Parallel Orthogonal Recursive Bisection

Team Metropolis:
James Farzi, JJ Lay, Graham West

April 19, 2019

Outline

1. Introduction
2. Implementation
   - `main`
   - Importing Data
   - Tree Structure
     - Building the tree
     - Searching the tree
   - Parallel sorting
     - Changes
     - `adaptBins`
3. Validation
   - MATLAB visualizations
   - Other tests
4. Results
5. Conclusions
   - Challenges
   - Successes
   - Future Work

Introduction

Introduction

Expansion upon previous parallel sorting project

Objectives:

- Given set of data
- Develop parallel orthogonal recursive bisection (ORB) algorithm
- Utilize a k-d tree to organize data
- Maximize use of MPI using multiple nodes
- Require both serial/parallel build/search operations
- Search the k-d data with a list of points and 3 radii

SUBLISTSSSSSS

Workflow:

- Used C++ w/ C MPI calls
- Valgrind/gdb for debugging
- Using Git effectively (multiple branches, few merge conflicts)
- Extreme coding if FUN...and powerful
- Prototyping: we each wrote our own, implementation based on Graham's MATLAB code

Implementation

`main`

Our `main` was quite simple due to our organization of the project into many levels of functions

We also were able to use much of the basic initialization and data importing functions from the previous project

---

Algorithm 1: `main`$(\cdots)$

Initialize MPI
Set number of files, lines per file to read
import the $data$
Initialize $tree$
`buildTree`$(data, tree, comm, \cdots)$
Search the tree with `search501`$(\ tree, \cdots)$
Finalize MPI

Importing Data

Importing the data:

`listFiles(···)`

- Fetches a list of data filenames using OS calls (random order)

`distributeFiles(···)`, `receiveFiles(···)`

- Isend/Recv the list of filenames
- Round robin distribution of files

`importFiles(···)`

- Reads the received filenames
- Read a set nFiles and nLinesPerFile
- Returns a 1D array of length $4 \times$ nFiles $\times$ nLinesPerFile
- nFiles $\geq$ nNodes

Tree Structure

Old tree struct:

- Contained extra debugging fields
- Contained completely unused fields
- Originally used doubles
- tree naming

struct Tree { Tree *p; // Parent Tree *l; // Left child Tree *r; // Right child
MPI_Comm parentComm, leftComm, rightComm, thisComm;
float x1; // Min x float x2; // Max x float y1; // Min y float y2; // Max y
float z1; // Min z float z2; // Max z
float c[4]; // Center of this tree float radius;
float d[4]; // Data point }

C Constants

definitions.h:

A header file containing numerous pre-process identifiers (#define):

- _INDEX_, _X_, _Y_, _Z_
- Count limits (adapt bins max iterations, max nLinesPerFile, etc.)
- MPI tags (bin edge, bin count, uniformity, etc.)

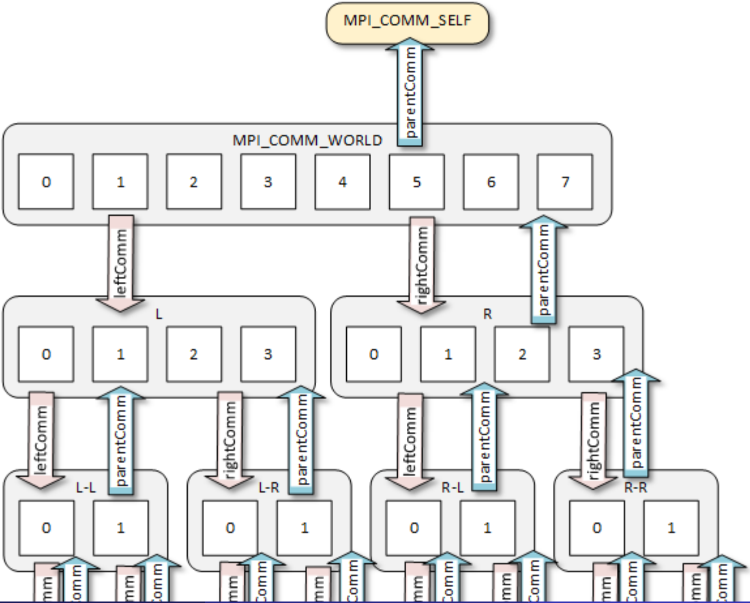
Building the tree

To build the tree, we use several functions which perform different aspects/sections of the task

Functions:

- `buildTree`
- `buildTree_serial`
- `buildTree_parallel`
- `getSortDim`

Building the tree



Building the tree

`buildTree` checks the number of compute nodes in the current communicator and determines whether to call the parallel or serial versions of the code

Algorithm 2: `buildTree`$(data, tree, comm, \cdots)$

1: $q =$ Size of current communicator
2: **if** $q > 1$ **then**
3: `buildTree_parallel`$(data, tree, comm, \cdots)$
4: **else**
5: `buildTree_serial`$(data, tree, \cdots)$
6: **end if**

Building the tree

`buildTree_parallel` performs ORB using a multiple compute nodes

Algorithm 3: `buildTree_parallel`($data$, $tree$, $comm$, $\cdots$)

1: Call `getSortDim`($\cdots$): calculates x, y, z mins, maxs, ranges, partition center, and returns $sortDim$
2: Sort $data$ over $sortDim$ using `parallelSort`($data$, $sortDim$, $comm$, $\cdots$)
3: **if** $myRank < numNodes/2$ **then**
4: Create $tree.L$, $commL$
5: `buildTree_parallel`($data$, $tree.L$, $comm$, $\cdots$)
6: **else**
7: Create $tree.R$, $commR$
8: `buildTree_parallel`($data$, $tree.R$, $comm$, $\cdots$)
9: **end if**

It is assumed that $tree.n > 1$ will never occur in `build/tree_parallel` since we usually deal with large amounts of data

Building the tree

`buildTree_serial` performs ORB using a single compute node

Algorithm 4: `buildTree_serial`($data$, $tree$, $\cdots$)

if $tree.n > 1$ **then**
    Calculate x, y, z mins, maxs, ranges, and partition center
    Sort $data$ over $sortDim = \text{argmax}(x, y, z \text{ ranges})$
    Split $data$: $dataL, dataR$
    if $|dataL| > 0$ **then**
        Create $tree.L$
        `buildTree_serial`($dataL$, $tree.L$, $\cdots$)
    end if
    if $|dataR| > 0$ **then**
        Create $tree.R$
        `buildTree_serial`($dataR$, $tree.R$, $\cdots$)
    end if
else
    Store $data$ (a single point)
end if

Building the tree

`getSortDim` finds the longest axis and stores several key tree fields

Algorithm 5: `getSortDim`($data$, $tree$, $comm$, $\cdots$)

1: Each process gets it local x, y, z min and max
2: Rank 0 receives these, determines the global x, y, z min and max, determines the sortDim, and Bcast's all of these values back to the other nodes
3: The global mins/maxs, partition center, and partition radius are stored in $tree$
4: return $sortDim$

Searching the tree

`searchTree_serial` returns the number of points within a given radius about a given point

Algorithm 6: `searchTree_serial`$(tree, rad, point)$

$found = 0$
$d = \sqrt{\sum_{i=1}^{3} (point[i] - tree.c[i])^2}$
if $d \leq rad + tree.rad$ **then**
    if $tree.L = NULL$ && $tree.R = NULL$ **then**
        return 1
    else
        if $tree.L$!= $NULL$ **then**
            $found$ += `searchTree_serial`$(tree.L, rad, point)$
        end if
        if $tree.R$!= $NULL$ **then**
            $found$ += `searchTree_serial`$(tree.R, rad, point)$
        end if
    end if
end if

Searching the tree

`search501` reads the 501-st data file and loops through the points contained within (as well as the three given radii), calling `searchTree_serial` for each

---

Algorithm 7: `search501`($tree$, $path$, $\cdots$)

1:

Parallel sorting

We had to make several significant alterations to our `parallelSort` program in order to integrate it into our KD tree project

Changes:

- Make rank 0 do work
- Use specified communicator
- Conversion to function
- better `adaptBins`

Parallel sorting

Making rank 0 do work:

- Initially, rank 0 was just a master node which coordinated the other worker nodes
- This technique is very inefficient for parallel ORB since it requires us to switch to serial mode sooner
- The solution involved 1) cleverly altering a large number of if statements in the code and 2) changing how certain types of sends/recvs were handled

Parallel sorting

Using a specified communicator:

- Initially, `parallelSort` and all of its associated functions used MPI_COMM_WORLD (hard-coded)
- To use a specified communicator $comm$, it must be passed as an argument into any function that uses it
- This required a simple but tedious process of editing

Building the tree

Here is how `parallelSort` is structured now that it is a function

Algorithm 8: `parallelSort`($data$, $rows$, $myRank$, $sortDim$, $comm, \cdots$)

Locally sort $data$ on each compute node using a qsort
Determine the global min/max of the $sortDim$
Create linearly spaced bin edges over range on rank 0 and Bcast
Bin the $data$ on each compute node and accumulate on rank 0
Calculate $uniformity$
while $uniformity < threshold$ && $iterations < M$ **do**
    Adapt the bin edges on rank 0 and Bcast
    Bin the $data$ on each compute node and accumulate on rank 0
    Calculate $uniformity$
end while
Swap $data$ between compute nodes and do data cleanup

Parallel sorting

We also wished to modify our original `adaptBins` function

Old `adaptBins`:

- Local method
- Based on the normalized gradient of the bin counts
- Scaled so that bin edges remain properly ordered
- Scale decreases over time to avoid oscillations
- **Pros:** able to handle nonlinearities in distribution, good at fine-tuning
- **Cons:** edges from from dense regions are slow to converge, slower with more nodes

$$
\begin{aligned}
\Delta C &= 2.0(C_{i+1}^m - C_i^m)/(C_{i+1}^m + C_i^m) \\
\Delta E &= E_{i+1}^m - E_i^m \\
S(m) &= 1 - (1 - 0.1)(1 - \exp(-0.03m)) \\
E_i^{m+1} &= E_i^m + 0.475\big(S(m)\Delta C \Delta E\big)
\end{aligned}
\tag{1}
$$

Parallel sorting

We also wished to modify our original `adaptBins` function

New `adaptBins`:

- Global method
- Based on the integrated, linearly interpolated, cumulative distribution
- Bin edges placed where linear interpolation would assume uniformity
- **Pros:** fast initial convergence in approximately linear regions, same speed with more nodes
- **Cons:** can oscillate near dense regions

$$\hat{C}(x) = \hat{C}(E^m_{i'}) + C^m_{i'} \frac{x - E^m_{i'}}{E^m_{i'+1} - E^m_{i'}} = (i+1)\frac{D}{N} \tag{2}$$

$$E^{m+1}_i = E^m_{i'} + \left((i+1)\frac{D}{N} - C(E^m_{i'})\right)(E^m_{i'+1} - E^m_{i'})/C^m_{i'} \tag{3}$$

ALTERNATE
Since both methods' pros and cons are disjoint, alternating between them gives a method which can outperform either individually

Demos:

- thin dense distribution at boundary, nBins = 2, 3, 10
- wide distribution in center, nBins = 2, 3, 10
-

Validation

Validation

MATLAB Demos:

- 2D animation of MATLAB prototype
- 3D visualization at the end of the parallel phase of the C++ implementation

Validation

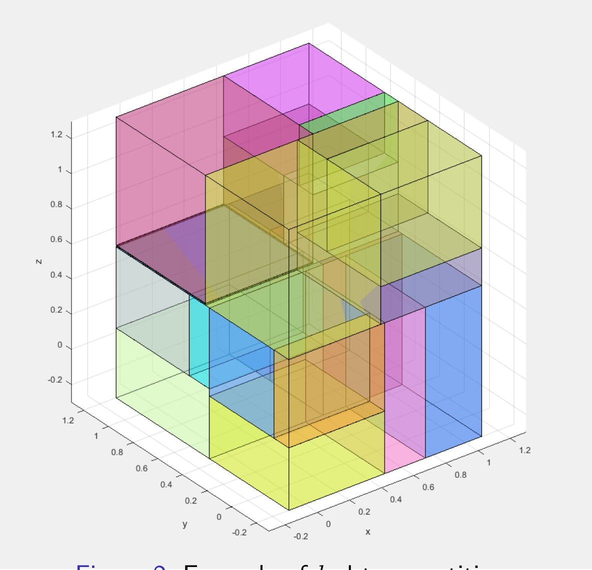


Figure 2: Example of k-d tree partitions

Validation

Other validation methods:

- Set search sphere center on a data point, use tiny radius, find 1 point
- Set an arbitrary search sphere point, increase radius, points found increases monotonically
- Consistent results for different numbers of nodes
- `dumpTree` writes each compute node's tree to a file for analysis

Results

Conclusions

Challenges

Challenges:

- `parallelSort` conversions
- memory leaks
- `malloc` when you should `realloc`
- multiple communicators (comm)
- `adaptBins` convergence problems
- debug print statement clutter
- array out of bounds issues
- inconsistent usage pointer-to-pointer calls for *data[] and *rows (due to `swapArrayParts`)
- no planning for function arguments and return values (constant editing of h-files)
- testing was difficult due to cluster overloading and hardware errors

Challenges

Obnoxious personality quirks and idiotic coding habits:

- Graham:
  - Fixates on dumb, small things; slows team progress (can't see the forest for the trees)
- James:
  -
- JJ:
  - Insistent usage of Visual Studio replaces neatly arranged tabs with ugly, inconsistent spaces (also doesn't update Makefile)
  - SO MUCH debug `cout` clutter

Successes

Successes:

- few merge conflicts and fast debugging through extreme coding and Git branches
- visualizing output through MATLAB
- efficient delegation of tasks

Successes

Helpful personality quirks and proper coding habits:

- Graham:
  - I can do math
- James:
  - Engineering mindset provides more efficient solutions to problems
- JJ:
  - C++ guru

Future Work

Future work:

- cloud computing
- use of coding techniques for personal research