5.3 Overview of Trained Network

In this table, I group Experiments(Trained Network) that serve for same experimentation purpose together.

Trained Network	Dataset used	Layer(s)	dilation rate	Training Epoch(s)	Min.Val MSE	Optimizer
Simplistic Experiment as Benchmark						
A	No.1	30	12	162	0.00072596	SGD based ADAM
B	No.10	30	12	162	0.11119231	SGD based ADAM
Experiments for Selection of Hyper-parameters						
C	No.1	30	20	205	0.00103128	SGD based ADAM
D	No.1	100	12	174	0.00033686	SGD based ADAM
E	No.1	30	12	162	0.00076923	MBGD based ADAM
Experiment of Exploration on Gaussian Noise Reduction						
F	No.2	30	12	206	0.08382587	SGD based ADAM
G	No.3	30	12	206	0.02911259	SGD based ADAM
H	No.4	30	12	206	0.00993774	SGD based ADAM
I	No.11	30	12	206	1.03353448	SGD based ADAM
J	No.12	30	12	206	0.81546657	SGD based ADAM
K	No.13	30	12	206	0.73586103	SGD based ADAM
Experiment of Exploration on Dealing with Gaussian Blurring						
L	No.5	30	12	191	0.00075352	SGD based ADAM
Experiment of Exploration on Dealing with Gaussian Blurring and Gaussian Noise Reduction						
M	No.6	30	12	191	0.00332484	SGD based ADAM
Experiment of Exploration on Shape Generality						
N	No.8	30	12	67	0.00312558	SGD based ADAM
O	No.9	30	12	67	0.00055956	SGD based ADAM
Experiment of Addition of Elliptical Cylinder Shapes						
P	No.7	30	12	162	0.00758779	SGD based ADAM
Q	No.14	30	12	162	5.22642440	SGD based ADAM

Table 5.1: Overview of Trained Network

This table summarizes the datasets, the number of layers, the dilation rate, the minimum validation error MSE (Min Val.MSE), the number of training epochs, and the optimizer. The trained networks are grouped according to the aim of the study (Experiments for selection of Hyper parameters,....).

Actually I set up multiple experiments for different purposes. The simplistic experiment is evaluating the neural network performance naively. Since we will evaluate the robustness of mixed-scale dense network when learning more complicated cases, like addition of Gaussian noise and Gaussian blur, shape generality, there is a need to keep the hyper-parameters in all experiment set-ups. So, I organize another 3 experiments(C,D,E) with quite different hyper-parameters setting based on the same dataset to select better the hyper-parameters combination by considering factors of error and time consumed in model training .

5.3.1 Groups of Trained Network for different purpose

5.3.1.1 Group of Simplistic Experiment as Benchmark

Trained Network	Number of Density(s) involved	Material(s) involved	Shape(s) involved in Training Data
A	1	PPMA	ellipsoid and paraboloid
B	4	PPMA Aluminum Al_2O_3 PET	ellipsoid and paraboloid

Table 5.2: Overview on Group of Simplistic Experiment as Benchmark

We are starting with the most simplistic cases. Trained networks A and E are based on dataset 1 and 10 respectively, which have no gaussian noise or gaussian blurring added. The difference between them is the number of materials involved. Trained network A is based on only 1 material while trained network E is based on 4 materials.

So,we can take these two trained network's performance as reference when comparing with other experiments that are serving for other purposes.

5.3.1.2 Group of Experiments for Selection of Hyper-parameters

Trained Network	Training Duration	Layers	dilation rate	Optimizer	Training Epoch	Min.Val MSE
A	Moderate	30	10	SGD based ADAM	162	0.00072596
C	Modeate	30	20	SGD based ADAM	205	0.00103128
D	Very Long	100	10	SGD based ADAM	174	0.00033686
E	Longer	30	10	MBGD based ADAM	162	0.00076923

Table 5.3: Overview on Group of Experiment for Selection of Hyper-parameters

I set up this set of experiments for hyper-parameter selection purpose. Even if trained network D which has 100 hidden layers has minimum validation mean square error, its training cost in terms of time is too long, I rejected it. Trained network C has larger dilation rate, it has larger receptive field, but it seems it does not have better results than the other trained network A in terms of minimum validation error. Trained Network E has similar minimum validation error as A, but it has longer training time when mini-batch is applied. Finally, I select hyper-parameters with trained network A for experiments set up for other purposes.

5.4 Simplistic Experiment as Benchmark for other Experiments

The simplistic experiment is divided into single density case and diverse densities case. The average values of error metrics are obtained by taking all testing data of 100 pictures into account for each experiment.

The reconstruction performance is related to the NMSE error evaluation. The best case has minimum NMSE value among all testing pictures, we treat it as the best reconstruction by neural network.

5.4.1 Single density

5.4.1.1 Testing Error of Simplistic Model of Single Density

Trained Network Applied	Index	Average NMSE	Average MSE	Average SSIM	Average PSNR
A	Phase	0.02671	0.001866	0.9110	79.4854
A	Attenuation	0.02671	8.6769e-10	0.9999	94.6807

Table 5.4: Testing Error of Simplistic Model of Single Density

The testing error for attenuation performs better than for the phase except for the average NMSE. The level of magnitude of phase projection is larger than attenuation projection for thousands of times, and the error of phase projection is larger than the error for attenuation projection. Since this is the single density case, phase is always proportional to attenuation with an unique ratio everywhere. At the output layer, each output channel is linear combination of last hidden layer channels, these two outputs are proportional everywhere. Therefore, attenuation and phase have identical NMSE value for the single density case.

5.4.1.2 Corresponding Testing Error of Contrast Transfer Function Method

Index	Average NMSE	Average MSE	Average SSIM	Average PSNR
Phase	0.8879	5.6607	0.5693	46.0678
Attenuation	3.0561	3.5476e-05	0.9891	52.5542

Table 5.5: Corresponding Testing Error of Contrast Transfer Function Method for Simplistic Model of Single Density

The attenuation and phase reconstruction by MSDNet performs better than contrast transfer function in terms of all error metrics. We will evaluate the best and worst reconstruction implied by NMSE visually next.