DL BASED OFDM CHANNEL ESTIMATION USING SUPER RESOLUTION AND IMAGE RESTORATION TECHNIQUES

by

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BONAFIDE CERTIFICATE

Certified that this project report entitled "**DL BASED OFDM CHANNEL ESTIMATION USING SUPER RESOLUTION AND IMAGE RESTORATION TECHNIQUES"** is a bonafide work of **SAI PAAVAN– 19BEC1164, V. V. DHANVANTH – 19BEC1354, and NITHISH – 19BEC1362** who carried out the Project work under my supervision and guidance for **ECE4006 Wireless Mobile Communications.**

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ABSTRACT

In this project, we present a deep learning algorithm for channel estimation in communication systems. We consider the time–frequency response of a fast fading communication channel as a 2D image. The aim is to find the unknown values of the channel response using some known values at the pilot locations. To this end, a general pipeline using deep image processing techniques, image super-resolution (SR), and image restoration (IR) is proposed. This scheme considers the pilot values, altogether, as a low-resolution image and uses an SR network cascaded with a denoising IR network to estimate the channel. Moreover, the implementation of the proposed pipeline is presented. The estimation error shows that the presented algorithm is comparable to the minimum mean square error (MMSE) with full knowledge of the channel statistics, and it is better than an approximation to linear MMSE. The results confirm that this pipeline can be used efficiently in channel estimation.

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CHAPTER 1
INTRODUCTION

- Orthogonal frequency-division multiplexing(OFDM) is a modulation method that has been widely used in communication systems to address frequency-selective fading in wireless channels. **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. The conventional pilot-based estimation methods, I.e., Least Square (LS) and Minimum Mean Square Error(MMSE) have their own drawbacks. LS estimation takes no information about the statistics of the channel but MMSE estimation results in a better performance by utilizing the statistics of the channel.

1.1 Methodology

- Model the channel time-frequency response as an image.
- Consider the channel response in the pilot positions as a LR image and the estimated channel response as the proposed HR
- Use DL-based image super-resolution and image denoising techniques to estimate the channel

CHAPTER 2

BLOCK DIAGAM CONVOLUTION NEURAL NETWORK

2.1 BLOCK DIAGRAM

The four main features of the basic block diagram (given below) are

- Feed the low resolution image to the SRCNN
- SRCNN model increases resolution by using interpolation method
- DNCNN model removes the noise from the high resolution image
- We predict pilot point from high resolution image

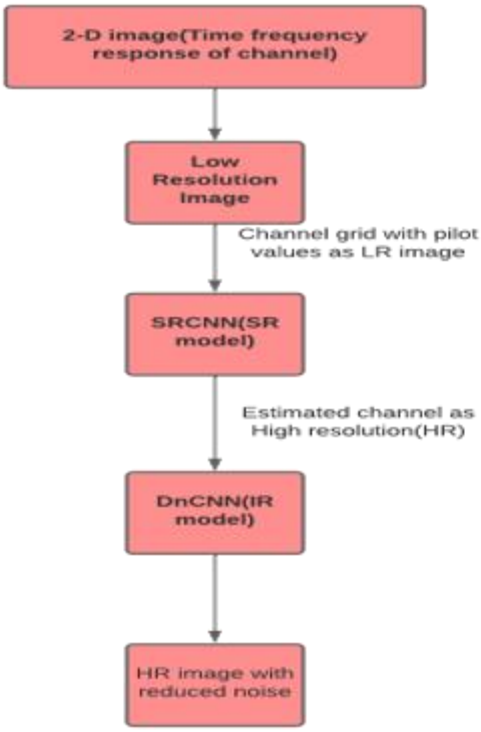


Figure 1. Block Diagram

2.2 INPUT IMAGE OF DATA

- Time-frequency response of a fast fading communication channel as a two-dimensional image

Input data dimensionality:

(40000,72,14)

40000: No. Of channels

72: Frequency sub-carriers

14: Time slots

2.3 CONVOLUTION NEURAL NETWORK OF MODEL

2.3.1 NEURAL NETWORK OF SRCNN MODEL

SRCNN first uses an interpolation scheme to find the approximate values of the high resolution image (channel) and afterwards, improves the resolution using a three-layer convolutional network. 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

```
Model: "functional_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 72, 14, 1)]       0
_________________________________________________________________
conv2d (Conv2D)              (None, 72, 14, 64)        5248
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 72, 14, 32)        2080
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 72, 14, 1)         801
=================================================================
Total params: 8,129
Trainable params: 8,129
Non-trainable params: 0
_________________________________________________________________
```

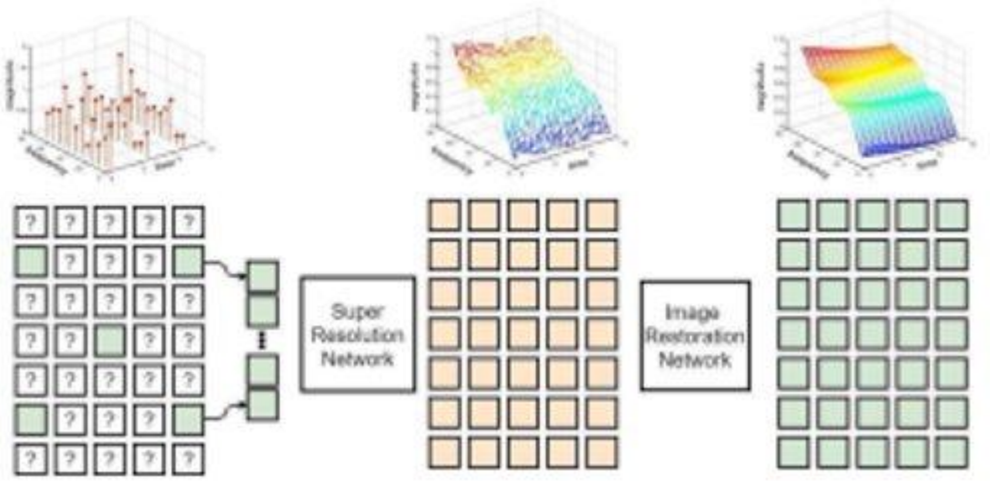
2.3.2 NEURAL NETWORK OF DNCNN MODEL

DnCNN (details in [11]) is a residual-learning based network which composed of 20 convolutional layers. The first layer uses 64 filters of size $3 \times 3 \times 1$ followed by a ReLU. Each of the succeeding 18 convolutional layers uses 64 filters of size $3 \times 3 \times 64$ followed by batch-normalization and ReLU. The last layer uses one $3 \times 3 \times 64$ filter to reconstruct the output

```
__________________________________________________________________________________________________
batch_normalization_34 (BatchNo (None, None, None, 6 256         conv2d_43[0][0]
__________________________________________________________________________________________________
activation_36 (Activation)      (None, None, None, 6 0           batch_normalization_34[0][0]
__________________________________________________________________________________________________
conv2d_44 (Conv2D)              (None, None, None, 6 36928       activation_36[0][0]
__________________________________________________________________________________________________
batch_normalization_35 (BatchNo (None, None, None, 6 256         conv2d_44[0][0]
__________________________________________________________________________________________________
activation_37 (Activation)      (None, None, None, 6 0           batch_normalization_35[0][0]
__________________________________________________________________________________________________
conv2d_45 (Conv2D)              (None, None, None, 1 577         activation_37[0][0]
__________________________________________________________________________________________________
subtract_1 (Subtract)           (None, None, None, 1 0           input_4[0][0]
                                                                 conv2d_45[0][0]
==================================================================================================
Total params: 670,529
Trainable params: 668,225
Non-trainable params: 2,304
```

.

2.3.3 PIPELINE FOR DL BASED CHANNEL ESTIMATION



.

2.4 SOFTWARE SPECIFICATIONS

- For the channel modeling and pilot transmission, we have used widely used LTE simulator developed by university of Vienna, Vienna LTE-A simulator
- Keras and Tensorflow using a GPU backend are used for implementation of our proposed scheme

CHAPTER 3
MODEL IMPLEMENTATION AND ANALYSIS

This section describes system implementation and results with inferences.

3.1 CHANNEL ESTIMATION THEORY

Channel estimation is an indispensable part of a coherent OFDM system. With channel estimation, OFDM systems can use coherent detection to obtain a 3 dB signal-to-noise ratio (SNR) gain over differential detection. For OFDM systems with multiple transmit and/or receive antennas for system capacity or performance improvement, channel information is essential to diversity combining, interference suppression, and signal detection. In summary, the accuracy of channel state information greatly influences the overall system performance

3.2 CHANNEL NET IMPLEMENTATION

A. Channel Image

In this work, we focus on one link between a pair of Tx and Rx antennas, i.e., we have Single-input, Singleoutput (SISO) communication link. For this 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). An example of the normalized real/imaginary 2D-image for a sample channel time-frequency grid with ND = 14 time slots and NS = 72 subcarriers (based on Long-Term Evolution (LTE) standard)

B. Network Structure

The overview of the proposed pipeline for DL-based channel estimation, named ChannelNet, is illustrated in Fig. 2. The goal is to estimate the whole time-frequency of the channel using the transmitted pilots. Similar to LTE standard, Latticetype pilot arrangement has been used for pilot transmission. The estimated value of the channel at the pilot locations hˆLS p (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 hˆLS p as the vectorised low resolution input image

• In the second stage, we freeze the weights of the SR network and find the parameters of the denoising network by defining Hˆ = fR(Z; ΘD) and minimizing the loss function C2:

$$C_2 = \frac{1}{\|\mathcal{T}\|} \sum_{\mathbf{h}_p \in \mathcal{T}} \|\hat{\mathbf{H}} - \mathbf{H}\|_2^2,$$

3.2 RESULTS AND INFERENCES

CASE	MEAN SQUARE ERROR(MSE)
Case 1	0.055
Case 2	0.1766
Case 3	0.0939
Case 4	0.069
Case 5	0.048

- Case 1:- Pilot=48,SNR = 22
- Case 2:- Pilot=48,SNR = 12
- Case 3:- Pilot=48,SNR = 25
- Case 4:- Pilot=8,SNR = 20
- Case 5:- Pilot= 48, SNR = 22
- (Kernel Initializers: Glorot uniform)

These are the MSE values for each case.

And with respect to MSE we obtain performance of each model as :

Case 5> Case 1> Case 4> Case 3> Case 2.

WMC MODEL AND NEURAL NET OF MODEL (CASE - 5)

- Here we have changed the hyper-parameter i.e. Kernel Initializer from he_normal to glorot_uniform and reduced the convolutional layers from 18 to 15 in DNCNN model and still obtained competitive results with respect to model discussed in the base paper.
- Total parameters in WMC model(DNCNN) : 5,58,977
- Total parameters in ChannelNet(DNCNN) : 6,70,529.

```
activation_15 (Activation)      (None, None, None, 6 0          batch_normalization_14[0][0]
________________________________________________________________________________________________
conv2d_25 (Conv2D)              (None, None, None, 1 577        activation_15[0][0]
________________________________________________________________________________________________
subtract (Subtract)             (None, None, None, 1 0          input_4[0][0]
                                                                 conv2d_25[0][0]
================================================================================================
Total params: 558,977
Trainable params: 557,057
Non-trainable params: 1,920
________________________________________________________________________________________________
None

Epoch 1/5
70/70 [==============================] - ETA: 0s - loss: 0.0389 - mean_squared_error: 0.0389
Epoch 00001: val_loss improved from inf to 0.00879, saving model to DNCNN_check.h5
70/70 [==============================] - 2279s 33s/step - loss: 0.0389 - mean_squared_error: 0.0389 - val_loss: 0.0088 - val_
mean_squared_error: 0.0088
Epoch 2/5
```

CHAPTER 4

CONCLUSION AND FUTURE WORK

4.1 CONCLUSION

- Here we implemented ChannelNet, initial DL-based algorithm for channel estimation in communication systems. In this method, we have considered the time-frequency response of a fading channel as a 2D-image and applied SR and IR algorithms to find the whole channel state based on the pilot values.
- From the model introduced in this project we have observed that our model is performing better than the model introduced in base paper in selective situations.

4.2 FUTURE WORK

- Our WMC model got better results than channelNet by changing hyper parameters there may be chance of getting better results
- Implementing advanced SRCNN and DNCNN model we may get better understanding results

CHAPTER 5

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