# Conjugate Gradient Solver for SU(2) 

 Staggered Fermion on GPU
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## Outline

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## Motivation

## $\mathrm{SU}(2)$ Gauge Theory with many flavor = Candidate of Beyond Standard Model (Walking Techni-Color)

Strongly Interacting System<br>=> Lattice Simulation is useful tool

HMC Simulation \& Measurement
=> Need to Solve Linear Equation s=Dx (x is unknown)
Conjugate Gradient or it's modification is widely used.
GPU is effective for sparse matrix calculation

## Staggered Fermion

## Way out of Nielsen Ninomiya No-go theorem


$S_{F}=\frac{1}{2} \sum_{n, \mu} \eta_{\mu}(n)\left[\bar{\chi}(n) U_{\mu}(n) \chi(n+\hat{\mu})-\bar{\chi}(n) U_{\mu}^{\dagger}(n-\hat{\mu}) \chi(n-\hat{\mu})\right]+M \sum_{n} \bar{\chi}(n) \chi(n)$ $\eta_{\mu}(n)=(-1)^{n_{1}+n_{2}+\cdots+n_{\mu-1}}$
=>
$\bar{S}_{F}=\frac{1}{2} \sum_{n, \mu}\left[\bar{\chi}(n) U_{\mu}^{\prime}(n) \chi(n+\hat{\mu})-\bar{\chi}(n) U_{\mu}^{\prime \dagger}(n-\hat{\mu}) \chi(n-\hat{\mu})\right]+M \sum_{n} \bar{\chi}(n) \chi(n)$

$$
U_{\mu}^{\prime}(n)=\eta_{\mu}(n) U_{\mu}(n)
$$

Hyper Cube (16 DOF)

$$
=>
$$

Considered as 4 dirac and "4 taste"


## Even-Odd Preconditioning (Checkerboard)



## Even Site:

( ix $+i y+i z+i t) \% 2=0$

$$
\left(\begin{array}{cc}
m & D_{E O} \\
D_{O E} & m
\end{array}\right)=\left(\begin{array}{cc}
1 & 0 \\
D_{O E} \frac{1}{m} & 1
\end{array}\right)\left(\begin{array}{cc}
m & 0 \\
0 & m-D_{O E} \frac{1}{m} D_{E O}
\end{array}\right)\left(\begin{array}{cc}
1 & D_{E O} \\
0 & 1
\end{array}\right)
$$

Inverse
$\left(\begin{array}{cc}m & D_{E O} \\ D_{O E} & m\end{array}\right)^{-1}=\left(\begin{array}{cc}1 & -D_{E O} \\ 0 & 1\end{array}\right)\left(\begin{array}{cc}m & 0 \\ 0 & \left.\begin{array}{cc}m-D_{O E} \frac{1}{m} D_{E O}\end{array}\right)^{-1}\left(\begin{array}{cc}1 & 0 \\ -D_{O E} \frac{1}{m} & 1\end{array}\right)\end{array}\right.$
Determinant

$$
\operatorname{det}\left(\begin{array}{cc}
m & D_{E O} \\
D_{O E} & m
\end{array}\right)=\operatorname{det}\left(\begin{array}{cc}
m & 0 \\
0 & m-D_{O E} \frac{1}{m} D_{E O}
\end{array}\right)
$$

## Conjugate Gradient $b=A x$

## Initial Condition

$$
d_{0}=r_{0}=b-A x_{0}
$$

Iteration $\mathrm{i}=0, \mathrm{I}, 2, \ldots$

$$
\begin{array}{ccc}
x_{i+1}=x_{i}+\alpha_{i} d_{i} & 2 & \text { Solution } \\
d_{i+1}=r_{i+1}+\beta_{i+1} d_{i} \cdots & 5 \text { Update Direction } \\
r_{i+1}=r_{i}-\alpha_{i} A d_{i} & \cdots & 3
\end{array}
$$

Coefficients are

$$
\begin{align*}
\alpha_{i} & =\frac{\left(r_{i}, r_{i}\right)}{\left(d_{i}, A d_{i}\right)} \\
\beta_{i+1} & =\frac{\left(r_{i+1}, r_{i+1}\right)}{\left(r_{i}, r_{i}\right)} \tag{4}
\end{align*}
$$

## Conjugate Gradient $b=A x$

Initial Condition

$$
d_{0}=r_{0}=b-A x_{0}
$$

Iteration $\mathrm{i}=0, \mathrm{I}, 2, \ldots$

$$
\begin{array}{rlr}
\alpha_{i} & =\frac{\left(r_{i}, r_{i}\right)}{\left(d_{i}, A d_{i}\right)} & \\
r_{i+1} & =r_{i}-\alpha_{i} A d_{i} & \text { Residual } \\
x_{i+1} & =x_{i}+\alpha_{i} d_{i} & \text { Solution } \\
\beta_{i+1} & =\frac{\left(r_{i+1}, r_{i+1}\right)}{\left(r_{i}, r_{i}\right)} & \\
d_{i+1} & =r_{i+1}+\beta_{i+1} d_{i} & \\
\text { Update Direction }
\end{array}
$$

Example $b=A x$ with $A=\left(\begin{array}{ll}1 & 2 \\ 2 & 5\end{array}\right) \quad b=\binom{1}{0}$

$$
\begin{gathered}
d_{0}=r_{0}=b-A x_{0} \quad \alpha_{i}=\frac{\left(r_{i}, r_{i}\right)}{\left(d_{i}, A d_{i}\right)} \quad x_{i+1}=x_{i}+\alpha_{i} d_{i} \\
r_{i+1}=r_{i}-\alpha_{i} A d_{i} \quad \beta_{i+1}=\frac{\left(r_{i+1}, r_{i+1}\right)}{\left(r_{i}, r_{i}\right)} \quad d_{i+1}=r_{i+1}+\beta_{i+1} d_{i} \\
\times 2
\end{gathered}
$$

$$
\left(d_{i}, r_{j}\right)=0 \text { for } i<j \quad\left(r_{i}, r_{j}\right)=0 \text { for } i \neq j
$$

This guarantees $\quad r_{N}=0$

## Comments on $\mathrm{b}=\mathrm{Ax}$

It needs efforts to find the solution.
On the other hand,
It is very easy to check the solution.

This property is crucial for Mixed Precision CG


## Defect Correction and Reliable Update

Defect Correction
SP: CG Solver, with $\mathrm{d}_{0}=\mathrm{r}_{0}$
DP: Sum SP solution to DP solution
DP: Calculate residual vector and set it as SP source

$$
\left(d_{i}, r_{j}\right)=0 \text { for } i<j \text { Is reset in defect correction }
$$

Reliable Update
SP: CG Solver, without refreshing $\mathrm{d}_{0}$ -
DP: Sum SP solution to DP solution
DP: Calculate residual vector and set it as SP source

Convergence is faster for Reliable Update

## GPU (Graphic Processor Units)



Originally Developed forVideo Gamers many core (~1000) works for SIMD
(Single Instruction Multiple Data) simultaneously
Nvidia's recent product have several level of memory with different size and access time to the computing cores

## Coding with CUDA

## CPU Code



## Tuning of GPU

Principle $=$ Let processors works all time. => reduce the time to get / send data

Memory
Turn on/off LI Cache, Texture, Shared Memory

## Coallese <br> Reorder the data as GPU friendly

Magic Number (depend on the architecture) Warp, Block Size, ....

Reordering the Operation
Recycle the data on the cache as much as possible

## Coallece


global memory


## Example of Mixed Precision CG

## L24^3T48 Lattice, Beta=2.7, aM $=0.25$, Naive Staggered <br> === DOUBLE PRECISION ===

----- (vR,vR)/(vSrc,vSrc): $1.00000000 \mathrm{E}+00$ $===\mathrm{CG}$ SINGLE PRECISION
---- S, T, U : 3.051239
---- S, T, U : 2.67133
$===$ DOUBLE PRECISION ===
----- (vR,vR)/(vSrc,vSrc): 3.75744317E-08
=== CG SINGLE PRECISION ===
$\begin{array}{lllll}\text {----- S, T, U : } & 9.14439850 \mathrm{E}+01 & 8.18142605 \mathrm{E}+00 & 2.74593925 \mathrm{E}+00 \\ -----S, T, U & 2.68391886 \mathrm{E}-04 & 2.98086998 \mathrm{E}-05 & 7.48642242 \mathrm{E}-06\end{array}$
=== DOUBLE PRECISION ===
----- (vR,vR)/(vSrc,vSrc): $3.43825294 \mathrm{E}-14$
=== CG SINGLE PRECISION ===
----- S, T, U : 8.44834140E-05 7.48642378E-06 2.51462211E-06
_---- S, T, U : $3.13231913 \mathrm{E}-10 \quad 3.60102989 \mathrm{E}-11 \quad 1.46738698 \mathrm{E}-11$
=== DOUBLE PRECISION ===
----- (vR,vR)/(vSrc,vSrc): 6.73919755E-20
=== CG SINGLE PRECISION ===
----- S, T, U : $1.67335437 \mathrm{E}-10 \quad 1.46738732 \mathrm{E}-11 \quad 4.63271088 \mathrm{E}-12$
----- S, T, U : $4.74928462 \mathrm{E}-16 \quad 5.84574362 \mathrm{E}-17 \quad 3.02788868 \mathrm{E}-17$
=== DOUBLE PRECISION ===
----- (vR,vR)/(vSrc,vSrc): $1.39060504 \mathrm{E}-25$
=== MIXED PRECISION CG CONVERGED ===
Time-CG[sec] 1.340796

## Summary and Comments

SU(2) gauge theory
=> Candidate of Beyond Standard Moded
Lattice Simulation
=> Large Part is Solving Linear Problem of Dirac Operator
Speed up of Conjugate Gradient
Even Odd Preconditioning
Mixed Precision
Defect Correction, Reliable Update
I GPU ~ I Node of Super Computer
Special Thanks, Aoyama-san (KMI)

