Echocardiography Segmentation with Enforced Temporal Consistency

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3rd LabEx PRIMES Industry Day, Lyon, 20 June 2022

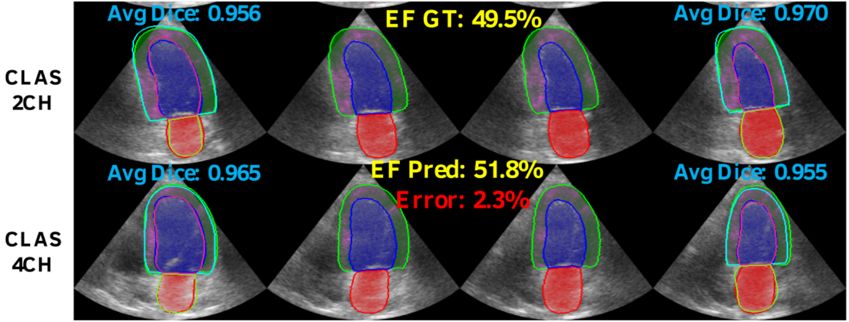
Academic Background

- **B.Sc. + M.Sc. Computer Science**
  Université de Sherbrooke (2016-2019, 2019-)
  M.Sc. Advisor: P.-M. Jodoin
  M.Sc. Subject: Cardiac Segmentation with Anatomical Constraints
- **Joint Ph.D. Computer Science**
  Université de Sherbrooke / INSA Lyon (2020-2023)
  Advisors: P.-M. Jodoin, O. Bernard, N. Duchateau
  Subject: Hypertension Characterization using Echocardiography

Current State of Echocardiography Segmentation: The Good

Automatic 2D+time echocardiography segmentation using deep neural networks:

- ☑ Intra-observer variability

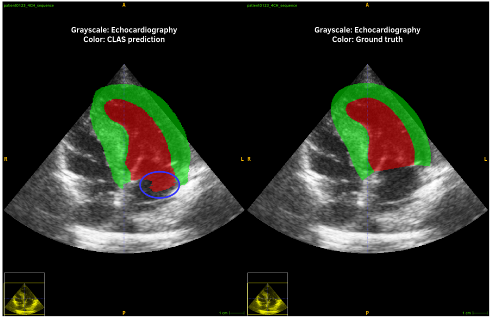


[Wei *et al.*, MICCAI 2019]

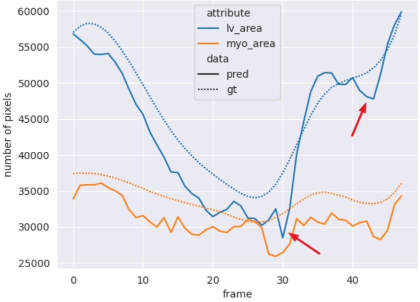
Current State of Echocardiography Segmentation: The Bad

Automatic 2D+time echocardiography segmentation using deep neural networks:

- ✗ Failures on individual frames
- ✗ Temporal consistency



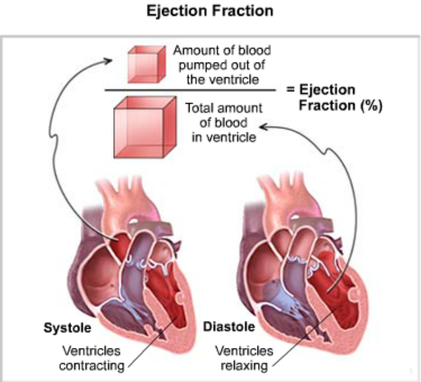
Example of degenerated frame in echo. sequence

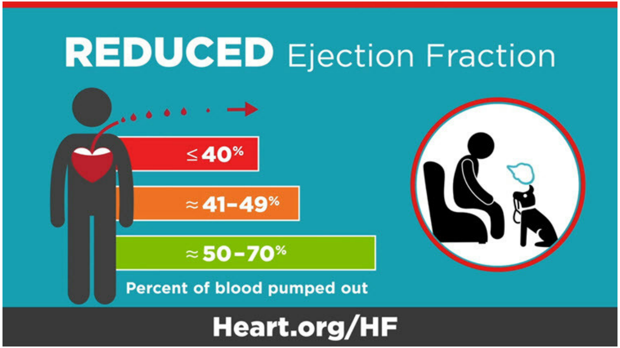


[**Painchaud** *et al.*, in press, IEEE TMI 2022]

Path to Clinical Use

- Methods' **clinical relevance** measured by impact on **ejection fraction** estimation



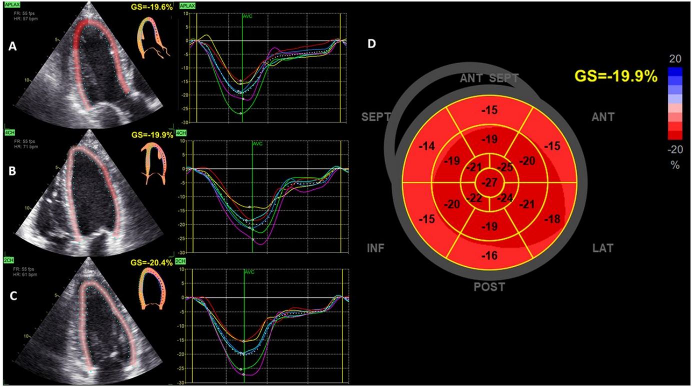


Source: Emory University

Source: American Heart Association

Path to Clinical Use

- Methods' **clinical relevance** measured by impact on **ejection fraction** estimation
- Physicians use **measures over time** to guide diagnosis (e.g. GLS)



[Abou *et al.*, Heart 2020]

Temporally Consistent Echocardiography Segmentation

What?

Add a **hard temporal consistency constraint** to echocardiography segmentation

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Temporally Consistent Echocardiography Segmentation

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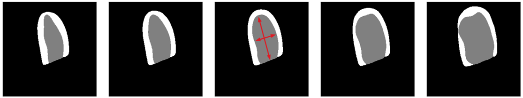
Add a **hard temporal consistency constraint** to echocardiography segmentation

How?

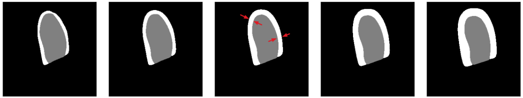
1. Define temporally inconsistent segmentations based on **shape attributes variations**
2. Learn an **interpretable representation** of cardiac shapes that models the shape attributes
3. Leverage the representation to **post-process temporal inconsistencies** in echocardiography segmentations ***a posteriori***

Cardiac Shape Attributes

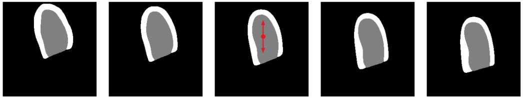
1. Define (7) **shape attributes** computable from segmentations
2. Identify **variation thresholds** from reference segmentations



Left ventricle area



Myocardium area



Y center of mass

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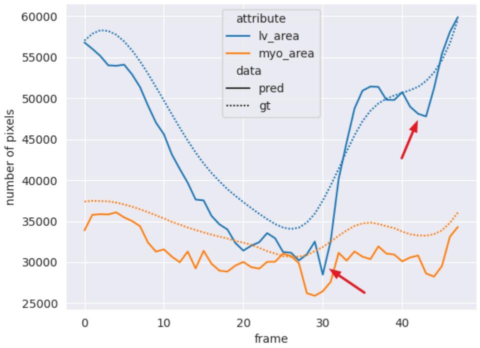


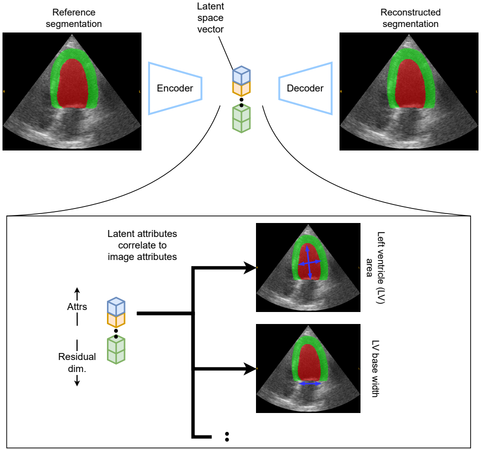
[**Painchaud** *et al.*, in press, IEEE TMI 2022]

Cardiac Shape Autoencoder

AR-VAE[1] to disentangle shape attributes:

1 shape attr. $\leftrightarrow$ 1 latent dim.

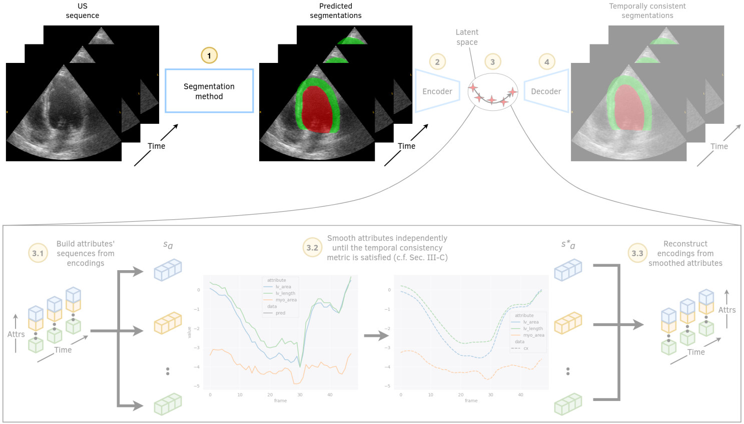
+ residual dimensions



[1] [Pati *et al.*, Neural Comput & Applic 2021]

Temporal Regularization Framework

1. Perform 2D+time segmentation using a **black-box method**
2. **Smooth** temporal inconsistencies in the latent space



[**Painchaud** *et al.*, in press, IEEE TMI 2022]

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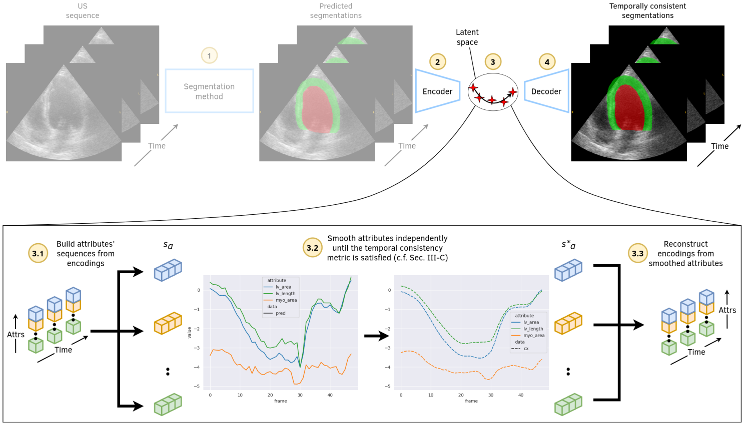

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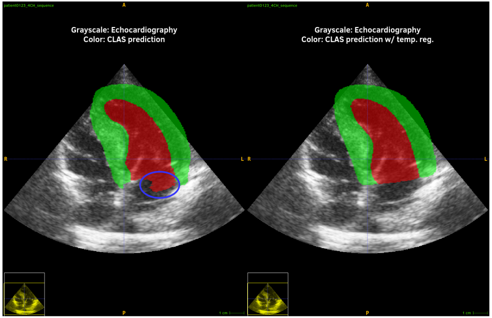
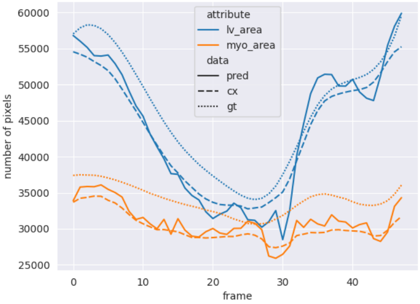
Results

Segmentations after temporal post-processing:

- ☑ Improved accuracy across cycle
- ☑ Temporal consistency



Degenerated frame smoothed using neigh. frames



[**Painchaud** *et al.*, in press, IEEE TMI 2022]

Post-processing and latent manipulation results: https://youtu.be/rBUx4JOz-7o

Thank you for listening! Questions?

CRSNG NSERC

Québec
Fonds de recherche – Nature et technologies
Fonds de recherche – Santé
Fonds de recherche – Société et culture

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Supplementary Materials: Videos

- Temporal regularization results: https://youtu.be/098NddEb2_k
- Latent attribute manipulation: https://youtu.be/_qb9muKyMIQ

Temporal Consistency Results

TABLE II: Temporal consistency of SOTA segmentation methods, with and without our temporal regularization. [Left] Number of sequences with at least one temporally inconsistent frame w.r.t its neighboring frames, out of a **total of 98 sequences**. [Right] Ratio between the Laplacian of an attribute at a given frame, as defined in eq. (3), and the maximum threshold above which the value for that attribute are considered temporal inconsistent. The ratio is averaged over all attributes and all frames, regardless of whether they are temporally consistent or not.

Methods	Original	Gaussian filter	VAE	Cardiac AR-VAE		
				-	Temp. reg. attrs.	Temp. reg.
CLAS [1]	68 / .211	41 / .143	56 / .199	54 / .212	1 / .083	**0 / .069**
DeepLabv3 [10], [11]	98 / .879	86 / .237	98 / .871	98 / .892	81 / .277	**1 / .125**
ENet [12], [13]	98 / .700	85 / .238	98 / .681	98 / .655	67 / .221	**0 / .114**
LUNet [7]	98 / .594	79 / .214	98 / .591	98 / .641	61 / .220	**0 / .113**
U-Net [5], [6]	98 / .562	83 / .218	98 / .558	98 / .584	53 / .198	**0 / .110**

[**Painchaud** *et al.*, in press, IEEE TMI 2022]

Segmentation Accuracy Results

TABLE III: Accuracy of SOTA segmentation methods, with and without our temporal regularization, on all frames of the full cycles from the CAMUS dataset. [Left] Average Dice score and [Right] Hausdorff distance (in mm).

Methods	Original	Gaussian filter	VAE	Cardiac AR-VAE		
				-	Temp. reg. attrs.	Temp. reg.
CLAS [1]	**.953** / 4.4	**.953** / 4.3	**.953** / **4.0**	**.953** / **4.0**	**.953** / **4.0**	.952 / **4.0**
DeepLabv3 [10], [11]	.946 / 4.8	**.951** / 4.4	.945 / 4.8	.945 / 4.8	.949 / 4.4	**.951** / **4.2**
ENet [12], [13]	.943 / 5.1	.946 / 4.8	.943 / 4.9	.944 / 4.8	.947 / 4.5	**.949** / **4.3**
LUNet [7]	.947 / 4.6	.951 / 4.3	.947 / 4.6	.947 / 4.6	.950 / 4.3	**.952** / **4.1**
U-Net [5], [6]	.951 / 4.3	.954 / 4.0	.951 / 4.3	.950 / 4.3	.953 / 4.1	**.955** / **3.9**

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Clinical Metrics Results

TABLE IV: Clinical metrics of SOTA segmentation methods, with and without our temporal regularization. [Left] MAE on the 2D ejection fraction (EF) computed from A4C segmentations. [Right] Number of frames with anatomical errors, as defined in [12], out of a **total of 4531 frames** from all frames across all sequences.

Methods	Original	Gaussian filter	VAE	Cardiac AR-VAE		
				-	Temp. reg. attrs.	Temp. reg.
CLAS [1]	4.2 / 6	4.6 / 2	4.3 / 1	4.1 / 1	4.1 / **0**	**4.0** / **0**
DeepLabv3 [10], [11]	2.8 / 12	**2.7** / 13	2.9 / 1	**2.7** / 3	**2.7** / 3	3.6 / **0**
ENet [12], [13]	3.2 / 11	**2.9** / 20	3.4 / 5	**2.9** / **0**	**2.9** / **0**	3.3 / **0**
LUNet [7]	3.1 / 11	**2.7** / 8	3.1 / **0**	**2.7** / 1	2.8 / 1	3.6 / **0**
U-Net [5], [6]	**2.7** / 1	2.9 / 6	2.9 / 6	2.8 / 3	3.0 / **0**	3.8 / **0**

[**Painchaud** *et al.*, in press, IEEE TMI 2022]

Publications

1. **N. Painchaud**, N. Duchateau, O. Bernard, and P.-M. Jodoin, "Echocardiography Segmentation with Enforced Temporal Consistency," *in press*, IEEE TMI, May. 2022.
2. **N. Painchaud**, Y. Skandarani, T. Judge, O. Bernard, A. Lalande, and P.-M. Jodoin, "Cardiac Segmentation With Strong Anatomical Guarantees," IEEE TMI, Nov. 2020.
3. **N. Painchaud**, Y. Skandarani, T. Judge, O. Bernard, A. Lalande, and P.-M. Jodoin, "Cardiac MRI Segmentation with Strong Anatomical Guarantees," MICCAI 2019.