

Graph Cuts Approach to the Problems of Image Segmentation

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(Adapted from Antong Chen)

Outline

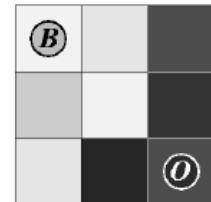
- Image Segmentation and Graph Cuts
 - Introduction
- Glance at Graph Theory
- Graph Cuts and Max-Flow/Min-Cut Algorithms
- Solving Image Segmentation Problem
- Experimental Examples

Image Segmentation and Graph Cuts – Introduction

- An image segmentation problem can be interpreted as partitioning the image elements (pixels/voxels) into different categories
- A Cut of a graph is a partition of the vertices in the graph into two disjoint subsets
- Constructing a graph with an image, we can solve the segmentation problem using techniques for graph cuts in graph theory

Constructing a Graph from an Image

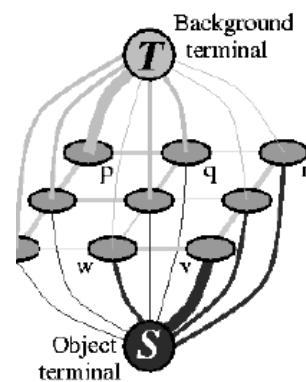
- Two kinds of vertices
- Two kinds of edges
- Cut - Segmentation



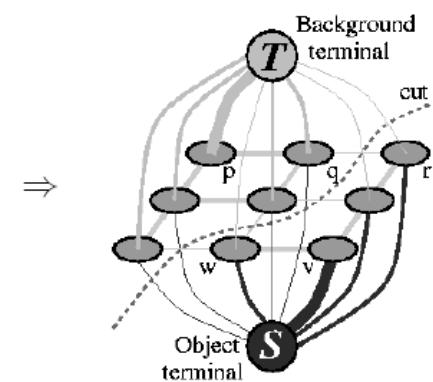
(a) Image with seeds.



(d) Segmentation results



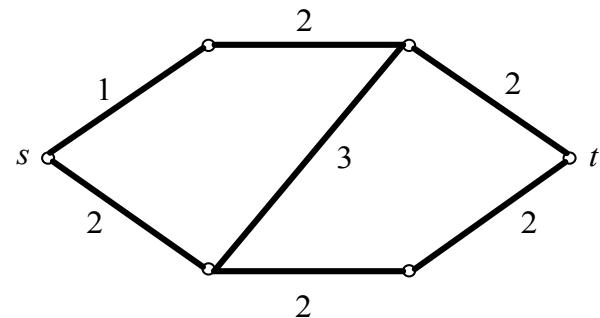
(b) Graph.



(c) Cut.

Glance at Graph Theory

- Undirected Graph
- An undirected graph $G = (V, E)$ is defined as a set of nodes (vertices V) and a set of undirected edges E that connect the nodes.
- Assigning each edge $e \in E$ a weight w_e , the graph becomes an undirected weighted graph.



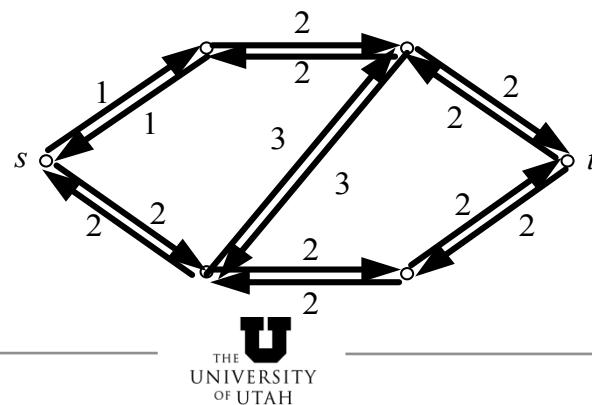
Glance at Graph Theory

- Directed Graph
 - A directed graph is defined as a set of nodes (vertices V) and a set of ordered set of vertices or directed edges E that connect the nodes
- For an edge $e=(u,v)$, u is called the tail of e, v is called the head of e.
- This edge is different from the edge $e'=(v,u)$

$$G = (V, E)$$

$$e' = (v, u)$$

$$e = (u, v)$$



Glance at Graph Theory

- A cut is a set of edges $C \subset E$ such that the two terminals become separated on the induced graph

$$G' = (V, E \setminus C)$$

- Denoting a source terminal as s and a sink terminal as t , a cut (S, T) of $G = (V, E)$ is a partition of V into S and $T = V \setminus S$, such that $t \in T$ and $s \in S$

Graph Cuts and Max-Flow/Min-Cut Algorithms

- A flow network is defined as a directed graph where an edge has a nonnegative capacity
- A flow in G is a real-valued (often integer) function that satisfies the following three properties:
 - Capacity Constraint:
 - For all $u, v \in V, f(u, v) \leq c(u, v)$
 - Skew Symmetry
 - For all $u, v \in V, f(u, v) = -f(v, u)$
 - Flow Conservation
 - For all $u \in (V \setminus \{s, t\}), \sum_{v \in V} f(u, v) = 0$

How to Find the Minimum Cut?

- Theorem:
 - In graph G , the maximum source-to-sink flow possible is equal to the capacity of the minimum cut in G .
 - (L. R. Foulds, Graph Theory Applications, 1992 Springer-Verlag New York Inc., 247-248)

Maximum Flow and Minimum Cut Problem

- Some Concepts
 - If f is a flow, then the net flow across the cut (S, T) is defined to be $f(S, T)$, which is the sum of all edge capacities from S to T subtracted by the sum of all edge capacities from T to S
 - The capacity of the cut (S, T) is $c(S, T)$, which is the sum of the capacities of all edges from S to T
 - A minimum cut is a cut whose capacity is the minimum over all cuts of G .

Algorithms to Solve Max-Flow Problem

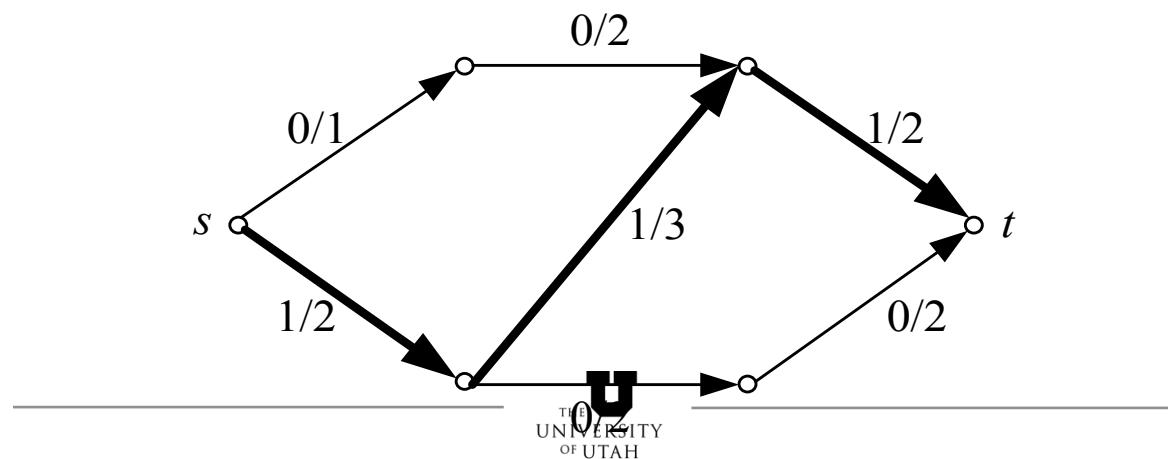
- Ford-Fulkerson Algorithm
- Push-Relabel Algorithm
- New Algorithm by Boykov, etc.

Ford-Fulkerson Algorithm

- Main Operation
- Starting from zero flow, increase the flow gradually by finding a path from s to t along which more flow can be sent, until a max-flow is achieved
- The path for flow to be pushed through is called an augmenting path

Ford-Fulkerson Algorithm

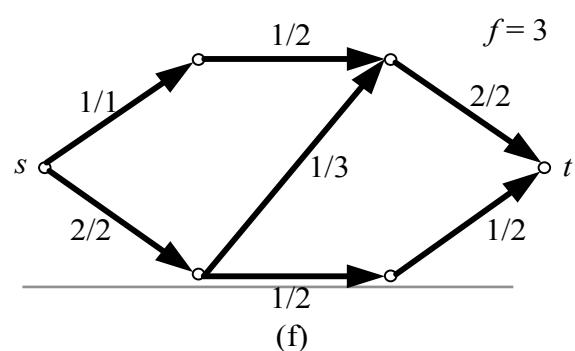
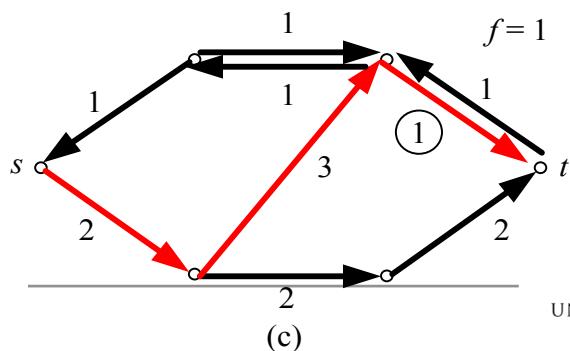
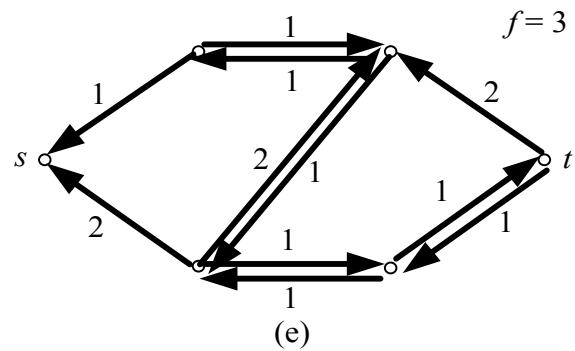
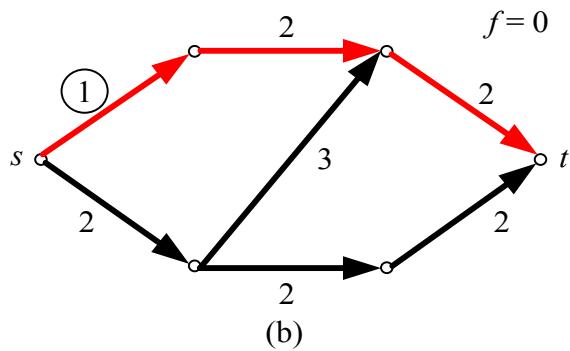
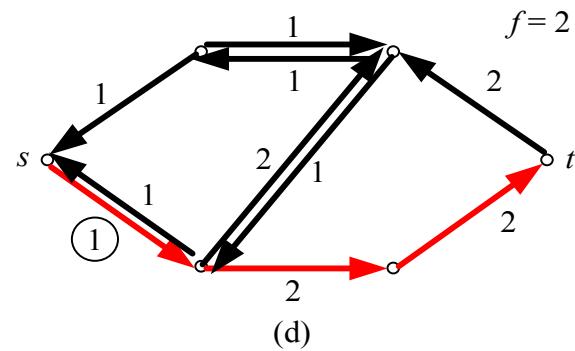
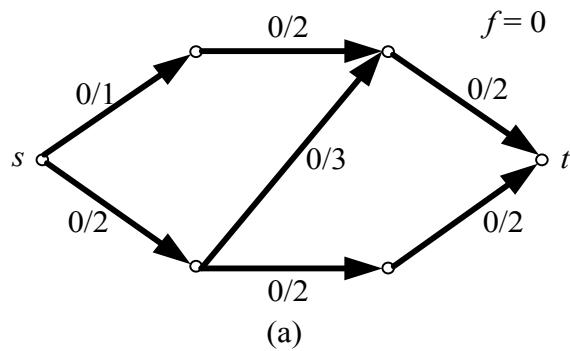
- The Ford-Fulkerson algorithm uses a residual network of flow in order to find the solution
- The residual network is defined as the network of edges containing flow that has already been sent
- In the graph shown below, there is an initial path from the source to the sink, and the middle edge has a total capacity of 3, and a residual capacity of $3-1=2$



Ford-Fulkerson Algorithm

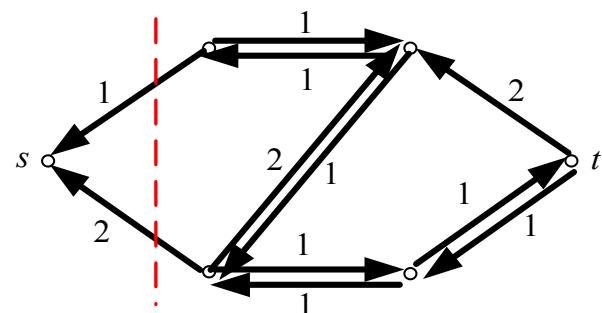
- Assuming there are two vertices, u and v , let $f(u, v)$ denote the flow between them, $c(u, v)$ be the total capacity, $cf(u, v)$ be the residual capacity, and there should be,
 - $cf(u, v) = c(u, v) - f(u, v)$
- Given a flow network and a flow f , the residual network of G is $G_f = (V, E_f)$ where $E_f = \{(u, v) \in V \times V : c_f(u, v) > 0\}$
- Given a flow network and a flow f , an augmenting path P is a simple path from s to t in the residual network
- We call the maximum amount by which we can increase the flow on each edge in an augmenting path P the residual capacity of P , given by,
 - $cf(P) = \min\{cf(u, v) : (u, v) \text{ is on } P\}$

Algorithm Execution Example



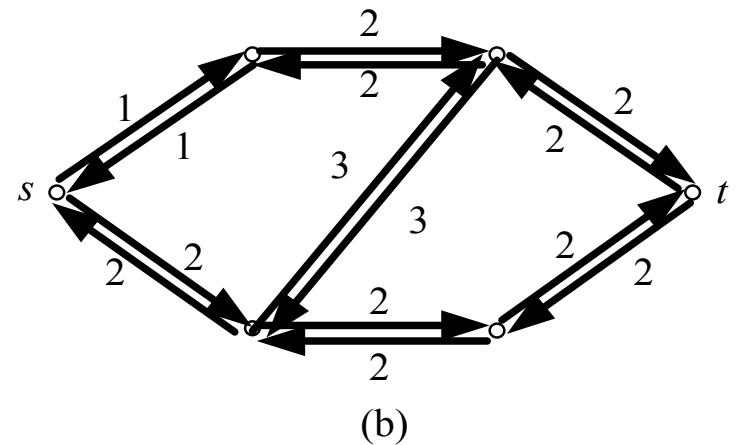
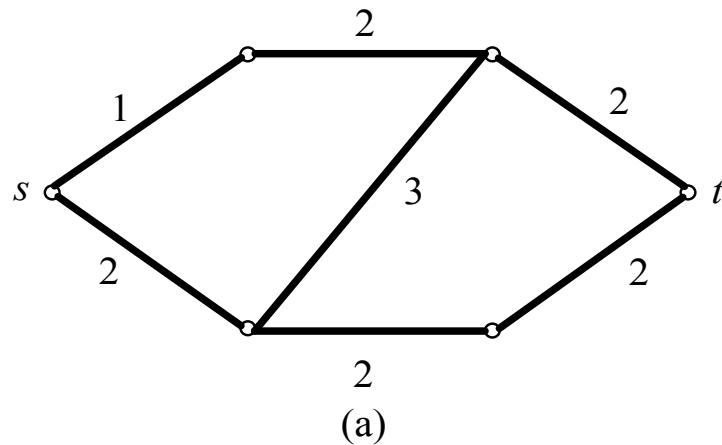
Finding the Min-Cut

- After the max-flow is found, the minimum cut is determined by
 - $S = \{\text{All vertices reachable from } s\}$
 - $T = G \setminus S$



Special Case

- As in some applications only undirected graph is constructed, when we want to find the min-cut, we assign two edges with the same capacity to take the place of the original undirected edge



Algorithm Framework

The basic Ford-Fulkerson algorithm

for each edge $(u, v) \in E$

do

$$f(u, v) \leftarrow 0$$

$$f(v, u) \leftarrow 0$$

while there exists a path P from s to t

in the residual network G_f

do $c_f(P) \leftarrow \min\{c_f(u, v) : (u, v) \text{ is on } P\}$

for each edge (u, v) in P

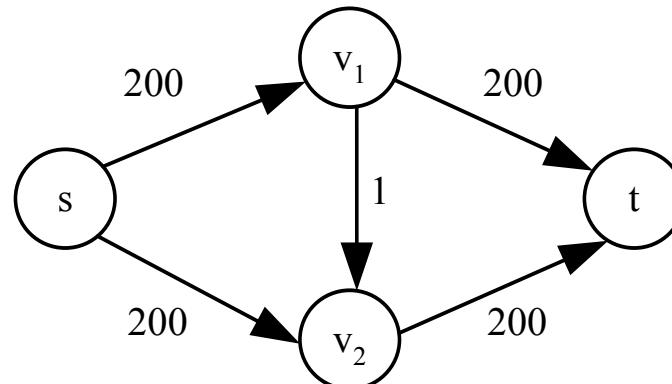
do

$$f(u, v) \leftarrow f(u, v) + c_f(P)$$

$$f(v, u) \leftarrow -f(u, v)$$

Ford-Fulkerson Algorithm Analysis

- Running time of the algorithm depends on how the augmenting path is determined
 - If the searching for augmenting path is realized by a breadth-first search, the algorithm runs in polynomial time of
 - $O(|E|f_{\max}|)$
- In extreme cases efficiency can be reduced drastically.
 - Below, applying Ford-Fulkerson algorithm needs 400 iterations to get the max flow of 400



Push-Relabel Algorithm

- This algorithm does not maintain a flow conservation rule, there is $\forall u \in V \setminus \{s\}, \exists f(V, u) \geq 0$
- We call the total net flow at a vertex u the excess flow into u , given by $e(u) = f(V, u)$. We say that a vertex $u \in V \setminus \{s, t\}$ is overflowing if $e(u) = f(V, u) > 0$
- Height Function:
 - Let $G = (V, E)$ be a flow network with source s and sink t , let f be a preflow (the flow satisfying the skew symmetry, capacity constraint, and the condition above) in G . A function $h : V \rightarrow \mathbf{N}$ is a height function if $h(s) = |V|$, $h(t) = 0$, and for every residual edge $(u, v) \in E_f$

Push-Relabel Algorithm Stages

Initialize-Preflow (G, s)

for each vertex $u \in V$
do

$$h[u] \leftarrow 0$$

$$e[u] \leftarrow 0$$

$$h(s) \leftarrow |V|$$

for each edge $(u, v) \in E$
do

$$f[v, u] \leftarrow 0$$

$$f[u, v] \leftarrow 0$$

for each vertex $u \in \text{Adj}(s)$
do

$$f[s, u] \leftarrow c(s, u)$$

$$f(u, s) \leftarrow -c(s, u)$$

$$e[u] \leftarrow c(s, u)$$

$$e[s] \leftarrow e[s] - c(s, u)$$

Push-Relabel Algorithm Stages

Push (u, v)

Applied when: u is overflowing,

$$c_f(u, v) > 0, \text{ and } h(u) = h(v) + 1$$

Action:

Push $d_f(u, v) = \min(e[u], c_f(u, v))$ units of flow from u to v :

$$d_f(u, v) \leftarrow \min(e[u], c_f(u, v))$$

$$f[u, v] \leftarrow f[u, v] + d_f(u, v)$$

$$f[v, u] \leftarrow -f[u, v]$$

$$e[u] \leftarrow e[u] - d_f(u, v)$$

$$e[v] \leftarrow e[v] + d_f(u, v)$$

Push-Relabel Algorithm Stages

Relable (u)

Applied when: u is overflowing and for all $v \in V$ such that

$$(u, v) \in E_f, \text{ we have } h(u) \leq h(v)$$

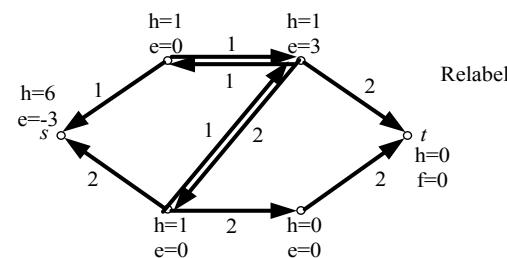
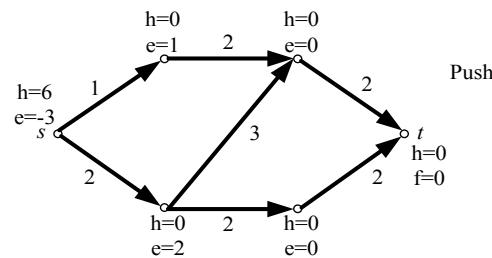
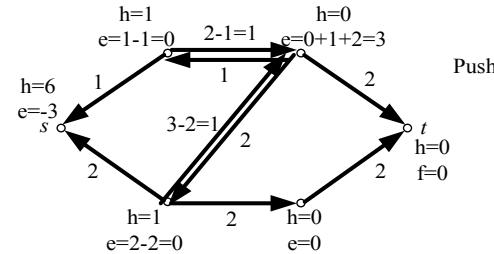
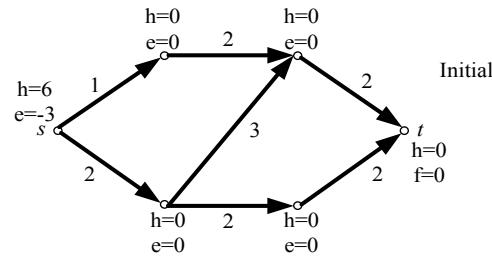
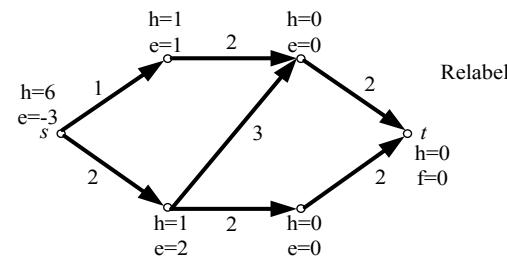
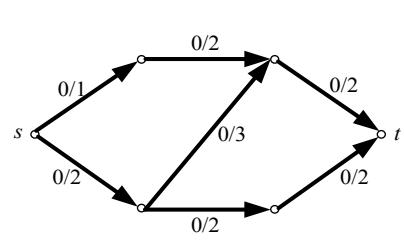
Action: Increase the height of u :

$$h(u) \leftarrow 1 + \min(h(v) : (u, v) \in E_f)$$

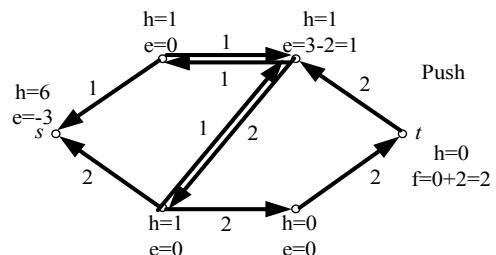
Push-Relabel Algorithm Framework

- Generic-Push-Relabel (G)
 - Initialize-Preflow (G, s)
 - while there exists an applicable push or relabel operation do
 - select an applicable push or relabel operation and perform it

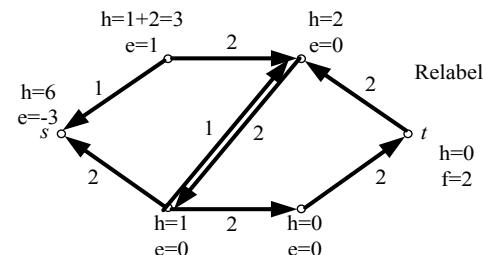
Push-Relabel Algorithm Example



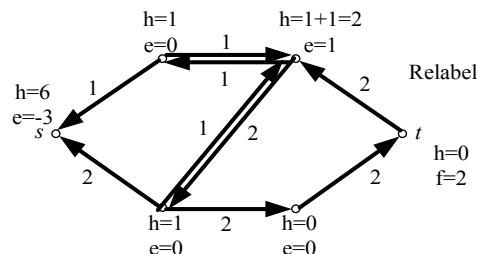
Push-Relabel Algorithm Example



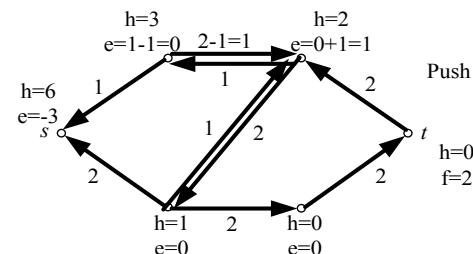
Push



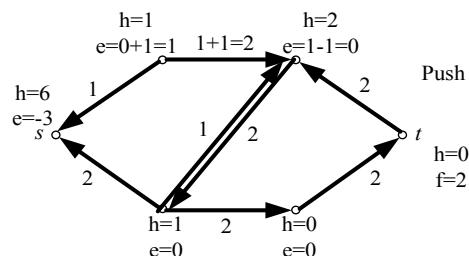
Relabel



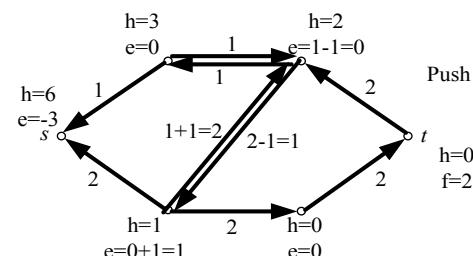
Relabel



Push

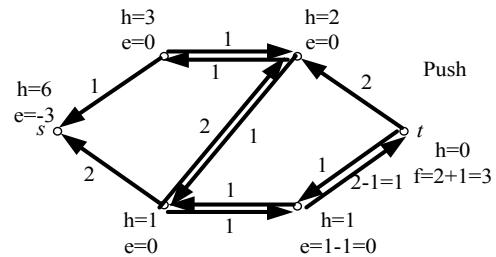
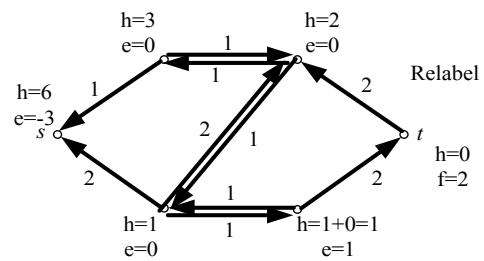
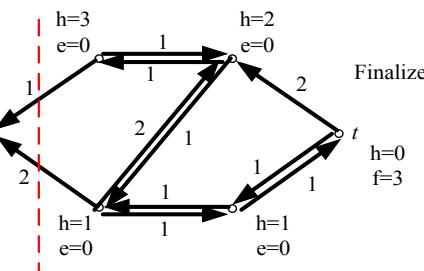
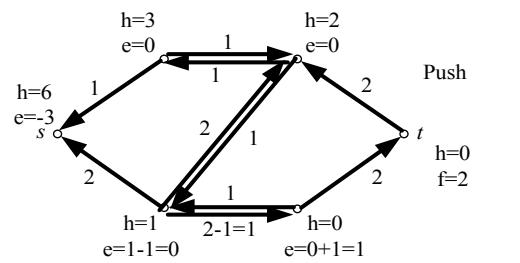


Push



Push

Push-Relabel Algorithm Example



Push-Relabel Algorithm Analysis

- The algorithm complexity is bounded to $O(V^2E)$
- Improved algorithms using highest-level selection rule and FIFO-rule (queue based selection rule) can reduce the complexity to $O(V^2\sqrt{E})$
- Optimizing the program by using bucket data structure based on any of the improved algorithms can yield $O(VE)$

Solving Image Segmentation Problem

- Data element set P representing the image pixels/voxels
- Neighborhood system as a set N representing all pairs {p,q} of neighboring elements in P (ordered or unordered)
- A be a vector specifying the assignment of pixel p in P, each A_p can be either in the background or the object

$$A = (A_1, A_2, \dots, A_p, \dots, A_{|P|})$$

- A defines a segmentation of P

Cost of Segmentation

$$E(A) = \lambda \cdot R(A) + B(A)$$

$$R(A) = \sum_{p \in P} R_p(A_p)$$

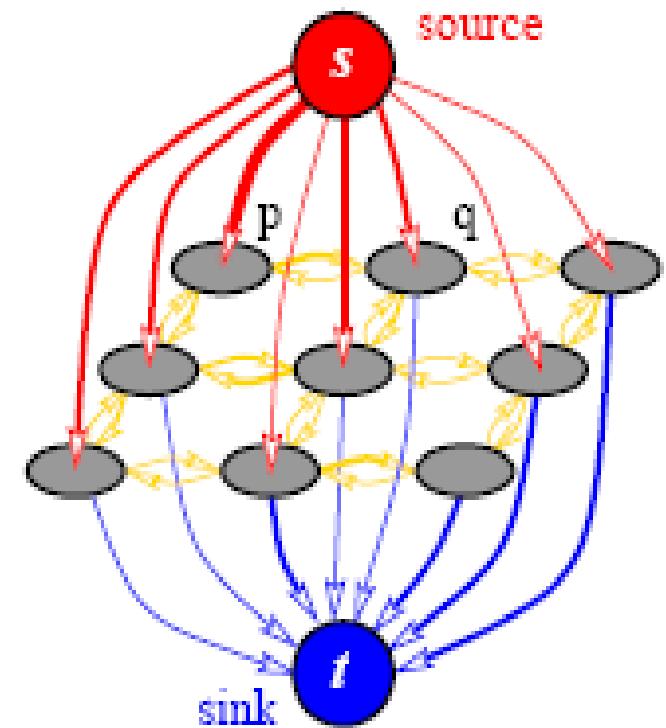
$$\delta(A_p, A_q) = \begin{cases} 1 & A_p \neq A_q \\ 0 & A_p = A_q \end{cases}$$

$$B(A) = \sum_{p \in P} \sum_{\{p,q\} \in N} B_{\{p,q\}} \cdot \delta(A_p, A_q)$$

- $R(A)$ defines the penalties for assigning A_p to object or background, which are $R_p(\text{"obj"})$ and $R_p(\text{"bkg"})$
- $B(A)$ describes the boundary properties of the segmentation, $B_{\{p,q\}}$ is large when p and q are similar, it is close to 0 when p and q are very different

Graph Construction

Edge	Weight	Condition
n-link $\{p, q\}$	$B_{\{p, q\}}$	$\{p, q\} \in N$
t-link $\{p, s\}$	$\lambda \cdot R_p(\text{"bkg"})$	$p \in P, p \in \underline{OUB}$
	K	$p \in O$
	0	$p \in B$
t-link $\{p, t\}$	$\lambda \cdot R_p(\text{"obj"})$	$p \in P, p \in \underline{OUB}$
	0	$p \in O$
	K	$p \in B$



n-link Construction

$$B_{\{p,q\}} \propto \exp\left(-\frac{(I_p - I_q)^2}{2\sigma^2}\right) \cdot \frac{1}{dist(p,q)}$$

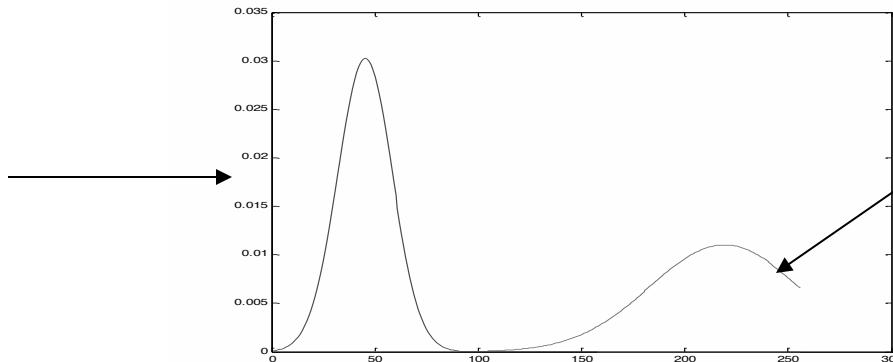
- I_p and I_q are the intensities of pixel p and q
- σ sets the penalty of discontinuities between pixels of similar intensities, when $|I_p - I_q| < \sigma$ the penalty is large, when $|I_p - I_q| > \sigma$ the penalty is small
- $dist(p, q)$ penalizes the distance between p and q, and generally when they are in the neighborhood system this term is one

t-link Construction

- $R_p(\text{"obj"}) = -\ln \Pr(I_p | O)$
- $R_p(\text{"bkg"}) = -\ln \Pr(I_p | B)$

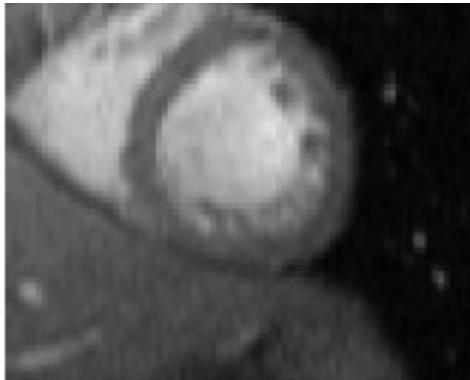
$$K = 1 + \max_{p \in P} \left(\sum_{q: \{p,q\} \in N} B_{\{p,q\}} \right)$$

Estimated
Background
Intensity
Distribution
Based on
Background
Seeds

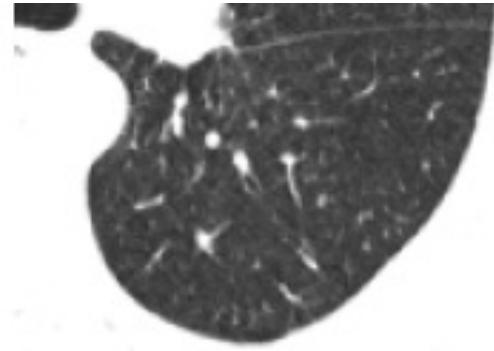


Estimated
Object Intensity
Distribution
Based on
Background
Seeds

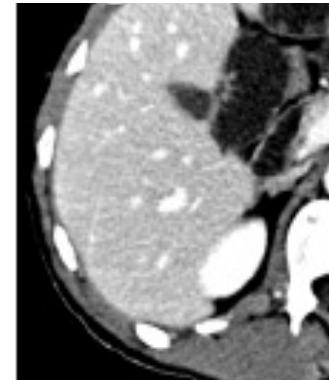
Experimental Data



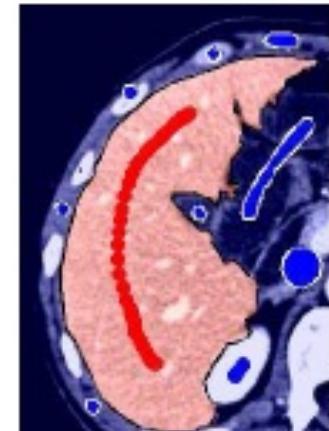
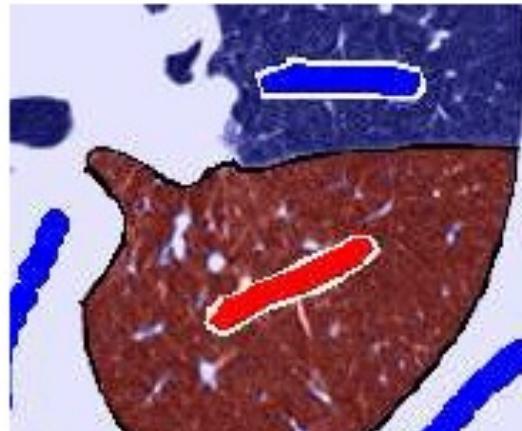
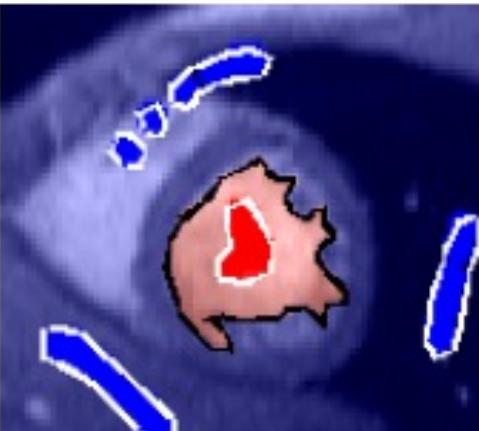
(c) Cardiac MR



(e) Lung CT



(g) Liver MR



Reference

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