A Project Report

On

Application of AI in wireless communications

BY

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ABSTRACT

The study of Deep Learning to model and solve various problems in communication channels has attracted a lot of interest and research over the years. In this report, we first examine the role of DL in communication channels, then we review related literature to get an idea of the problems faced in various communication channels. After choosing the problem of channel estimation, we then go through 3 papers of interest, and finally come up with novel ways to apply them to different challenges.

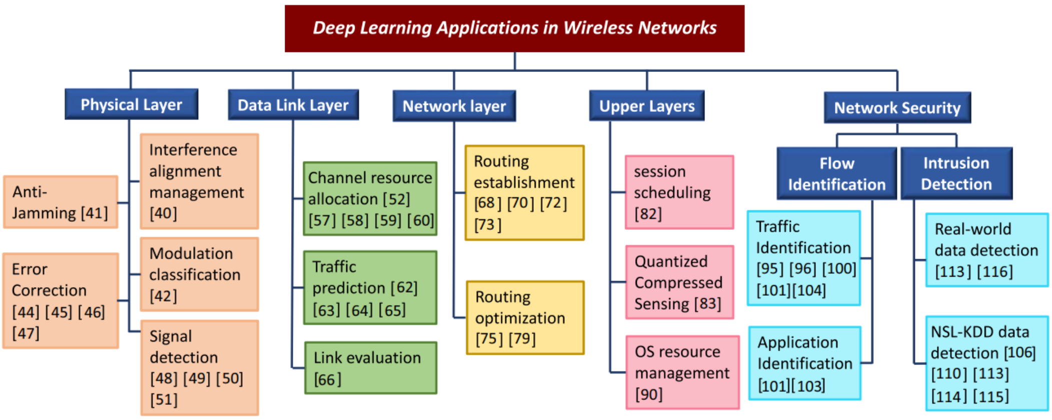
CONTENTS

`1. INTRODUCTION

1.1 Deep Learning in Communication Channels

Deep learning (DL) is developing into a potent way to add intelligence to wireless networks with large-scale topology and complex radio circumstances. DL is a promising machine learning tool to handle the accurate pattern identification from complex raw data. In DL, many layers of neural networks are used to extract acute features from high-dimensional raw data in a manner like the brain. It can be used to analyse a large number of network metrics, such as latency, loss rate, link signal-to-noise ratio, etc., in order to determine the network dynamics, such as hotspots, interference distribution, congestion locations, traffic bottlenecks, spectrum availability, etc. DL can therefore investigate very complicated wireless networks with numerous nodes and fluctuating link quality.

Applications of DL algorithms include resource allocation and access control at several network layers, including the physical layer modulation and coding, the data link layer resource access control, the routing layer path search, and the traffic balancing layer. Other network features, such network security, detecting data compression, etc., can be improved with the help of DL.



The applications of DL in data link layer are mostly focusing on resource allocation, traffic prediction, and link evaluation problems, which yield promising performance improvement,etc.

After careful literature review, I decided to focus on the problem of channel estimation.

1.2 Channel estimation

All communication signals pass via a medium (referred to as a channel), where the signal is subject to distortion or other types of noise. Remove the noise and distortion that the channel added to the received signal in order to properly and error-free decode the stream. Finding out the characteristics of the channel that the signal has passed through is the first step in accomplishing this. The term "channel estimation" refers to the method or procedure used to describe the channel.

The steps are as follows:

i) Create a mathematical model utilising a channel matrix to relate the "broadcast signal" and the "recieved signal."

ii) Send a recognisable signal (often referred to as a "reference signal" or "pilot signal") and then listen for the received signal.

iii) We can identify each component of the channel matrix by comparing the broadcast and received signals.

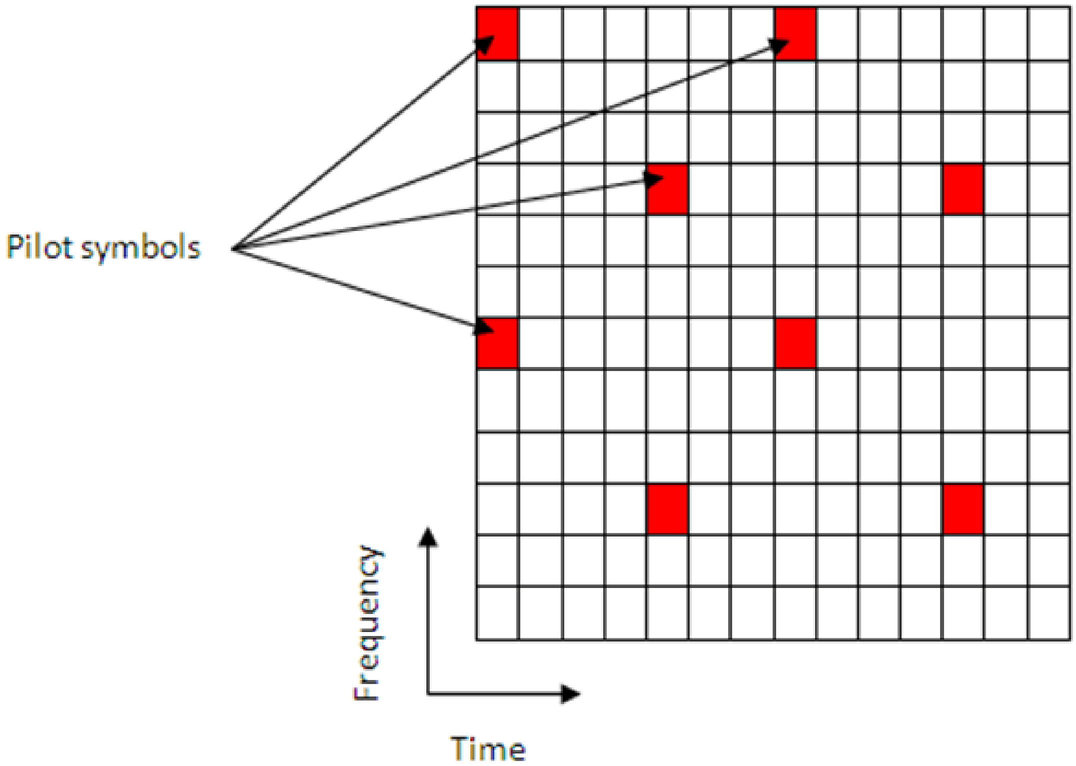
//this website has more, add if you want.

1.3 OFDM AND PILOT SYMBOLS

Orthogonal frequency-division multiplexing is a data transmission method in which a single information stream is divided among several closely spaced narrowband subchannel frequencies as opposed to a single Wideband channel frequency. In conventional single-channel modulation schemes, each data bit is transmitted serially or sequentially. In OFDM, multiple bits can be transmitted concurrently or simultaneously in separate substream channels. This makes the system less susceptible to interference and enables more efficient data bandwidth.

In a communication channel, the received signal is usually distorted by channel characteristics. In order to recover the transmitted symbols, the channel effect must be estimated and compensated at the receiver.

Generally, the receiver estimates the channel using some symbols named pilots which their positions and values in time-frequency are known to both transmitter and receiver.



2. Deep Learning-Based Channel Estimation

2.1 Classical methods of estimation

In an OFDM system, for the k th time slot and the i th subcarrier, the input-output relationship is represented as:

$$Y_{i,k} = H_{i,k}X_{i,k} + Z_{i,k}.$$

Considering an OFDM subframe of size $N_S \times N_D$, time slot index k is between $[0, N_D - 1]$ and the range of the subcarrier index i is $[0, N_S - 1]$. In [1], $Y_{i,k}, X_{i,k}$, and $Z_{i,k}$ are the received signal, transmitted OFDM symbol and white Gaussian noise, respectively. $H_{i,k}$ is the (i, k) element of $\mathbf{H} \in \mathbb{C}^{N_S \times N_D}$. $\mathbf{H}$ represents time-frequency response of the channel for all subcarriers and time slots.

To estimate the channel, specifically in the channels with fading, the time domain response is represented as $\mathbf{H} = \{\mathbf{h}[1], \mathbf{h}[2], \dots, \mathbf{h}[N_D]\}$, where each $\mathbf{h}[k]$ is the channel frequency response at the k th time slot.

Least Squares Method:

The LS method estimates the channel at the pilot positions. If we consider the LS estimated channel as a diagonal matrix $\mathbf{H}_p^{\mathrm{LS}} \in \mathbb{C}^{N_P \times N_P}$, $\mathbf{H}_p^{\mathrm{LS}}$ can be estimated by solving:

$$\hat{\mathbf{H}}_p^{\mathrm{LS}} = \underset{\mathbf{H}_p}{\arg\,\mathrm{m}} \;\; \|\mathbf{y}_p - \mathbf{H}_p\mathbf{x}_p\|_2^2,$$

where $\|\cdot\|_2$ is the $\ell 2$ distance and $\hat{\mathbf{H}}_p^{\mathrm{LS}} \in \mathbb{C}^{N_P \times N_P}$ is the estimated diagonal matrix. $\mathbf{x}_p$ contains the known pilot values and $\mathbf{y}_p$ is the corresponding observations. The optimization of (2) results in $\hat{\mathbf{h}}_p^{\mathrm{LS}} = \mathrm{diag}\left(\hat{\mathbf{H}}_p^{\mathrm{LS}}\right) = \mathbf{y}_p/\mathbf{x}_p$.

Mininum Mean Squared Error(MMSE):

A better choice than LS, is MMSE estimator which is obtained by multiplying the LS estimates at the pilot-symbol positions with a filtering matrix $\mathbf{A}_{\mathrm{MMSE}} \in \mathbb{C}^{N_L \times N_P}$[12 :

$$\hat{\mathbf{h}}_d^{\mathrm{MMSE}} = \mathbf{A}_{\mathrm{MMSE}}\hat{\mathbf{h}}_p^{\mathrm{LS}},$$

where $\hat{\mathbf{h}}_d^{\mathrm{MMSE}} \in \mathbb{C}^{N_L \times 1}(N_L = N_S \times N_D)$ is the vectorized MMSE estimation of the channel response $\mathbf{H}$ at subframe d.

$$\mathbf{A}_{\mathrm{MMSE}} = \mathbf{R}_{\mathbf{h}_d\mathbf{h}_p}\left(\mathbf{R}_{\mathbf{h}_p\mathbf{h}_p} + \sigma_n^2\left(\mathbf{x}\mathbf{x}^{\mathrm{H}}\right)^{-1}\right)^{-1},$$

where the matrix $\mathbf{R}_{\mathbf{h}_d\mathbf{h}_p} = \mathbb{E}\{\mathbf{h}_d\mathbf{h}_p^{\mathrm{H}}\}$ denotes the channel correlation matrix between desired subframe and pilot-symbols and the matrix $\mathbf{R}_{\mathbf{h}_p\mathbf{h}_p} = \mathbb{E}\{\mathbf{h}_p\mathbf{h}_p^{\mathrm{H}}\}$ is the channel correlation matrix at the pilot-symbols.

To use the MMSE in practical scenarios, some approaches are presented which reduce the complexity of this scheme and use an estimation of the channel statistics instead of the exact information. In [3], an approximated linear version of the MMSE (ALMMSE), is proposed in fast fading channels which its complexity is much less than the original MMSE due to reducing the size of the correlation and the filtering matrix.

2.2 FRAMEWORK

In this method, the time-frequency grid of the channel response is modeled as a 2D-image which is known only at the pilot positions. This channel grid with several pilots is considered as a low-resolution (LR) image and the estimated channel as a high-resolution (HR) one. A two-phase approach is presented to estimate the channel grid. First, an image superresolution (SR) algorithm is used to enhance the resolution of the LR input. Afterwards, an image restoration (IR) method is utilized to remove the noise effects.

We have Single-input, Singleoutput (SISO) communication link. the channel time-frequency response matrix H (of size NS ×ND) between a transmitter and a receiver, which has complex values, can be represented as two 2D-images (one 2D-image for real values and another one for imaginary values).

2.3 MODEL

The estimated value of the channel at the pilot locations $\hat{\mathbf{h}}_p^{\mathrm{LS}}$ (which might be noisy) is considered as the LR and noisy version of the channel image. To obtain the complete channel image a two-stage training approach is presented:

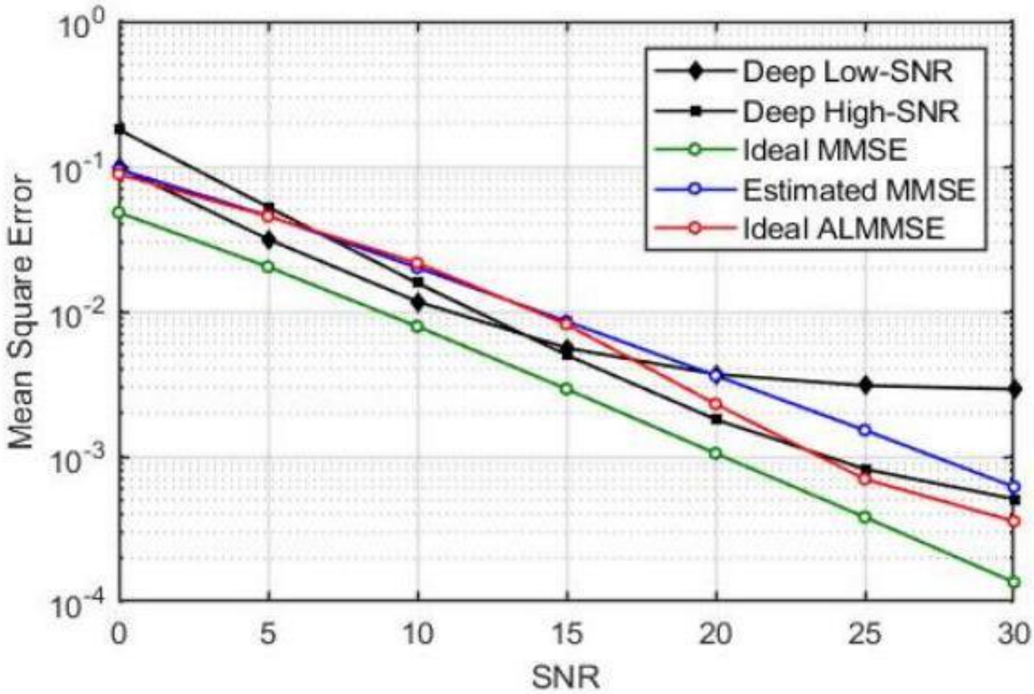
- In the first stage, an SR network is implemented which takes $\hat{\mathbf{h}}_p^{\mathrm{LS}}$ as the vectorized low resolution input image (once the real-part and then the imaginary-part) and estimates the unknown values of channel response $\mathbf{H}$.
- In the second stage to remove the noise effects, a denoising IR network is cascaded with the SR network.

SRCNN:

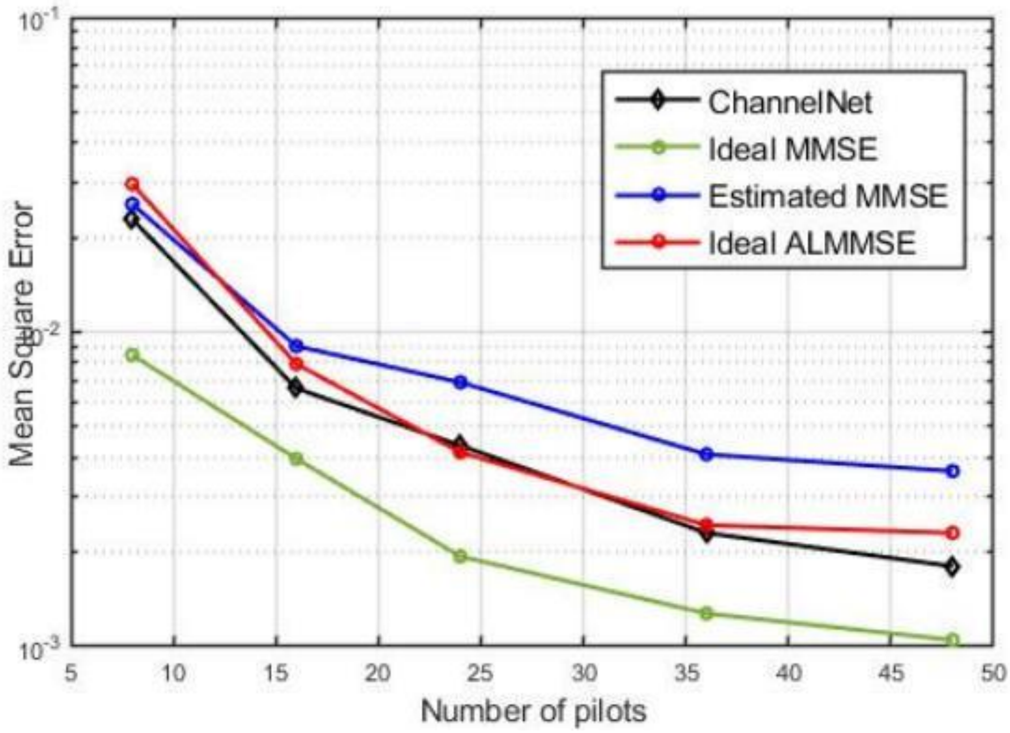
The first convolutional layer uses 64 filters of size 9 × 9 and the second layer uses 32 filters of size 1 × 1, both followed by ReLu activation. The final layer uses only one filter of size 5 × 5 to reconstruct the image

DnCNN is a residual-learning based network which composed of 20 convolutional layers. The first layer uses 64 filters of size 3 × 3 × 1 followed by a ReLU. Each of the succeeding 18 convolutional layers uses 64 filters of size 3 × 3 × 64 followed by batch-normalization and ReLU. The last layer uses one 3 × 3 × 64 filter to reconstruct the output.

2.4 Results



Channel Estimation MSE in terms of SNR for VehA channel model.



Mean square error for channel estimation in terms of pilot number

The results show that the performance of ChannelNet is highly competitive with the MMSE algorithm.

3. Channel Estimation for One-Bit Multiuser Massive MIMO Using Conditional GAN

3.1 FRAMEWORK

M ASSIVE multiple-input multiple-output (MIMO) is a key technology to improve the system capacity and spectrum utilization in 5G wireless communications systems. current massive MIMO systems are typically equipped with high resolution analog-to-digital converters (ADC), which results in high power consumption and hardware complexity. To address this issue, massive MIMO with one-bit ADCs is recommended to be an alternative solution.

We explore a cGAN based DL channel estimation framework for a massive MIMO system with one-bit ADCs. In a generator, we design an encoder-decoder CNN with a U-Net structure [15] to estimate channel matrices from highly quantized observations. The discriminator, which is a regular CNN, is utilized to evaluate the quality of estimated channels from the generator.

3.2 GENERATIVE ADVERSERIAL NETWORKS(GAN)

A generative framework called GANs has been presented, in which the training stage pits a generator against a discriminator. The generator gets better at producing samples that are comparable to the genuine samples thanks to the discriminator's feedback. The most popular GAN and its variations are utilised in computer vision.

A conditional GAN is suggested based on the GAN framework, where the context information is provided to the generator and the discriminator in order to create samples with a particular property. The label information was initially provided as a condition so that the generator could produce corresponding samples given a specific category.

3.3 MODEL

We consider the received signal $\mathbf{Y}$, pilot sequence $\mathbf{\Phi}$, and channel matrix $\mathbf{H}$ as two-channel images with the dimension of $M \times \tau \times 2, K \times \tau \times 2$, and $M \times K \times 2$, respectively. Two channels of the image represent the real and imaginary part of a complex matrix. Then, we can regard the channel estimation problem as an image-to-image translation problem, where we need to translate a low-resolution image with quantized $\mathbf{Y}$ to a high-resolution image with full channel matrix $\mathbf{H}$.

3.3 RESULTS

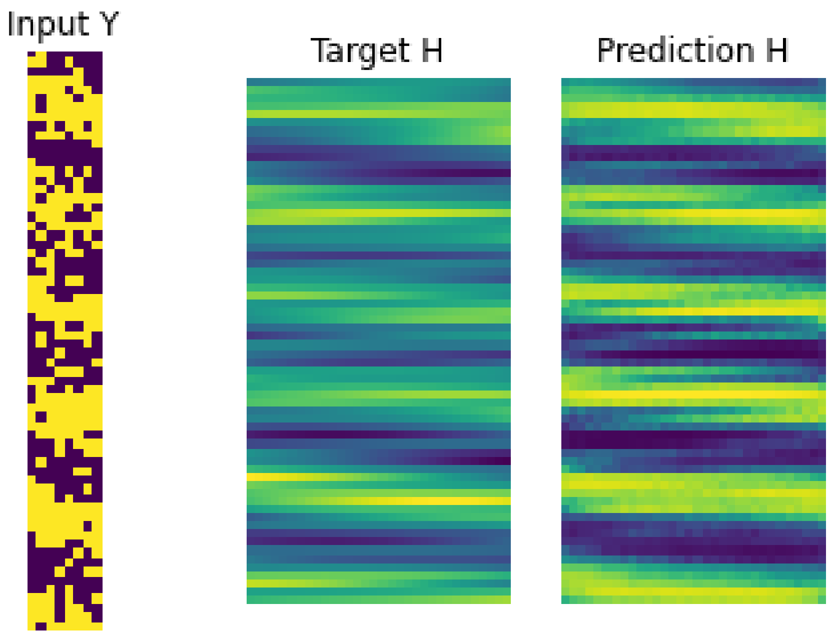
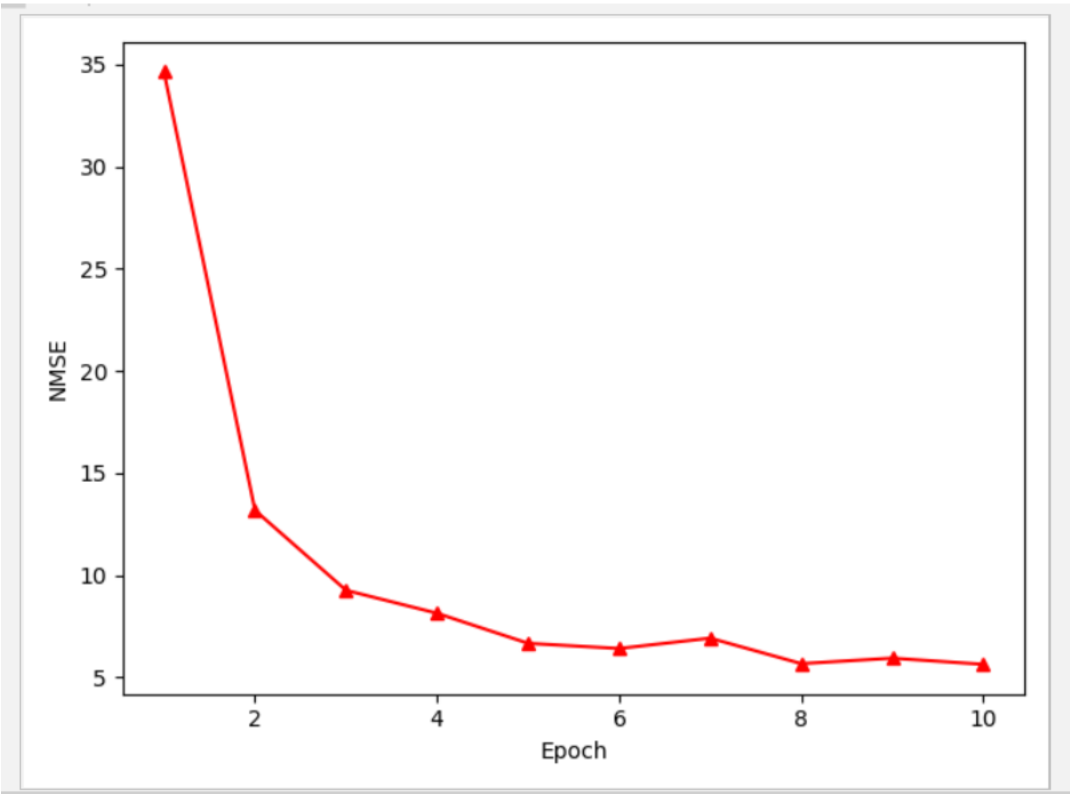


Image of target channel vs predicted channel



Plot of NMSE vs number of epochs

These plots and images were generated on my own computer.

4. Deep Learning-Based End-to-End Wireless Communication Systems With Conditional GANs as Unknown Channels

4.1 FRAMEWORK

The transmitter and the receiver correspond to the auto-encoder and auto-decoder, respectively .The transmitter learns to encode the transmitted symbols into encoded data, x, which is then sent to the channel while the receiver learns to recover the transmitted symbols based on the received signal, y, from the channel. As a result, the traditional communication modules at the transmitter, such as the encoding and modulation, are replaced by a DNN while the modules at the receiver, such as the decoding and the demodulation, are replaced by another DNN.

CNNs are employed for alleviating curse of dimensionality. From the experimental results, the transmitter with convolutional layers can learn to encode the transmit data into a high dimensional embedding vector, which can be effectively decoded by the receiver.

ISSUE:the backpropagation algorithm, which is used to train the weights of DNNs, is blocked by the unknown CSI, preventing the overall learning of the end-to-end system. To address the issue, we use a conditional GAN to learn the channel effects and to act as a bridge for the gradients to pass through. By the conditional GAN, the output distribution of the channel can be learned in a data-driven manner and therefore many complicated effects of the channel can be addressed.

it is appropriate to employ convolutional layers to deal with the ISI channels since the effect of the channel can be expressed by the convolutional operation in the ISI channel.

With the conditional GAN, the gradients can be backpropagated to the transmitter even if channels are unknown.

4.2 MODEL

A system for end-to-end communication develops DNNs that are optimised for the transmitter and receiver. The end-to-end system cannot learn overall because the unknown CSI blocks the backpropagation process, which is required to train the weights of DNNs. We utilise a conditional GAN to learn the channel effects and serve as a bridge for the gradients to cross in order to solve the problem. The conditional GAN enables data-driven learning of the channel's output distribution, allowing for the resolution of various complex channel effects.

The information bits, or s, are created at random, and the channel set's instantaneous CSI is sampled at random to create the training data set. The transmitter, receiver, and channel generator in the conditional GAN can be trained iteratively based on the training data due to changing objectives in modules. By adjusting the other components' settings, each component is trained. When training the receiver and transmitter, the goal is to reduce the end-to-end loss.

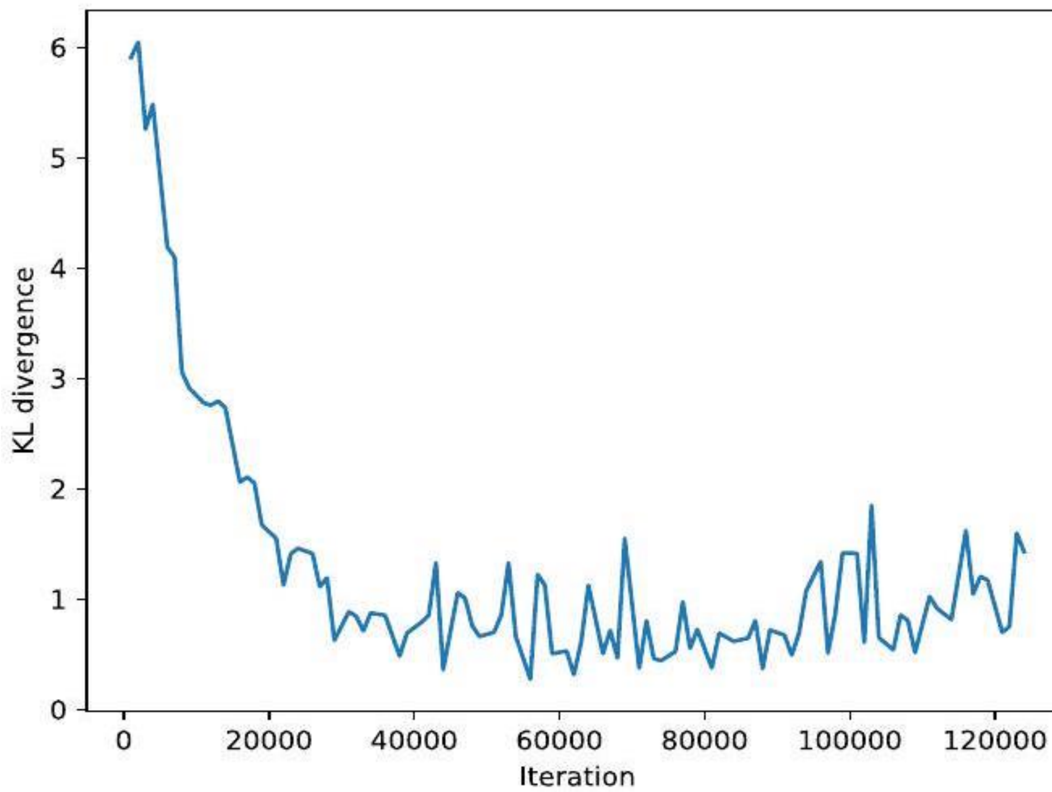
Type of layer	Kernel size/Annotation	Output size
Transmitter		
Input	Input layer	$K \times 1$
Conv+Relu	5	$K \times 256$
Conv+Relu	3	$K \times 128$
Conv+Relu	3	$K \times 64$
Conv	3	$K \times 2$
Normalization	Power normalization	$K \times 2$
Receiver		
Conv+Relu	5	$K \times 256$
Conv+Relu	5	$K \times 128$
Conv+Relu	5	$K \times 128$
Conv+Relu	5	$K \times 128$
Conv+Relu	5	$K \times 64$
Conv+Relu	5	$K \times 64$
Conv+Relu	5	$K \times 64$
Conv+Sigmoid	3	$K \times 1$
Generator		
Conv+Relu	5	$K \times 256$
Conv+Relu	3	$K \times 128$
Conv+Relu	3	$K \times 64$
Conv	3	$K \times 2$
Discriminator		
Conv+Relu	5	$K \times 256$
Conv+Relu	3	$K \times 128$
Conv+Relu	3	$K \times 64$
Conv+Relu	3	$K \times 16$
FC +Relu	100	100
FC+Sigmoid	1	1

4.3 RESULTS

In our trials, AWGN channels, Rayleigh channels, and frequency-selective multipath channels are all taken into account. The output of an AWGN channel, y, is equal to the sum of the input signal, x, plus the Gaussian noise, w, or y = x + w. When there are several things in the surroundings that disperse the radio signal before it reaches the receiver, Rayleigh fading is a good model for narrowband wireless channels. The Rayleigh channel output is given by the formula $\mathbf{y} = h_n \cdot \mathbf{x} + \mathbf{w}$, where $h_n \sim \mathcal{CN}(0,1)$. When developing transceivers, the time-varying channel coefficient hn must be taken into consideration. As a result, channel estimate is necessary to obtain the instantaneous CSI, which the receiver uses to identify transmitted data. With frequency-selective channels, radio signals travel down numerous pathways that have different amplitudes, phases, and delay periods. As a result, the received signal experiences unwanted frequency-selective fading and time dispersion. The baseband complex channel impulse response can be expressed as

$$h(t) = \sum_{k=0}^{K_p} b_k e^{j\theta_k} p(t - \tau_k),$$

There are Kp pathways in total, bk, k, and k indicate the path gain, phase shift, and time delay of the kth path, respectively, and p(t) is the shaping pulse in the communication system. This formula can be used to explain the baseband complex channel impulse response. In our simulation, we take into account a three-tap channel with an equal average power, where , $\mathbb{E}|b_k|^2 = 1$, and $\tau_k = 0, T, 2T$, where T is the symbol duration.



KL divergence of the generated channel distribution and real channel distribution.

From the figure, the KL divergence deceases with the training iterations, indicating that the generated distribution converges to the target distribution p_{data} .

The simulation results on the AWGN channels, Rayleigh fading channels, and frequency-selective channels confirm the effectiveness of the proposed method, by showing similar or better performance compared with the traditional approaches, which are designed based on expert knowledge and channel models.

5. FURTHER APPLICATIONS

5.1 Transfer Learning(TL) Approach

In the paper titled “Deep Transfer Learning for Site-Specific Channel Estimation in Low-Resolution mmWave MIMO” the authors have considered the problem of channel estimation in low-resolution multiple-input multiple-output (MIMO) systems operating at millimeter wave (mmWave) and present a deep transfer learning (DTL) approach that exploits previously trained models to speed up site adaptation.

They have used Transfer Learning to speed the retraining of a low-resolution DL-based channel estimation algorithm in which the deployment is distinct from the training conditions. This is done to turn the model from site-independent to site-specific. Taking inspiration from this method, in order to achieve better results, we can use the model described in paper#1 and 2 as the model and use deep TL to model site specific channels.

A deep neural network (DNN) is trained with data from a source scenario and adapted for deployment in a target scenario that correspond to a mismatched propagation environment.

The proposed DTL approach could reduce the computational cost of the training stage without decreasing the estimation accuracy.

5.2 UAV APPLICATIONS

In the paper titled “Distributed Conditional Generative Adversarial Networks (GANs) for Data-Driven Millimeter Wave Communications in UAV Networks” a novel framework is proposed to perform data-driven air-to-ground channel estimation for millimeter wave (mmWave) communications in an unmanned aerial vehicle (UAV) wireless network. In order to train each UAV's stand-alone channel model through a conditional generative adversarial network (CGAN) along each beamforming direction, an efficient channel estimation method is first devised to gather mmWave channel information. Then, a cooperative framework based on a distributed CGAN architecture is created to enable each UAV to cooperatively learn the mmWave channel distribution in a completely distributed way, thereby expanding the application scenarios of the trained channel model into a wider spatiotemporal domain.

We can apply the C-GAN model used in paper#3, and model the system effectively by adding autoencoders and autodecoders at the transmitter and receiver respectively, along with reducing channel parameters by using CNN’s to eliminate the curse of dimensionality.

5.3 MARITIME COMMUNICATIONS

In the paper titled “A Novel CNN-based Autoencoder with Channel Feedback for Intelligent Maritime Communications” a novel convolutional neural networks (CNN) -based autoencoder with channel feedback (CNN-AE-CF) for intelligent maritime communications with complex and changeable environment is proposed. The authors leverage Rician fading channel to simulate the marine environment, in which CNN-AECF is trained.

We can use the model discussed in paper#3 to model Rician noise like we have done for the other 3 types, and this should help us to efficiently model the end to end communication system for maritime communications.

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