

Minimal Component-Hypertrees

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Introduction and Related Works

Background
Theory

Proposed Method
Algorithms

Conclusion

Introduction and Related Works

Introduction

- ▶ Mathematical Morphology;

Introduction

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- ▶ Connected components (CCs) can give information about the characteristics of an object;

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- ▶ Connected components (CCs) can give information about the characteristics of an object;

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Introduction

Components Trees (Salembier et al., 1998)

- ▶ A graph (tree) that represents the inclusion relation of connected components of level sets of an image;

$$f : \mathcal{D} \subset \mathbb{Z}^n \rightarrow \{0, \dots, K-1\}$$

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$$X_\lambda(f) = \{p \in \mathcal{D} : f(p) \geq \lambda\}$$



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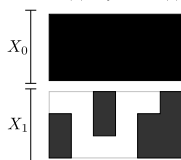
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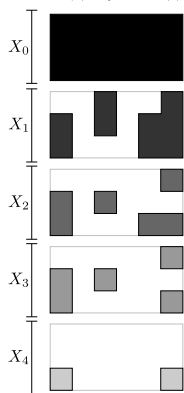
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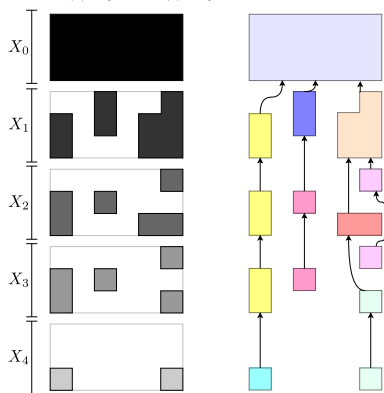
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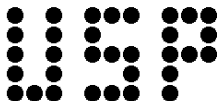
Connected Components

- ▶ Closely related to the the chosen connectivity;

Introduction

Connected Components

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- ▶ Groups of close objects can be considered as a single component;

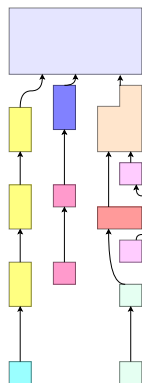
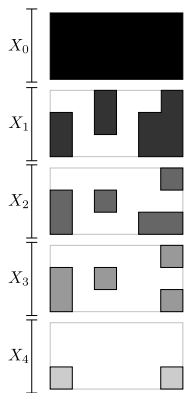
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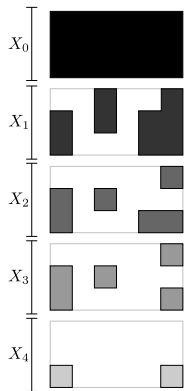
Introduction

Components Trees

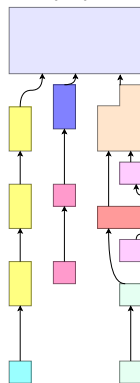
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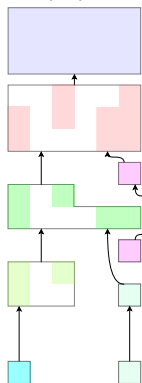
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3×3



5×3



Introduction

Component-Hypertrees (Passat and Naegel, 2011)

- ▶ Another hierarchy of connected components: multiple connectivities;

Introduction

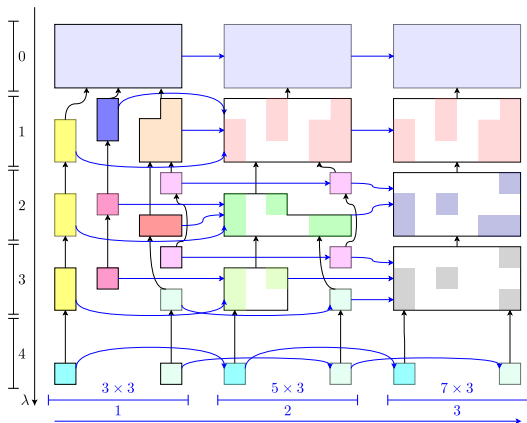
Component-Hypertrees (Passat and Naegel, 2011)

- ▶ Another hierarchy of connected components: multiple connectivities;
- ▶ A bigger neighborhood may connect disjoint components built from a smaller neighborhood;

Introduction

Component-Hypertrees

- ▶ Graph that represents both inclusions based on level sets and neighborhoods: *component-hypertree*.



Introduction

Component-Hypertrees

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Introduction

Component-Hypertrees

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- ▶ Includes information of all individual component trees and inclusion of nodes from consecutive trees;

Introduction

Component-Hypertrees

- ▶ Not as widely adopted as component trees:
- ▶ Includes information of all individual component trees and inclusion of nodes from consecutive trees;
- ▶ Cost in memory and processing times is multiplied by the number of neighborhoods;

Introduction

Component-Hypertrees

- ▶ Definition for mask-based connectivities (Passat and Naegel, 2011);
 - ▶ Focused on the theory of hypertrees;

Introduction

Component-Hypertrees

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- ▶ Efficient way of updating a tree for the next neighborhood (Morimitsu et al., 2015);

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Component-Hypertrees

- ▶ Definition for mask-based connectivities (Passat and Naegel, 2011);
 - ▶ Focused on the theory of hypertrees;
- ▶ Efficient way of updating a tree for the next neighborhood (Morimitsu et al., 2015);
- ▶ To the best of our knowledge, there was no optimized way of storing hypertrees efficiently;

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Component-Hypertrees

- ▶ Definition for mask-based connectivities (Passat and Naegel, 2011);
 - ▶ Focused on the theory of hypertrees;
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- ▶ To the best of our knowledge, there was no optimized way of storing hypertrees efficiently;
- ▶ This is the problem we want to solve;

Background

Theory

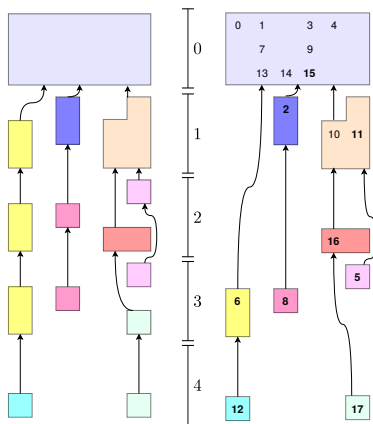
Max-tree

- ▶ Max-tree: efficient way of implementing a component tree;

Theory

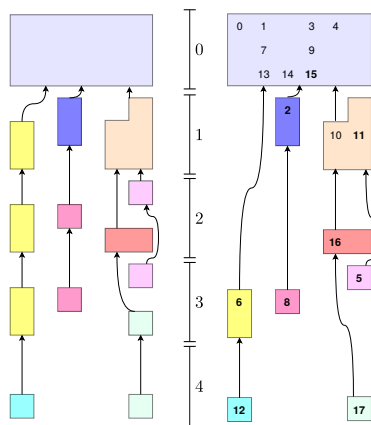
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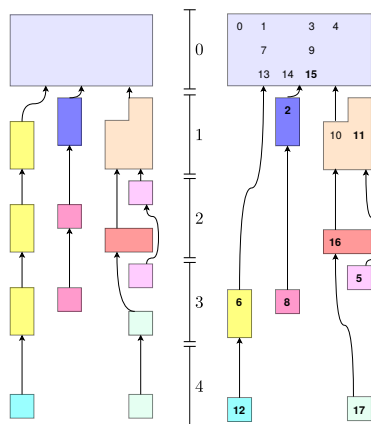
Max-tree



- ▶ Nodes are stored only once;
- ▶ Each pixel is stored only in the smallest node that contains it;
- ▶ Construction algorithm is optimized, i.e., it already allocate the nodes without repetition;

Theory

Max-tree



- ▶ Nodes are stored only once;
- ▶ Each pixel is stored only in the smallest node that contains it;
- ▶ Construction algorithm is optimized, i.e., it already allocates the nodes without repetition;

- ▶ We want a similar structure for component-hypertrees.

Naive approach

Simplified component-hypertree

- ▶ Naive approach: Build each max-tree separately;
- ▶ Merge nodes from consecutive trees;

Naive approach

Simplified component-hypertree

- ▶ Naive approach: Build each max-tree separately;
- ▶ Merge nodes from consecutive trees;
- ▶ Approach works, but it is not efficient:
 - ▶ Does not use previous computations;
 - ▶ Repeated nodes in different trees;

Proposed Method

Proposed approach

Simplified component-hypertree

- ▶ Proposed approach:

Proposed approach

Simplified component-hypertree

- ▶ Proposed approach:
 - ▶ Supposes a construction algorithm that uses previously computed max-tree and update them for the next neighborhood;
 - ▶ Keep track of changes to allocate only new nodes and arcs;

Algorithms

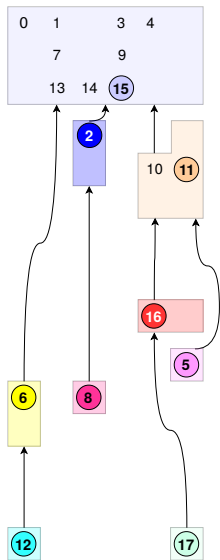
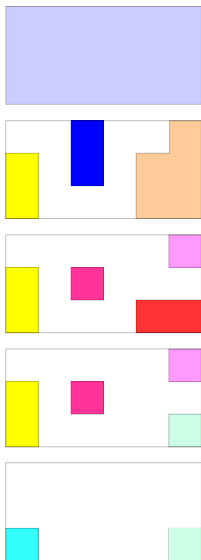
- ▶ Unordered union-find based version;

Algorithms

- ▶ Unordered union-find based version;
- ▶ Let \mathcal{A} be a set of pair of neighboring pixels. Then, the algorithm follows this template:
 1. Initialize the max-tree with each pixel as a node; //makeset
 2. For each pair $(p, q) \in \mathcal{A}$:
 - 2.1 Connect p to q in the max-tree; //union (Wilkinson et al., 2008)

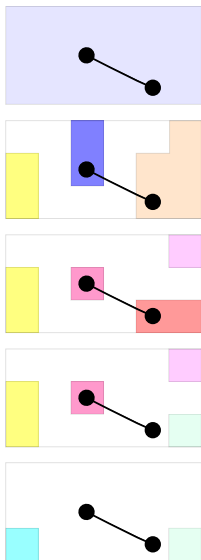
Algorithms

Union



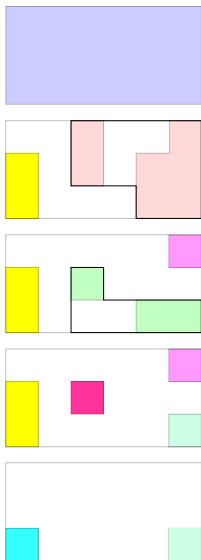
Algorithms

Union



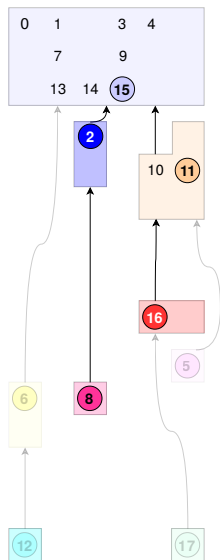
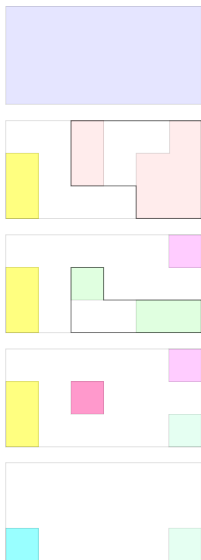
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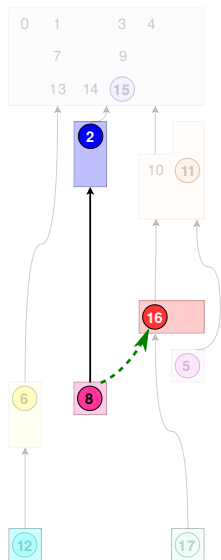
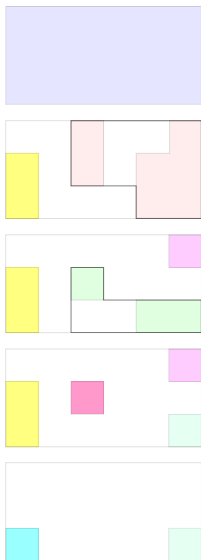
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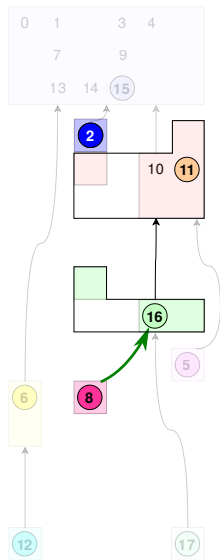
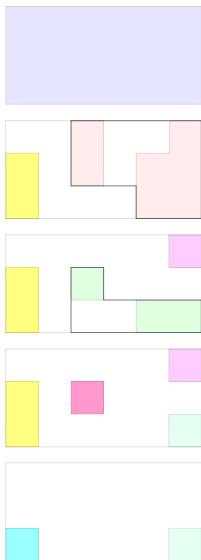
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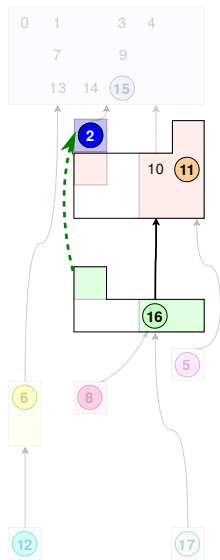
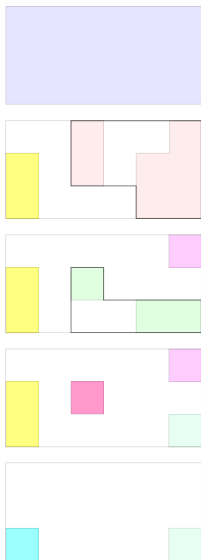
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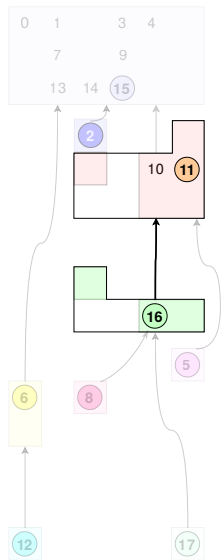
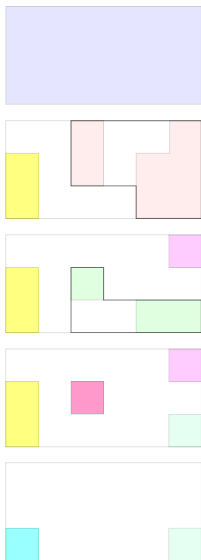
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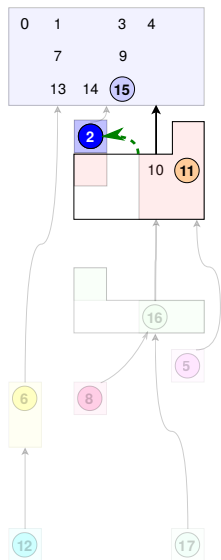
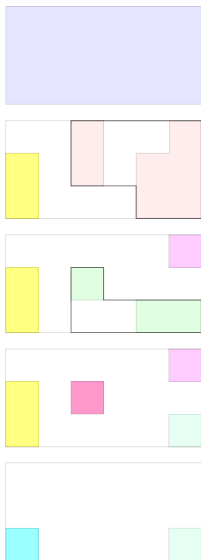
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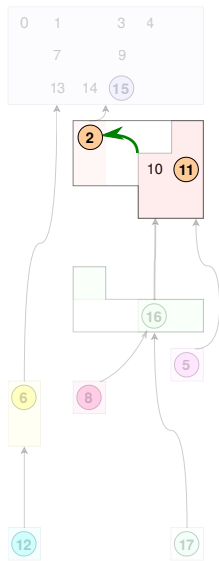
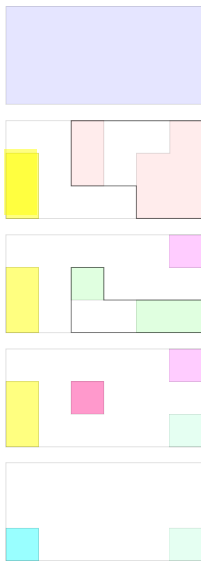
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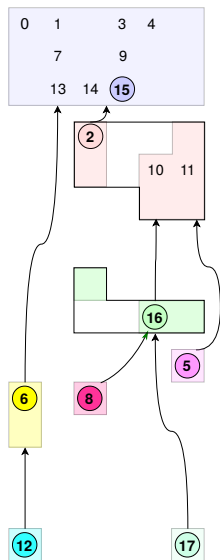
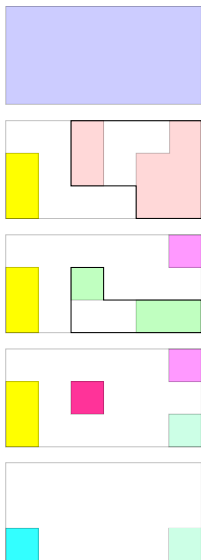
Algorithms

Union



Algorithms

Union



Algorithms

Union

- ▶ In the max-tree, connecting two pixels consists of merging two separate paths of the tree into one;

Algorithms

Hypertree Template

Let $\mathbb{A} = (\mathcal{A}_1, \dots, \mathcal{A}_n)$ be a sequence of n increasing sets of neighboring pixels. Then, the hypertree construction algorithm follows the template below:

1. Initialize the max-tree;
2. For $1 \leq i \leq n$:
 - 2.1 For (p, q) neighbors in \mathcal{A}_i :
 - 2.1.1 Connect p and q in the max-tree, looking for new nodes and arcs not present in step $i - 1$;
 - 2.2 Update the allocated hypertree based on new nodes and arcs;

Algorithms

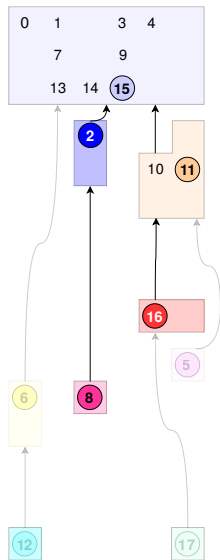
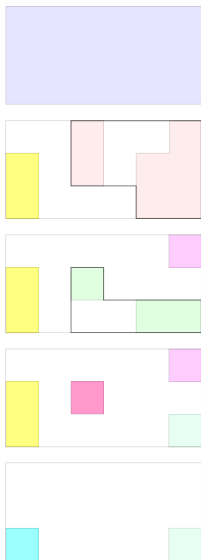
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1. Initialize the max-tree;
2. For $1 \leq i \leq n$:
 - 2.1 For **“relevant”** (p, q) in \mathcal{A}_i : //e.g. Morimitsu et al. (2015)
 - 2.1.1 Connect p and q in the max-tree, looking for new nodes and arcs not present in step $i - 1$;
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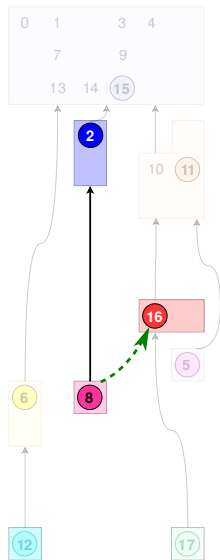
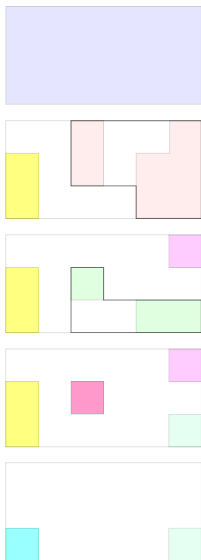
Algorithms

New nodes and arcs



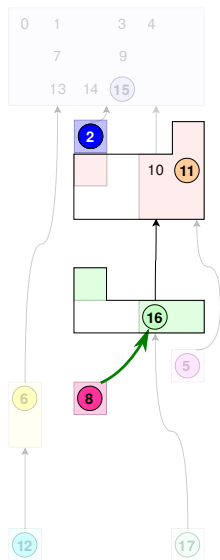
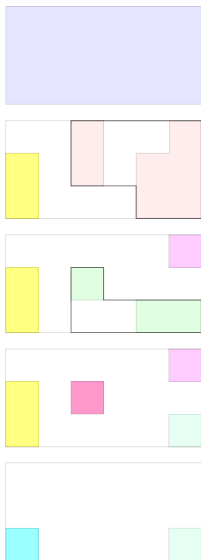
Algorithms

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Algorithms

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Algorithms

New nodes and arcs

- ▶ Detection of new nodes is found through changes in parent relation during the connect procedure;

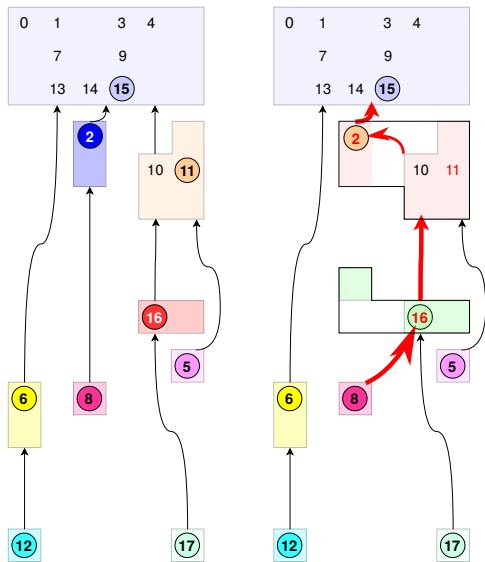
Algorithms

New nodes and arcs

- ▶ Detection of new nodes is found through changes in parent relation during the connect procedure;
- ▶ A node with a new child from the other path is a new node, since it contain at least a new pixel;
- ▶ All ancestors in this path, up to the common ancestor, will also now contain this new pixel and will be part of a new node.

Algorithms

New nodes and arcs



Algorithms

New nodes

- ▶ Mark all nodes (i.e., add their representative to a queue) in a path when a change in parenthood happens;
- ▶ Marked nodes are used to allocate new nodes;
 - ▶ Sometimes two marked nodes represent a same new node.
 - ▶ Usage of the *find* operation to avoid duplicated nodes;

Algorithms

New arcs

- ▶ Allocating arcs from new nodes:
 - ▶ For all new nodes, find their respective parent (from the max-tree) in hypertree and allocate these arcs;

Algorithms

New arcs

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- ▶ Allocating arcs pointing from old nodes to new nodes:
 - ▶ Allocate arcs that trigger a change in parenthood in the connect procedure;

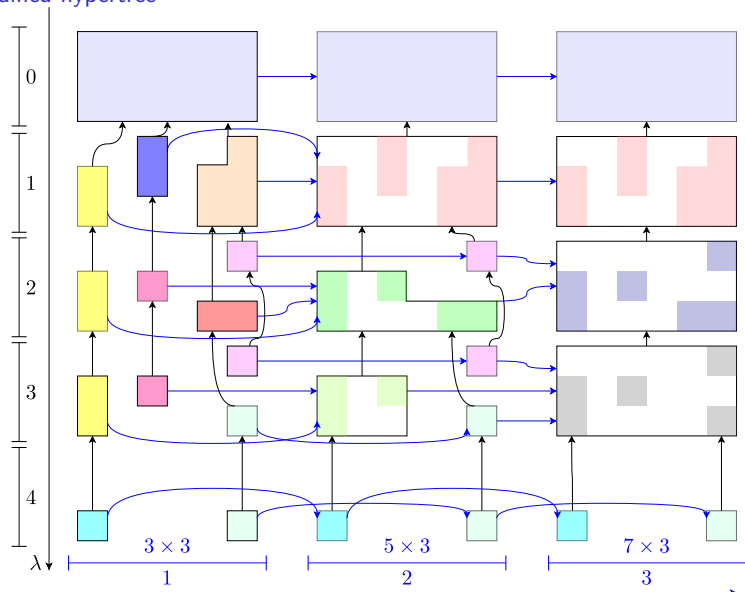
Algorithms

New arcs

- ▶ Allocating arcs from new nodes:
 - ▶ For all new nodes, find their respective parent (from the max-tree) in hypertree and allocate these arcs;
- ▶ Allocating arcs pointing from old nodes to new nodes:
 - ▶ Allocate arcs that trigger a change in parenthood in the connect procedure;
 - ▶ Find all nodes from the previous tree with the same representative as the new nodes and link them with an arc;

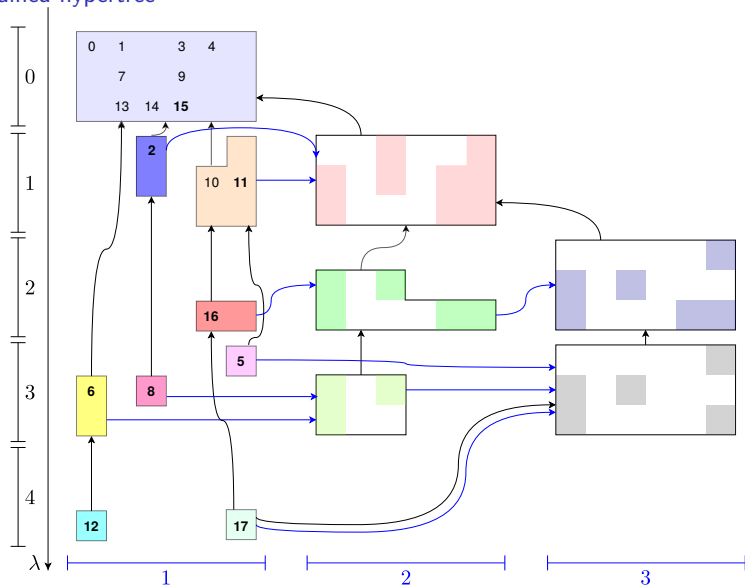
Theory

Obtained-hypertree



Theory

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Theory

Max-trees vs. Obtained Component-Hypertrees

- ▶ Nodes are stored only once;
 - ▶ Each pixel is stored only in the smallest node that contains it;
 - ▶ Construction algorithm does not allocate repeated nodes.
- ▶ ✓;
 - ▶ Each pixel is stored only in the smallest node that contains in the first tree;
 - ▶ ✓;

Theory

Max-trees vs. Obtained Component-Hypertrees

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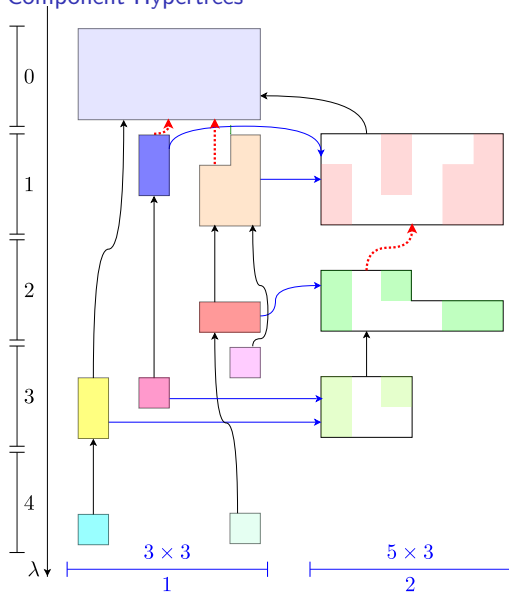
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 - ▶ All arcs give relevant information regarding inclusion relation.
- ▶ ✓;
 - ▶ Each pixel is stored only in the smallest node that contains in the first tree;
 - ▶ ✓;
 - ▶ Removes most arcs that give redundant information regarding inclusion relation.

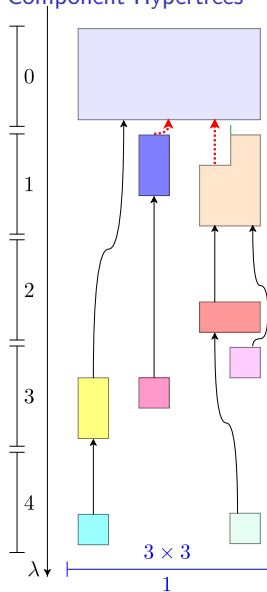
Theory

Minimal Component-Hypertrees



Theory

Minimal Component-Hypertrees



Theory

Minimal Component-Hypertrees

- ▶ The obtained hypertree has the smallest¹ number of nodes and arcs such that:

¹except for double arcs

Theory

Minimal Component-Hypertrees

- ▶ The obtained hypertree has the smallest¹ number of nodes and arcs such that:
 1. All original inclusion relations are preserved;
 2. All nodes can be reconstructed without depending on nodes with higher connectivity index;

¹except for double arcs

Experiments

Time consumption

- ▶ Updating the max-tree is the most time consuming step;

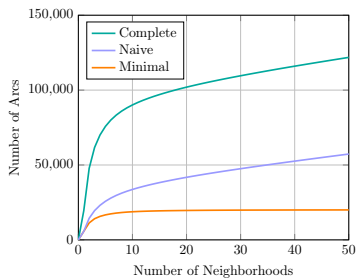
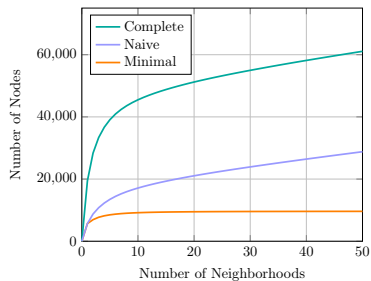
Experiments

Time consumption

- ▶ Updating the max-tree is the most time consuming step;
- ▶ For an optimized implementation using 50 square neighborhoods:
 - ▶ Total time ranging from 1 (0.25 mega-pixels) to 60s (8 mega-pixels);
 - ▶ Only 3% to 6% of time used to allocate structures;

Experiments

Memory saving



Experiments

Memory saving

- ▶ Memory saved, in average, for $n = 10$:
 - ▶ about 80% compared to the complete representation;
 - ▶ about 50% compared to the naive implementation;

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Memory saving

- ▶ Memory saved, in average, for $n = 10$:
 - ▶ about 80% compared to the complete representation;
 - ▶ about 50% compared to the naive implementation;
- ▶ This percentage increases as n increases since the number of new nodes decreases;

Conclusion

Conclusion

- ▶ Algorithms for efficient storage of component-hypertrees was proposed;
- ▶ Big saves in storage compared to other approaches;
- ▶ Allocation of nodes and arcs is fast;
- ▶ Computation of attributes will be presented in a later date (ISMM 2019);

Last Remarks

- ▶ Thank you!
- ▶ Questions? You can also check our poster;

Acknowledgements

This study was financed in part by the CAPES - Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (Finance Code 001); FAPESP - Fundação de Amparo a Pesquisa do Estado de São Paulo (Proc. 2018/15652-7); CNPq - Conselho Nacional de Desenvolvimento Científico e Tecnológico (Proc. 428720/2018-8).

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