Graph cut based segmentation of cardiac ventricles in MRI: a shape-prior based approach

Caroline Petitjean
A joint work with Damien Grosgeorge, Pr Su Ruan, Pr JN Dacher, MD

October 22, 2014
First of all…

- A little presentation 😊
- Electronics and Signal processing engineer (1999)
  Non rigid registration using statistical variational approaches.
  Application to the analysis and the modelling of the myocardial function in MRI
Assistant Professor (since 2005) at the University of Rouen (LITIS Lab)

- Image analysis and pattern recognition
  Mostly for:
  - medical image segmentation (model-based, PDE-based…)
  - medical image classification
  But also:
  - image retrieval

Close collaboration with medical doctors (nuclear medicine doctors, radiologists…)

Close collaboration with Laurent (the one here in this room) and other colleagues
Graph cut based segmentation of cardiac ventricles in MRI: a shape-prior based approach

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Cardiovascular diseases:

- A major cause of death in many countries
- **Magnetic Resonance Imaging (MRI)** is a good tool to assess the cardiac contractile function
Cardiovascular diseases:
- A major cause of death in many countries [Roger et al, 2012]
- MRI is a good tool to assess the cardiac contractile function

The aim is to compute the ventricle volume, the wall thickness...
• Cardiac ventricle segmentation: a challenging task
• In clinical routine:
• Manual segmentation:
  • Long and tedious task (20 minutes per patient)
  • Prone to intra and inter expert variabilities
• Many research efforts
  • Some software tools exist especially for the LV
  • Problems remain for the right ventricle (RV)
Related works

cardiac image segmentation

- Pixel-based methods: dedicated method
  - Thresholding, active contours, mathematical morphology…

- Prior information will help/constrain the segmentation in noisy, fuzzy image, or image with occlusions
  - Example: shape of the ventricle
Related works segmentation with shape prior

Suppose I have a bunny model...

In 2D: a binary map
Image segmentation with shape prior

Several ways to do it (*I’ll present the 3 main ways*)

1) Active Shape Models (Cootes 1995)
   
   • Assumes that you have a dataset of representative contours of the shape
1) Active Shape Models (Cootes 1995)

- Assumes that you have a dataset of representative contours of the shape
  - Align all shapes
1) Active Shape Models (Cootes 1995)

- From the set of aligned shapes, you can compute
  - an average shape
  - a PCA on the contour points

Thus you get the major variability axis of the shape set

(called a Point Distribution Model (PDM))
1) Active Shape Models (Cootes 1995) (ASM–AAM)

• Once you have the average shape and the way shapes usually vary

→ Use the PDM for segmentation with deformable models

→ The segmentation result is constrained to lie within the major variabilities axis

Example:
(72 points)
ASM : segmentation

- Initialization
ASM: segmentation

- 100 iterations
ASM : segmentation

• 200 iterations
ASM : segmentation

- 350 iterations

Problem: What if the shape to be segmented does not lie within the dataset variability?

Other issue: point labelling can be very tedious
2) Segmentation may be considered as a minimization problem (e.g., active contours, graph cut...):

\[ S = \arg \max \quad D(S) + R(S) + P(S) \]

- **Data-driven term**: (e.g., based on image gradient, on histogram of the object/background....)
- **Regularization term**: (e.g., smoothness and geometric properties on the contour....)
- **Shape prior term**

Very simple example with Prior being a binary map:

\[ P(S) = \sum_{all \ pixels \ p} (S(p) - Prior(p))^2 \]
2) Problem: How to register the shape model to the image?

A usual solution is to proceed iteratively:
Alternate between model position estimation & segmentation…
How to represent the shape model?

**Explicit representation**

PDM \[\text{[Cootes et al, 1995]}\]

- PCA

**Implicit representation**

Signed Distance Function
\[\text{[Leventon et al, 2000]}\]

- The average distance is not a distance anymore \[\text{[Pohl et al, 2007]}\]
- Easier implementation
- Labelling the data with corresponding points is quite tedious
3) Registration-based segmentation (single atlas)

Image segmentation with shape prior

Apply transformation to the labelled atlas

$T_{Atlas \rightarrow CT}$
Image segmentation with shape prior

3) Registration-based segmentation (multiple atlases)

I Non-rigid registration
- Similarity measures
- Deformation model

II Majority voting
- Atlas selection

III Post-processing
- EM segmentation
- Graph-cuts

Lotjonen 2010
Image segmentation with shape prior

3) Registration-based segmentation (multiple atlases)

Another example of local label fusion:

For each pixel $x$, compute the probability to have label $l$:

$$P(L(x) = l | L'_n(x), I(x), I'_n(x)) = \frac{1}{\sqrt{2\pi\sigma_i}} e^{-\frac{[I(x) - I'_n(x)]^2}{2\sigma_i^2}} \cdot \delta_{l,L'_n(x)}$$

$L'_n(x)$ and $I'_n(x)$: label and intensity of atlas $n$

$$L(x) = \arg\max \sum_{\text{all atlases } n} P(L(x) = l | L'(x), I(x), I'_n(x))$$

We also want adjacent pixels to $x$ to have an opinion of the label of $x$!

$$P(L(x) = l | L'_n(x + \Delta x), I(x), I'_n(x + \Delta x)) = \frac{1}{\sqrt{2\pi\sigma_i}} e^{-\frac{[I(x) - I'_n(x+\Delta x)]^2}{2\sigma_i^2}} \cdot \frac{1}{\sqrt{2\pi\sigma_d}} e^{-\frac{D(\Delta x)^2}{2\sigma_d^2}} \cdot \delta_{l,L'_n(x+\Delta x)}$$
3) Registration-based segmentation (multiple atlases)

Issues: Segmentation results heavily relies on the registration quality

How to chose the optimal number of atlases?
Our approach

- **RV segmentation**: image intensity alone is not enough, requires prior shape information

- → Collaboration with Rouen University Hospital (Radiology Dept)

- → Cardiac radiologists have provided us with 48 MRI exams with segmented RV (around 750 images)

Construction of a shape model for the design of our RV segmentation method

Organization of a segmentation competition in Oct’12 (MICCAI workshop)
Our approach

Our aim is to:
- Construct a shape model, based on the manual segmentations
- Use this model in a minimization based segmentation framework

We chose the graph cuts approach (GC) [Boykov et Jolly, 2001]
- The global minimum of the energy function is guaranteed
- The framework is versatile enough to incorporate
- Complexity in 2D is very low
Consider the observation field $y_i$ (the image)
Graph cut: basic principle

- Each pixel is considered as a node
Graph cut: basic principle

Consider binary segmentation.

We introduce 2 special nodes $S$ and $T$, linked to the pixels $\rightarrow t$-links
Graph cut: basic principle

- Links are weighted with a region-based term $R_i(\omega)$ (data-driven)

$$R_i(S) = -\ln \Pr(y_i|T)$$
$$R_i(T) = -\ln \Pr(y_i|S)$$

How to design $R_i$?
The more similar the pixels are to S or T, the stronger the t-links
Graph cut: basic principle

- Links are weighted with a region-based term $R_i(\omega)$ (data-driven)
Let’s add a link between neighboring pixels: \textit{n-links}

- $S$ (étiquette $\omega = 0$)
- $T$ (étiquette $\omega = 1$)
Graph cut: basic principle

- N-links are weighted by a regularization term $B_{i,j}$

$$B_{i,j} = \exp \left\{ -\frac{(y_i - y_j)^2}{2\sigma^2} \right\}$$

How to design $B_{ij}$?
The more similar the pixels (in terms of grey levels), the stronger the n-link.

Damien Grosgeorge - LITIS - RFIA 2012
To obtain a segmentation (= a labelling), the graph is cut

\[ S \text{ (label } \omega = 0) \]

The nodes are divided into 2 groups, one contains the source and the other the sink.

\[ T \text{ (label } \omega = 1) \]

**Cost function associated to a cut:**

\[ E(L) = \sum_i R_i(L_i) + \lambda \sum_{i,j \in N} B_{i,j} \cdot \delta(L_i \neq L_j) \]

The best segmentation is obtained when \( E(L) \) is minimum.

But how to get \( L \) such that \( E(L) \) is minimum?

\[ \rightarrow \text{Use optimization algorithm called min-cut max-flow} \quad [\text{Boykov & Kolmogorov, 2004}] \]

We have just seen binary segmentation...

The framework has been extended to multi-label segmentation...
GC used as an interactive segmentation tool

Boycov, IJCV, 2006
A word on GrabCut…

- Variant of Graph Cut: Interactive Foreground Extraction using Iterated Graph Cuts
• We want to **automatically** segment the cardiac ventricles in MR image where **borders are not well defined** and ventricles shapes are highly variable.

• We construct a **shape model** from manually labelled data.

  ➔ We use the **Signed Distance Function** representation for our shape model.

  **No anatomical landmarks**
Back to our problem...

• We use the model within the GC framework:
• We design the graph cost function as:

\[ E(L) = \sum_i R_i(L_i) + \sum_i P_i(L_i) + \lambda \sum_{i,j \in N} B_{i,j} \cdot \delta(L_i \neq L_j) \]

Additional term linked to the shape prior
Our GC based approach with shape prior

- Overview:

1/3 patients is used for model construction
Remaining 2/3 is used for testing
A few results

- Comparaison without and with an a priori
Some quantitative results

- Comparison of manual contours and automated contours with the Dice metric:
  - Overlap measure
    \[ D(A, B) = \frac{2|A \cap B|}{|A| + |B|} \]

<table>
<thead>
<tr>
<th></th>
<th>ED (dilatation)</th>
<th>ES (contraction)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RV (red)</td>
<td>0.87 ± 0.06</td>
<td>0.73 ± 0.16</td>
</tr>
<tr>
<td>LV (cyan)</td>
<td>0.95 ± 0.03</td>
<td>0.80 ± 0.26</td>
</tr>
<tr>
<td>Myocardium (blue)</td>
<td>0.81 ± 0.08</td>
<td>0.77 ± 0.19</td>
</tr>
</tbody>
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- One of the best results in our RVSC challenge …
• Application to some other segmentation contexts (3D)
Associated publications

• Our prior-based segmentation approach applied to RV:

• The Right Ventricle Segmentation challenge at MICCAI’12:

• A review of LV and RV segmentation methods:
Thank you!

• For listening…
• Any questions?