Introduction to Image Processing #2/7

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 Outline

Outline



Image as a Graph

- From Image to Graph
- Sub-Graphs for the Binary Case

When Trees Appear

- Connected Component Labeling
- Distance Map
- Trees from Image Values

3 Application

- Filtering
- Segmentation
- Cutting Graphs

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Outline

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- Distance Map
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- Filtering
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Outline

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Image as a Graph

When Trees Appear Applications Conclusion From Image to Graph Sub-Graphs for the Binary Case

Outline



Image as a Graph From Image to Graph

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When Trees Appear

- Connected Component Labeling
- Distance Map
- Trees from Image Values

3 Application

- Filtering
- Segmentation
- Cutting Graphs

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From Image to Graph Sub-Graphs for the Binary Case



Consider this tiny 2D gray-level image (left):





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From Image to Graph Sub-Graphs for the Binary Case



A pixel (abrev. for "picture element") is

- a tile in the 2D plane of an image and its associated gray value
- a couple (image, point)

The right figure:

- separates pixels with lines (cyan)
- highlights pixel centers with dots (green)

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From Image to Graph Sub-Graphs for the Binary Case

About Graph (1/3)



- An undirected graph G is an ordered pair (V, E) such as:
 - V is a set of vertices—or nodes,
 - *E* is a set of *edges*, unordered pairs of vertices.
- We say that:
 - an edge connects its pair of endvertices,
 - two vertices are *adjacent* if an edge exists between them.
- Some curiosities:
 - a loop is an edge whose endvertices are the same vertex,
 - an edge is *multiple* if there is another edge with the same endvertices.
- A *simple graph* is a graph with no multiple edges or loops so *V* and *E* are not multisets.

From Image to Graph Sub-Graphs for the Binary Case

About Graph (2/3)



- The (open) *neighborhood*—or set of neighbors—of a vertex v consists of all its adjacent vertices not including v.
- A *path* is a sequence of vertices such that from each of its vertices there is an edge to the successor vertex.
- A graph is *connected* if a path can be established from any vertex to any other vertex of a graph.
- A *component* of a graph is a maximally connected subgraph.
- The *connectivity* of a graph is the minimum number of vertices needed to disconnect this graph.

From Image to Graph Sub-Graphs for the Binary Case

About Graph (3/3)



- A *walk* is an alternating sequence of vertices and edges:
 - it is closed if its first and last vertices are the same,
 - it is simple if every vertex is incident to at most two edges,
 - it is a cycle if it is both closed and simple.
- The Jordan curve theorem (topology) states that every non-self-intersecting closed curve in the plane divides the plane into an "inside" and an "outside".
- The *distance* between two vertices is the length of a shortest path between them.

From Image to Graph Sub-Graphs for the Binary Case

Further Readings



graph

http://en.wikipedia.org/wiki/Graph_(mathematics)

grid

http://en.wikipedia.org/wiki/Grid_graph

theory

http://en.wikipedia.org/wiki/Graph_theory

topics

http://en.wikipedia.org/wiki/List_of_graph_theory_topics

glossary

http://en.wikipedia.org/wiki/Glossary_of_graph_theory

From Image to Graph Sub-Graphs for the Binary Case

Turning an Image into a Graph

- Image points are natural candidate to be vertices.
- So we just need edges.
- In an image, pixels are adjacent (they touch each other) and a point has neighbors (the other points that are just around).
- Then let's go...

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From Image to Graph Sub-Graphs for the Binary Case

4-Connectivity

A pixel (red) has 4 neighbors (blue) and the graph is a square grid:



We have a 4-connectivity graph... except for border pixels!

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Dealing with Borders (1/2)

We extend our graph outside the image domain:



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Dealing with Borders (2/2)

- Only vertices from the original domain are considered as image points (green).
- And now those vertices have 4 neighbors (blue), yet outside the image domain.

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An Image as an Example

Values (gray-levels from image pixels) are associated with graph vertices.



From these values, we can derive some sub-graphs and then process the image.

Image as a Graph

When Trees Appear Applications Conclusion From Image to Graph Sub-Graphs for the Binary Case

Outline



Image as a Graph

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- Sub-Graphs for the Binary Case

When Trees Appear

- Connected Component Labeling
- Distance Map
- Trees from Image Values

3 Application

- Filtering
- Segmentation
- Cutting Graphs

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Binary Image

A binary image contains only two values:

- true = white = the object
- false = black = the backgroung (not the object)



Is there one (thin) object in this image or several ones?

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Sub-Graphes

We have a couple of sub-graphes, one for the object (left) and one for the background (right):



How many components do these sub-graphes have?

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8-Connectivity (1/2)

We move to 8-connectivity; now a pixel has 8 neighbors:





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8-Connectivity (2/2)

Now the object sub-graph is connected—it thus has a single component:



Yet, this component contains a cycle (orange) and the Jordan theorem ("inside/ouside") do not apply!

just count the number of backgroung component given the 8-connectivity...

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Always use a different connectivity for the object than for the background

either object=4 and background=8 or the contrary.



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An Issue that Really Matters

That issue is of prime importance for:

 algorithms that deal with several growing components at the same time

because a component is a well-defined region of an image

cycles to have an inside and and ouside

because a cycle is a contour or a propagation front in an image

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When the pixel is an hexagonal tile:

- what is the underlying graph?
- what is the connectivity?
- is there any problem with components and cycles?
- and what about the notion of distance?

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From Image to Graph Sub-Graphs for the Binary Case



If the image is 3D:

- what are the possible connectivities?
- and what connectivities are dual in the binary case?

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Exercise 3

Design an algorithm that extracts the inner 8-connectivity contour of object components.



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Foreword Connected Component Labeling Distance Map Trees from Image Values Further Readings

Foreword

The simplest structure that defines a raw binary 2D image *I* is such as:

- *I* is a 2D matrix so, given a point p = (r, c),
 - I_{r,c} is a pixel value
 - *I*(*p*) is another notation for this value
- at any point p, we have $I(p) \in true$, false
- a vertex v of the object sub-graph G
 - is represented by a point of the image
 - verifies *I*(*v*) = *true*
- if G is not connected, the object has several components.

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Foreword Connected Component Labeling Distance Map Trees from Image Values Further Readings

Outline



- From Image to Graph
- Sub-Graphs for the Binary Case



When Trees AppearConnected Component Labeling

- Distance Map
- Trees from Image Values

3 Applicatio

- Filtering
- Segmentation
- Cutting Graphs

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Foreword Connected Component Labeling Distance Map Trees from Image Values Further Readings

State of the Problem

Consider a binary image in which the object part represents screws and bolts (left):



we want an image where every component is assigned to a label

with a particular label for the background.

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State of the Problem

- each component can be represented by a spanning tree
 - this tree can be a rooted tree
 - its root node is representative
- each tree has its own label
- so we have a disjoint-set data structure—or forest of trees
- last the background is processed in a specific way

http://en.wikipedia.org/wiki/Spanning_tree_(mathematics)
http://en.wikipedia.org/wiki/Disjoint-set_data_structure

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Tarjan's Union-Find Algorithm (1/2)

initialization $I \leftarrow 0$ —CURRENT LABEL for all p $L(p) \leftarrow 0$ —BACKGROUND first pass for all p (in video scan) such as I(p) = true $parent(p) \leftarrow p$ —MAKE A NEW (SINGLETON) SET/TREE for all ante-video neighbors n of p such as I(n) = true $do_union(n, p)$ second pass for all p (in reverse video scan) such as I(p) = true if parent(p) = p —ROOT POINT $I \leftarrow I + 1$ $L(p) \leftarrow I - \text{NEW LABEL}$ else $L(p) \leftarrow L(parent(p))$ —LABEL PROPAGATION

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Tarjan's Union-Find Algorithm (2/2)

```
Auxiliary functions: do_union(n, p) {
  r \leftarrow \text{find}_{root}(n)
  if r \neq p —TWO TREES SHOULD MERGE
    parent(r) \leftarrow p
}
find_root(x) : point {
  if parent(x) = x —ROOT POINT
    \rightarrow X
  else — RECURSIVE CALL WITH TREE COMPRESSION
    \rightarrow find_root(parent(x))
}
```

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Foreword Connected Component Labeling Distance Map Trees from Image Values Further Readings

Outline



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A Need for Distances

Distance-related information is useful in practice; for instance:

- obviously the distance between two points
- the distance of a point to an object
- and also the object which a point is the closest to
- some distances between a couple of objects

• etc.

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Distances (1/2)

A distance between 2 elements x and y of a set is a function to \mathbb{R} which satisfies:

- $d(x,y) \geq 0$,
- d(x, y) = 0 if and only if x = y,
- d(x, y) = d(y, x) (symmetry),
- $d(x,z) \le d(x,y) + d(y,z)$ (triangle inequality).

If the set is \mathbb{R}^n , elements are vectors: $x = (.., x_i, ..)$ where x_i is the *i*th coordinate of *x*.

The p-norm distance (Minkowsky distance of order p) is:

$$L_p(x,y) = \left(\sum_{i=1}^n |x_i - y_i|^p\right)^{1/p}$$
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Distances (2/2)

We have: Manhattan distance

Euclidean distance

Chebyshev distance

$$L_{1}(x, y) = \sum_{i=1}^{n} |x_{i} - y_{i}|$$

$$L_{2}(x, y) = \sqrt{\sum_{i=1}^{n} |x_{i} - y_{i}|^{2}}$$

$$L_{\infty} = \max_{i \in [1,n]_{\mathbb{N}}} |x_{i} - y_{i}|$$

With 2D points, we can write:

$$\begin{array}{lll} L_1(p,p') &=& |r-r'|+|c-c'| \\ L_2(p,p') &=& \sqrt{(r-r')^2+(c-c')^2} \\ L_\infty(p,p') &=& \max(|r-r'|, |c-c'|) \end{array}$$



http://en.wikipedia.org/wiki/Distance

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Distances as Defined by Graphs (1/3)

Since we have graphs, we can directly use the notion of distance between vertices:



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Distances as Defined by Graphs (2/3)

With the 4-connectivity, we have the Manhattan distance (also named city-block or taxi-cab).



Manhattan distance to a point (black = the point; dark and light grays = resp. short and long distances)



http://en.wikipedia.org/wiki/Taxicab_geometry_ > ()

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Distances as Defined by Graphs (3/3)

With the 8-connectivity, we have the chessboard distance.



chessboard distance to a point

Both the Manhattan and the chessboard distances are quite poor approximations of the Euclidean distance.

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Distance Map

A distance map is an image D whose any value D(p) is the distance between p and an object.

Below the screws and bolts binary image (left) and its distance map (right):





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Computing a Distance Map (1/2)

The following algorithm computes a distance map with a chamfer propagation:

initialization for all p $D(p) \leftarrow 0$ if $I(p) = true, \infty$ otherwise forward pass for all p = (r, c) taken in video scan

video scan means "for each row (from up to down), for each column (from left to right), do something"

backward pass
for all
$$p = (r, c)$$
 taken in reverse video scan
if $D(p) \neq 0$
 $D(p) \leftarrow min(D(p), D_{r+1,c} + 1, D_{r,c+1} + 1)$

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Computing a Distance Map (2/3)

Remark that:

- its complexity is O(N) with N being the number of image pixels,
- the complexity constant factor is a multiple of the connectivity,
- this algorithm is *sequential* (contrary of parallel).

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Foreword Connected Component Labeling Distance Map Trees from Image Values Further Readings

Computing a Distance Map (3/3)

Left as an exercise:

how to make this algorithm compute distances that are closer to Euclidean ones?

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Foreword Connected Component Labeling Distance Map Trees from Image Values Further Readings

Computing Influence Zones (1/3)

Example:

- we have a binary image representing several objects,
- so we perform connected component labeling (left),
- and we want to obtain their influence zones (right).





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Computing Influence Zones (2/3)

With *L* being the label image and *Z* the expected result: initialization for all p if I(p) = true $D(p) \leftarrow 0$, $Z(p) \leftarrow L(p)$ else $D(p) = \infty$ forward pass for all p = (r, c) taken in video scan if $D(p) = \infty$ $d \leftarrow D(p)$ if $D_{r-1,c} + 1 < d$ $d \leftarrow D_{r-1,c}, I \leftarrow Z_{r-1,c}$ if $D_{r,c-1} + 1 < d$ $d \leftarrow D_{r,c-1}, I \leftarrow Z_{r,c-1}$ if $d \neq \infty$ $D(p) \leftarrow d$, $Z(p) \leftarrow I$

backward pass left as an exercice

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Foreword Connected Component Labeling Distance Map Trees from Image Values Further Readings

Computing Influence Zones (3/3)

We want a map (image) so that at any point we are able to trace the shortest path towards the closest object.

- what data structure do we need for this map?
- how should we modify the previous algorithm?
- given a border point of an object, what is the underlying data structure?

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Foreword Connected Component Labeling Distance Map Trees from Image Values Further Readings

Outline



- From Image to Graph
- Sub-Graphs for the Binary Case



When Trees Appear

- Connected Component Labeling
- Distance Map
- Trees from Image Values

3 Applicatio

- Filtering
- Segmentation
- Cutting Graphs

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Foreword Connected Component Labeling Distance Map Trees from Image Values Further Readings



Consider the following image whose values are 8-bit quantized:



It has foor different ordered values v_i :

- black ($v_1 = 0$), dark gray ($v_2 = 85$), light gray ($v_3 = 170$), and white ($v_4 = 255$).

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The components of every G_i are depicted below (leftmost is G_1 ; rightmost is G_4):



- There is a natural inclusion: any component of G_i is included in a component of G_{i+1}.
- So all these components can be structured by an inclusion tree.



Min-Tree

This tree whose leaf nodes are the image *regional minima* is called the image *min-tree*:



A regional minima is a flat component whose outer contour is higher.

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Min/Max-Tree (1/2)



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Foreword Connected Component Labeling Distance Map Trees from Image Values Further Readings

Min/Max-Tree (2/2)



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臣

Foreword Connected Component Labeling Distance Map Trees from Image Values Further Readings

Further Readings (1/2)



tree in graph theory

http://en.wikipedia.org/wiki/Tree_(graph_theory)

tree data structure

http://en.wikipedia.org/wiki/Tree_data_structure

tree traversal

http://en.wikipedia.org/wiki/Tree_traversal

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Foreword Connected Component Labeling Distance Map Trees from Image Values Further Readings

Further Readings (2/2)



depth-first search

- http://en.wikipedia.org/wiki/Depth-first_search
- http://en.wikipedia.org/wiki/Iterative_deepening_ depth-first_search
- http://en.wikipedia.org/wiki/Best-first_search

breadth-first search

http://en.wikipedia.org/wiki/Breadth-first_search

A* search algorithm

http://en.wikipedia.org/wiki/A*_search_algorithm

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Filtering Segmentation Cutting Graphs

Outline



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Filtering Segmentation Cutting Graphs

Removing Stars in Galaxy Images



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Identifying Boxes in Comic Strips



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Filtering Segmentation Cutting Graphs



when replacing the notion of pixels by the one of primitives, e.g., regions, we end up with high-level methods

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Filtering Segmentation Cutting Graphs

Outline



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Filtering Segmentation Cutting Graphs

Region Adjacency Graph (1/4)



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Filtering Segmentation Cutting Graphs

Region Adjacency Graph (2/4)



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Filtering Segmentation Cutting Graphs

Region Adjacency Graph (3/4)



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Filtering Segmentation Cutting Graphs

Region Adjacency Graph (4/4)



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Filtering Segmentation Cutting Graphs

Road Identification (1/4)



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Road Identification (2/4)



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Road Identification (3/4)



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Filtering Segmentation Cutting Graphs

Road Identification (4/4)



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Text Recognition (1/8)

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Text Recognition (2/8)



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Text Recognition (3/8)



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Text Recognition (4/8)



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Text Recognition (5/8)



Filtering Segmentation Cutting Graphs

Text Recognition (6/8)



Filtering Segmentation Cutting Graphs

Text Recognition (7/8)



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Filtering Segmentation Cutting Graphs

Text Recognition (8/8)



Filtering Segmentation Cutting Graphs

Outline



- From Image to Graph
- Sub-Graphs for the Binary Case

When Trees Appear

- Connected Component Labeling
- Distance Map
- Trees from Image Values



Applications

- Filtering
- Segmentation
- Cutting Graphs

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Filtering Segmentation Cutting Graphs

Definitions



- A *cut* is a partition of the vertices of a graph into two sets; a *cut edge* is an egde whose endvertices do not belong to the same set.
- The cut *size* is the number of its cut edges; in weighted graphs, the size is the sum of the cut edges' weights.
- A cut is a *min-cut* if the size of the cut is not larger than the size of any other cut.
- A cut is a *max-cut* if the size of the cut is not smaller than the size of any other cut.

http://en.wikipedia.org/wiki/Cut_(graph_theory)

Filtering Segmentation Cutting Graphs





- Finding a min-cut can be solved by polynomial-time algorithms.
- Finding a max-cut is an NP-complete problem.
- The *m*ax-flow problem is the dual of the min-cut problem.

http://en.wikipedia.org/wiki/Complexity_classes_P_and_NP

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Filtering Segmentation Cutting Graphs

Results



Leo Grady et al., Siemens Corporate Research, Princeton, Marcola Social



Having a structure (graph, tree, and so on) is often not enough!

We need another theoretical framework to put upon this structure to process images.

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