4 Dataset

The input data to the neural network will be the stack of phase contrast images at different distances and the expected output will be stack of corresponding attenuation and phase projection images.

4.1 Random Phantoms Generation and Image Formation

4.1.1 Homogeneity of Phantoms

Because of the weak transfer of low frequency information made by Fresnel transform, phase retrieval from Fresnel diffraction patterns is inherently sensitive to noise in low frequency range. However, this issue was addressed by introducing a homogeneous object assumption. In this case, it is done by introducing a scaled version of the attenuation image as prior knowledge on the phase[2]. It based on two assumptions. Firstly, the object has homogeneous composition (a unique ratio between real and imaginary parts of the refractive index, and density variations are allowed). Secondly, the composition of the sample is known. The materials used for phantoms are according to [2].

4.1.2 Theoretical values for the different materials in the phantom

material	$\mu(cm^{-1})$	$2\pi\delta/\lambda(cm^{-1})$	δ/β
Al	6.65	1220	367
Al_2O_3	6.29	1790	570
PET	0.637	702	2200
PP	0.328	481	2930

Table 4.1: Theoretical values for the different materials in the phantom[2]

4.1.3 Shapes in Phantom and Projection of Phantoms

The Shepp-Logan phantom consisting of 10 ellipses of constant intensity does not suit the diversity of objects for different imaging tasks, we use TomoPhantom [30] that is a software package to generate 2D–4D analytical phantoms for CT image reconstruction instead. It can generate 3D shapes of ellipsoid, paraboloid, gaussian, cuboid, elliptical cylinder. The size, position and orientation of phantoms can be set in generation. So we will generate 3D shapes in experimentation, and then produce projection of these 3D shapes. which are 2D. The shapes selected for phantom generation are ellipsoid, paraboloid and elliptical cylinder. As there is a limitation of software design, the orientation setting of elliptical cylinder does not work, the elliptical cylinder shapes in 2D analytical projections seem similar, so elliptical cylinder will not be generally used in following experiments. Since the derivative of Gaussian function will be Gaussian still and not suitable for differential tomography[31], it will not be used.

We will prepare phantoms generation for attenuation and phase respectively, they have same patterns but different density for each of phantom image produced. And the density setting of 3D phantom generation would be according to table of theoretical values for the different materials in the phantom above. In generation, each shape in phantom will be randomly given a density. The single density phantom means single density involved throughout all shapes in phantom, and diverse density phantoms have more densities involved. Instead of numerical projection of 3D phantoms, we use analytical tomographic projection provided by TomPhantom package[30] that is more realistic. The analytical projection is based on mathematical expression of shapes while numerical projection is the summation of numerical values of 3D phantoms along projection direction. We will produce 1 pair of attenuation and phase projections along certain projection direction in 3D phantom pair for all of phantom images.

4.1.4 Phase Contrast Image Generation

The phase contrast image formation will be according to Eqs.1.10, 1.14 and 1.16, but dealing in Fourier domain first, and then reverse to spatial domain by inverse Fourier transform. Because of that, the partial Gibbs effect is occurring. As there are sharp variations present in phantom projections, to recover them, more high frequencies should be involved, however, due to limitation of 2D FFT capacity in figuring it out, the fringe is present in inverse 2D FFT result of phase contrast images. It has image enhancement effect, but it is not expected to be large. So we use the down-sampling in phase contrast image formation.

The size of phantom projection image is 1024×1024, the phase contrast images formed is 512×512. For projection image, we set pixel size to be 7.0×10^{-7}, correspondingly the pixel size becomes halved when down-sampling. In k-space of 2D FT:

$$\Delta x, y = \frac{1}{2 \cdot k_{max(x,y)}} \qquad k_{max(x,y)} = \frac{1}{pixel \quad size} \tag{4.1}$$

So we can obtain more high frequency part in 2D signal and the partial Gibbs effect could be partially alleviated. We also add white Gaussian noise based on PPSNR in dB that prevents the outlier in noise generation:

$$PPSNR = 20 \log_{10} \frac{signal_{max}}{noise_{max}} \tag{4.2}$$

4.2 Datasets Prepared

In this table, I group datasets depending on the gaussian noise and gaussian blur that are added to the clean images, depending on the density (single density or multiple densities) and depending on the shapes used.

Dataset	Density Composition	Shape(s)	Added Noise Level (PPSNR)	Gaussian Blur	Number of input output pairs
			Pattern 1		
No.1	single density	ellipsoid paraboloid	no noise	no blurring	1000
No.2	single density	ellipsoid paraboloid	6dB	no blurring	1000
No.3	single density	ellipsoid paraboloid	12dB	no blurring	1000
No.4	single density	ellipsoid paraboloid	24dB	no blurring	1000
No.5	single density	ellipsoid paraboloid	no noise	kernel size: 5× 5 standard deviation:2	1000
No.6	single density	ellipsoid paraboloid	12dB	kernel size: 5× 5 standard deviation:2	1000
			Pattern 2		
No.7	single density	ellipsoid paraboloid elliptical cylinder	no noise	no blurring	1000
			Pattern 3		
No.8	single density	ellipsoid	no noise	no blurring	1000
			Pattern 4		
No.9	single density	paraboloid	no noise	no blurring	1000
			Pattern 5		
No.10	diverse density	ellipsoid paraboloid	no noise	no blurring	1000
No.11	diverse densities	ellipsoid paraboloid	6dB	no blurring	1000
No.12	diverse densities	ellipsoid paraboloid	12dB	no blurring	1000
No.13	diverse densities	ellipsoid paraboloid	24dB	no blurring	1000
			Pattern 6		
No.14	diverse densities	ellipsoid paraboloid elliptical cylinder	no noise	no blurring	1000

Table 4.2: Datasets Prepared

In the following, we will compare the neural network performance with the one of contrast transfer function (CTF) . When solving the inverse problem, the contrast transfer function takes 4 phase contrast images at different distances as input to compute the projection, I will do the same for the neural network. There will be 4 input channels and each input channel is a phase contrast image at a certain distance. In the phase contrast generation, the distances are set according to [2], i.e.[2, 10, 20, 45] mm.