Data-Parallel Mesh Connected Components Labeling and Analysis

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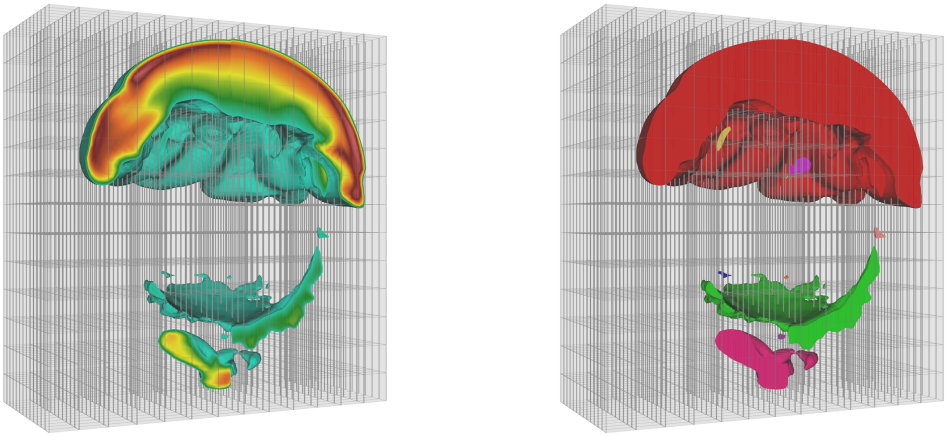

(a) Isovolume mesh extracted from a 21 billion cell structured grid decomposed across 2197 processors.

(b) Isovolume mesh colored by connected component label.

Figure 1: *Example input data-set and connected components labeling algorithm result. The algorithm uses a multi-stage appraoch to resolve the global connectivity of the 2.62 billion cell isovolume.*

Abstract

We present a data-parallel algorithm for identifying and labeling the connected sub-meshes within a domain-decomposed 3D mesh. The identification task is challenging in a distributed-memory parallel setting because connectivity is transitive and the cells composing each sub-mesh may span many or all processors. Our algorithm employs a multi-stage application of the Union-find algorithm and a spatial partitioning scheme to efficiently merge disjoint sets and produce a global labeling of connected sub-meshes. Marking each vertex with its corresponding sub-mesh label allows us to isolate mesh features based on topology, enabling new sub-mesh analysis capabilities. We briefly discuss two specific applications of the algorithm and present results from a weak scaling study. We demonstrate the algorithm at concurrency levels up to 2197 cores and analyze meshes containing up to 68 billion cells.

Categories and Subject Descriptors (according to ACM CCS): D.1.3 [Programming Techniques]: Concurrent Programming—Parallel programming, F.1.2 [Computation by Abstract Devices]: Modes of Computation—Parallelism and concurrency, I.3.5 [Computational Geometry and Object Modeling]: Geometric algorithms, languages, and systems—

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1 Introduction

Parallel scientific simulations run on today's state of the art petascale and terascale computing platforms generate massive quantities of high resolution mesh-based data. Scientists rely on deployed scientific visualization tools to explore and analyze the data-sets produced by these simulations. Applying traditional scalar field visualization methods, such as isosurface or isovolume extraction, to these massive data-sets generates complex derived geometry with intricate structures that are not easily isolated or further analyzed using a standard visualization tool set.

In these instances, representations of the topological structure of a mesh can be helpful. A labeling of the connected components in a mesh provides simple and intuitive topological characterization of which parts of the mesh are connected to each other. Each connected component is a unique sub-mesh that contains a sub-set of cells that are directly or indirectly connected via series of cell abutments.

The global nature of connectivity poses a challenge for parallel algorithms. Distributed-memory computers are the dominant resource for parallel scientific computing applications. In this setting pieces of the mesh are distributed across processors and the entire data-set is too large to fit into the memory of single processor. Cells comprising connected sub-meshes may span any set of processors and cell neighbor information may only exist on a single processor. These factors constrain the approaches available to resolve connectivity.

We have developed a novel data-parallel connected components labeling algorithm for analyzing data-sets in this context. Our multi-stage algorithm constructs a unique label for each connected component identified and marks each vertex with its corresponding connected component label. The final labeling enables:

- Calculation of aggregate quantities for each connected component.
- Feature based filtering of connected components.
- Calculation of statistics on connected components.

The algorithm provides an intuitive tool for domain scientists with applications where physical structures, for example individual fragments of a specific material, correspond to the connected components contained in simulation data-set. This paper presents an outline of the algorithm (Section 4), an overview of two specific applications of the algorithm (Section 5), and results from a weak scaling performance study (Section 6).

2 Related Work

Research into connected components algorithms has focused primarily on applications in computer vision and graph theory. Several efficient serial algorithms have been developed. We review these serial algorithms, survey existing parallel algorithms, and then discuss implications of these approaches in a distributed-memory parallel setting.

2.1 Applications of connected components

2.1.1 Computer Vision

Labeling connected components in binary images is a common image segmentation technique used in computer vision [RW96]. To gain efficiency, labeling algorithms use sweeps that exploit the structured grid nature of image data. Algorithms focus on providing results for four- or eight-connected neighborhoods. These optimizations do not easily generalize to the problem of resolving connectivity in unstructured meshes.

2.1.2 Graph Theory

The cell abutment relationships in an unstructured mesh can be encoded into a sparse undirected graph representation, so methods for finding the connected components of graphs can potentially be made applicable mesh-based data. Connected components algorithms are used in various graph theory applications to identify partitions. There are two common approaches. The first employs a series of Depth-first or Breadth-first searches [HT71]. Initially all vertices are unmarked. Each search starts at an unmarked vertex walking the graph edges and marking each reached vertex. New searches are executed until all vertices are marked. Each search yields a tree which corresponds to a single connected component. This approach is analogous to a region growing scheme.

The second approach uses the Union-find algorithm [CSRL01] for disjoint-sets. This is typically used for tracking how connected components evolve as edges are added to a graph. This incremental approach requires only local connectivity information and efficiently handles merging disjoint-sets as each new edge is added. The Union-find algorithm and data structures are also used to efficiently construct topological representations such as a Contour Tree [CSA00] or Reeb Graph [TGSP09] of a data-set. We use the serial Union-find algorithm as a key building block for our approach. It is discussed in detail in 3.1.

2.2 Parallelism

2.2.1 Parallelism in computer vision and graph algorithms

[AP92, CT92] provide overviews of several parallel computer vision algorithms for connected components labeling, including a few approaches for distributed-memory machines. Like the serial computer vision algorithms, these approaches make communication assumptions that require structured grid connectivity.

Much of the research into parallel algorithms for graph connected components has focused on shared-memory ar-

chitectures [HW90, AW91]. [CAP88] provides a parallel algorithm using the Union-find algorithm that is structurally similar to a connected components algorithm. They obtained speedups on a shared-memory machine, but observed poor performance when mapping their algorithm to a PRAM model on a distributed-memory machine.

[KLCY94, MP10] both use a hybrid local-global approach on distributed-memory machines. [KLCY94] uses a Breadth-first search to resolve local connectivity, followed by a global PRAM step to incorporate edges that cross processors. [MP10] presents a distributed-memory Union-find algorithm that employs a strategy similar to ours. They using the Union-find algorithm in both local and global step. Unlike our approach, their global stage distributes the Union-find data structure across several processors. The path-compression and union-by-rank heuristics used to gain efficiency in the serial case are not completely reproduced, leading to increased parallel communication in the global phase.

A naive distributed-memory implementation of the graph search approach would have a runtime proportional to the number of cells in the largest sub-mesh and would require complex communication to track visited cells as mesh regions grow across processors. The runtime of this approach would be unacceptable for datasets with sub-meshes on the order of the size of the entire mesh. A naive distributed-memory implementation of the Union-find algorithm is difficult due to the indirect memory access patterns used by the disjoint-set data structures to gain efficiency. Both of these approaches map conceptually well to a PRAM model of computation, however they are difficult to implement efficiently in a distributed-memory parallel context.

2.2.2 Parallelism strategy for end user tools

Our algorithm is intended for data-sets so large that they cannot fit into the memory of a single node. Popular end user visualization tools for large data, such as EnSight [Com09], ParaView [AGL05], and VisIt [CBB*05], follow a distributed-memory parallelization strategy. Each of these tools instantiate identical visualization modules on every MPI task, and the MPI tasks are only differentiated by the sub-portion of the larger data-set they operate on. The tools rely on the data-set being decomposed into pieces (often referred to as domains), and partition the pieces over their MPI tasks. This approach has been shown to work well to date, with the most recent example demonstrating VisIt to perform well on trillions of cells with tens of thousands of processors [CPA*10]. Our algorithm fits well in the setting provided by today's distributed-memory large data visualization tools and has been implemented as a module inside VisIt.

Our algorithm uses a multi-stage approach were local connectivity is resolved within a processor to reduce the communication required to resolve global connectivity. A novel contribution of our approach is a compression from a potential label set with a size on the order of the total number of cells, to a much smaller intermediate labeling that can be used during the global resolve. Our approach also handles the constraint that connectivity information across processors is not known a priori, a problem that does not occur in general graph applications.

3 Algorithm building blocks

This section describes three fundamental building blocks used by our multi-stage algorithm. The first is the serial Union-find algorithm which allows us to efficiently identify and merge connected components. The second is a parallel balanced spatial partitioning scheme which allows us to efficiently compute mesh intersections across processors. The third is the practice of generating ghost data, which, if available, allows us to use an optimized variant of our algorithm.

3.1 Union-find

The Union-find algorithm is an important building block for our approach. The algorithm enables efficient management of partitions. It provides two basic operations: UNION and FIND. The UNION operation creates a new partition by merging two subsets from the current partition. The FIND operation determines which subset of a partition contains a given element.

To efficiently implement these operations, relationships between sets are tracked using a disjoint-set forest data structure. In this representation each set in a partition points to a root node containing a single representative set used to identify the partition. The UNION operation uses a union-by-rank heuristic to update the root node of both partitions to the representative set from the larger of the two partitions. The FIND operation uses a path-compression heuristic which updates the root node of any traversed set to point to the current partition root. With these optimizations each UNION or FIND operation has an amortized run time of $O(\alpha(N))$ where N is the number of sets and $\alpha(N)$ is the inverse Ackermann function [Tar75]. $\alpha(N)$ grows so slowly that it is effectively less than four for all practical input sizes. The disjoint-set forest data structure requires $O(N)$ space to hold partition information and the values used to implement the heuristics. The heuristics used to gain efficiency rely heavily on indirect memory addressing and do not lend themselves to direct a distributed-memory parallel implementation.

3.2 Balanced Spatial Partitioning

To determine if a component on one processor abuts a component on another processor (meaning they are actually part of the same component), we will need to relocate the components (or parts of them) to guarantee that components that are spatially next to each other can be directly compared. We do this with a "balanced spatial partitioning," which partitions two- or three-dimensional space into $N_{processors}$

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pieces. If the partition were to divide space into regions that cover appreciably different numbers of elements, it would lead to load imbalances and potentially exhaust memory. Therefore, we want the partitioning to be "balanced," meaning there are roughly the same number of cells in each of the partition's pieces.

The algorithm to determine a balanced spatial partitioning is recursive. We start by creating a region that spans the entire data-set. On each iteration and for each region that represents more than 1/Nth of the data (measured in number of elements covered), we try to select "pivots", which are possible locations to split a region along a given axis. This axis changes on each iteration. All elements are then traversed, and their positions with respect to the pivots are categorized. If a pivot exists that allows for a good split, then the region is split into two sub-regions and recursive processing continues. Otherwise we choose a new set of pivots, whose choice incorporates the closest matching pivots from the previous iteration as extrema. If a good pivot is not found after some number of iterations, we use the best encountered pivot and accept the potential for load imbalance.

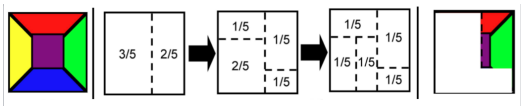

Figure 2: *The process for constructing a balanced spatial partitioning. On the left, the cells from the original mesh. Assume the red portions are on processor 1, blue on 2, and so on. The iterative strategy starts by dividing in X, then in Y, and continues until every region contains approximately $1/N_{processors}$ of the data. Each processor is then assigned one region from the partition and we communicate the data so that every processor contains all data for its region. The data for processor 3 is shown on the far right.*

After constructing a balanced spatial partition, we assign one portion of the partition to each MPI task and then redistribute the cells such that each MPI task contains every cell from its partition. Cells that span multiple partitions are duplicated.

3.3 Ghost Cells

When a large data-set is decomposed into domains, interpolation artifacts can occur along domain boundaries. The typical solution for this problem is to create "ghost cells," a redundant layer of cells along the boundary of each domain. Ghost cells are either pre-computed by the simulation code and stored in files or calculated at run-time by the postprocessing tool. More discussion of ghost cells can be found in [ILC10, CBB*05].

Ghost cells can provide benefits beyond interpolation. They also can be used to identify the location of the boundary of a domain and provide information about the state of the abutting cell in a neighboring domain. It is in this way that we use ghost cells for this algorithm. Note that this paper uses ghost cells that are generated at run-time and uses the collective pattern described in [CBB*05], not the streaming pattern described in [ILC10].

4 Algorithm description

Our algorithm identifies the global connected components in a mesh using four phases. We first identify the connected components local to each processor (Phase 1) and then create a global labeling across all processors (Phase 2). We next determine which components span multiple processors (Phase 3). Finally, we merge the global labels to produce a consistent labeling across all processors (Phase 4). This final labeling is applied to the mesh to create per-cell labels which map each cell to the corresponding label of the connected component it belongs to.

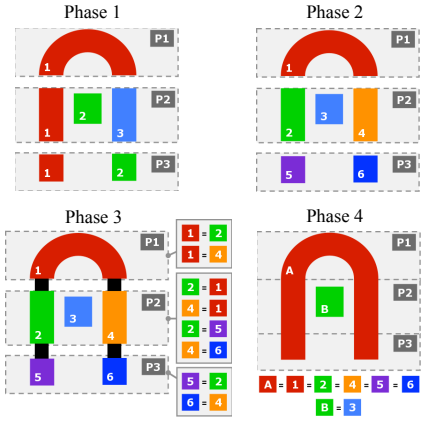

Figure 3: *Example illustrating the four phases of our algorithm on a simple data-set decomposed onto three processors.*

We present two variants of the algorithm. This first provides a general solution, applicable to any domain-decomposed 3D mesh. The second algorithm is an optimized variant of the first which can be used if ghost data is available for the mesh. The optimizations in the second variant greatly reduce the communication and processing required to resolve global connectivity.

4.1 General Algorithm

Phase 1: Identify components within a processor

The purpose of this phase is for each processor to label the connected components for its portion of the data As mentioned in section 2, the Union-find algorithm efficiently constructs a partition through an incremental process. A partition with one subset for each point in the mesh is used to initialize the Union-find data structure. We then traverse the

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cells in the mesh. For each cell, we identify the points incident to that cell. Those points are then merged ("unioned") in the Union-find data structure.

In pseudocode:

```
UnionFind uf;
For each point p:
   uf.SetLabel(p, GetUniqueLabel())
For each cell c:
   pointlist = GetPointsIncidentToCell(c)
   p0 = pointlist[0]
   For each point p in pointlist:
      if (uf.Find(p0) != uf.Find(p))
         uf.Union(p0, p)
```

The running time of this phase is dependent on the number of union operations, the number of find operations, and the complexity of performing a given union or find. The number of finds is equal to sum over all cells of how many points are incident to that cell. Practically speaking, the number of points per cell will be small, for example eight for a hexahedron. Thus the number of finds is proportional to the number of cells. Further, the number of unions will be less than the number of finds. Finally, although the runtime complexity of the Union-find algorithm is nuanced, each individual union or find is essentially a constant time operation, asymptotically-speaking. Thus the overall run time of this phase is proportional to the number of cells.

Phase 2: Component re-label for cross-processor comparison

At the end of Phase 1, on each processor, the components within that processor's data have been identified. Each of these components has a unique local label and the purpose of Phase 2 is to transform these identifiers into unique global labels. This will allow us to perform parallel merging in subsequent phases. Phase 2 actually has two separate re-labelings. First, since the Union-find may create non-contiguous identifiers, we transform the local labels such that the numbering ranges from 0 to N_P, where N_P is the total number of labels on processor P. For later reference, we denote $N = \sum N_P$ as the total number of labels over all processors. Second, we construct an unique labeling across the processors by adding an offset to each range. We do this by using the MPI rank and determining how many total components exist on lower MPI ranks. This number is then added to component labels. At the end of this process, MPI rank 0 will have labels from 0 to $N_0 - 1$, MPI rank 1 will have labels from N_0 to $N_0 + N_1 - 1$ and so on. Finally, a new scalar field is placed on the mesh, associating the global component label with each cell.

Phase 3: Merging of labels across processors

At this point, when a component spans multiple processors, each processor's sub-portion has a different label. The goal of Phase 3 is to identify that these sub-portions are actually part of a single component and merge their labels. We do this by re-distributing the data using a balanced spatial partition (see 3.2) and employing a Union-find strategy to locate abutting cells that have different labels. The Union-find strategy in this phase has four key distinctions from the strategy described in Phase 1.

- The labeling is now over cells (not points), which is made possible by the scalar field added in Phase 2.
- We merge based on cell abutment, as opposed to Phase 1, where we merged when two points were incident to the same cell.
- Each cell is initialized with the unique global identifier from the scalar field added in Phase 2, as opposed to the arbitrary unique labeling imposed in Phase 1.
- Whenever a union operation is performed, we record the details of that union for later use in establishing the final labeling.

In pseudocode:

```
CreateBalancedSpatialPartition()
UnionFind uf;
For each cell c:
  uf.SetLabel(c, label[c])
For each cell c:
  For each neighbor n of c:
       if (uf.Find(c) != uf.Find(n))
            uf.Union(n, c)
            RecordMerge(n, c)
```

After the union list is created, we discard the re-distributed data and each processor returns to operating on its original data.

Phase 4: Final assignment of labels

Phase 4 incorporates the merge information from Phase 3 with the labeling from Phase 2. Recall that in Phase 2 we construct a globally unique labeling of per-processor components and denoted N as the total number of labels over all processors. The final labeling of components is constructed as follows:

- After Phase 3, each processor is aware of the unions it performed, but not aware of unions on other processors. However, to assign the final labels, each processor must have the complete list of unions. So we begin Phase 4 by broadcasting ("all-to-all") each processor's unions to construct a global list.
- Create Union-find data structure with N entries and each entry having the trivial label.

```
UnionFind uf
For i in 0 to N-1:
   uf.SetLabel(i, i)
```

- Replay all unions from the global union list.

```
For union in GlobalUnionList:
   uf.Union(union.label1, union.label2)
```

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The Union-find data structure can now be treated as a map. Its “Find" method transforms the labeling we constructed in Phase 2 to a unique label for each connected component.

- Use the “Find" method to transform the labeling from the scalar array created in Phase 2 to create a final labeling of which connected component each cell belongs to.

```
For each cell c:
  val[c] = uf.Find(val[c])
```

- Optionally transform the final labeling so that the labels range from 0 to $N_C - 1$, where N_C is the total number of connected components.

Note that the key to this construction is that every processor is able to construct the same global list by following the same set of instructions. They essentially “replay" the merges from the global union list in identical order, creating an identical state in their Union-find data structure.

4.2 Ghost cell optimized algorithm

One of the strengths of the general algorithm is that local connectivity, which encapsulates the majority of cell abutments, is resolved concurrently on each processor. After Phase 2 completes, the only cells that can contribute and merge labels across processors are those cells that could potentially abut cells residing other processors. If we can identify which cells intersect the spatial boundary of each processor, we can limit the re-distribution in Phase 3 to this subset of cells. Processing a reduced set of cells in Phase 3 can lead to significant performance gains.

We created an optimized variant of the general algorithm using this strategy. To do so we add Phase 0, a new prepossessing step, and modify Phase 3 to down-select amount of re-distributed cells. Phases 1, 2, and 4 are reused from the general algorithm.

Phase 0: Identify cells at processor boundaries

The goal of this preprocessing phase is to identify cells that abut the spatial boundary of the data contained on each processor. Using ghost data we can easily identify boundary cells as those that are adjacent to ghost data. We cannot directly use the ghost cells to represent processor boundaries because they may have been transformed by an earlier operation, such as isovolume, in a way that alters global connectivity. We also remove any ghost cells after the boundary is identified for this reason.

In pseudocode:

```
For each cell c:
  boundary[c] = false
  if (not IsGhostCell(c))
    For each neighbor n of c:
      if IsGhostCell(n):
        boundary[c] = true
RemoveGhostCells()
```

	Number of components
Isosurface	2023812
Isovolume	2010473

Table 1: *Number of components after applying algorithm. It is expected that the number of isovolume components will be slightly less than the number of isosurface components, since they contribute a different number at the boundary of the problem. Consider the two-dimensional shape S, where points P in S satisfy* $0.5 \leq \sqrt{P_x{}^2 + P_y{}^2} \leq 1.0$. *Further consider the case when the problem domain is limited to positive X and Y. Then, an isosurface that isolates S will have two components (the quarter-circles at radius* 0.5 *and* 1.0*), while an isovolume that isolates S will have just one.*

Phase 3’: Merging of labels across processors

In Phase 3’ we create the spatial partition using only the set of boundary cells identified in Phase 0, in contrast to the general algorithm which re-distributes all of cells. We identify abutment and construct each processor’s union list using the same Union-find strategy from Phase 3 in the general algorithm. By using the boundary information identified in Phase 0, we down-select the number of cells re-distributed by an order of magnitude. This greatly reduces the amount of communication and the complexity of the intersection tests used to identify cell abutment.

5 Applications

The labeling produced by a connected components algorithm opens up new analysis capabilities. Having a topological description of the connected components of a mesh allows us to isolate features in ways fundamentally different from standard visualization tools. To demonstrate this, we present two analysis applications on real data-sets that were enabled by our algorithm. We also report the performance characteristics of our algorithm on these data-sets.

5.1 Turbulent flow

TODO: Kelly will write motivation. Hank’s thoughts: science problem ... want to understand worm behavior. Maybe some discussion of birth, death, marriage, divorce, but discussion is conn comp-centric. 4K cubed data. Create “isovolumes" to isolate worms. Will probably reference 1. Needed to locate conn comps so we could do that analysis. Will probably be a reference to Figure 4. This is just my thoughts, Kelly, I defer to you and feel free to deviate.

We now present performance characteristics for calculating the connected components for this data. Our actual analysis used isovolumes and data with no ghost cells. For this paper, we added the option to calculate ghost data and also repeated the analysis with isosurfaces, giving a total of four tests. The data sizes involved are in Table 2. The overall per-

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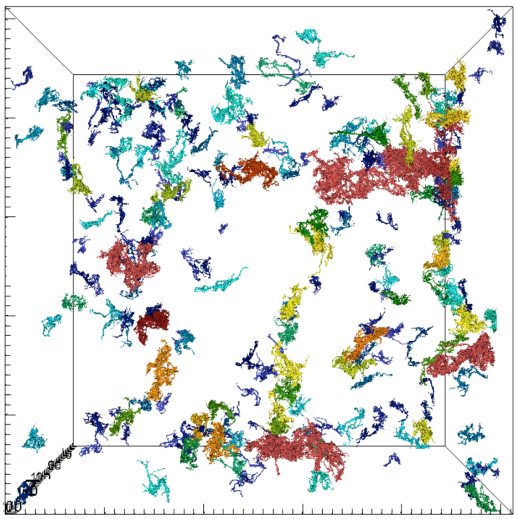

Figure 4: *This figure shows the 224 "worms" that have volume larger than a certain threshold. Each worm is colored by its volume.*

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	Num cells wo/ ghosts	Num cells w/ ghosts
Input data-set	68.7 billion	77.2 billion
After isosurface	1.08 billion	1.21 billion
After isovolume	1.81 billion	2.04 billion

Table 2: *Number of cells processed. The input mesh was a* 4096^3 *rectilinear grid of hexahedral cells (voxels). For the first test, applying an isosurface, the cell types are triangles. For the second test, applying an isovolume, the cells types are hexahedrons, tetrahedrons, wedges, and pyramids.*

formance is described in Table 3 and the per-phase performance is described in Table 4.

5.2 Turbulent flow in a nuclear reactor

In [FLPS08], Fischer et al use the Nek5000 code to simulate the flow of coolant around a 217-fuel rod nuclear reactor. In this simulation, coolant flows through the assembly with a strong bias along a fixed axis (the "Z-axis"), with each rod also being aligned this axis. It is not desirable for the coolant to travel directly down this fixed axis. If one of the rods is "hot," the ideal scenario is for coolant to absorb heat and then move away, letting other material come in to continue the cooling process. One important question is where "pockets" of coolant are transferring through the assembly most quickly. Since each rod is aligned with the z-axis, this is equivalent to locating regions with significant x,y-velocity, which can be accomplished via an isosurface operation on this derived field. Of course, only regions above a certain

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Algorithm	Ghost	Iso	CC
Isosurf. wo/ Ghost	-	16.3s	30.2s
Isosurf. w/ Ghost	18.5s	17.1s	16.9s
Isovol. wo/ Ghost	-	24.4s	108.5
Isovol. w/ Ghost	18.3s	26.3s	69.6s

Table 3: *Performance of connected components identification algorithm in the context of overall performance, including time to calculate a layer of ghost cells ("Ghost"), apply either an isosurface or isovolume algorithm ("Iso"), and apply the connected components identification algorithm ("CC"). Note that read times regularly exceed one minute and vary greatly due to disk contention, caching by the operating system, and other factors. (All tests read the same data.)*

Algorithm / Phase	0	1	2	3	4
Isosurf. wo/ Ghost	-	4.4s	0.01s	24.2s	1.5s
Isosurf. w/ Ghost	4.2s	4.3s	0.01s	5.0s	3.1s
Isovol. wo/ Ghost	-	12.5s	0.03s	89.2s	6.7s
Isovol. w/ Ghost	12.9s	13.2s	0.03s	37.9s	5.4s

Table 4: *Performance of connected components algorithm.*

size criteria represent significant trends, so we once again only study components above a size threshold.

This simulation takes place on a 1.012 billion cell unstructured mesh of hexahedrons. There was no ghost data available and we could not calculate it for comparison's sake as we did in section 5.1. We used 30 nodes of Argonne National Laboratory's "Eureka" machine, with each node containing two 2.0 GHz quad-core Xeons (a total of 240 MPI tasks). The resulting isosurface had 3.04 million cells spread over 25,189 components. By discarding components below a size threshold, we arrived at 214 "large" components. These components almost all resided at the exterior of the assembly, meaning that coolant is communicating better in the exterior than in the interior. The resulting visualizations can be seen in Figure 5 and specific performance measures can be found in Table 5.

Stage	Time
Read	14.7s
Isosurface	1.1s
Phase 1	0.1s
Phase 2	0.01s
Phase 3	0.5s
Phase 4	0.1s

Table 5: *Performance of connected components algorithm on reactor coolant simulation.*

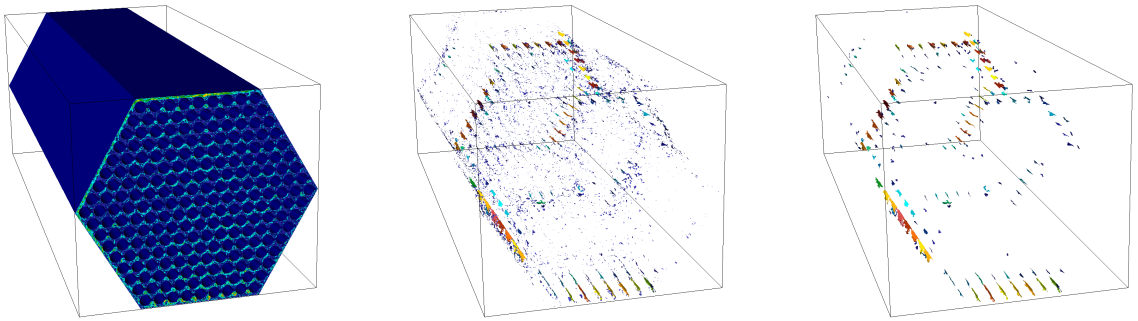

Figure 5: *Connected components for a nuclear reactor coolant simulation on a 1.03 billion cell unstructured mesh. On the left is the full assembly, in the middle is an image showing all components that have high transverse velocity, and on the right is just the large components. Note that the large components occur mostly near the exterior of the assembly.*

6 Performance study

To explore to the performance characteristics of our algorithm, we conducted a weak scaling study that looked at concurrency levels up to 2197 cores with data-set sizes up to 21 billion cells. We ran this study on a 216 node linux cluster, where each node has two six-core 2.8GHz Intel Westmere processors installed. The system has 96GB of memory per node (8GB per core) and 20TB of aggregate memory.

6.1 Problem setup

We used synthetic data as input, upsampling structured grid data from a core-collapse supernova simulation produced by the Chimera code [BMH*08]. This data-set was selected because it contains large isovolume components that span many processors. To test weak scaling we upsampled the input data-set creating new data-sets composed of 10 million cells per processor. We extract isovolumes from the upsampled structured grid to create an unstructured mesh for input to the connected components algorithm. Table 6 outlines the number of cores and the corresponding data-sets used in our scaling study. Figure 1 shows a rendered view of the isovolume data-set and labeling result for the largest run of the scaling study. We tested both the general and ghost cell optimized variant of the algorithm.

Num cores	Input mesh size	Isovol. mesh size
$2^3 = 8$	80 million	10.8 million
$3^3 = 27$	270 million	34.9 million
$4^3 = 64$	640 million	80.7 million
$5^3 = 125$	1.25 billion	155.3 million
$6^3 = 216$	2.16 billion	265.7 million
$7^3 = 343$	3.43 billion	418.7 million
$8^3 = 512$	5.12 billion	621.5 million
$9^3 = 729$	7.29 billion	881.0 million
$10^3 = 1000$	10 billion	1.20 billion
$11^3 = 1331$	13.3 billion	1.59 billion
$12^3 = 1728$	17.2 billion	2.06 billion
$13^3 = 2197$	21.9 billion	2.62 billion

Table 6: *Scaling study data-set sizes. We targeted processor counts equal to powers of three to maintain an even spatial distribution after upsampling. The highest power of three processor count available on our test system was* $13^3 = 2197$ *processors. This allowed us to study processor counts from 8 to 2197 and initial mesh sizes from 80 million to 21 billion cells. The isovolume operation creates a new unstructured mesh consisting of portions of approximately 1/8th of the cells from the initial mesh.*

6.2 Performance

Figure 6 presents the timing results from our scaling study. As expected, the timings for phases 1,2, and 4 are consistent between both variants of the algorithm. At 125 processors and beyond the largest subset of the isovolume on a single processor approaches the maximum size, 10 million cells. At this point we expect weak scaling for Phase 1. This is confirmed by flat timings for Phase 1 beyond 125 processors. The ghost cell optimized variant dramatically outperforms the general algorithm in Phase 3. These timings demonstrate the benefit of having ghost data available to identify per processor spatial boundaries. The small amount of additional preprocessing time required for Phase 0 allows us to reduce the number of cells transmitted and processed in Phase 3 by an order of magnitude.

By upsampling we maintain a fixed amount of data per-processor, however the number of connectivity boundaries in the isovolume increases as the number of processors used

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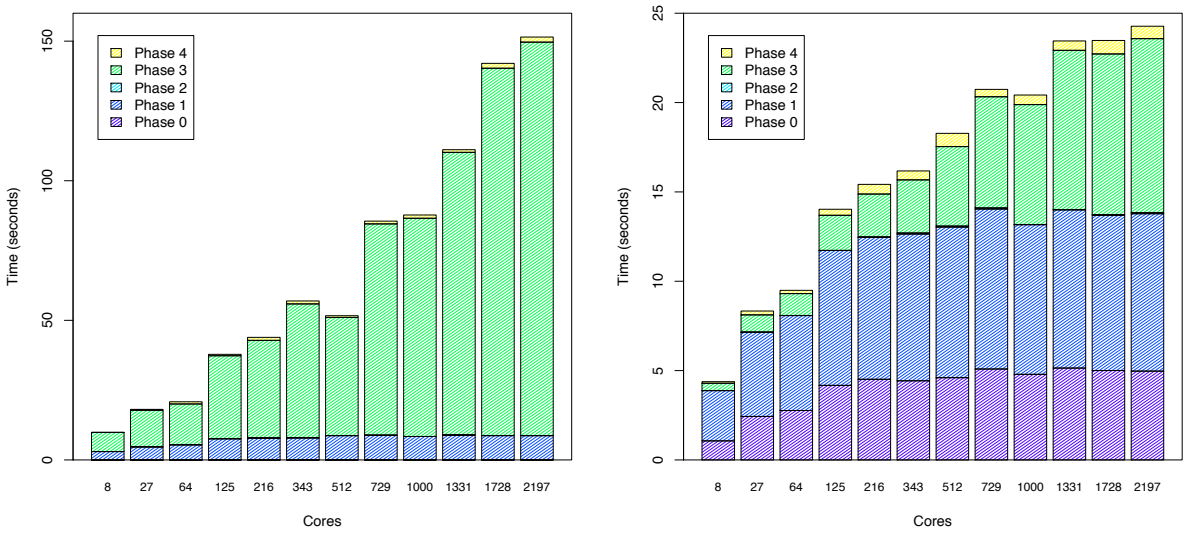

(a) General algorithm (w/o ghost data)

(b) Optimized algorithm (using ghost data)

Figure 6: *Scaling study timings for connected components identification algorithm. Phase 3 timings are significantly reduced by using ghost zones. Note that the two tables have different scales, going up to 150 seconds without ghost data, but only up to 25 seconds with ghost data.*

Num cores	Num cells in largest comp.	Cores holding largest comp.	Num global union pairs
$2^3 = 8$	10.1 million	4	16
$3^3 = 27$	32.7 million	17	96
$4^3 = 64$	76.7 million	29	185
$5^3 = 125$	146.6 million	58	390
$6^3 = 216$	251.2 million	73	666
$7^3 = 343$	396.4 million	109	1031
$8^3 = 512$	588.9 million	157	1455
$9^3 = 729$	835.5 million	198	2086
$10^3 = 1000$	1.14 billion	254	2838
$11^3 = 1331$	1.51 billion	315	3948
$12^3 = 1728$	1.96 billion	389	5209
$13^3 = 2197$	2.49 billion	476	6428

Table 7: *Largest component information and number of global union pairs transmitted. As the size of the data-set increases we see a linear correlation (0.994322) between the number of cores spanned by the largest connected component of the isovolume and the number of union pairs transmitted in Phase 4.*

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in decomposition increases. This is reflected by the linear growth in both the number of union pairs transmitted in Phase 4 and the number of cores spanned by the largest connected component (See Table 7).

7 Conclusion

We have presented a novel data-parallel algorithm that identifies and labels the connected components in a domain-decomposed mesh. Our algorithm is designed to fit well into currently deployed distributed-memory visualization tools. The labeling produced by our algorithm provides a topological characterization of a data-set that enables new types of analysis. We presented two applications which demonstrate our approach is suitable for analyzing the massive data-sets created by today's parallel scientific simulations. Our scaling study highlighted a significant speed up in runtime when ghost data is available. It also pointed out the best target for optimization is the implementation of the balanced spatial partitioning scheme used to re-distribute cells in Phase 3.

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TODO: AK for TACC / Longhorn, perhaps Argonne computing (Fischer)?

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