# A GPU/Multi-core Accelerated Multigrid Preconditioned Conjugate Gradient Method for Adaptive Mesh Refinement 

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In this talk We will describe

- A new method for computing the pressure projection step of our coupled level set and volume of fluid (CLSVOF) code on adaptive meshes using the multigrid preconditioned conjugate gradient method.
- Steps involving the GPU acceleration of the code.


## Outline

1 Governing Equations for two-phase flow

- Background and Related Work

2 Mathematical Formulation

- An Improved Projection Algorithm for Adaptive Meshes
- Restriction and Prolongation Operators
- Convergence

3 Results and Discussion

4 GPU Acceleration

5 Microfluids Gallery

$$
\begin{gathered}
\rho_{L} \frac{D \mathbf{u}_{L}}{D t}=-\nabla p_{L}+2 \mu_{L} \nabla \cdot \mathcal{D}+\rho_{L} \mathbf{g}, \quad \nabla \cdot \mathbf{u}_{L}=0, \quad \mathbf{x} \in \text { liquid, } \\
\rho_{g} \frac{D \mathbf{u}_{g}}{D t}=-\nabla p_{g}+2 \mu_{g} \nabla \cdot \mathcal{D}+\rho_{g} \mathbf{g}, \quad \nabla \cdot \mathbf{u}_{g}=0, \quad \mathbf{x} \in \text { gas }, \\
D=\frac{\nabla \mathbf{u}+(\nabla \mathbf{u})^{T}}{2}
\end{gathered}
$$

## Governing Equations for two-phase flow (cont)

Interfacial Conditions

$$
\begin{gathered}
\left(2 \mu_{L} \mathcal{D}-2 \mu_{g} \mathcal{D}\right) \cdot \mathbf{n}=\left(p_{L}-p_{g}+\sigma \kappa\right) \mathbf{n} \quad \text { and } \quad \mathbf{u}_{L}=\mathbf{u}_{g}, \quad \mathbf{x} \in \Gamma, \\
\mathbf{u}_{L}=\mathbf{u}_{g}, \quad \mathbf{x} \in \Gamma \\
\frac{d \mathbf{x}}{d t}=\mathbf{u}(\mathbf{x}(t), t), \quad \mathbf{x} \in \Gamma \\
\kappa=\nabla \cdot \mathbf{n}, \quad \mathbf{x} \in \Gamma
\end{gathered}
$$



Weak solutions of the following equations satisfy the interfacial boundary conditions:

$$
\begin{gathered}
\rho \frac{D \mathbf{u}}{D t}=\nabla \cdot(-p l+2 \mu D)+\rho g z-\sigma \kappa \nabla H \\
\nabla \cdot \mathbf{u}=0 \quad \frac{D \phi}{D t}=0 \quad \kappa(\phi)=\nabla \cdot \frac{\nabla \phi}{|\nabla \phi|} \\
H(\phi)= \begin{cases}1 & \phi \geq 0 \\
0 & \phi<0\end{cases} \\
\rho=\rho_{L} H(\phi)+\rho_{G}(1-H(\phi)) \quad \mu=\mu_{L} H(\phi)+\mu_{G}(1-H(\phi))
\end{gathered}
$$

Y.C. Chang, T.Y. Hou, B. Merriman, and S. Osher, A Level Set Formulation of Eulerian Interface Capturing Methods for Incompressi Fluid Flows, J.Comput.Phys.,124 (1996), pp. 449-464.

## Staggered grid discretization



The cell centered variables $\phi_{i, j}$ and $p_{i, j}$ are approximations to $\phi\left(x_{i}, y_{j}\right)$ and $p\left(x_{i}, y_{j}\right)$ respectively where $x_{i}=(i+1 / 2) \Delta x$ and $y_{j}=(j+1 / 2) \Delta y$. The horizontal face centered velocity, $u_{i+1 / 2, j}^{f c}$, is an approximation to $u\left(x_{i+1 / 2}, y_{j}\right)$ where $x_{i+1 / 2}=(i+1) \Delta x$ and $y_{j}=(j+1 / 2) \Delta y$. The vertical face centered velocity, $v_{i, j+1 / 2}^{f c}$, is an approximation to $v\left(x_{i}, y_{j+1 / 2}\right)$ where $x_{i}=(i+1 / 2) \Delta x$ and $y_{j+1 / 2}=(j+1) \Delta y$.

## Projection method

1. Coupled level set and volume of fluid interface advection: $\frac{D \phi}{D t}=0$,

$$
\frac{D F}{D t}=0 .
$$

2. Velocity advection: $\frac{D \mathbf{u}}{D t}=0, \mathbf{F}^{f c, a d v e c t}=\left(\frac{\mathbf{u}^{c c, *}-\mathbf{u}^{c c, n}}{\Delta t}\right)^{c \rightarrow f}$
3. Viscous force term (sub-cycling algorithm):
$1 \mathbf{u}^{c c,(0)}=\mathbf{u}^{c c, *}$
2 For $k=1, \ldots K$,

$$
\begin{aligned}
\mathbf{u}^{c c,(k)} & =\mathbf{u}^{c c,(k-1)}+\frac{\Delta t}{K} \frac{1}{\rho^{c c}\left(\phi^{n+1}\right)} \nabla \cdot\left(2 \mu\left(\phi^{n+1}\right) D^{(k-1)}\right) \\
\mathbf{3} \mathbf{F}^{f c, v i s c} & =\left(\frac{\mathbf{u}^{c c,(K)}-\mathbf{u}^{c c,(0)}}{\Delta t}\right)^{c \rightarrow f}
\end{aligned}
$$

5. Project velocity:

$$
\begin{gathered}
\mathbf{V}^{f c}=\mathbf{u}^{f c, n}+\Delta t\left(\mathbf{F}^{f c, a d v e c t}+\mathbf{F}^{f c, v i s c}+g \mathbf{z}-\sigma \kappa \nabla H / \rho\right) \\
\nabla \cdot \frac{1}{\rho} \nabla p=\frac{1}{\Delta t} \nabla \cdot \mathbf{V}^{f c} \\
\mathbf{u}^{f c, n+1}=\mathbf{V}^{f c}-\Delta t \frac{\nabla p}{\rho}
\end{gathered}
$$

## Pressure Poisson Equation

We will be concerned with the solution of the pressure Poisson equation

$$
\begin{equation*}
\nabla \cdot \frac{1}{\rho} \nabla p=F \tag{1}
\end{equation*}
$$

The phase density $\rho$ is represented in liquid and gas phases by $\rho=\rho_{L} H(\phi)+\rho_{G}(1-H(\phi))$, where $H(\phi)$ is a Heaviside function equal to 1 in liquid and 0 in gas.

## 1D Discretization of Pressure Equation

$$
\begin{gather*}
\frac{1}{\rho_{i+\frac{1}{2}}} \frac{p_{i+1}-p_{i}}{\Delta x}-\frac{1}{\rho_{i-\frac{1}{2}}} \frac{p_{i}-p_{i-1}}{\Delta x}=\Delta x F_{i},  \tag{2}\\
\mathrm{~N}=7 \\
\mathrm{p}_{0}
\end{gather*} \mathrm{p}_{1} \quad \mathrm{p}_{2} \quad \mathrm{p}_{3} \quad \mathrm{p}_{4} \mathrm{p}_{5} \mathrm{p}_{6},
$$

## MGPCG-AMR, 2D discretization of pressure equation

$$
\begin{aligned}
& \beta_{i+1 / 2, j}\left(p_{i+1, j}-p_{i, j}\right)-\beta_{i-1 / 2, j}\left(p_{i, j}-p_{i-1, j}\right)+ \\
& \beta_{i, j+1 / 2}\left(p_{i, j+1}-p_{i, j}\right)-\beta_{i, j-1 / 2}\left(p_{i, j}-p_{i, j-1}\right)=f_{i, j} \Delta x^{2}
\end{aligned}
$$



## Matrix for Pressure Projection Step

Solve $\quad \nabla \cdot \beta \nabla p=f \quad \rightarrow \quad A x=b$

$$
\begin{aligned}
& A=\left|\begin{array}{lllllllll}
a & b & & & d & & & & \\
c & a & b & & & d & & & \\
& c & a & b & & & \cdot & & \\
& & \cdot & \cdot & \cdot & & & \cdot & \\
e & & & \cdot & \cdot & \cdot & & & d \\
& e & & & \cdot & \cdot & \cdot & & \\
& & \cdot & & & c & a & b & \\
& & & \cdot & & & c & a & b \\
& & & & e & & & c & a
\end{array}\right| \\
& a=-\left(\beta_{i+1 / 2, j}+\beta_{i-1 / 2, j}\right)-\left(\beta_{i, j+1 / 2}+\beta_{i, j-1 / 2}\right) \\
& b=\beta_{i+1 / 2, j} \quad c=\beta_{i-1 / 2, j} \quad d=\beta_{i, j+1 / 2} \quad e=\beta_{i, j-1 / 2}
\end{aligned}
$$

In multiphase flows, the condition number of the discretization matrix for eqn. 1 grows with the density ratio. In this table, the condition number is calculated for the discretization matrix of a 1D two phase flow in the domain $[0,1]$ following eqn. 2 , and with the phase interface occurring at $x=0.25$. The example flow has a density of 1 in the first phase on the interval $[0,0.25)$ and $\alpha$ in a second phase on the interval $(0.25,1]$. Values represent a discretization with 256 grid points and were calculated in MATLAB using the built in condition number function cond().

| $\alpha$ | 1 | $10^{-1}$ | $10^{-2}$ | $10^{-3}$ | $10^{-4}$ | $10^{-5}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Density Ratio | 1 | 10 | $10^{2}$ | $10^{3}$ | $10^{4}$ | $10^{5}$ |
| Condition \# | 205 | $1.2 \times 10^{3}$ | $1.2 \times 10^{4}$ | $1.2 \times 10^{5}$ | $1.2 \times 10^{6}$ | $1.2 \times 10^{7}$ |

## Introduction - Condition Number and Problem Geometry



The condition number of the discretization matrix is not as sensitive to the problem geometry as it is to the density ratio. The corresponding condition numbers for these figures are 6,132,300 (left), 1,861,000 (middle) and 2,548,900 (right) using a 2D version of discretization eqn. 2 on a $64 \times 64$ grid.


## Other possible MG Approaches for Inc. Two Phase Flow

- Klaus Stuben, Patrick Delaney, Serguei Chmakov, Algebraic Multigrid (AMG) for Ground Water Flow and Oil Reservoir Simulation
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- F. Lossaso, F. Gibou, and R. Fedkiw. Simulating water and smoke with an octree data structure. ACM Trans. Graph., 23:457462, 2004.
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## MG-MGPCG Algorithm for Adaptive Meshes



MG-MGPCG on level $\ell+1$ requires calculations at levels $\ell$ and $\ell-1$

## MG-MGPCG AMR Algorithm

Given $x^{0}, r=b-A x^{0}, x=x^{0}, \delta x=0$
Repeat until $\|r\|<\epsilon$

1. Call relax! $\left(\delta x, r, \ell^{\text {max }}\right)$ on finest level
2. Let $x=x+\delta x, r=r-A(\delta x)$

Recursive Routine relax!(sol, rhs, $\ell$ )
if Coarsest Level then
Solve exactly using MGPCG
else
(a) Presmoothing Step
for $i=1$ to presmooth do
Smooth using MGPCG on level $\ell$ until $\left\|r_{\ell}\right\|<\frac{\epsilon}{10}$
end for
(b) Restriction Step
(i) restrict! (r) to covered level $\ell-1$ cells and exposed level $\ell-1$
cells neighboring a covered cell.
(ii) cor $=0$
(c) Relaxation on Next Coarser Level Call relax! cor $^{\text {coarse }}$, rhs $^{\text {coarse }}, \ell-1$ )
(d) Prolongate the Correction to the present level / cells covering coarse
level $\ell-1$ cells and one layer of "'virtual" level $\ell$ cells. sol $=s o l+I$ (cor)
(e) Postsmoothing Step
for $i=1$ to postsmooth do
Smooth using MGPCG on level $\ell$
end for
end if


## Improved MGPCG AMR Algorithm

Given $x^{0}, r=b-A x^{0}, x=x^{0}, \delta x=0$
$z=0$
Call relax $\operatorname{AMR}\left(z, r, \ell^{\text {max }}\right)$
$\rho=z \cdot r$
if $n=1$ then

$$
p=z
$$

else

$$
\begin{aligned}
& \beta=\frac{\rho}{\rho_{\text {old }}} \\
& p=z p
\end{aligned}
$$

end if
$\alpha=\frac{\rho}{p \cdot(A p)}$
$\rho_{\text {old }}=\rho$
$x=x+\alpha p$
$r=r-\alpha A p$


## Improved MGPCG AMR Algorithm (cont.)

```
Recursive Routine relaxAMR(sol, rhs, \(\ell\) )
if Coarsest Level then
    Solve exactly using MGPCG
else
    (a) Presmoothing Step
    for \(i=1\) to presmooth do
        Smooth using ILU on level \(\ell\)
    end for
    (b) Restriction Step
                            (i) restrict( \(r\) ) to covered level \(\ell-1\) cells and recalculate \(r\) on exposed level \(\ell-1\) cells
    neighboring a covered cell.
            (ii) \(c o r=0\)
    (c) Relaxation on Next Coarser Level
        Call relaxAMR! (cor \({ }^{\text {coarse }}\), rhs \(^{\text {coarse }}, \ell-1\) )
    (d) Prolongate the Correction to the present level \(\ell\) cells covering coarse
    level \(\ell-1\) cells and one layer of 'virtual') level \(\ell\) cells.
            \(\mathrm{sol}=\mathrm{sol}+I(\) cor \()\)
    (e) Postsmoothing Step
    for \(i=1\) to postsmooth do
        Smooth using ILU on level \(\ell\)
    end for
end if
```



## MGPCG-AMR: Real and Fictitious Cells



Coarse and fine grid levels depicting real and fictitious cells


## MGPCG-AMR: Restriction, Prolongation, Smoother

Restriction (real cells):

$$
r_{i_{c}, j_{c}}^{\ell}=r_{i_{f}, j_{f}}^{e l l+1}+r_{i_{f}+1, j_{f}}^{e l l+1}+r_{i_{f}, j_{f}+1}^{e l l+1}+r_{i_{f}+1, j_{f}+1}^{\mathrm{ell}+1}
$$

Restriction (fictitious cells):

$$
r_{i_{c}, j_{c}}^{\ell}=r_{i_{f}, j_{f}}^{e l l+1}
$$

Prolongation (real cells):

$$
p_{i_{f}, j_{f}}^{\ell+1}=p_{i_{c}, j_{c}}^{\ell} \quad p_{i_{f}+1, j_{f}}^{\ell+1}=p_{i_{c}, j_{c}}^{\ell} \quad p_{i_{f}, j_{f}+1}^{\ell+1}=p_{i_{c}, j_{c}}^{\ell} \quad p_{i_{f}+1, j_{f}+1}^{\ell+1}=p_{i_{c}, j_{c}}^{\ell}
$$

Prolongation (fictitious cells):

$$
p_{i_{f}, j_{f}}^{\ell+1}=p_{i_{c}, j_{c}}^{\ell}
$$

Smoother (real cells):

$$
p^{k+1}=p^{k}+M\left(b-A p^{k}\right)
$$

Smoother (fictitious cells):

$$
p^{k+1}=p^{k}
$$

## Restriction Operator - Matrix Representation

$$
\left[\begin{array}{ccccccccc}
1 & 0 & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & 0  \tag{3}\\
0 & 1 & & & & & & & \\
\vdots & & \ddots & & & & & & \\
\vdots & & & 1 & 1 & 1 & 1 & & \\
\vdots & & & & & & & \ddots & \\
0 & & & & & & & & 1
\end{array}\right]\left[\begin{array}{c}
p_{1}^{\ell+1} \\
p_{2}^{\ell+1} \\
\vdots \\
p_{i 1}^{\ell+1} \\
p_{i 2}^{\ell+1} \\
p_{i 3}^{\ell+1} \\
p_{i 4}^{\ell+1} \\
\vdots \\
p_{N}^{\ell+1}
\end{array}\right]=\left[\begin{array}{c}
p_{1}^{\ell} \\
p_{2}^{\ell} \\
\vdots \\
p_{i}^{\ell} \\
\vdots \\
p_{N}^{\ell}
\end{array}\right]
$$

$$
\left[\begin{array}{cccccc}
1 & 0 & \cdots & \cdots & \cdots & 0  \tag{4}\\
0 & 1 & & & & \\
\vdots & & \ddots & & & \\
\vdots & & & 1 & & \\
\vdots & & & 1 & & \\
\vdots & & & 1 & & \\
\vdots & & & 1 & & \\
\vdots & & & \ddots & \\
0 & & & & & 1
\end{array}\right]\left[\begin{array}{c}
p_{1}^{\ell} \\
p_{2}^{\ell} \\
\vdots \\
p_{i}^{\ell} \\
\vdots \\
p_{N}^{\ell}
\end{array}\right]=\left[\begin{array}{c}
p_{1}^{\ell+1} \\
p_{2}^{\ell+1} \\
\vdots \\
p_{i 1}^{\ell+1} \\
p_{i 2}^{\ell+1} \\
i_{i 3}^{\ell+1} \\
p_{i 4}^{\ell+1} \\
\vdots \\
p_{N}^{\ell+1}
\end{array}\right]
$$

The convergence conditions are the same as those for MGPCG

- The MG smoother is symmetric
- The restriction operator is the transpose of the prolongation operator
- The matrix A in the smoothing step is symmetric


## 2D Test Problem


a.




| Blocking Factor | 2 <br> Adaptive Levels |  |  |  | 1 | 3 | 5 | 1 | 4 |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |

## 2D Test Problem Speedup

| Blocking Factor |  | 2 |  | 4 | 8 |  |  | 8 | 6 |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Adaptive Levels | 1 | 3 | 6 | 1 | 3 | 6 | 1 | 3 | 6 |
| ILU | $1.91 X$ | $3.43 X$ | $3.39 X$ | $1.99 X$ | $3.07 X$ | $4.03 X$ | $1.01 X$ | $1.97 X$ | $2.81 X$ |
| ICRB | $1.79 X$ | $3.32 X$ | $3.67 X$ | $1.83 X$ | $2.88 X$ | $4.01 X$ | $0.91 X$ | $2.13 X$ | $2.76 X$ |
| GSRB | $1.86 X$ | $3.19 X$ | $3.14 X$ | $1.84 X$ | $2.95 X$ | $3.78 X$ | $0.92 X$ | $2.07 X$ | $2.74 X$ |



| Blocking Factor | 2 |  |  |  |  | 4 |  |  | 8 |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Adaptive Levels | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| ILU Smoother |  |  |  |  |  |  |  |  |  |
| PCG | 3.839 | 18.45 | 71.11 | 3.326 | 14.24 | 49.79 | 4.154 | 22.22 | 69.70 |
| MG | 2.156 | 9.432 | 40.46 | 1.704 | 6.140 | 24.02 | 2.146 | 7.410 | 21.68 |
| MGPCG | 1.884 | 6.295 | 19.05 | 1.747 | 5.220 | 14.63 | 1.999 | 6.007 | 17.53 |
| ICRB Smoother |  |  |  |  |  |  |  |  |  |
| PCG | 4.158 | 19.67 | 75.61 | 3.682 | 15.28 | 56.82 | 4.770 | 27.19 | 84.94 |
| MG | 2.227 | 9.916 | 41.31 | 1.910 | 6.958 | 30.35 | 2.490 | 10.10 | 28.47 |
| MGPCG | 2.354 | 7.083 | 19.36 | 2.263 | 5.950 | 16.96 | 2.686 | 7.559 | 20.33 |
| GSRB Smoother |  |  |  |  |  |  |  |  |  |
| PCG | 4.023 | 19.99 | 78.66 | 3.735 | 15.43 | 58.33 | 4.801 | 26.19 | 86.51 |
| MG | 2.145 | 9.708 | 41.06 | 1.860 | 7.086 | 31.98 | 2.485 | 10.10 | 29.68 |
| MGPCG | 2.331 | 7.149 | 20.20 | 2.241 | 6.191 | 17.67 | 2.571 | 8.001 | 20.19 |



## 3D Test Problem Speedup

| Blocking Factor |  | 2 |  |  | 4 |  | 8 | 3 |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Adaptive Levels | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| ILU | $1.14 X$ | $1.50 X$ | $2.12 X$ | $0.98 X$ | $1.18 X$ | $1.64 X$ | $1.07 X$ | $1.23 X$ | $1.24 X$ |
| ICRB | $0.95 X$ | $1.40 X$ | $2.13 X$ | $0.84 X$ | $1.17 X$ | $1.79 X$ | $0.93 X$ | $1.34 X$ | $1.40 X$ |
| GSRB | $0.92 X$ | $1.36 X$ | $2.03 X$ | $0.83 X$ | $1.14 X$ | $1.81 X$ | $0.97 X$ | $1.26 X$ | $1.47 X$ |



| Blocking Factor | 2 |  |  |  | 4 |  |  | 8 |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Adaptive Levels | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| ILU Smoother |  |  |  |  |  |  |  |  |  |
| PCG | 32.33 | 126.5 | 468.1 | 33.69 | 122.0 | 528.6 | 47.32 | 198.3 | 759.9 |
| MG | 10.52 | 41.69 | 145.6 | 9.874 | 35.71 | 133.4 | 13.91 | 57.37 | 202.2 |
| MGPCG | 5.445 | 15.06 | 43.66 | 5.796 | 14.84 | 48.74 | 7.113 | 21.28 | 70.07 |
| ICRB Smoother |  |  |  |  |  |  |  |  |  |
| PCG | 40.15 | 171.9 | 636.1 | 42.80 | 160.6 | 705.6 | 68.93 | 269.2 | 1056 |
| MG | 14.93 | 64.01 | 226.1 | 14.61 | 61.08 | 226.1 | 24.02 | 102.5 | 371.9 |
| MGPCG | 7.606 | 19.93 | 56.83 | 8.794 | 19.45 | 62.45 | 10.49 | 28.93 | 94.08 |
| GSRB Smoother |  |  |  |  |  |  |  |  |  |
| PCG | 41.07 | 179.2 | 648.8 | 43.11 | 167.0 | 710.2 | 70.00 | 276.3 | 1078 |
| MG | 15.99 | 67.29 | 230.4 | 15.42 | 63.24 | 234.9 | 26.03 | 106.8 | 395.9 |
| MGPCG | 8.063 | 22.38 | 57.47 | 8.451 | 21.61 | 65.76 | 10.39 | 31.77 | 94.70 |



## 3D Whale Problem Speedup

| Blocking Factor |  | 2 |  | 4 | 8 |  |  | 3 | 3 |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Adaptive Levels | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | $3.89 X$ |
| ILU | $1.93 X$ | $2.77 X$ | $3.33 X$ | $1.70 X$ | $2.41 X$ | $2.74 X$ | $1.96 X$ | $2.70 X$ | $2.89 \times$ |
| ICRB | $1.96 X$ | $3.21 X$ | $3.98 X$ | $1.66 X$ | $3.14 X$ | $3.62 X$ | $2.29 X$ | $3.54 X$ | $3.95 X$ |
| GSRB | $1.98 X$ | $3.01 X$ | $4.01 X$ | $1.82 X$ | $2.93 X$ | $3.57 X$ | $2.51 X$ | $3.36 X$ | $4.18 X$ |



With recent advances in GPU technology, parallel CFD codes are able to be accelerated on distributed hybrid architectures with multiple cores sharing a single GPU. We have done this for the NASA FUN3D code.
A.C. Duffy, D.P. Hammond, E.J. Nielsen. Production level CFD code acceleration for hybrid many-core architectures. Submitted to Parallel Computing, Under Revision.

| Architecture | Cores | L1 Cache | L2 Cache | Memory Access Speed |
| :---: | :---: | :---: | :---: | :---: |
| G80 | 112 | $16 \mathrm{~KB}^{1}$ | $128 \mathrm{~KB}^{2}$ | $57.6 \mathrm{~GB} / \mathrm{s}^{2}$ GDDR3 |
| GT200 | 240 | $24 \mathrm{~KB}^{1}$ | $256 \mathrm{~KB}^{2}$ | $102 \mathrm{~GB} / \mathrm{s}^{\text {GDDR3 }}$ |
| Fermi | 448 | $48 / 16 \mathrm{~KB}^{3}$ | 768 KB | $144 \mathrm{~GB} / \mathrm{s}^{\text {GDDR5 }}$ |

GPU architecture evolution from G80, which approximately coincided with the release of Intel's quad core CPUs, to Fermi which coincided with the release of Intel's six core processors. GPU advancements over the last few years have noticeably outpaced those of CPUs. Representative GPUs are: G80-GeForce 8800 GT, GT200-Tesla C1060, Fermi-Tesla C2050. ${ }^{1}$ shared memory, ${ }^{2}$ texture memory, ${ }^{3}$ Configurable L1/shared memory

We have previously developed acclerated GSRB and ICRB smoothers using the PGI Fortran compiler with accelerator directives.

- The PGI compiler allows for simple code porting for GPUs
- Directives are similar to those of OpenMP, the accelerator code will be ignored if the compiler option is not used (e.g. when no accelerators or when not using the PGI compiler)
- Acts as a wrapper, code is converted to CUDA C

- Simplest smoother, easy to port to GPU.
- Slow converging

$$
\begin{aligned}
& \text { Given } x^{0}, r=b-A x^{0}, x=x^{0} \\
& x=x+D^{-1} r \\
& r=b-A x
\end{aligned}
$$

## PGI Fortran Code for Simple 1-D problem

!\$acc region
do iterates $=1$, maxiterates
do $i=$ is, ie
$x(i)=\left(b(i)-L(i-1) \times \_\right.$old $(i-1)-U(i+1) x$ _old $\left.(i+1)\right) / D E(i)$
end do
do $\mathrm{i}=\mathrm{is}$, ie
x_old(i)=x(i)
end do
end do
!\$acc end region

## Symmetric-Gauss-Seidel

- Symmetric Gauss Seidel smoothers lead to faster convergence compared to Jacobi smoothers, but are not vectorizable in their natural form.
- A Red-Black ordering allows Gauss Seidel to be vectorized, simple ex.

$$
\left.\left|\begin{array}{cccc||l}
2 & -1 & 0 & 0 \\
-1 & 2 & -1 & 0 \\
0 & -1 & 2 & -1 \\
0 & 0 & -1 & 2
\end{array}\right|\left|\begin{array}{l}
x_{1} \\
x_{2} \\
x_{3} \\
x_{4}
\end{array}\right| \rightarrow\left|\begin{array}{cccc||l}
2 & 0 & -1 & 0 \\
0 & 2 & -1 & -1 \\
-1 & -1 & 2 & 0 \\
0 & -1 & 0 & 2
\end{array}\right| \begin{aligned}
& x_{1} \\
& x_{3} \\
& x_{2} \\
& x_{4}
\end{aligned} \right\rvert\,
$$

## Symmetric Red-Black GS

$$
\begin{aligned}
& \left|\begin{array}{cc}
D^{R} & C^{T} \\
C & D^{B}
\end{array} \| \begin{array}{c}
x_{R} \\
x_{B}
\end{array}\right|=\left|\begin{array}{c}
r_{R} \\
r_{B}
\end{array}\right| \\
& x_{R}^{*}=\left(D^{R}\right)^{-1} r_{R} \\
& x_{B}=\left(D^{B}\right)^{-1}\left(r_{B}-C x_{R}^{*}\right) \\
& x_{R}=\left(D^{R}\right)^{-1}\left(r_{R}-C^{T} x_{B}\right)
\end{aligned}
$$

## Symmetric Red-Black GS (cont)

$$
\begin{aligned}
& \mathrm{M}=\left\lvert\, \begin{array}{cc}
\left(D^{R}\right)^{-1}+\left(D^{R}\right)^{-1} C^{T}\left(D^{B}\right)^{-1} C\left(D^{R}\right)^{-1} & -\left(D^{R}\right)^{-1} C^{T}\left(D^{B}\right)^{-1} \\
-\left(D^{B}\right)^{-1} C\left(D^{R}\right)^{-1} & \left(D^{B}\right)^{-1}
\end{array}\right. \\
& x^{n+1}=x^{n}+M\left(r-A x^{n}\right) \\
& \text { 1. } r^{*}=r-A x^{n} \\
& \text { 2. } x^{n+1}=x^{n}+M r^{*}
\end{aligned}
$$

## MG Smoothers - Incomplete Cholesky (IC)

IC factorizations are often used as the preconditioner themselves, but here we use IC as a smoother for multigrid.

- Fastest MG smoother
- Factorization ensures M maintains same sparse structure as A
- The standard IC preconditioner cannot be vectorized.


## MG Smoothers - ICRB

We can again use a Red-Black ordering just as in the GSRB case here to vectorize the IC algorithm following the method of Ortega*, then the algorithm is the same as for the GSRB case with $D^{B}$ replaced by $\left(D^{B}\right)^{*}$.

$$
\left|\begin{array}{cc}
D^{R} & C^{T} \\
C & D^{B}
\end{array}\right| \rightarrow\left|\begin{array}{cc}
l & 0 \\
C\left(D^{R}\right)^{-1} & I
\end{array}\right| \begin{array}{cc}
D^{R} & 0 \\
0 & \left(D^{B}\right)^{*}
\end{array}\left|\left|\begin{array}{cc}
I & \left(D^{R}\right)^{-1} C^{T} \\
0 & I
\end{array}\right|\right.
$$

$\left(D^{B}\right)^{*}=\operatorname{diagonal}\left(D^{B}-C\left(D^{R}\right)^{-1} C^{T}\right)$
*James Ortega, "Introduction to Parallel and Vector Solution of Linear Systems", Springer, 1988.

- Using the PGI Fortran compiler, the smoothers are limited to a $2 X$ speedup due to costly data transfer overhead. Switching to a CUDA C implementation will allow us to store the $A$ matrix coefficients permanently on the GPU, and should provide for more substantial speedup.
- An iterative refinement technique has been employed to reduce the residual error by 18 orders of magnitude in single precision, which is optimal for GPU acceleration.
- We plan to develop the new CUDA C implementation using a GPU sharing model such as was done on the NASA FUN3D code. This will allow the code to be accelerated by a multicore processor (current capability) and a GPU simultaneously



## Microfluidic T-Junction




## Microfluidic T-Junction - COMSOL/4 Cores



## Microfluidic T-Junction



Simulation using data from Roper's Lab


## Microfluidic T-Junction



Simulation using data from Roper's Lab

## QUESTIONS?

