Applying Transfer Learning Techniques to Massive MIMO Networks
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Introduction

Massive multiple-input multiple-output (MIMO) technology is expected to play a pivotal role in 5G wireless communication systems. This technology consists of a base station (BS) which can contain up to thousands of antennas [1]. The benefit of the base station consisting of this many antennas is that this system could potentially reduce multiuser interference and provide an increase in cell throughput [1]. To obtain this potential benefit, the Channel State Information (CSI) must be exploited. Currently, in frequency division duplex/off system, the downlink CSI is obtained at the user equipment during the training period and returns back to the BS through feedback links [1]. There are many different methods used to reduce feedback overhead. The goal of this work is to explore transfer learning for CSI estimation and study its performance as a function of the number of antennas.

Objectives:
1. Apply transfer learning techniques to channel estimation.
2. Reduce the training time of the Convolutional Neural Network (CNN) which will lead to better CSI estimates.
3. Study the effect of the number of antennas on the performance.

Methodology

In the past, the main method used to recover CSI was to use Compressed Sensing (CS) based algorithms. However, when using CS-based algorithms to recover CSI, this has not yielded successful results. A new method was to apply a deep learning technology called CsiNet to recover CSI [1]. CsiNet is a novel sensing and recovery mechanism that learns to effectively use channel structure from training the samples [1]. CsiNet learns a transformation from CSI to a near optimal number of codewords and inverse transformation from code words to CSI [1]. CsiNet exploits the CNN for the encoder and decoder and in turn can exploit the spatial locality correlation by enforcing a local connectivity pattern among the neurons of the adjacent layers [1]. In [1], the authors proved that when they applied CsiNet to recover CSI, this lead to better results than previous CS-based algorithms that were used.

CsiNet Architecture:
- First layer (encoder): convolutional layer that takes the channel matrix H as the input. This layer uses kernels to generate two feature maps.
- Next layer (encoder): reshape the feature map into a vector and use a fully connected layer to generate the codeword.
- First layer (decoder): once the codeword is obtained, map the codeword back into the channel matrix form. This layer uses the codeword that was generated from the decoder as the input. The outputs of this layer are two matrices, which are an initial estimate of the channel matrix.
- Next layer (decoder): the initial estimate of the channel matrix is fed as an input into several RefineNet units. The purpose of the RefineNet units is to refine the reconstruction of the channel matrix. Two RefineNet units are used sequentially as part of the decoder network as they provide good performance.
- Final layer (output): the channel matrix is fed as the input to the final convolutional layer and a sigmoid function is used to scale the values.

Analysis and Results

Proposed Work:
- Apply transfer learning to each layer of the CNN in the CsiNet Architecture.
- By applying transfer learning to each layer of the Neural Network, this will lead to decreasing the training time of the overall model.
- CsiNet currently uses an architecture with the BS consisting of 32 antennas. This number of antennas at the BS is considered quite low for a massive MIMO network. We propose that the number of antennas should be increased at the BS and this will provide a more accurate representation of a massive MIMO network.
- Use pre-trained networks to see if they can outperform CsiNet and other architectures commonly used for reducing CSI feedback with a dataset that consists of more than 32 antennas. This number of antennas at the BS is considered quite low for a massive MIMO network. We propose that the number of antennas should be increased at the BS and this will provide a more accurate representation of a massive MIMO network.

Table 1: MIMO channel errors under different compression rates

<table>
<thead>
<tr>
<th>Method</th>
<th>Inset</th>
<th>Outset</th>
</tr>
</thead>
<tbody>
<tr>
<td>LASSO</td>
<td>0.24</td>
<td>0.26</td>
</tr>
<tr>
<td>TVMM</td>
<td>0.16</td>
<td>0.19</td>
</tr>
<tr>
<td>CsiNet</td>
<td>0.12</td>
<td>0.15</td>
</tr>
<tr>
<td>RefineNet</td>
<td>0.10</td>
<td>0.13</td>
</tr>
<tr>
<td>CsiNet</td>
<td>0.10</td>
<td>0.13</td>
</tr>
<tr>
<td>RefineNet</td>
<td>0.08</td>
<td>0.12</td>
</tr>
</tbody>
</table>

Fig. 3. Architecture of RefineNet [3]

Fig. 4. Results of CsiNet [1]

Fig. 5. Reconstruction images for different compression rates for different algorithms [1]

Summary/Conclusions

The purpose of this thesis is to apply transfer learning to channel estimation for massive MIMO networks. The goals of this thesis are to reduce training time of the model, improve CSI performance, and to provide a more accurate representation of a fine tuned massive MIMO network that implements more antennas at the base station. The aspiration is that transfer learning can be applied to all areas of wireless communications and not just to channel estimation of massive MIMO networks.

Key References


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Fig. 1. General Structure of the COST 2100 Channel Model [2]

Fig. 2. Architecture of CsiNet [1]