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ExTreeM: Scalable Augmented Merge Tree Computation via Extremum Graphs

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RP





Motivation





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ExTreeM-Algorithm





ExTreeM-Algorithm





ExTreeM-Algorithm







- use path compression:
 - each vertex points to largest neighbor
 - maxima point to themselves
 - in each step replace your pointer with the pointer of your pointer
 - repeat until all pointers converge to the maxima

$$(0) \rightarrow (1) \rightarrow (2) \rightarrow (2)$$





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Critical Point Computation

lower link, for split tree upper link





• critical points are characterized by the connectivity of their upper and

Critical Point Computation

- critical points are characterized by the connectivity of their upper and lower link, for split tree upper link
- a vertex can only be a split / merge saddle if its upper link vertices lead to at least two distinct maxima through a monotone path • this is already recorded in the descending manifold



Critical Point Computation









Extremum Graph Computation

























Merge Tree Augmentation





Results

Dataset

Jet in Crossflow [18] $1408 \times 1080 \times 1100$ (0.03) Unstructured Richtmyer-Meshk $\sim 7 \times 10^6$ vertices, $\sim 42 \times 10^6$ edges Perlin Noise

1024³ (23.20%)



				0.5.5			4		
	Dataset		Algorithm	SU	56T	32T	16T	8T	
	ctBones [41]		PPP	3.48	1.74	1.90	2.50	3.96	
	128 ³ (3.26%)		FTM-Tree	14.34	7.17	5.13	4.37	5.08	5
	Backpack [24]	1	ExTreeM	-	4.42	4.67	6.81	10.58	14
	$512 \times 512 \times 373$ (4)	.79%)	PPP ETM Tree	3.03	13.41	15.59	21.89	34.97	64
			F1M-free ExTreeM	14.52	21.58	45.28	40.27	44.09	60
	Magnetic Reconnecti	on [20]	PPP	2.95	63.72	73.39	103.75	164.92	210
	512° (8.84%)		FTM-Tree	42.35	914.22	787.64	865.48	830.96	820
	Rayleigh-Taylor instab	ility [11]	ExTreeM	-	14.21	21.50	39.16	72.56	137
	1024 ³ (0.30%))	PPP ETM Tree	8.01	113.76	157.82	262.92	482.16	738
	Neurons in Marmos	et [16]	ExTreeM	10.41	32.34	37.39	48.04	67.86	- 370
	$1024 \times 1024 \times 314$ (1	.5.21%)	PPP	2.05	66.18	76.14	105.82	157.29	280
	Kingsnake [36]	ExTreeM	-	36.34	43.99	59.17	93.39	128
	1024 × 1024 × 795 (4	4.71%)	PPP	2.79	97.97	118.47	170.53	272.38	445
	Jet in Crossflow [$1408 \times 1080 \times 1100$	18]	Ex Tree M	- 11 20	14.26	21.39	37.51	71.55	134
	Richtmyer-Meshkov inst	ability [10]	ExTreeM	-	39.15	56.85	98.95	182.57	287
	$1536 \times 1536 \times 1408$ ((0.31%)	PPP	5.01	196.00	258.66	422.94	756.77	1316
	Unstructured Richtmyer-M	feshkov [10]	ExTreeM	-	1.48	1.76	2.57	4.12	e
	\sim 7×10 ⁶ vertices, \sim 42×10 ⁶ e	edges (12.82%)	FTM-Tree	67.85	100.42	93.76	87.38	92.12	94
	Perlin Noise		Ex TreeM	- 1 83	2.24	2.60 4.43	3.41 5.92	4.58 9.17	15
	256^3 (23.28%))	FTM-Tree	139.85	313.26	281.10	273.31	207.78	272
	Perlin Noise		ExTreeM	-	148.81	181.72	243.14	379.63	490
	1024 ³ (23.20%)	PPP	1.41	209.42	251.81	373.76	604.46	892
	Algorithm		2	U	4		-	>0	
	ExTreeM			-	·		14	.2	2(
%)	PPP	1	1.2	20		1:	59).7	1
kov [10]	ExTreeM			-	·		1		18
s (12.82%)	FTM-Tree	6	7.8	85	5	1	00).4	Ľ
	ExTreeM			-	•	14	48	8.8	3
	DDD		1	11		2	$\cap c$) /	1′
	PPP		T.,	+1	•	2	05	·	T/

-							
4 T	2T	1T					
2.11	3.27	5.98					
5.74	10.86	20.36					
5.74	6.47	9.66					
4.01	25.25	45.23					
4.44	91.50	172.45					
1.73	51.31	79.02					
0.79	105.52	195.81					
0.57	395.35	726.40					
0.62	924.67	931.89					
7.31	268.47	503.67					
8.87	1513.28	3009.64					
5.77	725.51	1284.83					
5.01	149.20	262.18					
0.86	445.43	887.27					
8.17	235.03	434.40					
5.99	823.12	1641.87					
4.80	270.67	521.87					
3.16	2386.21	4609.00					
7.42	502.10	844.03					
5.27	2110.14	4163.87					
5.97	11.60	21.68					
4.69	94.48	100.61					
5.58	9.67	16.60					
8.48	22.65	39.29					
2.25	204.69	273.59					
0.85	897.46	1811.55					
2.84	1766.66	3285.86					

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Conclusion

Contributions:

- generic merge tree computation scheme
- novel merge tree algorithm with high parallel efficiency and low memory footprint
- open-source implementation in the Topology ToolKit

Future Work:

- **Triplet Merge Tree or Parallel Peak Pruning** GPU and distributed versions of ExTreeM
- adapting the generic concept with other merge tree algorithms e.g.



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