

Image Segmentation via Graph-Cuts

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Outline

Graph Theory

- Flow Networks and Graph Cuts
- Maximum Flow Algorithms
- Discrete Energy Minimization
- Euclidean Metric Approximation
- Riemannian Metric Approximation

Graph Cut Segmentation

- Idea and Motivation
- Geodesic Segmentation
- Chan-Vese Minimization

Conclusion

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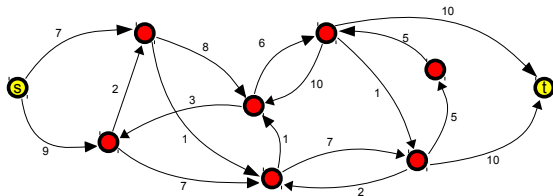
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Flow Network

Definition

A **directed graph** $\mathcal{G} = (V, E)$ where V is the set of graph nodes and $E \subseteq V \times V$ is the set of graph edges. Each edge $(u, v) \in E$ has a real-valued **capacity** $c_{uv} \geq 0$. Further, there are two distinguished nodes in V , called **terminal nodes**: the **source**, denoted s and the **sink**, denoted t .

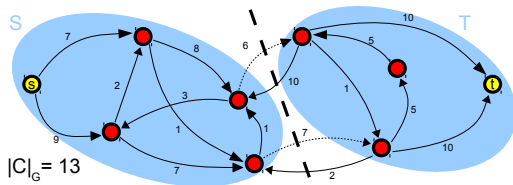


Cut

Definition

An ***st*-cut** \mathcal{C} is a partition of the set V into two disjoint subsets S and $T = V \setminus S$ such that $s \in S$ and $t \in T$. Cut **capacity** $|\mathcal{C}|_G$ is the sum of the capacities of the edges going from S to T :

$$|\mathcal{C}|_G = \sum_{(u,v) \in E, u \in S, v \in T} c_{uv}$$



Minimum and Maximum Cuts

- ▶ There are $2^{|V|-2}$ possible *st*-cuts
- ▶ **Minimum cut** is a cut with the **smallest possible** capacity
 - ▶ Problem of finding a minimum cut has **polynomial** time complexity
 - ▶ We will discuss algorithms later
- ▶ **Maximum cut** is a cut with the **largest possible** capacity
 - ▶ Problem of finding a maximum cut is **NP-hard**
- ▶ There may be **several** minimum and maximum cuts

Flow

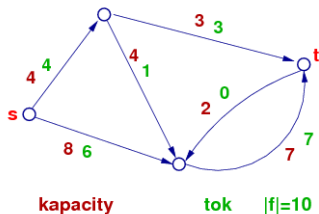
- ▶ **Flow** in network $G = (V, E)$ is a mapping $f : E \rightarrow \mathbb{R}_0^+$ satisfying

- ▶ **Capacity constraint:** $0 \leq f_{uv} \leq c_{uv}$ for all $u, v \in V$
- ▶ **Continuity condition:** for all $u \in V \setminus \{s, t\}$ holds:

$$\sum_{v \in V} (f_{uv} - f_{vu}) = 0.$$

- ▶ The **value of the flow** outgoing from source s is

$$|f| = \sum_{v \in V} f_{sv}.$$



Maximum Flow and Minimal Cut Duality

- ▶ **Maximal flow** is a flow with the maximal value.
- ▶ Ford-Fulkerson:
 - ▶ problem of finding **minimal cut** is equivalent to problem of finding **maximal flow**.
 - ▶ **capacity** of minimal cut is **equal to the value** of maximal flow.
 - ▶ **edges belonging to minimal cut** are those which capacity is **fully saturated** by the flow.

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Ford-Fulkerson

- ▶ Obecný **iterativní framework** pro hledání maximálního toku.
- ▶ Sestrojíme **reziduální síť**.
- ▶ Najdeme **zlepšující cestu** v reziduální síti z uzlu s do uzlu t .
- ▶ **Zvýšíme tok** po dané cestě o hodnotu hrany s nejmenší kapacitou na této cestě.
- ▶ Výpočet opakujeme dokud je možné najít další zlepšující cestu.
- ▶ V obecném případě složitost $O(E|f|)$, kde E je počet hran a $|f|$ hodnota maximálního toku.
- ▶ Nemusí konvergovat pro sítě s neceločíselnými kapacitami.

Edmonds-Karp

- ▶ Zvláštní případ metody **Ford-Fulkerson**.
- ▶ Dvě varianty:
 - ▶ Zlepšování toku vždy po **nejkratší cestě**. Složitost $O(VE^2)$.
 - ▶ Zlepšování toku vždy po **nejširší cestě**. Složitost $O(E \log(EU))$, kde U je nejvyšší kapacita vyskytující se v síti.
- ▶ **Záruka konvergence** i pro síť s iracionálními kapacitami hran.

Dinitz

- ▶ Zlepšování toku po **všech nejkratších cestách** naráz.
- ▶ Pomocí **prohledávání do šířky** jsou nalezeny všechny nejkratší cesty v reziduální síti.
- ▶ Obdržíme podsíť nejkratších cest, která **neobsahuje smyčky**.
- ▶ V získané podsíti najdeme maximální tok pomocí **prohledávání do hloubky**.
- ▶ Lze ukázat, že v další iteraci bude délka nejkratších cest ostře větší.
- ▶ Složitost $O(V^2E)$. V praxi **výrazně rychlejší**, než Edmonds-Karp.

Push-Relabel

- ▶ V současnosti pravděpodobně **nejrychlejší a nejvyužívanější metody** pro obecné grafy.
- ▶ Pro každý uzel si udržujeme **předpokládanou délku nejkratší cesty k uzlu t** .
- ▶ Uzly mohou obsahovat přebytky toku (aktivní uzly).
- ▶ Optimistické **prostrkávání toku** do uzlů u kterých předpokládáme, že jsou blíže uzlu t .
- ▶ Rozhodování vždy pouze na základě **lokálních informací**.
Vhodné k paralelizaci a lokalizaci výpočtu v paměti.
- ▶ Pro rychlý výpočet ovšem třeba pravidelně provádět **globální update** informací.
- ▶ Složitost záleží na **strategii volby aktivního uzlu**:
 - ▶ Naivní implementace $O(V^2E)$
 - ▶ First-in First-out strategie $O(V^3)$
 - ▶ Nejvzdálenější aktivní uzel $O(V^2\sqrt{E})$

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What energy functions can be minimized via graph cuts?

- ▶ [Kolmogorov, Zabih] Let E be a function of n binary variables of type

$$E(x_1, \dots, x_n) = \sum_i E^i(x_i) + \sum_{i < j} E^{i,j}(x_i, x_j).$$

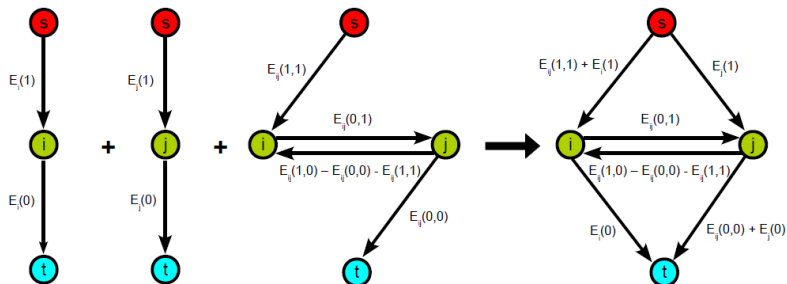
Then, E is **graph-representable** if and only if each term $E^{i,j}$ satisfies the inequality

$$E^{i,j}(0, 0) + E^{i,j}(1, 1) \leq E^{i,j}(0, 1) + E^{i,j}(1, 0).$$

- ▶ Necessary and sufficient condition to be able to compute the exact **global minimum** of E using a single graph cut.

Graph Construction

- A graph $G = (V, E)$ is built where V contains the two terminal nodes s and t representing the labels 0 and 1, respectively, and a node for each variable x_j .



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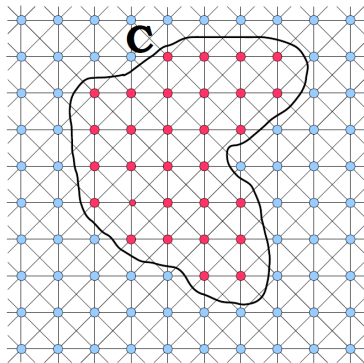
Conclusion

Cut metrics

- ▶ Given a **regular orthogonal grid** and **neighbourhood \mathcal{N}**
- ▶ $|\mathcal{C}|_{\mathcal{G}}$ - Cut metric. Sum of weights of **edges connecting inner and outer nodes**
- ▶ For any contour - $|\mathcal{C}|_{\mathcal{G}} \approx |\mathcal{C}|_{\varepsilon}$ and $|\mathcal{C}|_{\mathcal{G}} \rightarrow |\mathcal{C}|_{\varepsilon}$ with increasing grid resolution and neighbourhood density

The Goal

How to set edge weights w_k ?



Cauchy-Crofton Formula

- ▶ The **Cauchy-Crofton formula** establishes a connection between Euclidean length $L(\mathcal{C})$ of a curve \mathcal{C} in \mathbb{R}^2 and a measure of a set of lines intersecting it:

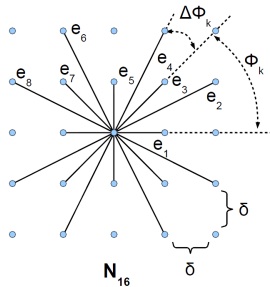
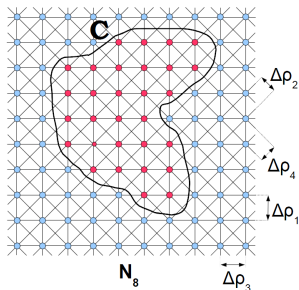
$$L(\mathcal{C}) = \frac{1}{2} \int n_c d\mathcal{L}$$

where n_c is the number of intersections n_c with lines \mathcal{L} .

- ▶ Consider the set of all lines \mathcal{L} given by polar formula $\mathcal{L}(\phi, \rho)$. Then the Cauchy-Crofton formula can be written as

$$L(\mathcal{C}) = \frac{1}{2} \int_{-\infty}^{\infty} \int_0^{\pi} n_c(\phi, \rho) d\phi d\rho.$$

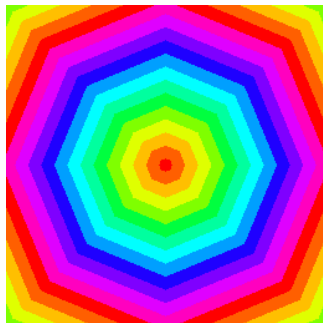
Discretization and Boykov's Approach



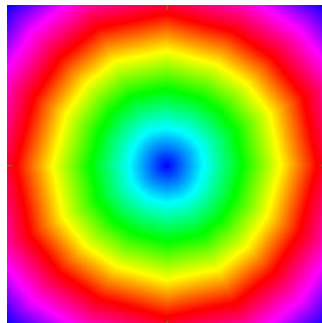
$$|C|_\varepsilon = \int_0^\pi \int_{-\infty}^{+\infty} \frac{n_c(\phi, \rho)}{2} d\rho d\phi \approx \sum_{k=1}^n \left(\sum_i \frac{n_c(k, i)}{2} \Delta\rho_k \right) \Delta\phi_k \approx \sum_{k=1}^n n_c(k) \frac{\Delta\rho_k \Delta\phi_k}{2}$$

$$\text{Weights (2D isotropic case): } w_k = \frac{\Delta\rho_k \Delta\phi_k}{2} \quad \Delta\rho_k = \frac{\delta^2}{|e_k|}$$

Distance maps



N8



N16

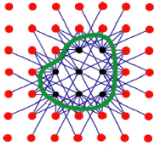
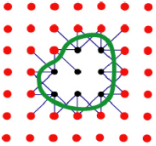
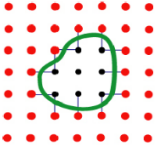
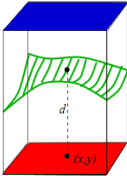
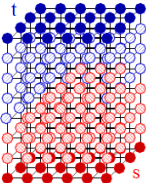
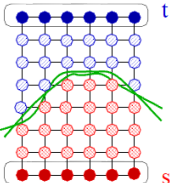
Extension to 3D

Cauchy-Crofton

$$|\mathcal{C}^2|_\varepsilon = \frac{1}{\pi} \int n_c d\mathcal{L}$$

Using the same derivative steps

$$w_k = \frac{\Delta\rho_k \Delta\phi_k}{\pi} \quad \Delta\rho_k = \frac{\delta_x \delta_y \delta_z}{|e_k|}$$



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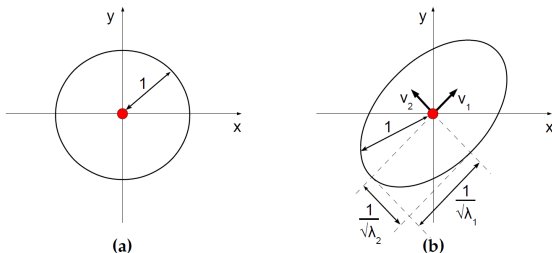
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Riemannian Spaces

- ▶ In Riemannian geometry, each point of the space is associated with a **metric tensor** M that controls how inner product of two vectors is calculated ("**space stretching**").
- ▶ In N -dimensional space, the tensor is a **symmetric positive definite N -by- N matrix** (a bilinear form) that varies smoothly over the space.
- ▶ In case M is constant, the Riemannian norm of a vector u is calculated as:

$$|u|_{\mathcal{R}} = \sqrt{u^T \cdot M \cdot u}.$$



Edge Weights

- ▶ Weights approximating a **Riemannian metric** (Boykov):

$$w_k^{\mathcal{R}} = w_k^{\mathcal{E}} \cdot \frac{\det M}{(u_k^T \cdot M \cdot u_k)^p}$$

where u_k is a unit vector in the direction of e_k , $w_k^{\mathcal{E}}$ is the weight for the Euclidean metric approximation and p equals to 3/2 and 2 in 2D and 3D, respectively.

- ▶ **Euclidean metric** a special case where $M_{\text{const}} = I$

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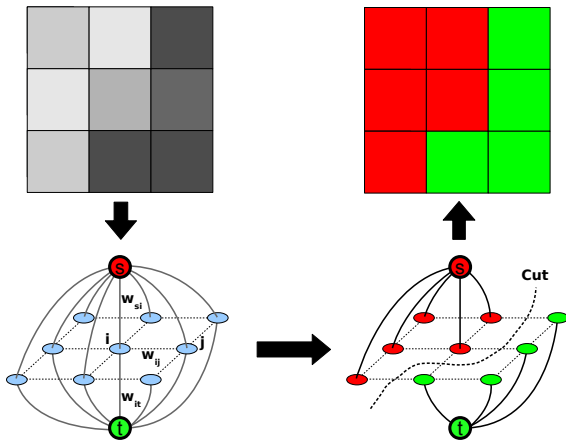
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Graph Cut Segmentation Framework



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How to set the weights?

- ▶ Geodesic Active Contours energy:

$$E_{GAC}(\mathcal{C}) = \int_0^1 g(|\nabla G_\sigma * I(\mathcal{C}(q))|) |C'(q)| dq$$

- ▶ t-links: 0 or large value (hard constraints)
- ▶ n-links - Riemannian tensors

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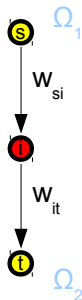
Chan-Vese Functional

$$E_{CV}(C, c_1, c_2) = \mu L(C) + \lambda_1 \int_{\Omega_1} (f(x) - c_1)^2 dx + \lambda_2 \int_{\Omega_2} (f(x) - c_2)^2 dx$$

T-link weights:

$$w_{si} = \lambda_2 (f(i) - c_2)^2$$

$$w_{it} = \lambda_1 (f(i) - c_1)^2$$



N-link weights: $w_{ij} = \mu w_k$ - see Page 21

Graph Cut Based Chan-Vese Minimization Overview

Key observation

It is possible to setup w_{ij} , w_{si} and w_{it} such that **capacity of any cut approximates the CV energy** of the corresponding segmentation for **fixed** c_1 and c_2 .

Alternating minimization scheme:

1. Obtain an **initial estimate** of c_1 and c_2
2. Construct graph and find **globally minimal segmentation** with respect to the **fixed** mean values
3. Update c_1 and c_2
4. Repeat from 2 until reaching a **steady state**

How to initialize c_1 and c_2 ?

Algorithm idea

Minimize the Chan-Vese functional with a **relaxed regularization** term:

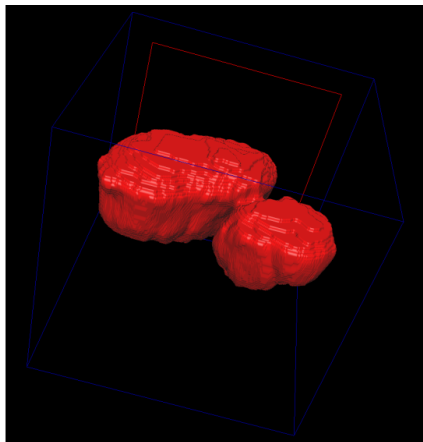
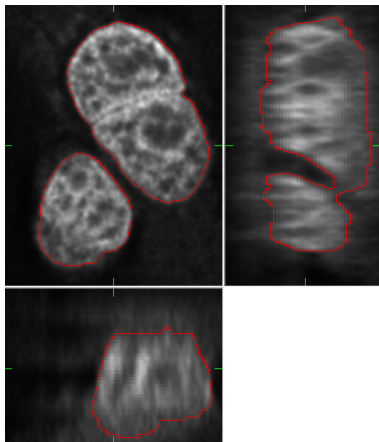
$$E(C, c_1, c_2) = \lambda_1 \int_{\Omega_1} (f(x) - c_1)^2 dx + \lambda_2 \int_{\Omega_2} (f(x) - c_2)^2 dx$$

- ▶ A significantly **simpler** problem
- ▶ Weighted KMeans clustering
 - ▶ Only data terms are compared in each pixel
 - ▶ Corresponds to finding a minimum cut with **zero N-link** weights

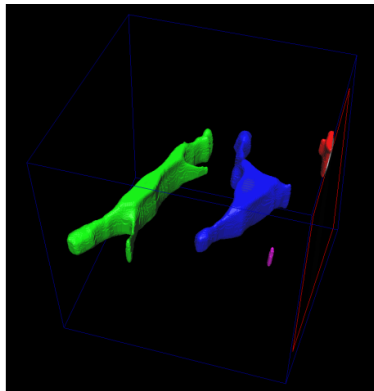
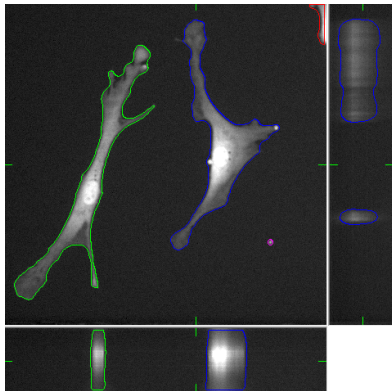
Properties

- ▶ Advantages:
 - ▶ Simple and fast (and “automatic”)
 - ▶ Reflects λ_1 and λ_2
 - ▶ Very good estimate for small μ
 - ▶ Requires **less iterations** of the main algorithm
- ▶ Disadvantages:
 - ▶ Only an approximation, **initialization dependent**
 - ▶ Does not guarantee reaching a global minimum

Chan-Vese Segmentation - Examples (1)

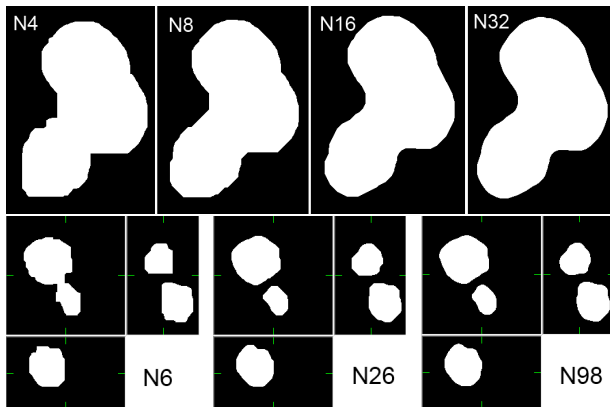


Chan-Vese Segmentation - Examples (2)



Boundary Smoothness

- ▶ Depends strongly on the **neighbourhood size**:



- ▶ Large neighbourhoods are **computationally expensive**

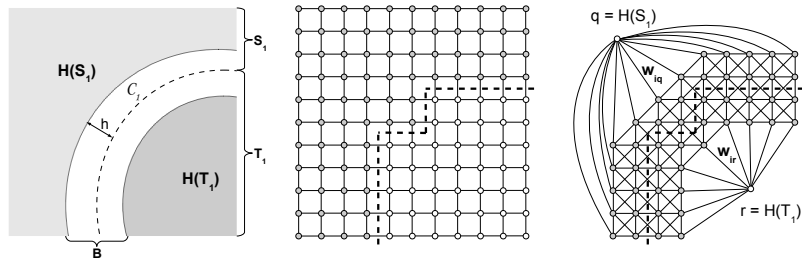
Two-Stage Algorithm

Key observation

Segmentations are different but very close to each other.

Two-stage algorithm:

1. **Coarse segmentation** using a **small** neighbourhood
2. **Refinement** of the segmentation in a **narrow band** around the boundary using a **large** neighbourhood



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- ▶ Graph-cut framework is powerful tool for **discrete function minimization**.
- ▶ Finding of minimal cut is a **polynomial problem** and we obtain **global optimum**.
- ▶ GC allows **interactive segmenation**.
- ▶ **Geodesic segmentation** can easily be implemented using graph-cuts.
- ▶ We have presented an **iterative algorithm for Chan-Vese minimization**.
- ▶ The **neighbourhood** system of the grid is related to boundary **smoothness**. **Two stage-minimization** reduces memory demands.
- ▶ <http://cbia.fi.muni.cz/projects/graph-cut-library.html>