Enhancing cardiac image segmentation through persistent homology regularization

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Cardiac image segmentation

- Global impact of cardiovascular diseases (CVDs)
- Importance of early diagnosis in preventing CVDs
- The process of whole heart segmentation (WHS) and its significance in clinical applications

Deep learning algorithms

- Recent advancements in machine learning models for cardiac magnetic resonance (CMR) image segmentation
- Need for extreme accuracy in cardiac image segmentation
- Rise of deep learning algorithms to improve accuracy

Diagnosing diseases with deep learning

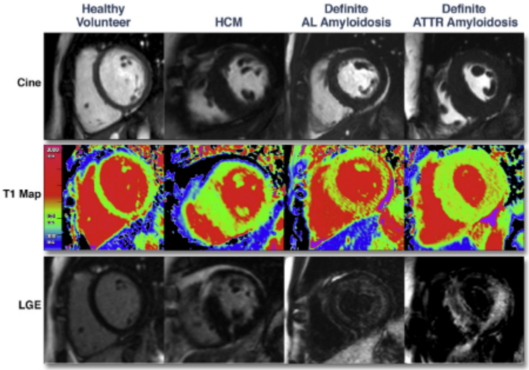

Figure: From top to bottom: CMR end-diastolic cine still, shortened modified look-locker inversion recovery native T1 map, and late gadolinium enhancement (LGE) images. From left to right: healthy volunteer, hypertrophic cardiomyopathy (HCM), definite immunoglobulin light-chain amyloidosis (AL amyloidosis), and definite transthyretin amyloidosis (ATTR amyloidosis) patients. Source of the image: *Fontana et al., 2014*

Problems with deep learning CMR segmentation

- The complexity of the heart as a multi-element organ
- The difficulties in comparing different methods due to differences in datasets and evaluation metrics
- The limitations of using fully convolutional networks (FCNs) for heart segmentation

Problems with deep learning CMR segmentation

- Benefits of incorporating prior knowledge in medical image analysis
- Improved accuracy of models with prior knowledge [Masoud et al., 2016]

Topology priors in segmentation

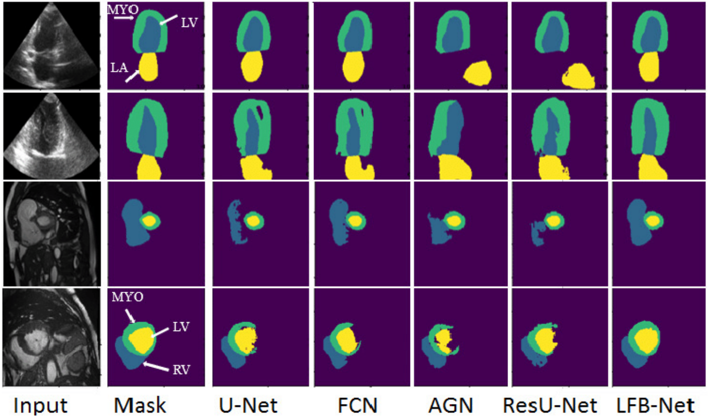

Figure: Examples of multi-label cardiac image segmentation results. [Rows 1-2] long-axis echocardiography and [Rows 3-4] short axis cine-MRI segmentation. RV: Right ventricular cavity; LV: Left ventricular cavity; MYO: Myocardium; and LA: Left atrium. Source of the image: *Berihu Girum et al., 2021*

Prior knowledge of topology in segmentation

The use of topology in cardiac image segmentation has several benefits:

- Topology can be used to identify and quantify the topological features of an object
- Topology can be used to track the progression of changes in the topological structure of an object over time
- Topological analysis exhibits robustness against noise

Prior knowledge of topology in segmentation

(a) $UNet$ (b) CCA (c) $TP_{i,j\geq i}$

Figure: Topological post-processing enables expressive correction of U-Net and connected component analysis errors. Source of the image: *Clough et al., 2020*

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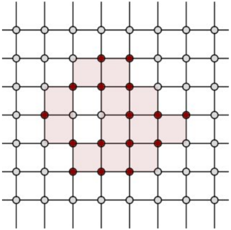
Geometrical Cubes

Cubical graphs are

- Useful when analyzing digital image data
- Located in a grid
- Sized fixed by the grid



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We want a generalization of the concept of a square or a cube to any number of dimensions

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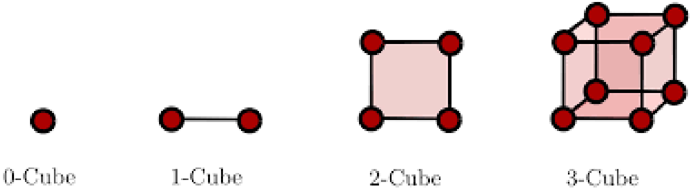


- A 0-cube corresponds to a vertex
- A 1-cube corresponds to an edge
- A 2-cube corresponds to a square
- A 3-cube corresponds to a cube

Cubical complexes

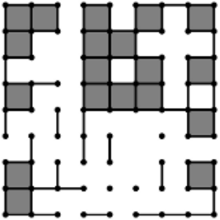
Definition

A **cubical complex** K is a collection of n-cubes so that if $c \in K$ and $c' \subseteq c$, then $c' \in K$.

Cubical complexes

$K = \{\text{vertices}, \text{edges}, \text{squares}, \dots\}$

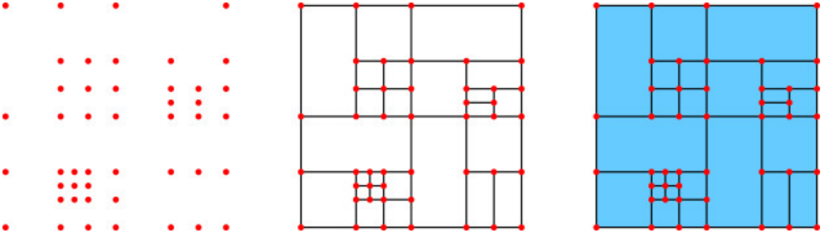
- $e \in K$, with e an edge, then the vertices of the edge $v_1, v_2 \in e$ will also be included in K.
- $s \in K$, with s a square, then the vertices and edges of the square $v_1, v_2, \dots \in s$ and $e_1, e_2, \dots \in s$ will also be included in K.
- ...



Filtration

Definition

A **filtration** is a sequence of cubical complexes $\{K_i\}_{i \in I}$ such that $K_0 \subseteq \cdots \subseteq K_n$.



Persistent homology

We use filtrations to analyze topological features across multiple scales.

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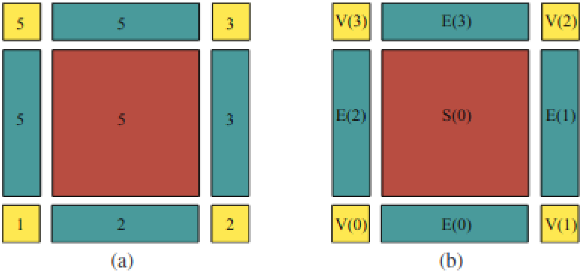
Definition

Let K be a cubical complex. A real-valued function $f: K \to \mathbb{R}$ is **monotonic** if $f(\sigma) \leq f(\tau)$ when $\sigma \subseteq \tau$.

From monotonicity we derive that $K(a) = f^{-1}(-\infty, a]$ is a subcomplex of K for every $a \in \mathbb{R}$. We call $K(a)$ the sublevel set of the point a.

$$\ldots \subseteq K(a_{i-2}) \subseteq K(a_{i-1}) \subseteq K(a_i) \subseteq K(a_{i+1}) \subseteq K(a_{i+2}) \subseteq \ldots$$

- Lower-star filtration



Persistence diagrams

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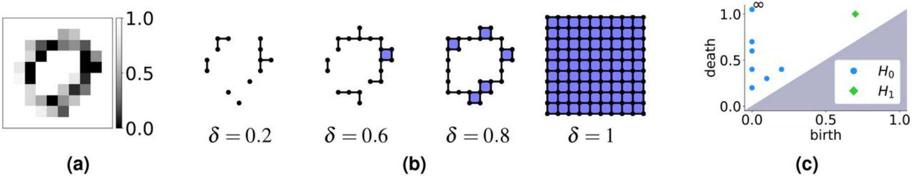

$$\ldots \subseteq K(a_{i-3}) \subseteq \boxed{K(a_{i-2}) \subseteq K(a_{i-1}) \subseteq K(a_i) \subseteq K(a_{i+1})} \subseteq K(a_{i+2}) \subseteq \ldots$$

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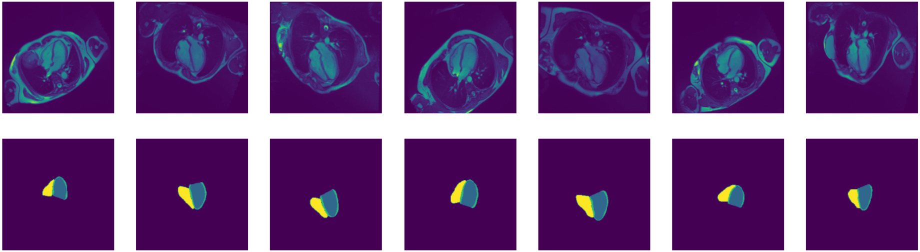
Dataset

The dataset

- focuses on the right ventricle segmentation from CMR
- obtained from the second edition of the M&Ms Challenge [Campello et al., 2021]
- contains 360 CMR studies
- is divided in short-axis and long-axis 4-chamber views that are labeled at the end-diastolic (ED) and end-systolic (ES) phases



Preprocessing

- 720 long-axis images
- Input images were rescaled to values in the interval [0,1]
- Four channels were considered in the labels
- The selected input shape was $128 \times 128 \times 1$
- The selected output shape of $128 \times 128 \times 4$

Neural network hyperparameters

Neural network hyperparameters

Accuracy measures:

- Categorical Cross Entropy Accuracy: $\mathrm{CE} = -\sum_i^{N_{classes}} y_i \log(\hat{y}_i)$
- Intersection-Over-Union: $\mathrm{IoU} = \dfrac{|Y \cap \hat{Y}|}{|Y \cup \hat{Y}|}$
- Dice Coefficient: $\mathrm{DC} = \dfrac{2|Y \cap \hat{Y}|}{|Y| + |\hat{Y}|}$

Optimizer:

- The selected optimizer is Adam, with a learning rate of $\mathrm{lr} = 0.001$

Cost function

Cost function:

$$\mathcal{L} = \mathcal{L}_{\textit{Dice}}(Y, \hat{Y}) + \alpha \mathcal{L}_{\textit{Pixel-Wise}}(Y, \hat{Y}) + \beta \mathcal{L}_{\textit{Regularizer}}(Y, \hat{Y}),$$

$\alpha = 2.0$, $\beta = 0.0025$

We used the following topological regularizers:

- Difference of total persistences
- Bottleneck distance

We employed topological regularizers to compare the deviation between the model's predictions and actual labels in segmentations of the right ventricle (RV), left ventricle (LV), and myocardium (MYO).

Model

- The selected model is a U-Net neural network
- Input's data shape is $128 \times 128 \times 1$
- Output's data shape is $128 \times 128 \times 4$
- Convolution layers with 2×2 and 3×3 filters
- Dropouts of 10% and 20% of the neurons
- RELU activation function

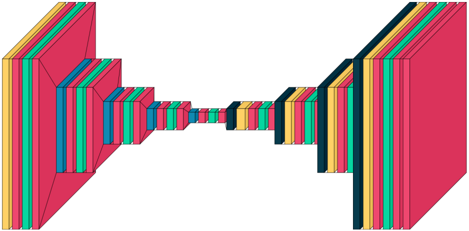


Figure: 3-D visualization of the model's downsampling and upsampling paths.

Notation

The term channel refers to the segmentation of the right ventricle (0), left ventricle (1), myocardium (2), or background (3).

Losses:

- GL := Dice Loss + Pixel-Wise Loss
- BL(channel) := Bottleneck Loss applied to a specific channel for dimension 0 and 1. We have that BL(channel) = α(bottleneck distance for dimension 0) + β(bottleneck distance for dimension 1), with $\alpha = 1.1$ and $\beta = 1.25$.
- TP := Difference of total persistences on all channels and dimensions

Accuracies:

- CE := Categorical Cross Entropy Accuracy
- MeanIoU := Intersection-Over-Union
- DC := Dice Coefficient

Results

Table: Comparison of results of the combination of geometric losses without a topological regularizer vs results from the calculation of BL loss for each channel, $i = 0, \ldots, 3$.

Metric	GL	GL+BL(0)	GL+BL(1)	GL+BL(2)	GL+BL(3)
MeanIoU accuracy (%)	61.0391	64.2347	66.0457	65.7243	63.1268
CE accuracy (%)	95.2583	96.1227	96.4405	96.3299	96.0592
DC accuracy (%)	96.2591	96.9546	97.1654	97.0742	96.8970

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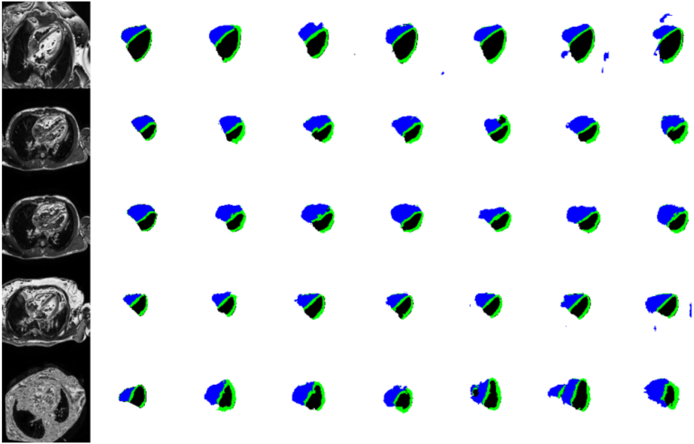

Figure: Example of segmentations using different methods. From left to right: input images, labels, and segmentation methods BL(0)+GL, BL(1)+GL, BL(2)+GL, BL(3)+GL, TP+GL, and GL alone.

Results

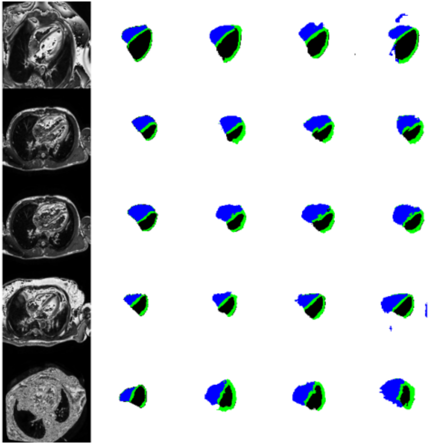

Figure: Example of segmentations using different methods. Left to right: input images, labels, and segmentation methods BL(0)+GL, BL(1)+GL, and GL.

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- We found promising results, indicating that the use of topological regularization did in fact lead to an improvement in segmentation accuracy
- However, there is still room for improvement in terms of the computational efficiency of these methods

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- Vectorization of persistence diagrams
- Applying methods to reduce computation time: *convolutional persistence* [Solomon et al., 2022]
- Ensemble deep learning models for segmentation
- Apply topological regularizers to the short-axis dataset
- Apply topological regularizers to a larger neural network using the whole dataset