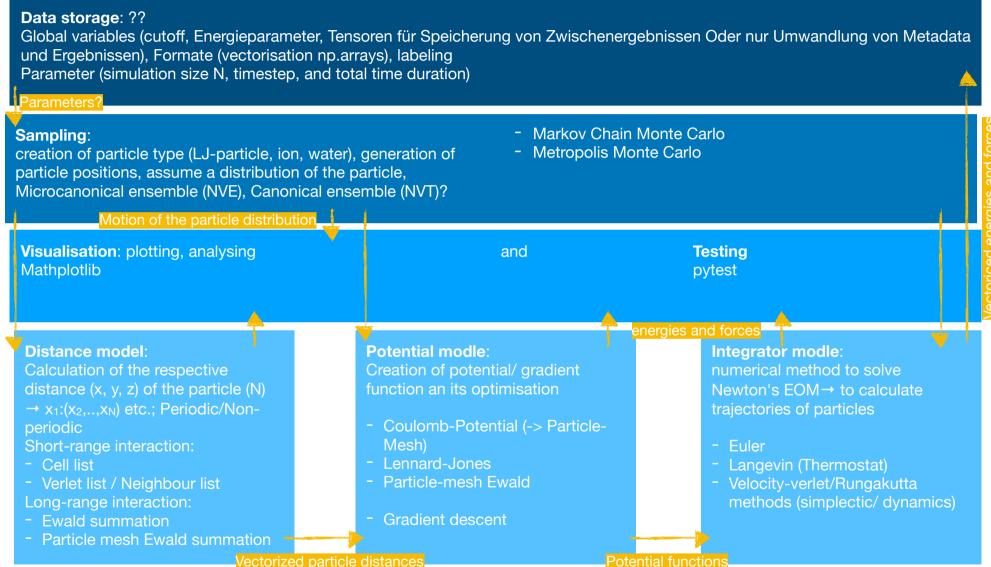
Computational Science

Molecule Dynamic simulation

Task:

Implementation of an MD-simulation for Lennard-Jones particles/ ions/ water in 2D and 3D. →interaction between the particles an thereby causes spatial motion by iterativ calculations

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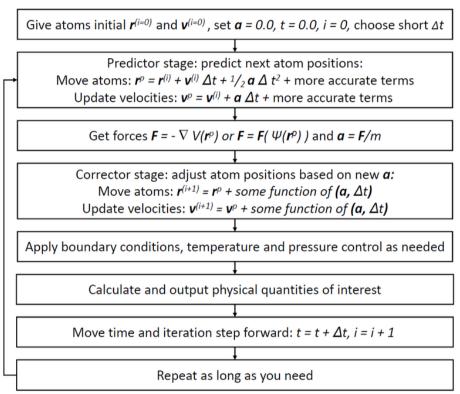


Workflow

So, 13.01.19

- finale aufgaben Verteilung
- modules diskutieren
- Labeling festlegen (formate, Bezeichnungen, Abkürzungen, Parameter)
- Input und Output formate und Benennungen definieren
- Ziele festlegen für Fortschritt bis zum nächsten Treffen
- Parallelization strategies ? Domain decomposition method
- (Distribution of system data for parallel computing)

Simplified schematic of the molecular dynamics algorithm



Selbstständige Arbeitsphase

- Ziele umsetzen für Fortschritt bis zum nächsten Treffen

So, 20.01.19?

- Fortschritte präsentieren Fehler Probleme diskutieren

Overview: Aufgabe für (Person): Phillip (P), Felix (F), Malte (M), Joana (J)

MODUL	INPUT	TASK	OUTPUT	TESTING	VISUALISATION
DATA STORAGE		? Configuration ?			
SAMPLING 13.01.19 (P, F, M, J)	N = number of particle - generate configuration -	 configuration ? Dann in: ? Markov Chain Monte Carlo Metropolis Monte Carlo 	2D: Np.array([x_position 1:N],[y_position 1:N]) 3D: Np.array([x_position 1:N],[y_position 1:N], [z_position 1:N])	-	- distribution of particle plotten
DISTANCE	2D: Np.array([x_position 1:N],[y_position 1:N]) 3D: Np.array([x_position 1:N],[y_position 1:N], [z_position 1:N])		2D: Np.array([x_i 1:N], [dis_x_i+1 1:N],, [dis_x_N 1:N]); wie y, z 3D:		
POTENTIAL				 energy consistency Use simple potential with work and compare 	
INTEGRATOR					

Information about modules

DATA STORAGE MODULE

????

SAMPLING MODULE

Initial configuration (markow chain, Particles equispaced in a box; 2D/3D)

MONTE CARLO

INPUT	ОИТРИТ	
initial configuration r(0), potential, size, beta, step	Position r, potential(r)	

- (1) Start with initial configuration $\mathbf{r}^{(0)}$ and set k = 0.
- (2) Fork=1,...,K:
 - (a) Sample random vector $\eta \in \mathbb{R}^N$ with $\eta_i \sim N(0, \sigma^2)$, i.e. an isotropic multivariate Gaussian distribution/ or function with variances σ^2 .
 - (b) Propose new configuration $\mathbf{r'} = \mathbf{r}^{(k)} + \eta$.
 - (c) Accept new configuration with probability $p_{\rm acc} = \min \left\{ 1, \exp \left(\frac{\phi({\bf r}') \phi({\bf r}^k)}{k_B T} \right) \right\}$

If accepted, set $\mathbf{r}^{(k+1)} = \mathbf{r}'$, otherwise $\mathbf{r}^{(k+1)} = \mathbf{r}^{(k)}$.

Markov Chain Monte Carlo

- create samples from a possibly multi-dimensional continuous random variable, with probability density proportional to a known function.
- these samples can be used to evaluate an integral over that variable, as its expected value or variance.
- in Markov chain Monte Carlo methods are autocorrelated.
- a equilibrium distribution which is proportional to the function given.

Metropolis Monte Carlo

- Konfigurationen gemäß ihrer Boltzmann-Wahrscheinlichkeit + einfachen arithmetischen Durchschnitt
- zuerst eine zufällige Bewegung ausgeführt
- dann die Boltzmann-Wahrscheinlichkeit einer solchen Bewegung ausgewertet wird und die Wahrscheinlichkeit mit einer Zufallszahl verglichen wird.
- Ist die Boltzmann-Wahrscheinlichkeit der Bewegung größer als die Zufallszahl, wird die Bewegung akzeptiert. Andernfalls wird das System auf seine ursprüngliche Konfiguration zurückgesetzt.

Vor- und Nachteile: ?

- not interested in the statistics of momenta anymore, so we integrate them out
- · sampling the probability density.
- simple version of Monte Carlo is Metropolis Monte Carlo

DISTANCE MODULE

INPUT	OUTPUT	
Position r, potential(r)	Matrix distances x1 x2 xN	

- calculation of distances between particles in MD Energy and force Calculation
- Introduce a cutoff and considering only the nearest neighbours within the radius; for LJ.Potential rc= 2.5 σ
 - Reduce effort: loop over all pairs of particle (i,j) = (j,i)

Verlet list

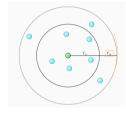
- For each particle i, a Verlet list hat lists all other particles j within a smaller distance than rc+ rs
- Update the neighbour list every Ns tilmestep
- $r_s > N_s v_{\text{tVD}} \delta t$ type speed of particles
- Choice between hash table and array

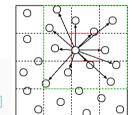
Cell-linked list: get complexity down

- domain into cells with an edge length greater than or equal to the cut-off radius of the interaction to be computed
- particles sorted into cells and the interactions are computed between particles in the same or neighbouring cells
- Needed array HEAD and array LIST
- Think about parallelisation

Cell decomposition approach

- partition the domain into cells and build a cell-linked list
- Verlet list by searching only in the neighbouring cells instead of considering all particles
- Dirty flag?





POTENTIAL MODULE

description how the particles will interact in the simulation; two main approximations: Born-Oppenheimer approximation (dynamics of electrons), point particles that follow classical Newtonian dynamics (nuclei, which are much heavier than electrons)

Coulomb-Potential (-> Particle-Mesh)

$$\phi_i(\mathbf{r}) = \frac{1}{4\pi\varepsilon_0} \frac{q_i}{|\mathbf{r} - \mathbf{r_i}|}$$

$$\frac{1}{4\pi\varepsilon_0} = c_0^2 \mu_0 = \frac{c_0^2 \mu_0}{c_0^2 + c_0^2} = c_0^2 \times 10^{-7} \,\mathrm{H \cdot m^{-1}} = 8.987 \times 10^9 \,\mathrm{Nm^2 C^{-2}}$$

Lennard-Jones

Particle-mesh Ewald

INTEGRATOR MODULE

Präsentation