Parallel Particle Swarm Optimization on Inverse kinematics

第六組
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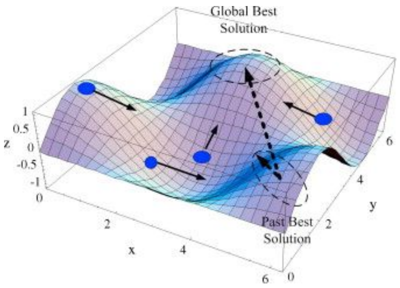
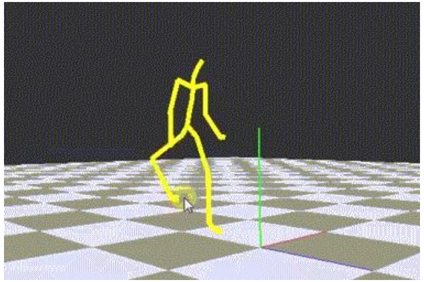
劉禮榮 10967241





Outline

Introduction to Inverse Kinematics

Introduction to Particle Swarm Optimization

Related Work

Paralle Particle Swarm Optimization

Experiment

Demo

Reference

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- Introduction to Inverse Kinematic
- Introduction to Particle Swarm Optimization
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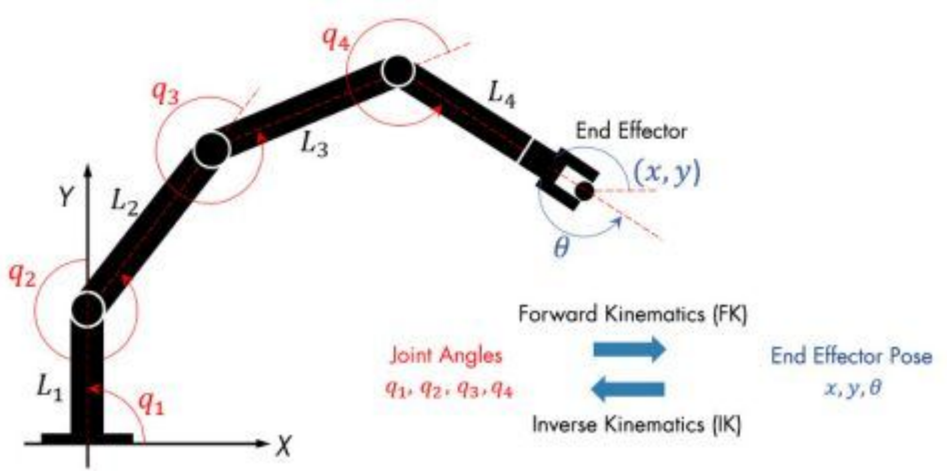
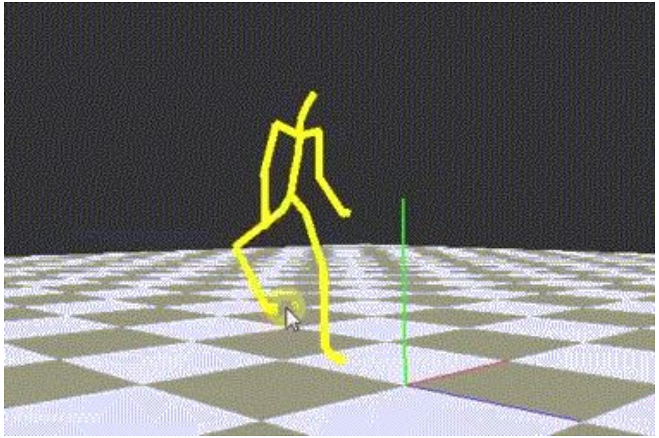
Introduction to Inverse Kinematics

[Neutrino's Blog：電腦動畫中的反向動力法 (Inverse Kinematics)]()

> 常見的方法包含 Cyclic Coordinate Descent 方法、Jacobian Pseudoinverse 方法、Jacobian Transpose 方法、Levenberg-Marquardt Damped Least Squares 方法、Quasi-Newton and Conjugate Gradient 方法、神經網路方法



https://www.mathworks.com/discovery/inverse-kinematics.html



https://nagachiang.github.io/assets/images/IK.gif

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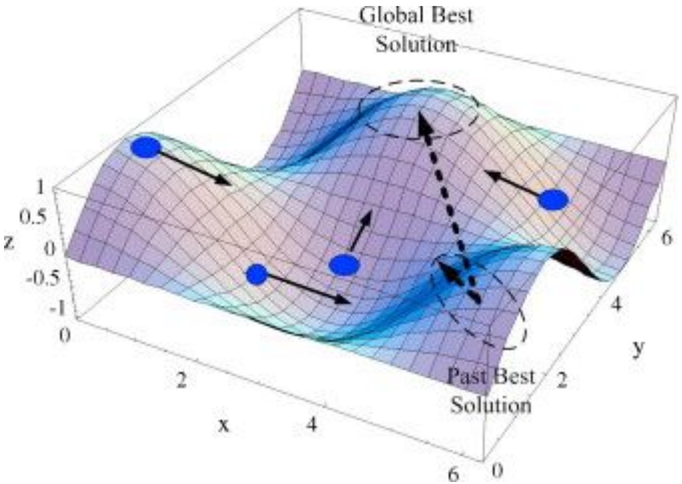
Introduction to Particle Swarm Optimization

$$V_{ij}^{t+1} = wV_{ij}^{t} + c_1 r_1^t \left(pbest_{ij} - X_{ij}^{t}\right) + c_2 r_2^t \left(gbest_j - X_{ij}^{t}\right)$$

$$X_{ij}^{t+1} = X_{ij}^{t} + V_{ij}^{t+1}$$



https://de.mathworks.com/matlabcentral/fileexchange/43541-particle-swarm-optimization-pso

1. Initialization
   1.1. For each particle i in a swarm population size P:
      1.1.1. Initialize X_i randomly
      1.1.2. Initialize V_i randomly
      1.1.3. Evaluete the fitness $f(X_i)$
      1.1.4. Initialize $\boldsymbol{pbest}_i$ with a copy of X_i
   1.2. Initialize $\boldsymbol{gbest}$ with a copy of X_i with the best fitness
2. Repeat until a stopping criterion is satisfied:
   2.1. For each particle i:
      2.1.1. Update V_i^t and X_i^t according to Eqs. (1) and (2)
      2.1.2. Evaluete the fitness $f(X_i^t)$
      2.1.3. $\boldsymbol{pbest}_i \longleftarrow X_i^t$ if $f(\boldsymbol{pbest}_i) < f(X_i^t)$
      2.1.4. $\boldsymbol{gbest} \longleftarrow X_i^t$ if $f(\boldsymbol{gbest}) < f(X_i^t)$

Particle Swarm Optimization: A Powerful Technique for Solving Engineering Problems
by Bruno Seixas Gomes de Almeida and Victor Coppo Leite

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Particle swarm optimization within the CUDA architecture,by Luca Mussi,Stefano Cagn ,Conference: Genetic and Evolutionary Computation Conference - GECCO 2009

Parallel asynchronous particle swarm optimization, by Byung-Il Koh , Alan D. George. Int J Numer Methods Eng. 2006 July 23

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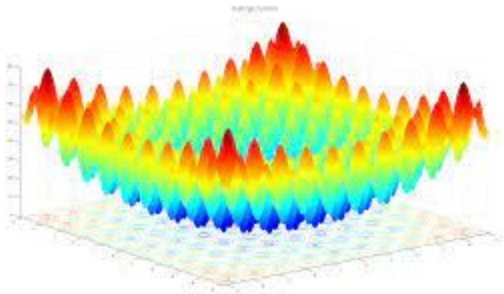
   1.2. Initialize $gbest$ with a copy of $X_i$with the be

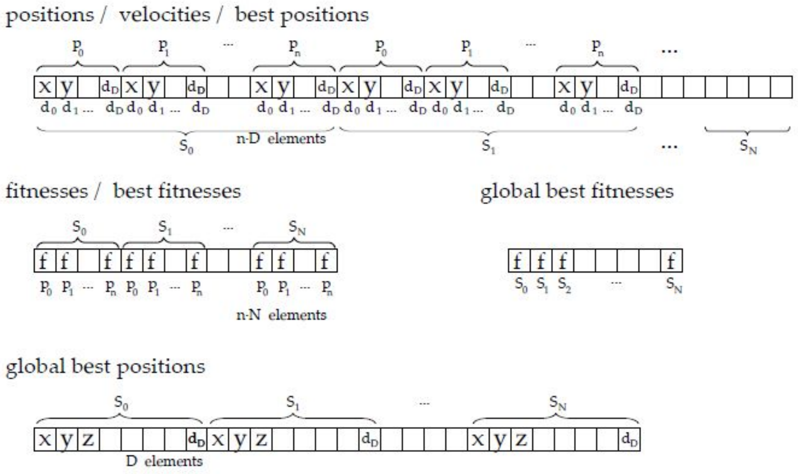
Related Work

- Master processor
  1. Initializes all optimization parameters and particle positions and velocities;
  2. Holds a queue of particles for slave processors to evaluate;
  3. Updates particle positions and velocities based on currently available information p^i, p^g;
  4. Sends the position x^i of the next particle in the queue to an available slave processor;
  5. Receives cost function values from slave processors;
  6. Checks convergence.
- Slave processor
  7. Receives a particle position from the master processor;
  8. Evaluates the analysis function $f(x^i)$ at the given particle position x^i;
  9. Sends a cost function value to the master processor.

Related Work

Rastrigin's function





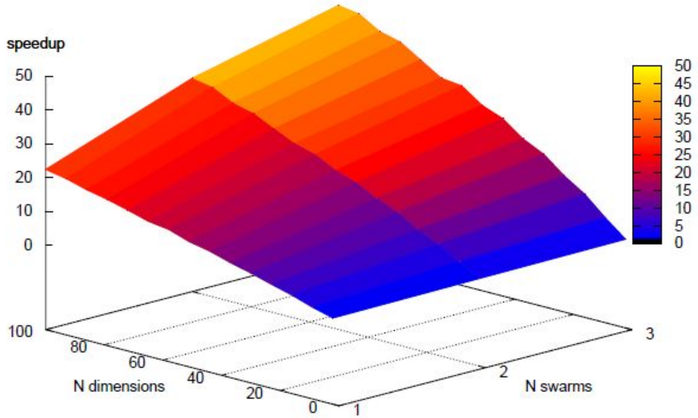


Figure 3: CUDAPSO vs sequentialPSO: Speedup

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Related Work

Paralle Particle Swarm Optimization

- OpenMP
- CUDA

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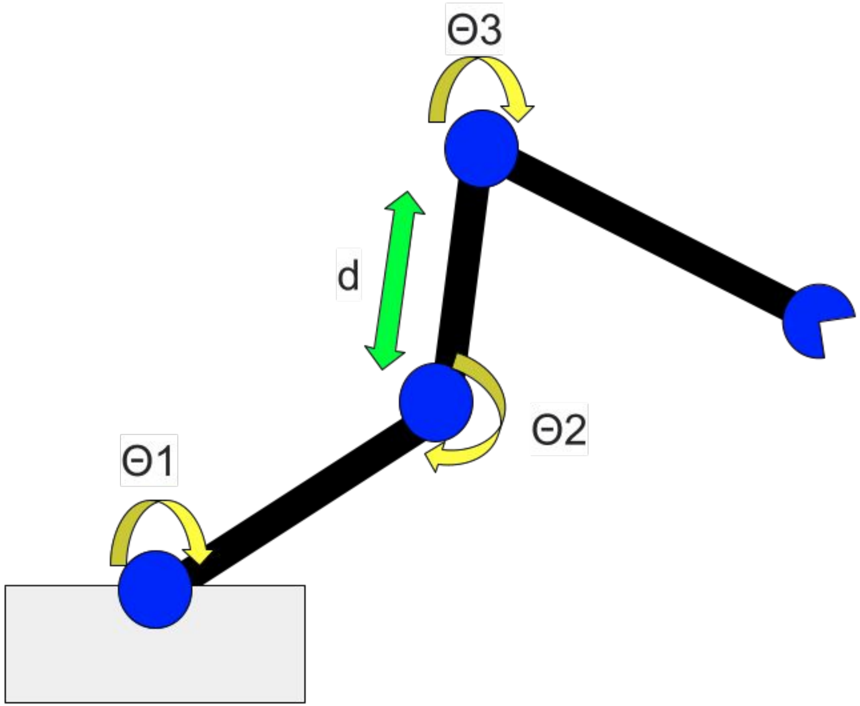
Problem Definition



Paralle Particle Swarm Optimization : CUDA

1. Introduce MTGP32 random number generator
2. Reduce memory copy between host to device
3. Reduction when evaluating pBestFit

Paralle Particle Swarm Optimization : CUDA

random number generator is needed when :

1. particle is out of bound
2. generating R1 R2

Generating 32768 * 128 * 256 random floats between 1000000 and 0 costs:

5.65640s for GPU with 128 * 256 threads

57.94887s for CPU

Paralle Particle Swarm Optimization : CUDA

Reduce memory copy between host to device

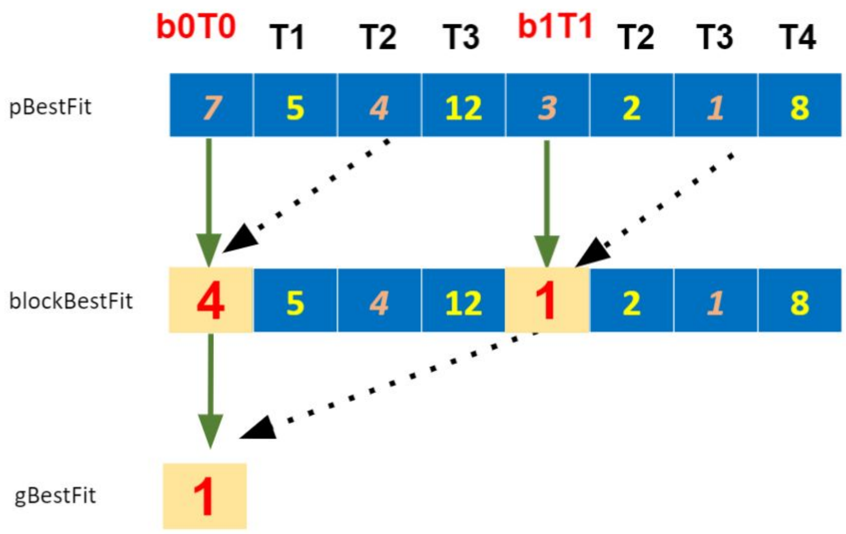
```
            Type  Time(%)      Time     Calls       Avg       Min       Max  Name
 GPU activities:   97.63%  549.72ms     10000  54.972us  44.575us  104.93us  deviceSearch(double*, dou
e*, double*, double*, double*, double*, int*, int*, curandStateMtgp32*)
                    2.37%  13.345ms     20038     665ns     543ns  126.14us  [CUDA memcpy HtoD]
                    0.00%  4.5130us         6     752ns     672ns     928ns  [CUDA memcpy DtoH]
                    0.00%     832ns         1     832ns     832ns     832ns  [CUDA memset]
      API calls:   70.77%  567.56ms     10000  56.756us  2.0550us  510.99us  cudaDeviceSynchronize
                   16.23%  130.14ms        17  7.6553ms  1.2310us  130.00ms  cudaMalloc
                    9.16%  73.466ms     20017  3.6700us  2.2340us  947.63us  cudaMemcpyToSymbol
                    3.69%  29.599ms     10000  2.9590us  2.6690us  256.10us  cudaLaunchKernel
                    0.07%  557.79us        27  20.659us  4.9910us  35.661us  cudaMemcpy
                    0.03%  253.08us         1  253.08us  253.08us  253.08us  cuDeviceTotalMem
                    0.02%  182.71us        17  10.747us  1.3650us  95.969us  cudaFree
```

CUDA MEMCPY HtoD Only costs 2.37%

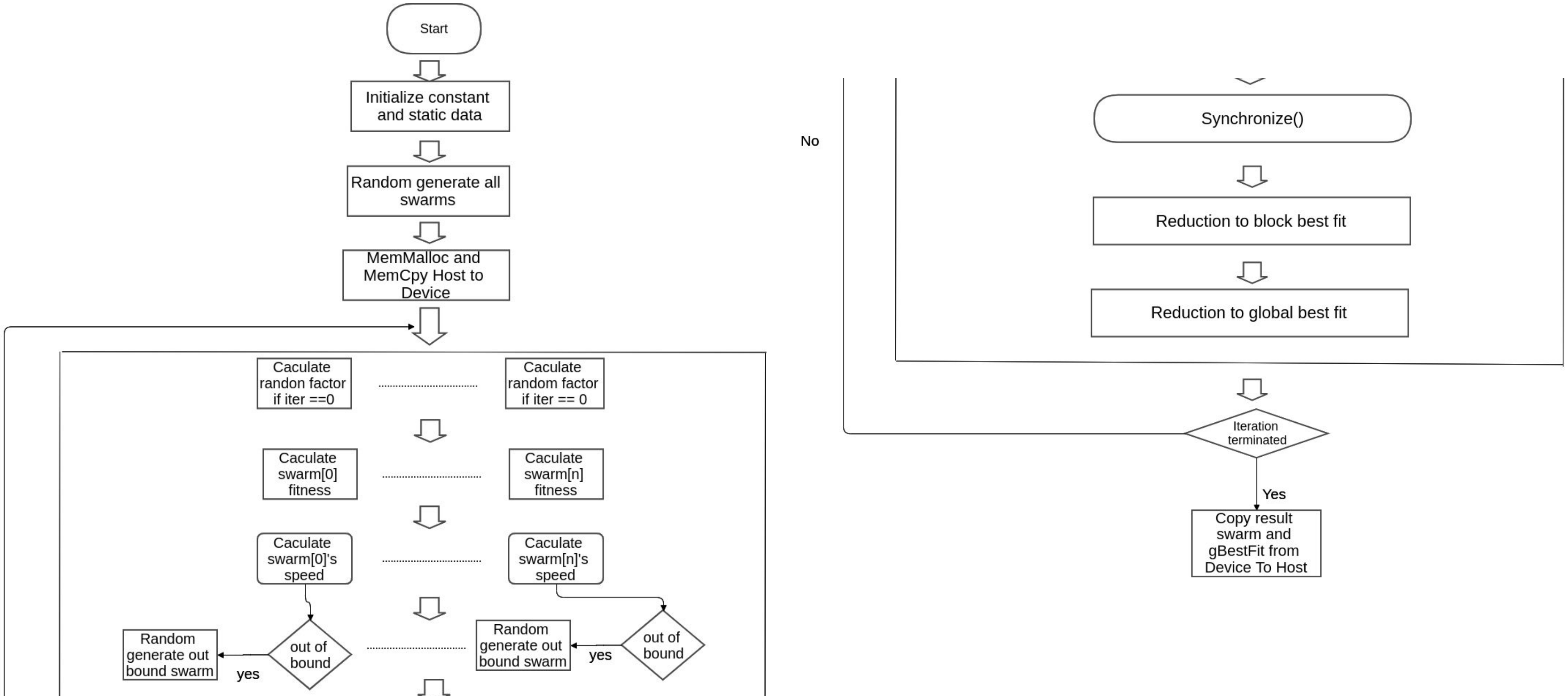
CUDA MEMCPY DtoH Only costs 0.00%

Paralle Particle Swarm Optimization : CUDA

1. Reduction when evaluating pBestFit



Paralle Particle Swarm Optimization : CUDA



Paralle Particle Swarm Optimization : OpenMP

work sharing:

#pragma omp parallel for

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   1.2. Initialize $\boldsymbol{gbest}$ with a copy of X_i with the best fitness
2. Repeat until a stopping criterion is satisfied:
   2.1. For each particle i:
      2.1.1. Update V_i^t and X_i^t according to Eqs. (1) and (2)
      2.1.2. Evaluete the fitness $f(X_i^t)$
      2.1.3. $\boldsymbol{pbest}_i \longleftarrow X_i^t$ if $f(\boldsymbol{pbest}_i) < f(X_i^t)$
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Experiment--Platform

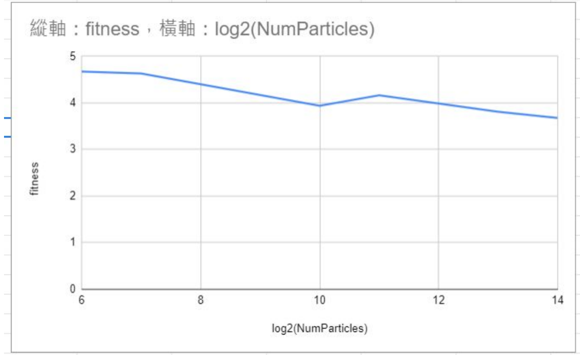
Parallel platform:

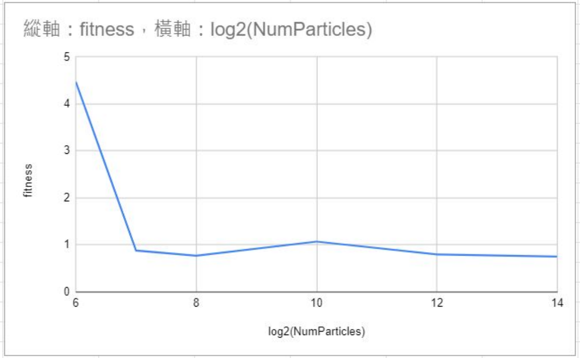
- OpenMp
- Cuda
- C++

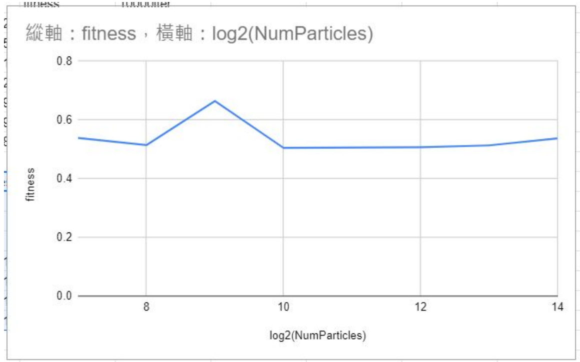
Demo platform:

- Qt

Experiment--CUDA evaluation

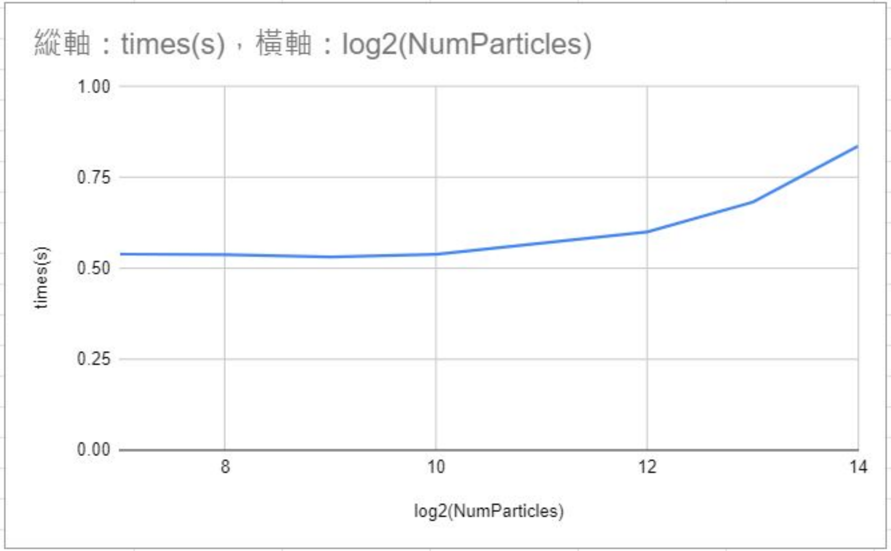


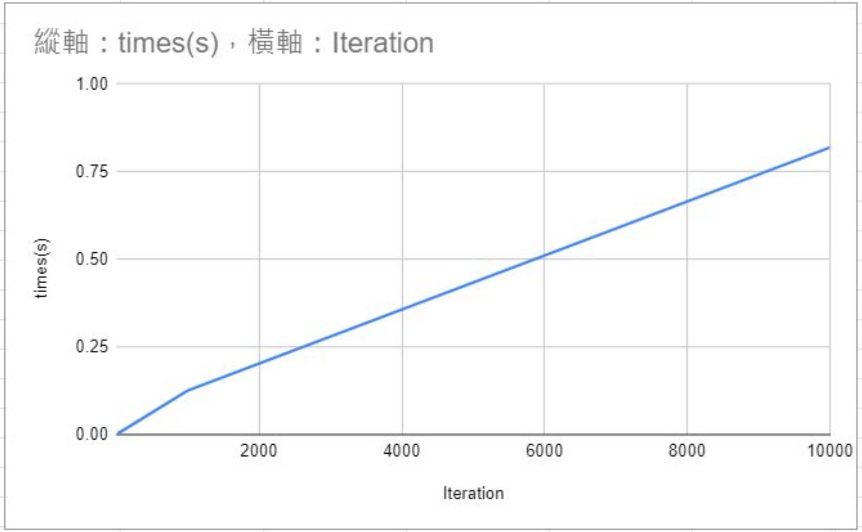




10, 100, 10000 iteration: log2(NumParticle) to fitness

Experiment--CUDA evaluation

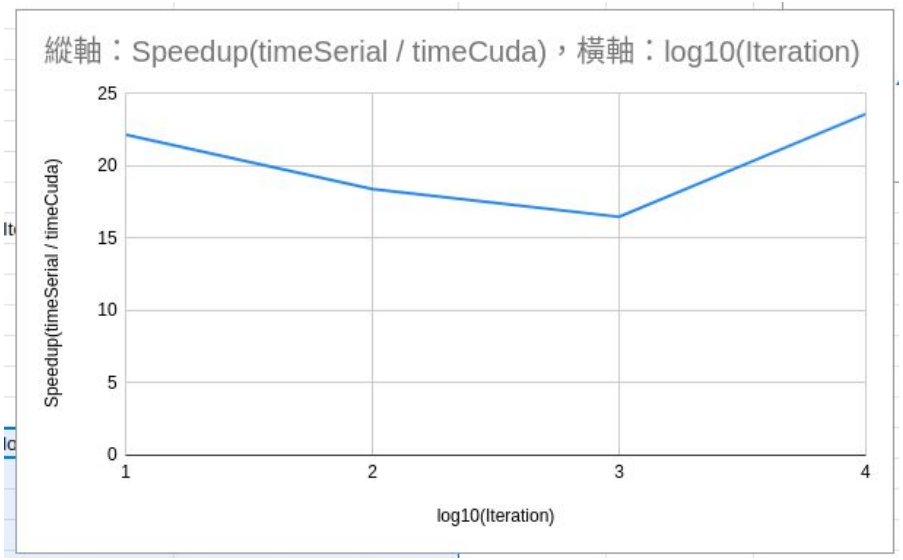




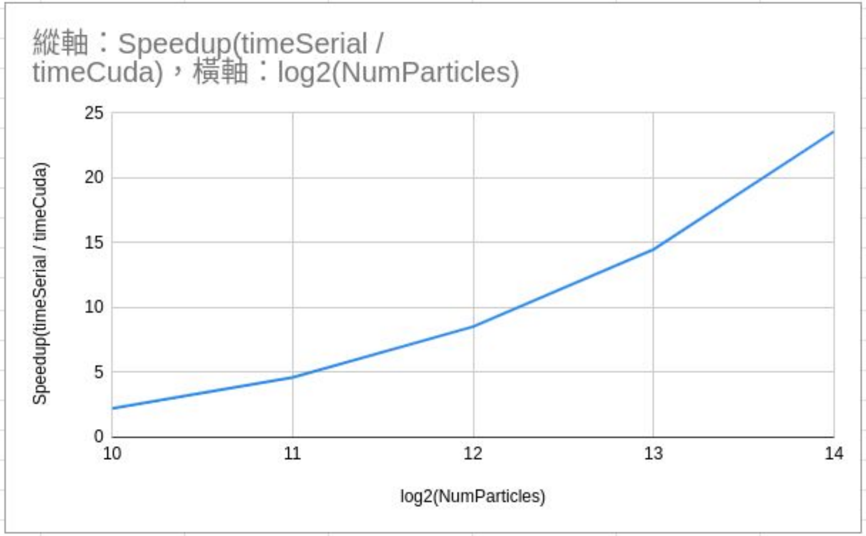
10000 iteration: log2(NumParticle) to time

16384NumParticles: iteration to time

Experiment--CUDA vs Serialize

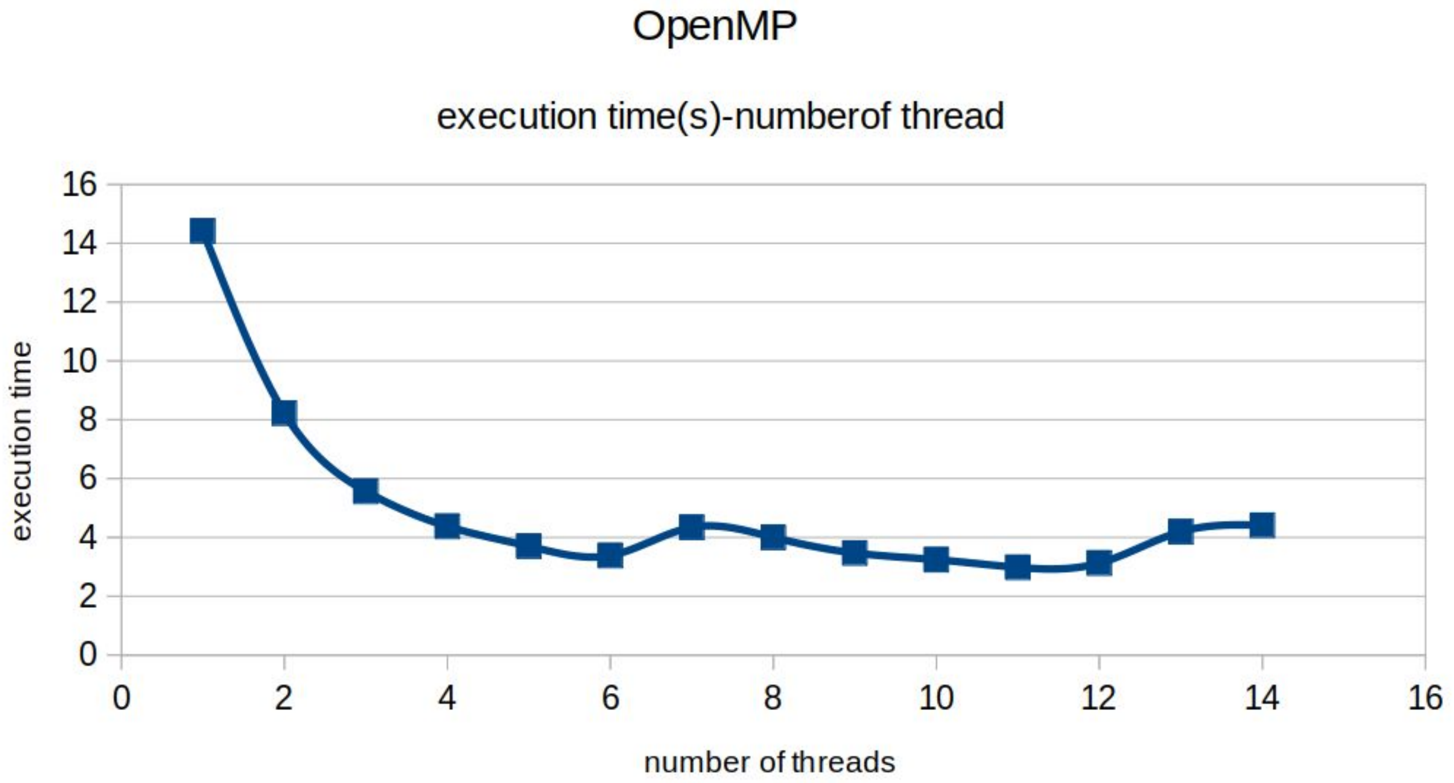


16384NumParticles: log10(Iterations) to time

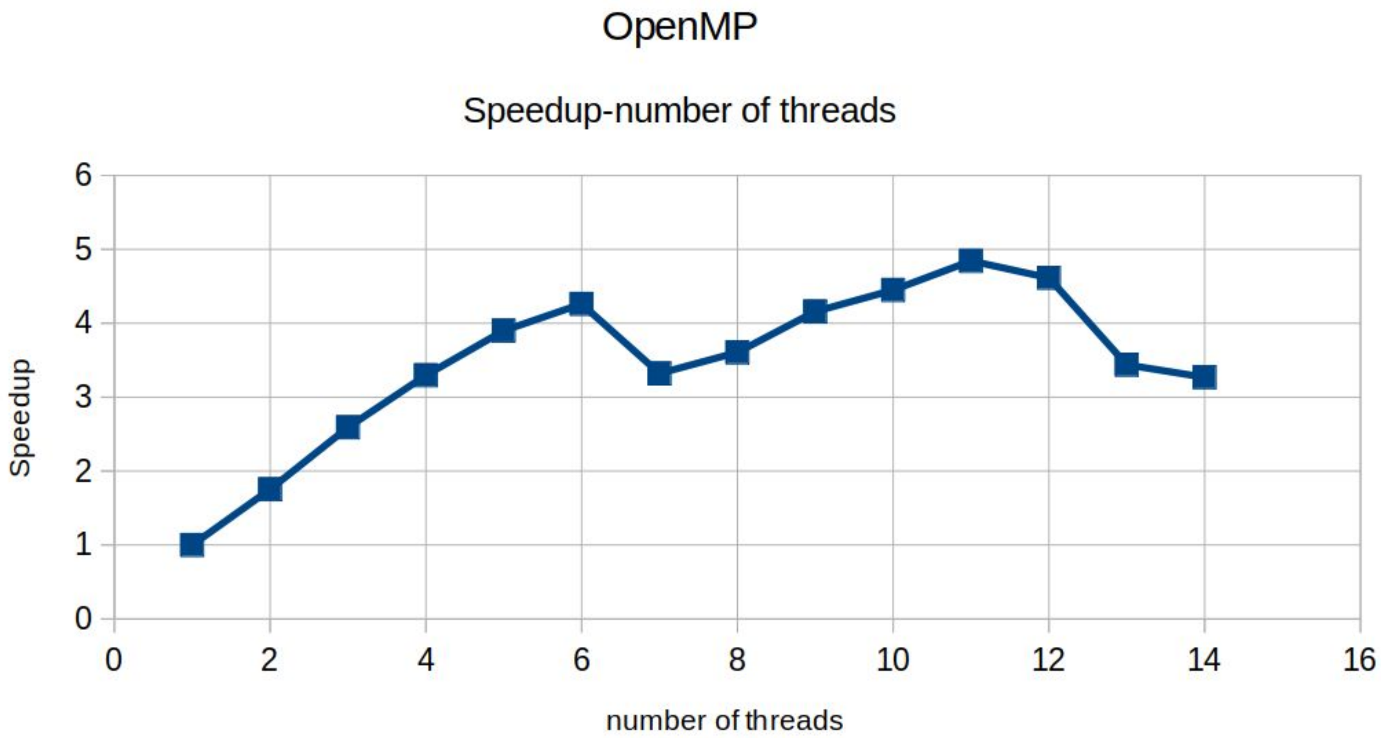


10000iteration: log2(NumParticles) to time

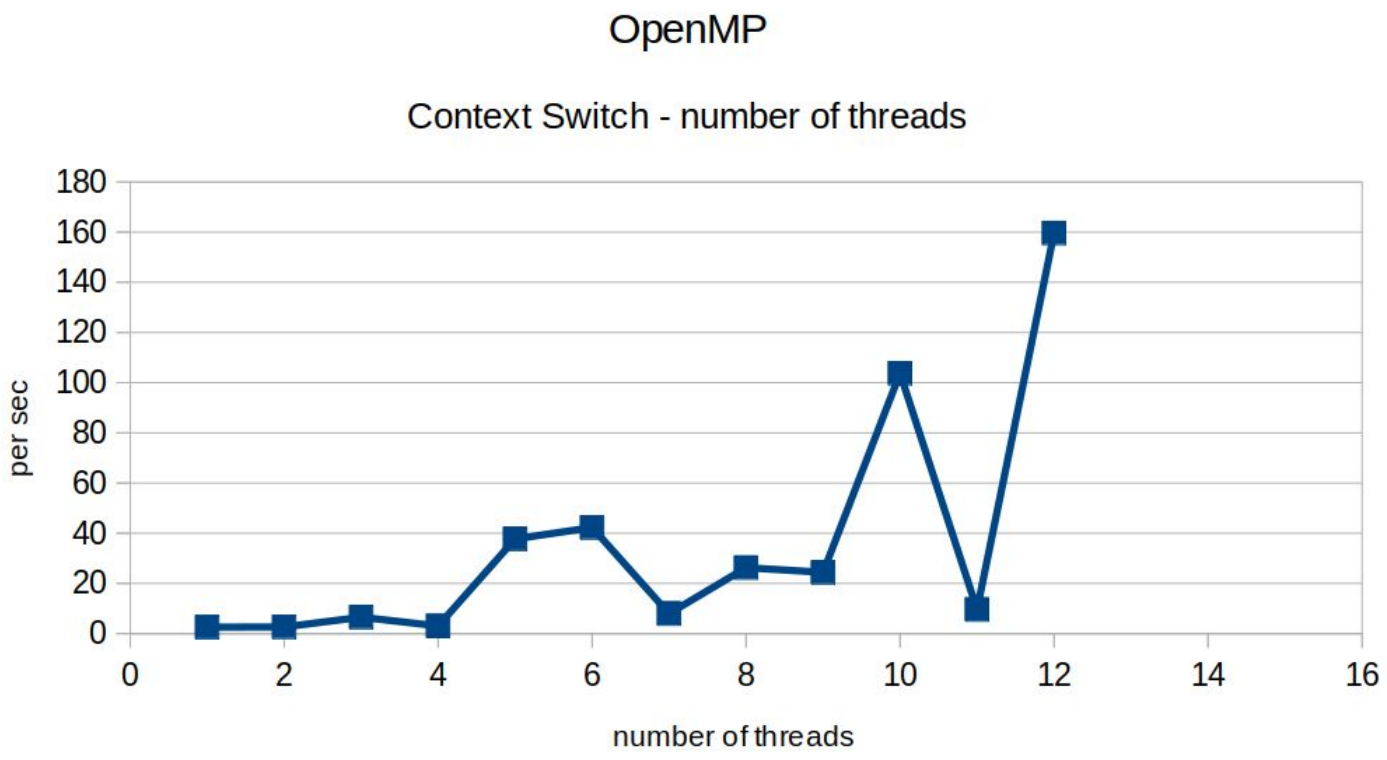
Experiment--OpenMP



Experiment--OpenMP

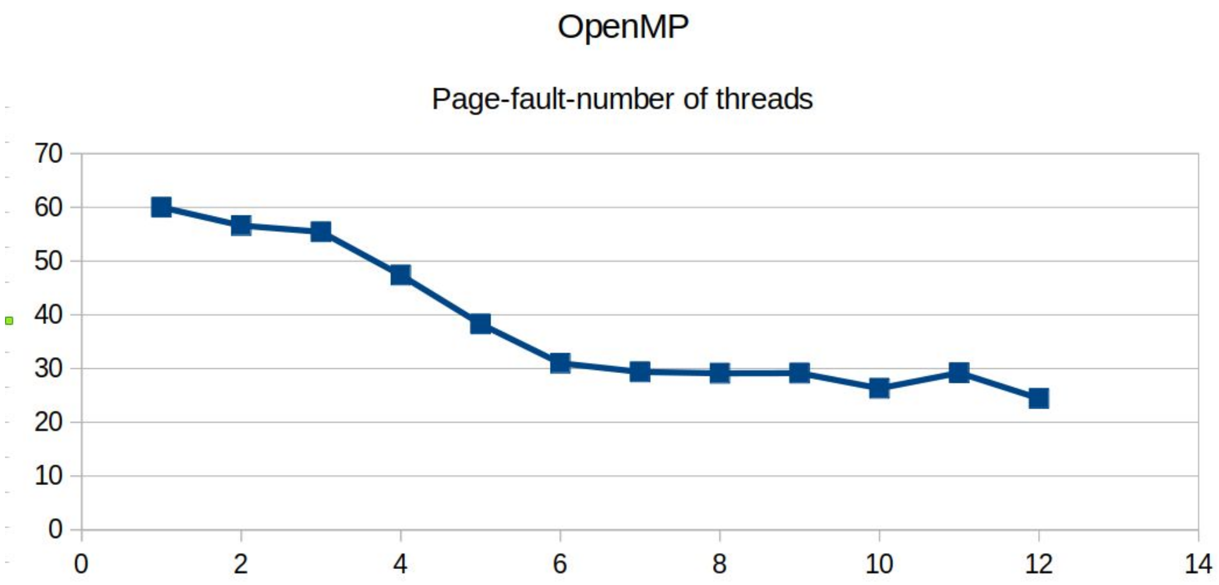


Experiment--OpenMP



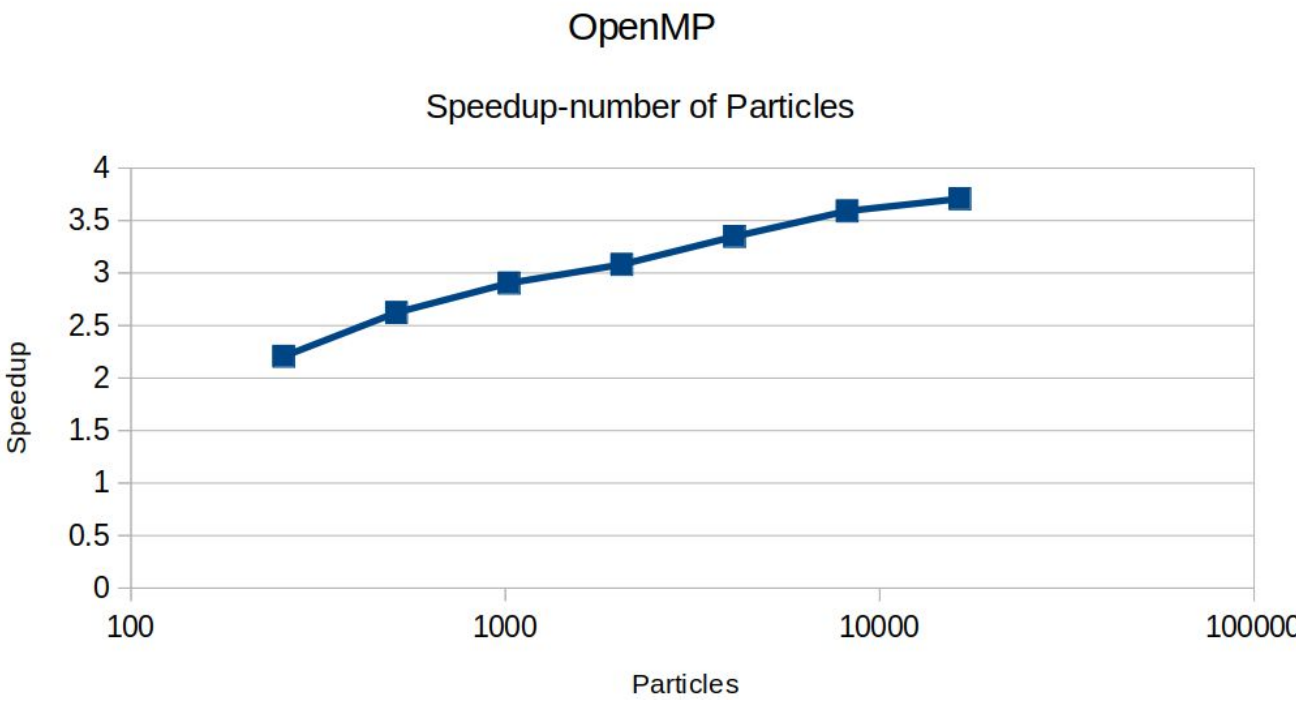
Experiment--OpenMP

4 Threads



Experiment--OpenMP

4 Threads



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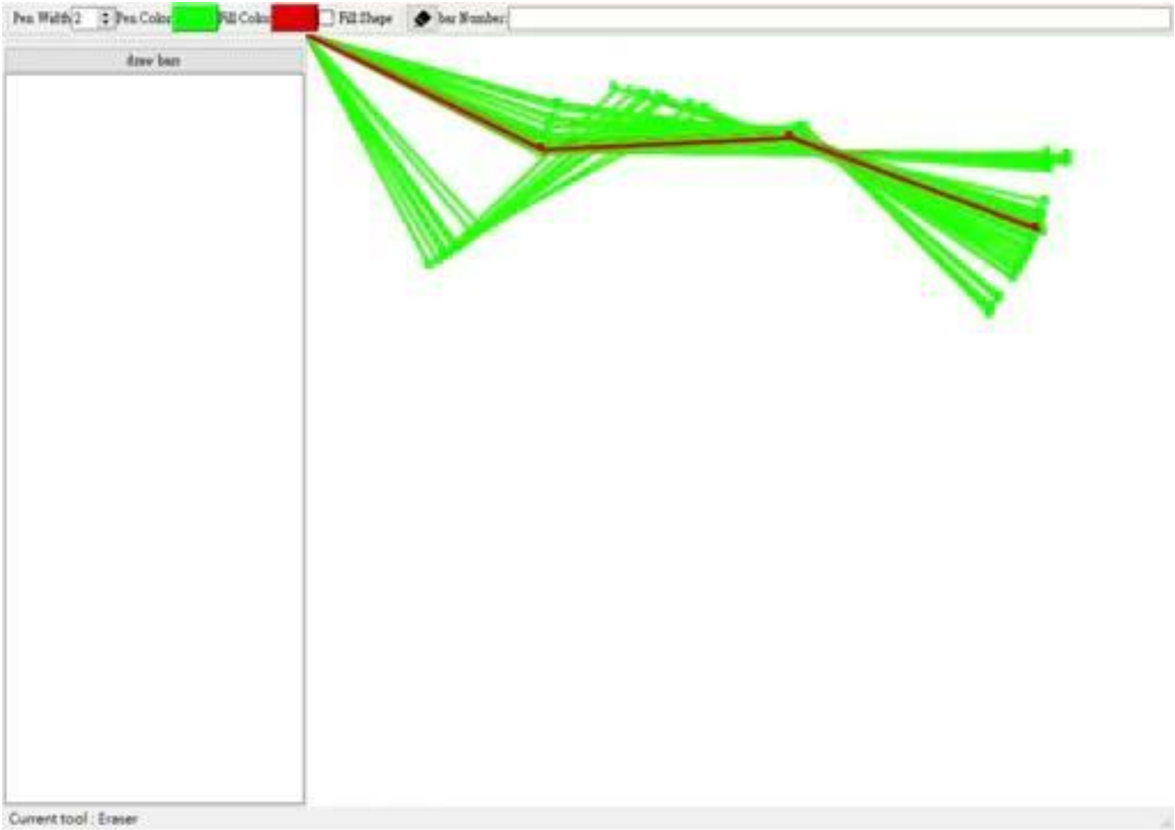
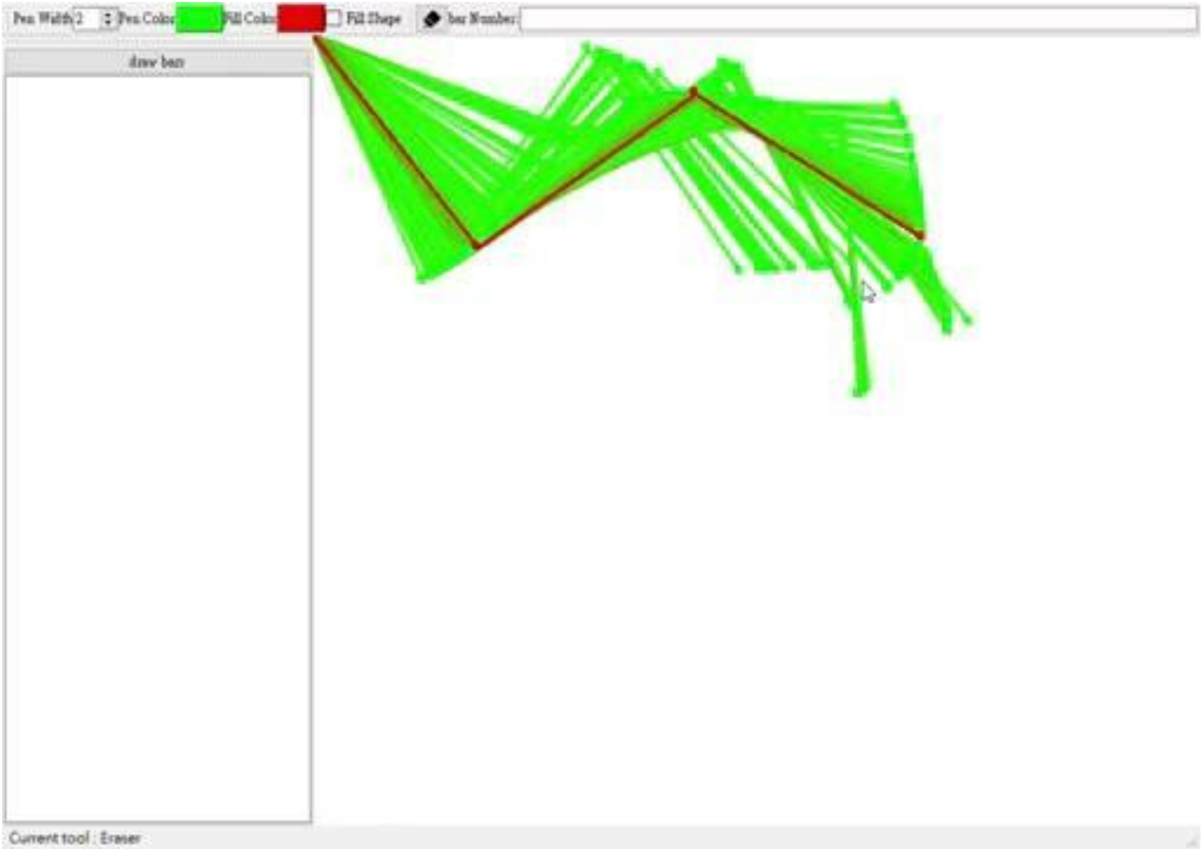
Demo--serialize 3000iter 15 times slow



gBest is at: a1:0.453, a2:0.489, a3:0.357,d2: 4.791
arm position:(6.0000, 3.000)
time elapsed: 3.53499s
fitness: 0.505182

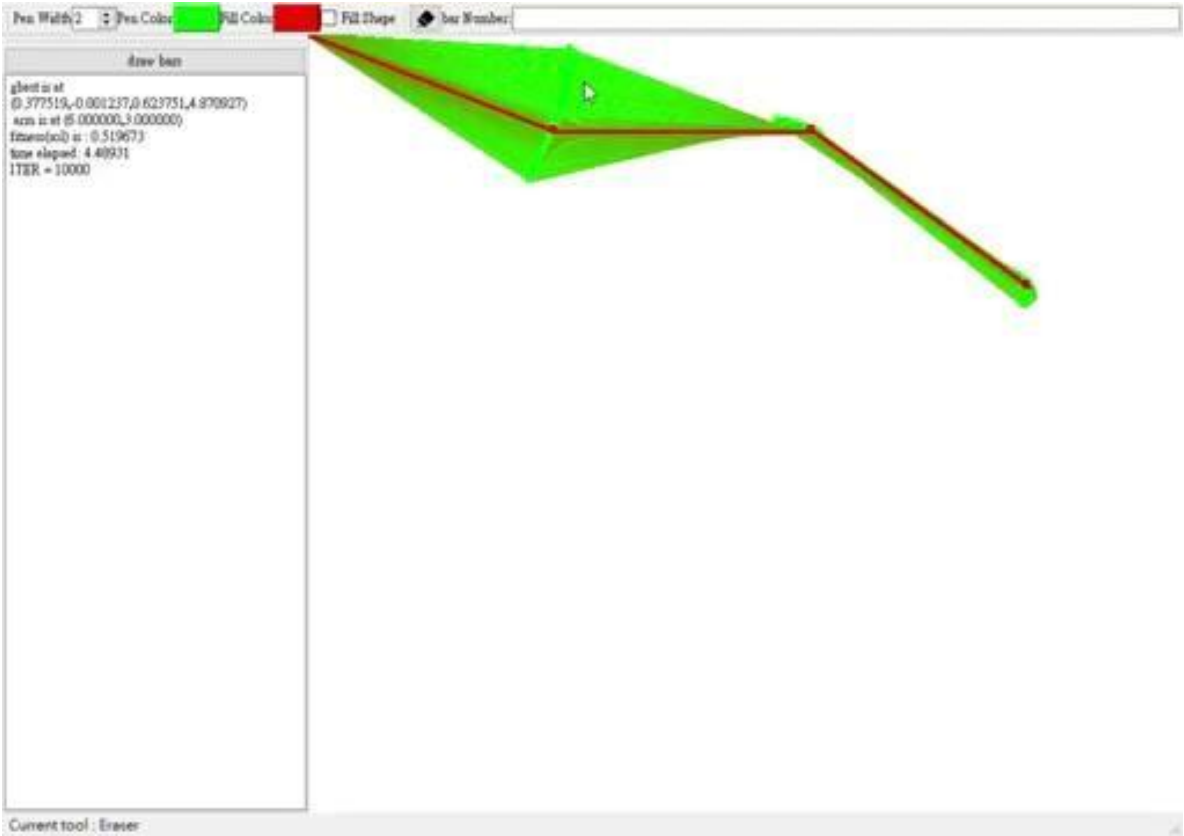
Demo--openMP 3000iter 15 times slow



gBest is at: a1:0.894, a2:-0.599, a3:0.599,d2: 4.960
arm position:(6.0000, 3.000)
time elapsed: 0.6425s
fitness: 0.505182

6.99745X

Demo--openMP 10000iter 15 times slow



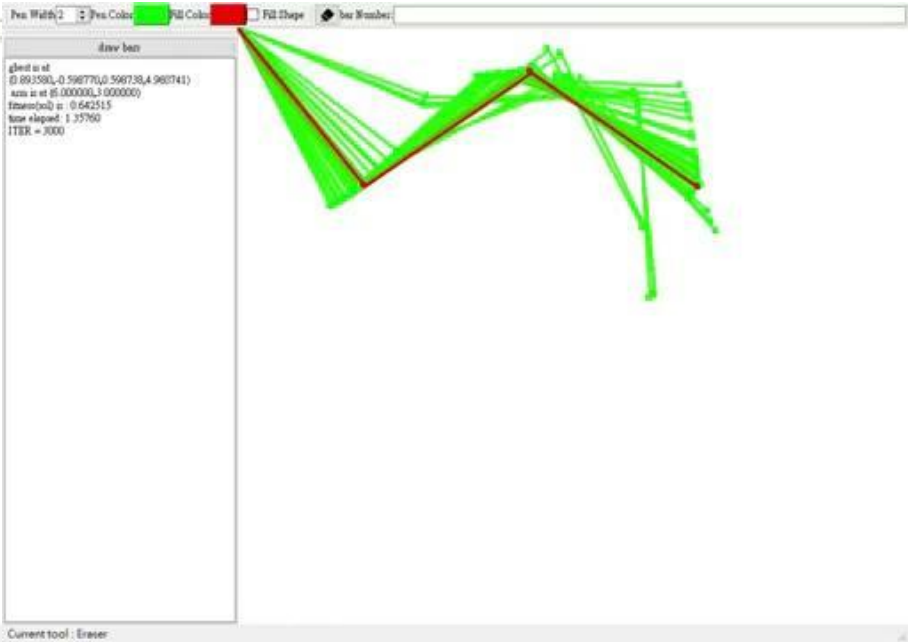
gBest is at: a1:0378, a2:-0.001, a3:0.624,d2: 4.871
arm position:(6.0000, 3.000)
time elapsed: 4.409s
fitness: 0.519673

Demo--cuda 3000 iter 15 times slow

gBest is at: a1:0.234, a2:0.119, a3:1.037,d2: 5.163
arm position:(6.0000, 3.000)
time elapsed: 0.332s
fitness: 0.505182

10.6468X

Demo--cuda and openMP 3000iter normal speed



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Conclusion:

openMP and CUDA can significantly speedup PSO when solving Inverse Kinematics

CUDA done better when the problem size increases;

It is much more easier to parallelize PSO by openMP

Future work:

Real time tracing Inverse Kinematics

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Particle Swarm Optimization:A Powerful Technique for Solving Engineering Problems. IntechOpen.
PySwarms (2021), Lj Miranda, https://github.com/ljvmiranda921/pyswarms.

Thank you for your attention