LSL3D: a run-based CCL algorithm for 3D volumes

COMPAS 2022

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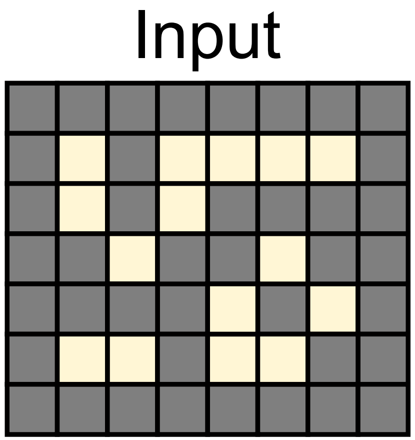
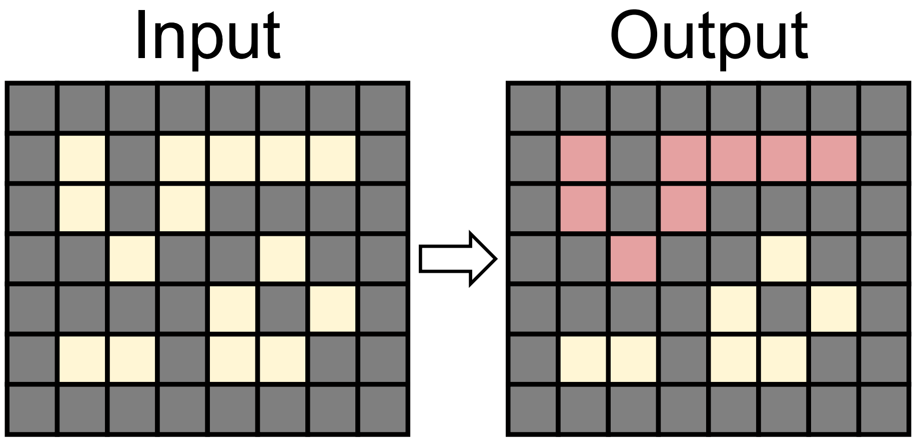
July 6, 2022

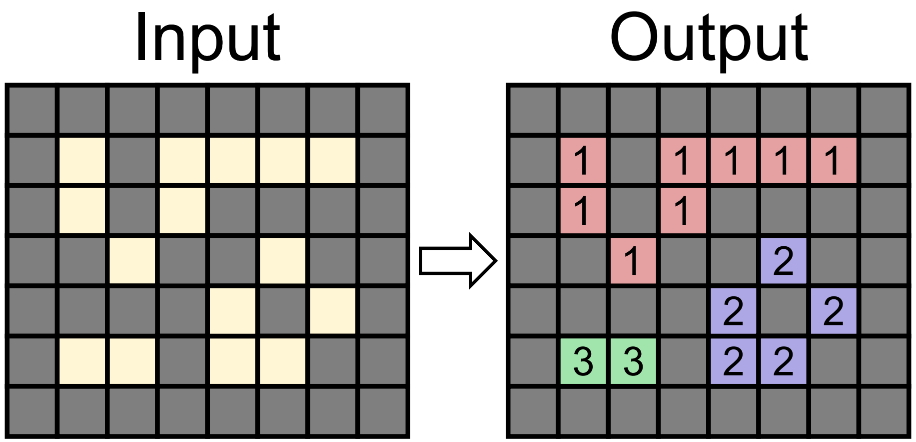
Connected Component Labeling



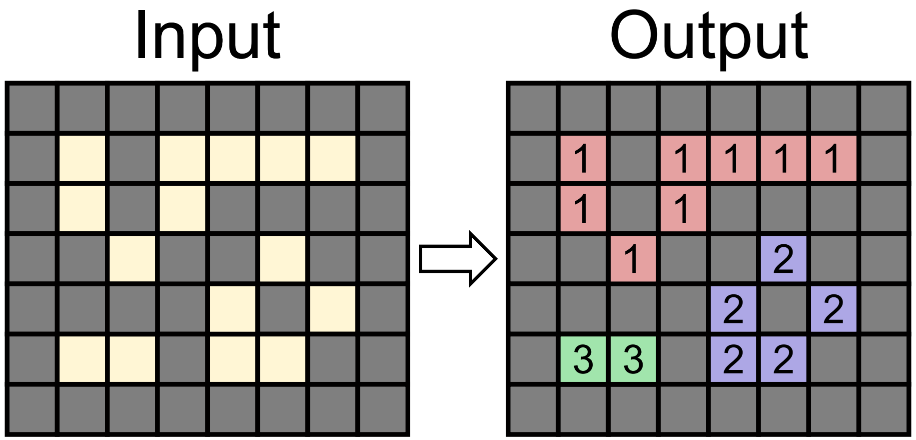
Connected Component Labeling



Connected Component Labeling



Connected Component Labeling



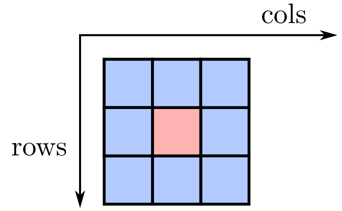
Applications: autonomous driving, biology, pre-processing for *AI*

Goals: ⇒ Performance: for real-time applications
⇒ Regularity: reduce sensitivity to image type

State of the Art: Pixel-based 2D

Naive approach: test all neighbouring pixels

Naive mask



State of the Art: Pixel-based 2D

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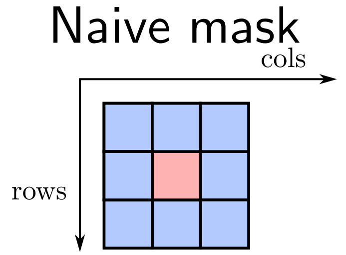
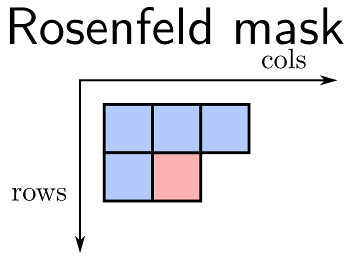


Pixel-based: Rosenfeld [1], *SAUF* [2], *LEB* [3], *PRED* [4]



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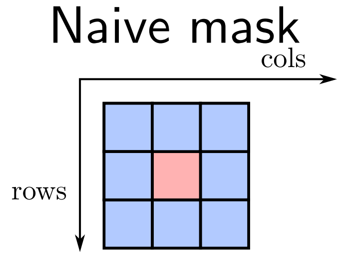

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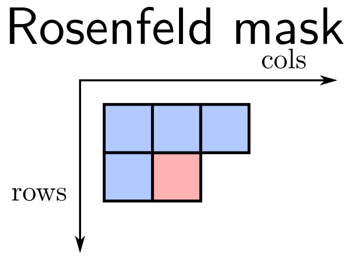
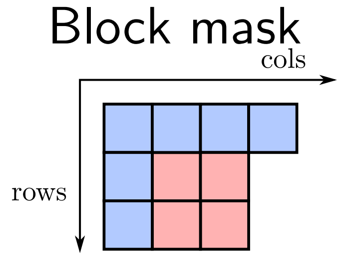


Block-based: *BBDT* [7], *Spaghetti* [8]



State of the Art: Pixel-based 2D

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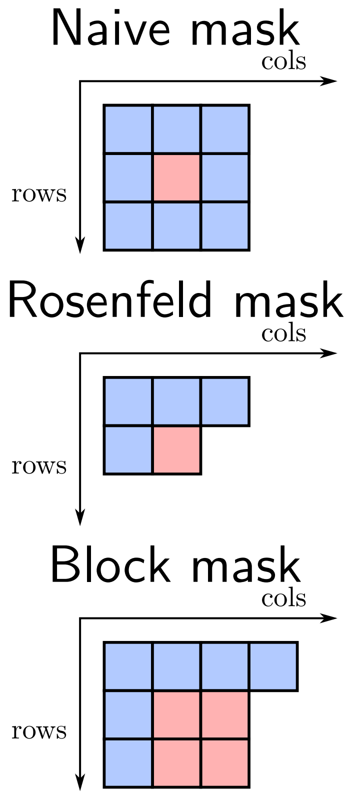
Pixel-based: Rosenfeld [1], *SAUF* [2], *LEB* [3], *PRED* [4]

Block-based: *BBDT* [7], *Spaghetti* [8]

3D algorithms: usually extensions of 2D algorithms



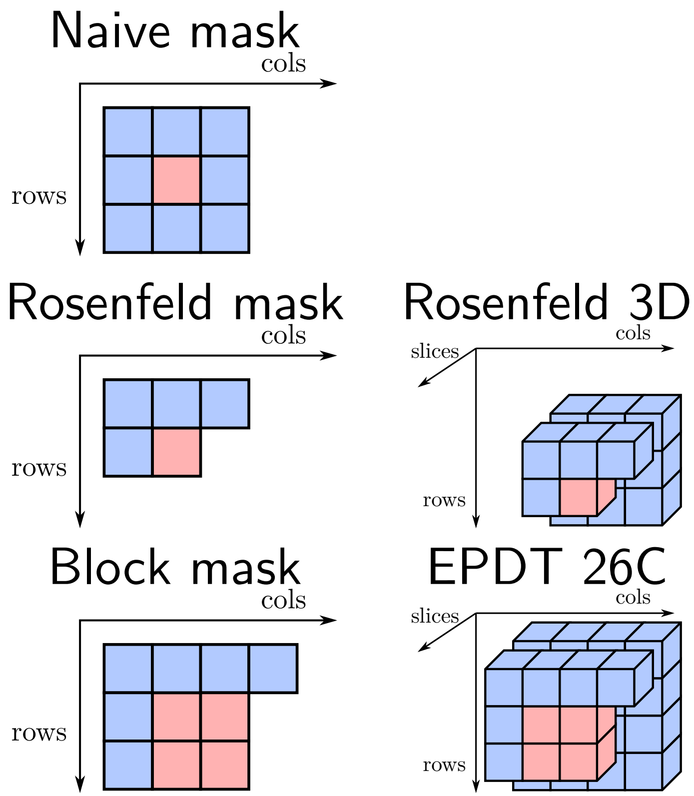
State of the Art: Pixel-based 2D→ 3D

Naive approach: test all neighbouring pixels

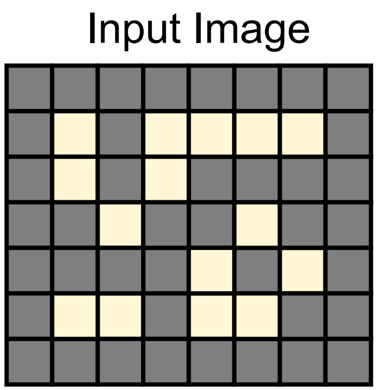
Pixel-based: Rosenfeld [1], *SAUF* [2], *LEB* [3], *PRED* [4]
⇒ Rosenfeld 3D, *SAUF 3D* [5], *LEB 3D* [6], *PRED 3D* [5]

Block-based: *BBDT* [7], *Spaghetti* [8]
⇒ *EPDT* (19C, 22C, 26C) [9]

3D algorithms: usually extensions of 2D algorithms



State of the Art (segment-based)



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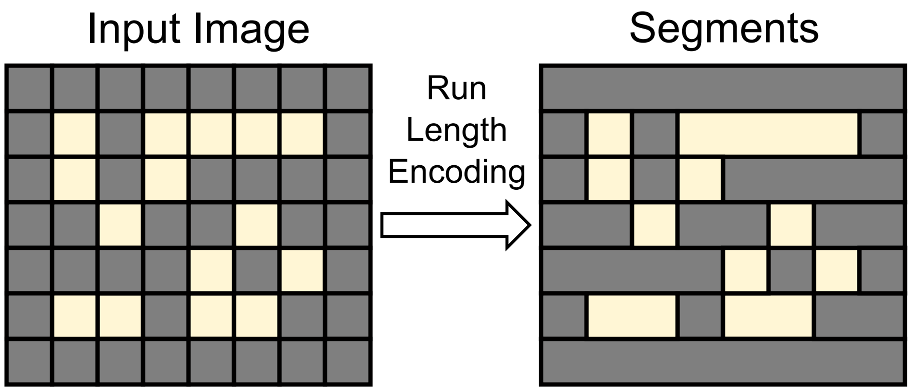

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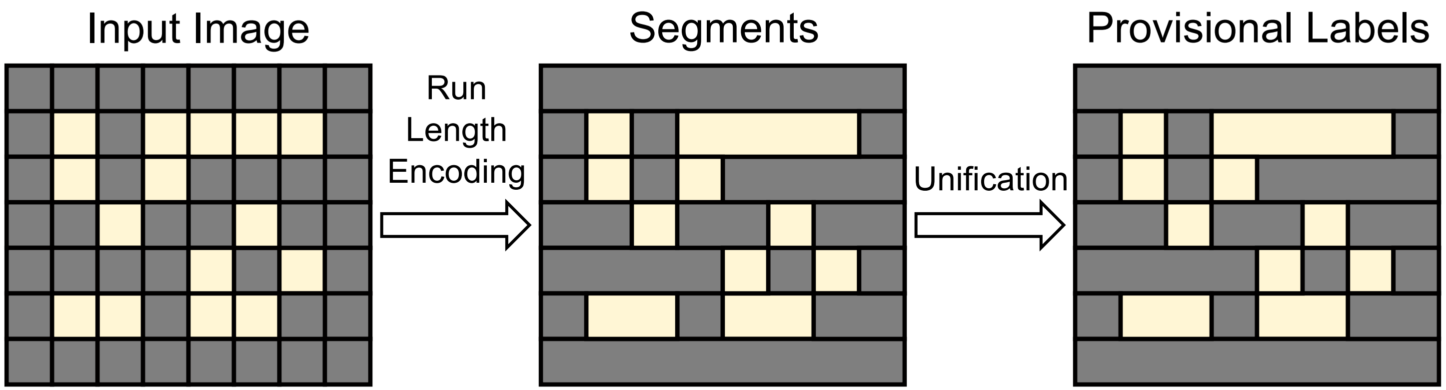

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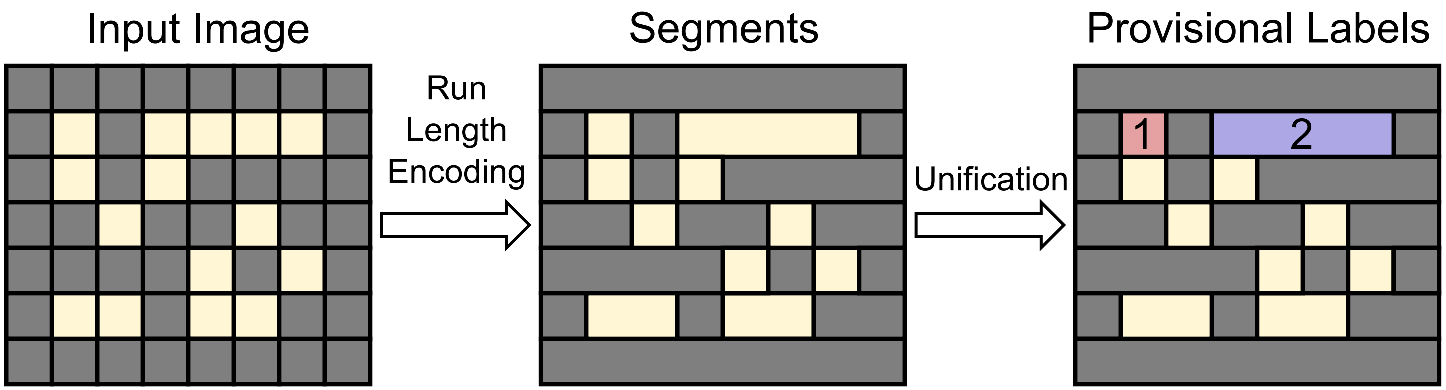

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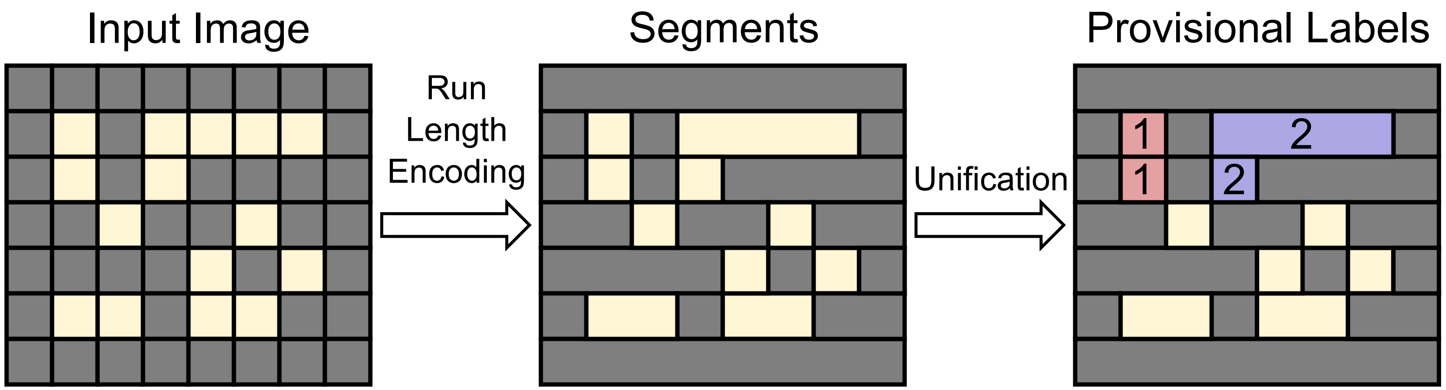

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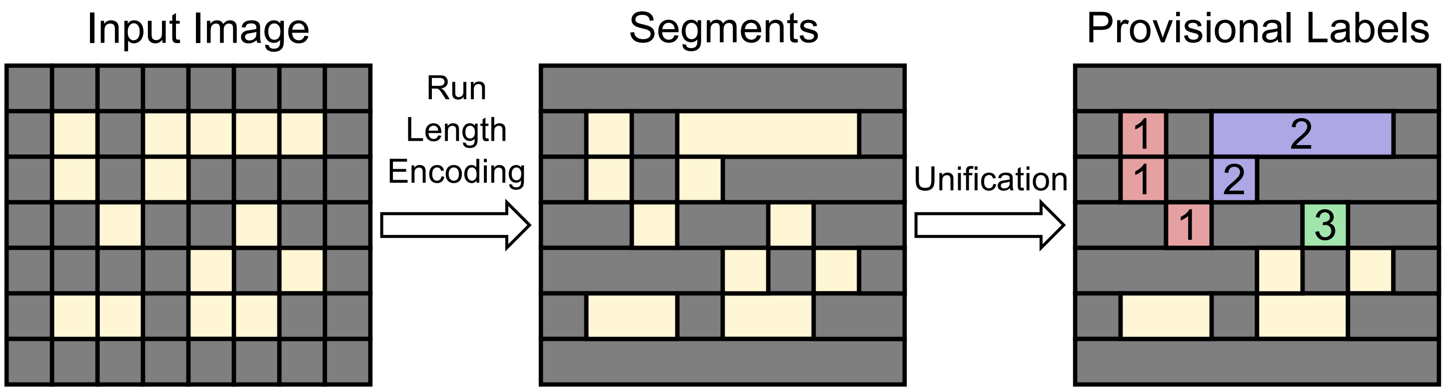

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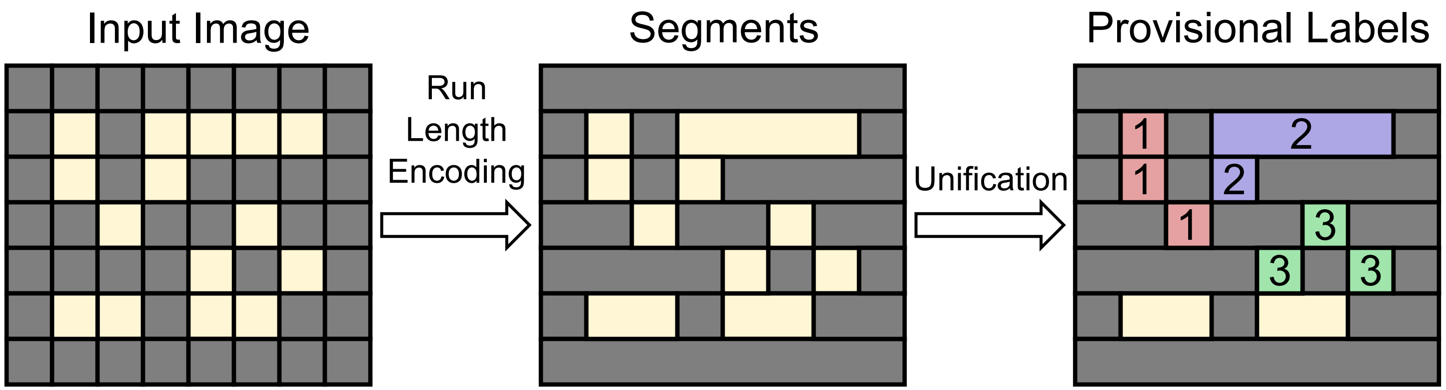

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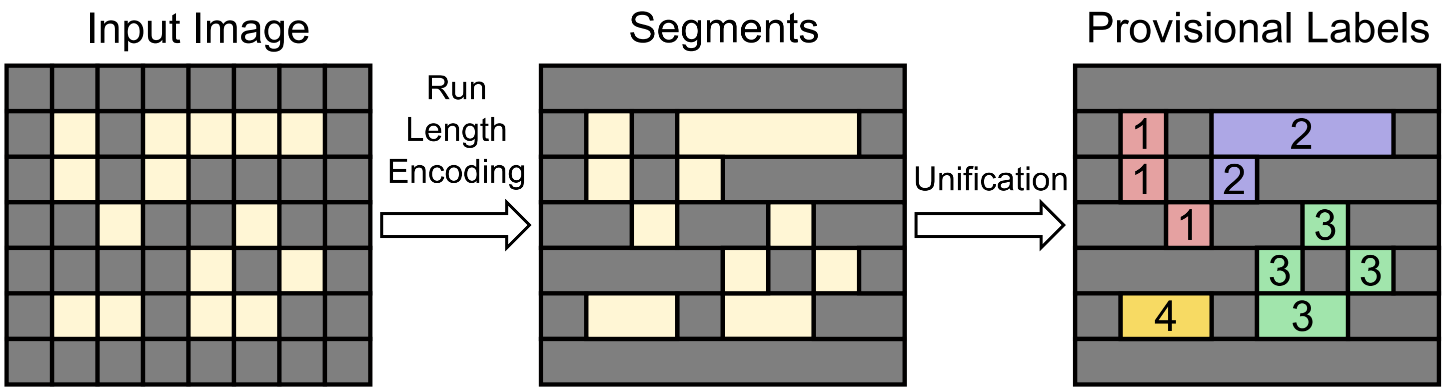
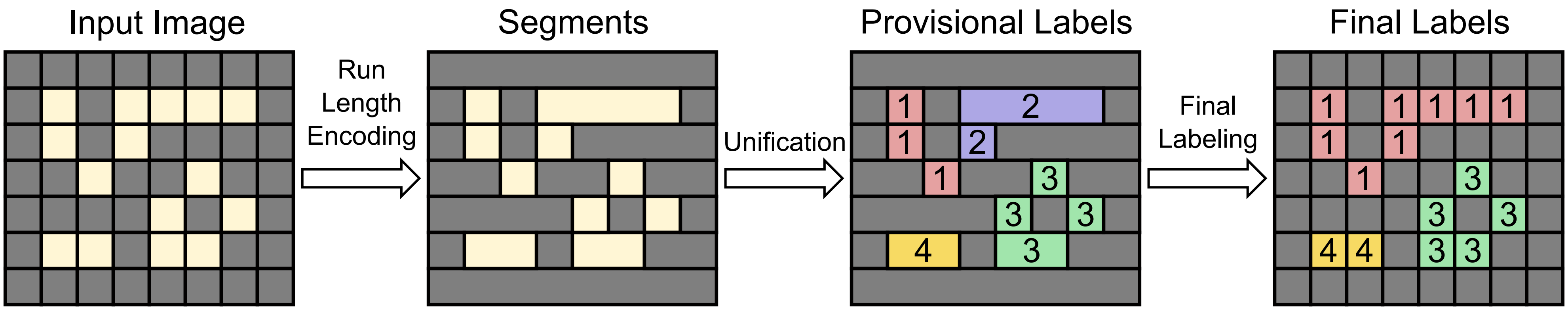
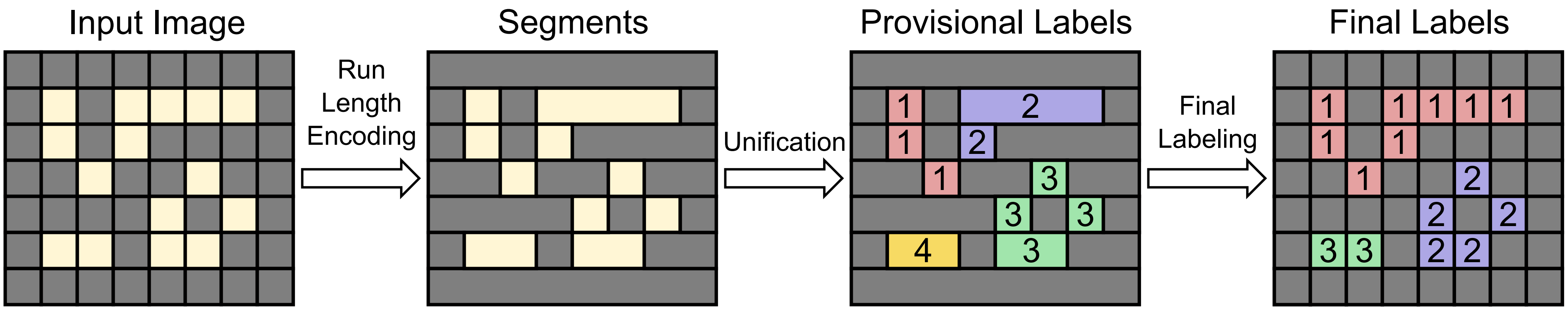


State of the Art (segment-based)

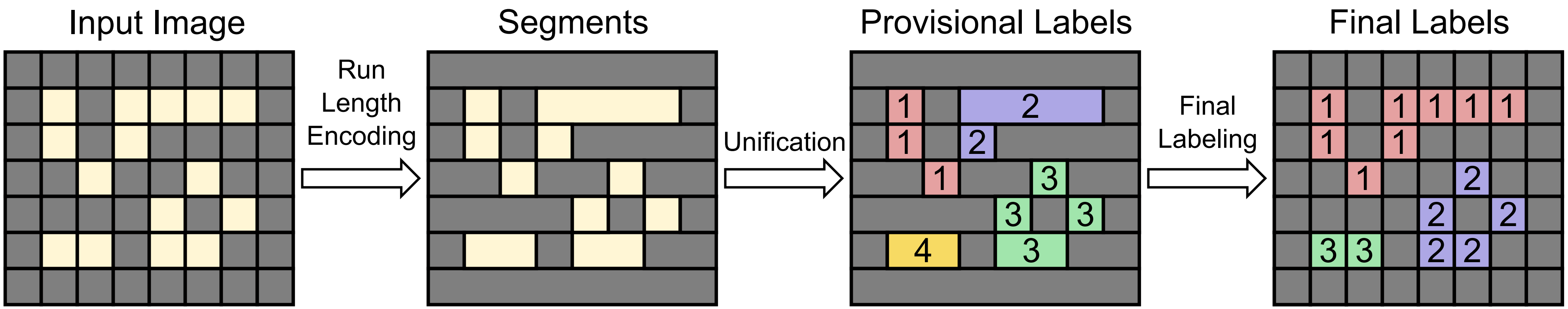


State of the Art (segment-based)



Segment-based: *RBTS* [10] ⇒ *RBTS 3D* [6]
LSL [11][12] ⇒ *LSL3D* is missing

State of the Art (segment-based)



Segment-based: *RBTS* [10] ⇒ *RBTS 3D* [6]
LSL [11][12] ⇒ *LSL3D* is missing

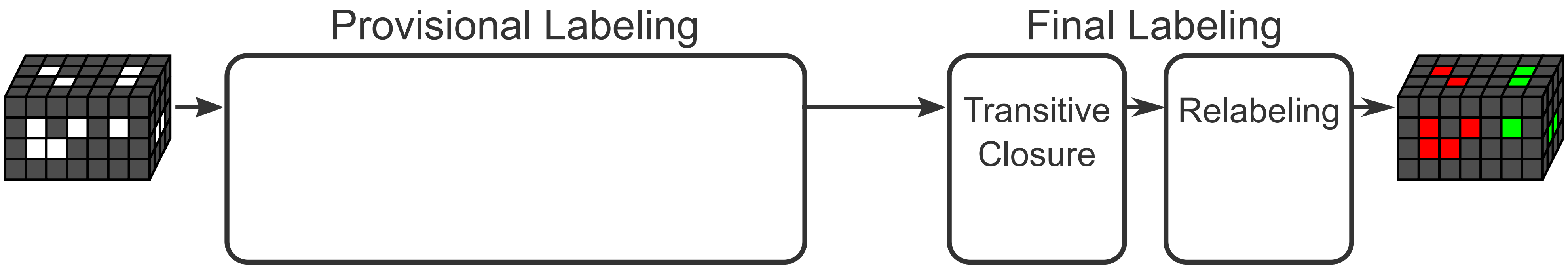
This contribution: LSL3D, a new segment-based algorithm

Step 1: Extension of *LSL* to 3D images

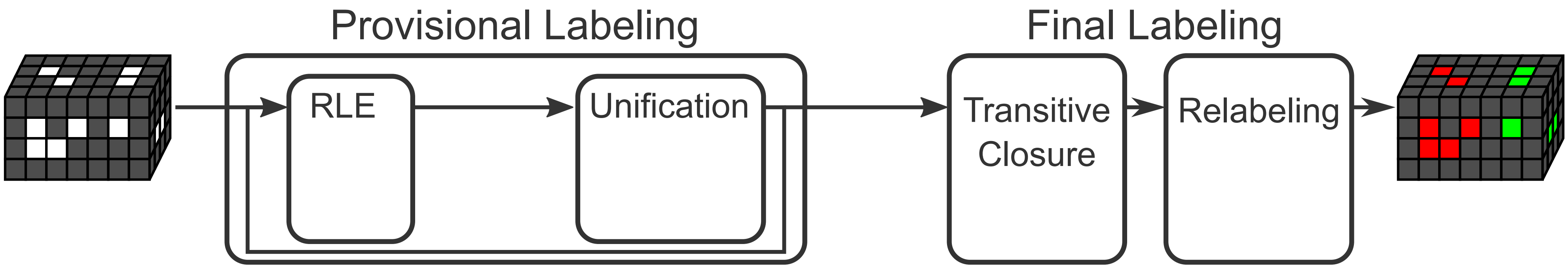
Step 2: Segment overlap detection with Finite State Machine (FSM)

Step 3: Computational re-use & simplification of FSM

Algorithm structure: Direct algorithms



Algorithm structure: LSL3D



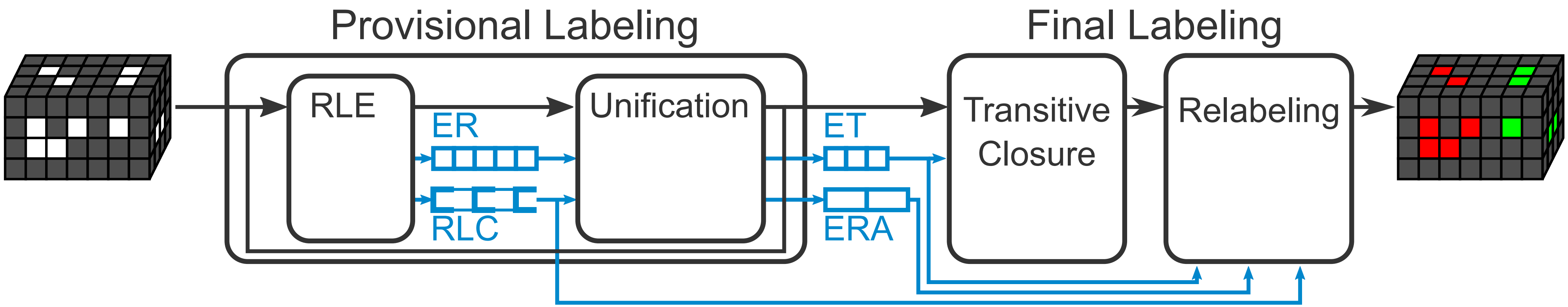
Run-Length Encoding (RLE) algorithm: pixels → segments

Unification: segments → provisional labels

Transitive Closure: provisional labels → final labels

Relabeling: write final labels

Algorithm structure: LSL3D



Run-Length Encoding (RLE) algorithm: pixels → segments

⇒ store segments (start & end) into RLC table & ER table (pixel pos. → segment id)

Unification: segments → provisional labels

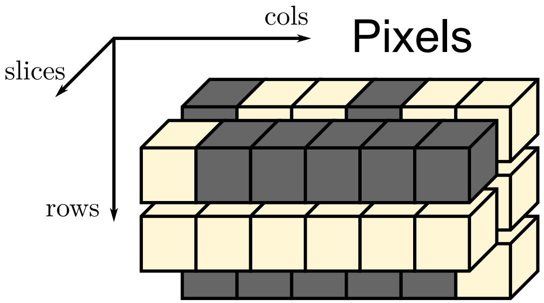
⇒ detect segments overlaps between lines, store provisional labels into ERA table

Transitive Closure: provisional labels → final labels

Relabeling: write final labels

Step 1: Extension of LSL to 3D volumes

RLE algorithm: Same as in 2D
Unification 3D: between 5 lines (vs 2 in 2D)



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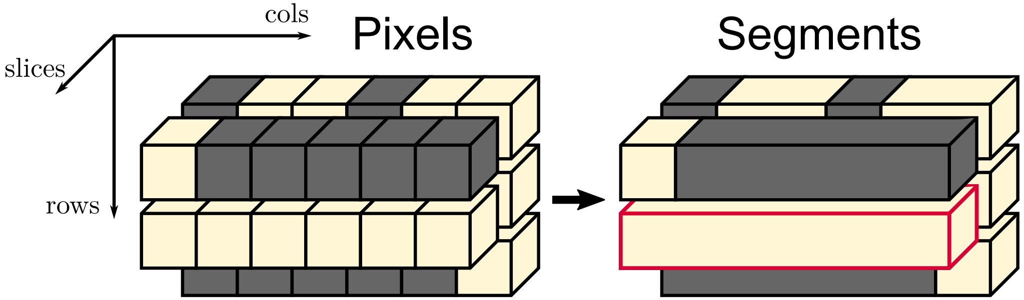

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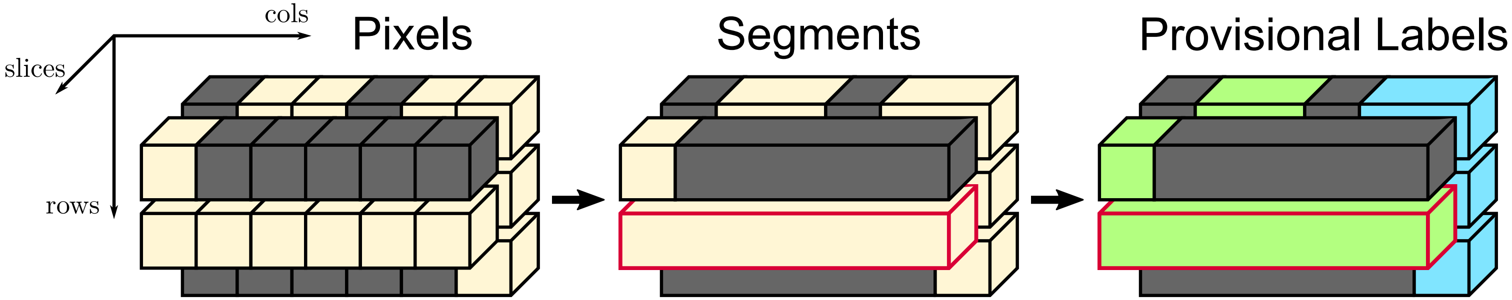

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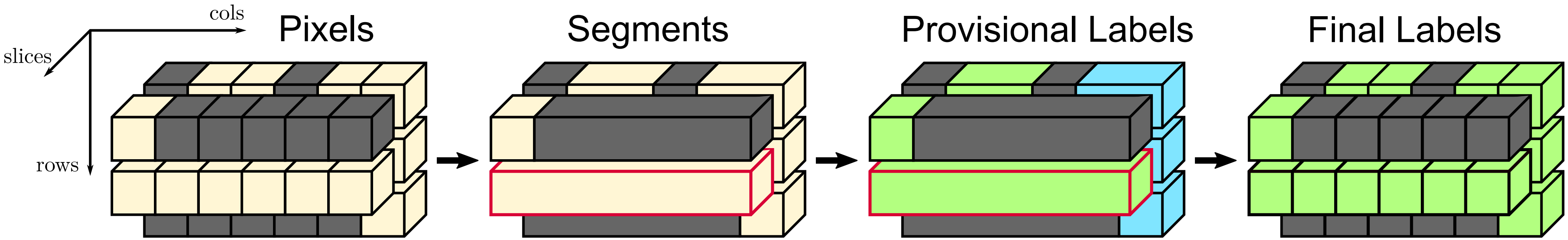
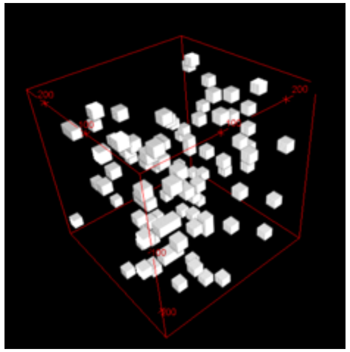


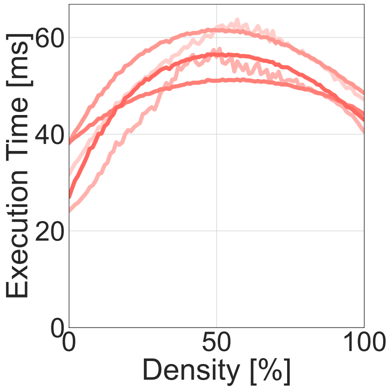
Random datasets: State of the Art

Benchmark: *YACCLAB* [13]
Hardware: Xeon Gold 6126

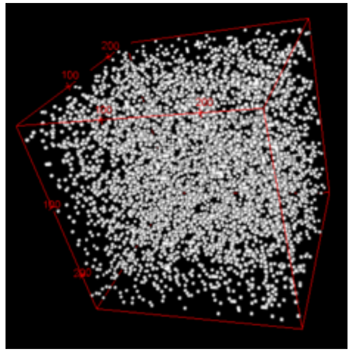
density $= \frac{\text{foreground pixels}}{\text{image size}}$
granularity $=$ cube size

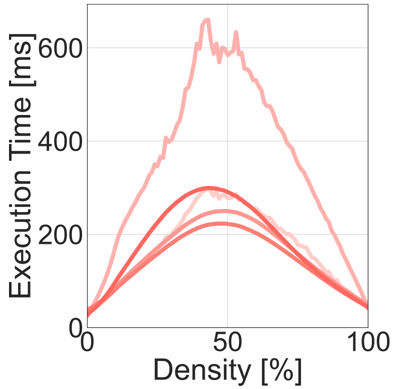
g = 16
(simple)





g = 1
(complex)





- LEB_3D
- RBTS_3D
- SAUFpp_3D
- PREDpp_3D
- EPDT_3D_22c

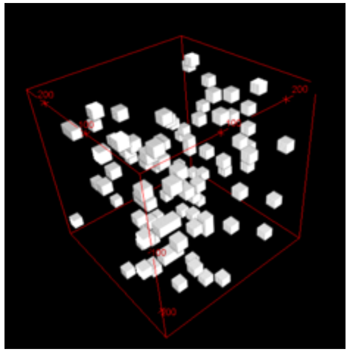
Random datasets: LSL3D

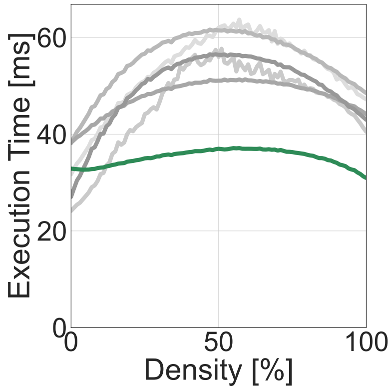
Benchmark: *YACCLAB* [13]
Hardware: Xeon Gold 6126

density $= \frac{\text{foreground pixels}}{\text{image size}}$
granularity $=$ cube size

- LEB_3D
- RBTS_3D
- SAUFpp_3D
- PREDpp_3D
- EPDT_3D_22c
- LSL_ER

g = 16
(simple)





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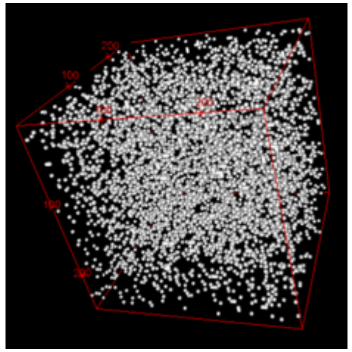
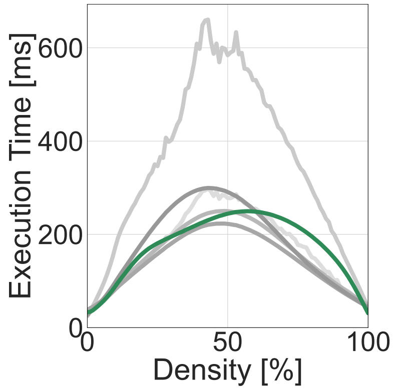
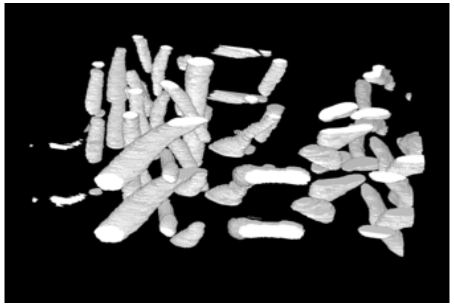




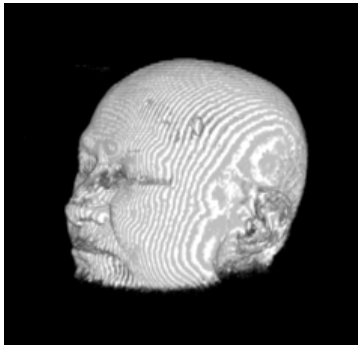
Medical datasets

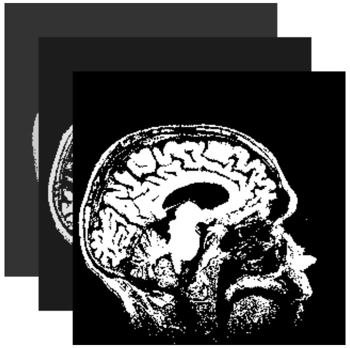
Mitochondria
(3 × 3D images)
1024 × 768 × 165



density = 5.8%
run/MPxls = 1500
CCs/MPxls = 0.31
⇒ simple images

OASIS
(373 × 3D images)
256 × 256 × 128

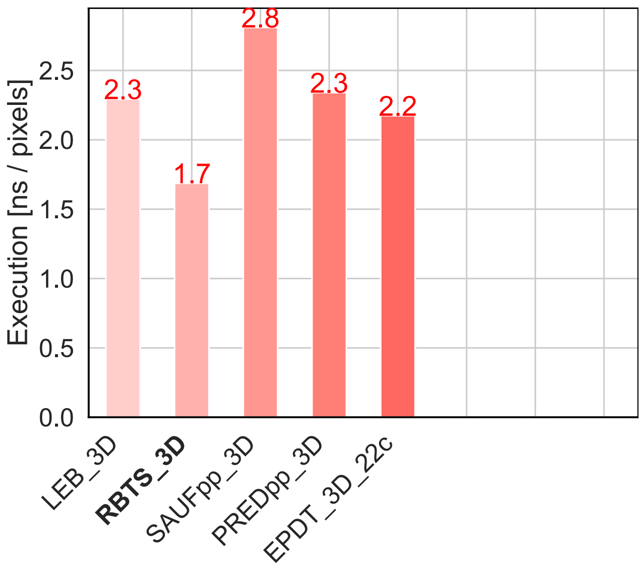


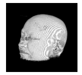


density = 19.8%
run/MPxls = 28 000
CCs/MPxls = 380
⇒ complex images

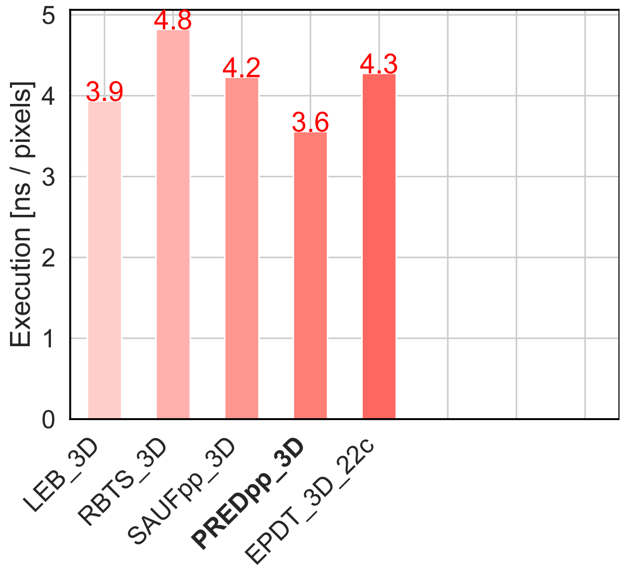
Medical datasets: State of the Art

Mitochondria
(simple)



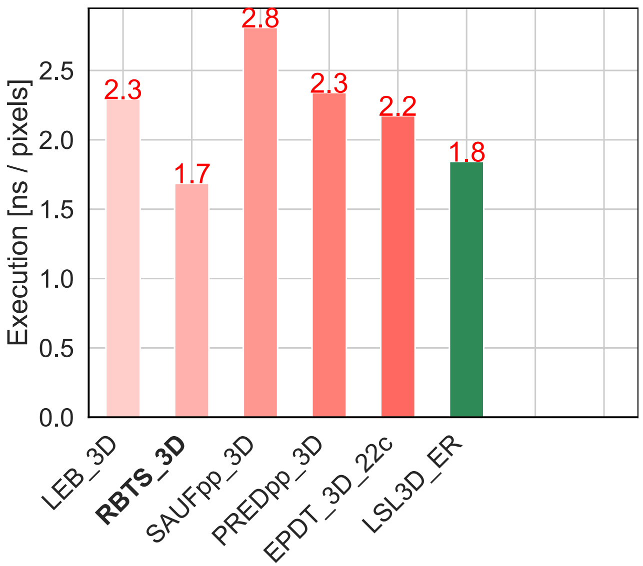


OASIS
(complex)

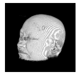


Medical datasets: LSL3D

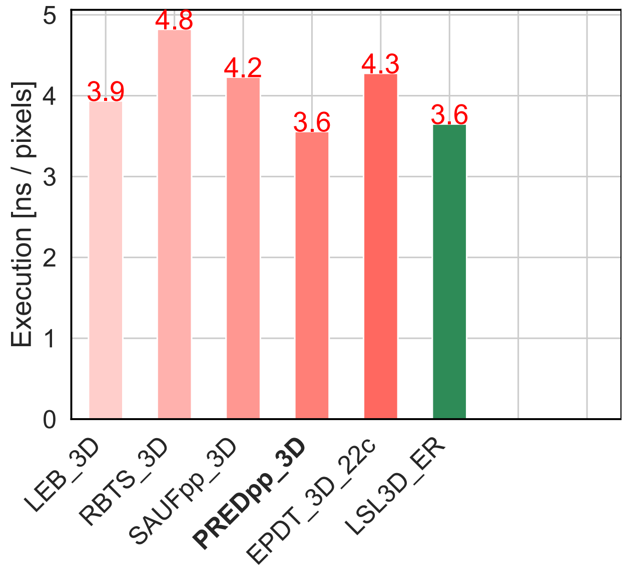
Mitochondria
(simple)



slower by $\times 0.9$ than *RBTS 3D*



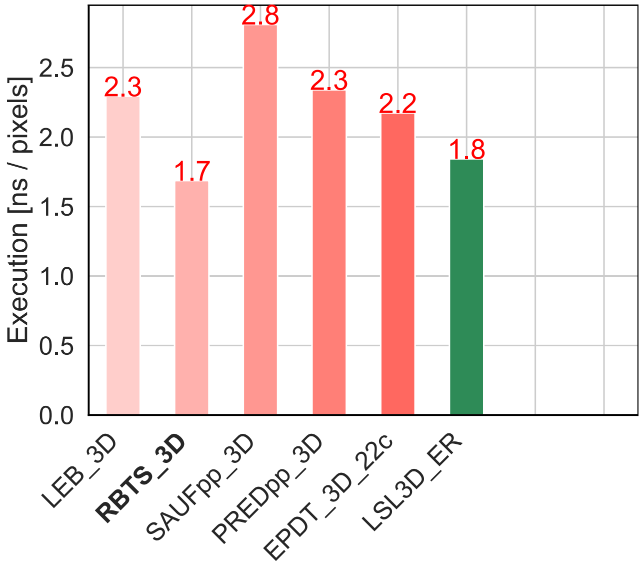
OASIS
(complex)

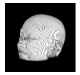


roughly as fast as *PRED++ 3D*

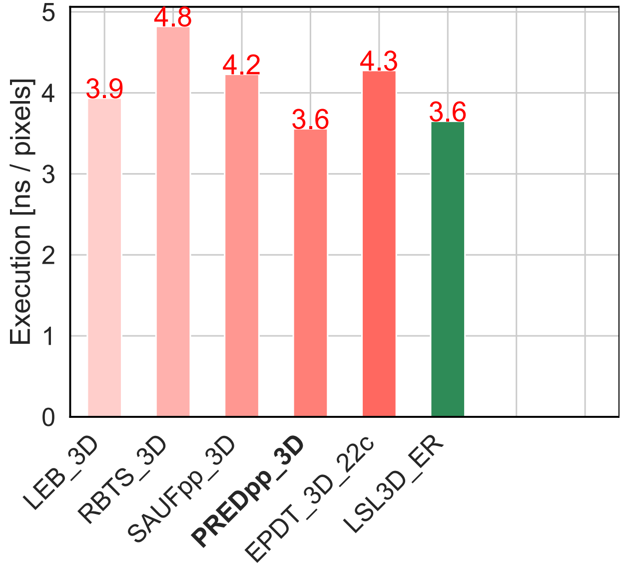
Medical datasets: LSL3D

Mitochondria
(simple)





OASIS
(complex)

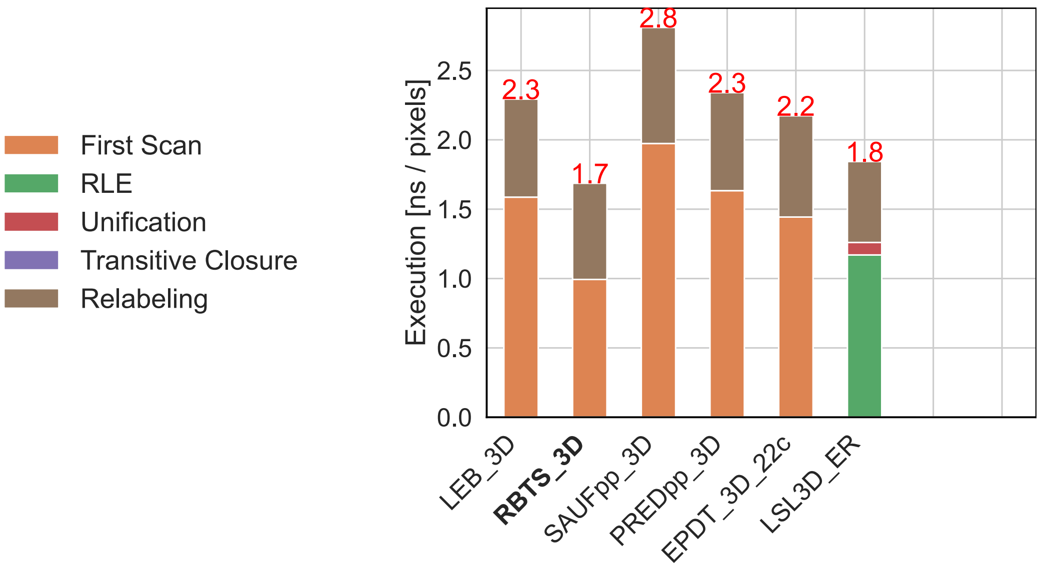


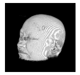
slower by $\times$0.9 than *RBTS 3D*
faster by $\times$ 1.3 than *PRED++*

roughly as fast as *PRED++ 3D*
faster by 1.3 than *RBTS*

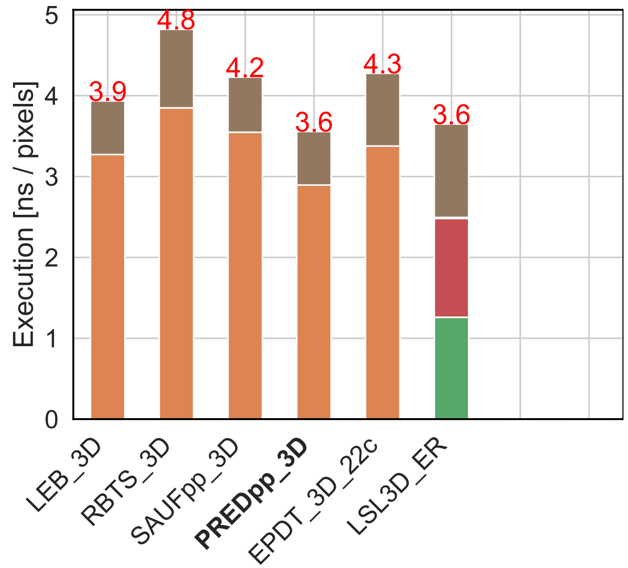
Medical datasets: LSL3D (steps)

Mitochondria
(simple)





OASIS
(complex)



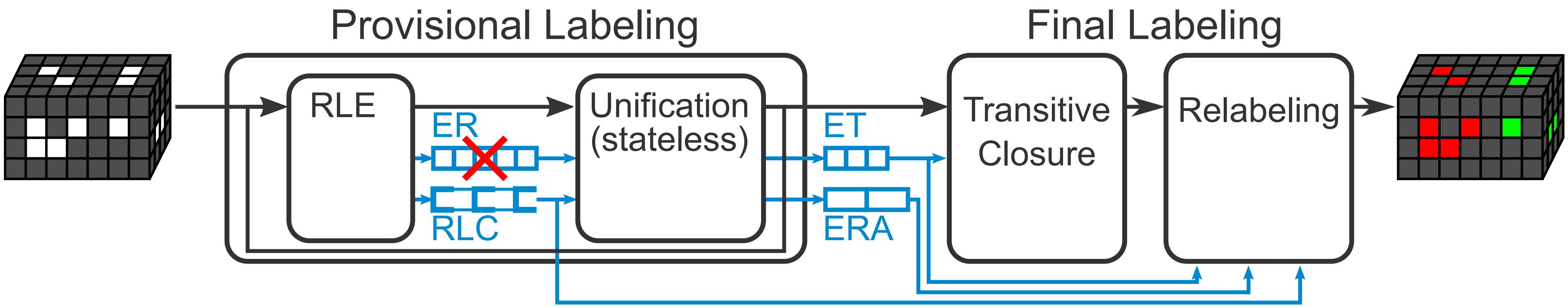
slower by $\times 0.9$ than *RBTS 3D*
faster by $\times$ 1.3 than *PRED++*

roughly as fast as *PRED++ 3D*
faster by 1.3 than *RBTS*

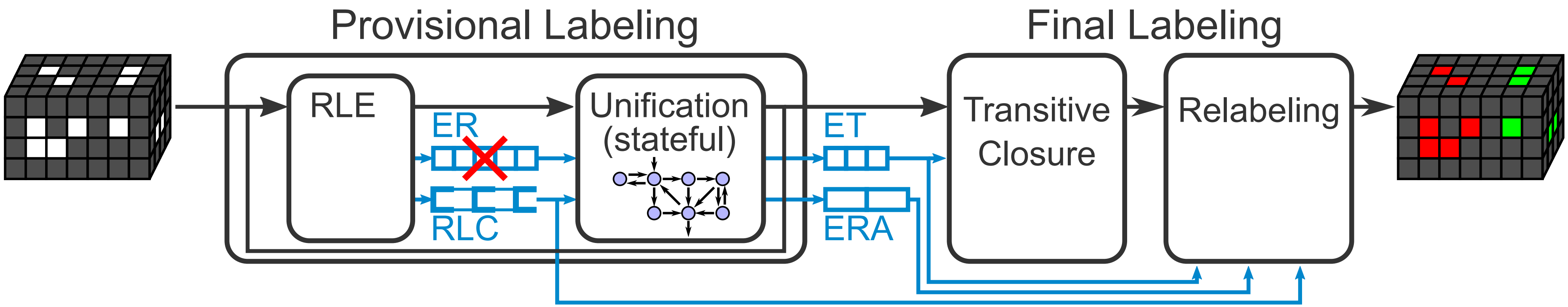
$\Rightarrow$ Performant & Regular

$\Rightarrow$ RLE & Unification expensive

Step 2: Finite-State Machine-based unification

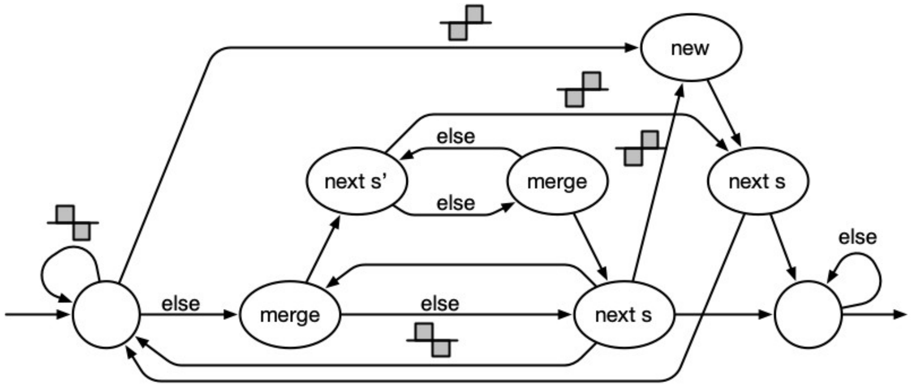


Step 2: Finite-State Machine-based unification



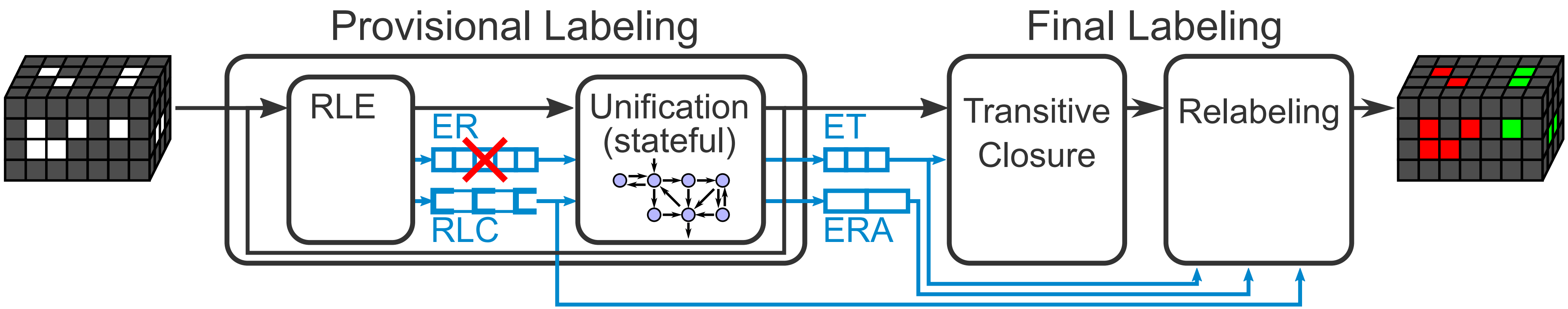
Overlap detection without ER:
⇒ Finite-State Machine (FSM)

transition = segment configuration
merging lines ⇒ iteration



2D FSM (8 states, 14 transitions)

Step 2: Finite-State Machine-based unification



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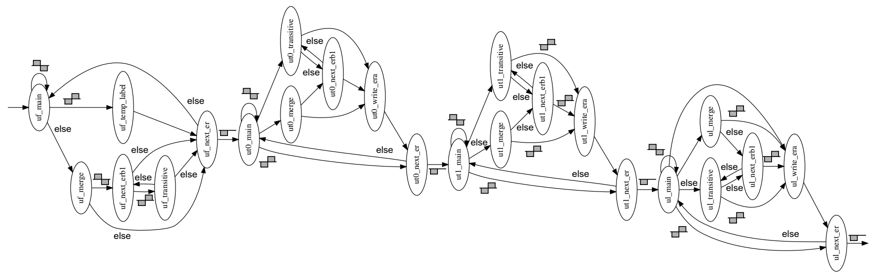
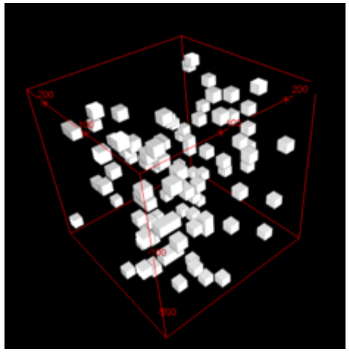


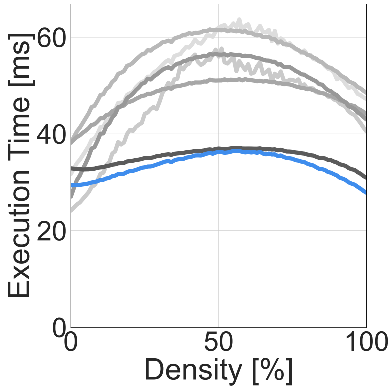
3D FSM (27 states, 55 transitions)

Random datasets: LSL+FSM

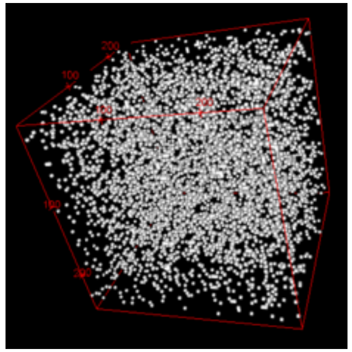
Benchmark: *YACCLAB*
Hardware: Xeon Gold 6126

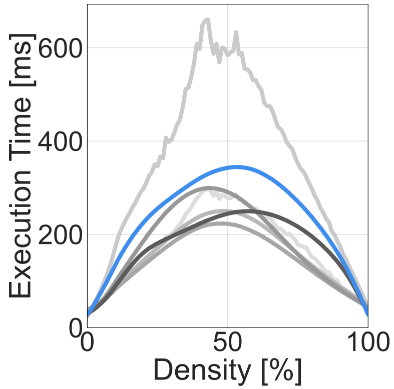
$g = 16$
(simple)





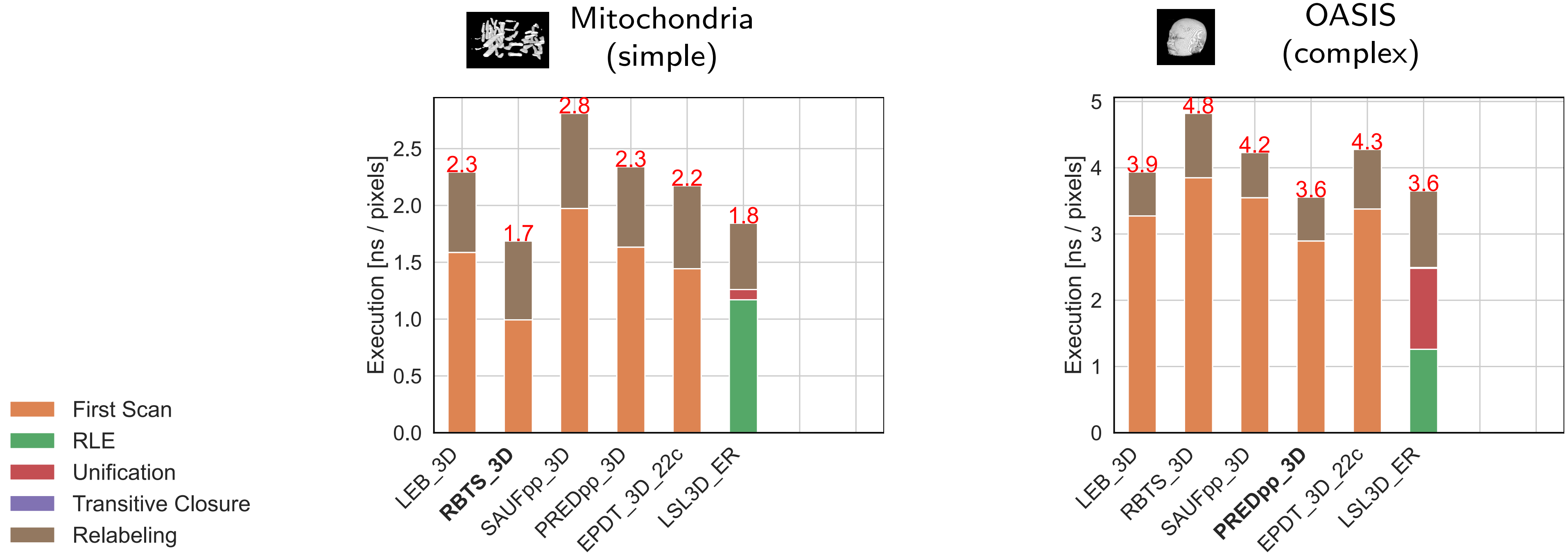
$g = 1$
(complex)



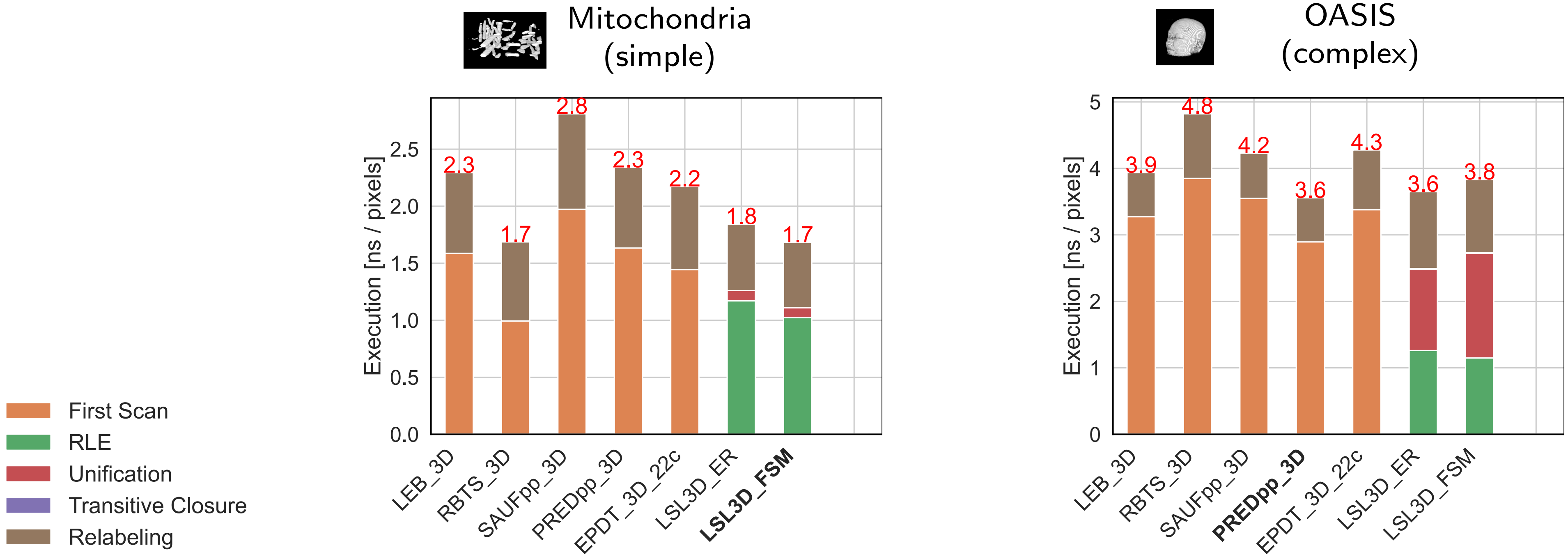


- LEB_3D
- RBTS_3D
- EPDT_3D_19c
- EPDT_3D_22c
- LSL_ER
- LSL_FSM

Medical datasets: LSL+FSM

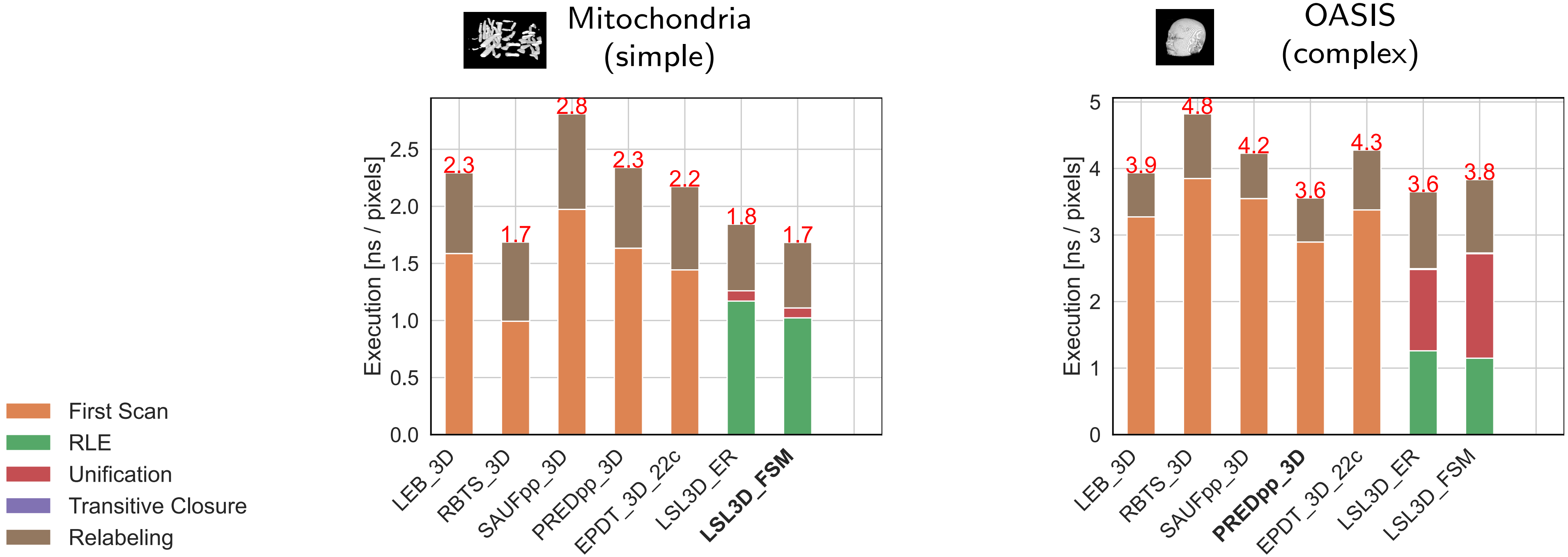


Medical datasets: LSL+FSM



LSL_FSM faster than LSL_ER by $\times$ 1.1   LSL_FSM slower than LSL_ER by $\times$ 0.95

Medical datasets: LSL+FSM



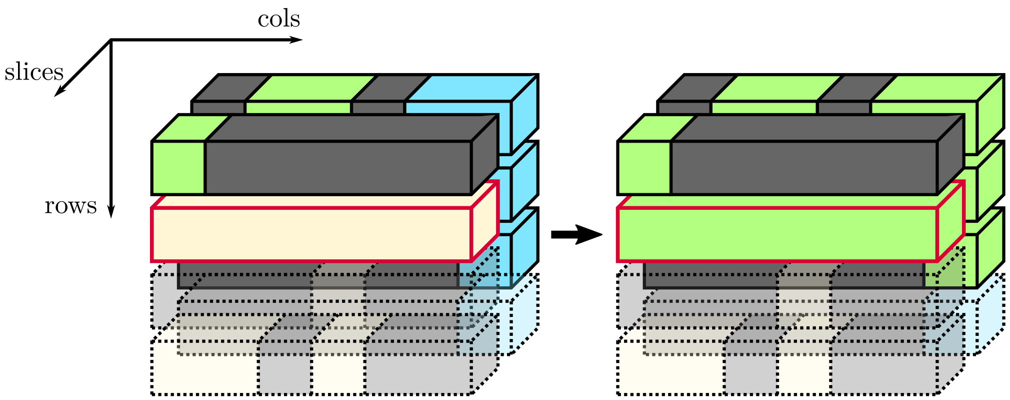
`LSL_FSM` faster than `LSL_ER` by $\times$ 1.1 `LSL_FSM` slower than `LSL_ER` by $\times$ 0.95

FSM issues $\Rightarrow$ FSM is large (27 states, 55 transitions)

$\Rightarrow$ decreased branch predictor accuracy, especially on complex images

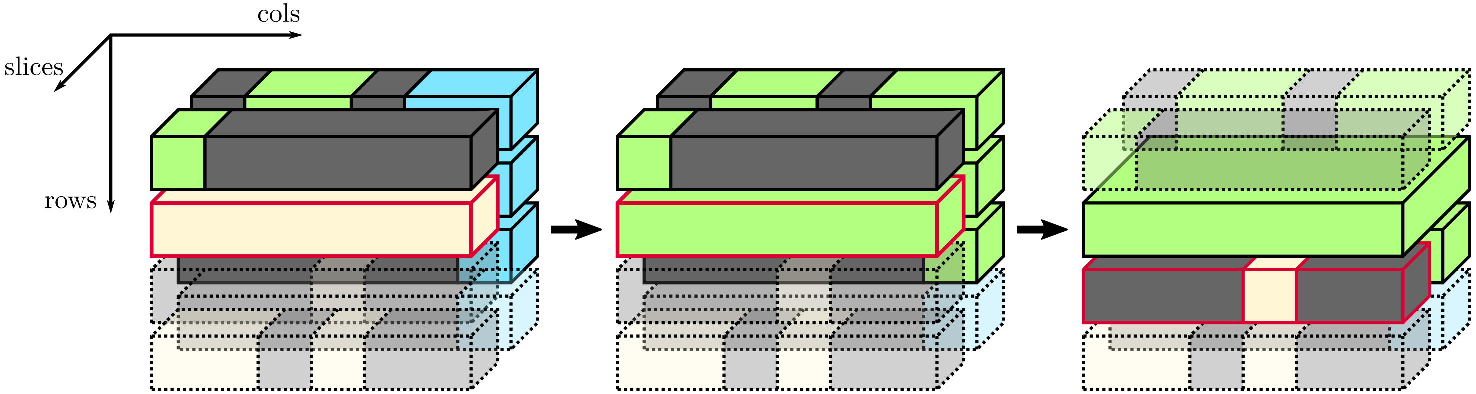
Step 3: Double-Line mechanism

Unification: 3 lines re-processed during next iteration



Step 3: Double-Line mechanism

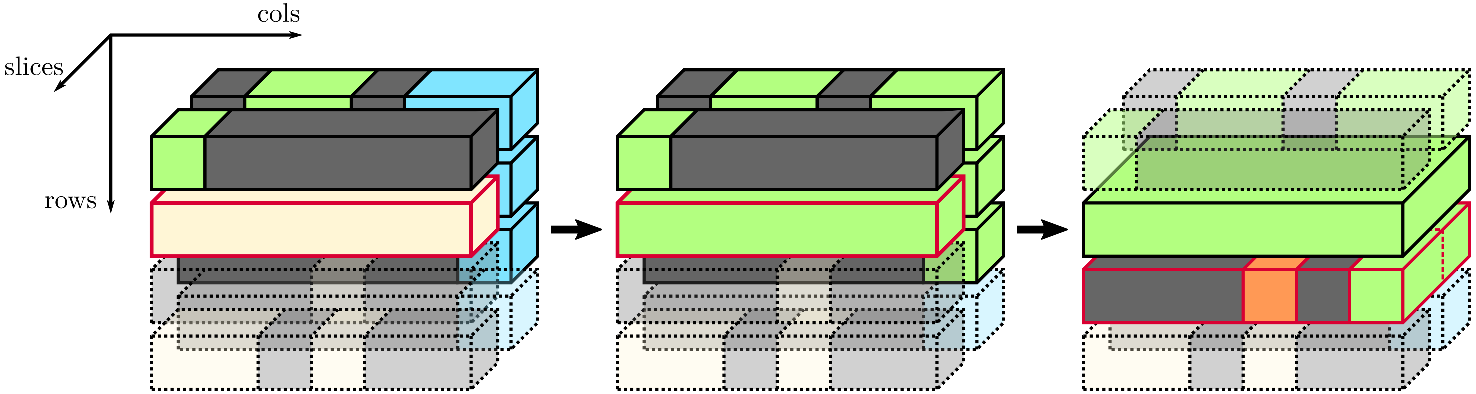
Unification: 3 lines re-processed during next iteration
Idea: Computational re-use by caching partial results (*double-line*):



Step 3: Double-Line mechanism

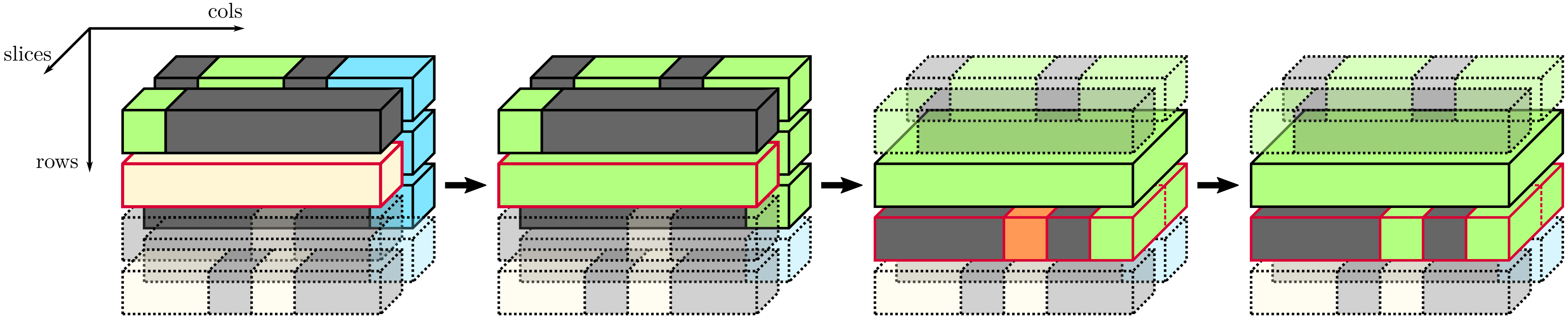
Unification: 3 lines re-processed during next iteration

Idea: Computational re-use by caching partial results (*double-line*):



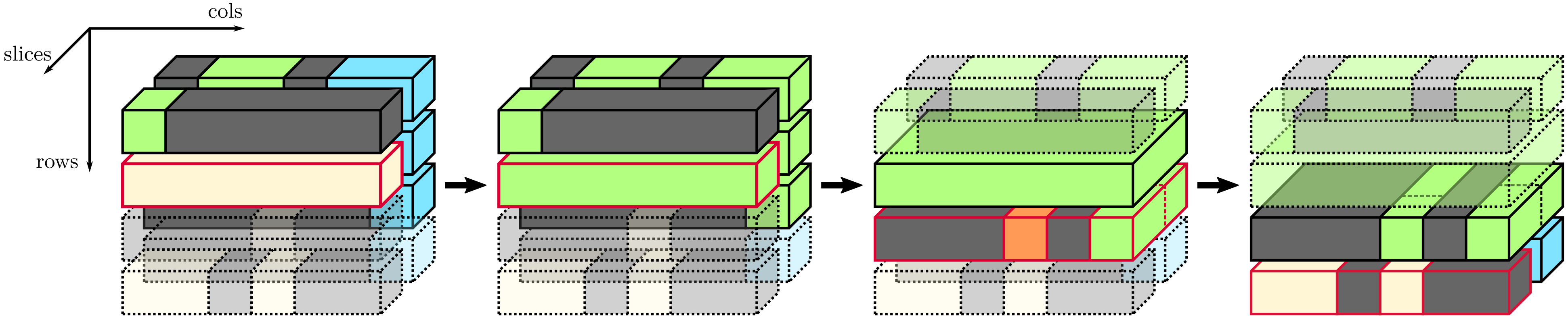
Step 3: Double-Line mechanism

Unification: 3 lines re-processed during next iteration
Idea: Computational re-use by caching partial results (*double-line*):



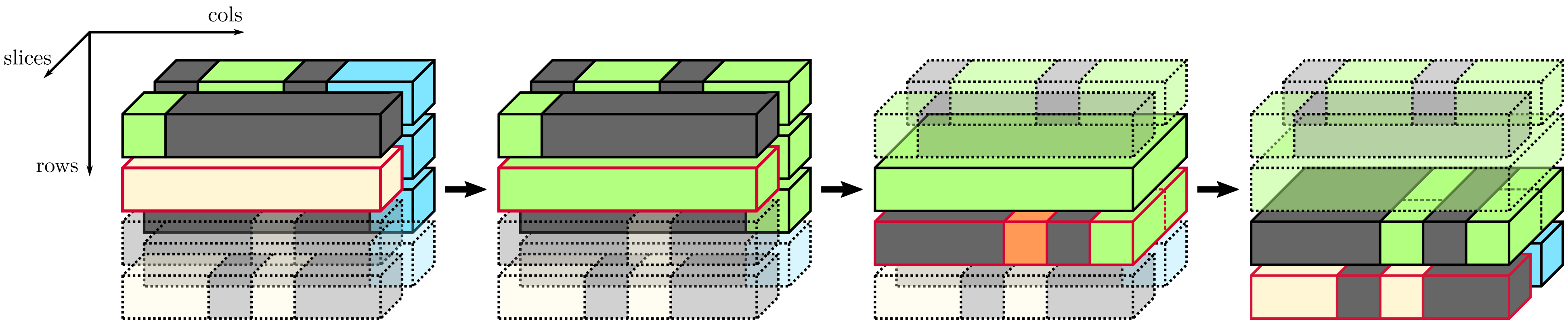
Step 3: Double-Line mechanism

Unification: 3 lines re-processed during next iteration
Idea: Computational re-use by caching partial results (*double-line*):



Step 3: Double-Line mechanism

Unification: 3 lines re-processed during next iteration
Idea: Computational re-use by caching partial results (*double-line*):



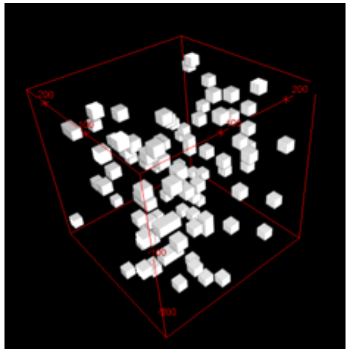
⇒ fewer operations
⇒ simpler FSM (9 states, 18 transitions)

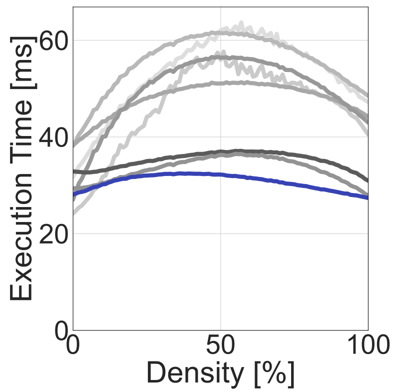
Random datasets: LSL+FSM+DOUBLE

Benchmark: *YACCLAB*
Hardware: Xeon Gold 6126

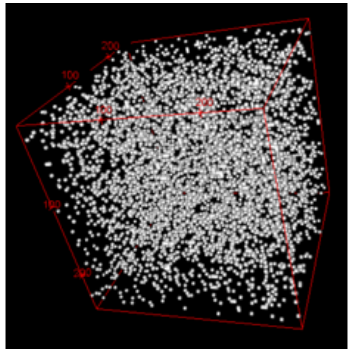
- LEB_3D
- RBTS_3D
- EPDT_3D_19c
- EPDT_3D_22c
- LSL_ER
- LSL_FSM
- LSL_FSM_DOUBLE

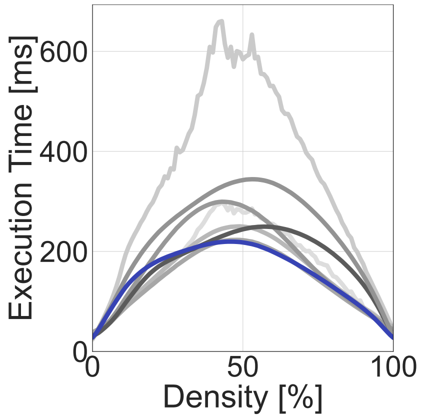
g = 16
(simple)





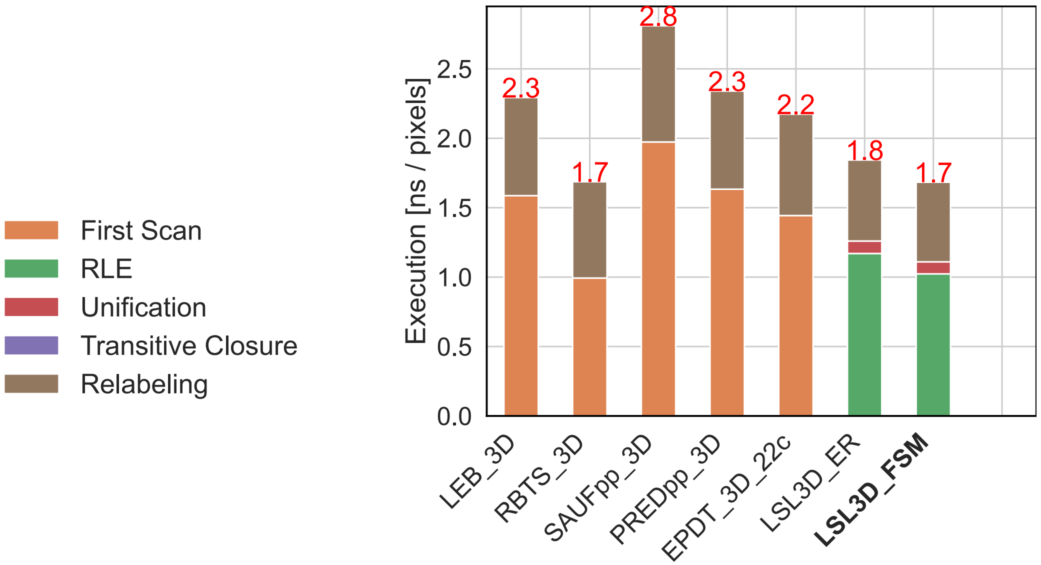
g = 1
(complex)

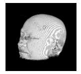




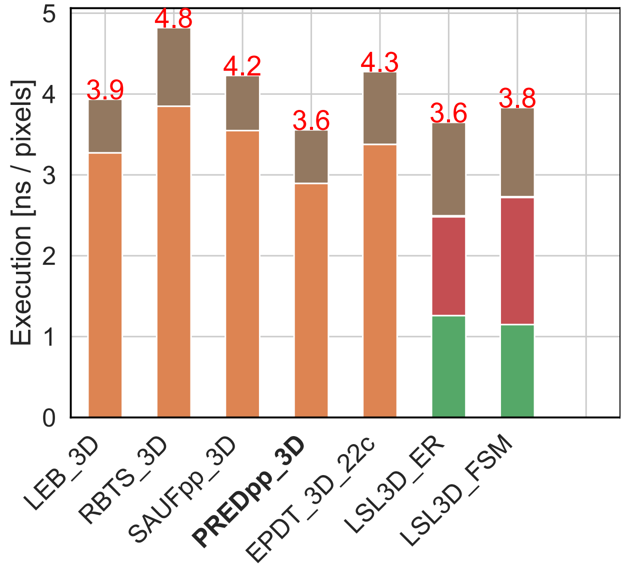
Medical images: LSL+FSM

Mitochondria (simple)





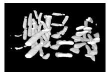
OASIS (complex)

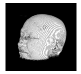


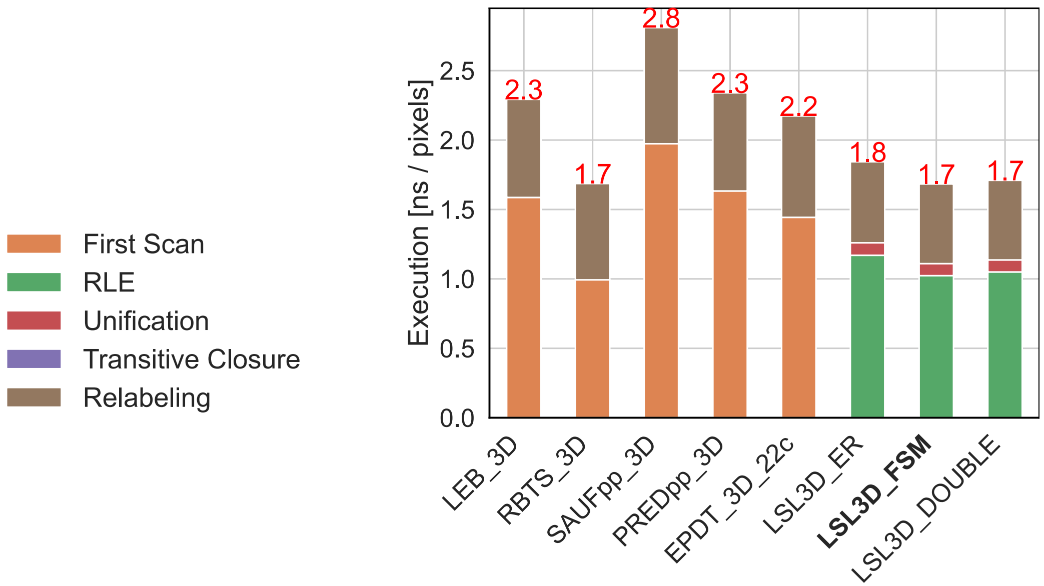
LSL_FSM faster than LSL_ER by × 1.1

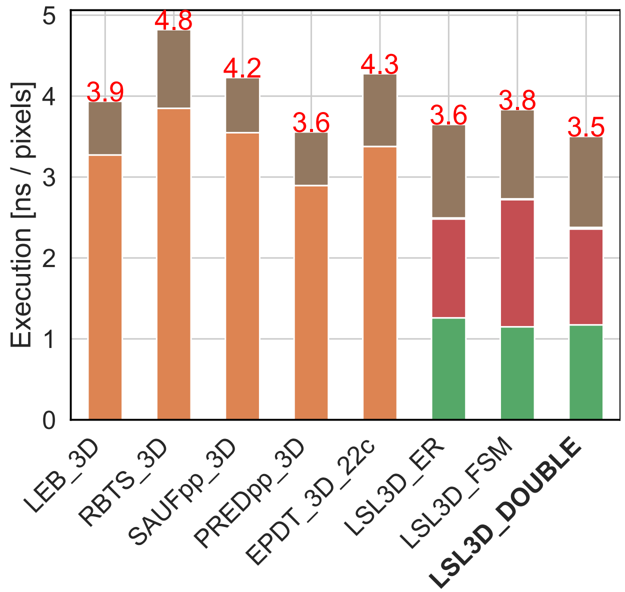
LSL_FSM slower than LSL_ER by × 0.95

Medical images: LSL+FSM+DOUBLE


Mitochondria
(simple)


OASIS
(complex)





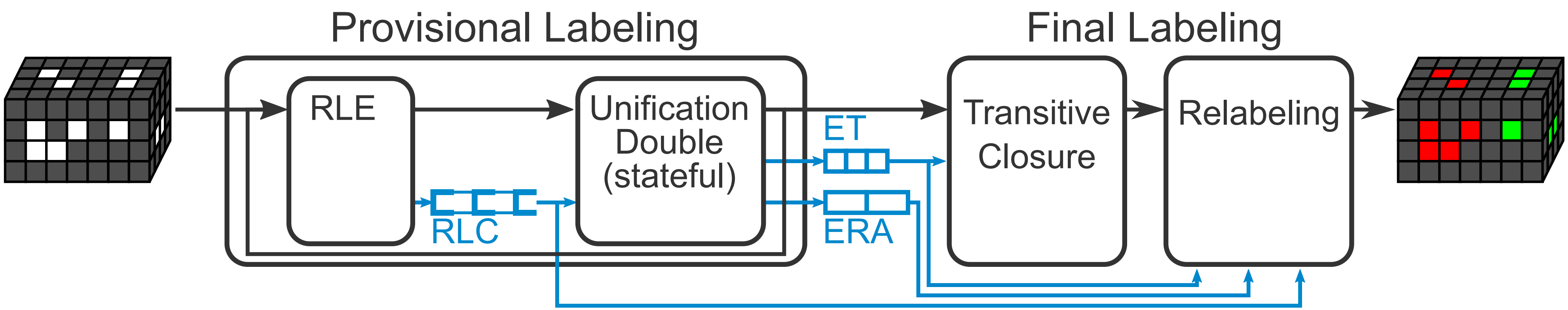
LSL_DOUBLE faster than LSL_ER by $\times$ 1.1

LSL_DOUBLE as fast as LSL_ER

$\Rightarrow$ Faster & Regular

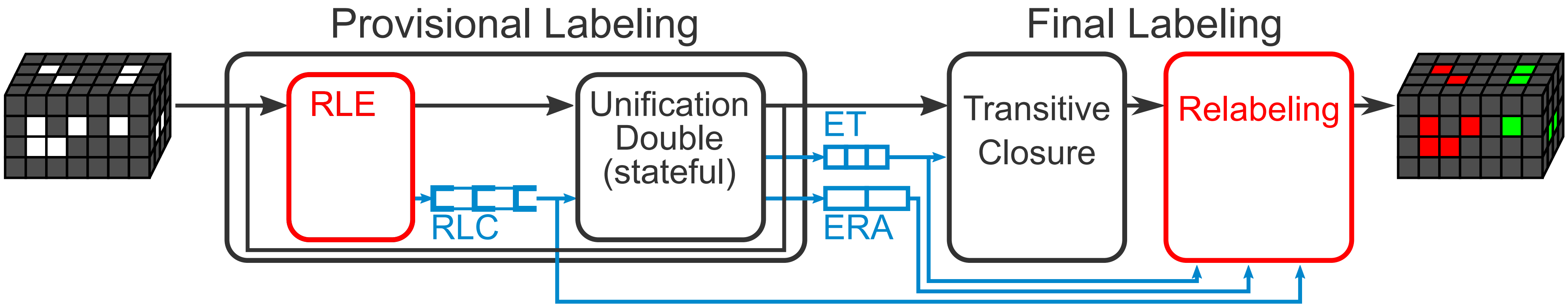
LSL3D with Hardware acceleration

Performance evaluation: RLE, Unification, Transitive Closure, Relabeling



LSL3D with Hardware acceleration

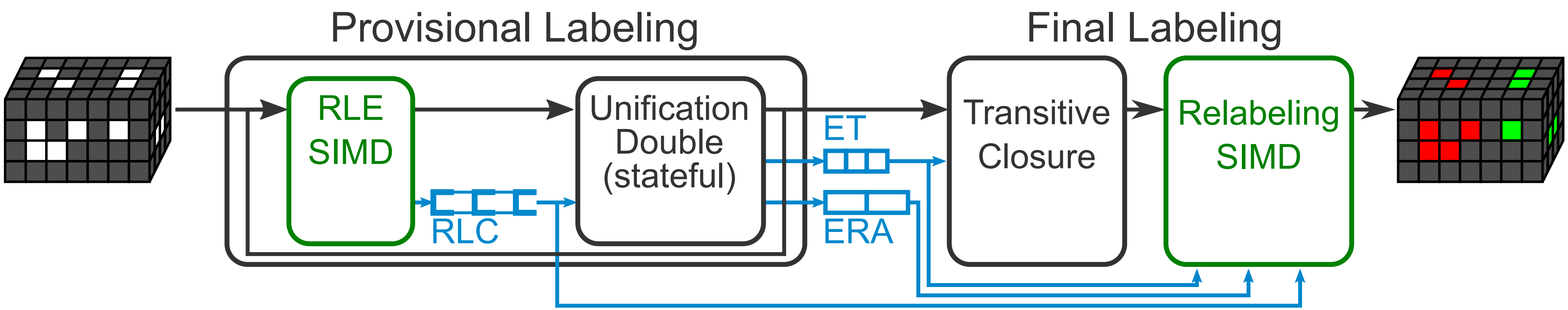
Performance evaluation: RLE, Unification, Transitive Closure, Relabeling
⇒ 70-90% of execution time



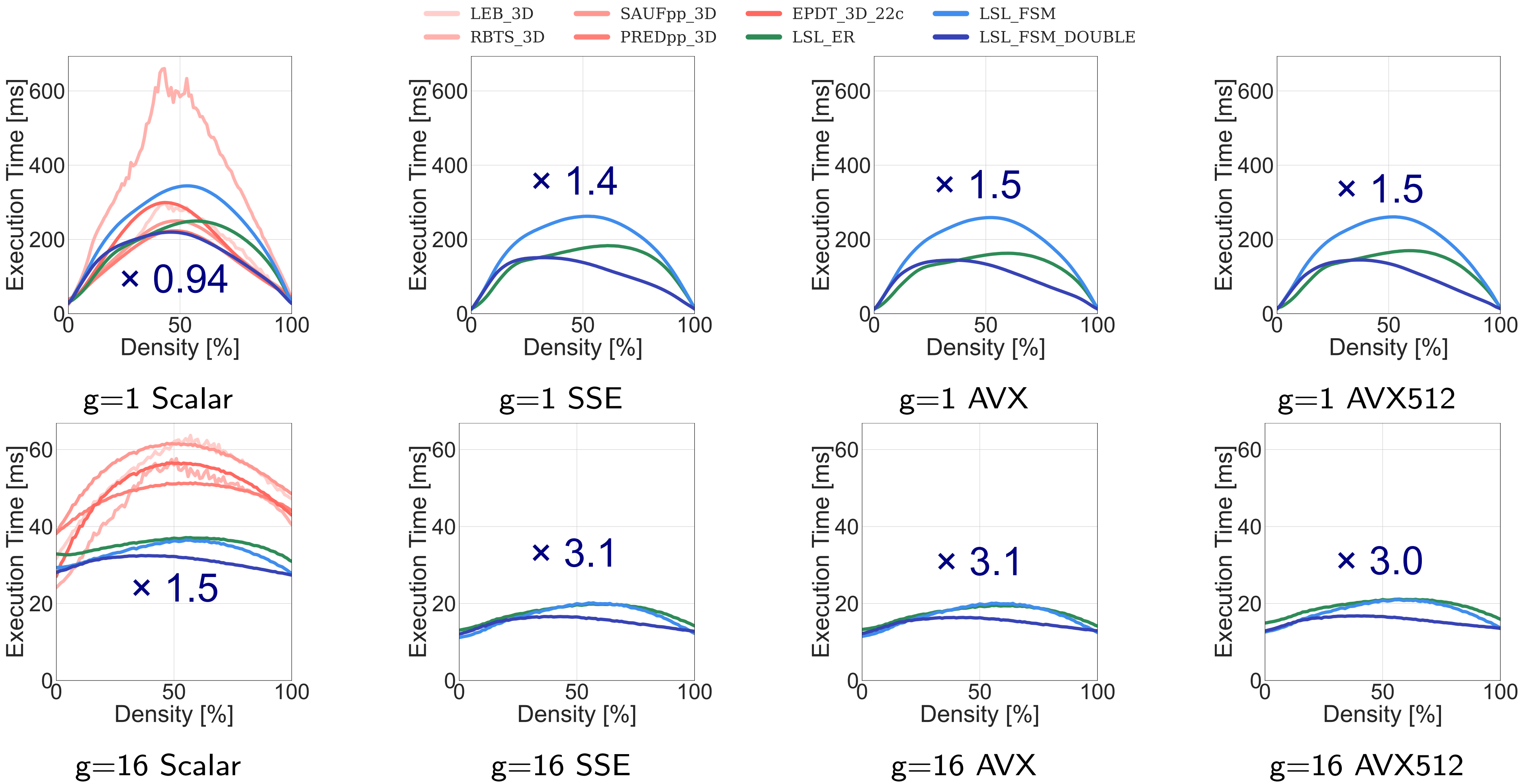
LSL3D with Hardware acceleration

Performance evaluation: RLE, Unification, Transitive Closure, Relabeling
⇒ 70-90% of execution time

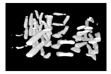
Fortunately: RLE and Relabeling benefit from instruction level parallelism [14]
Single Instruction Multiple Data (SIMD): *SSE4*, *AVX2* and *AVX512*



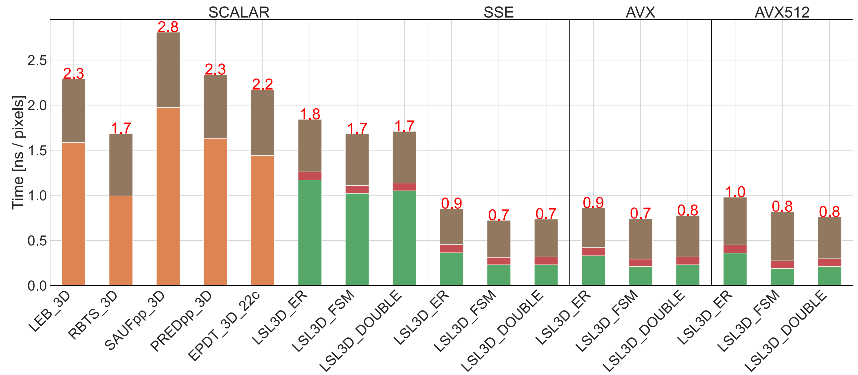
Random datasets: LSL3D with SIMD



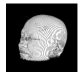
Medical datasets: LSL3D with SIMD



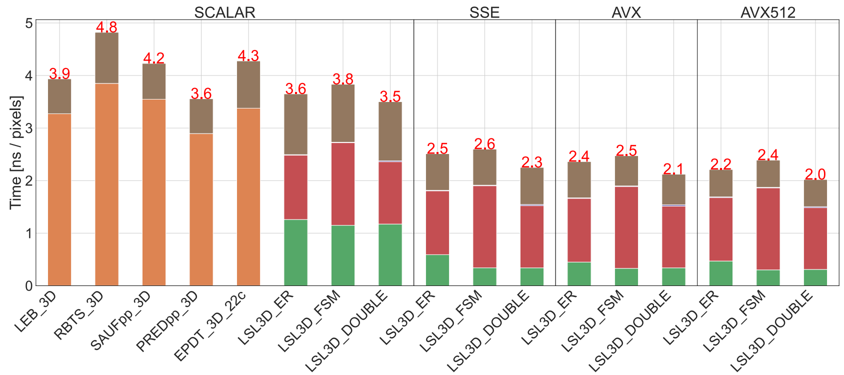
Mitochondria (simple)



- First Scan
- RLE
- Unification
- Transitive Closure
- Relabeling



OASIS (complex)



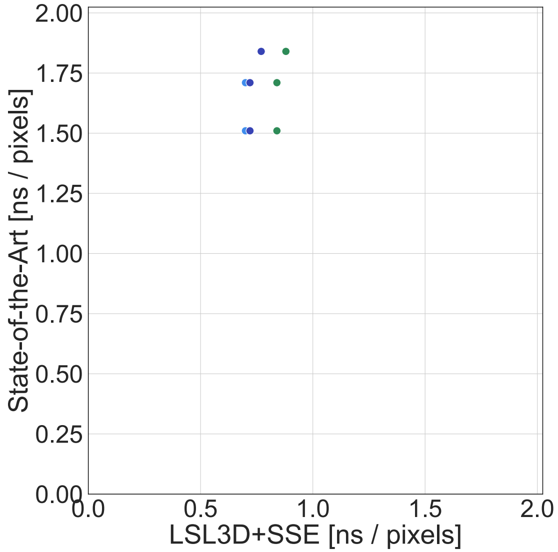
SSE ⇒ faster than State-of-the-Art

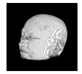
AVX & AVX512: no significant speed-up compared to SSE

Medical datasets: Individual images

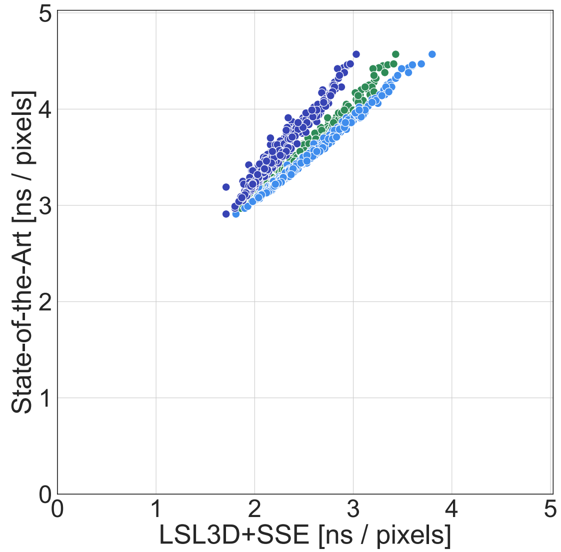
LSL3D vs best results of State-of-the-Art algorithms (1 point = 1 image)

Mitochondria
(simple)





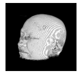
OASIS
(complex)



Medical datasets: Individual images

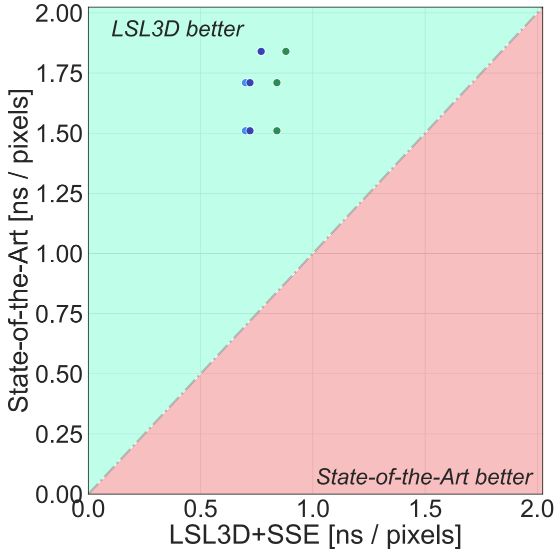
LSL3D vs best results of State-of-the-Art algorithms (1 point = 1 image)

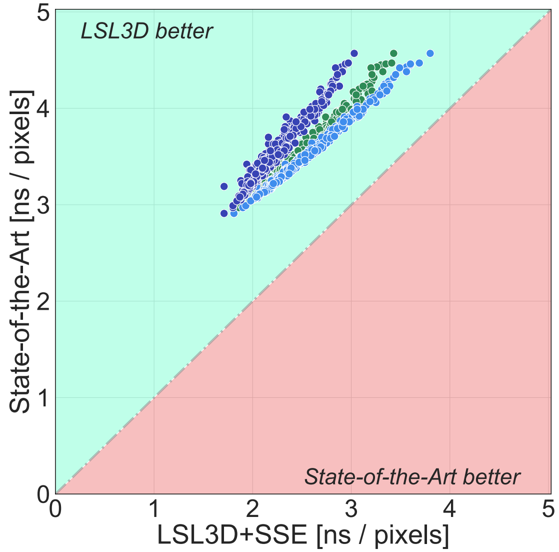
Mitochondria (simple)



OASIS (complex)

- LSL3D_ER
- LSL3D_FSM
- LSL3D_DOUBLE



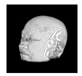


⇒ always faster than best State-of-the-Art

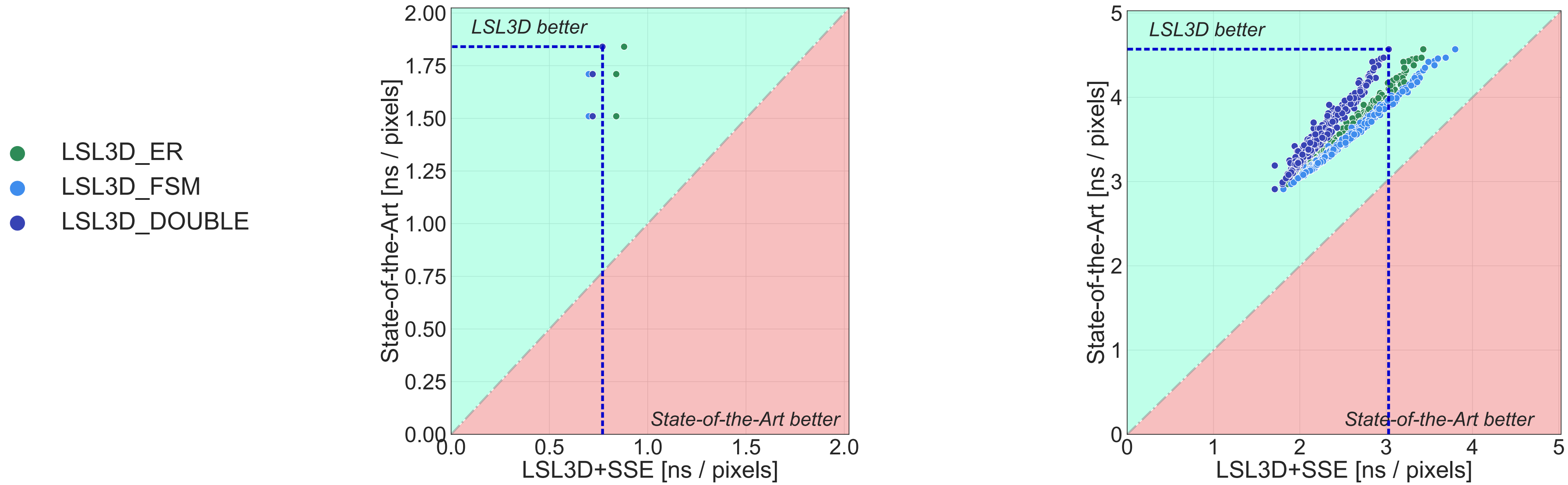
Medical datasets: Individual images

LSL3D vs best results of State-of-the-Art algorithms (1 point = 1 image)

Mitochondria
(simple)



OASIS
(complex)



⇒ always faster than best State-of-the-Art

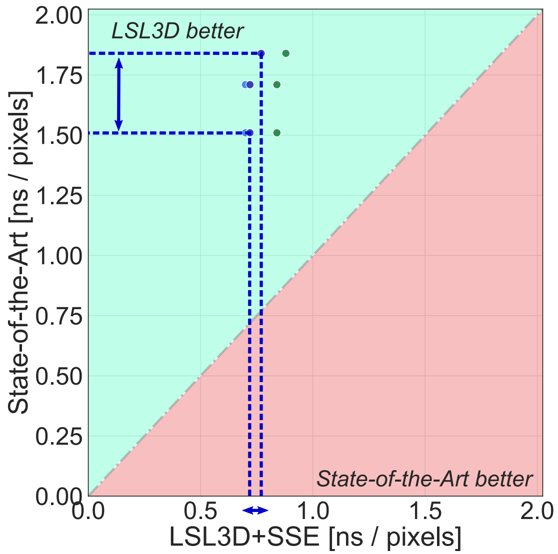
⇒ at least ×1.5 faster than best State-of-the-Art on worst-cases

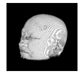
Medical datasets: Individual images

LSL3D vs best results of State-of-the-Art algorithms (1 point = 1 image)

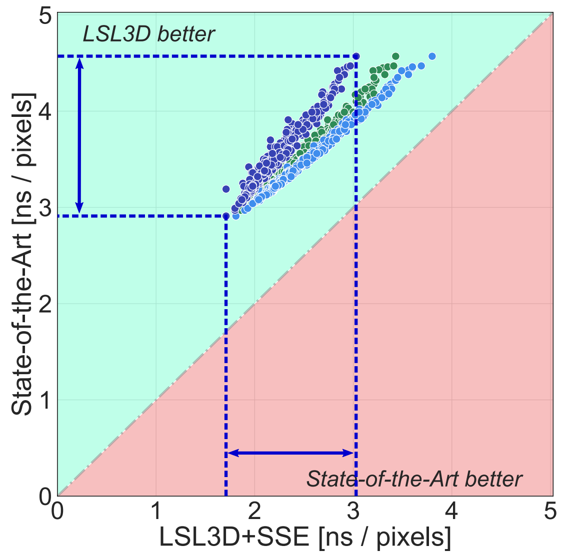
- LSL3D_ER
- LSL3D_FSM
- LSL3D_DOUBLE

Mitochondria (simple)





OASIS (complex)



⇒ always faster than best State-of-the-Art

⇒ at least ×1.5 faster than best State-of-the-Art on worst-cases

⇒ less sensitive to image variations

Conclusion

We propose a new *CCL* algorithm for 3D images that is based upon

1. a segment-based approach
2. an optimized FSM for merging segments with cache re-use mechanism (*double-line*)
3. an efficient SIMD implementation

Goals accomplished ⇒ faster than State-of-the-Art (or equivalent)
⇒ lower sensivity to image characteristics

Future work: parallelization on multi-core CPU and GPU

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- L. Lacassagne and B. Zavidovique, “Light speed labeling: Efficient connected component labeling on RISC architectures,” *Journal of Real-Time Image Processing*, vol. 6, pp. 117–135, June 2011.
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