CS 5220 Final Project
Alternating Direction Implicit

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Abstract

1 Alternating Direction Implicit

1.1 Application

Alternating direction implicit (ADI) is an iterative method for solving multidimensional partial differential equations(PDEs) using finite difference method. The ADI method is most used to solve parabolic equations on rectangular domains, such as heat conduction and diffusion equations in two or more dimensions. An alternative solver for heat conduction equation is Crank-Nicolson method, which is implicit in time and unconditionally stable. Crank-Nicolson method inverts a matrix at each time step and it soon becomes clumsy when the problem size keeps increasing. ADI, in comparison, reduces the two-dimensional problem to a succession of many one-dimensional problems. Another thing to note is that ADI method is easily extended to solve 3D problems at the price of losing its unconditional stability.

1.2 Algorithm

Given a heat conduction equation with boundary condition,

$$div(\mathbf{a}(\mathbf{x})\nabla\mathbf{u}) = \mathbf{f}, \quad \mathbf{x} \in \Omega$$

$$\mathbf{u}(\mathbf{x}) = \mathbf{g}(\mathbf{x}), \quad \forall\mathbf{x} \in \partial\Omega$$

The central idea of the ADI method is to obtain a solution by evolving

$$\frac{\partial\tilde{\mathbf{u}}}{\partial t} = div(\mathbf{a}(\mathbf{x})\nabla\tilde{\mathbf{u}}) - \mathbf{f}$$

to a steady state, i.e., when $||\frac{\partial\tilde{u}}{\partial t}||_2 = 0$. For simplicity of our discussion, we assume $\mathbf{a}$ to be constant along one direction (in 2D). The ADI method approximate the process using:

$$(\mathbf{I} - \frac{dt}{2}\alpha_x\Delta_x)\mathbf{u}^*_{k+1} = (\mathbf{I} + \frac{dt}{2}\alpha_x\Delta\mathbf{x} + dt\alpha_y\Delta y)\mathbf{u}_k - dt\mathbf{f}$$

$$(\mathbf{I} - \frac{dt}{2}\alpha_y\Delta_y)\mathbf{u}_{k+1} = \mathbf{u}^*_{k+1} - \frac{dt}{2}\alpha_y\Delta_y\mathbf{u}_k$$

The ADI method solves the 2D problem first in the x direction and then in the y direction, thus giving rise to the name Alternating Direction.

There are two matrix-vector multiplications and two backsolve in each iteration. For the matrix-vector multiplication, it consists the sum of difference operators and identity matrices. For the difference operator that approximates differential:

$$\Delta_x\mathbf{u} = (u_{i+1} - u_{i-1})/2\Delta x$$

so the linear system is tridiagonal. Similarly, we will backsolve a tridiagonal linear system twice to get the final answer.

For a tridiagonal system, we have fast algorithms to compute them directly. For matrix-vector multiplication, a naive implementation will work because it is not computationally intense enough for further optimization. For backsolving tridiagonal system, we use Thomas algorithm.

For a tridiagonal square matrix,

$$\mathbf{A}\mathbf{x} = \mathbf{b}$$

Thomas algorithm first computes the LU factorization

$$\mathbf{L}\mathbf{U}\mathbf{x} = \mathbf{b}$$

and then it solves the problem sequentially

$$\mathbf{U}\mathbf{x} = \mathbf{L}^{-1}\mathbf{b}$$

$$\mathbf{x} = \mathbf{U}^{-1}\mathbf{L}^{-1}\mathbf{b}$$

The matrices $\mathbf{L}$ and $\mathbf{U}$ have only one sub/super-diagonal because they are factorized from a tridiagonal one. The two backsolve can be done easily using one `for` loop to iterate through their sub/super-diagonal elements.

For the final implementation, we have

1. Apply forward operator Δ_x to $\mathbf{u}$.
2. Apply forward operator Δ_y to $\mathbf{u}$.
3. Sum the results up and subtract $dt\mathbf{f}$.
4. Backsolve the problem in the x direction.
5. Subtract $\frac{dt}{2}\alpha_y\Delta_y\mathbf{u}_k$ from the result.
6. Backsolve the problem in the y direction.

1.3 Convergence

The relaxation of

$$\frac{\partial \tilde{\mathbf{u}}}{\partial t} = div(\mathbf{a}(\mathbf{x})\nabla\tilde{\mathbf{u}}) - \mathbf{f}$$

gaurantees to converge to the actual solution. If we look at the error between $\mathbf{u}(\mathbf{x},t)$ and exact solution $\mathbf{u}(\mathbf{x})$,

$$\tilde{\mathbf{e}} = \mathbf{u}(\mathbf{x},t) - \mathbf{u}(\mathbf{x})$$

Insert this into the relaxation equation:

$$\frac{\partial}{\partial t}(\tilde{\mathbf{u}} - \mathbf{u}) = div(\mathbf{a}(\mathbf{x})\nabla(\tilde{\mathbf{u}} - \mathbf{u}))$$

$$\Rightarrow \frac{\partial}{\partial t}\tilde{\mathbf{e}} = div(\mathbf{a}(\mathbf{x})\nabla\tilde{\mathbf{e}})$$

Examine the following equation:

$$\frac{1}{2}\int_\Omega \tilde{\mathbf{e}}\frac{\partial\tilde{\mathbf{e}}}{\partial t}d\mathbf{x} = \frac{1}{2}\int_\Omega \tilde{\mathbf{e}}div(\mathbf{a}(\mathbf{x})\nabla\tilde{\mathbf{e}})d\mathbf{x}$$

Note that our boundary condition is fixed and so we have $\tilde{e} \equiv 0\ \forall \mathbf{x} \in \partial\Omega$. Then we can apply the divergence theorem ($\div(\rho\mathbf{w}) = \rho div(\mathbf{w}) + \nabla\rho\cdot\mathbf{w}$) to get:

$$\frac{1}{2}\int_\Omega \frac{\partial^2\tilde{\mathbf{e}}}{\partial t^2}d\mathbf{x} = -\frac{1}{2}\int_\Omega \mathbf{a}(\mathbf{x})(\nabla\tilde{\mathbf{e}})^2 d\mathbf{x}$$

Write it in norm:

$$\frac{1}{2}\frac{d}{dt}\int_\Omega ||\tilde{\mathbf{e}}||_2^2 d\mathbf{x} = -\frac{1}{2}\int_\Omega \mathbf{a}(\mathbf{x})|\nabla\tilde{\mathbf{e}}|^2 d\mathbf{x} < 0$$

So the derivative of the error norm $||\tilde{\mathbf{e}}||_2^2$ is strictly decreasing and therefore will converge to 0.

Although the convergence is gauranteed, an implementation that uses fixed timestep can easily take up to $10,000$ steps before the error becomes acceptable. One important idea from Douglas' paper is that the algorithm will use variable timesteps to speed up the convergence. If we look at the value of $\mathbf{u}$ as a sum of Fourier modes, each mode will converge at different rate for each timestep. So we will sweep through different timesteps to ensure all modes will converge more evenly. We determine the range of timesteps to take based on the size of our domain (which will limit the possible Fourier modes).

2 Implementation

2.1 C code

We started our work from a reference implementation of the Douglas ADI method using C++. We used this code both as a starting point to optimize the implementation of the algorithm, and later as a reference to check the correctness of our results.

The C++ code performs well when handling general problems, but it is not as easy for us to fine tune it for Totient. Therefore, we decided to rewrite it in C and apply techniques that we ahve learned in this course.

One challenge is to determine the data structure we will use. Because Douglas ADI method performs linear operations in both x and y directions, there does not exist one unique data structure that we can use to avoid striding across the data array. We decided to store the original data columnwise because most of the operations can be done in x direction. We perform a matrix transpose before applying the y-backsolver so that we can take advantage of spatial locality of the data. As in matrix multiplication project, the cost to transpose a matrix before carrying out the operation is compensated by the speedup from better data access.

We also tried to use `float` instead of `double` data type for faster computation. However, because each ADI iteration only stops when the difference between two consecutive matrices is smaller than our threshold ε (in our case, it is set to be 10^{-6}), we ended up taking many more steps than before and losing performance as a result. In the end, we kept using double as our data type throughout the program.

3 Optimization

3.1 Bottleneck

We used Intel Amplifier to find the bottleneck in our code. In both of the C++ and C code, the performance bottleneck is applying backsolve operators in the x and y directions. A sample report from initial stage of the optimization looks like:

```
Function                    Module       CPU Time  Spin Time  Overhead Time
--------------------------  -----------  --------  ---------  -------------
solve_tri_special           douglas-adi    0.804s         0s             0s
relaxOperation              douglas-adi    0.408s         0s             0s
[Outside any known module]  [Unknown]      0.254s         0s             0s
__intel_ssse3_rep_memcpy    douglas-adi    0.193s         0s             0s
transpose                   douglas-adi    0.121s         0s             0s
apply_tri_special           douglas-adi    0.020s         0s             0s
apply_tri_special_plus      douglas-adi    0.016s         0s             0s
main                        douglas-adi    0.013s         0s             0s
__svml_cos4                 douglas-adi    0.001s         0s             0s
__svml_cos4_l9              douglas-adi    0.001s         0s             0s
normInf                     douglas-adi    0.001s         0s             0s
```

It is not surprising that the backsolver takes most of the time since it is more expensive to compute at each step. It is noteworthy, however, the backsolver takes less than 50% of the total computation time. The function `relaxOperation()` alone takes approximately half as long to compute and all it does is adding and subtracting matrix values.

The result is likely caused by a cache miss in our naive attempt to implement the calculation using a single `for` loop.

3.2 Cache Friendly Operations

In the original code, we have operations like

```
for (int i = 0; i < n*n; i++) {
        ustar[i] -= 0.5*u_t[i];
}
```

We examined the individual function using the Intel Amplifier and observed that it the for loop took much longer than it should. So we created new functions to optimize their cache memory usage by using blocks. We modified a cache efficient matrix transpose program for our purpose and made it work:

```
void transpose_cache(double* restrict dst,const double* restrict src, size_t n){
    __assume_aligned(dst, 64);
    __assume_aligned(src, 64);
    size_t block=64;
    for(size_t i = 0; i < n-block; i += block)
        for(size_t j=0; j < n; ++j ){
            for(size_t b = 0; b < block ; ++b){
                dst[j*n+b]=src[b*n+j];
            }
        }
    size_t start = n - n%block;
    for(size_t j=0; j < n; ++j )
        for(size_t b = start; b < n; ++b){
            dst[j*n+b]=src[b*n+j];
        }
}
```

In addition to matrix tranpose, the function is also modified to carry out (2D) vector subtract, addition and transposed addition. After the change, the new report looks like

```
Function                     Module                      CPU Time
---------------------------  --------------------------  --------
solve_tri_special            douglas-adi                   0.990s
[Outside any known module]   [Unknown]                     0.276s
__intel_ssse3_rep_memcpy     douglas-adi                   0.119s
vec_transpose_add            douglas-adi                   0.085s
transpose_cache              douglas-adi                   0.056s
vec_subtract                 douglas-adi                   0.054s
vec_subtract_half            douglas-adi                   0.052s
apply_tri_special_plus       douglas-adi                   0.036s
main                         douglas-adi                   0.023s
apply_tri_special            douglas-adi                   0.021s
__svml_cos4_l9               douglas-adi                   0.003s
malloc                       libc-2.12.so                  0.003s
_int_free                    libc-2.12.so                  0.002s
normInf_cache                douglas-adi                   0.002s
```

The hotspots reports don't necessarily reflect the exact behavior of the program, because the second one is running OpenMP with only 1 threads (it will slow down the serial code), but we can see qualitatively that the most computation is now concentrated at the backsolver.

3.3 Vectorization

For vectorization, we largely reply on the compiler to do the work. We used `_mm_malloc` to tell intel compiler to assign aligned memory blocks so that our calculation can be vectorized. Correspondingly, we used `_mm_free()` to free the memory after using them.

We tried to allocate scratch space for intermediate steps, but it didn't not work in our favor. When we allocated scratch space for backsolvers, they showed little contribution to the overall speed. However, as we started parallelization, they greatly reduced the speed of program, so we decided to allocate memory space in the function as they do not seem to be the limiting factor of our computation speed.

In addition to that, we experimented with different compiler flags to get better performance for the code. In the end, we decided to use the following set of flags:

```
 -O3 -no-prec-div -xcore -ansi-alias \
-opt-prefetch -ftree-vectorize \
-vec-threshold0 -ip
```

3.4 Other changes

We here report some other changes that brought performance to our code.

In the original code, we calculate the difference norm between two iterations only after one complete sweep ($dt_0 \to dt_{max} \to dt_0$), since the calculating the norm and saving/updating the matrix from last step $\mathbf{u}_{k-1}$ is expensive. For a problem of size 2000-by-2000, it takes about 72 iterations for the problem to converge and that is three timestep sweeps. If we look back at the cost of `memcpy` and `normInf`, we can check the difference norm more frequently and stop the iteration earlier.

We do one more difference norm calculation halfway through the time sweep and check if we can stop then. For 2000-by-2000 case, we can stop the problem at 60 iterations, thus saving us the cost to compute the extra steps.

The other improvement we have is that we do not explicitly form the tridiagonal matrix in question. Instead, we compute them on the fly based on the parameter we are given for the problem. This way, we do not have to use extra memory space to save the matrix, and there is little redundant computation since most of the computation does not take much work. We increased the arithematic intensity of our code by eliminating the use of unnecessary memory space.

3.5 OpenMP and Load Balancing

We use OpenMP for parallel computation of our code. Because it is costly to enter an OpenMP section, we have to use it sparingly. After experimenting with different strategy, it turns out that the only section that worths any parallelization is the backsolving part. The parallelization is easy in the sense that we are solving a series of independent linear system in 1D. However, we have to transpose the matrix $\mathbf{u}_k$ and subtract $\frac{dt}{2}\alpha_y\Delta_y\mathbf{u}_k$ from it, which makes a barrier between the two backsolvers indispensable.

In a naive implementation of OpenMP, we are faced with enormous wait time in the hotspots report. This is probably because the solution $\mathbf{u}_k$ has a highly non-uniform distribution across the 2D space. As a result, a static scheduling will cause hugh load imbalance and thus slowing down our program. We tried different scheduling for the OpenMP (static, guided and dynamic). In the end, we chose to use `schedule(dynamic,8)` because it yields the best performance.

4 Performance

4.1 Comparison with Previous Work

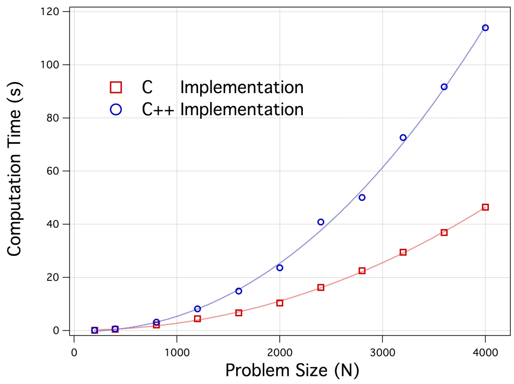

Figure 1: *The speed comparison of C vs. C++ implementation.*

The beginning - for small code, it's not advantageous. But we can tell that our new C code works far better for large cases.

4.2 Strong & Weak Scaling

Strong / weak scaling study.

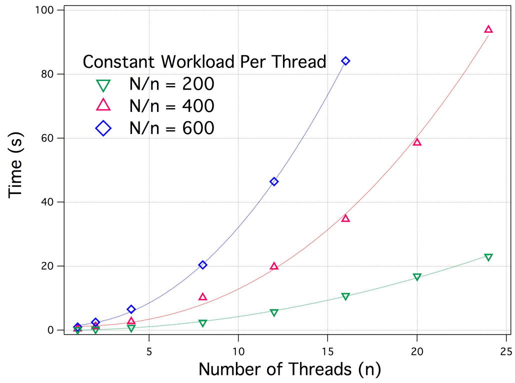

Figure 2: *Weak scaling for C code.*

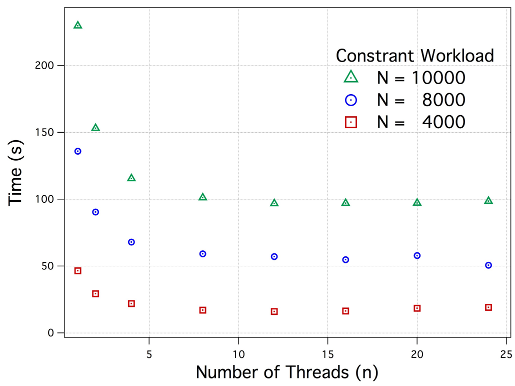

Figure 3: *Strong scaling for C code.*

5 Discussion

5.1 What has been done

What have we done.

5.2 What might be interesting to look into

What can be done.