CS 5220

Project 2 - Shallow Water Simulation

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October 19, 2015

1 Introduction

Define structured grid computations
Define shallow water simulations
Math overview and associated abstractions in code

2 Design Decisions

The following sections describe the implementation changes from the original code found at https://github.com/cornell-cs5220-f15/water.

2.1 Memory Layout

The original solution a two dimensional vectors of 3-vectors to represent U_t , $F(U)_x$, and $G(U)_y$. During each time step, the solution accesses each element in the 2-D grid sequentially. Then, the vector<vector<real>> representation leads to memory accesses that are not local spatially.

Therefore, our solution chooses to use 3 separate two dimensional vectors per objects, U_t , $F(U)_x$, and $G(U)_y$. Thus, we are required in general to perform three loop iterations in place of a single loop in the original solution. But this approach leverages spatial locality, especially in compute_step and limited_derivs functions.

2.2 Vectorization

By observing the profiling information, we noticed that the original solution spends majority of its computational time in the functions limited_derivs, compute_step and compute_fg_speeds. By adopting the newer memory layout, we enabled spatially local memory accesses. We were also able to decompose for loops in the solution to improve vectorization. Refer to ipo_out_vectorization.optrpt in https://github.com/sheroze1123/water/tree/vectorization for more information.

In compute_fg_speeds, we performed two separate loops to compute flux and wave speeds. The flux computation and the wave speed computation for the complete grid is not handled by the Physics class. We used #pragma simd directives to instruct the compiler the ability to vectorize

these computations. The compiler was successfully able to vectorize these functions with an estimated potential speedup of 6.7.

limited_derivs uses the limdiff function in minmod.h. To improve the vectorization of this computation, we changed the implementation of limdiff in the following ways.

- 1. limdiff now performs the computation on the complete grid instead of at one grid point.
- 2. limdiff was decomposed as limdiff_x and limdiff_y to perform the limiter along the x dimension and the y dimension separately while still retaining unit stride.

2.3 Parallelization

The updated memory layout is amenable to parallelization via OpenMP, particular during the costly operations of limited_derivs and compute_step.

At the beginning of a call to limited_derivs we initialize a team of threads using #pragma omp parallel. Each application of the limiter to the components of U_t , $F(U)_x$, and $G(U)_y$ can be computed in parallel since we removed the data dependencies by creating 3 separate two dimensional arrays per component. We use the #pragma omp for directive to parallelize the grid computation of each component.

In compute_step, we initialize a team of threads using #pragma omp parallel. The predictor step is now performed in parallel. Then, we create a barrier before proceeding to the corrector step since the the corrector step needs information from the predictor. After computing the corrector step, we perform a barrier before finally copying back to storage in parallel. The performance increase we observed via parallelization reached up to 3+ speedup. Results are plotted in section 3.2.

2.4 Domain Decomposition

2.4.1 General Setup

We decomposed the main grid into equally sized sub-grids, by first copying each sub-grid into a separate array. Each sub-grid array contains its part of the main grid an outer layer of ghost cells which contain information about the neighboring cells or the cells on the opposite side of the main grid if the sub-domain is close to the boundary of the main grid as we use periodic boundary condition. We then perform some number of time steps on each independent sub-grid and finally synchronize by copying back the sub-grid (without the ghost cells) onto the main grid.

2.4.2 Ghost cells

The width of the layer of ghost cells for each sub-grid is 3t, where t is the number of time steps we wish to advance before synchronizing back onto the main grid. For each sub-grid, we declare a simulation object, and run the simulation essentially in the same manner as we would on the whole grid, except we never apply periodic boundary conditions on the sub-grids. Because of this, at each time step we perform without synchronization, we "loose" 3 layers of ghost cells, in the sense that the computation within this layer is erroneous. However, the rest of the grid is not contaminated with error, as information spreads through our simulation only by 3 layers per time step.

2.4.3 Estimating the wave speed

One of the big barrier to parallelizing this simulation is that we need to estimate the wave speed at each time step to be able to estimate a how big of a time step we can perform for the next iteration. Hence to allow each sub-grid to run from time t=0 to time t=tfinal, we would need know in advance the speeds at time t, t+dt1, t+(dt1+dt2)... $t+sum_{i=1}^{k-1}dti$ which we obviously don't have access to at time t. The problem is that we need to know at least a lower bound for all dt(j) as the number of time steps we will take to reach tfinal is directly proportional to the number of ghost cells we need to allocate for each sub-grid. Our solution is to estimate a lower bound for dtj as dtj = (1/k)*dt1 for all j, where k is some fixed constant (we have k=2 for example). Furthermore, for each sub-grid at each time checks independently if the dtj is lower than (1/k)*dt1, our program throws an error and stops (but no synchronization to do this check). A better alternative, which we have not yet implemented would be to stop the computation if dtj is lower than k*dt1, double k and start the computation all over again from time t.

3 Analysis

3.1 Profiling

The following time profiles were obtained on a 200x200 grid by advancing 100 frames.

3.1.1 Original solution

We began the optimization by analyzing the time profiles of the original code. The following table shows the top 4 functions by CPU time.

Module	CPU Time	Spin Time	Overhead Time
shallow	$2.529 \mathrm{s}$	$0\mathrm{s}$	$0\mathrm{s}$
shallow	$1.210 \mathrm{s}$	$0\mathrm{s}$	0 s
shallow	$0.426 \mathrm{s}$	$0\mathrm{s}$	0 s
libc-2.12.so	$0.027 \mathrm{s}$	$0 \mathrm{s}$	0 s
libc-2.12.so	$0.025 \mathrm{s}$	0 s	$0\mathrm{s}$
	shallow shallow shallow libc -2.12.so	Shallow 2.529s Shallow 1.210s Shallow 0.426s libc - 2.12.so 0.027s	shallow 2.529 s 0s shallow 1.210 s 0s shallow 0.426 s 0s libc - 2.12.so 0.027 s 0s

3.1.2 Memory Layout Update

3.1.3 Vectorization

Profiling of vectorization shows good improvements in performance, especially in the limited_derivs and compute_fg_speeds functions, but a reduction in performance in the compute_step function. The repetition of limdiff_x and limdiff_y is due to separation of components and axes in limited_derivs.

Function	Module	CPU Time	Spin Time	Overhead Time
compute_step	shallow	2.136 s	0 s	0 s
limited_derivs	shallow	0.448s	$0\mathrm{s}$	0 s
compute_fg_speeds	shallow	0.362 s	$0\mathrm{s}$	0 s
limdiff_y	shallow	$0.204 \mathrm{s}$	0 s	0 s
limdiff_x	shallow	$0.201 \mathrm{s}$	$0\mathrm{s}$	0 s
limdiff_x	shallow	$0.200 \mathrm{s}$	$0\mathrm{s}$	0 s
limdiff_y	shallow	$0.200 \mathrm{s}$	0 s	0 s
limdiff_x	shallow	$0.197 \mathrm{s}$	$0\mathrm{s}$	0 s
limdiff_x	shallow	0.192 s	0 s	0 s
limdiff_y	shallow	0.192 s	$0\mathrm{s}$	0 s
limdiff_x	shallow	$0.188 \mathrm{s}$	$0\mathrm{s}$	0 s
limdiff_y	shallow	$0.186 \mathrm{s}$	0 s	0 s
limdiff_y	shallow	$0.184 \mathrm{s}$	$0\mathrm{s}$	0 s
vector < float , allocator < float >>::operator[]	shallow	$0.062 \mathrm{s}$	0 s	0 s
vector < float , allocator < float >>::operator[]	shallow	0.061 s	$0\mathrm{s}$	0 s
vector <float ,="" allocator<float="">>::operator[]</float>	shallow	$0.051\mathrm{s}$	$0\mathrm{s}$	$0\mathrm{s}$

3.1.4 Parallelization

3.1.5 Domain Decomposition

3.2 Scaling Study

3.2.1 Strong Scaling Study

Using a 500x500 grid and 100 frames, we observe the speedup with respect to the number of threads in our parallel implementation.

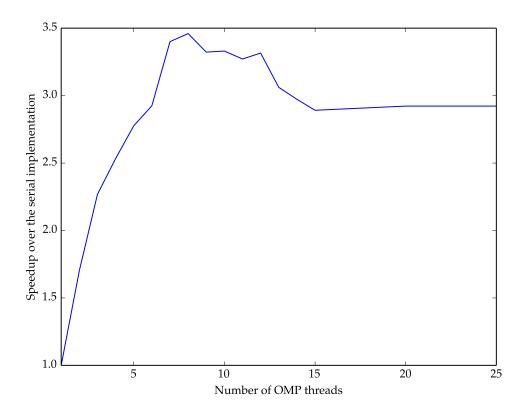


Figure 1: Speedup as a function of the number of threads

3.2.2 Weak Scaling Study

We vary the threads but keep the problem size/thread constant.

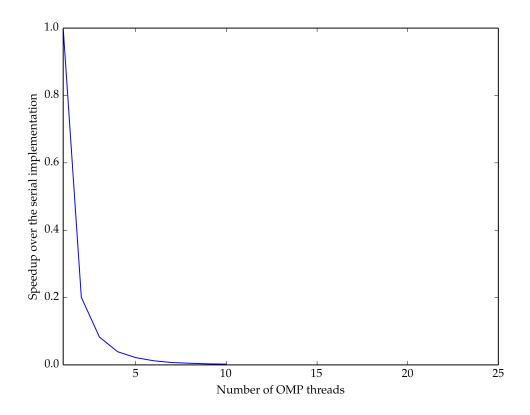


Figure 2: Speedup as a function of the number of threads

References

[1] Data Alignment to Assist Vectorization. (n.d.). Retrieved September 30, 2015, from https://software.intel.com/en-us/articles/data-alignment-to-assist-vectorization