

PHYS5120 HW2

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October 4, 2022

1. Molecular Dynamics simulations of Lennard-Jones Argon

The experimental data for Lennard-Jones argon:

$$\epsilon/k_B = 119.8 \text{ K}, \sigma = 3.405 \text{ \AA}, M = 0.03994 \text{ kg/mol}$$

Use the "md.py" code provided here to run a MD simulation at the temperature $T = 180 \text{ K}$ and the density $\rho = 1340 \text{ kg/m}^3$. The simulation equilibrium should be at least 10 picoseconds.

1. Calculate the temperature and the number density in reduced units.

The unit of temperature in reduced unit is given by:

$$\begin{aligned} T &= \frac{T(\text{K})}{\epsilon/k_B} \\ &= \frac{180 \text{ K}}{119.8 \text{ K}} \\ &= 1.50 \end{aligned}$$

The unit of number density in reduced unit is given by:

$$\begin{aligned} \rho &= \frac{\rho(\text{kg/m}^3)}{M/N_A \sigma^3} \\ &= \frac{1340 \text{ kg/m}^3}{1680 \text{ kg/m}^3} \\ &= 0.7976 \end{aligned}$$

*L^AT_EX source code: <https://github.com/rstanuwijaya/hkust-computational-material/>

2. Choose a proper time step. Plot kinetic energy, potential energy, and total energy versus simulation time. Are they stable?

The reduced unit time is:

$$t_0 = \sigma \sqrt{m/\epsilon} = \sigma \sqrt{\frac{M}{N_A} \frac{1}{(\epsilon/k_B)k_B}} = 2.157 \times 10^{-12} \text{ s}$$

Therefore, the total simulation time in reduced unit is:

$$t_{\text{total}} = 10 \times 10^{-12} \text{ s} / t_0 = 4.63 \approx 5$$

If we choose the total simulation steps to be 1000, then the time step is:

$$\Delta t = \frac{t}{1000} = 0.005$$

We run the simulation using time step $dt = 0.005$, using 1000 iterations of production run and 1000 iterations of equilibrium run. The results of equilibrium run are shown in Fig. 1. The energy is stable, and the potential energy is always negative. Note that we have also tried using different number of iterations (5000 and 10000), in which the results are similar.

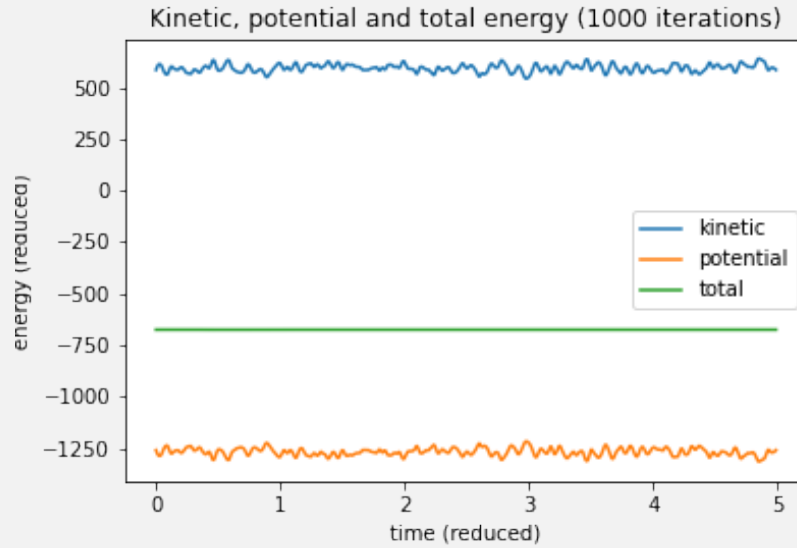


Figure 1: Energy versus simulation time.

Note that the reduced unit of energy is given by: $\epsilon = 1.65 \times 10^{-21} \text{ J}$ and the reduced unite of time is given by: $t_0 = 2.157 \text{ ps}$.

- Output unfolded coordinates as well as velocities in the Gromacs gro format: <http://manual.gromacs.org/archive/5.0.3/online/gro.html>. The length unit is nanometer (nm); the time unit is picosecond (ps); the velocity unit is nm/ps. A sample gro file for a MD trajectory is provided here. Save the trajectory on your machine (not canvas.ust.hk) and visualize it using the VMD software: <http://www.ks.uiuc.edu/Research/vmd/>. In VMD, choose CPK as the drawing method (Graphics -> Representations -> Drawing Method) Attach one VMD screen shot in your PDF report. If your time step is very small, you do not need to write down every MD step, why? Use the saved gro file to do the following analyses.

We have modified the `simulate()` function to output the coordinates and velocities in the Gromacs gro format for all of the 1000 frames. The output file is named `argon.gro`. The VMD screen shot is shown in Fig. 2.

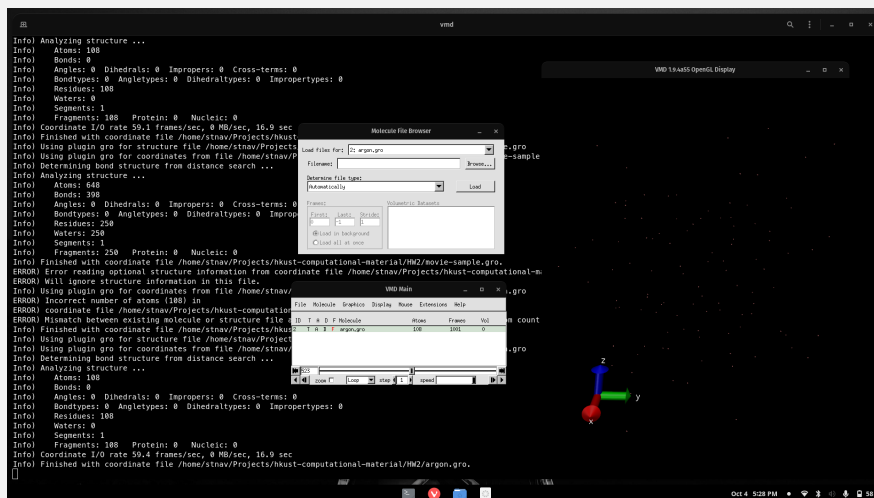


Figure 2: Argon gas simulation using VMD.

In the case of using a smaller time step, not all of the frames are important as the particle movement will be slower and the file size grows linearly with the number of frames used in the Gromacs file.

4. Write your own code to plot the radial distribution function of argon.

Let $h(r)$ be the histogram of the (**minimum image**) distance between all particle pairs throughout all the frames in the simulation and $n(r) = h(r) * 2 / (N_{\text{atoms}} N_{\text{frames}})$ as the normalized distance histogram per atom per frame, i.e. $\sum n(r) = N$. The radial distribution is defined as:

$$g(r + 0.5dr) = \frac{n(r)}{\rho dV} = \frac{n(r)}{4\pi\rho r^2 dr}$$

The implementation can be found directly in the appendix.

The radial distribution function of argon for ($N_{\text{cell}} = 3$) is shown in Fig. 3. As we can see from the figure, the plot is very similar to the one in the lecture notes for $r < L_{\text{box}}/2 \approx 2.57$ where the function suddenly decays. To obtain the radial distribution for larger r , we can try to increase the simulation box size by increasing N_{cell} to 4 or 5. However, this will increase the simulation time significantly.

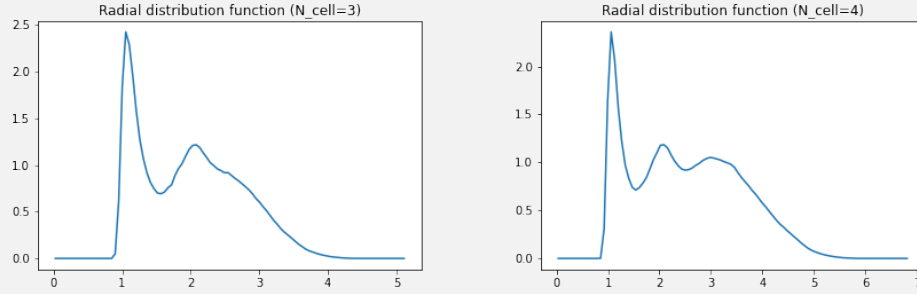


Figure 3: Radial distribution of argon for $N_{\text{cell}} = 3$ and $N_{\text{cell}} = 4$.

5. Calculate the diffusion constant (coefficient) using both the Einstein relation 1 and the Green-Kubo method. Are the two results consistent? Because of periodic boundary conditions, we have folded and unfolded coordinates. Which one should be used to calculate the mean squared displacement? Why?

Recall the Einstein relation:

$$D = \frac{1}{6N_{\text{atom}}} \sum_i^{N_{\text{atom}}} \frac{d[r_i(t+dt) - r_i(t)]^2}{dt}$$

And the Green-Kubo relation:

$$D = \frac{1}{3N_{\text{atom}}} \int \sum_i^{N_{\text{atom}}} x[v_i(t+dt) \cdot v_i(t)] dt$$

Note that for Einstein diffusion coefficient, the coordinates system used should be the unfolded coordinates. However, since the simulation uses the folded coordinates, we can see there will be some discrepancy with the diffusion constant found using the Green-Kubo relation.

The results of the velocity autocorrelation for each frames obtained using the two methods are shown in Fig. 4. We can observe that the two results are consistent but the autocorrelation obtained using Einstein method is scaled by a factor of ~ 0.5 . The corresponding diffusion constant given by the two methods are:

$$\begin{aligned} D_{\text{einstein}} &= 3.716 \\ D_{\text{green-kubo}} &= 7.417 \end{aligned}$$

as we have argued above, the correct diffusion constant should be $D_{\text{green-kubo}}$.

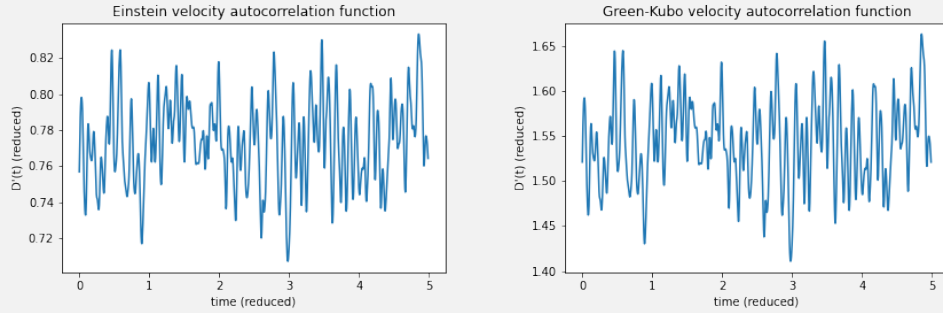


Figure 4: Velocity autocorrelation for each frames obtained using the Einstein relation and the Green-Kubo relation.

2. Appendix

(a) Python code for MD simulation

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3 from math import sqrt, pi
4 from itertools import product
5
6 sigma = 34.05 # nm
7 t0 = 2.157 # ps
8 n_bins = 100
9
10 T_0 = 1.50 # temperature
11 rho = 0.7976 # density of Argon in reduced units
12 # T_0 = 0.71 # temperature
13 # rho = 0.844 # density of Argon in reduced units
14
15 n_frames = 1000
16 dt = 5/n_frames # time step size
17 N_cell = 4 # number of fcc unitcells in one direction
18 N = 4 * N_cell ** 3 # the total number of particles in the system
19 L_box = (N / rho) ** (1 / 3.0) # length of the whole simulation box
20 L_cell = L_box / N_cell # length of a unitcell
21 F = np.zeros((N, N, 3)) # matrix that contains all forces
22 ind = np.triu_indices(N, k=1) # indices of upper triangular matrix
23
24
25 def IC_pos(N_cell, L_cell):
26     '''
27     use fcc structure to initialize positions
28     '''
29     pos = [[[x, y, z],
30             [x, 0.5 + y, 0.5 + z],
31             [0.5 + x, y, 0.5 + z],
32             [0.5 + x, 0.5 + y, z]]
33             for x, y, z in product(range(N_cell), range(N_cell), range(N_cell))]
34     pos = np.array(pos).reshape((-1, 3))
35     return pos * L_cell
36
37
38 def IC_vel(N):
39     '''
40     Maxwell-Boltzman distribution is a normal distribution
41     '''
42     vel = np.sqrt(T_0) * np.random.randn(N, 3)
43     vel -= np.average(vel, axis=0)
44     return vel
45
46
47 def find_force(pos, L_box=L_box):
48     '''
49     Minimum image convention.
50     '''
```

```

51     r_vec = pos[ind[0]] - pos[ind[1]]
52     r_vec = r_vec - np rint(r_vec / L_box) * L_box
53     r_sq = np.sum(r_vec**2, axis=1)
54     F_vec = -(48 / r_sq ** 7 - 24 / r_sq ** 4)[: , None] * r_vec
55     F[ind[0], ind[1]] = F_vec
56     pot = np.sum(4 / r_sq ** 6 - 4 / r_sq ** 3)
57     P = np.sum(F_vec * r_vec)
58     return np.sum(F, axis=0) - np.sum(F, axis=1), pot, P
59
60
61 def time_step(pos, vel, F):
62     vel += 0.5 * F * dt
63     pos = pos + vel * dt
64     pos_folded = np.mod(pos, L_box)
65     # pos = np.mod(pos + vel * dt, L_box) # why both pos and pos_folded?
66     F, pot, P = find_force(pos_folded)
67
68     vel += 0.5 * F * dt
69     kin = 0.5 * np.sum(vel**2)
70     return pos, vel, F, pot, kin, P
71
72
73 def min_dist(r):
74     if r > L_box/2:
75         return r - L_box
76     elif r < -L_box/2:
77         return r + L_box
78     else:
79         return r
80
81
82 def simulate(f, h_r, bins, drs, dvs):
83     kins, pots, Ps = [], [], []
84     pos = IC_pos(N_cell, L_cell)
85     prev_pos = pos
86     vel = IC_vel(N)
87     prev_vel = vel
88     dr, dv = 0, 0
89     F = find_force(pos)[0]
90     for i in range(2*n_frames):
91         pos, vel, F, pot, kin, P = time_step(pos, vel, F)
92         if i > n_frames: # production run
93             kins.append(kin)
94             pots.append(pot)
95             Ps.append(P)
96
97         SI_pos = pos*sigma
98         SI_vel = vel*sigma/t0
99
100         f.write('MD of 1 Argon t=%10.5f\n' % (i * dt * t0))
101         f.write('%5d\n' % (N))
102         for j in range(N):
103             f.write('%5d%-5s%5d%8.3f%8.3f%8.3f%8.4f%8.4f%8.4f\n' %
104                     (j, 'ARGON', 'Ar', j,

```

```

105             SI_pos[j][0], SI_pos[j][1], SI_pos[j][2],
106             SI_vel[j][0], SI_vel[j][1], SI_vel[j][2]))
107         f.write('%10.5f%10.5f%10.5f\n' %
108             (L_box*sigma, L_box*sigma, L_box*sigma))
109
110         r_vec = pos[ind[0]] - pos[ind[1]]
111         r_vec = r_vec - np rint(r_vec / L_box) * L_box
112         r_sq = np.sum(r_vec**2, axis=1)
113         h_r += np.histogram(np.sqrt(r_sq), bins)[0]
114
115         drs.append(np.average(np.sum((pos-prev_pos)**2, axis=1)))
116         dvs.append(np.average(np.sum((vel*prev_vel), axis=1)))
117     else: # equillirum run
118         vel *= np.sqrt(N * 3 * T_0 / (2 * kin))
119         prev_pos = pos
120         prev_vel = vel
121
122     return np.array(kins), np.array(pots), np.array(Ps)
123
124
125 # The simulation starts here
126 if __name__ == "__main__":
127     h_r = np.zeros(n_bins)
128     bins = np.linspace(0, L_box, n_bins+1)
129
130     drs = []
131     dvs = []
132
133     with open('argon.gro', 'w') as f:
134         kins, pots, Ps = simulate(f, h_r, bins, drs, dvs)
135         times = np.arange(len(kins)) * dt
136         T = np.mean(kins * 2 / (3 * N)) # temperature
137         P = 1 - np.mean(Ps) / (3 * N * T) - 16 * np.pi * \
138             rho / (3 * T * L_box**3) # compressibility factor
139         P = P * T * rho # pressure here
140         # print(T, P) # how about thermal fluctuation?
141         # print(pots)
142
143     # plot the energy vs time results
144     plt.plot(times, kins)
145     plt.plot(times, pots)
146     plt.plot(times, kins+pots)
147     plt.legend(['kinetic', 'potential', 'total'])
148     plt.xlabel('time (reduced)')
149     plt.ylabel('energy (reduced)')
150     plt.title(f'Kinetic, potential and total energy ({n_frames} iterations)')
151     plt.savefig('images/energy.png')
152     plt.show()
153
154     n_r = (h_r*2/((N-1)*(n_frames-1)))
155     g_r = n_r/(4/3*pi*((bins[1:]**3 - (bins[:-1])**3)*rho)
156     plt.plot(bins[:n_bins]+(bins[1]-bins[0])/2, g_r)
157     plt.title(f'Radial distribution function (N_cell={N_cell})')
158     plt.savefig(f'images/g_r(N_cell={N_cell}).png')

```



```

159     plt.xlabel('r (reduced)')
160     plt.ylabel('g(r)')
161     plt.show()
162
163     V_ac_einstein = np.array(drs)/(6*dt**2)
164     V_ac_gkb = np.array(dvs)/3
165
166     D_einstein = np.sum(V_ac_einstein)*dt
167     D_gkb = np.sum(V_ac_gkb)*dt
168     plt.plot(times, V_ac_einstein)
169     plt.title('Einstein velocity autocorrelation function')
170     plt.xlabel('time (reduced)')
171     plt.ylabel('D\'(t) (reduced)')
172     plt.savefig('images/V_ac_einstein.png')
173     plt.show()
174
175     plt.plot(times, V_ac_gkb)
176     plt.title('Green-Kubo velocity autocorrelation function')
177     plt.xlabel('time (reduced)')
178     plt.ylabel('D\'(t) (reduced)')
179     plt.savefig('images/V_ac_gkb.png')
180     plt.show()
181
182     print('Average Einstein diffusion coefficient', D_einstein)
183     print('Average Green-Kubo diffusion coefficient', D_gkb)
184     print('Ratio', D_gkb/D_einstein)

```

(b) Compiling VMD from source on linux

Just writing here in case I forget how to do it again or other students asks you in the future. The VMD on Windows has an installer, but on linux you have to compile it from source. Luckily, I found a tutorial on youtube on how to do it: <https://www.youtube.com/watch?v=7YA7IyxrxKw>, but it requires root permission to install. In short:

- (i) Download the source code from <https://www.ks.uiuc.edu/Research/vmd/>
- (ii) Run `./configure`
- (iii) `cd src && sudo make install`
- (iv) VMD should be installed systemwide to `/usr/local/bin/vmd`