

20th EG/VGTC Conference on Visualization



Rapid k-d tree construction for sparse volume data

Stefan Zellmann*, Jürgen Schulze**, Ulrich Lang*

* University of Cologne

** University of California San Diego





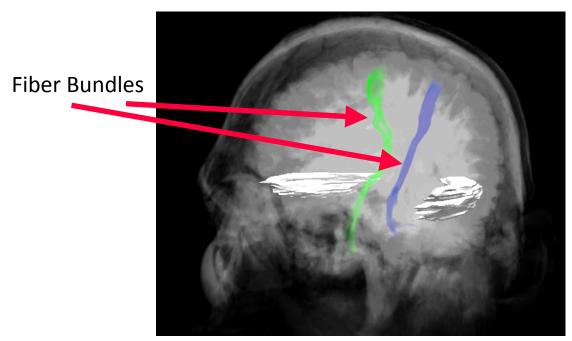
Sparse Volume Data

- Background: stereotactic operation planning
 - Insert "brain pacemaker" at designated position, Parkinson treatment.
 - Pacemaker: tiny probe, pushed using a stereotactic needle
- Datasets with multiple (~10-15) volume channels:
 - CT, T1/T2 MRI + Functional MRI
 - *Probabilistic* Fiber Tracking with FSL ([0..1] density volumes, each voxel denotes probability that fibers overlap)
 - Fiber bundles extremely sparse
 - Blood vessels as separate channel, also rather sparse
- Our goal (long term): real-time (VR-ready) visualization of multiple sparse channels





Sparse Volume Data



MR data set with two fiber bundles - each fiber bundle is a sparse volume channel

Objective: find path way for operation w/o penetrating vessels, liquor or fiber bundles.

Planning process guided by visualization

Visualization:

- Interactive (3D stereo)
- User can switch channels on/off
- Separate transfer function per volume channel





Sparse Volume Rendering

- Many channels, will likely not all fit into VRAM
 - even then, bandwidth is the limiting factor
 - ==> we simply need spatial indexing for sparse channels
- Mandatory: interactive transfer function editing
 - hard problem: rebuild spatial index in real-time
 - luckily, single channel moderately sized (256³ to 512³)

- We base our work on previous work from Vidal et al.: *Simple empty-space removal for interactive volume rendering* (2008)
- First build a summed volume table (SVT) for the whole volume

0	0	0	1	2
0	0	1	0	0
1	0	3	2	2
0	0	1	1	0
0	0	0	1	0

0	0	0	1	3
0	0	1	2	4
1	1	5	8	12
1	1	6	10	14
1	1	6	11	15





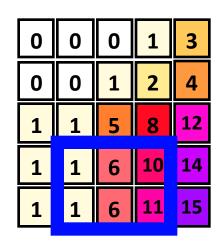
- This is actually a (2D) summed *area* table (very similar in 3D)
- Constant time occupancy queries

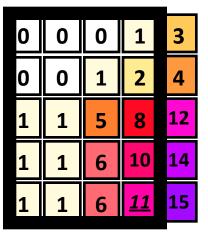
0	0	0	1	3
0	0	1 2		4
1	1	5	8	12
1	1	6	10	14
1	1	6	11	15

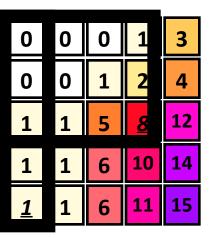


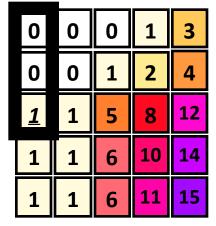
k-d Tree Construction for Sparse Volumes

- This is actually a (2D) summed area table (very similar in 3D)
- Constant time occupancy queries









1.) Density in this box?

D=

2.) Density in that bigger box

11

3.) Minus densityin those two boxes- (8+1)

4.) But wait, we subtracted this here twice!

7





- So that seems about right
- With SVTs it's eight rather than four memory accesses

0	0	0	1	2
0	0	1	0	0
1	0	3	2	2
0	0	1	1	0
0	0	0	1	0



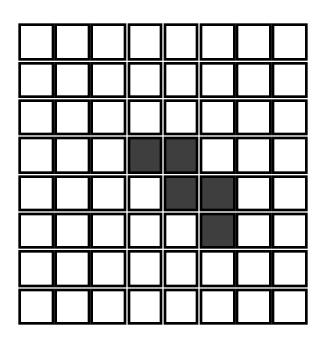
- With SVTs we can find tight bounding boxes around occupied regions
- Let's consider a different case: binary voxels, and sparse

	1	2	2	2	2
	1	3	4	4	4
	1	3	5	5	5
	1	3	5	5	5
	1	3	5	5	5





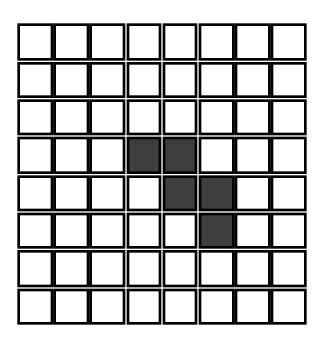
- We just find an initial bounding box and shrink it iteratively
- Density: 5



	1	2	2	2	2
	1	3	4	4	4
	1	3	5	5	5
	1	3	5	5	5
	1	3	5	5	5



- We just find an initial bounding box and shrink it iteratively
- First in x-direction. Still 5



\square						
		1	2	2	2	2
		1	3	4	4	4
		1	3	5	5	5
		1	3	5	5	5
		1	3	5	5	5



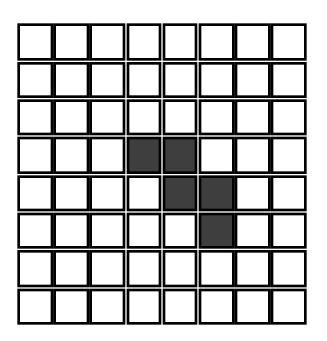
- We just find an initial bounding box and shrink it iteratively
- First in x-direction. And still.. 5

	1	2	2	2	2
	1	3	4	4	4
	1	3	5	5	5
	1	3	5	5	5
	1	3	5	5	5





- We just find an initial bounding box and shrink it iteratively
- Ok, no step further, next we'd be < 5

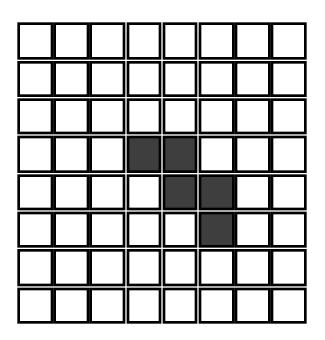


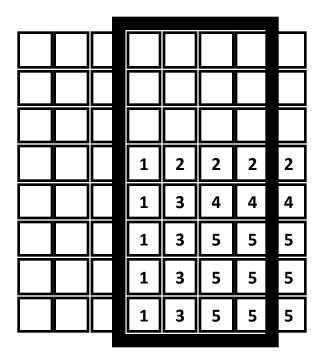
	1	2	2	2	2
	1	3	4	4	4
	1	3	5	5	5
	1	3	5	5	5
	1	3	5	5	5





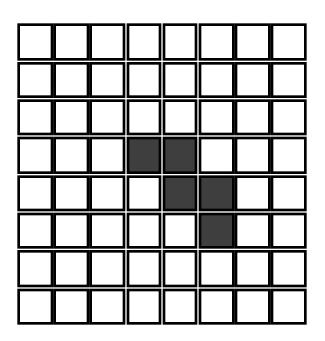
- We just find an initial bounding box and shrink it iteratively
- negative x. Density is 5

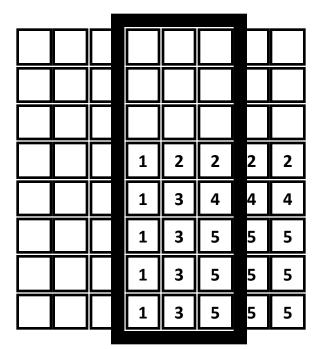






- We just find an initial bounding box and shrink it iteratively
- negative x so here's a slope again, so full stop







- We just find an initial bounding box and shrink it iteratively
- same thing with y and -y

	1	2	2	2	2
	1	3	4	4	4
	1	3	5	5	5
	1	3	5	5	5
	1	3	5	5	5



- We just find an initial bounding box and shrink it iteratively
- same thing with y and -y

	1	2	2	2	2
	1	3	4	4	4
	1	3	5	5	5
	1	3	5	5	5
	1	3	5	5	5



- We just find an initial bounding box and shrink it iteratively
- same thing with y and -y

	1	2	2	2	2
	1	3	4	4	4
	1	3	5	5	5
	1	3	5	5	5
	1	3	5	5	5



- We just find an initial bounding box and shrink it iteratively
- same thing with y and -y

	1	2	2	2	2
	1	3	4	4	4
	1	3	5	5	5
	1	3	5	5	5
	1	3	5	5	5



- We just find an initial bounding box and shrink it iteratively
- Found an AABB, contains all the voxels, since density is 5

	1	2	2	2	2
	1	3	4	4	4
	1	3	5	5	5
	1	3	5	5	5
	1	3	5	5	5





Two-Phase Algorithm

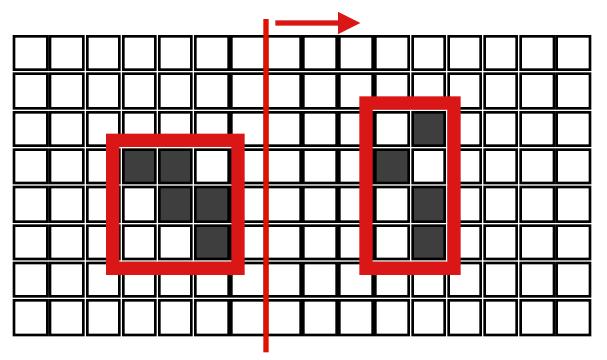
- Phase 1: (SVT Phase) construct SVT
- Phase 2: (Split Phase) use SVT to top-down construct k-d tree





Greedy Top-Down Construction

- Similar to binned surface area heuristic builders for triangles
 - Candidate planes, minimize cost function based on box volumes: $C(p) = V(B_L(p)) + V(B_R(p))$
 - Binary Split until certain criteria like min. AABB volume etc. apply

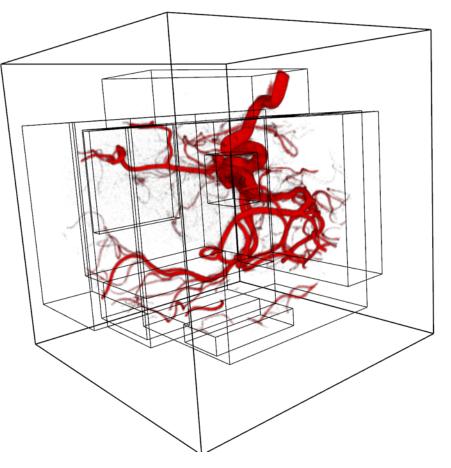






Greedy Top-Down Construction

- Result: non-overlapping boxes that we can sort back-to-front (k-d tree traversal)
- Volume rendering for each box
- Or an outer loop over boxes for the ray marcher

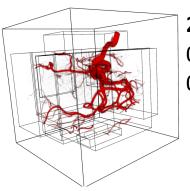




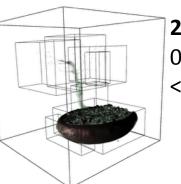


Problem with the Approach

- Serial construction algorithm dominated by SVT construction time
 - SVT invalid after transfer function has changed

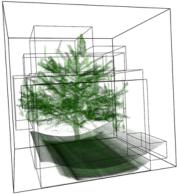


256³ voxels 0.180 sec. SVT construction 0.002 sec. top-down build

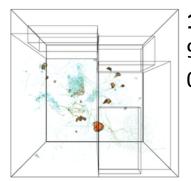


256³ voxels

0.180 sec. SVT construction < 0.001 sec. top-down build



512² x 499 voxels 1.436 sec. SVT construction 0.007 sec. top-down build



1000² x 910 voxels 9.361 sec. SVT construction 0.020 sec. top-down build

Parallel Construction Algorithm

- Multi-Core CPU: build only partial SVTs (in parallel!)
 - Volume bricks that fit into L1 memory (on our machine: 32³ bricks)
- Whenever we want to find a tight AABB:
 - First find tight AABBs in L1 within bricks (in parallel!)
 - Then trivially combine the AABBs (serial min/max combine) to find the global tight AABB
- Enables parallelism with an otherwise rather serial algorithm
- Memory accesses fully cached
- Top-down construction slightly more time-consuming
 - Shifts construction time SVT construction to top-down builder





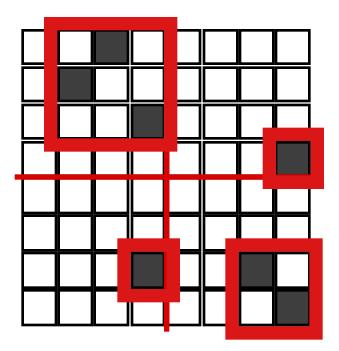
Find Bounds with Partial SVTs

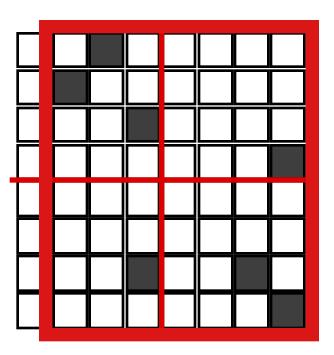
	1					
1	2	2				
1	2	3				
1	2	3			1	
		1		1	1	
		1		1	2	





Find Bounds with Partial SVTs





Find **local bounds** in parallel and in L1

Find **global bounds** with trivial combine



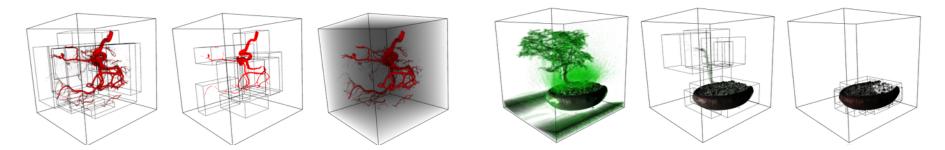


Results

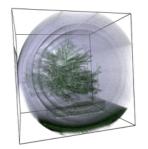
4 datasets (3 well-known, 1 from microbiology, courtesy Kei Ito, University of Cologne), **3 transfer functions**

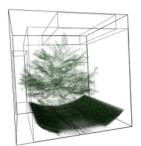
256³ voxels

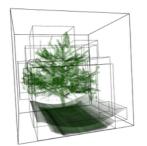
256³ voxels



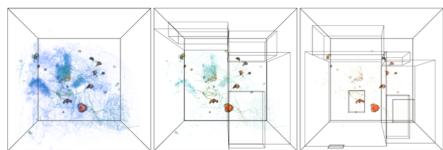
512² x 499 voxels







1000² x 910 voxels

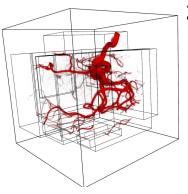




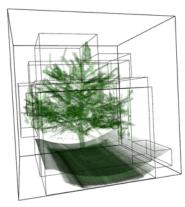


Results

Intel Core i7-3960X processor, 6 Cores, 12 Threads, **Times in sec., three different transfer functions**



2	256 ³ vo	xels			256 ³ vo	oxels		
		SVT	SPLIT	TOTAL		SVT	SPLIT	TOTAL
	SERIAL	0.179	0.002	0.181	SERIAL	0.180	0.001	0.181
	PAR.	0.020	0.002 - 0.016	0.022 - 0.036	PAR.	0.026	0.003 - 0.014	0.029 - 0.040



512 ² x 499 voxels						1000 ² x 910 voxels			
		SVT	SPLIT	TOTAL			SVT	SPLIT	TOTAL
	SERIAL	1.436	0.004	1.440		SERIAL	9.361	0.020	9.381
	PAR.	0.192	0.036 - 0.148	0.226 - 0.340		PAR.	1.103	1.692 - 4.114	2.795 - 5.217





Conclusion

- Parallel *k*-d tree construction algorithm based on prior work by Vidal et al. (2008)
- Optimized for multi-core architecture
- Good scalability for moderately sized data sets, promising for larger data sets
 - Just meets our use case: moderately sized volumes from radiology
- Whole idea based on keeping underlying SVT data set in thread-local L1 memory to exploit parallelism
 - Wagers SVT construction time for split-plane sweeping overhead
 - A win: SVT construction time *the* dominant bottleneck with serial variant of the algorithm
- Future work: scale with larger datasets, distributed memory systems, construction on the GPU