A VARIATIONAL METHOD FOR SCAR SEGMENTATION WITH MYOCARDIAL CONTOUR CORRECTION IN DE-CMR IMAGES

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Motivation

- Cardiac MR images:
  - Good contrast between soft tissues
  - The full heart can be imaged
  - There are many modalities: CINE, Tagging, DE-CMR...
- DE-CMR allows the identification of scarred tissue in the myocardium.
Review of DE-CMR Segmentation

- Most current methods restrict the segmentation of the myocardium.
  - It simplifies the problem.
  - What if there are misalignments in the myocardial mask?

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<tr>
<th>Method</th>
<th>Myocard. Contours</th>
<th>Scar identification method</th>
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<td>TFA1 [5]</td>
<td>Fixed</td>
<td>2 step thresholding</td>
<td>FP, FN removal by feature analysis, region growing and hole filling</td>
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Objectives

- To propose a segmentation method for DE-CMR that:
  - Is able to modify the myocardial contours if necessary
  - Provides smoothness to the myocardial contours.
  - At the same time, uses the information provided by a CINE segmentation to increase robustness.

- To explore how the state of the art segmentation methods behave:
  - when the myocardial contours have misalignments.
  - with non ischemic myocardiopathies.
Variational Framework

\[ \mathcal{L} = \{C, H, S, B\} \quad \text{DE-CMR labels} \]
\[ \mathcal{A} = \{C, M, B\} \quad \text{CINE labels} \]

- C: Blood cavity
- M: Myocardium
- B: Background
- H: Healthy tissue
- S: Scar

Convex Potts Model (From [7])

\[
\min_{u(x) \in \Delta_+} \Psi(u) = \sum_{l \in \mathcal{L}} \int_{\Omega} \left( f_l(x) u_l(x) + g_l(x) \left| \nabla u_l(x) \right| \right) dx
\]

Data Fidelity

Contour Regularization

\[ f_{L_i}(x) = -\ln \left( P \left( L_i(x) \mid I(x) \right) \right) \]

Label Posterior Probability Formulation

\[
P(L_i|I) = \frac{\sum_{k=1}^{K} P(I|A_k, L_i) P(L_i|A_k) P(A_k)}{\sum_{j=1}^{L} \sum_{k=1}^{K} P(I|A_k, L_j) P(L_j|A_k) P(A_k)}
\]

\[
P(I|A_k, L_i)
\]
  - Models the probabilistic distribution of \( I(x) \).
  - Assumption of independence with respect to \( \hat{A}(x) \).
  - The Rician distribution is chosen for the blood and the myocardial tissues.

\[
P(A_k)
\]
  - Probability of the CINE label \( A_k \).
  - Decays with the distance to the CINE ROI \( k \).
  - The binary indicator function for all \( A_k \) are smoothed with a Gaussian kernel and normalized.
**Label Posterior Probability Formulation**

\[
P(L_i | I) = \frac{\sum_{k=1}^{K} P(I | A_k, L_i) P(L_i | A_k) P(A_k)}{\sum_{j=1}^{L} \sum_{k=1}^{K} P(I | A_k, L_j) P(L_j | A_k) P(A_k)}
\]

- Controls the influence of the CINE segmentation and the image likelihood **locally**.
- The value at each location is a linear combination of 3 extreme situations:
  - Fully trust the CINE probability
  - Fully trust the a priori tissue probability...
    - ...at the epicardial border
    - ...at the endocardial border
  - Weights are computed using the edge information of the DE-CMR image.
The regularization local weights $g_i(x)$ depend on the image gradient \textit{AND} the CINE segmentation:

\[
\begin{align*}
    g_C(x) &= \gamma_0 H(1 - a_1(x), \varepsilon) + \gamma_c r(x) H(a_1(x), \varepsilon) \\
    g_H(x) &= \gamma_0 H(1 - a_2(x), \varepsilon) + \gamma_t r(x) H(a_2(x), \varepsilon) \\
    g_S(x) &= g_H(x) \\
    g_B(x) &= \gamma_0 H(1 - a_3(x), \varepsilon) + \gamma_c r(x) H(a_3(x), \varepsilon) \\
    r(x) &= H \left( (3/2)\sigma_{b(x)} - b(x), \varepsilon \right)
\end{align*}
\]
Experimental Setup

- 11 studies from Hypertrophic Cardiomyopathy patients.
- Quality metric: Dice Index (DI)

\[ DI = \frac{2|GT \cap S|}{|GT| + |S|} \]
## Experimental Results

<table>
<thead>
<tr>
<th>Study</th>
<th>TFA1</th>
<th>TFA2</th>
<th>PWD</th>
<th>PROP</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.407</td>
<td>0.638</td>
<td>0.533</td>
<td>0.688</td>
</tr>
<tr>
<td>2</td>
<td>0.554</td>
<td>0.595</td>
<td>0.359</td>
<td>0.677</td>
</tr>
<tr>
<td>3</td>
<td>0.674</td>
<td>0.569</td>
<td>0.620</td>
<td>0.700</td>
</tr>
<tr>
<td>9</td>
<td>0.183</td>
<td>0.213</td>
<td>---</td>
<td>0.207</td>
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DI between the scar and healthy tissue ROIs yielded by the considered segmentation methods.
Conclusions

• A variational segmentation method for DE-CMR where:
  • The scar is identified
  • The myocardial contours may be modified.
  • The data fidelity uses a Bayesian approach that takes into account both the image intensity probability distributions and a registered myocardial segmentation coming from CINE.
  • The CINE myocardial segmentation is also used to compute the regularization weights.
• The correction of the myocardial contours improves the scar identification.
• The correction is stronger in the volumes with lower CINE myocardial alignment.
Thank you!