Master Seminar: Deep Learning for Medical Applications

Neural Implicit Representation for Medical Shapes

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Johns Hopkins Whiting School of Engineering

Outline

- Introduction
- Related Papers
  - MedShapeNet - A Large-Scale Dataset of 3D Medical Shapes for Computer Vision
  - ImplicitAtlas: Learning Deformable Shape Templates in Medical Imaging
  - 4D Myocardium Reconstruction with Decoupled Motion and Shape Model
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Introduction

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What is Neural Implicit Representation (NIR)?

- Representing a signal with a continuous implicit function parametrized by the weights of a neural network [1]

- Typical implicit function
  - signed distance function (SDF) [2]
  - occupancy function [3]

- A few synonyms for NIR exist [1, 4, 5]

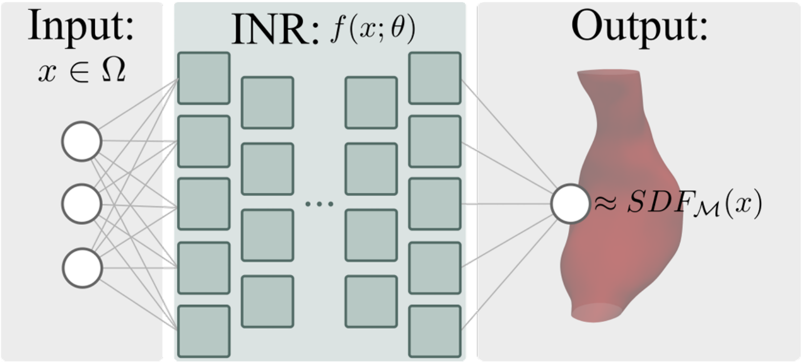

Figure 1. Schematic overview of an implicit neural representation parametrizing an SDF [5]

[1] Sitzmann V, Martel J, Bergman A, Lindell D, Wetzstein G, "Implicit Neural Representations with Periodic Activation Functions," in Advances in Neural Information Processing Systems, 2020, pp. 7462–7473.
[2] Park J, Florence P, Straub J, Newcomb R, Lovegrove S, "DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation," in 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 165-174.
[3] Mescheder L, Oechsle M, Niemeyer M, Nowozi S, Geiger A, "Occupancy networks: Learning 3d reconstruction in function space," in Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2019, pp. 4460–4470.
[4] Yang J, Wickramasinghe U, Ni B, Fua P, "ImplicitAtlas: Learning Deformable Shape Templates in Medical Imaging," in 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022, pp. 15840-15850.
[5] Yuan X, Liu C, Wang Y, "4D Myocardium Reconstruction with Decoupled Motion and Shape Model," in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023.
[6] Alblas D, Brune C, Yeung K, Wolterink J, "Going off-grid: continuous implicit neural representations for 3D vascular modeling," in International Workshop on Statistical Atlases and Computational Models of the Heart, 2022, pp. 79-90.

Background

- First frequent mentions for shape representation around 2019 [2, 3, 7]
- Extensive research efforts on representing general 3D shapes [2, 3, 7, 8]
- Some popular architectures include:
  - DeepSDF [2]
  - Occupancy Networks [3]
- Applications in medical imaging include reconstruction, registration, segmentation, compression and neural rendering [9]

[2] Park J, Florence P, Straub J, Newcomb R, Lovegrove S, "DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation," in 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 165-174.
[3] Mescheder L, Oechsle M, Niemeyer M, Nowozi S, Geiger A, "Occupancy networks: Learning 3d reconstruction in function space," in Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2019, pp. 4460–4470.
[7] Niemeyer M, Mescheder L, Oechsle M, Geiger A, "Occupancy Flow: 4D Reconstruction by Learning Particle Dynamics," in 2019 IEEE/CVF International Conference on Computer Vision (ICCV), 2019, pp. 5378-5388.
[8] Peng S, Niemeyer M, Mescheder L, Pollefeys M, Geiger A, "Convolutional occupancy networks," in Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part III 16, 2020, pp. 523–540.
[9] Molaei A, Aminimahr A, Tavakoli A, Kazerouni A, Azad B, Azad R, Merhof D, "Implicit neural representation in medical imaging: A comparative survey," in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023, pp. 2381–2391.

Motivation for NIR for Medical Shapes

- Potential use of shape features for diagnosis, treatment and monitoring [10]
- NIR because of the benefits compared to other ways of representation [2, 3, 6]
  - Smoother results
  - Higher resolution
  - Less memory
- Challenges of NIR
  - Limited generalization to unknown shapes [11]
  - Acquisition of ground truth data [9]

[2] Park J, Florence P, Straub J, Newcomb R, Lovegrove S, "DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation," in 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 165-174.
[3] Mescheder L, Oechsle M, Niemeyer M, Nowozi S, Geiger A, "Occupancy networks: Learning 3d reconstruction in function space," in Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2019, pp. 4460–4470.
[6] Alblas D, Brune C, Yeung K, Wolterink J, "Going off-grid: continuous implicit neural representations for 3D vascular modeling," in International Workshop on Statistical Atlases and Computational Models of the Heart, 2022, pp. 79-90.
[7] Mescheder L, Oechsle M, Niemeyer M, Nowozi S, Geiger A, "Occupancy networks: Learning 3d reconstruction in function space," in Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2019, pp. 4460–4470.
[8] Peng S, Niemeyer M, Mescheder L, Pollefeys M, Geiger A, "Convolutional occupancy networks," in Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part III 16, 2020, pp. 523–540.
[9] Molaei A, Aminimahr A, Tavakoli A, Kazerouni A, Azad B, Azad R, Merhof D, "Implicit neural representation in medical imaging: A comparative survey," in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023, pp. 2381–2391.
[10] Li J, ..., Egger J, "MedShapeNet – A Large-Scale Dataset of 3D Medical Shapes for Computer Vision," 2023.
[11] Chou G, Chugunov I, Heide F, "Gensdf: Two-stage learning of generalizable signed distance functions," in Advances in Neural Information Processing Systems, vol. 35, pp. 24905–24919, 2022.

Related Papers

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MedShapeNet - A Large-Scale Dataset of 3D Medical Shapes for Computer Vision [10]

[10] Li J, ..., Egger J, "MedShapeNet – A Large-Scale Dataset of 3D Medical Shapes for Computer Vision," 2023.

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Overview – MedShapeNet [10]

- Idea: build a large collection of medical shapes
- Motivation
  - Address problem of data scarcity
  - Enable the adaption of existing computer vision algorithms
  - Support exploration of the use of shape features
- Possible Applications
  - Reconstruction
  - Shape completion
  - Classification
  - Models for Virtual Reality, Augmented Reality, Mixed Reality and 3D printing

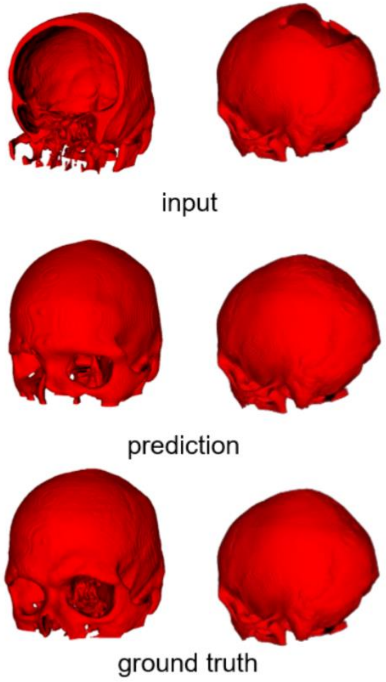

Figure 2. Skull reconstruction [10]

[10] Li J, ..., Egger J, "MedShapeNet – A Large-Scale Dataset of 3D Medical Shapes for Computer Vision," 2023.

Method

- Building a collection of over 100.000 medical shapes [10]
- Access through two interfaces: Web-based Interface and Python API [10]
- GitHub to manage the collection, feature requests and open-source applications utilizing MedShapeNet [10]

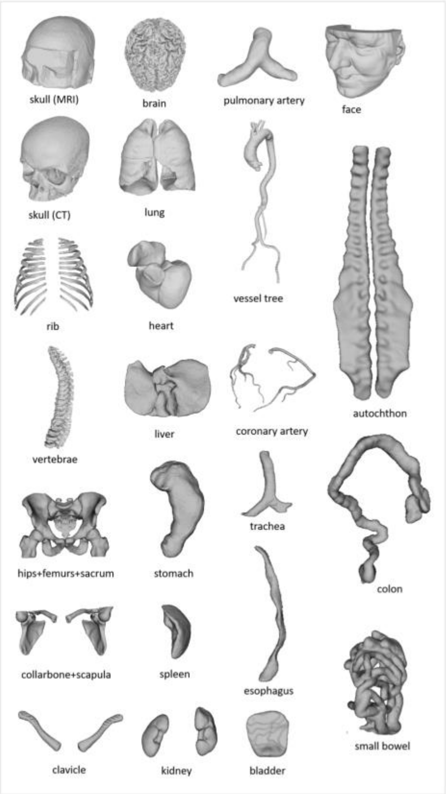

Figure 3. Example shapes in MedShapeNet [10]

[10] Li J, ..., Egger J, "MedShapeNet – A Large-Scale Dataset of 3D Medical Shapes for Computer Vision," 2023.

ImplicitAtlas: Learning Deformable Shape Templates in Medical Imaging [4]

[4] Yang J, Wickramasinghe U, Ni B, Fua P, "ImplicitAtlas: Learning Deformable Shape Templates in Medical Imaging," in 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022, pp. 15840-15850.

Overview – ImplicitAtlas [4]

- Idea: Use multiple templates to improve shape representation capability

- Motivation
  - Address the problems of
    - data scarcity
    - annotation noise
    - low-quality of models

- Possible Applications
  - Optimize annotations/ annotation process
  - Modeling changes over time

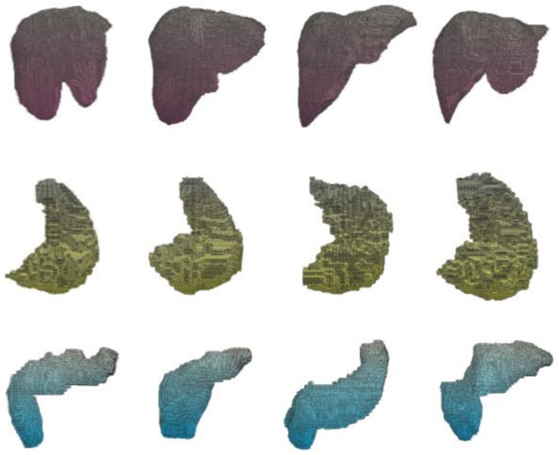

Figure 4. Example shapes of different organs (Section from Figure 1 in [4])

[4] Yang J, Wickramasinghe U, Ni B, Fua P, "ImplicitAtlas: Learning Deformable Shape Templates in Medical Imaging," in 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022, pp. 15840-15850.

Method

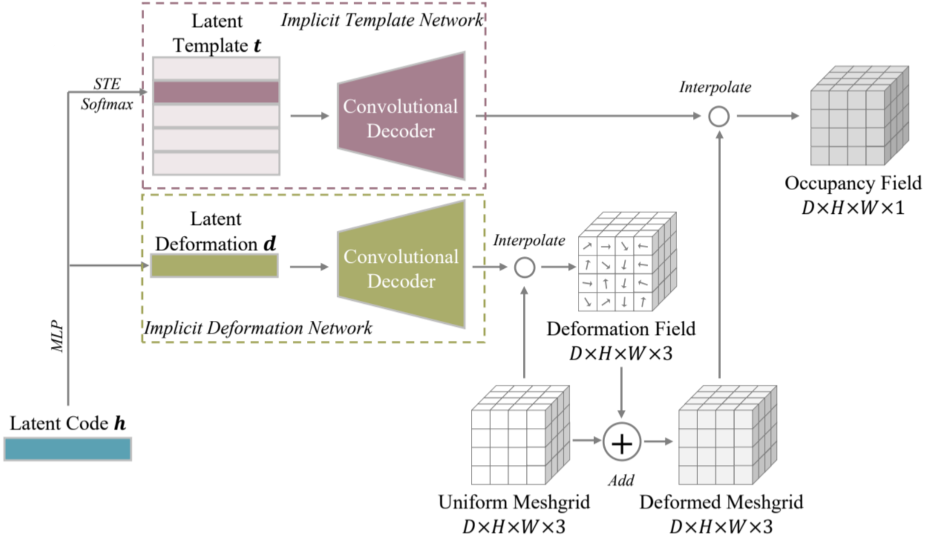

Figure 5. ImplicitAtlas's model pipeline [4]

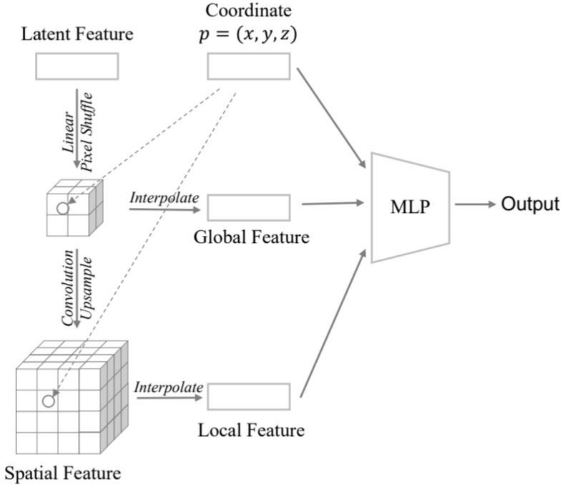

Figure 6. Architecture of the convolutional decoder [4]

[4] Yang J, Wickramasinghe U, Ni B, Fua P, "ImplicitAtlas: Learning Deformable Shape Templates in Medical Imaging," in 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022, pp. 15840-15850.

Experiments and Results (1/2)

- Quantitative Analysis

Method	Liver (K) DSC	Liver (K) NSD	Hippocampus (K) DSC	Hippocampus (K) NSD	Pancreas (K) DSC	Pancreas (K) NSD	Liver (U) DSC	Liver (U) NSD	Hippocampus (U) DSC	Hippocampus (U) NSD	Pancreas (U) DSC	Pancreas (U) NSD
MLP Decoder [38, 44]	96.32	95.20	93.21	91.50	94.83	95.55	93.12	71.23	90.20	63.05	89.46	65.15
+ Template [12, 72]	97.77	97.65	93.99	92.00	95.89	96.54	94.26	81.28	91.89	67.92	90.32	71.65
Conv Decoder [9, 45]	98.47	98.19	94.88	92.64	95.54	96.18	96.61	86.12	93.27	75.87	92.22	80.14
ImplicitAtlas	**98.58**	**98.69**	**96.42**	**94.72**	**96.85**	**97.30**	96.59	85.95	93.54	76.99	**93.38**	**81.11**
ImplicitAtlas + reg.	98.50	98.33	96.09	92.85	96.76	97.03	**96.72**	**86.90**	**93.99**	**77.47**	93.31	80.92

Figure 7. Reconstruction accuracy of different organs for known (K) and unknown (U) shapes (Metrics: Dice Similarity Coefficient (DSC) and Normalized Surface Dice (NSD)) [4]

[4] Yang J, Wickramasinghe U, Ni B, Fua P, "ImplicitAtlas: Learning Deformable Shape Templates in Medical Imaging," in 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022, pp. 15840-15850.

Experiments and Results (2/2)

- Qualitative Analysis

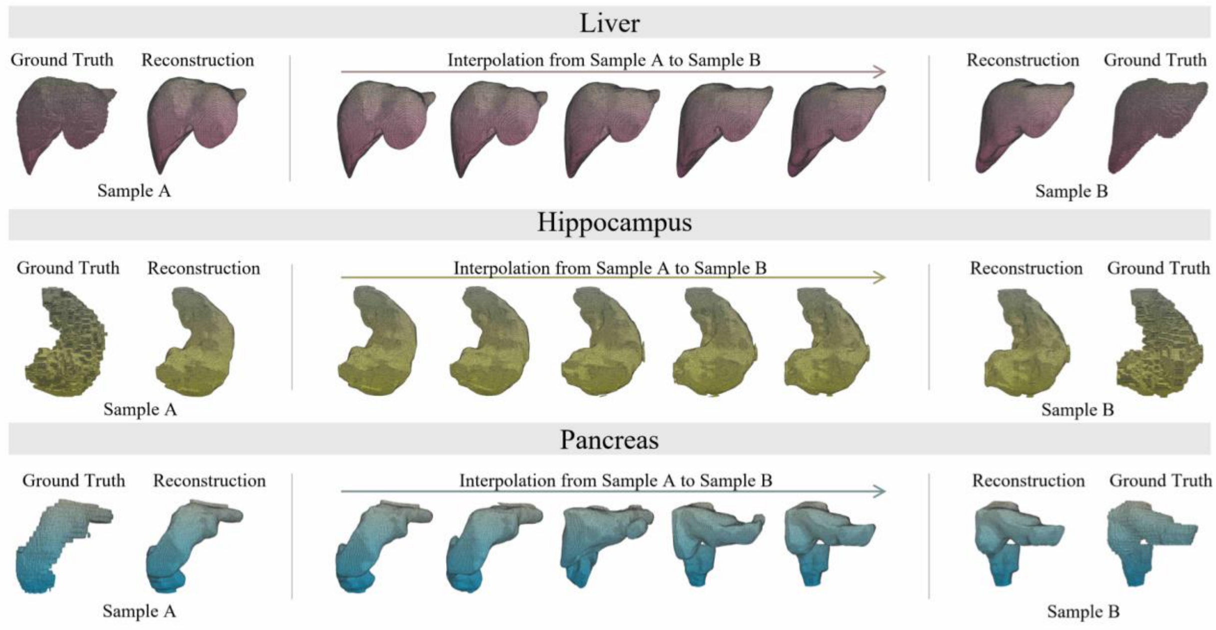

Figure 8. Shape reconstruction and interpolation results [4]

[4] Yang J, Wickramasinghe U, Ni B, Fua P, "ImplicitAtlas: Learning Deformable Shape Templates in Medical Imaging," in 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022, pp. 15840-15850.

4D Myocardium Reconstruction with Decoupled Motion and Shape Model [5]

[5] Yuan X, Liu C, Wang Y, "4D Myocardium Reconstruction with Decoupled Motion and Shape Model," in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023.

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Overview – 4D Myocardium Reconstruction [5]

- Idea: Learning motion from the representation of multiple shapes of the myocardium

- Motivation:
  - Support the diagnosis of cardiovascular diseases
  - Address the problem of large inter-slice spacing
  - Engage with the challenge of data-scarcity

- Possible Application:
  - Support diagnosis

[5] Yuan X, Liu C, Wang Y, "4D Myocardium Reconstruction with Decoupled Motion and Shape Model," in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023.

Method

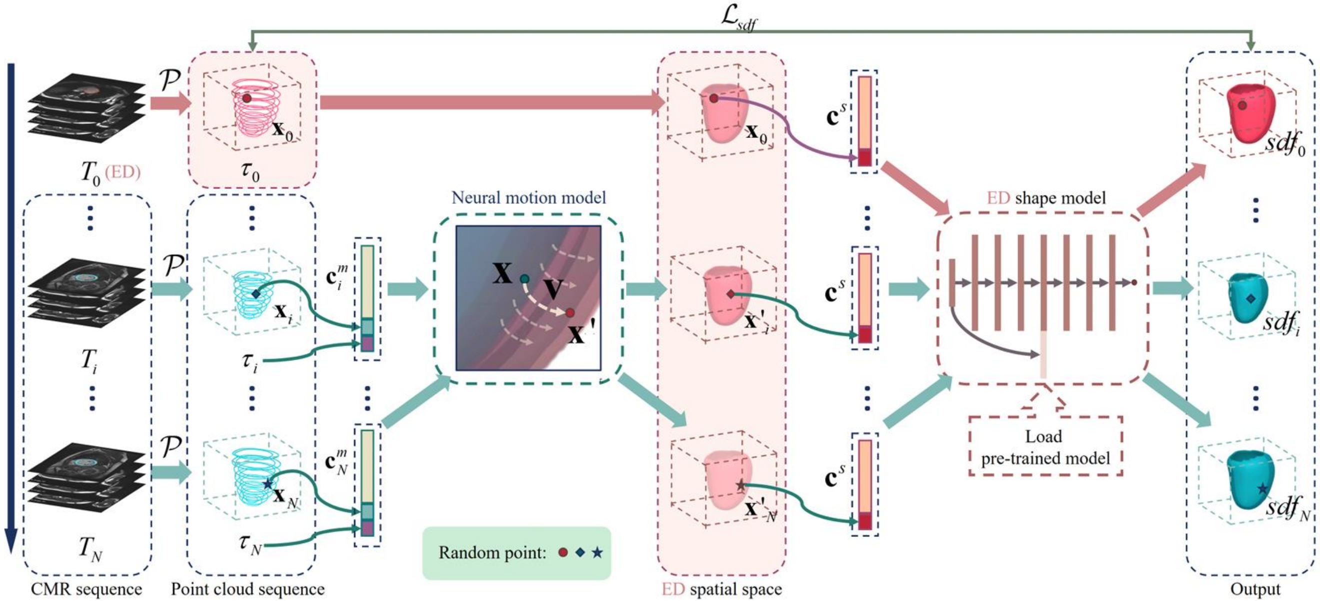

Figure 9. Model pipeline of the 4D Myocardium Reconstruction [5]

- Pre-training is enabled by the construction of the end-diastolic (ED)-space [5]

[5] Yuan X, Liu C, Wang Y, "4D Myocardium Reconstruction with Decoupled Motion and Shape Model," in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023.

Experiments and Results (1/3)

- Quantitative Analysis

Method	Input views	CD↓	EMD↓
Voxel2Mesh [39]	Volume	22.842	7.796
DeepSDF [32]	SAX	3.331	6.447
DIT [47]		7.553	7.645
DIF [12]		2.891	7.010
Ours		**2.634**	**6.173**
DeepSDF [32]	SAX+LAX	2.852	6.172
DIT [47]		8.156	6.878
DIF [12]		2.858	6.010
MulViMotion [26]		17.728	7.774
Ours		**2.627**	**3.603**

Figure 10. Comparison of quantitative results for different methods and input views (Metrics: Chamfer Distance (CD) and Earth Mover's Distance (EMD)) [5]

[5] Yuan X, Liu C, Wang Y, "4D Myocardium Reconstruction with Decoupled Motion and Shape Model," in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023.

Experiments and Results (2/3)

- Error visualization

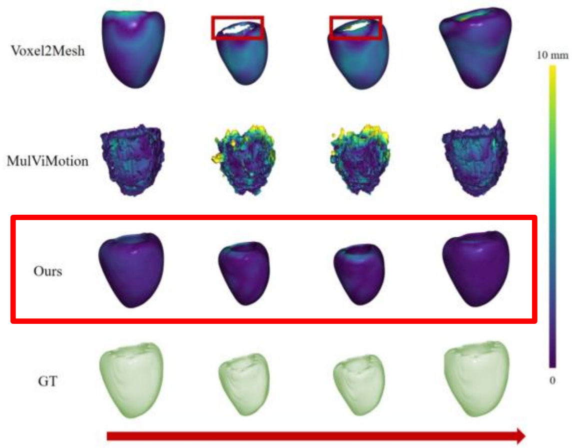

Figure 11. Error distribution of reconstruction results for explicit methods [5]

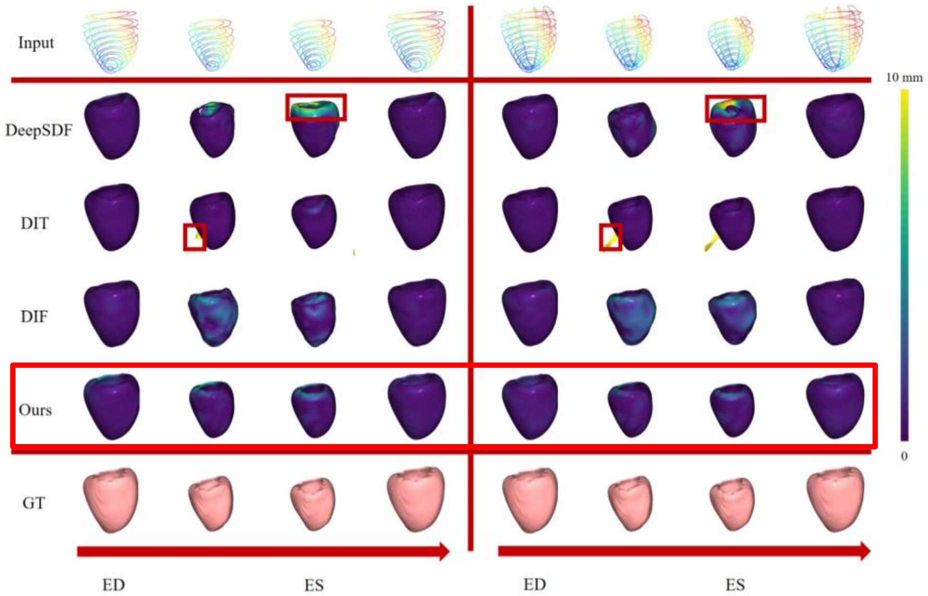

Figure 12. Error distribution of reconstruction results for implicit methods [5]

[5] Yuan X, Liu C, Wang Y, "4D Myocardium Reconstruction with Decoupled Motion and Shape Model," in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023.

Experiments and Results (3/3) – Potential Applications

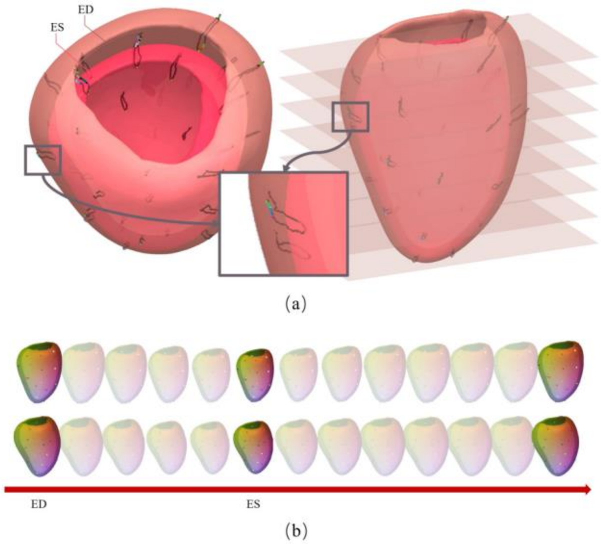

Figure 13. Example of dense motion estimation [5]

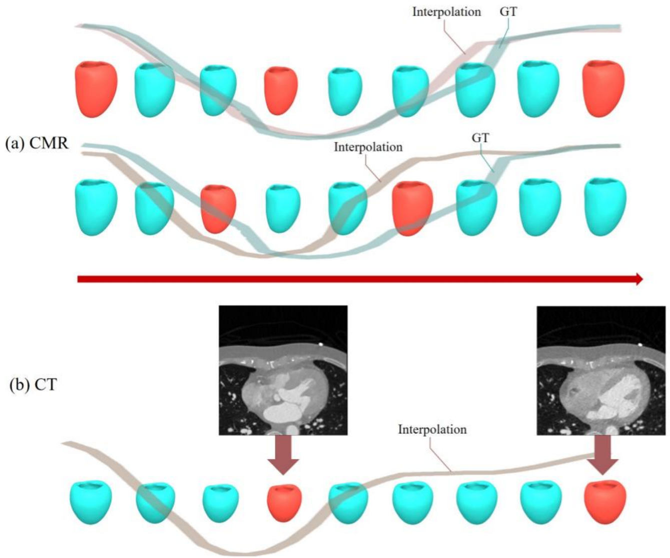

Figure 14: Results of the motion interpolation (Cyan meshes are interpolated) [5]

[5] Yuan X, Liu C, Wang Y, "4D Myocardium Reconstruction with Decoupled Motion and Shape Model," in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023.

Discussion and Personal Review

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Discussion

- Comparison
  - All papers address the problem of data-scarcity with different solutions [4, 5, 10]
  - ImplicitAtlas and 4D Myocardium Reconstruction
    - Different implicit functions used [4, 5]
    - Reconstruction results outperform existing methods [4, 5]
    - 4D Myocardium Reconstruction uses implicit shape representation to guide the motion estimation [5]

- Remaining challenges
  - MedShapeNet: extend effort, sensitive information [10]
  - ImplicitAtlas: limited to a single organ [4]
  - 4D Myocardium Reconstruction: improve results on data showing pathological findings [5]

[4] Yang J, Wickramasinghe U, Ni B, Fua P, "ImplicitAtlas: Learning Deformable Shape Templates in Medical Imaging," in 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022, pp. 15840-15850.
[5] Yuan X, Liu C, Wang Y, "4D Myocardium Reconstruction with Decoupled Motion and Shape Model," in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023.
[10] Li J, ..., Egger J, "MedShapeNet – A Large-Scale Dataset of 3D Medical Shapes for Computer Vision," 2023.

Personal Review

	+	−
MedShapeNet [10]	• Potentially useful tool for data-driven algorithms • Aim at public availability of the proposed dataset • Focus on potential uses cases	• No experiments to demonstrate applicability • Explicitly processed subset for Python API leaves the question of how reasonable the dataset is
ImplicitAtlas [4]	• Details are well explained or referenced • Extensive experiments • Comparison with other methods	• Emphasize that computing of templates happens at negligible cost but no evidence • Code is not publicly available
4D Myocardium Reconstruction [5]	• Extensive experiments • Comparison with other methods • Code is publicly available	• Complex paper which is hard to understand without additional sources

[4] Yang J, Wickramasinghe U, Ni B, Fua P, "ImplicitAtlas: Learning Deformable Shape Templates in Medical Imaging," in 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022, pp. 15840-15850.
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[10] Li J, ..., Egger J, "MedShapeNet – A Large-Scale Dataset of 3D Medical Shapes for Computer Vision," 2023.

Summary

Summary

- Three papers relevant for the topic of using NIR for medical shapes
  - MedShapeNet - A Large-Scale Dataset of 3D Medical Shapes for Computer Vision [10]
  - ImplicitAtlas: Learning Deformable Shape Templates in Medical Imaging [4]
  - 4D Myocardium Reconstruction with Decoupled Motion and Shape Model [5]

- Promising results and potential applications

- Some challenges remain for future research

[4] Yang J, Wickramasinghe U, Ni B, Fua P, "ImplicitAtlas: Learning Deformable Shape Templates in Medical Imaging," in 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022, pp. 15840-15850.
[5] Yuan X, Liu C, Wang Y, "4D Myocardium Reconstruction with Decoupled Motion and Shape Model," in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023.
[10] Li J, ..., Egger J, "MedShapeNet – A Large-Scale Dataset of 3D Medical Shapes for Computer Vision," 2023.

Thank you for your attention ☺
Any questions?

For further Reading:

Contact: laura.leschke@tum.de

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References

- [1] Sitzmann V, Martel J, Bergman A, Lindell D, Wetzstein G, "Implicit Neural Representations with Periodic Activation Functions," in Advances in Neural Information Processing Systems, 2020, pp. 7462–7473.
- [2] Park J, Florence P, Straub J, Newcomb R, Lovegrove S, "DeepSDF: Learning Continuous Signed Distance Functions for Shape Representation," in 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 165-174.
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- [6] Alblas D, Brune C, Yeung K, Wolterink J, "Going off-grid: continuous implicit neural representations for 3D vascular modeling," in International Workshop on Statistical Atlases and Computational Models of the Heart, 2022, pp. 79-90.
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- [9] Molaei A, Aminimahr A, Tavakoli A, Kazerouni A, Azad B, Azad R, Merhof D, "Implicit neural representation in medical imaging: A comparative survey," in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023, pp. 2381–2391.
- [10] Li J, ..., Egger J, "MedShapeNet – A Large-Scale Dataset of 3D Medical Shapes for Computer Vision," 2023.
- [11] Chou G, Chugunov I, Heide F, "Gensdf: Two-stage learning of generalizable signed distance functions," in Advances in Neural Information Processing Systems, vol. 35, pp. 24905–24919, 2022.

Backup Slides

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MedShapeNet [10] - Datasets Overview

Sources	Description	Dataset License
AbdomenAtlas [41]	25 organs and seven types of tumor	-
AbdomenCT-1K [42]	abdomen organs	**CC BY 4.0**
AMOS [43]	abdominal multi organs in CT and MRI	**CC BY 4.0**
ASOCA [44], [45]	normal and diseased coronary arteries	-
autoPET [46], [47], [48], [49]	whole-body segmentations	**CC BY 4.0**
AVT [50]	aortic vessel trees	**CC BY 4.0**
BraTS [51], [52], [53]	brain tumor segmentation	-
Calgary-campinas [54]	brain structure segmentations	-
Crossmoda [55], [56]	brain tumor and Cochlea segmentation	**CC BY 4.0**
CT-ORG [57]	multiple organ segmentation	**CC0 1.0**
Digital Body Preservation [58]	3D scans of anatomical specimens	-
EMIDEC [59], [60]	normal and pathological (infarction) myocardium	**CC BY NC SA 4.0**
Facial Models [61]	facial models for augmented reality	**CC BY 4.0**
FLARE [42], [62], [63], [64]	13 Abdomen organs	-
GLISRT [65], [66], [67]	brain structures	**TCIA Restricted**
HCP [68]	paired brain-skull extracted from MRIs	**Data Use Terms**
HECKTOR [69], [70]	head and neck tumor segmentation	-
ISLES22 [71]	ischemic stroke lesion segmentation	**CC-BY-4.0**
KiTS21 [72]	kidney and kidney tumor segmentation	**MIT**
LiTS [73]	liver tumor segmentation	-
LNDb [74], [75]	lung nodules	**CC BY NC ND 4.0**
LUMIERE [76]	longitudinal glioblastoma	**CC BY NC**
MUG500+ [77]	healthy and craniotomy CT skulls	**CC BY 4.0**
MRI GBM [78]	brain and GBM extracted from MRIs	**CC BY 4.0**
PROMISE [79]	prostate MRI segmentation	-
PulmonaryTree [80]	pulmonary airways, arteries and veins	**CC BY 4.0**
SkullBreak [81]	complete and artificially defected skulls	**CC BY 4.0**
SkullFix [81]	complete and artificially defected skulls	**CC BY 4.0**
SUDMEX CONN [82]	healthy and (cocaine use disorder) CUD brains	**CC0**
TCGA-GBM [53]	glioblastoma	-
3D-COSI [83]	3D medical instrument models	**CC BY 4.0**
3DTeethSeg [84], [85]	3D Teeth Scan Segmentation	**CC BY NC ND 4.0**
ToothFairy [86], [87]	inferior alveolar canal	**CC BY SA**
TotalSegmentator [88]	various anatomical structures	**CC BY 4.0**
VerSe [89]	large scale vertebrae segmentation	**CC BY 4.0**

Figure 14. Overview of dataset included in MedShapeNet [10]

[10] Li J, ..., Egger J, "MedShapeNet – A Large-Scale Dataset of 3D Medical Shapes for Computer Vision," 2023.

ImplicitAtlas [4] – Formular and Further Results

$$\mathcal{F}(\mathbf{h}, \mathbf{p}) = \mathcal{T}(\mathbf{t}(\mathbf{h}), \mathbf{p} + \mathcal{D}(\mathbf{d}(\mathbf{h}), \mathbf{p}))$$

Figure 15. Formulation of ImplicitAtlas [4]

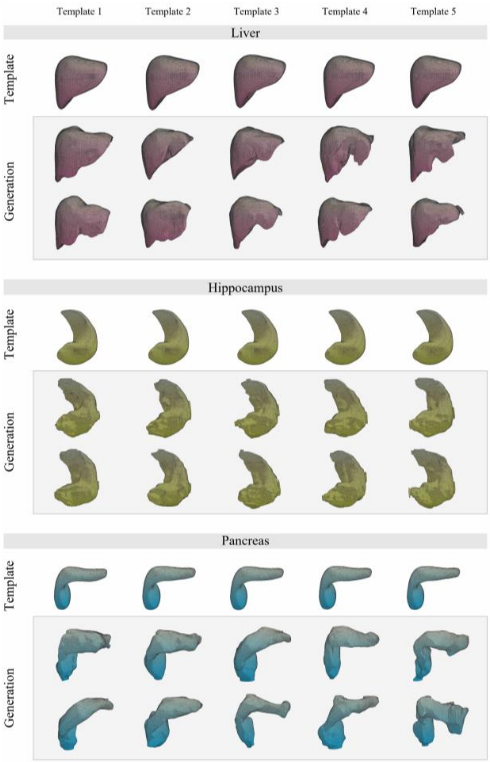

Figure 16. Projection of templates and generation results [4]

[4] Yang J, Wickramasinghe U, Ni B, Fua P, "ImplicitAtlas: Learning Deformable Shape Templates in Medical Imaging," in 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022, pp. 15840-15850.

ImplicitAtlas [4] – Further Results

D	MT	$\mathcal{L}_{LS}$	$\mathcal{L}_{DP}$	Liver (K) DSC	Liver (K) NSD	Hippocampus (K) DSC	Hippocampus (K) NSD	Pancreas (K) DSC	Pancreas (K) NSD	Liver (U) DSC	Liver (U) NSD	Hippocampus (U) DSC	Hippocampus (U) NSD	Pancreas (U) DSC	Pancreas (U) NSD
✓				98.22	98.01	95.62	91.17	96.15	95.62	96.52	85.43	93.18	74.54	90.61	74.43
	✓			82.65	26.18	80.13	30.98	55.39	15.66	79.24	22.42	76.82	27.21	51.64	14.16
✓	✓			**98.58**	**98.69**	**96.42**	**94.72**	96.85	97.30	96.59	85.95	93.54	76.99	93.38	81.11
✓	✓	✓		98.53	98.46	96.28	93.33	96.81	97.11	96.45	85.58	93.62	77.01	93.01	80.35
✓	✓		✓	98.52	98.42	96.32	93.10	**96.91**	**97.77**	96.69	86.21	93.79	77.13	**94.11**	**82.04**
✓	✓	✓	✓	98.50	98.33	96.09	92.85	96.76	97.03	**96.72**	**86.90**	**93.99**	**77.47**	93.31	80.92

Figure 17. Results of ablation study [4]

Method	Liver (K5) DSC	Liver (K5) NSD	Hippocampus (K5) DSC	Hippocampus (K5) NSD	Pancreas (K5) DSC	Pancreas (K5) NSD	Liver (U) DSC	Liver (U) NSD	Hippocampus (U) DSC	Hippocampus (U) NSD	Pancreas (U) DSC	Pancreas (U) NSD
MLP Decoder [38, 44]	96.67	96.51	93.52	91.31	95.20	95.83	88.33	43.90	83.62	45.07	68.97	27.70
+ Template [12, 72]	97.65	97.88	94.13	92.29	95.99	96.53	89.98	45.32	84.43	49.33	70.11	31.06
Conv Decoder [9, 45]	98.41	98.38	95.46	87.73	96.67	97.00	91.26	55.13	87.10	50.92	71.79	29.15
ImplicitAtlas	**98.89**	**99.53**	**97.02**	**96.37**	**97.23**	**98.14**	90.64	48.27	88.37	54.40	74.71	34.87
ImplicitAtlas + reg.	98.71	99.05	96.48	93.93	96.90	97.31	**92.06**	**57.69**	**89.97**	**59.39**	**81.34**	**46.78**

Figure 18. Results of the few-shot learning [4]

[4] Yang J, Wickramasinghe U, Ni B, Fua P, "ImplicitAtlas: Learning Deformable Shape Templates in Medical Imaging," in 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022, pp. 15840-15850.

ImplicitAtlas [4] – Further Results

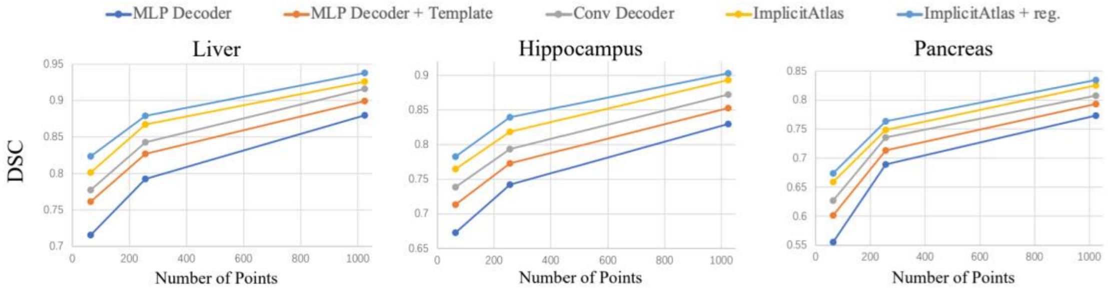

Figure 19. Results of shape completion from point annotations [4]

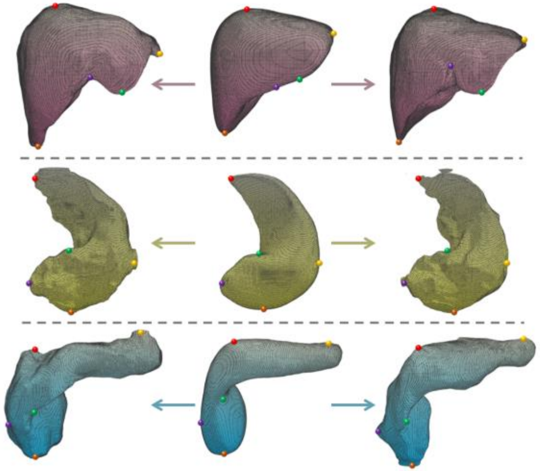

Figure 20. Estimated dense correspondence [4]

[4] Yang J, Wickramasinghe U, Ni B, Fua P, "ImplicitAtlas: Learning Deformable Shape Templates in Medical Imaging," in 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2022, pp. 15840-15850.

4D Myocardium Reconstruction [5] – Further Results

Dataset	Method	Dice↑	HD↓
ACDC 2017 dataset	Voxel2Mesh [39]	0.553	3.534
	DeepSDF [32]	0.697	3.257
	DIT [47]	0.702	3.011
	Ours	**0.765**	**2.789**
CT dataset	DeepSDF [32]	0.796	3.048
	DIT [47]	0.817	2.646
	Ours	**0.842**	**2.531**

Figure 21. Quantitative segmentation results [5]

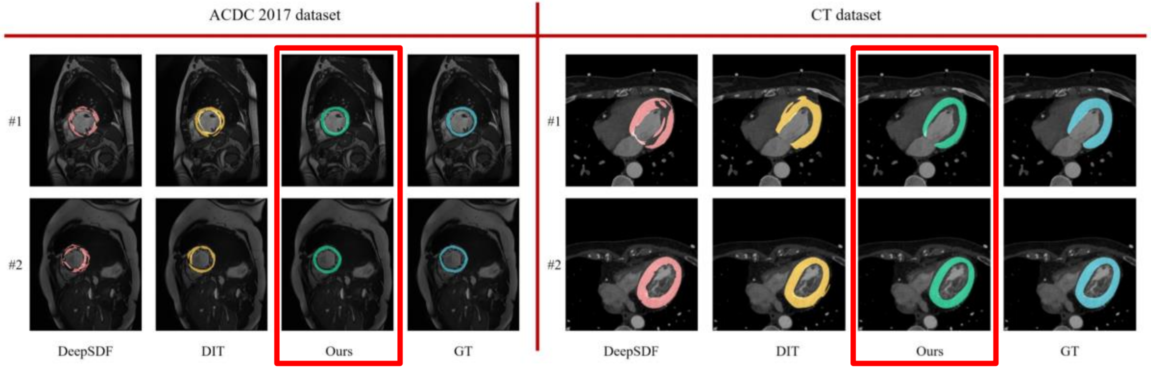

Figure 22. Qualitative segmentation results [5]

[5] Yuan X, Liu C, Wang Y, "4D Myocardium Reconstruction with Decoupled Motion and Shape Model," in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023.

4D Myocardium Reconstruction [5] – Further Results

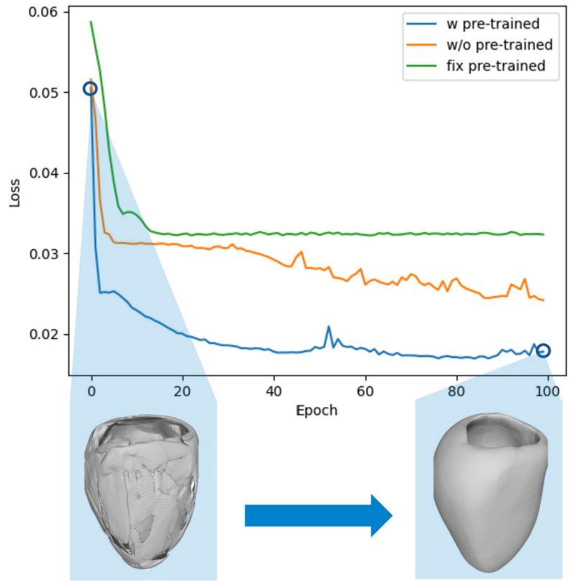

Figure 23. Results of ablation study on pre-training [5]

[5] Yuan X, Liu C, Wang Y, "4D Myocardium Reconstruction with Decoupled Motion and Shape Model," in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023.

4D Myocardium Reconstruction [5] – Pre-Training Pipeline

- Pipeline for ED shape model pre-training

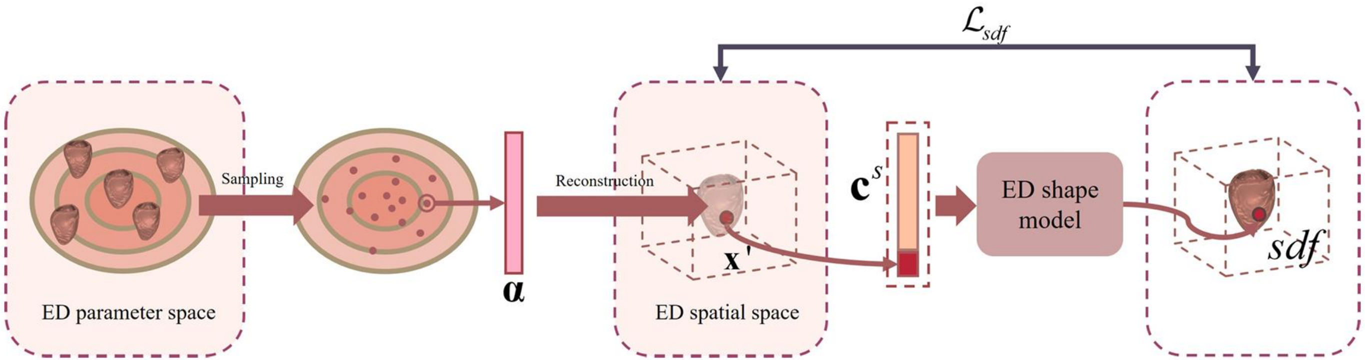

Figure 24. Pipeline of the ED shape model pre-training [3]

[5] Yuan X, Liu C, Wang Y, "4D Myocardium Reconstruction with Decoupled Motion and Shape Model," in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2023.