# Design and Implementation of a Power Watershed based Image Segmentation Method of Hepatic Lesion Detection

Final Presentation

Anna Werner
November 16, 2015
Computer Science Dept. 5 (Pattern Recognition)
Friedrich-Alexander University Erlangen-Nuremberg

FRIEDRICH-ALEXANDER
UNIVERSITÄT
ERLANGEN-NÜRNBERG
TECHNISCHE FAKULTÄT

## Overview

- Motivation
- Methods
- Experiments and Results
- Summary and Outlook

# Hepatic Lesions

= every disfunction, injury and violation of the liver

- In common sense: tumors
- Number of new patients with liver cancer increased by more than 3% yearly
- In 2012: 745000 liver cancer related deaths worldwide
- Five-year survival rate for liver cancer is 14%
- Liver as a prime candidate for metastases

# TACE - Transarterial Chemoembolization

- Palliative or bridging therapy
- Pre-procedure workup
  - Precise location within the liver
  - Quantification of tumor volume
  - Overview on integration into the blood vessel system

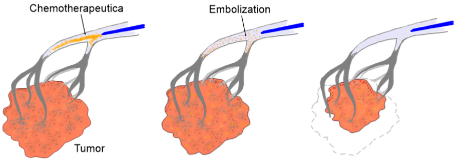


Fig.: Model of a transarterial chemoembolization procedure

# TACE - Transarterial Chemoembolization

Procedure

- Initial imaging to gain overview on vascularization
- Injection of chemotherapeutica in the feeding blood vessel
- Blocking of those blood vessels with embolization particles

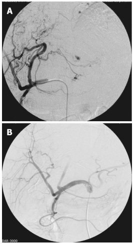


Fig.: (A) Initial imaging of vascularization and (B) after embolization

# Methods

## Power Watershed: A Unifying Graph-Based Optimization Framework

- article by C. Couprie, L. Grady et al. published in 2011
- graph-based segmentation algorithms built using set of core algorithms
  - graph cuts
  - random walker
  - shortest paths
  - watersheds
- all placed in common framework
- seen as instances of general seeded segmentation algorithm with different choices of two parameters

# Power Watershed Algorithm

New segmentation model defined by searching an optimum $x$ as the probability belonging to a label

$$\min_x \sum_{e_{ij} \in E} w_{ij}^p |x_i - x_j|^q + \sum_{v_i} w_{Fi}^p |x_i|^q + \sum_{v_i} w_{Bi}^p |x_i - 1|^q,$$

$$\text{s.t.} \quad x(F) = 1, \quad x(B) = 0,$$

$$s_i = 1 \text{ if } x_i \geq \frac{1}{2}, \quad 0 \text{ if } x_i < \frac{1}{2}.$$

- $e_{ij}$: edge connecting vertices $v_i$ and $v_j$
- $w_{ij}$: weight of the edge $e_{ij}$
- $p$ and $q$: parameters to model special algorithms

# Power Watershed Algorithm

| q \ p | 0 | finite | $\infty$ |
|---|---|---|---|
| 1 | Collapse to seeds | Graph cuts | Watershed |
| 2 | $l_2$ norm Voronoi | Random walker | Power watershed $q = 2$ |
| $\infty$ | $l_1$ norm Voronoi | $l_1$ norm Voronoi | if p=q, Shortest paths |

Tab.: Segmentation algorithms generated by the framework according to the choice of the parameters $p$ and $q$.

# Power Watershed Algorithm

- Basically Kruskal's algorithm for maximum spanning trees with two differences:
  - A forest is computed instead of a tree
  - Optimization performed on plateaus (a maximal set of nodes connected with edge of same weight)
- Advantages:
  - Asymptotic complexity in best-case scenario
  - Providing a unique segmentation

# Experiments on Weighting Functions

- Examination of the effect of weighting functions on performance
- Same functions reoccur between different graph-based algorithms
- Two possible changes:
  - Choice of parameter $\beta$
  - Replacing with another weighting function

# Gaussian Weighting Function

- Common choice for generating weights from image intensities
- Recommended troughout the segmentation literature
- $\beta$ is freely selectable and the best value can be found empirically

# Reciprocal Weighting Function

- Based on image intensities like Gaussian weighting function
- Claimed to outperform Gaussian function when applied to random walker and graph cuts

$$w_{ij} = \frac{1}{\mathrm{dist}(v_i, v_j)} \frac{1}{1 + \beta(g(v_i) - g(v_j))^2}$$

- No outstanding values when applied to medical data

# Power Watershed Algorithm on Hepatic Lesions

Comparison to other segmentation algorithms - Random Walker

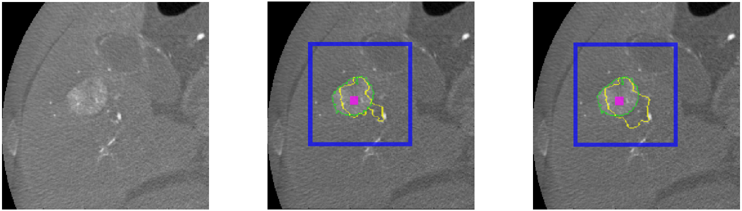

Fig.: Initial data, result of the power watershed algorithm and result of the random walker algorithm.

# Power Watershed Algorithm on Hepatic Lesions

Comparison to other segmentation algorithms - Random Walker

| Metrics / Algorithm | DC | MSE | ARI | HOM | COMPL |
|---|---|---|---|---|---|
| PW | 0.758 | 0.012 | 0.743 | 0.542 | 0.607 |
| RW | 0.680 | 0.018 | 0.658 | 0.504 | 0.436 |

# Power Watershed Algorithm on Hepatic Lesions

Comparison to other segmentation algorithms - Watersheds

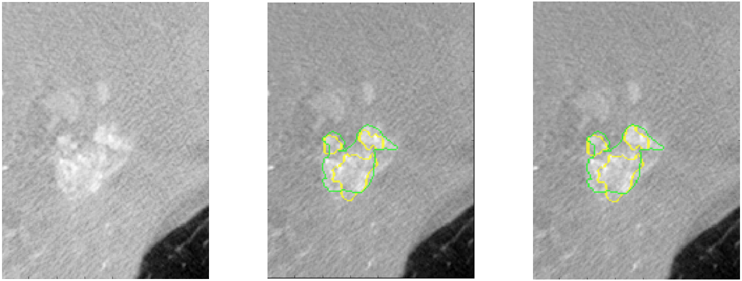

Fig.: Initial data, result of the power watershed algorithm and result of the watershed algorithm.

# Power Watershed Algorithm on Hepatic Lesions

Comparison to other segmentation algorithms - Watersheds

| Algorithm \ Metrics | DC | MSE | ARI | HOM | COMPL |
|---|---|---|---|---|---|
| PW | 0.656 | 0.020 | 0.633 | 0.382 | 0.568 |
| WS | 0.669 | 0.017 | 0.641 | 0.396 | 0.567 |

# Strength Map of Labels

- Points out which labels are the most uncertain
- Helps the user to gain a better segmentation
- Time saving because the next placement of seeds is predefined

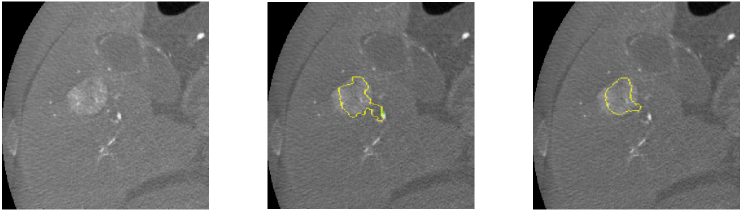

Fig.: The most uncertain labels are highlighted in green, the segmentation result is drawn in yellow and on the right after an additional placement of seeds.

# Summary

- Power watershed is an algorithm that is robust
- Better computation time than random walker
- But in case of too many plateaus high computation time
- Manipulation of the weighting function brought no improvement
- A strength map can simplify the work for the user

# Outlook

- Reduce computation time to make it capable of real-time segmentation
- Broadening to multilabel segmentation for vessel segmentation
- Improvement through combination with preprocessing steps

Thank you for your attention!