Parallel Locally-Ordered Clustering for Bounding Volume Hierarchy Construction

Daniel Meister and Jiří Bittner

Department of Computer Graphics and Interaction
Faculty of Electrical Engineering
Czech Technical University in Prague

Motivation: Interactive Ray Tracing

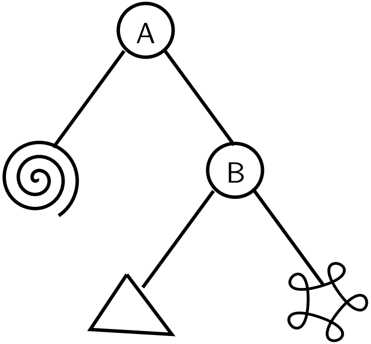
Fast BVH construction for geometry that is not known a priori

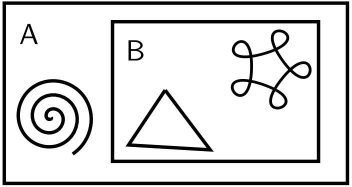
- Dynamic geometry changes in every frame
- Scene is assembled on the fly

[Benthin et al. 2017]

Bounding Volume Hierarchy (BVH)

- Ray tracing, collision detection, visibility culling
- Rooted tree of arbitrary branching factor
  - References to geometric primitives in leaves
  - Bounding volumes in interior nodes



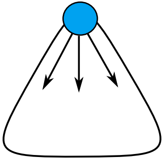


[Clark 1976]

BVH Construction Methods

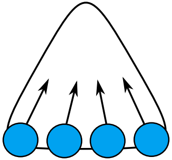
Top-down

- Surface Area Heuristic [Hunt et al. 2007]
- Binning [Ize et al. 2007, Wald 2007]
- k-means clustering [Meister and Bittner 2016]



Bottom-up

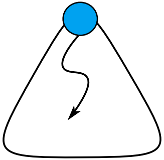
- Agglomerative clustering [Walter et al. 2008]
- Approximate aggl. clustering [Gu et al. 2013]



BVH Construction Methods

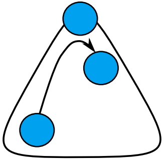
Insertion

- Heuristic greedy search [Goldsmith and Salmon 1987]
- Online construction [Bittner et al. 2015]



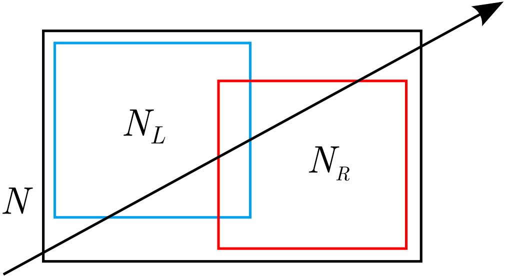
Optimization

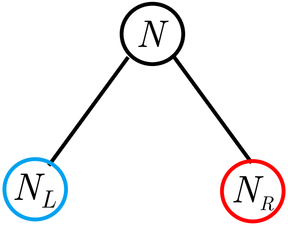
- Rotations [Kensler 2008, Kopta et al. 2012]
- Insertion-based optimization [Bittner 2013 et al.]
- Treelet restructuring [Karras and Aila 2013, Domingues and Pedrini 2015]



Surface Area Heuristic (SAH)

$$c(N) = \begin{cases} c_T + \frac{SA(N_L)}{SA(N)} c(N_L) + \frac{SA(N_R)}{SA(N)} c(N_R) & \text{if } N \text{ is interior node} \\ c_I |N| & \text{otherwise} \end{cases}$$

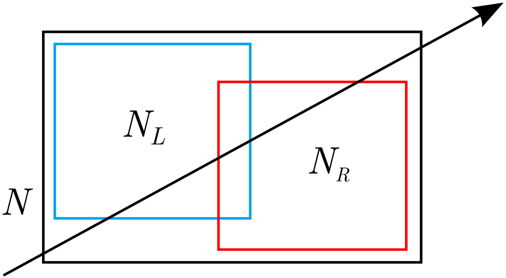


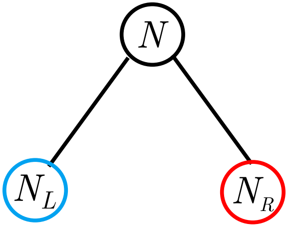


[MacDonald and Booth 1990]

Surface Area Heuristic (SAH)

$$c(N) = \begin{cases} c_T + \frac{SA(N_L)}{SA(N)} c(N_L) + \frac{SA(N_R)}{SA(N)} c(N_R) & \text{if } N \text{ is interior node} \\ c_I |N| & \text{otherwise} \end{cases}$$

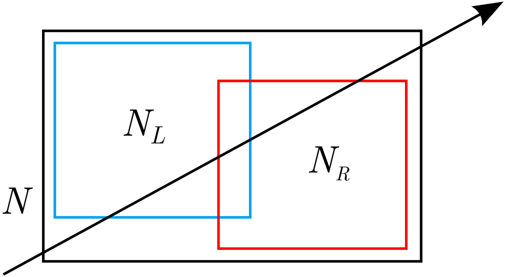


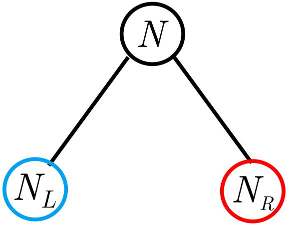


[MacDonald and Booth 1990]

Surface Area Heuristic (SAH)

$$c(N) = \begin{cases} c_T + \frac{SA(N_L)}{SA(N)} c(N_L) + \frac{SA(N_R)}{SA(N)} c(N_R) & \text{if } N \text{ is interior node} \\ c_I |N| & \text{otherwise} \end{cases}$$



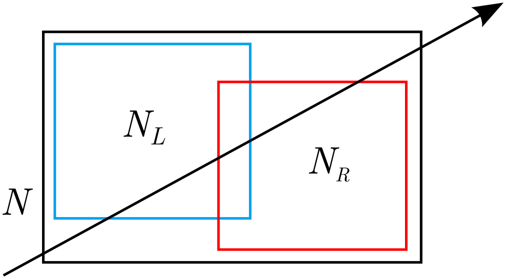


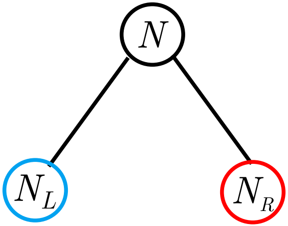
[MacDonald and Booth 1990]

Surface Area Heuristic (SAH)

$$c(N) = \begin{cases} c_T + \frac{SA(N_L)}{SA(N)} c(N_L) + \frac{SA(N_R)}{SA(N)} c(N_R) & \text{if } N \text{ is interior node} \\ c_I |N| & \text{otherwise} \end{cases}$$

$$c(N_{root}) = \frac{1}{SA(N_{root})} \left[c_T \sum_{N_i} SA(N_i) + c_I \sum_{N_l} SA(N_l) |N_l| \right]$$



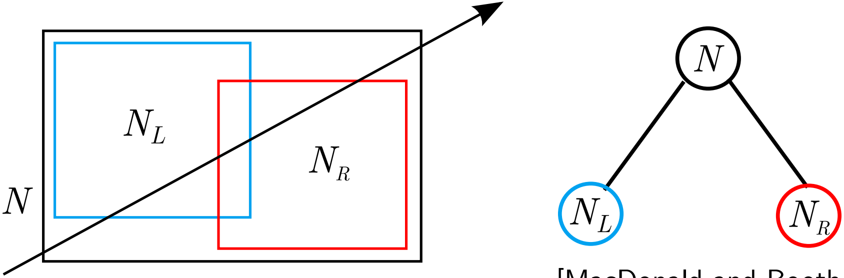


[MacDonald and Booth 1990]

Surface Area Heuristic (SAH)

$$c(N) = \begin{cases} c_T + \frac{SA(N_L)}{SA(N)} c(N_L) + \frac{SA(N_R)}{SA(N)} c(N_R) & \text{if } N \text{ is interior node} \\ c_I |N| & \text{otherwise} \end{cases}$$

$$c(N_{root}) = \frac{1}{SA(N_{root})} \left[c_T \sum_{N_i} SA(N_i) + c_I \sum_{N_l} SA(N_l)|N_l| \right] \propto \sum_{N_i} SA(N_i) \quad \text{if } |N_l| = 1$$



[MacDonald and Booth 1990]

Agglomerative Clustering

Agglomerative Clustering

Repeat until only one cluster remains

Agglomerative Clustering

Repeat until only one cluster remains

- Search for nearest neighbors for each cluster

Agglomerative Clustering

Repeat until only one cluster remains

- Search for nearest neighbors for each cluster
- Merge the *closest* cluster pair

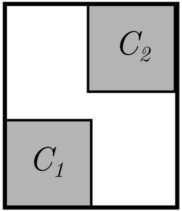
Agglomerative Clustering

Repeat until only one cluster remains

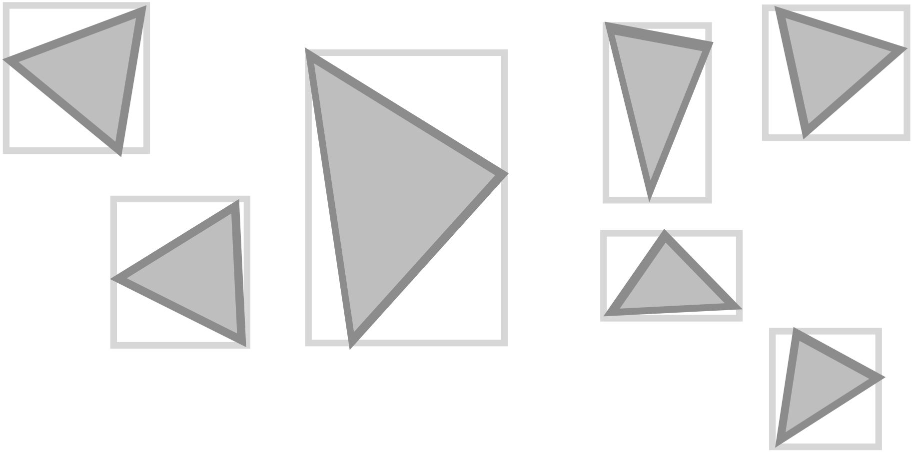
- Search for nearest neighbors for each cluster
- Merge the *closest* cluster pair

Distance between clusters C_1 and C_2 [Walter et al. 2008]

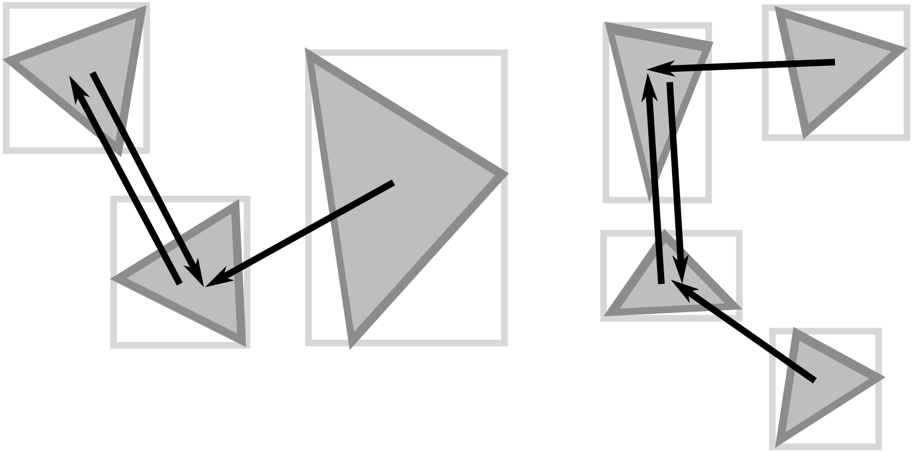
$$d(C_1, C_2) = SA(C_1 \cup C_2)$$



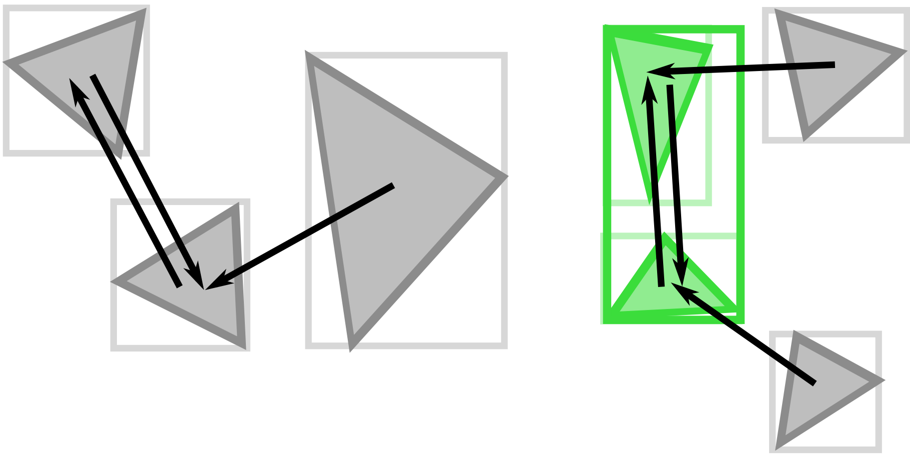
Agglomerative Clustering



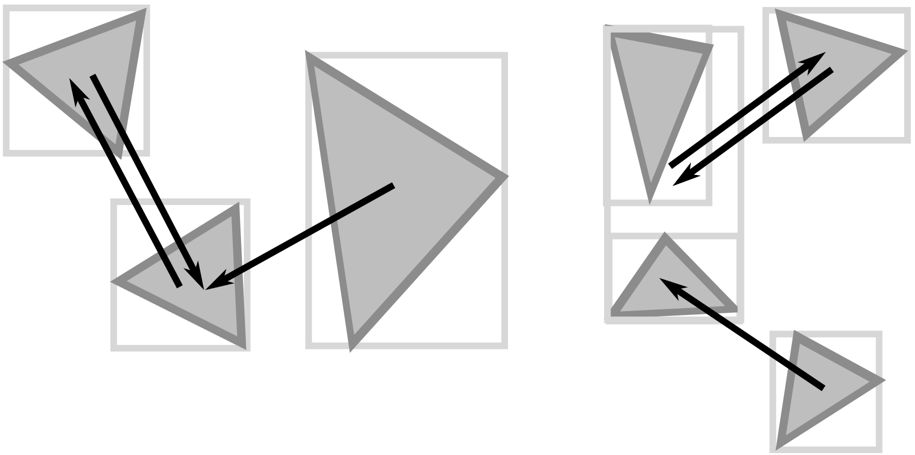
Agglomerative Clustering



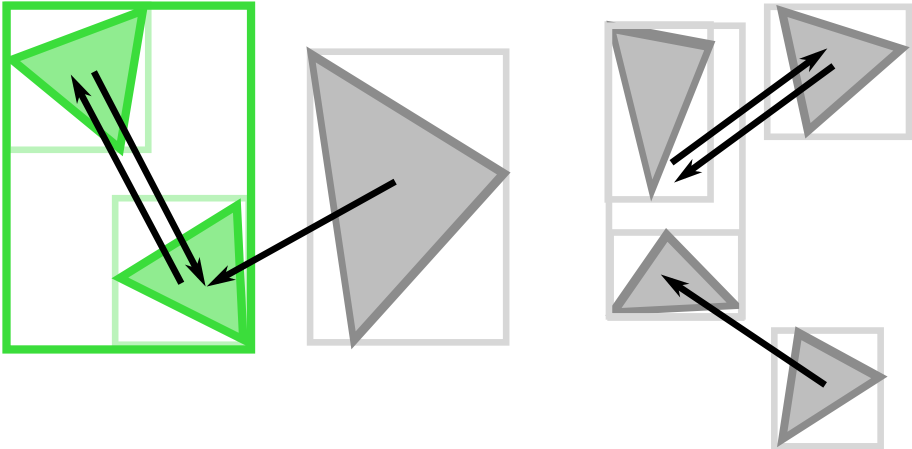
Agglomerative Clustering



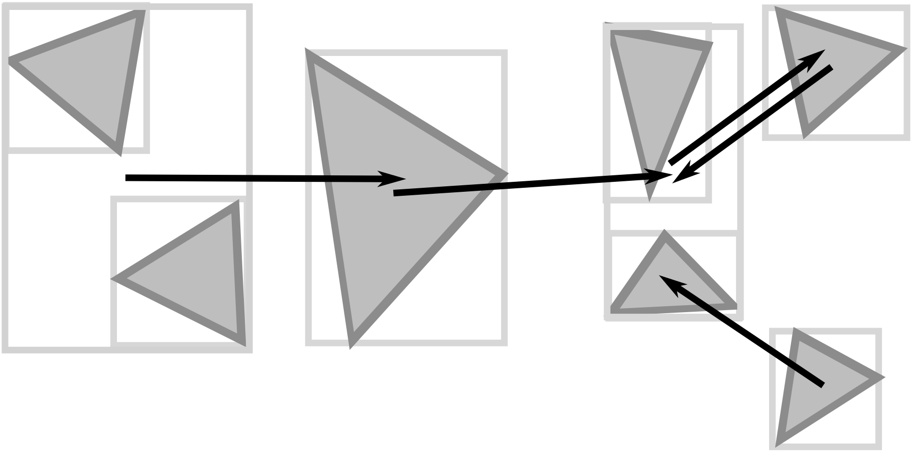
Agglomerative Clustering



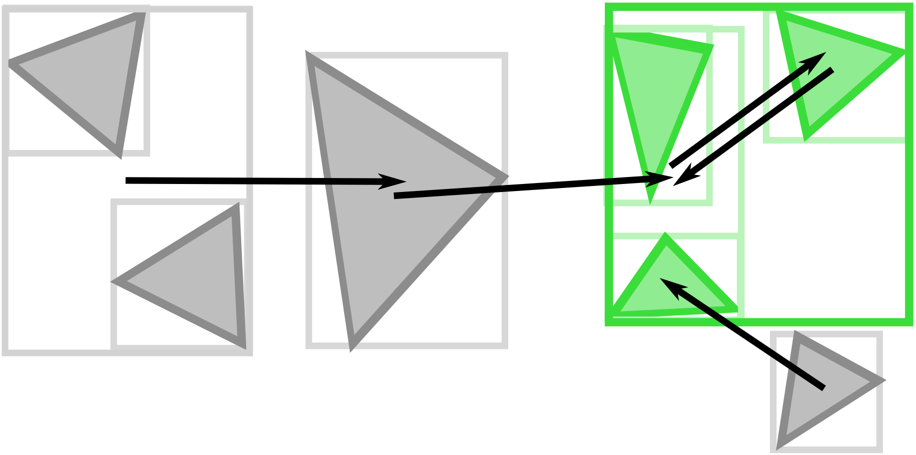
Agglomerative Clustering



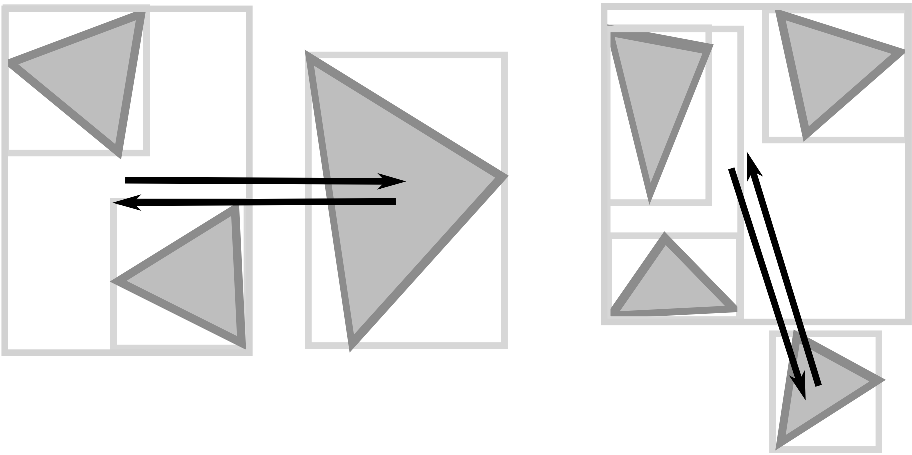
Agglomerative Clustering



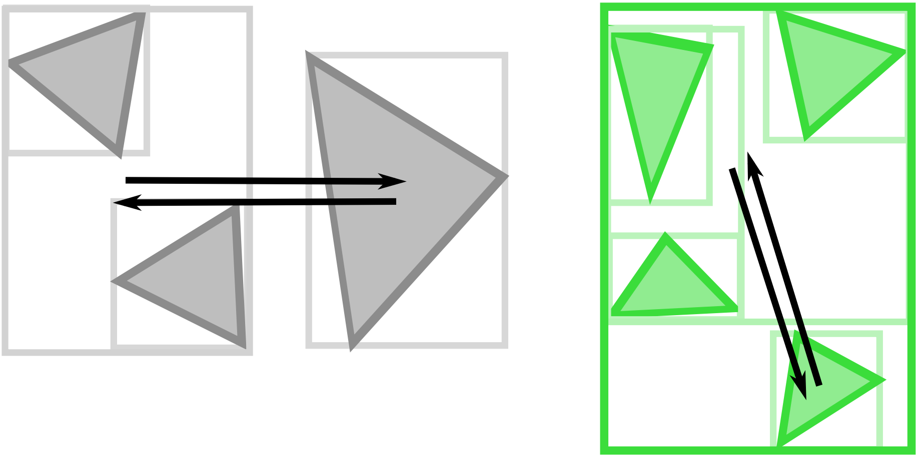
Agglomerative Clustering



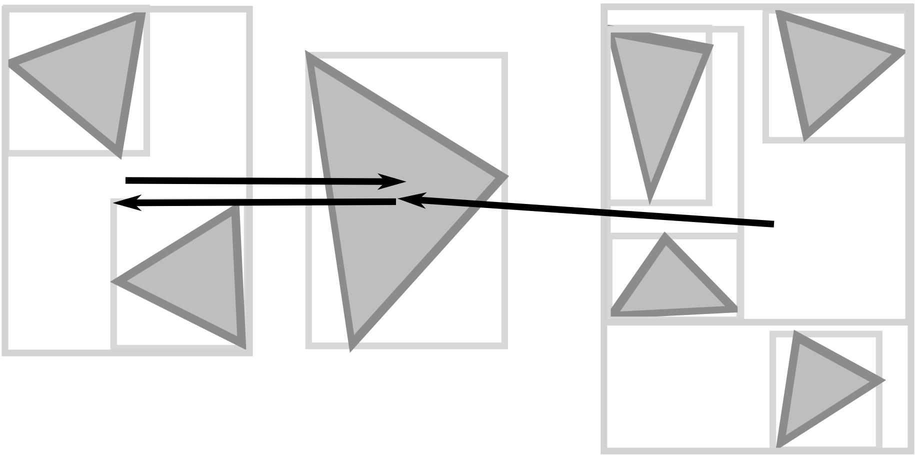
Agglomerative Clustering



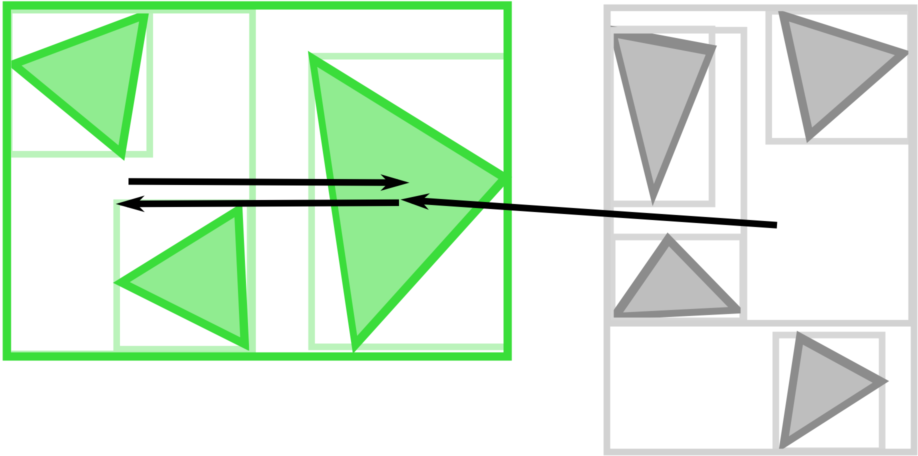
Agglomerative Clustering



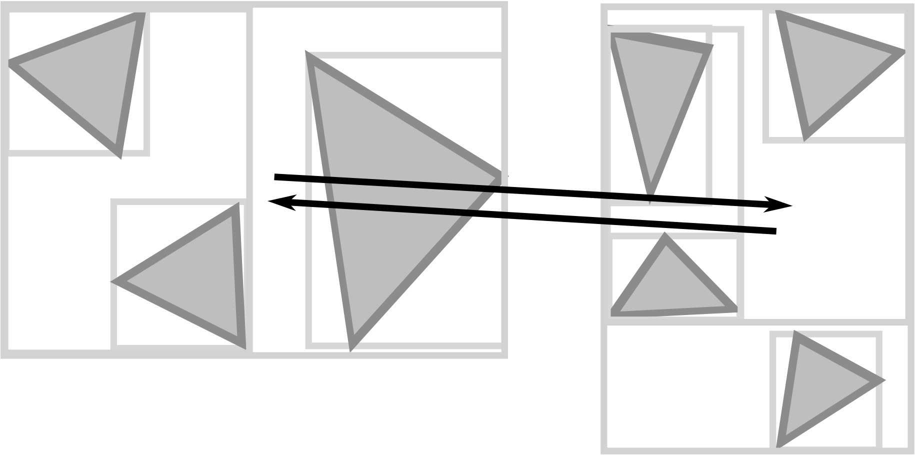
Agglomerative Clustering



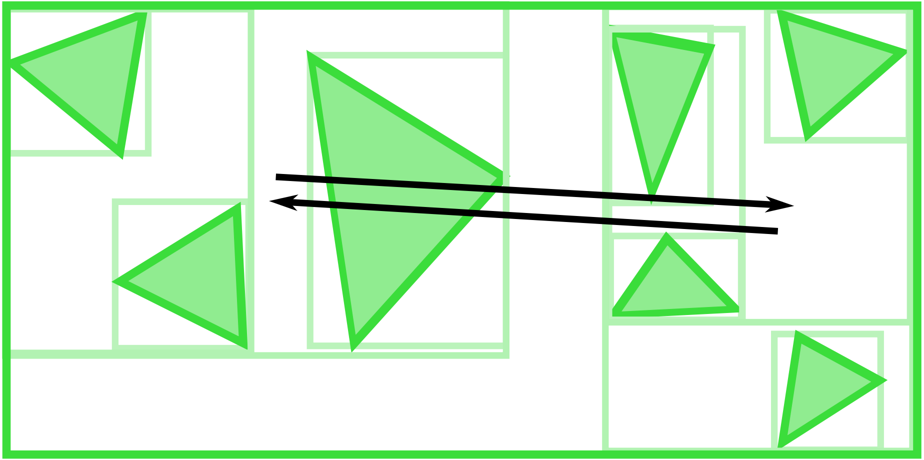
Agglomerative Clustering



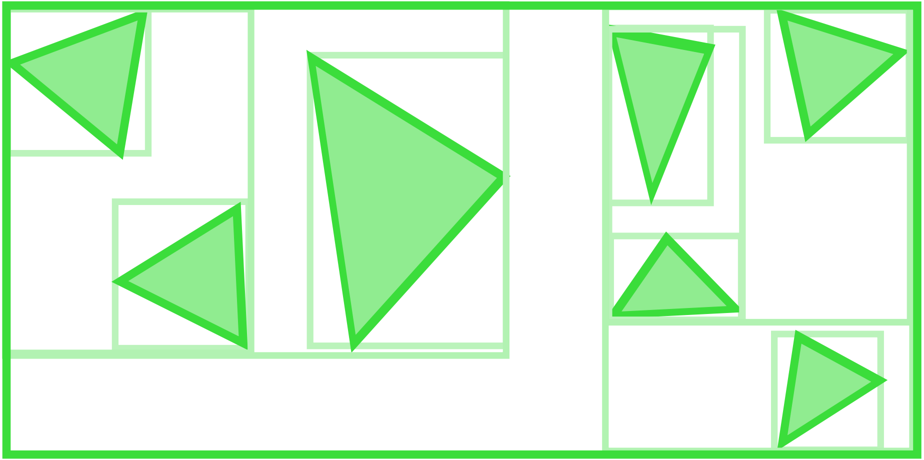
Agglomerative Clustering



Agglomerative Clustering



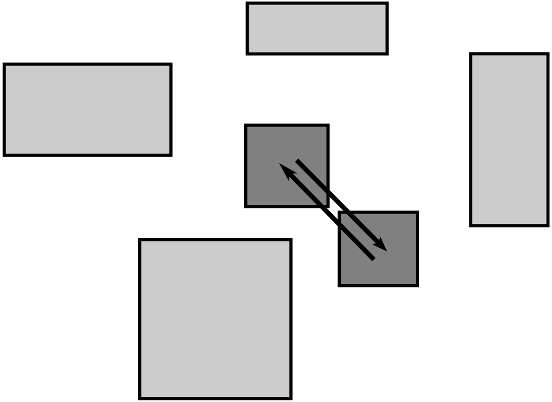
Agglomerative Clustering



Locally-Ordered Clustering

Non-decreasing property [Walter et al. 2008]

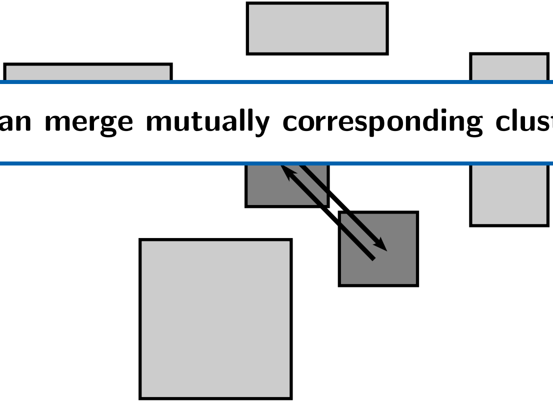
$$d(C_1, C_2) \leq d(C_1 \cup C_3, C_2) \;:\; \forall\; C_1, C_2, C_3$$



Locally-Ordered Clustering

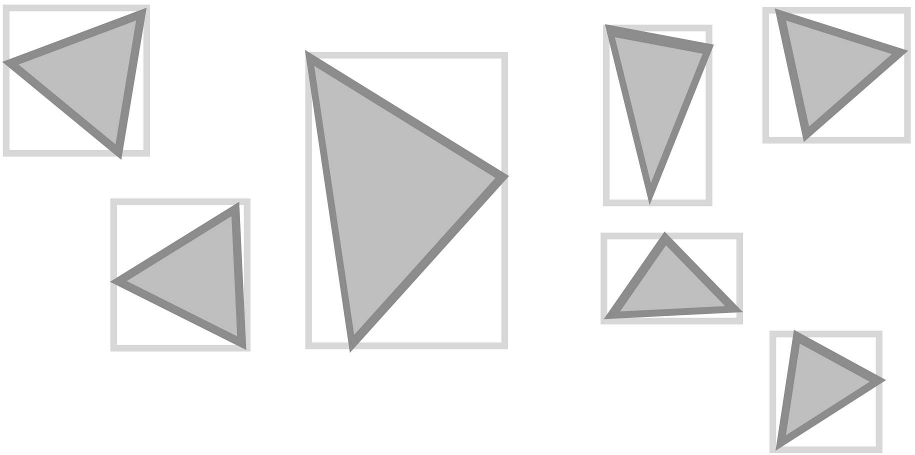
Non-decreasing property [Walter et al. 2008]

$$d(C_1, C_2) \leq d(C_1 \cup C_3, C_2) \;:\; \forall\; C_1, C_2, C_3$$

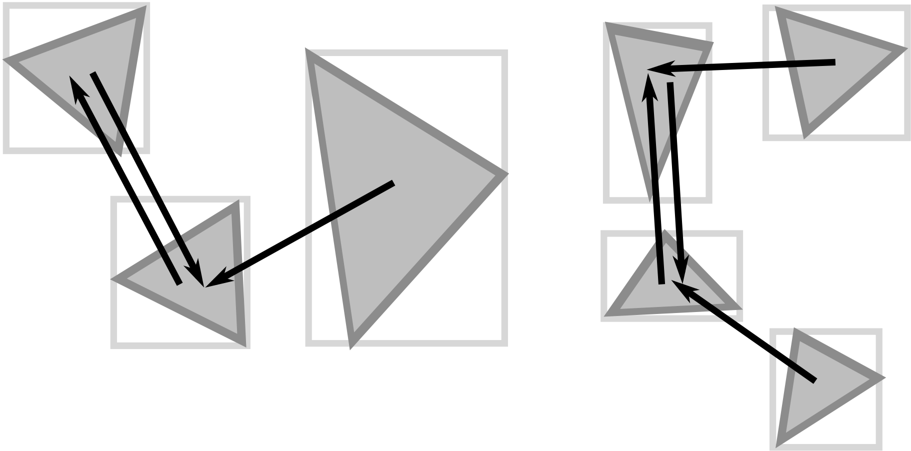


We can merge mutually corresponding clusters!

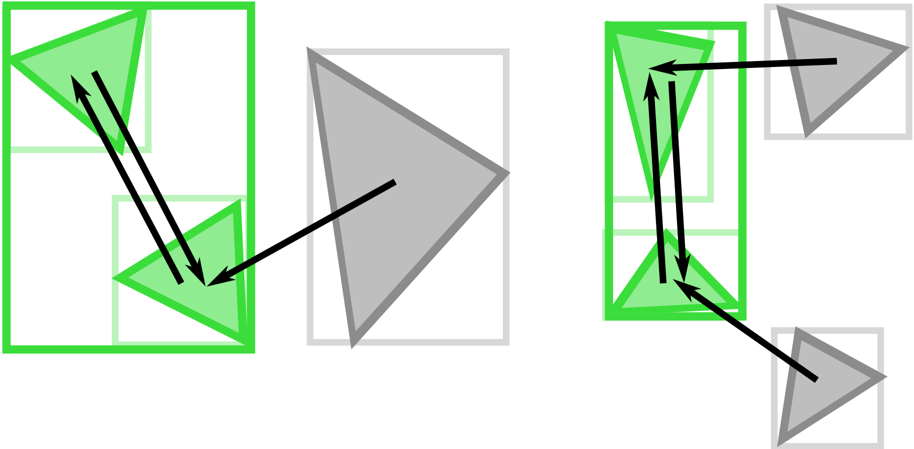
Parallel Locally-Ordered Clustering



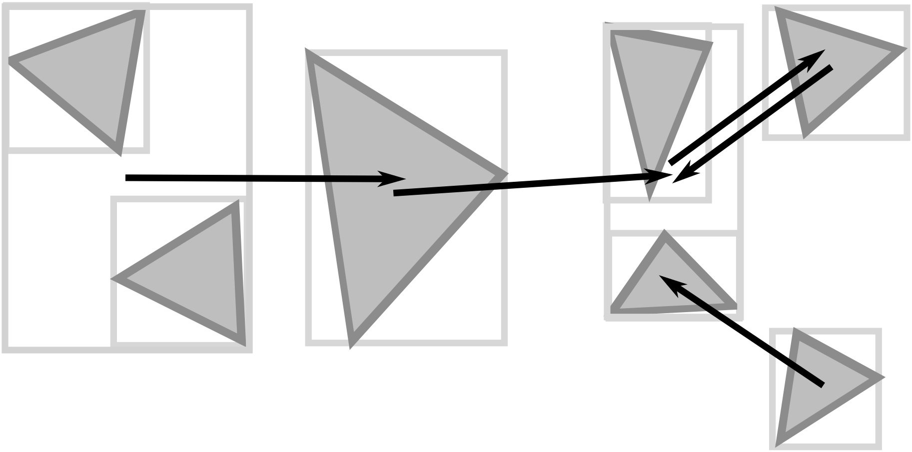
Parallel Locally-Ordered Clustering



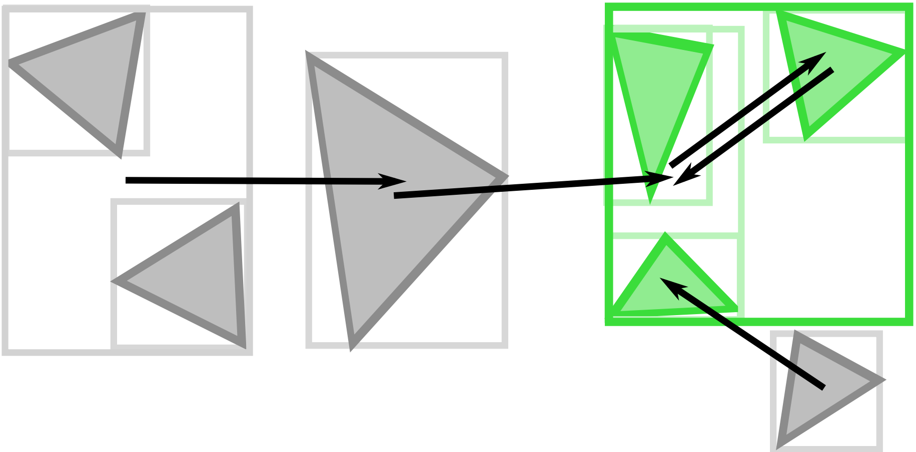
Parallel Locally-Ordered Clustering



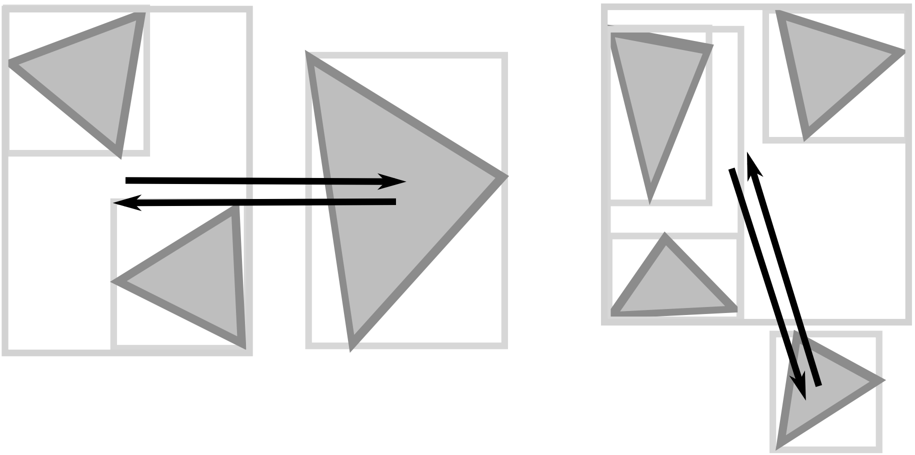
Parallel Locally-Ordered Clustering



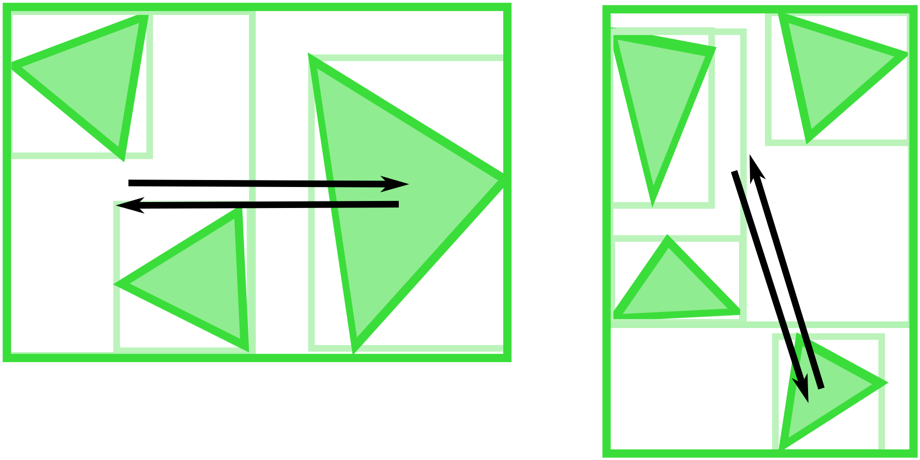
Parallel Locally-Ordered Clustering



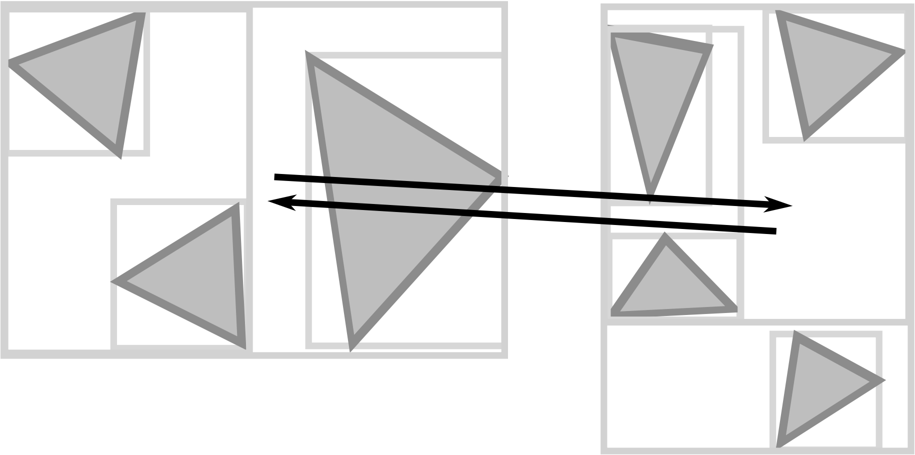
Parallel Locally-Ordered Clustering



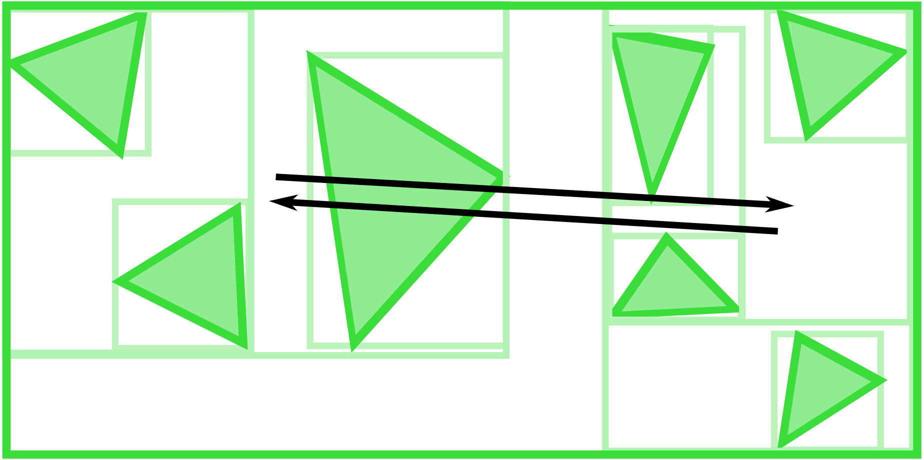
Parallel Locally-Ordered Clustering



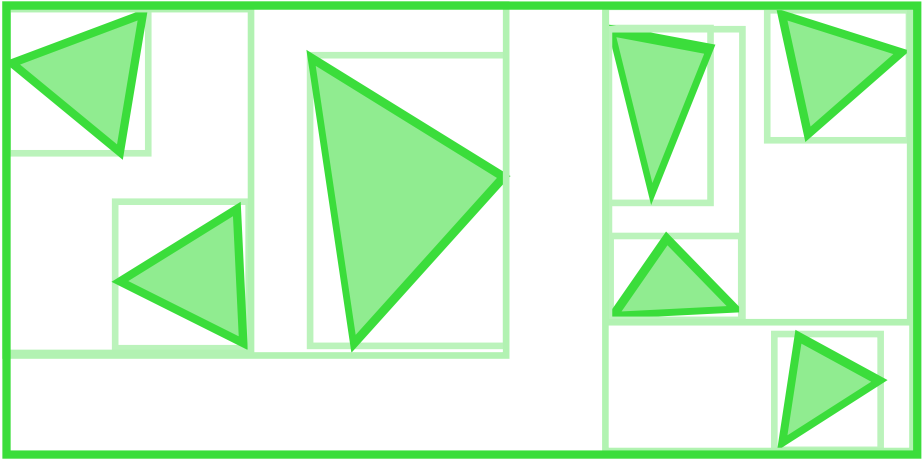
Parallel Locally-Ordered Clustering



Parallel Locally-Ordered Clustering



Parallel Locally-Ordered Clustering



Nearest Neighbor Search

Nearest Neighbor Search

Naïve approach

- Time complexity $\mathcal{O}(n^2)$
- Prohibitive for practical use

Nearest Neighbor Search

Naïve approach

- Time complexity $\mathcal{O}(n^2)$
- Prohibitive for practical use

kD-tree [Walter et al. 2008]

- Difficult to implement
- Not suitable for parallel processing

Nearest Neighbor Search

Naïve approach

- Time complexity $\mathcal{O}(n^2)$
- Prohibitive for practical use

kD-tree [Walter et al. 2008]

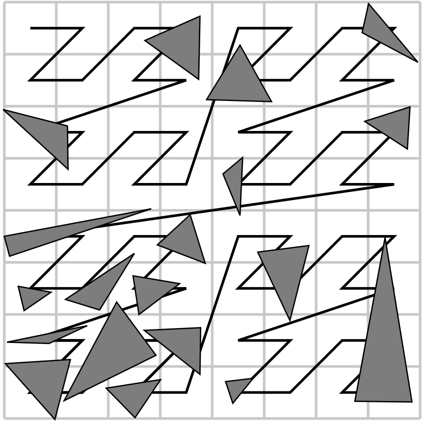
- Difficult to implement
- Not suitable for parallel processing

Morton curve (our approach)

- Sort clusters along the Morton curve
- Search in the sorted array around a given cluster
- Neighborhood around the cluster determined by radius parameter r

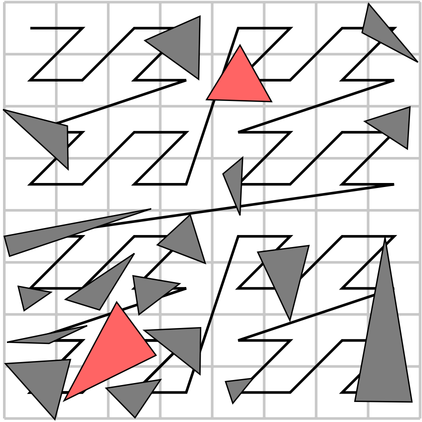
Approx. Nearest Neighbors along Morton Curve

Neighborhood determined by radius $r = 2$



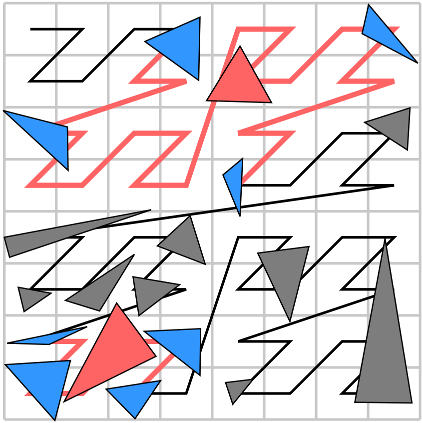
Approx. Nearest Neighbors along Morton Curve

Neighborhood determined by radius $r = 2$



Approx. Nearest Neighbors along Morton Curve

Neighborhood determined by radius $r = 2$



Algorithm Overview

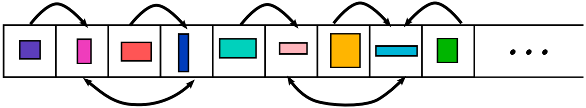
Algorithm Overview

Repeat until one cluster remains

Algorithm Overview

Repeat until one cluster remains

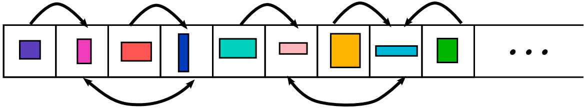
- Search nearest neighbor (in parallel)



Algorithm Overview

Repeat until one cluster remains

- Search nearest neighbor (in parallel)

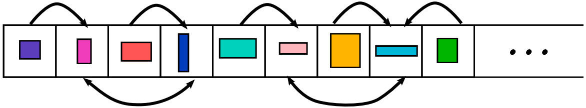


- Merge (in parallel)

Algorithm Overview

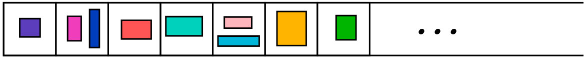
Repeat until one cluster remains

- Search nearest neighbor (in parallel)

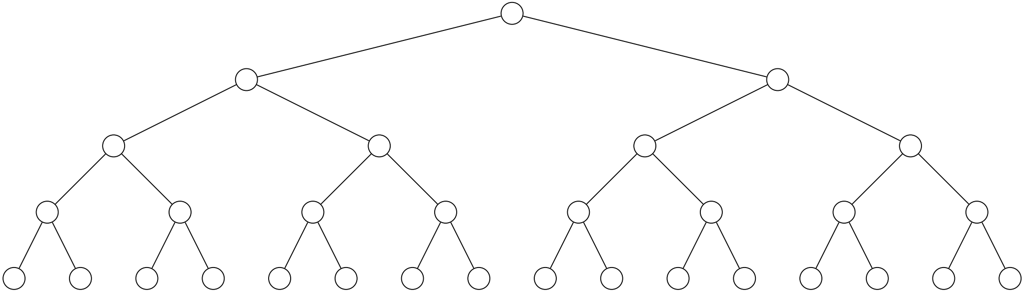


- Merge (in parallel)

- Compact via prefix scan (in parallel)

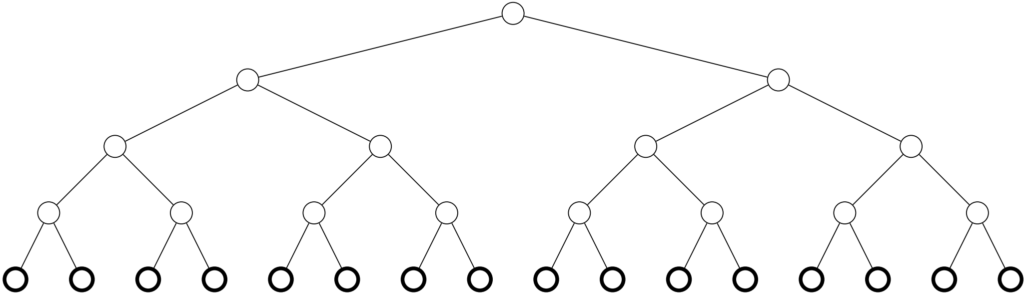


Parallel Subtree Collapsing



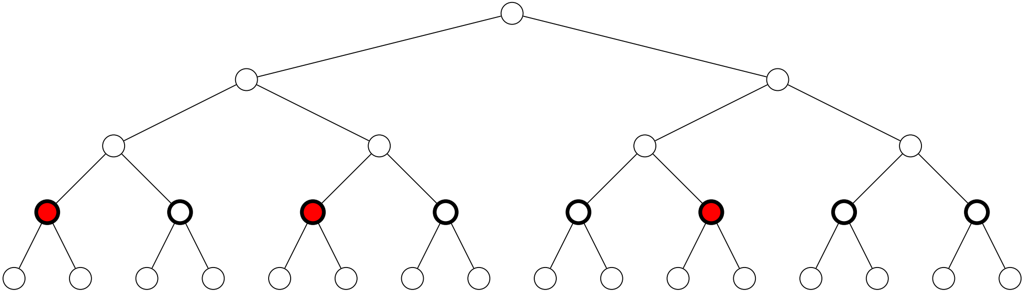
Parallel Subtree Collapsing

1. Decide whether collapsing pays off



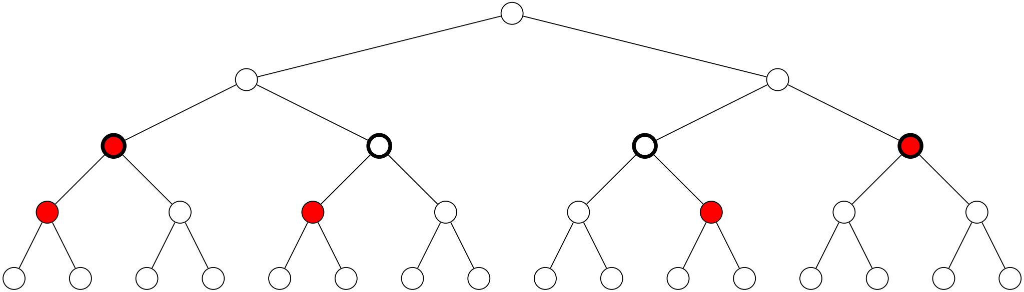
Parallel Subtree Collapsing

1. Decide whether collapsing pays off



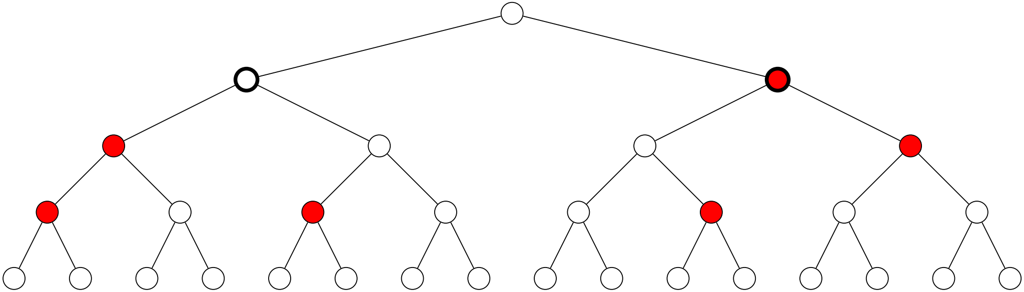
Parallel Subtree Collapsing

1. Decide whether collapsing pays off



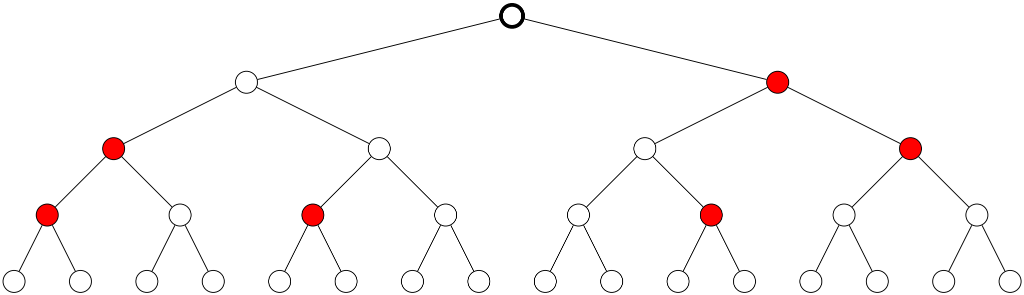
Parallel Subtree Collapsing

1. Decide whether collapsing pays off



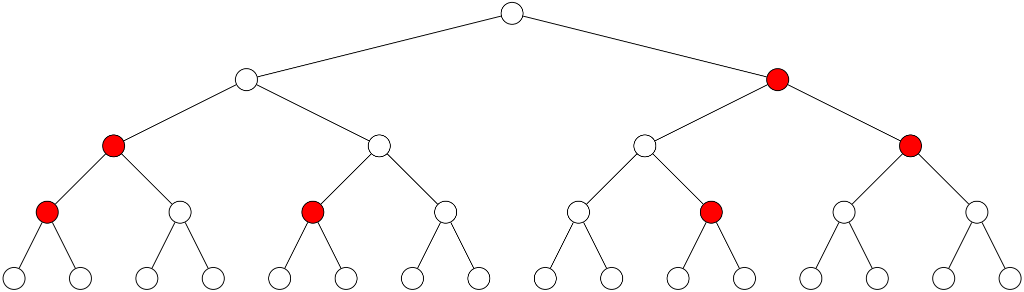
Parallel Subtree Collapsing

1. Decide whether collapsing pays off



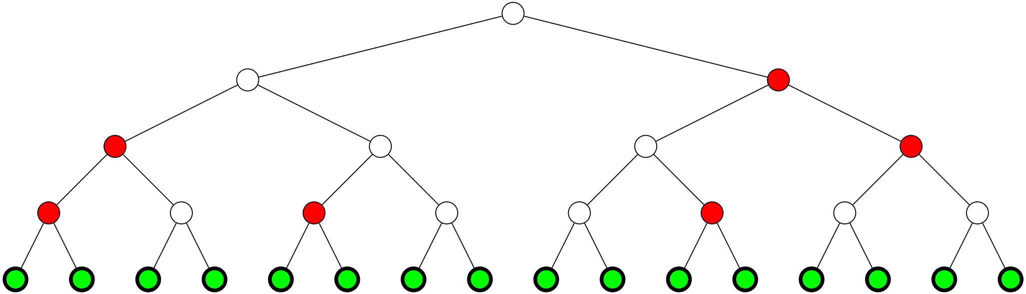
Parallel Subtree Collapsing

1. Decide whether collapsing pays off
2. Identify leaf nodes (i.e. roots of collapsed subtrees)



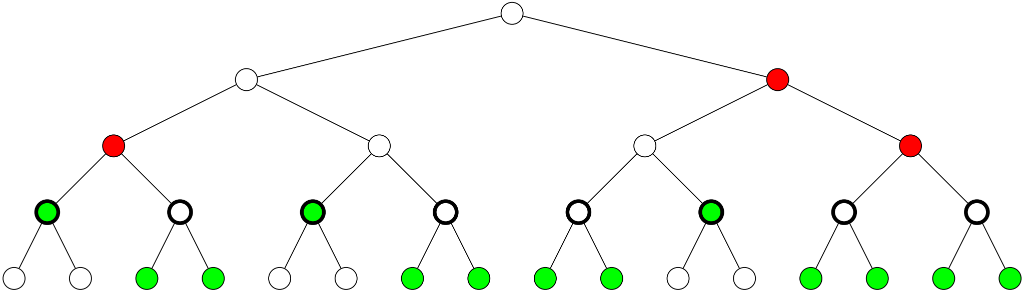
Parallel Subtree Collapsing

1. Decide whether collapsing pays off
2. Identify leaf nodes (i.e. roots of collapsed subtrees)



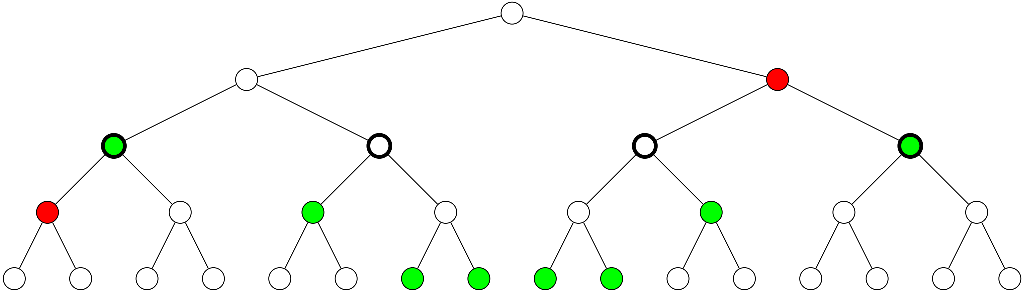
Parallel Subtree Collapsing

1. Decide whether collapsing pays off
2. Identify leaf nodes (i.e. roots of collapsed subtrees)



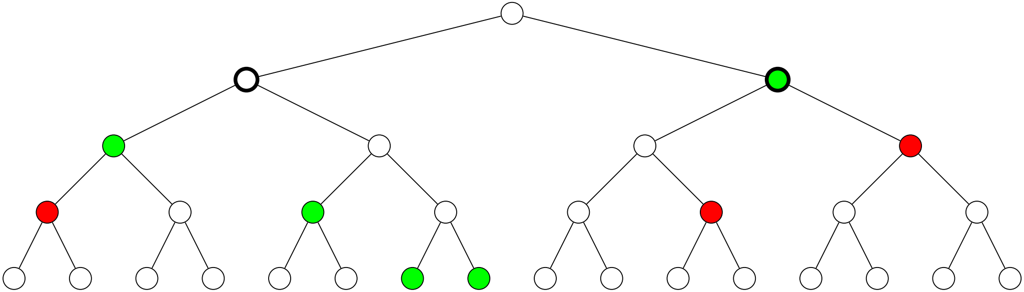
Parallel Subtree Collapsing

1. Decide whether collapsing pays off
2. Identify leaf nodes (i.e. roots of collapsed subtrees)



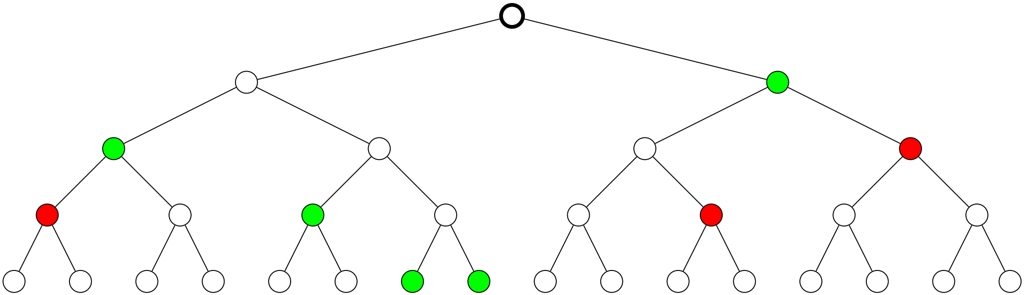
Parallel Subtree Collapsing

1. Decide whether collapsing pays off
2. Identify leaf nodes (i.e. roots of collapsed subtrees)



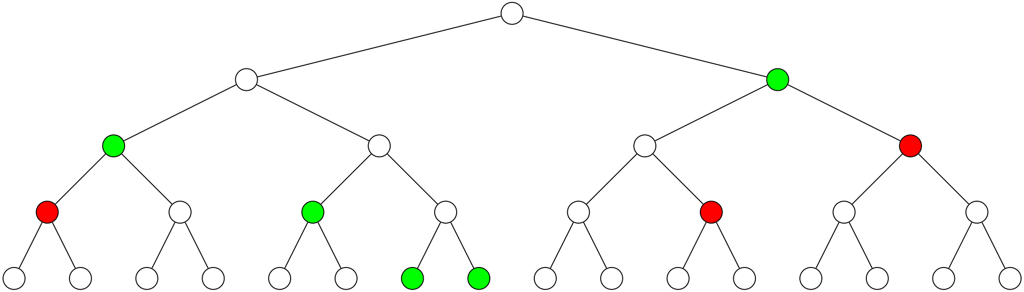
Parallel Subtree Collapsing

1. Decide whether collapsing pays off
2. Identify leaf nodes (i.e. roots of collapsed subtrees)



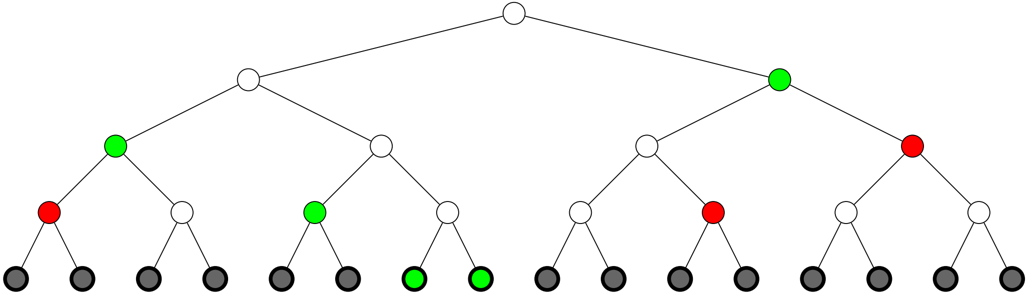
Parallel Subtree Collapsing

1. Decide whether collapsing pays off
2. Identify leaf nodes (i.e. roots of collapsed subtrees)



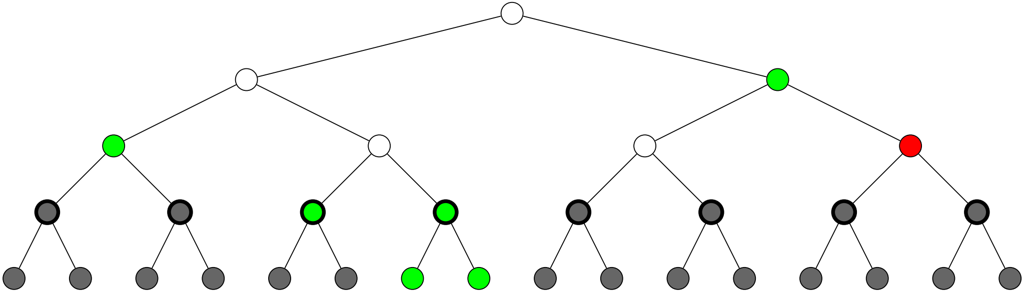
Parallel Subtree Collapsing

1. Decide whether collapsing pays off
2. Identify leaf nodes (i.e. roots of collapsed subtrees)
3. Mark nodes as valid or invalid



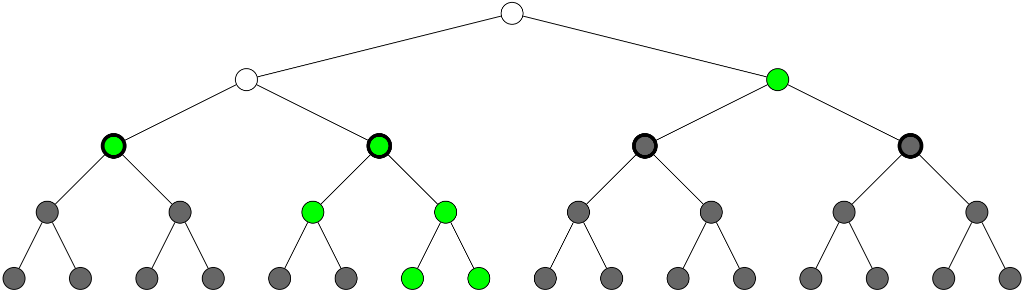
Parallel Subtree Collapsing

1. Decide whether collapsing pays off
2. Identify leaf nodes (i.e. roots of collapsed subtrees)
3. Mark nodes as valid or invalid



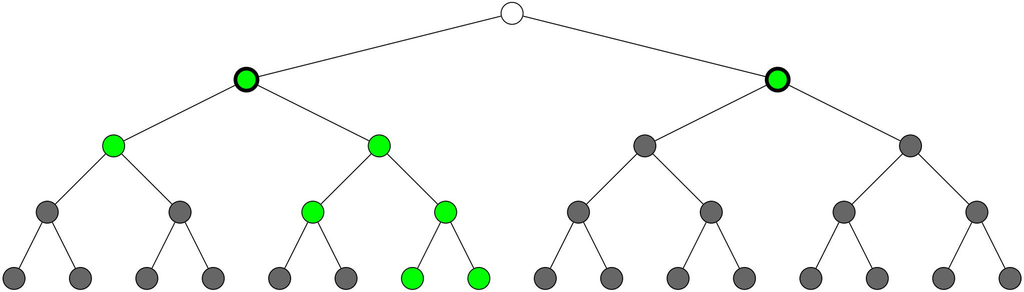
Parallel Subtree Collapsing

1. Decide whether collapsing pays off
2. Identify leaf nodes (i.e. roots of collapsed subtrees)
3. Mark nodes as valid or invalid



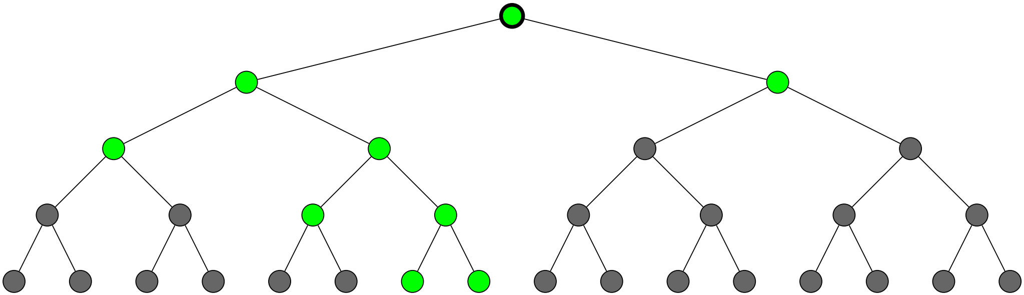
Parallel Subtree Collapsing

1. Decide whether collapsing pays off
2. Identify leaf nodes (i.e. roots of collapsed subtrees)
3. Mark nodes as valid or invalid



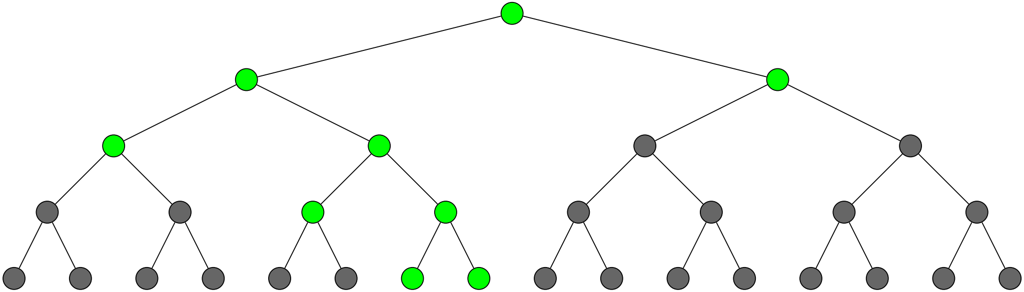
Parallel Subtree Collapsing

1. Decide whether collapsing pays off
2. Identify leaf nodes (i.e. roots of collapsed subtrees)
3. Mark nodes as valid or invalid



Parallel Subtree Collapsing

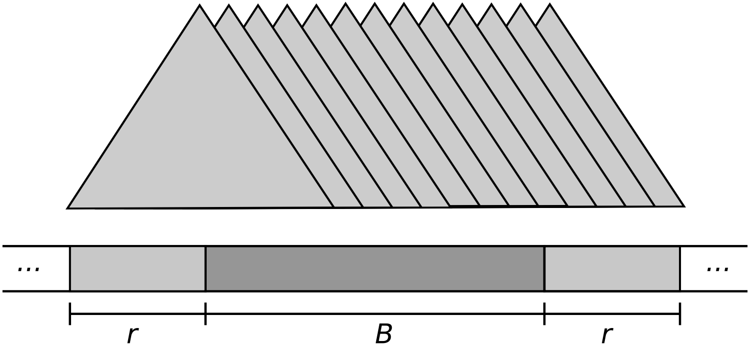
1. Decide whether collapsing pays off
2. Identify leaf nodes (i.e. roots of collapsed subtrees)
3. Mark nodes as valid or invalid



Implementation in CUDA

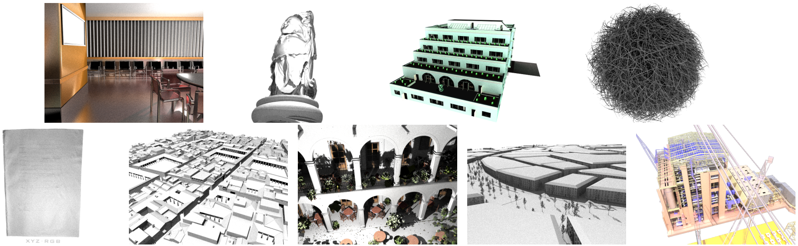
Shared memory cache of size $B + 2r$

- Block with B threads
- Radius r



Results

- 9 scenes (331k - 12759k tris)
- Path tracing (GPU ray tracing kernel [Aila and Laine 2009])
  - Low quality rendering (8 spp)
  - High quality rendering (128 spp)
- Intel Core I7-3770 3.4 GHz CPU (4 cores), 16 GB RAM
- NVIDIA GeForce GTX TITAN X (Maxwell), 12 GB RAM



Tested Methods

LBVH [Karras 2012]

- Spatial median splits

HLBVH [Garanzha et al. 2011]

- Spatial median and SAH splits

ATRBVH [Domingues and Pedrini 2015]

- Treelet restructuring by agglomerative clustering

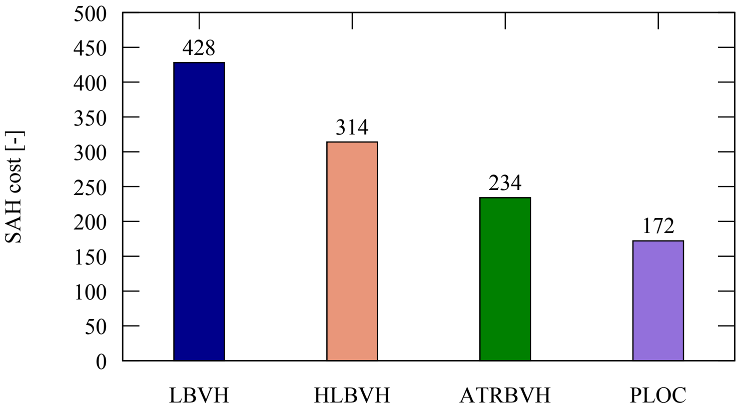
PLOC

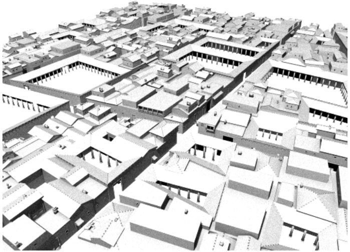
- Parallel locally-ordered clustering (our algorithm)

Adaptive leaf sizes, SAH cost constants $c_T = 3$, $c_I = 2$

Pompeii

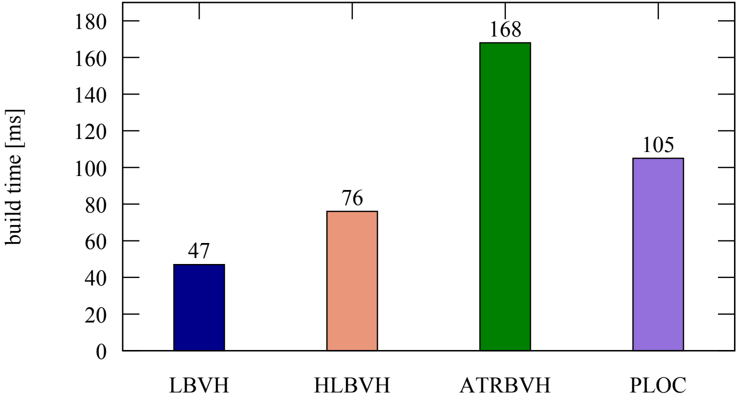
SAH cost (5632k tris, $r = 25$)

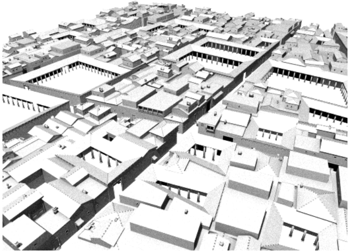




Pompeii

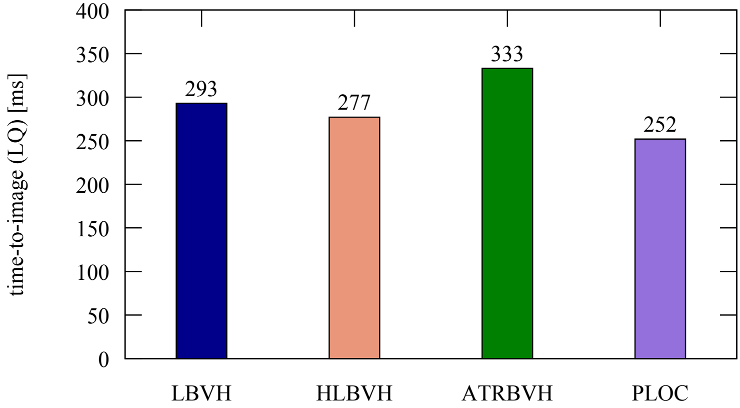
build time (5632k tris, $r = 25$)

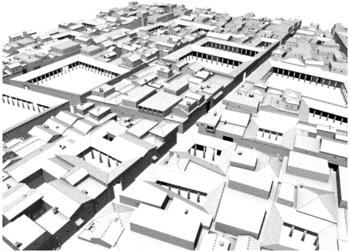




Pompeii

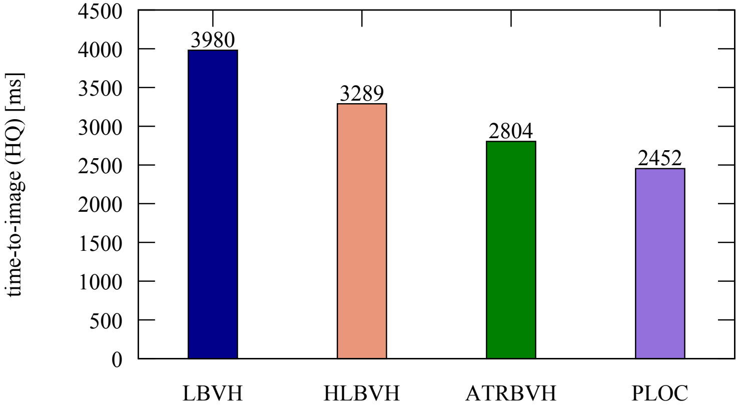
time-to-image LQ (5632k tris, $r = 25$)

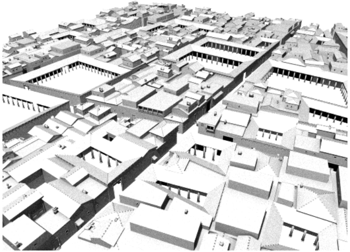




Pompeii

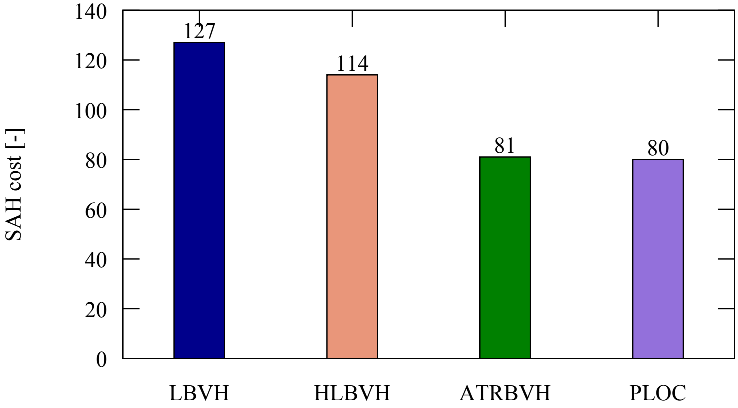
time-to-image HQ (5632k tris, $r = 25$)

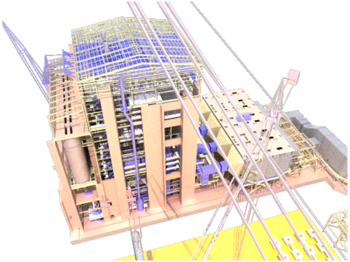




Powerplant

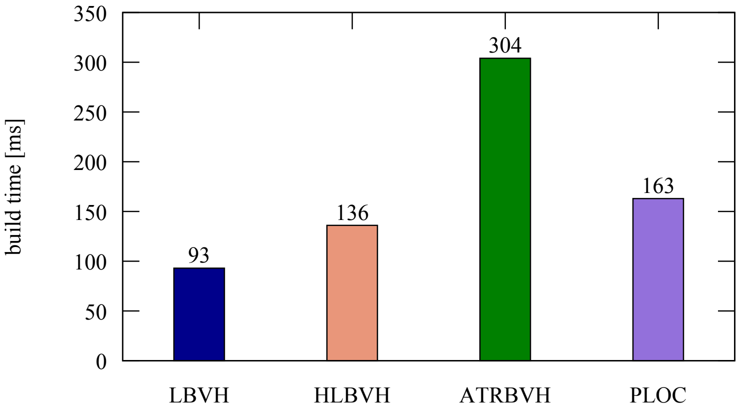
SAH cost (12759k tris, $r = 10$)

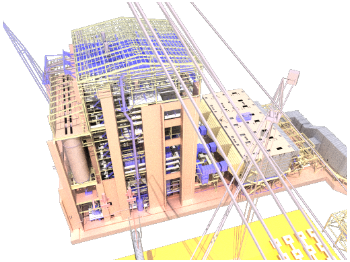




Powerplant

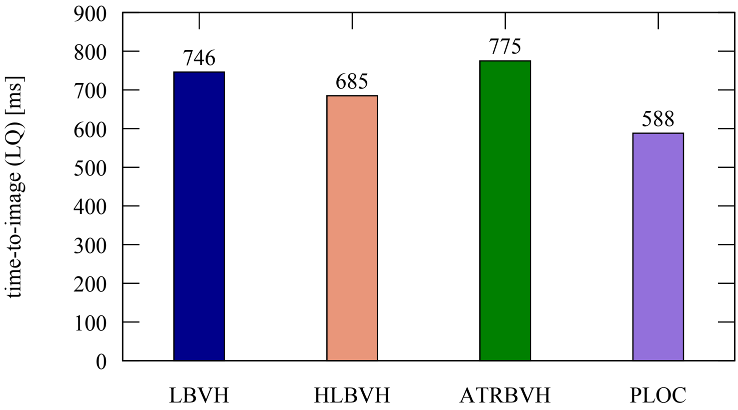
build time (12759k tris, $r = 10$)

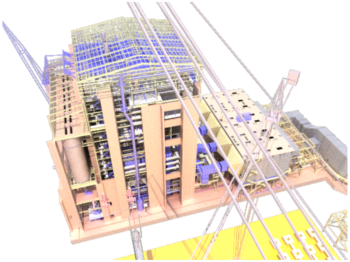




Powerplant

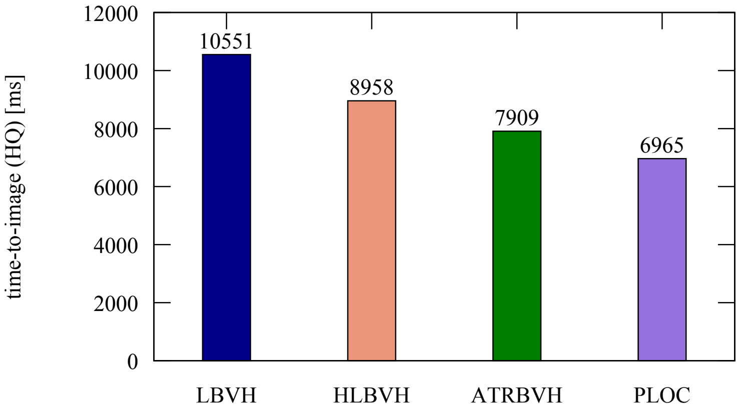
time-to-image LQ (12759k tris, $r = 10$)

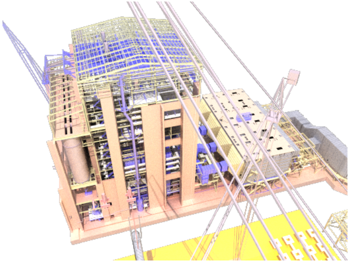




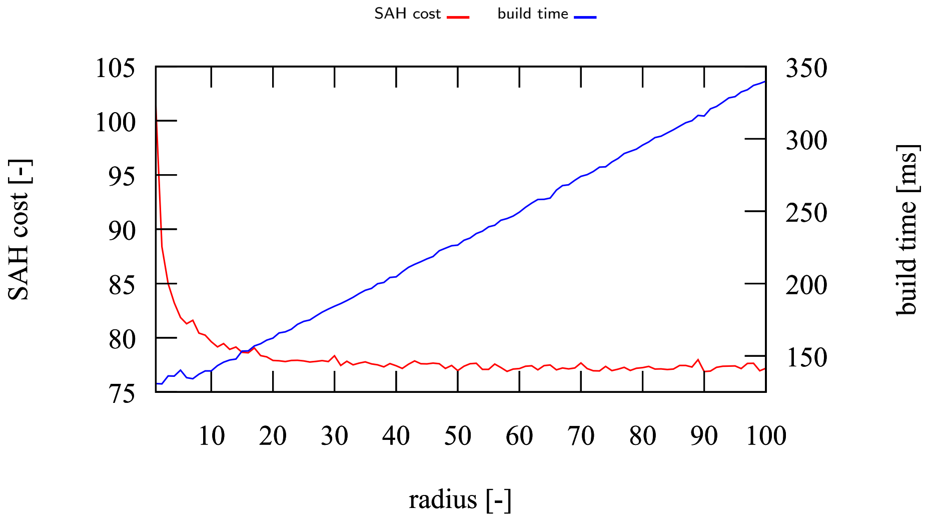
Powerplant

time-to-image HQ (2759k tris, $r = 10$)

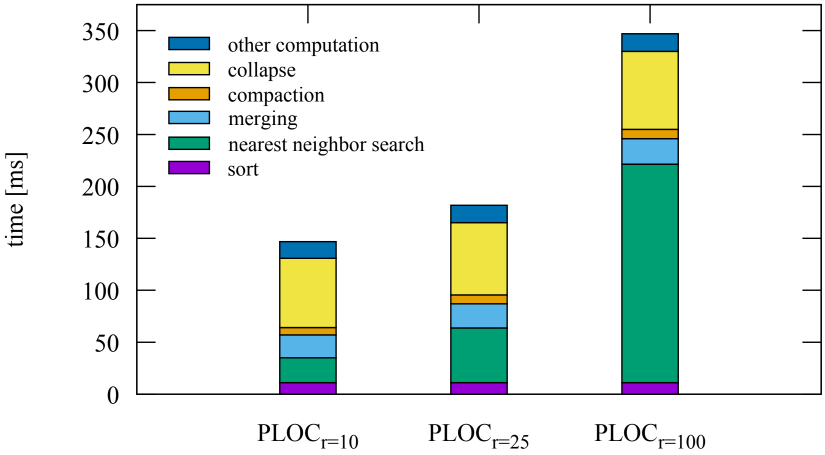




Powerplant


SAH cost
build time
SAH cost [-]
build time [ms]
radius [-]
105
100
95
90
85
80
75
350
300
250
200
150
10
20
30
40
50
60
70
80
90
100

Powerplant



time [ms]
350
300
250
200
150
100
50
0
other computation
collapse
compaction
merging
nearest neighbor search
sort
PLOC$_{r=10}$
PLOC$_{r=25}$
PLOC$_{r=100}$

Conclusion and Future Work

GPU-based BVH construction using appr. agglomerative clustering

- Efficient and extremely simple
- Parallel subtree collapsing
- Implementation in CUDA with released source codes

Future work

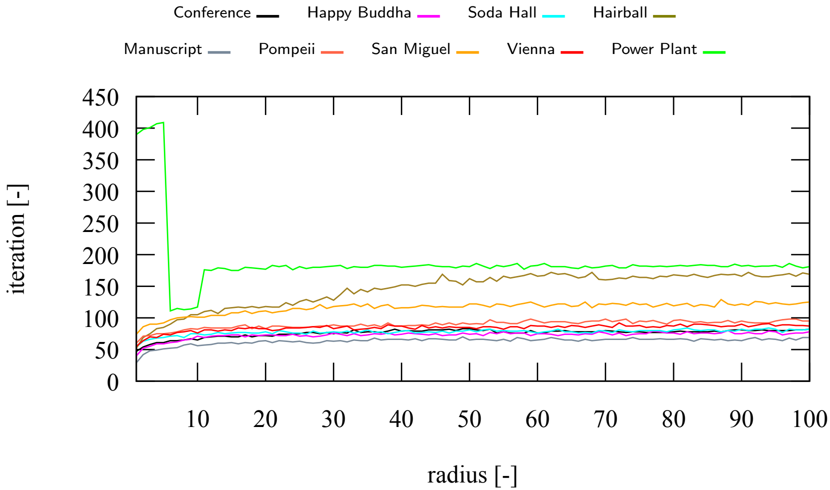
- Varying radius across different iterations
- Extended Morton codes [Vinkler et al. 2017]

Thank you for your attention!

The project website with source codes

`http://dcgi.fel.cvut.cz/projects/ploc/`

Iterations


Conference
Happy Buddha
Soda Hall
Hairball
Manuscript
Pompeii
San Miguel
Vienna
Power Plant
iteration [-]
radius [-]
0
50
100
150
200
250
300
350
400
450
10
20
30
40
50
60
70
80
90
100

Comparison with AAC

Approximate agglomerative clustering [Gu et al. 2013]