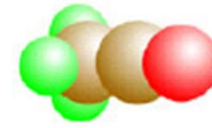


Applied Statistical Mechanics
Lecture Note - 11

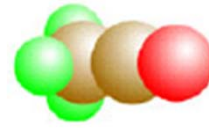


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Molecular Monte Carlo Method

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강정원

Contents



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- I. Theoretical Basis of Molecular Monte Carlo Method
- II. Implementation of Molecular Monte Carlo Method in NVT Ensemble
- III. Implementation of Molecular Monte Carlo Method in Other Ensembles



I-1. Introduction

■ Overview of Molecular Monte Carlo Method

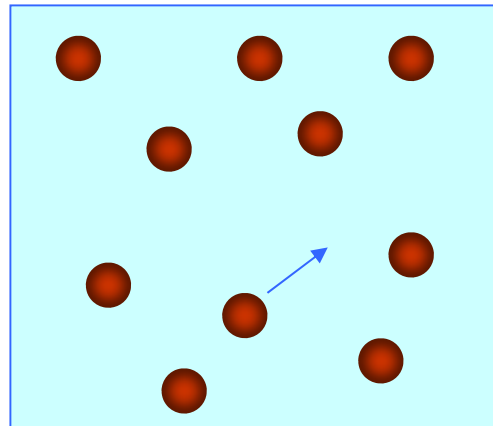
Objective

Calculation of Macroscopic Properties from Microscopic Properties (intermolecular forces...)

Averaging Method

Ensemble Averages

NVT Ensemble
NPT Ensemble
 μ *PT* Ensemble



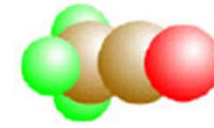
Generation of Random Configurations

Use of Random Number
Importance Sampling
Markov Chain
Metropolis Algorithm

Approximations

Periodic Boundary Condition
Minimum Image Convention
Long Range Correction
Neighborhood List

I-2. Averaging Method

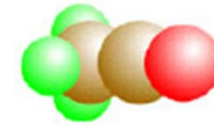


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- Statistical Mechanics : Theoretical Basis for derivation of macroscopic behavior from microscopic properties
- Configuration : position and momenta (\mathbf{r}^N and \mathbf{p}^N)
- Configurational Variable : $A(\mathbf{r}^N, \mathbf{p}^N)$
- Ensemble average
 - Weighted sum over all possible members of ensemble
 - Using classical mechanics

$$\langle A \rangle = \frac{1}{Q} \frac{1}{h^{3N} N!} \int dp^N \int dr^N A(p^N, r^N) \exp\{-\beta E(r^N, p^N)\}$$

$$Q = \frac{1}{h^{3N} N!} \int dp^N \int dr^N \exp\{-\beta E(p^N, r^N)\}$$



I-2. Averaging Method

■ Separation of Energy

- Total energy is sum of kinetic and potential parts

$$E(r^N, p^N) = K(p^N) + U(r^N)$$

- Kinetic parts can be treated separately from potential parts

$$\begin{aligned}
 Q &= \frac{1}{h^{3N} N!} \int dp^N \exp(-\beta \sum_i p_i^2 / 2m_i) \int dr^N \exp\{-\beta U(r^N)\} \\
 &= \frac{1}{\Lambda^{3N}} \boxed{\frac{1}{N!} \int dr^N \exp\{-\beta U(r^N)\}} Z_N \\
 &= \frac{1}{\Lambda^{3N}} \frac{1}{Z_N}
 \end{aligned}$$



I-2. Averaging Method

■ Ensemble Average of a property

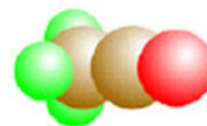
$$\langle A \rangle = \frac{1}{Z_N N!} \int dr^N A(r^N, p^N) \exp\{-\beta U(r^N)\} = \frac{\int dr^N A(r^N, p^N) \exp\{-\beta U(r^N)\}}{\int dr^N \exp\{-\beta U(r^N)\}}$$

- Monte Carlo Simulation calculates excess thermodynamic properties that result in deviation from ideal gas behavior

■ Metropolis Monte Carlo Method

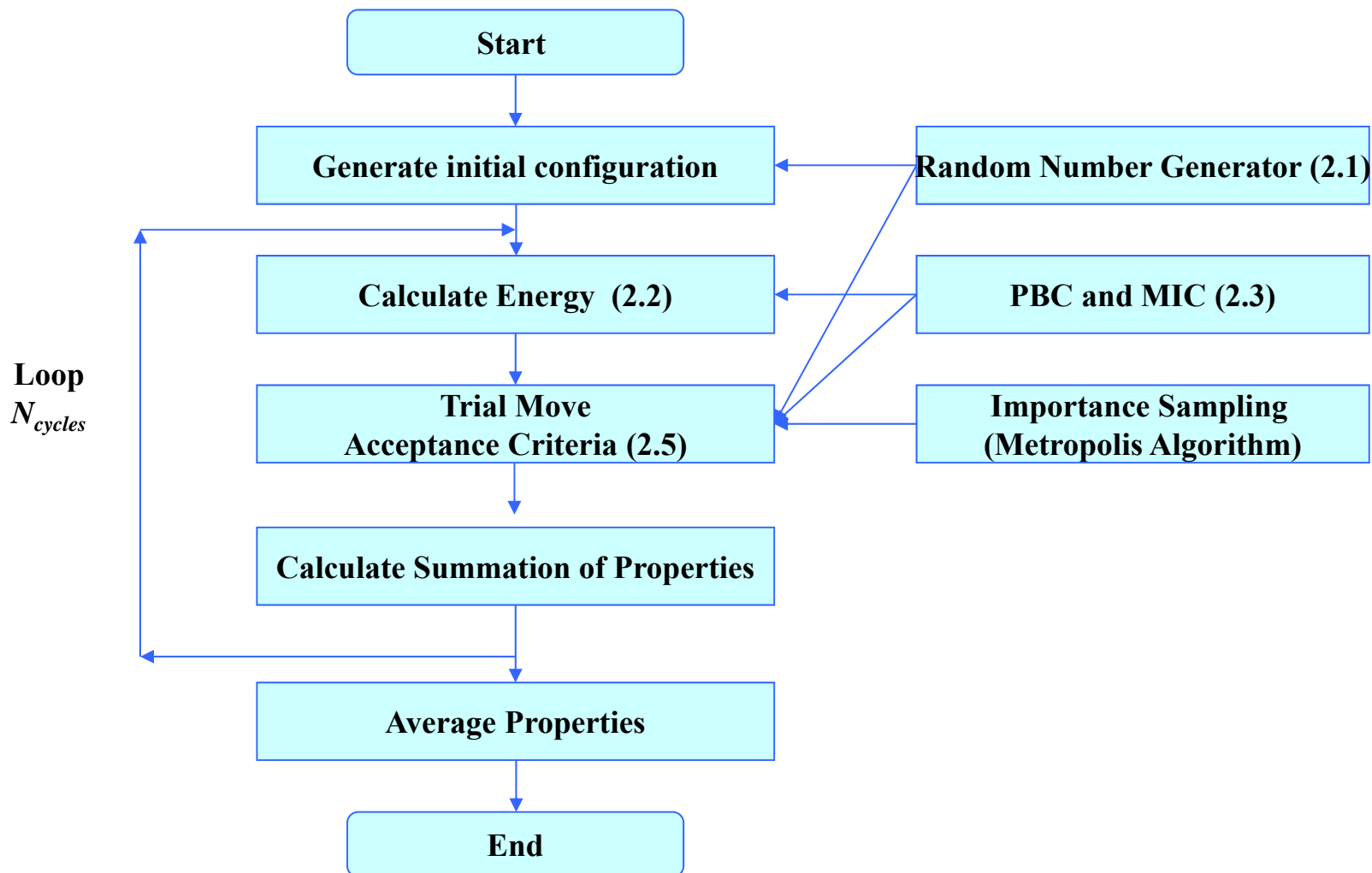
$$\langle A \rangle = \int \frac{\exp\{-\beta U(r^N)\}}{Z_N(r^N)} A(r^N) dr^N = \int \boxed{\mathcal{N}(r^N)} A(r^N) dr^N = \langle A \rangle_{\text{trials}, \mathcal{N}(r^N)}$$

probability of a given configuration r^N

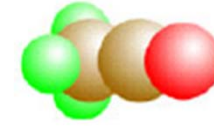


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I-3. General MMMC Scheme



II-1. Random Number Generation



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- There is nothing like “Random number generator “
 - “*Pseudo Random Number Generator* “
 - Most of the pseudo random number generator repeats “sequence”
 - It is important to know *how long is the sequence*

- Most FORTRAN, C compiler supplies random number generator based on **Linear Congruential Method**
 - The relationship will repeat when n greater than 32767

$$I_{n+1} = (aI_n + c) \bmod(m)$$

$$a, c > 0, m > l_0, a, c$$

Ex) Digital FORTRAN
RANDOM_NUMBER subroutine
Period = 10**18

II-1. Random Number Generation

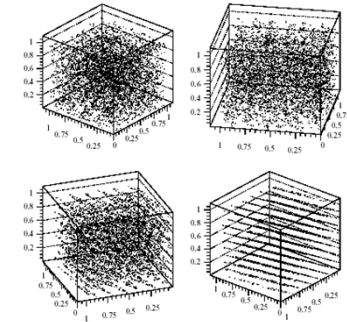


■ RANDU Algorithm

- 1960's , IBM

$$I_{n+1} = (65539 \times I_n) \bmod(2^{31})$$

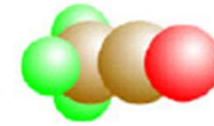
- This generator was found to have serious problem : “*The Marsaglia Effect*”



■ Improving the behavior of random number generator

- Two initial seed can extend the period grater than m

$$I_n = (a \times I_{n-1} + b \times I_{n-2}) \bmod(m)$$

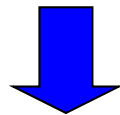


II-1. Random Number Generation

■ Using Random number generators

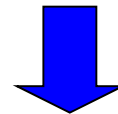
- Check the period
- Serial Test : (x,y) or (x,y,z)
- Be careful about dummy argument
 - Use different dummy argument for two different set of random numbers
 - Compiler's optimizer is trying to remove multiple calls to random number generator

```
X = RAND(IDUM) + RAND(IDUM)
```



```
X = 2.0 * RAND(IDUM)
```

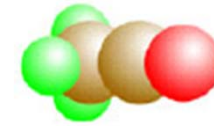
```
DO 1 I = 1,100  
    X = RAND(IDUM)  
1 CONTINUE
```



```
Not evaluating every steps  
Evaluated only once
```

You have to change
dummy argument
each calls

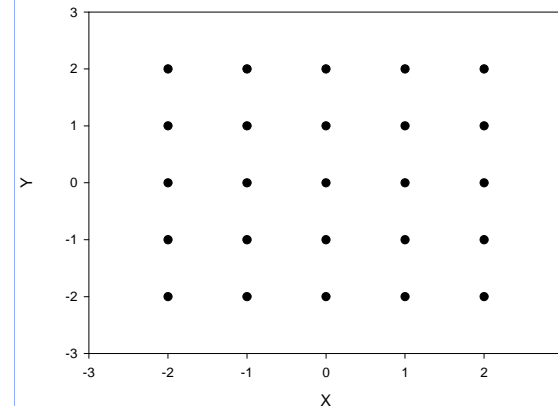
II-1. Random Number Generation



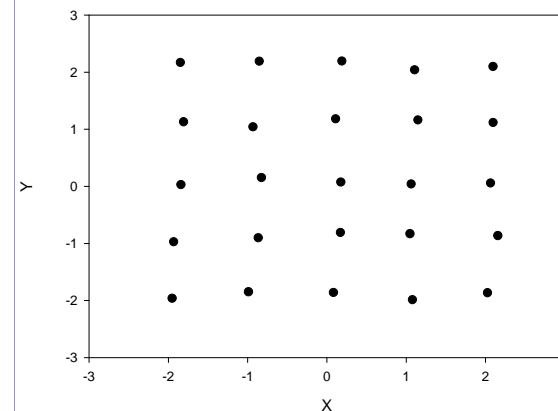
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■ Initializing Configuration (Example : 2D Space)

```
bx = rLx/float(nx)
by = rLy/float(ny)
do 60 ip= 1, np
    x(ip) = ( 0.5*(1.-float(nx)) +
             float(mod( ip-1, nx )) ) * bx
    y(ip) = ( 0.5*(1.-float(ny)) +
             float((ip-1)/ny) ) * by
60 continue
```



```
bx = rLx/float(nx)
by = rLy/float(ny)
do 60 ip= 1, np
    x(ip) = ( 0.5*(1.-float(nx)) +
             float(mod( ip-1, nx )) + 0.1*r2() ) * bx
    y(ip) = ( 0.5*(1.-float(ny)) +
             float((ip-1)/ny) + 0.1*r2() ) * by
60 continue
```



II-2. Calculating Potential Energy



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■ Potential Energy of N -interacting particles

$$U = \sum_i u_1(r_i) + \sum_i \sum_{j>i} u_2(r_i, r_j) + \sum_i \sum_{j>i} \sum_{k>j>i} u_3(r_i, r_j, r_k) + \dots$$



Effect of external field



Two-body interaction



Three-body interaction

II-2. Calculating Potential Energy



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- Typically, effect of external field is zero
- Two body interaction is the most important term in the calculations
 - Truncated after second term
- For some cases, three body interactions may be important
- Including three body interactions imposes a very large increase in computation time $t \propto N^m$
- Short range and long range interactions
 - Short range : Dispersion and Repulsion
 - Long range : Ionic interaction
 - Special methods are required for long range interactions due to limited size of simulation box

II-2. Calculating Potential Energy



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■ Naïve calculation

Summations are chosen to avoid duplicated evaluation and “self” interaction

$$U = \sum_{i=1}^{N-1} \sum_{j=i+1}^N u_2(r_{ij})$$

$$U = 4\epsilon \left[\left(\frac{\sigma}{r} \right)^{12} - \left(\frac{\sigma}{r} \right)^6 \right]$$

Pseudo Code

```

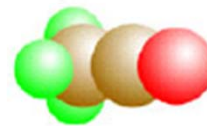
Loop i = 1, N-1
  Loop j = i+1, N
    Evaluate rij
    Evaluate Uij
    Accumulate Energy
  End j Loop
End i Loop
    
```

FORTTRAN Code

```

DO 10 I = 1, N
DO 20 J = I+1, N
  DX = X(I)-X(J)
  DY = Y(I)-Y(J)
  RIJ2 = DX*DX + DY*DY
  RIJ6 = RIJ2*RIJ2*RIJ2
  RIJ12 = RIJ6*RIJ6
  UTOT = UTOT + 1/RIJ12 - 1/RIJ6
20 CONTINUE
10 CONTINUE
    
```

II-3. Periodic Boundary Condition and Minimum Image Convention



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■ Problems

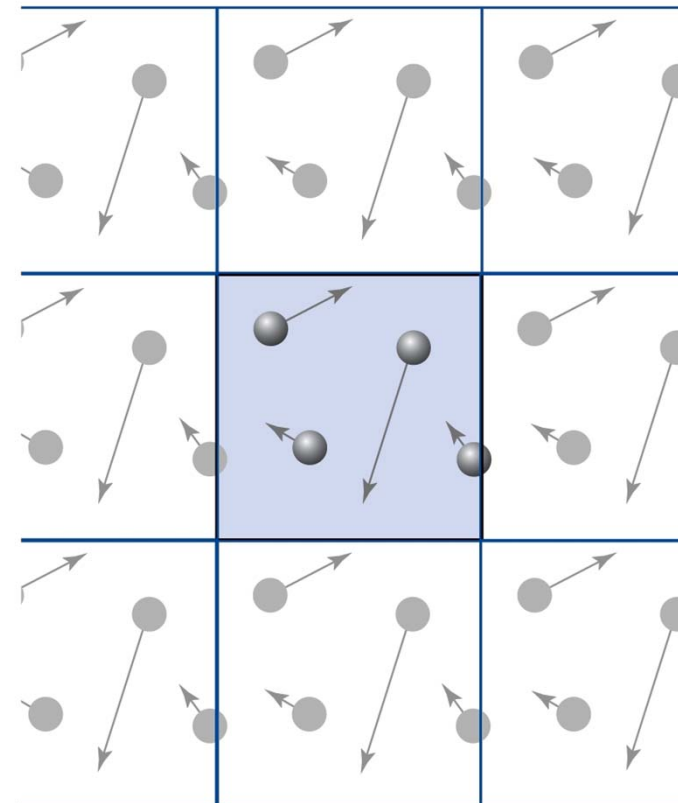
- Simulations are performed typically with a few hundred molecules arranged in a cubic lattice → computational limitation
 - Large fraction of the molecules can be expected in a surface rather than in the bulk
- Simulation require summation over almost infinite interactions
- PBC (Periodic Boundary Condition) and MIC (Minimum Image Convention) are used to avoid this problems

II-3. Periodic Boundary Condition and Minimum Image Convention

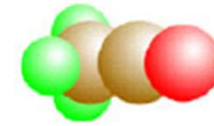


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- Periodic Boundary Condition
 - Infinite replica of the simulation box
 - Molecules on any lattice have mirror image counter parts in all the other boxes
 - Changes in one box are matched exactly in the other box → surface effects are eliminated

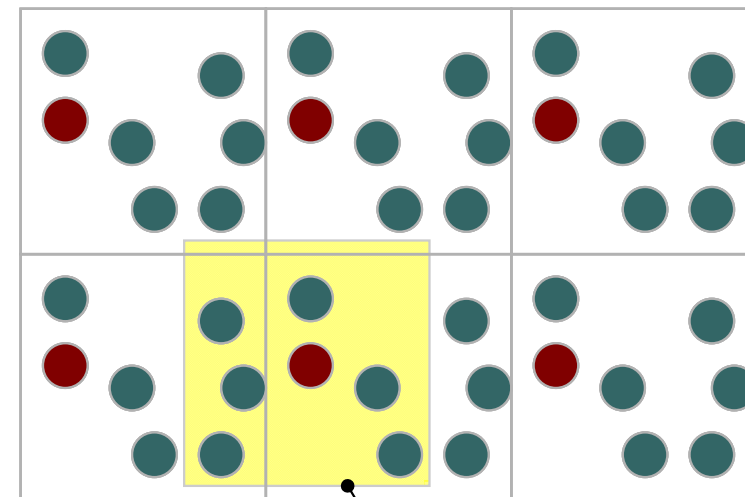


II-3. Periodic Boundary Condition and Minimum Image Convention



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- Minimum Image Convention
 - Summation over infinite array of periodic image \rightarrow impossible
 - For a given molecule, we position the molecule at the center of a box with dimension identical to simulation box
 - Assume that the central molecule only interacts with all molecules whose center fall within this region



Nearest images of colored sphere

II-3. Periodic Boundary Condition and Minimum Image Convention



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■ Implementing PBC

- Decision based : IF statement
- Function based : rounding , truncation, modulus

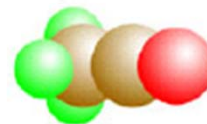
Decision

```
BOXL2 = BOXL/2.0  
IF(RX(I).GT.BOXL2) RX(I)=RX(I)-BOXL  
IF(RX(I).LT.-BOXL2) RX(I) = RX(I) + BOXL
```

Function

```
RX(I) = RX(I) - BOXL * AINT(RX(I)/BOXL)
```

II-3. Periodic Boundary Condition and Minimum Image Convention



■ Implementing PBC and MIC

Pseudo CODE

```
Loop i = 1, N - 1
  Loop j = i + 1, N
    Evaluate  $r_{ij}$ 
    Convert  $r_{ij}$  to its periodic image ( $r_{ij}'$ )
    if ( $r_{ij}' < \text{cutOffDistance}$ )
      Evaluate  $U(r_{ij})$ 
      Accumulate Energy
    End if
  End j Loop
End i Loop
```

FORTRAN CODE

```
do 10 ip= 1, Np-1
  xip = x(ip)
  yip = y(ip)
  do 20 jp= ip+1, Np
    xx = xip - x(jp)
    dx = dble( xx - rLx*anint( xx/rLx ) )
    yy = yip - y(jp)
    dy = dble( yy - rLy*anint( yy/rLy ) )
    rij2 = dx*dx + dy*dy
    if ( rij2 .lt. dcut2 ) then
      rij6 = 1.d0/(rij2*rij2*rij2)
      rij12 = rij6*rij6
      ham = ham + rij12 - rij6
      pre = pre + 2.d0*rij12 - rij6
    endif
  20 continue
10 continue
```

II-3. Periodic Boundary Condition and Minimum Image Convention



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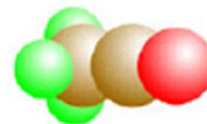
- Features due to PBC and MIC
 - Accumulated energies are calculated for the periodic separation distance
 - Only molecules within cut-off distance contributed to calculated energy
 - Caution : Cut-off distance should be smaller than the size of simulation box → if not, violation to MIC
 - Calculated potential = truncated potential
- Long range correction

$$X_{full} = X_c + X_{lrc}$$

$$E_{lrc} = 2\pi N\rho \int_{r_c}^{\infty} r^2 u(r) dr$$

- For NVT ensemble No. of particle and density (V) are const.
 - LRC can be added after simulation
- For other ensembles, LRC must be added during the simulation

II-4. Neighborhood List



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- In 1967, *Verlet* proposed a new algorithm to reduce computation time
- Instead of searching for neighboring molecules, the neighbors of the molecules are stored and used for the calculation
- Variable d is used to encompass slightly outside the cut-off distance
- Update of the list
 - update of the list / 10-20 steps
 - Largest displacement exceed d value



II-5. Metropolis Sampling Algorithm

- Average of a property

$$\langle A \rangle = \int \frac{\exp\{-\beta U(r^N)\}}{Z_N(r^N)} A(r^N) dr^N = \int \mathcal{N}(r^N) A(r^N) dr^N = \langle A \rangle_{\text{trials}, \mathcal{N}(r^N)}$$

- There are a lot of choice to make Markov process that follows a given PDF

$$\rho \pi = \rho \quad \sum_m \rho_m \pi_{mn} = \rho_n$$

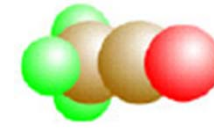
$$\sum_n \pi_{mn} = 1$$

“Microscopic reversibility”
Sufficient, but not necessary condition

$$\rho_m \pi_{mn} = \rho_n \pi_{nm}$$

This condition is not sufficient :
more conditions are required to setup transition matrix

II-5. Metropolis Sampling Algorithm



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- In 1953, Metropolis showed a transition probability matrix exists than ensures that the PDF is obeyed

$$\pi_{mn} = \alpha_{mn} \quad \rho_n \geq \rho_m, m \neq n$$

$$\pi_{mn} = \alpha_{mn} \left(\frac{\rho_n}{\rho_m} \right) \quad \rho_n < \rho_m, m \neq n$$

$$\pi_{mm} = 1 - \sum_{n \neq m} \pi_{mn}$$

- Other choice can also satisfies condition of microscopic reversibility (Barker , 1965)

$$\pi_{mn} = \alpha_{mn} \left(\frac{\rho_n}{\rho_n + \rho_m} \right) \quad m \neq n$$

$$\pi_{mm} = 1 - \sum_{n \neq m} \pi_{mn}$$

II-5. Metropolis Sampling Algorithm



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■ Metropolis Recipe

- with probability π_{mn} a trial state j for the move
- if $\rho_n > \rho_m$ accept n as new state
- Otherwise, accept n as the new state with probability $\rho_n > \rho_m$
 - Generate a random number R on $(0,1)$ and accept if $R < \rho_n / \rho_m$
- If not accepting n as new state, take the present state as the next one in Markov chain ($\pi_{mn} \neq 0$)

■ What is the value of α ?

$$\alpha_{mn} = 1/N_R \quad \text{if accepting}$$

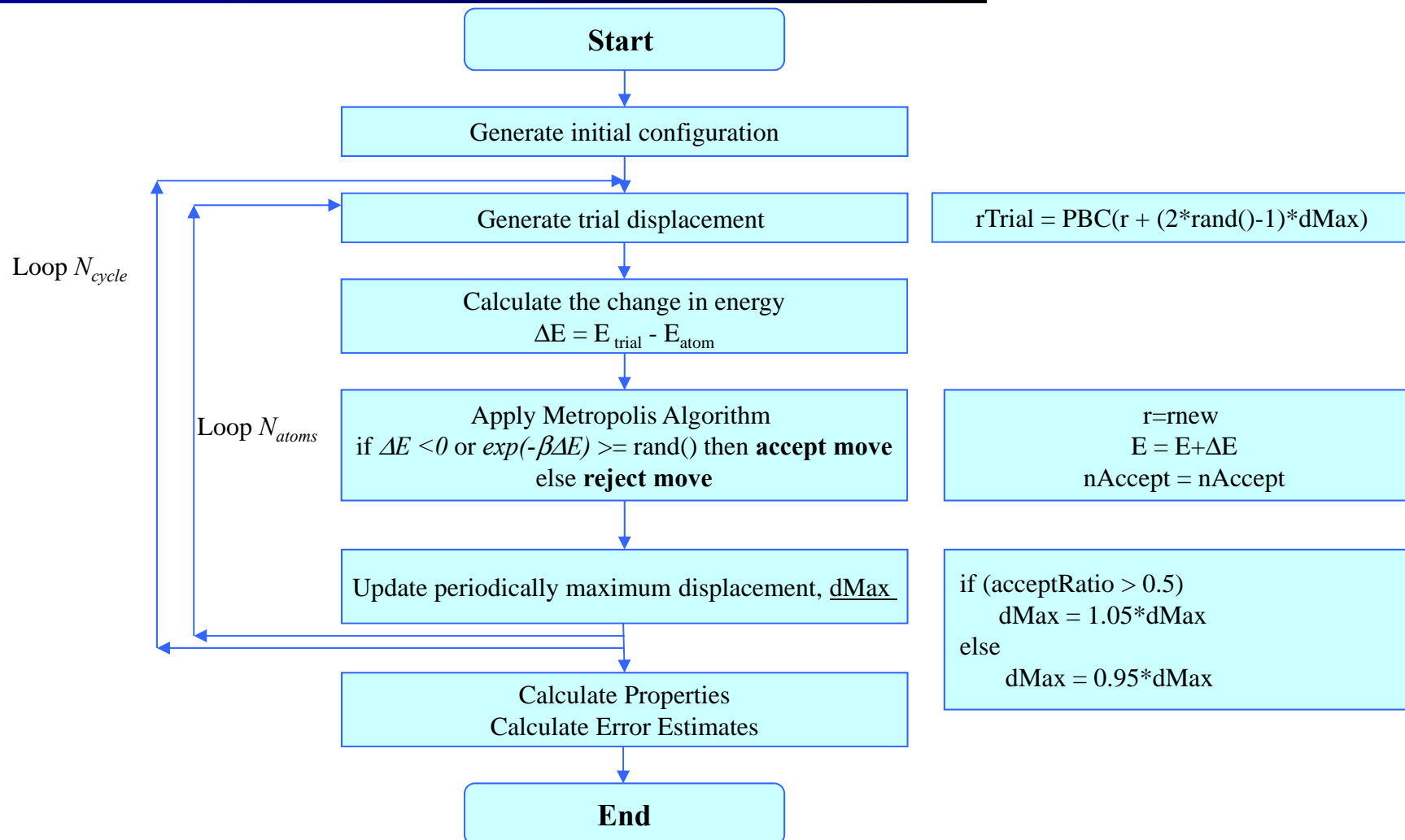
$$\alpha_{mn} = 0 \quad \text{if not accepting}$$

N_R : Number of accepted trials

II-6. Implementation



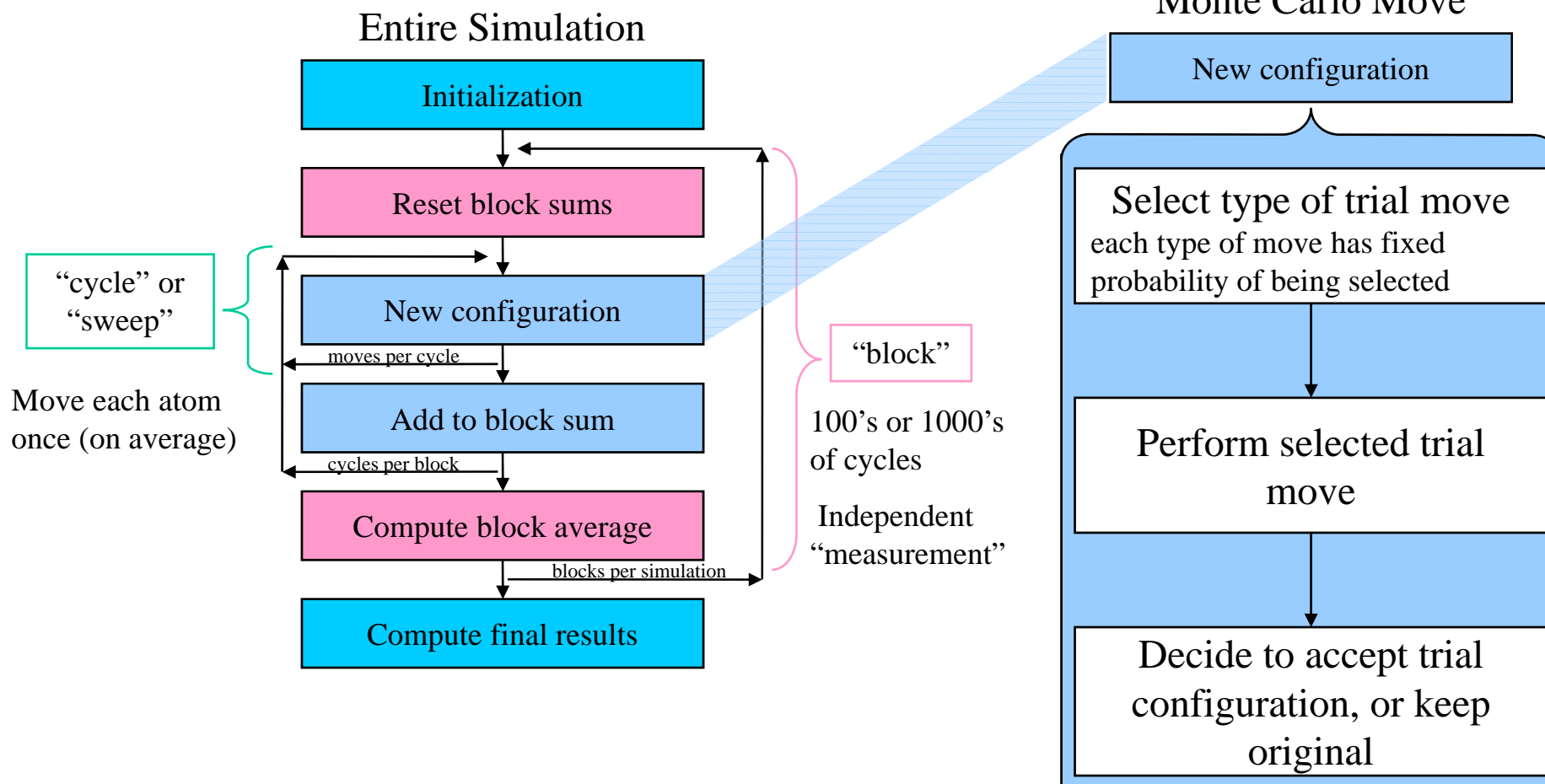
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II-6. Implementation



II-7. Averages and Error Estimates



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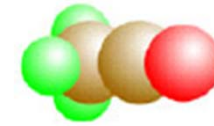
■ Equilibration period

- The averages are evaluated after “equilibration period”
- The equilibration period must be tested : cycle vs. properties
 - Ex) 20 000 run :
 - 1 to 10 000 : equilibration period
 - 10 001 to 20 000 : averages are accumulated

■ Error estimation

- Error estimation based on different simulation runs (with different initial configurations)
- Error estimation dividing total simulation runs into several blocks
 - common method

II-7. Averages and Error Estimates



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■ Average and Error Estimates

$$\langle A \rangle_{run} = \frac{1}{N - N_{equil} - 1} \sum_{i > N_{equil}} A_i$$

$$\langle A \rangle_b = \frac{1}{l} \sum_{i=1}^{N_b} A_i$$

$$\sigma = \sqrt{\frac{1}{N_b} \sum_{b=1}^{n_b} (\langle A \rangle_b - \langle A \rangle_{run})^2}$$



III-1. Introduction

■ MMC in different ensembles

- A very large number of systems for convenient calculation of time average macroscopic properties
 - Common macroscopic attributes
 - (N, V, E) : Microcanonical ensemble
 - (N, V, T) : Canonical ensemble
 - (N, P, T) : NPT ensemble
 - (μ, V, T) : Grand canonical ensemble
- } → No change in N, Closed system
- Change in N, Open system
- Microcanonical ensemble cannot be used in MMC because constant-kinetic energy constraint cannot be assumed
 - In thermodynamic limit all ensembles are equivalent and it is also possible to transform between ensembles. The choice of ensemble is completely a matter of convenience (which property ?)

III-1. Introduction



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■ Commonly encountered ensemble

Name	All states of:	Probability distribution	Schematic
Microcanonical (EVN)	given EVN	$\pi_i = \frac{1}{\Omega}$	
Canonical (TVN)	all energies	$\pi(E_i) = \frac{1}{Q} e^{-\beta E_i}$	
Isothermal-isobaric (TPN)	all energies and volumes	$\pi(E_i, V_i) = \frac{1}{\Delta} e^{-\beta(E_i + PV_i)}$	
Grand-canonical (TVμ)	all energies and molecule numbers	$\pi(E_i, N_i) = \frac{1}{\Xi} e^{-\beta(E_i + \mu N_i)}$	

III-1. Introduction



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■ Partition functions and bridge equation

Ensemble	Thermodynamic Potential	Partition Function	Bridge Equation
Microcanonical	Entropy, S	$\Omega = \sum 1$	$S / k = \ln \Omega(E, V, N)$
Canonical	Helmholtz, A	$Q = \sum e^{-\beta E_i}$	$-\beta A = \ln Q(T, V, N)$
Isothermal-isobaric	Gibbs, G	$\Delta = \sum e^{-\beta(E_i + PV_i)}$	$-\beta G = \ln \Delta(T, P, N)$
Grand-canonical	Hill, L = -PV	$\Xi = \sum e^{-\beta(E_i + \mu N_i)}$	$\beta PV = \ln \Xi(T, V, \mu)$

III-2. NVT Ensemble



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- Ensemble average : Boltzmann distribution as weighting factor

$$\langle A \rangle = \int \frac{\exp\{-\beta U(r^N)\}}{Z_N(r^N)} A(r^N) dr^N = \frac{\sum_i A(i) \exp(E(i))}{\sum_i \exp(E(i))}$$

- Weighted average

$$W(i) = \exp(-\beta E(i))$$

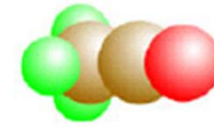
$$\langle A \rangle = \frac{1}{N} \sum_i A(i)$$

- For Other ensembles ? \rightarrow Tricky technique used : “Pseudo Boltzmann Factor”

$$W(i) = \exp(-\beta Y)$$

for NVT ensemble , $Y = E(i)$

III-3. NPT Ensemble



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- Thermodynamic properties

$$\langle A \rangle = \frac{\int_0^\infty \exp(-\beta p V) dV \int_V A(r^N, V) \exp\{-\beta U(r^N)\} dr^N}{\int_0^\infty \exp(-\beta p V) dV \int_V \exp\{-\beta U(r^N)\} dr^N}$$

- V can change

- Particles are confined in fluctuating length L
- Scaled coordinate :

$$\alpha_i = \mathbf{r}_i / L$$

- integration over total volume \rightarrow integration over unit cube Ω

$$\langle A \rangle = \frac{\int_0^\infty \exp(-\beta p V) dV \int_\Omega A((L\alpha)^N, V) \exp\{-\beta U((L\alpha)^N, V)\} d\alpha^N}{\int_0^\infty \exp(-\beta p V) dV \int_\Omega \exp\{-\beta U((L\alpha)^N, V)\} d\alpha^N}$$

III-3. NPT Ensemble



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■ Pesude Boltzmann Factor

$$Y = pV + E((L\alpha)^N, L) - NkT \ln V$$

■ Simple modification of NVT ensemble → Use ΔY instead of ΔU

■ Volume fluctuation

□ NVT ensemble

- Move 1 molecule at a time
- Calculate energies of remaining N-1 molecules

□ NPT ensemble

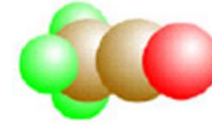
- Change in V affects the coordinates of all atoms
- N*N calculations are required
- Effective strategy : “Scaling Method”

$$E = 4\epsilon \sum \sum \left(\frac{\sigma_{ij}}{L\alpha_{ij}} \right)^{12} - 4\epsilon \sum \sum \left(\frac{\sigma_{ij}}{L\alpha_{ij}} \right)^6$$

$$E = E(12) + E(6)$$

$$E_{trial} = E(12) \left(\frac{L_{trial}}{L} \right)^{12} + E(6) \left(\frac{L_{trial}}{L} \right)^6$$

III-3. NPT Ensemble



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- “Scaling method” only applicable to relatively simple model potential → Scalable potential
 - if not, $N*(N-1)$ calculations are required for each volume fluctuation
- Trial moves : Displacement and volume fluctuation
 - Displacement on each atoms
 - Volume change
- When V change is attempted, long range correction must be re-evaluated

III-3. μVT Ensemble



■ Property average

$$\langle A \rangle = \frac{\sum_{n=0}^{\infty} \frac{\Lambda^{-3N}}{N!} \exp(\beta N \mu) \int_V A(r^N) \exp\{-\beta U(r^N)\} dr^N}{Z_{\mu VT}}$$



$$\beta \mu^{ideal} = \log(N/V) + 3 \log \Lambda$$

$$\langle A \rangle = \frac{\sum_{n=0}^{\infty} \exp(\beta N \mu^* - \ln N!) \int_V A(r^N) \exp\{-\beta U(r^N)\} dr^N}{Z_{\mu VT}}$$

$$\mu^* = \mu^{ex} + kT \ln \langle N \rangle$$

III-3. μVT Ensemble



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■ The Pseudo Boltzmann Factor

$$Y = -N\mu^* + kT \ln N! + E(r^N)$$

■ Attempted Trial Moves

- Particle displacement
- Particle insertion
- Particle deletion