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

Mason del Rosario

University of California, Davis

Davis, CA 95616

mdelrosa@ucdavis.edu

February 25, 2021

Contents

1 Introduction

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

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 a single (or multiple) user equipment(s) (UE) with a single antenna. 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

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

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

The resulting downlink and uplink channel state information (CSI) matrices are given as

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

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

To achieve near-capacity transmission rates, the transmitter needs access to an appropriate estimate of $\bar{\mathbf{H}}_d$ [2]. In time division duplex (TDD), downlink CSI estimation can be performed by using pilots in uplink frames due to channel reciprocity. In contrast, frequency domain duplex (FDD) does not admit channel reciprocity due to frequency-selective channels, and CSI estimates must be acquired using feedback.

Given their dimensionality, feeding back entire CSI matrices is impractical. Instead, we seek a compressed representation of a sparse transformation. We consider the angular-delay representation of CSI matrices. Denote the unitary DFT (inverse DFT) matrix $\mathbf{F} \in \mathbb{C}^{n_f \times n_f}$

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

($\mathbf{F}^H \in \mathbb{C}^{n_f \times n_f}$), and denote the spatial-frequency CSI matrix as $\bar{\mathbf{H}}$. The angular-delay domain representation $\mathbf{H}$ is given as

$$\mathbf{H} = \mathbf{F}^H \bar{\mathbf{H}} \mathbf{F}$$

1.2 Channel Model

For all CSI tests, we mainly rely on the COST2100 MIMO channel model [3]. We use two datasets with a single base station (gNB) and a single user equipment (UE) in the following scenarios:

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.

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

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,

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

for $n \in [1, \ldots, N]$ 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. 1).

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. 2) 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}.
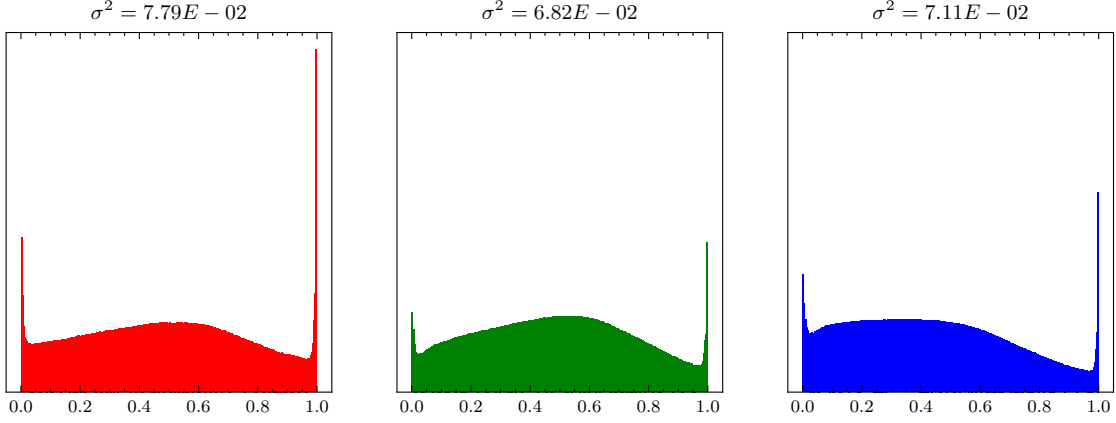

Figure 1: Distribution and variance of minmax-normalized ImageNet color channels ($N = 50000$) images.
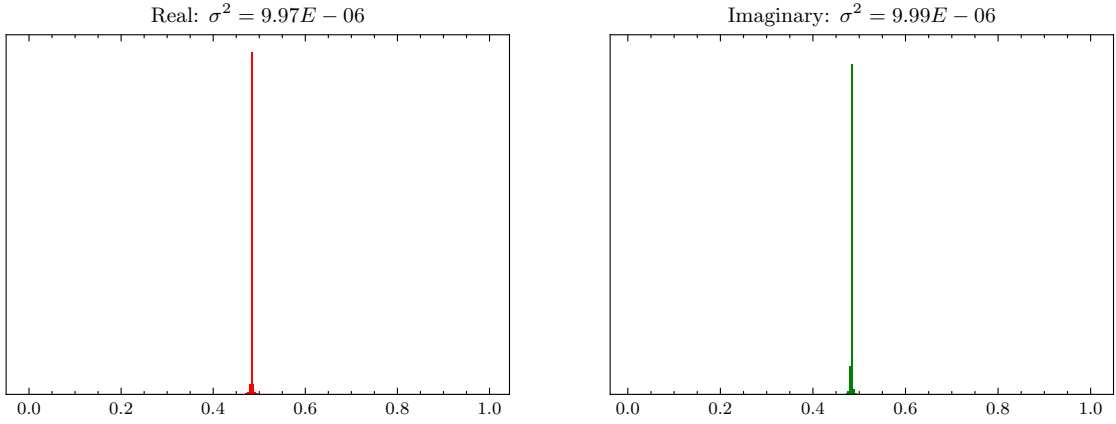

Figure 2: Distribution and variance of minmax-normalized COST2100 real/imaginary channels ($N = 99000$) images.

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris.

Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

2.1 Related Work

Several works have investigated normalization techniques for deep learning such as batch normalization [4], instance normalization [5], layer normalization [6], and group normalization [7]. These normalization techniques scale the outputs of latent layers in neural networks, which helps to solve the problem of covariate shift [4] 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 [8–10]. In [11], 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

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

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. **??**
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

$$z = \frac{x - \mu}{\sigma^2}. \tag{1}$$

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

$$\check{\mathbf{H}}_d^k = \frac{\mathbf{H}_d^k}{\|\mathbf{H}_d^k\|_2}. \tag{2}$$

Observe that (2) is similar to (1) 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 (2) 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. 3 with Fig. 2). Beyond desirable properties in the input
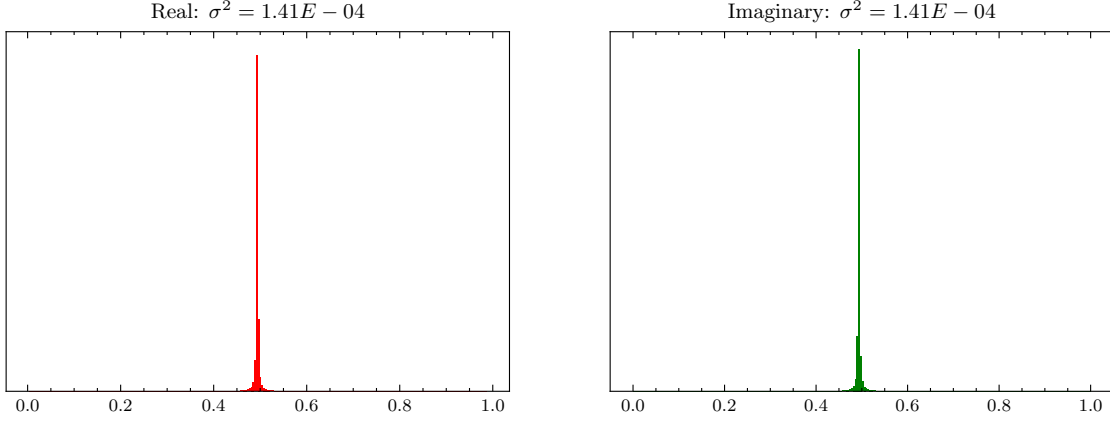

Figure 3: Distribution and variance of COST2100 real/imaginary channels under spherical normalization ($N = 99000$) images.

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,

$$\text{MSE} = \frac{1}{N} \sum_{k=1}^{N} \|\mathbf{H}_k - \hat{\mathbf{H}}_k\|^2, \tag{3}$$

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

$$\text{NMSE} = \frac{1}{N} \sum_{k=1}^{N} \frac{\|\mathbf{H}_k - \hat{\mathbf{H}}_k\|^2}{\|\mathbf{H}_k\|^2}. \tag{4}$$

---

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

9

Observe that when the $\mathbf{H}_k$ ($\hat{\mathbf{H}}_k$) in (3) is replaced with $\check{\mathbf{H}}_k$ ($\hat{\check{\mathbf{H}}}_k$), we have

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

which is equivalent to (4). 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. 4 demonstrates this improvement for CsiNet and CsiNet Pro on the COST2100 dataset. For both networks, the number of
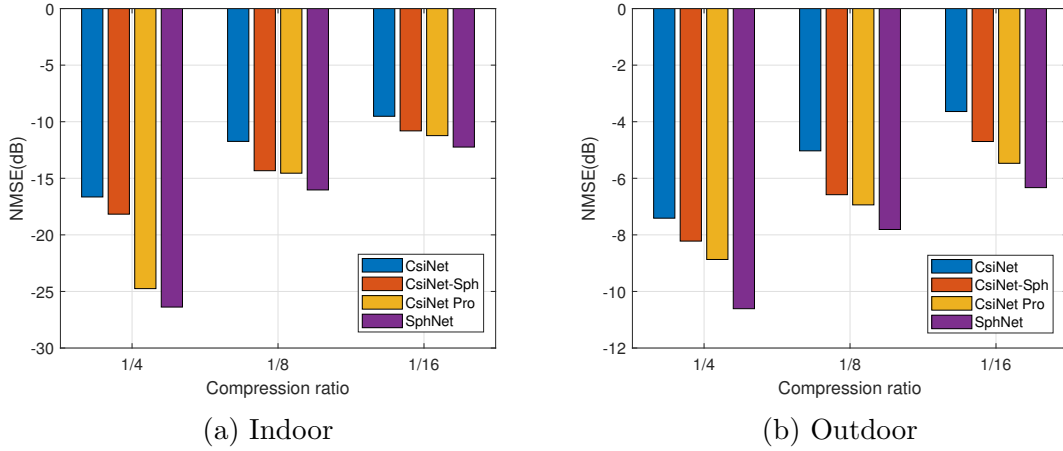

(a) Indoor   (b) Outdoor

Figure 4: Reconstruction error for CsiNet [12] and CsiNet Pro with and without spherical normalization. SphNet combines CsiNet Pro with spherical normalization [13].

2.2.3   Methods Subsection #2

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede.

Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

3 MarkovNet: A Deep Learning-based Differential Autoencoder

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus

a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

3.1   Related Work

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit.

Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

3.2 Methods

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

3.2.1 Notation

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet

ipsum. Nunc quis urna dictum turpis accumsan semper.

Table 4: Notations

Variable	Definition
M	Number of input hydrological variables denoted in Fig. **??**
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

3.2.2   Method Subsection #1

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus

a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

3.2.3 Methods Subsection #2

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

$$x_{n,i}^{(m)} = \sum_{j=1}^{T} z_{n-j+1}^{(m)} \times f_{j,i}^{(m)}, \tag{5}$$

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

4 Proposed Work

4.1 Proposed Work Section #1

4.1.1 Proposed Work Subsection #1

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

4.1.2 Proposed Work Subsection #2

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper. Lorem ipsum dolor sit amet, consectetuer

adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

5 Conclusion

Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Etiam lobortis facilisis sem. Nullam nec mi et neque pharetra sollicitudin. Praesent imperdiet mi nec ante. Donec ullamcorper, felis non sodales commodo, lectus velit ultrices augue, a dignissim nibh lectus placerat pede. Vivamus nunc nunc, molestie ut, ultricies vel, semper in, velit. Ut porttitor. Praesent in sapien. Lorem ipsum dolor sit amet, consectetuer adipiscing elit. Duis fringilla tristique neque. Sed interdum libero ut metus. Pellentesque placerat. Nam rutrum augue a leo. Morbi sed elit sit amet ante lobortis sollicitudin. Praesent blandit blandit mauris. Praesent lectus tellus, aliquet aliquam, luctus a, egestas a, turpis. Mauris lacinia lorem sit amet ipsum. Nunc quis urna dictum turpis accumsan semper.

References

[1] T. Oetiker, H. Partl, I. Hyna, and E. Schlegl, "The not so short introduction to latex2ε," *Electronic document available at http://www. tex. ac. uk/tex-archive/info/lshort*, 1995.

[2] A. Goldsmith, S. A. Jafar, N. Jindal, and S. Vishwanath, "Capacity limits of mimo channels," *IEEE Journal on selected areas in Communications*, vol. 21, no. 5, pp. 684–702, 2003.

[3] L. Liu, C. Oestges, J. Poutanen, K. Haneda, P. Vainikainen, F. Quitin, F. Tufvesson, and P. D. Doncker, "The cost 2100 mimo channel model," *IEEE Wireless Communications*, vol. 19, pp. 92–99, December 2012.

[4] S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," in *International conference on machine learning*, pp. 448–456, PMLR, 2015.

[5] X. Huang and S. Belongie, "Arbitrary style transfer in real-time with adaptive instance normalization," in *Proceedings of the IEEE International Conference on Computer Vision*, pp. 1501–1510, 2017.

[6] J. L. Ba, J. R. Kiros, and G. E. Hinton, "Layer normalization," *arXiv preprint arXiv:1607.06450*, 2016.

[7] Y. Wu and K. He, "Group normalization," in *Proceedings of the European conference on computer vision (ECCV)*, pp. 3–19, 2018.

[8] E. Ogasawara, L. C. Martinez, D. De Oliveira, G. Zimbrão, G. L. Pappa, and M. Mattoso, "Adaptive normalization: A novel data normalization approach for non-stationary time series," in *The 2010 International Joint Conference on Neural Networks (IJCNN)*, pp. 1–8, IEEE, 2010.

[9] S. Nayak, B. B. Misra, and H. S. Behera, "Impact of data normalization on stock index forecasting," *International Journal of Computer Information Systems and Industrial Management Applications*, vol. 6, no. 2014, pp. 257–269, 2014.

[10] X. Shao, "Self-normalization for time series: a review of recent developments," *Journal of the American Statistical Association*, vol. 110, no. 512, pp. 1797–1817, 2015.

[11] N. Passalis, A. Tefas, J. Kanniainen, M. Gabbouj, and A. Iosifidis, "Deep adaptive input normalization for time series forecasting," *IEEE transactions on neural networks and learning systems*, vol. 31, no. 9, pp. 3760–3765, 2019.

[12] C. Wen, W. Shih, and S. Jin, "Deep learning for massive mimo csi feedback," *IEEE Wireless Communications Letters*, vol. 7, pp. 748–751, Oct 2018.

[13] Z. Liu, M. del Rosario, X. Liang, L. Zhang, and Z. Ding, "Spherical normalization for learned compressive feedback in massive mimo csi acquisition," in *2020 IEEE International Conference on Communications Workshops (ICC Workshops)*, pp. 1–6, 2020.