

Particle Number Density Determination

Utilized image reconstruction to determine the particle number density n_d .

Crystalline Structure Formation:

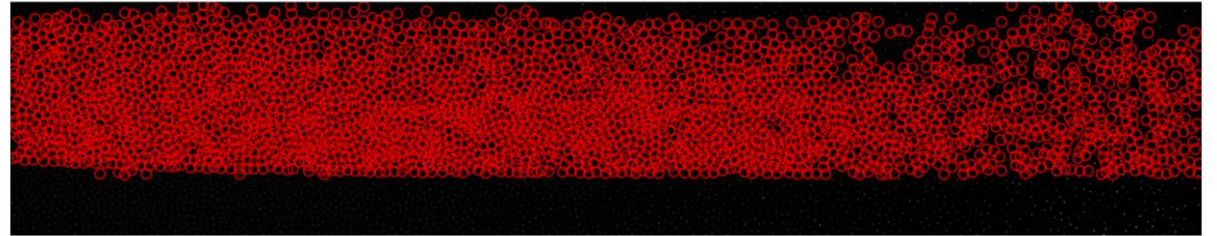
- Employed a stopping-process via polarity switching or RF-coil
- Resulted in the formation of a crystalline structure composed of particles.



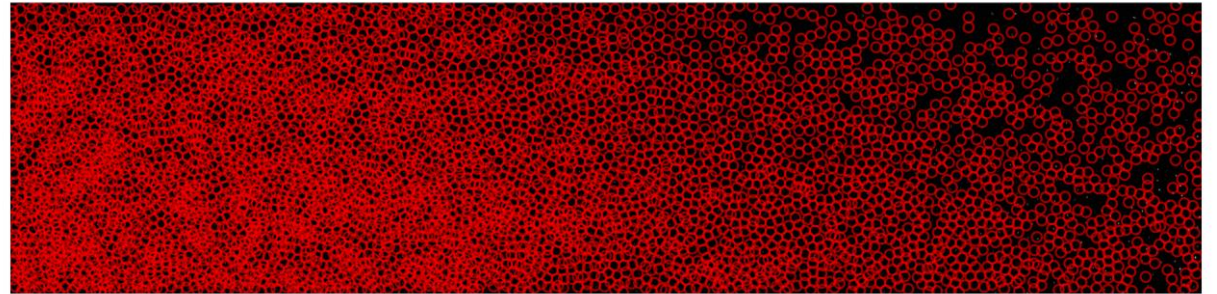
Density Determination Methodology:

- Extracting coordinates via tracking code.
Careful parameter selection is vital to avoid errors and exclude faint particles at different planes, see bottom image.

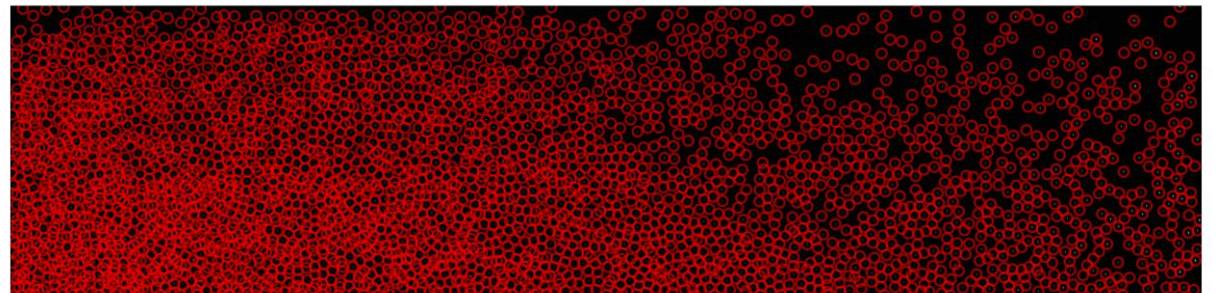
Particle Tracking 30 Pascal



Particle Tracking 40 Pascal



Particle Tracking 50 Pascal



```
210  ### 1.31 micrometer particles do have a psf of around 3 pixels [M.Y. Pustynnik et. al. (2016)]
211  ps_in_px = 9    #point spread function of particle; needs to be odd number (13 from agglomeration 24.06.2022, 9 from density 16.02.2023)
212  min_mass_cut = 70  #Brighthness Threshold = cancel out faint particles; from experience (200 from agglomeration 24.06.2022, 70 from density 16.02.2023)
213  iter_step_dr = 0.5 #from experience (accuracy and computationsla time taken into account)
```

Density Determination Methodology:

- Utilized data from particle tracking to determine the pair correlation function with density_2D_vsf [<https://link.aps.org/doi/10.1103/PhysRevResearch.2.033404>].
- Assumed a Wigner-Seitz cell to assess three-dimensional density [A. Melzer, Physics of Dusty Plasmas]..

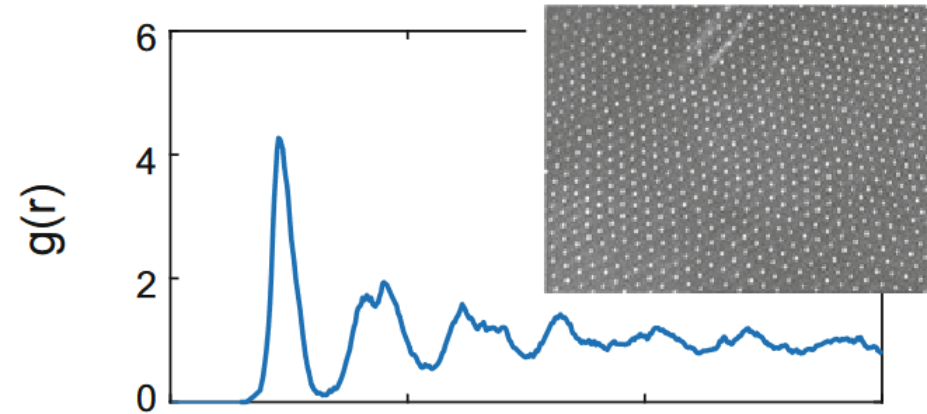
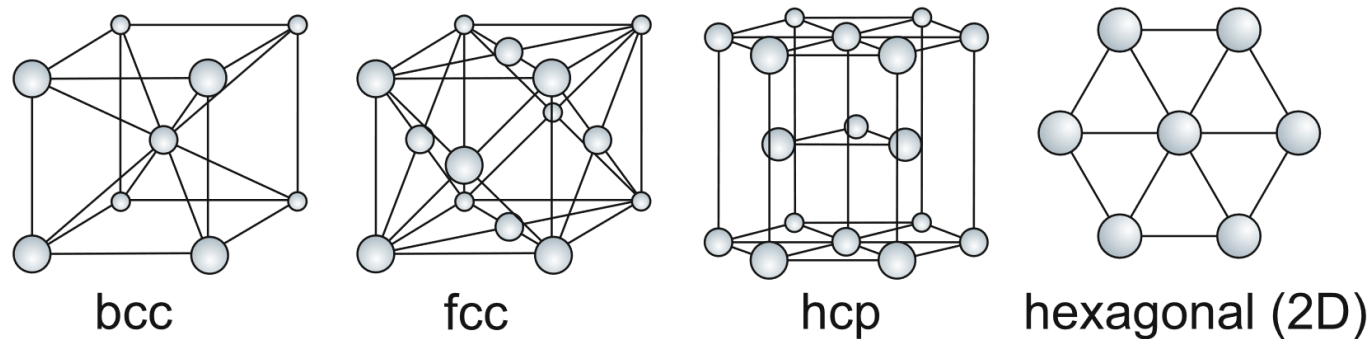


Fig. 5.1 Crystal structures in 3D: BCC, FCC and HCP. In 2D: hexagonal crystal structure. The BCC structure contains particles at the edges of a cube and an additional particle in the cube center. Likewise FCC contains additional particles at the cube faces. HCP is very similar to FCC where the ordering repeats every other layer instead of every third layer as in FCC

Mean Radius and Wigner-Seitz Radius Calculation:

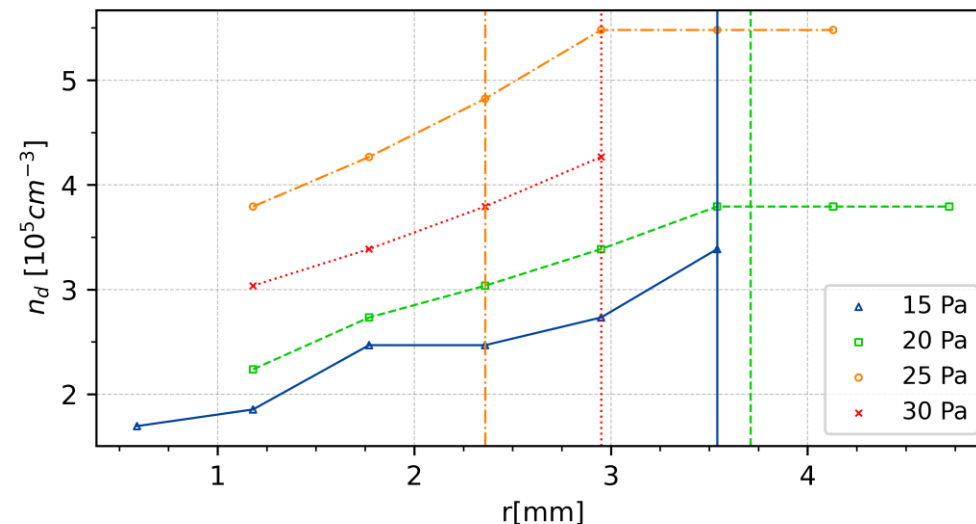
- The first peak in the distribution corresponds to the mean radius r_0 .
- Calculated the Wigner-Seitz radius $a=r_0/\rho$ with $\rho=1.79\pm0.07$ from simulations.

Particle Number Density Computation:

- Computed particle number density $n_d=3(4\pi a^3)$.
- Associated with a maximum uncertainty of up to $\pm 12\%$ [<https://doi.org/10.1063/1.4914468>].

Visualization:

- Figure illustrates the radial distribution of n_d from the tube axis.
- Measurements conducted at various pressures.



More Code Insight:

```
162  ### PREPERATION ###
163
164  #Frame pre analysis. Prepare frame for density calculations. Crop Image at particle population area.
165  frames = pims.open('densitydata/*.bmp')
166
167  img1 = frames[0]
168
169  cut_l = 1250
170  cut_r = 1650
171
172  img_1 = img1[cut_l:cut_r,:]
173
174
175  # Optionally, tweak styles.
176  mpl.rc('figure', figsize=(10, 5))
177  mpl.rc('image', cmap='gray')
178  plt.imshow(img_1)
179
180  ###
181
182  img_1 = gaussian_filter(img_1, sigma=1)
183  plt.imshow(img_1)
```

Read in and cut out the interesting part of the image. Find the correct cuts individually.

Apply `gaussian_filter` to improve quality and reduce noise.

More Code Insight:

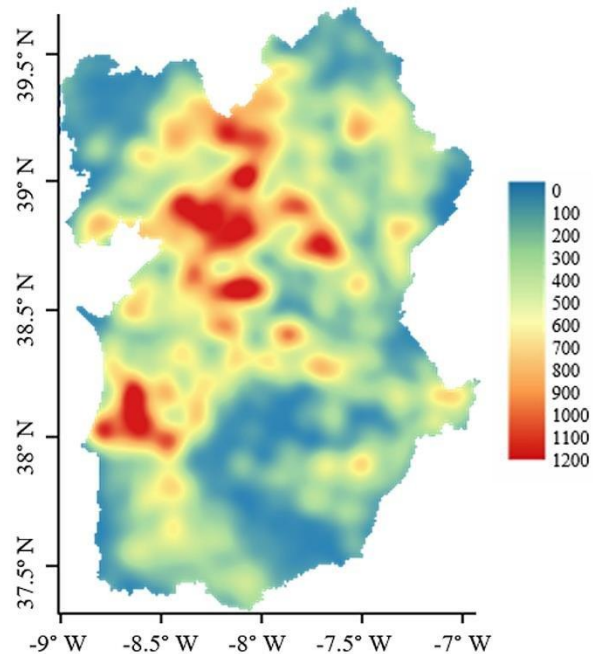
```
186 #https://michael-fuchs-python.netlify.app/2020/06/20/hdbscan/
187
188 #PSF = 3-12 depending on particle size and exposure time
189 #Brighthness Threshold = cancel out faint particles, depending on camera gain and exposure time
190 #doi = {10.1063/1.4914468}
191
192 df_located = tp.locate(img_1,9,70)      #(img, PSD, min_brighthness)
193
194 #
195 x_coords = df_located['x'].to_numpy()
196 y_coords = df_located['y'].to_numpy()
197 #
198 data = np.transpose(np.vstack((x_coords,y_coords)))
199
200 #PLOT
201 plot_kwds = {'alpha' : 0.25, 's' : 25, 'linewidths':1}
202 fig,ax = plt.subplots(dpi=600)
203 plt.imshow(img_1)
204 plt.scatter(data.T[0], data.T[1], color='r', **plot_kwds, facecolors='none')
```

Preadjust PSD and brightness threshold precisely

-> Go to **###Main Code###** and make it run -> Last step, create the plot.

Future Add On:

- Visualizing by 2D density mapping



Here is my aim at a more complete answer including choosing the color map and a logarithmic normalization of the color axis.

```
import matplotlib.pyplot as plt
import matplotlib.cm as cm
from matplotlib.colors import LogNorm
import numpy as np
x, y, z = np.loadtxt('data.txt', unpack=True)
N = int(len(z)**.5)
z = z.reshape(N, N)
plt.imshow(z+10, extent=(np.amin(x), np.amax(x), np.amin(y), np.amax(y)),
             cmap=cm.hot, norm=LogNorm())
plt.colorbar()
plt.show()
```

I assume here that your data can be transformed into a 2d array by a simple reshape. If this is not the case than you need to work a bit harder on getting the data in this form. Using `imshow` and not `pcolormesh` is more efficient here if you data lies on a grid (as it seems to do). The above code snippet results in the following image, that comes pretty close to what you wanted:

