# Scalable Algorithms for Distributed Memory Adaptive Mesh Refinement

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## Introduction

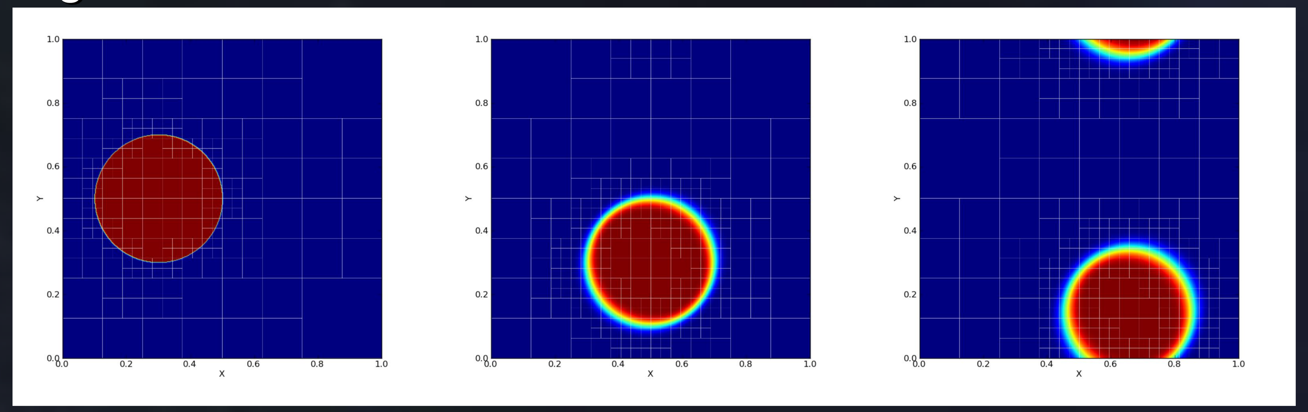
### Motivation

- Eulerian methods widely used in numerical cosmology, global atmospheric modeling, mantle convection modeling, etc.
- Requires simulation of large meshes ( e.g. size $10^{15}$)
- Intractable even on modern supercomputers

### Solution – Adaptive Mesh Refinement (AMR)

Every few iterations of the Euler method

- Refine zones that need finer precision
- Keep others at coarse granularity level or coarsen them
- Neighboring blocks remain within ±1 refinement level of their neighbors

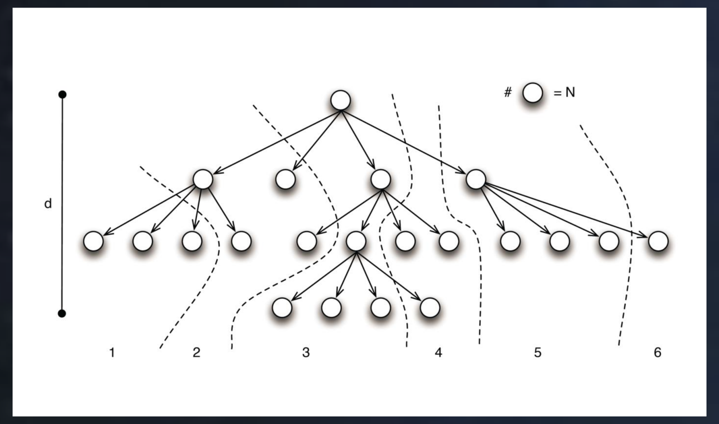


AMR mesh evolving over time. An example simulation of a circular fluid advected by a constant velocity field

## Need for Scalable Algorithms

### Traditional Algorithms

- Each process manages a set of neighboring blocks assigned to it through a space filling curve (e.g. Hilbert curve)



Tree partitioning for assignment to processes

### Limitations of Traditional Algorithms

- $O(\#blocks)$ memory per process to store the tree information
- $O(\log P)$ time to locate neighboring blocks
- $O(d)$ rounds of collective communication during mesh restructuring
- Centralized load balancing – takes O(#blocks) time and memory
- Does not allow coarsening of sibling blocks residing on different processors

### At extreme scale

- As available memory per process decreases, traditional algorithms pose memory bottleneck

## Scalable Algorithms

### Design

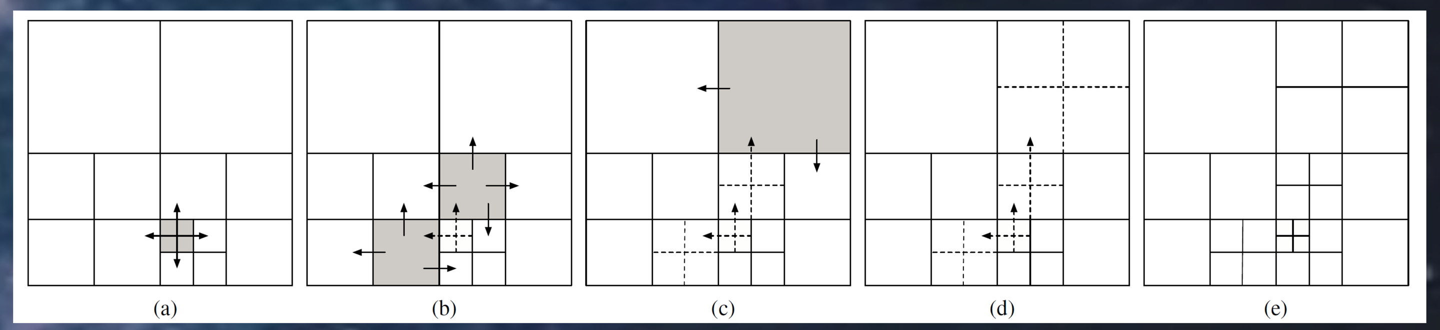
Each block acts as a first class entity – Charm++ object:

- Acts as a virtual processor – allowing overlap of computation with communication of other blocks on the same physical process
- Uniquely identified by its location in the refinement tree
- Dynamically placed on any physical process – facilitating dynamic load balancing
- Unit of algorithm expression – reduces implementation complexity
- End-point of communication – run-time system handles communication between arbitrary blocks
- $O(\frac{\#blocks}{P})$ memory per process to store the tree information

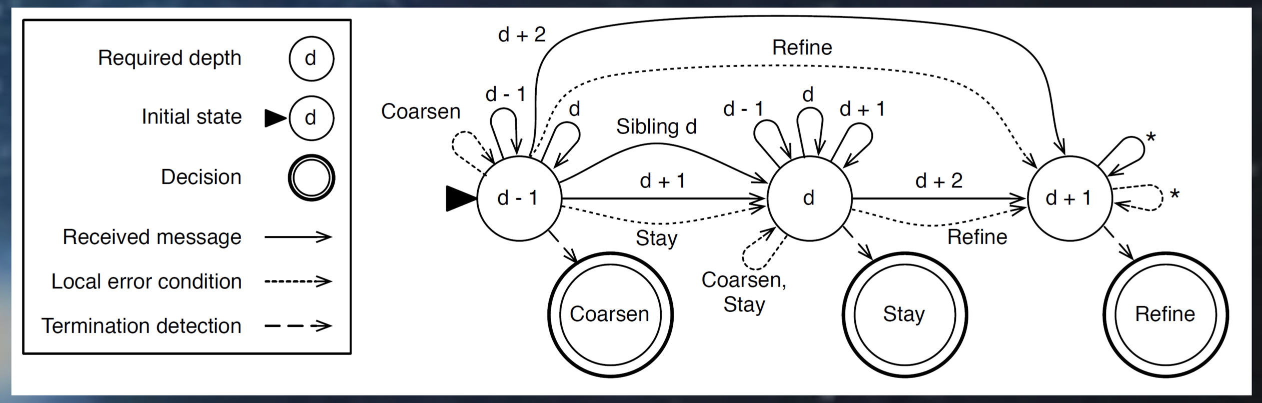
### The Mesh Restructuring Algorithm

Executes in two phases separated by a system quiescence state:

- Phase 1
  - Based on local error estimate, make one of the following decision: *refine, stay* or *coarsen*
  - Communicate *refine* and *stay* decision to neighboring blocks
  - Update decision based on the DFA below and communicate change in decision
  - Wait for system quiescence state – takes $O(\log P)$ time
- Phase 2
  - Create new blocks or destroy existing ones based on the refinement decision
  - Wait for system quiescence state




Propagation of refinement decision messages based on local-error criteria and near-neighbor communication

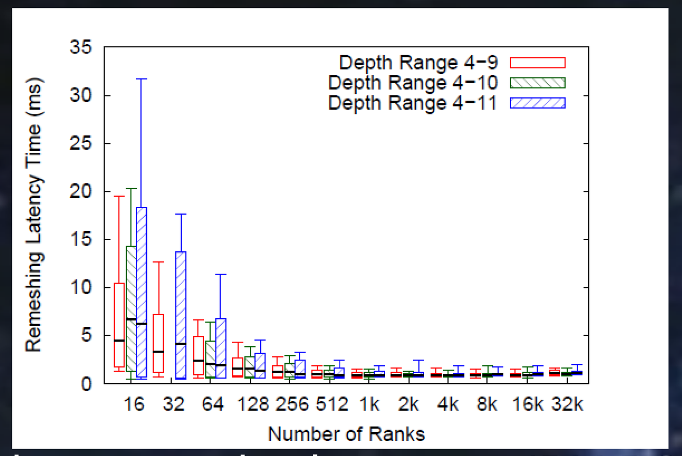



The finite state machine describing each block's decision process during the mesh restructuring algorithm

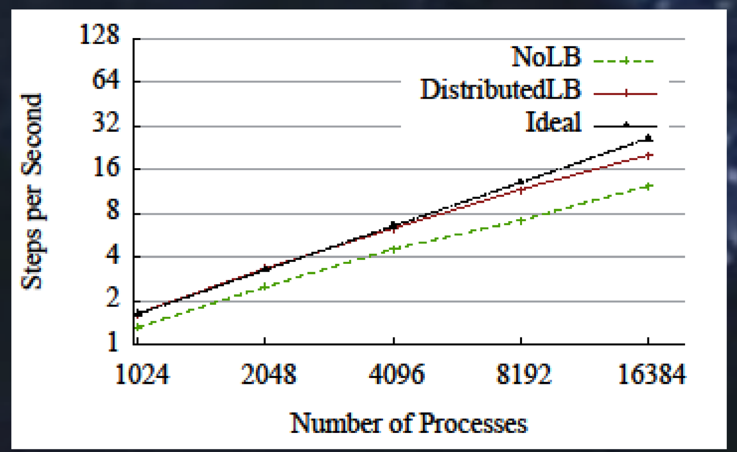
### Dynamic Distributed Load Balancing

- Load balance blocks across processors every few iterations
- Charm++ provided distributed load balancer – *Grapevine*
- Competitive with the centralized load balancers while incurring negligible overhead

## Experimental Results




Mesh restructuring latency on IBM BG/Q




Time steps per second strong scaling (max mesh depth: 15) on IBM BG/Q

## Conclusion

- Elevate blocks to first-class entities- Charm++ objects identified with bit-vector ids
  - No $O(P)$ data structures, constant time neighbor lookup
  - Enables asynchronous progress in computation
- Adapt mesh using near-neighbor point-to-point messages and quiescence detection
  - Only 2 quiescence states vs $O(d)$ reductions
  - Eliminate memory hungry collectives taking $O(d \log P)$ time
- Distributed dynamic load balancing of blocks

Enables high performance for much more deeply refined computations than are currently practiced

## References

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