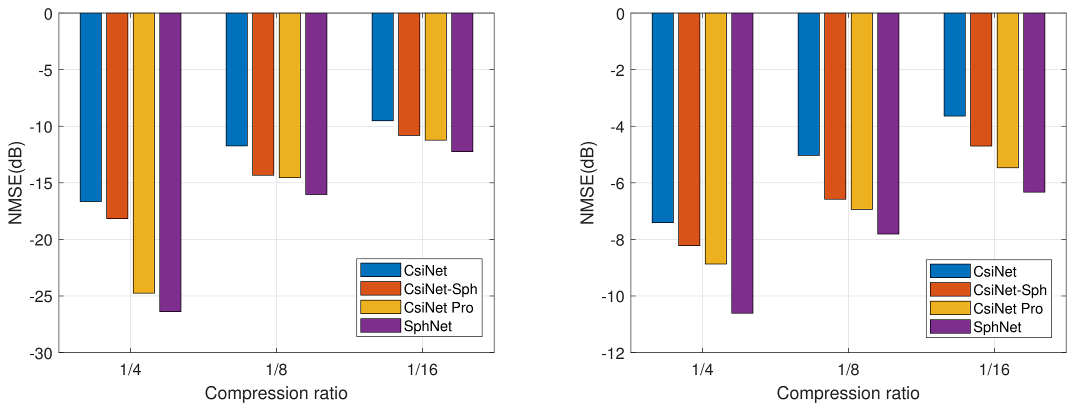
$$\mathrm{NMSE} = \frac{1}{N}\sum_{k=1}^{N} \frac{\|\mathbf{H}_k - \hat{\mathbf{H}}_k\|^2}{\|\mathbf{H}_k\|^2}. \tag{6}$$

Observe that when the $\mathbf{H}_k$ ($\hat{\mathbf{H}}_k$) in (5) is replaced with $\check{\mathbf{H}}_k$ ($\hat{\check{\mathbf{H}}}_k$), we have

$$\begin{aligned}
\frac{1}{N}\sum_{k=1}^{N} \|\check{\mathbf{H}}_k - \hat{\check{\mathbf{H}}}_k\|^2 &= \frac{1}{N}\sum_{k=1}^{N} \left\| \frac{\mathbf{H}_k}{\|\mathbf{H}_k\|^2} - \frac{\hat{\mathbf{H}}_k}{\|\mathbf{H}_k\|^2} \right\|^2 \\
&= \frac{1}{N}\sum_{k=1}^{N} \frac{\|\mathbf{H}_k - \hat{\mathbf{H}}_k\|^2}{\|\mathbf{H}_k\|^2},
\end{aligned}$$

which is equivalent to (6). Thus, a neural network optimized with MSE as the loss function and trained using spherically normalized data is in fact being optimized with respect to NMSE of the original data.

Training on spherically normalized data and optimizing with respect to NMSE can yield better accuracy. Fig. 5 demonstrates this improvement for CsiNet and CsiNet Pro on the COST2100 dataset. For both networks, the number of



(a) Indoor (b) Outdoor

Figure 5: Reconstruction error for CsiNet [11] and CsiNet Pro with and without spherical normalization. SphNet combines CsiNet Pro with spherical normalization [12].

2.2.3 Methods Subsection #2

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3 MarkovNet: A Deep Learning-based Differential Autoencoder

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3.2 Methods

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3.2.2 Method Subsection #1

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$$x_{n,i}^{(m)} = \sum_{j=1}^{T} z_{n-j+1}^{(m)} \times f_{j,i}^{(m)}, \tag{7}$$

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4 Proposed Work

4.1 Proposed Work Section #1

4.1.1 Proposed Work Subsection #1

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4.1.2 Proposed Work Subsection #2

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5 Conclusion

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