ISBN: 978-981-18-5852-9
WCSE 2022 Spring Event: 2022 9th International Conference on Industrial Engineering and Applications
doi: 10.18178/wcse.2022.04.073

Laplacian Densely connected Channel Estimation Network in NOMA System

Zhong Yu [1], Pan Wang [1+] and Yongbin Xie [1]

[1] Xi'an, China[1]School of Information and Communication Engineering
Xi'an University of Posts & Telecommunications

Abstract. Non-orthogonal multiple access (NOMA) is an essential technology in wireless communications because it can increase the number of users. However, it needs the accurate channel state information (CSI) to achieve successive interference cancellation (SIC) and the signal detection. To that end, we propose a laplacian densely connected channel estimation network in NOMA system. The network integrates the laplacian pyramid structure between the dense connected blocks to reconstruct the complete channel matrix based on channel matrix at pilot positions. The Laplacian pyramid structure can gradually increase the size of channel matrix which make full use of channel matrix information of different sizes, and the dense connected network reuse the network information to enhance the network performance. The 3rd Generation Partnership Project (3GPP) channel models and mean square error as estimation error are adopted to evaluate the network performance. The estimation error shows that the proposed network is better than least squares (LS) estimation with linear interpolation, and competitive to the minimum mean square error (MMSE) estimation.

Keywords: Channel estimation, densely connected network, image super-resolution, non-orthogonal multiple access (NOMA).

1. Introduction

Non-orthogonal multiple access (NOMA) can satisfy the growing communication demands in the next generation communication system. It introduces the controllable nonorthogonal in the power domain at the transmitter to enhance communication system capacity and spectrum effectiveness, which means the multiple users share time and frequency resources in the power domain[1]. The transmitter can assign power to multi users by superposition coding. The Successive Interference Cancellation (SIC) receiver removes the interference from other users signal and decodes its own signal by the Channel State Information (CSI)[2]. The CSI can be obtained by the pilot-aided channel estimation, including Least Square (LS) estimation and Minimum Mean Square Error (MMSE) estimation. LS estimation accuracy is low, and MMSE estimation has very low estimation error which requires channel statistics and noise variance as prior information. However, the prior information is difficult to obtain in the actual communication system, and MMSE estimation has a very high computational complexity because of matrix inverse. The traditional channel estimations cannot cope with complex channel environments and communication scenarios.

A novel linear estimation for NOMA system is proposed to improve the average effective signal-to-interference-and-noise ratio (SINR) of one strong user while guaranteeing a bounded average effective SINR of the weak user[3]. A least mean squares (LMS)-based channel estimation approach is presents for NOMA system[4]. These estimations are an improvement on the traditional methods, and they are incapable of capturing the change in the complicated channel information. Deep Learning based wireless communication techniques have aroused considerable interest among the academic due to its excellent learning ability including signal detection[5], active user detection[6], and modulation detection[7]. It provides another channel estimation method which learn the input-output mapping by data-driven. The Deep Neural Networks(DNN) is utilized to solve the joint channel estimation and SIC for downlink Multiple Input Multiple Output-NOMA system, which outperformed the traditional SIC method[8]. The combined convolutional neural network(CNN) feature extractor and long short-term memory (LSTM) network is incorporated into a NOMA system to end-to-end signal detection and implicit channel estimation, which shows robust and efficient[9]. The channel estimation is implicitly included in the above network which achieve better performance, whereas it is not able to provide the complete CSI. It is not effective for some

+ Corresponding author. Tel.:18220847442.
E-mail address: wp1901@stu.xupt.edu.cn.

scenarios such as transmitter power allocation. The super-resolution(SR) algorithm based on deep learning is used to deal with the channel estimation problem of OFDM systems, because the channel matrix can be considered as an image[10].

Motivated by this, we propose a Laplacian Densely connected Channel Estimation Network (LdEsNet) in NOMA systems which introduce the SR algorithm to solve the channel estimation. The proposed estimation network combines the laplacian pyramid structure and dense connected block to reconstruct the complete channel matrix by the channel matrix at pilot positions. The channel matrix reconstruction is divided into two stages to gradually enlarge the size of channel matrix, which make full use of the channel matrix information of different sizes. Furthermore, the densely connected reuses the network information, which decreasing the parameters number to some extent.

The remainder of the letter is organized as follows: Section 2 briefly introduce the NOMA system model. Section 3 presents the structure of the proposed channel estimation network. In section 4, the simulation results are presented and section 5 concludes the letter.

2. System Model

In this section, we consider a downlink NOMA system with one base station (BS) and two user equipment (UE) as shown in Fig. 1. The UE are deployed at different distances from the BS, and the channel gain of the proximal UE is higher than the remote UE. The channel gain determines transmit power coefficient, and the UE with high channel gain is allocated to low power.

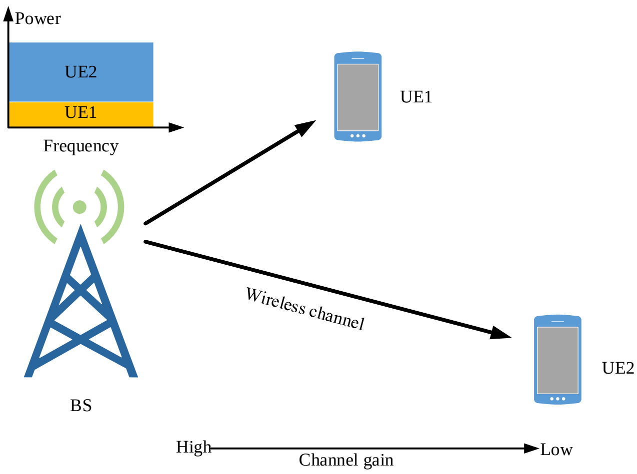

Fig. 1: Downlink NOMA system

The transmitted coded modulation signal of the i-th UE is denoted by $x_i\{i=1,2\}\in\mathbb{C}^{N_S\times N_D}$, and the power coefficient is $p_i\{i=1,2\}$, $p=\sum_{i=1}^{N}p_i=1$. The N_s is the number of time slots, and the N_D is the subcarriers numbers in the 5G New Radio (NR). The distance between UE1 and the BS is closer than UE2, so the power allocation is $p_1<p_2$. The two signals are superimposed as the NOMA signal X ,which pass through the channel to UE. $h_i\in\mathbb{C}^{N_S\times N_D}$ means the Rayleigh fading channel between the UE and the BS, and w_i means the additive white gaussian noise (AWGN) with zero mean and variance σ^2. The $\circ$ means the Hadamard product.

$$X=\sqrt{p_1}x_1+\sqrt{p_2}x_2 \tag{1}$$

$$y=h_i\circ X+w_i=h_i\circ(\sqrt{p_1}x_1+\sqrt{p_2}x_2)+w_i \tag{2}$$

The UE implement the SIC process to delete the other user signal after receiving the signal y. The SIC detect the signal in order of strength and weakness. At the near end UE1, the signal of UE2 can be directly detected, because the signal of UE2 has more power than UE1. The UE1 signal acquire by eliminating the UE2 inter-interference signal from the y.

$$y_1=h_1\circ X+w_1-h_1\circ\sqrt{p_2}x_2 \tag{3}$$

where the $h_1\sqrt{p_2}x_2$ is the reconstruction UE2 inter-interference signal, and the x_2 is the directly detection signal. The UE1 signal x_1 also can be detected from the residual signal y_1. The CSI is necessary both the signal decoding and SIC process in the UE, and it can be acquired by inserting the pilot symbol into the transmission signal X. The pilot signal received in the UE y_p can be expressed as:

$$y_p = h_p \circ x_p + w_p \tag{4}$$

where x_p is pilot symbols in the transmitter, and $h_p \in \mathbb{C}^{N_{PS}\times N_{PD}}$ is the channel matrix at pilot positions. w_p is AWGN at pilot positions. N_{PS} and N_{PD} are the number of time slot and subcarriers at pilot positions respectively.

The channel estimation at pilot positions h_p is estimated by the LS estimation, which is transformed into the following optimization problem:

$$\hat{H}_p^{LS} = \underset{H_p}{\arg\min} \left\| y_p - H_p \circ x_p \right\|_2^2 \tag{5}$$

where $\|\cdot\|_2$ means the L2 distance, and H_p is the estimated channel matrix. The optimization of (5) results in:

$$\hat{h}_p^{LS} = diag(\hat{H}_p^{LS}) = y_p \circ x_p^{\circ -1} \tag{6}$$

where $(\cdot)^{\circ -1}$ is the Hadamard inverse.

The traditional way to obtain the complete channel matrix $\hat{h}$ is to interpolate at the non-pilot positions. In this letter, the image super-resolution algorithm is introduced to map the h_p to $\hat{h}$.

3. Proposed Channel Estimation Network

3.1 Channel Image

The image SR algorithm reconstructs the high-resolution (HR) from low-resolution (LR), which is similar to the pilot-aided channel estimation. The mathematical form can be expressed as:

$$\hat{I}_y = f(I_x;\theta) \tag{7}$$

where I_x is the low-resolution image, $\hat{I}_y$ represents the recovered high-resolution image, f means the SR model with parameters of θ.

The channel estimation problem is transformed into a signal image SR problem. The channel matrix at pilot positions h_p is viewed as a low-resolution image, and the estimated channel matrix $\hat{h}$ is viewed as a high-resolution image which needs to be recovered. The real and imaginary parts of the channel coefficient matrix are divided into two parts like two images, because the neural network cannot process the complex value.

3.2 Network Structure

The proposed network is mainly composed of the densely connected conventional networks (DenseNet)[11] and the laplacian pyramid structure[12]. Densenet has been widely adopted in image super resolution problem by reusing the feature information. In each dense block, the input of the later layer is concatenation of all the previous layer feature, instead of features combing such as Residual Network (ResNet). There are two benefits: 1. The concatenation of feature enhances feature utilization, and mitigates the gradient vanishing. 2. The number of network parameters are reduced to some extent. In DenseNet, the HR image is reconstructed by a deconvolution layer of last layer, but one deconvolution layer is difficult to learn the complex mapping of LR image to HR image. The laplacian pyramid structure utilizes the multi-size deconvolution layer to restore image resolution step by step, which makes the network can learn the image characteristics of different sizes to enhance network performance.

Motivated by advantages of two network, we propose a Laplacian densely connected network which is specifically designed for channel estimation. The network structure is shown in Fig.2(a). The input of network is the channel matrix at pilot positions which is estimated by LS estimation. The first layer is a convolutional layer with 24 filters of size 3×3, which maps the input h_p of size $N_{PS}\times N_{PD}$ to output of size $N_{PS}\times N_{PD}\times 24$. Then the two dense blocks and deconvolutional layers are used to extract channel characteristic information, and gradually restore the matrix size. The first deconvolutional layer extends the matrix size to half the target matrix, and the second one expands the matrix to $N_S \times N_D$. The structure of dense block is shown in Fig.2(b). It contains bottleneck block, concatenation process, and transition layer. The input of bottleneck block is the concatenation of inputs all of previous bottleneck block, and the transition layer between two dense blocks reduces the number of characteristics images by convolution. The number of feature maps generated by each layer, the growth rate K, is 12. The bottleneck block includes batch normalized layer and two convolution layers, which shows as Fig.2(c). The size of the convolution kernel are 1×1 (Conv(1*1)) and 3×3 (Conv(3*3)), respectively. The batch normalized layer normalizes the inputs to increase network stability, and the Conv(1*1) layer is to reduce the number of input feature maps and computational cost. The Conv(3*3) layer is to extract channel characteristic information. The last reconstruction layer uses one filter of size 3×3 to reconstruct the complete estimated channel $\hat{h}$.

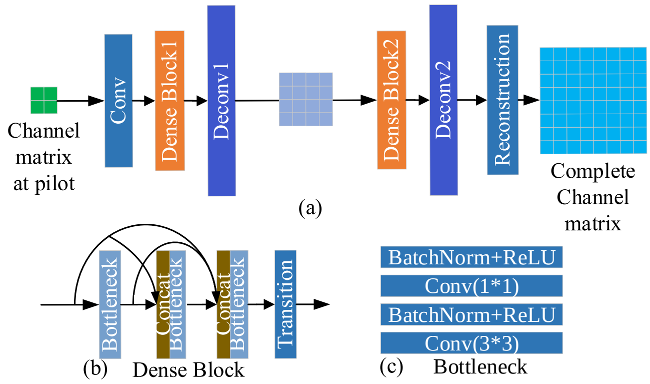

Fig. 2: (a) The structure of proposed channel estimation network; (b) The structure of the dense block; (c) The structure of the bottleneck block.

3.3 Training

The application of network is divided into two stages: off-line training and on-line deployment. The training stage can be Mathematically as:

$$\hat{h} = f(h_p;\theta) \tag{8}$$

where $\hat{h}$ is the estimated channel matrix, f is the network model, h_p is the channel matrix at pilot positions, and θ is the network parameters. The network utilizes the training set which is generated by the system model to learn the mapping from h_p to $\hat{h}$ through multiple iterations. The network parameters are updated in each iteration to reduce the value of the loss function.

The loss function C of the network is the MSE loss between the estimated channel $\hat{h}$ and the presupposed i-th UE channel h_i as follows:

$$C = \frac{1}{\|T\|}\sum_{h_p\in T}\|\hat{h}-h_i\| \tag{9}$$

where T is all training data sets, and $\|T\|$ is the size of the training sets. The network training goal is to minimize the loss function C by using some optimization algorithm like Stochastic gradient descent (SGD), Adaptive moment estimation (Adam) et al. The optimization process of the network determines the parameters θ, such as the weights at convolution layer and deconvolution layer. The trained network can be deployment in the communication system for channel estimation.

3.4 Complexity

In this section, the computational complexity analysis is presented to compare the complexities of the proposed network and traditional methods. The complexity of network models is measured by the number of floating-point operations (FLOPs). The FLOPs of one convolution layer is $O((2*C_{in}*K^2-1)*H*W*C_{out})$, where C_{in} and C_{out} represent the number of input channel and output channel, respectively. The K is the size of the convolution kernel. The symbols H and W denote the size of the output feature map. The required FLOPs of proposed network is $O(n_l(2*C_{in}*K^2-1)*H*W*C_{out})$. The n_l is the total number of convolutional layers and deconvolutional layers, because the deconvolutional layer required the same FLOPs as convolutional layer. The complexity of the traditional method LS is $O(L)$, where L is the length of signal sequence. The complexity of the MMSE method is larger than $O(L^{2.37})$ owing to the matrix inversion operation[13]. The proposed network is proportional to the input signal length L, which is pretty small compared with the MMSE estimator.

4. Simulation Results

In this section, the proposed channel estimation network is trained by using the simulation data and is compared with the traditional methods. In this experiment we consider a downlink NOMA system, and the size of NOMA signal is 52 subcarriers and 14 OFDM symbols. The ratio of the two UEs power distribution is 0.2:0.8. The NOMA signal and channel coefficient matrix are generated by MATLAB, and the channel model is the Extended Pedestrian A(EPA) model from 3gpp. The carrier frequency of the channel model is 2.1 GHz, the bandwidth is 10 MHz, and the UE speed is 5km/h. Totally 60,000 channel matrices are divided into 60% training, 20% test and 20% validation sets. The MSE between the estimated and the actual channel is to evaluate the performance of different channel estimation methods.

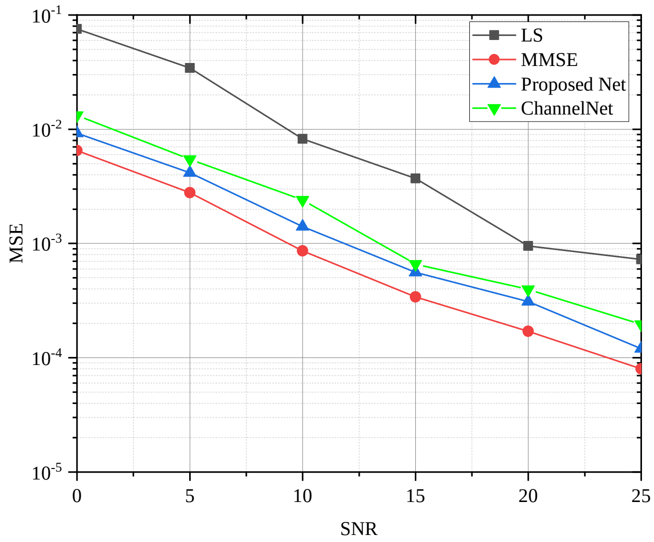

Fig. 3: Channel estimation MSE of different methods

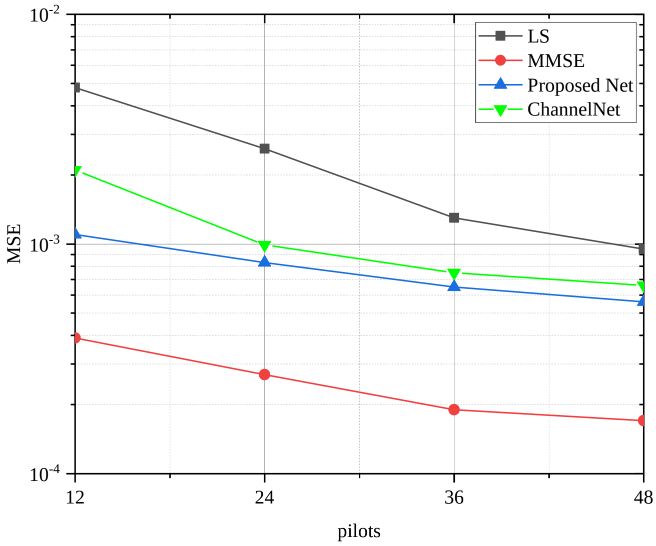

Fig. 4: Channel estimation MSE for different numbers of pilots

The channel estimation MSE under different SNR of the LS estimation, MMSE estimation, ChannelNet, and the proposed network shows in Fig.3. The number of pilots inserted into the signal is 48. The LS estimation uses the linear interpolation to recover the complete channel on the basic of the channel matrix at pilot positions, and the MMSE estimation utilizes the prior channel statistic and noise variance to recover the complete channel. Therefore, the MSE of MMSE can be treated as a lower bound with the performance of estimation. The ChannelNet is the channel estimation network in OFDM by using SRCNN, which is applied to NOMA system for comparison. The proposed network demonstrated superior performance over LS and ChannelNet estimation, and the one reason is that it learns channel matrix information of different sizes. The LdEsNet estimation shows close to MMSE estimation performance, and do not require the priori channel information.

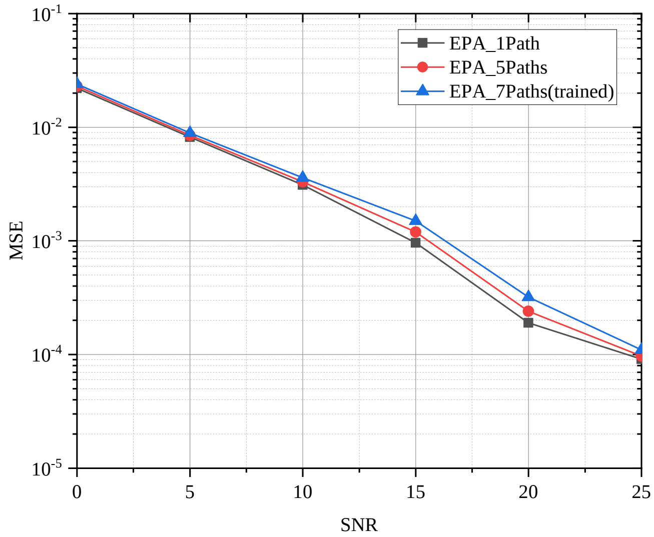

Fig. 5: Channel estimation MSE of EPA for different paths

The channel estimation MSE for different numbers of pilots at 20dB SNR is to assess the performance of estimation algorithm, and the simulation results is shown in Fig.4. The performance of LdEsNet is constantly improved with the numbers of pilots, and the reason is that the increased input data enhance the information available to the LdEsNet. The increase of the pilots enhances the performance of the estimation, but it will reduce the transmission efficiency of communication system. Besides, the LdEsNet has better performance at low pilot numbers.

To evaluate the LdEsNet performance when mismatch between training and application scenarios, we compare the channel estimation MSE of EPA model for different paths in Fig.5. The LdEsNet is trained under EPA with 7 paths, and tested under the EPA with 1 path, 5 paths, 7paths. The overall performance of LdEsNet is stable under EPA model with different paths.

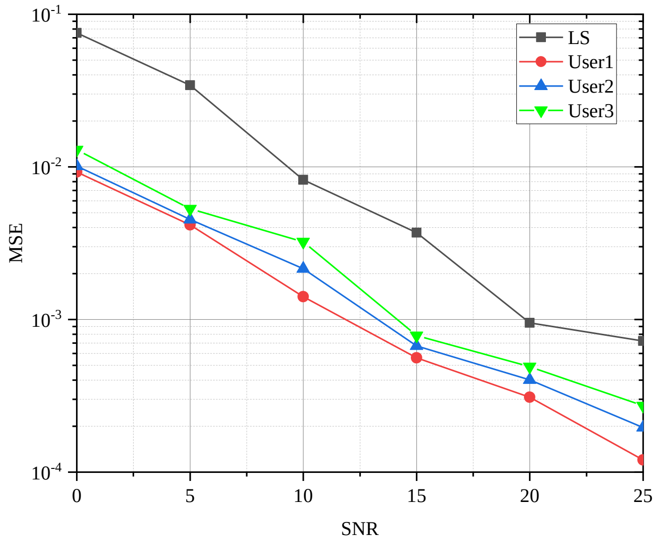

Fig. 6: Channel estimation MSE for different users

The test results of the proposed network in multi-user scenarios are shown in Fig.6. Three users use the same time-frequency resource, and the channel condition gradually deteriorates. User3 had the worst estimated performance because it was not learned by network training. However, it still has better performance than LS. The network can be applied to multi-user NOMA systems for channel estimation.

5. Conclusion

In this letter, we propose a laplacian densely connected channel estimation network in NOMA system. The receiver utilizes the proposed network to reconstruct the high-resolution complete channel matrix from the low-resolution channel matrix at pilot positions by LS estimation. The proposed network combines the dense network and laplacian pyramid structure, which can attain the channel characteristics of different sizes to improve the channel estimation performance. Besides, the network can be adapted for different communication scenarios, which requires the complete CSI. The simulation results show that the LdEsNet is more competitive which do not require the channel statistic and noise variance with the MMSE algorithm.

6. References

[1] Dai, L., Wang, B., Yuan, Y., Han, S., Chih-Lin, I., and Wang, Z., "Non-Orthogonal Multiple Access for 5G: Solutions, Challenges, Opportunities, and Future Research Trends," Ieee Communications Magazine, Vol. 9, pp. 74-81, Sep 2015.

[2] Akbar, A., Jangsher, S., and Bhatti, F. A., "NOMA and 5G emerging technologies: A survey on issues and solution techniques," Computer Networks, Vol., May 2021.

[3] Tan, Y., Zhou, J., and Qin, J., "Novel channel estimation for non-orthogonal multiple access systems," IEEE Signal Processing Letters, Vol. 12, pp. 1781-1785, 2016.

[4] Sekokotoana, L. E., Takawira, F., and Oyerinde, O. O., "Least Mean Squares Channel Estimation for Downlink Non-Orthogonal Multiple Access," 2019 IEEE AFRICON, AFRICON 2019, September 25, 2019 - September 27, 2019, Accra, Ghana, 2019, doi:10.1109/AFRICON46755.2019.9133868

[5] Wang, X., Zhu, P., Li, D., Xu, Y., and You, X., "Pilot-Assisted SIMO-NOMA Signal Detection With Learnable Successive Interference Cancellation," Ieee Communications Letters, Vol. 7, pp. 2385-2389, Jul 2021.

[6] Kim, W., Ahn, Y., and Shim, B., "Deep Neural Network-Based Active User Detection for Grant-Free NOMA Systems," Ieee Transactions on Communications, Vol. 4, pp. 2143-2155, Apr 2020.

[7] Xie, W., Xiao, J., Yang, J., Wang, J., Peng, X., Yu, C., and Zhu, P., "Deep Learning-Based Modulation Detection for NOMA Systems," Ksii Transactions on Internet and Information Systems, Vol. 2, pp. 658-672, Feb 2021.

[8] Lin, C., Chang, Q., and Li, X., "A Deep Learning Approach for MIMO-NOMA Downlink Signal Detection," Sensors, Vol. 11, Jun 2019.

[9] Xie, Y., Teh, K. C., and Kot, A. C., "Deep Learning-Based Joint Detection for OFDM-NOMA Scheme," Ieee Communications Letters, Vol. 8, pp. 2609-2613, Aug 2021.

[10] Soltani, M., Pourahmadi, V., Mirzaei, A., and Sheikhzadeh, H., "Deep Learning-Based Channel Estimation," Ieee Communications Letters, Vol. 4, pp. 652-655, Apr 2019.

[11] Huang, G., Liu, Z., van der Maaten, L., and Weinberger, K. Q. J. a. e.-p. (2016). Densely Connected Convolutional Networks. arXiv:1608.06993. https://ui.adsabs.harvard.edu/abs/2016arXiv160806993H

[12] Lai, W.-S., Huang, J.-B., Ahuja, N., and Yang, M.-H., "Deep laplacian pyramid networks for fast and accurate super-resolution," 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017, July 21, 2017 - July 26, 2017, Honolulu, HI, United states, 2017, pp. 5835-5843, doi:10.1109/CVPR.2017.618

[13] Coppersmith, D., and Winograd, S., "MATRIX MULTIPLICATION VIA ARITHMETIC PROGRESSIONS," Proceedings of the Nineteenth Annual ACM Symposium on Theory of Computing, New York, USA, 1987, pp. 1-6, doi:10.1145/28395.28396