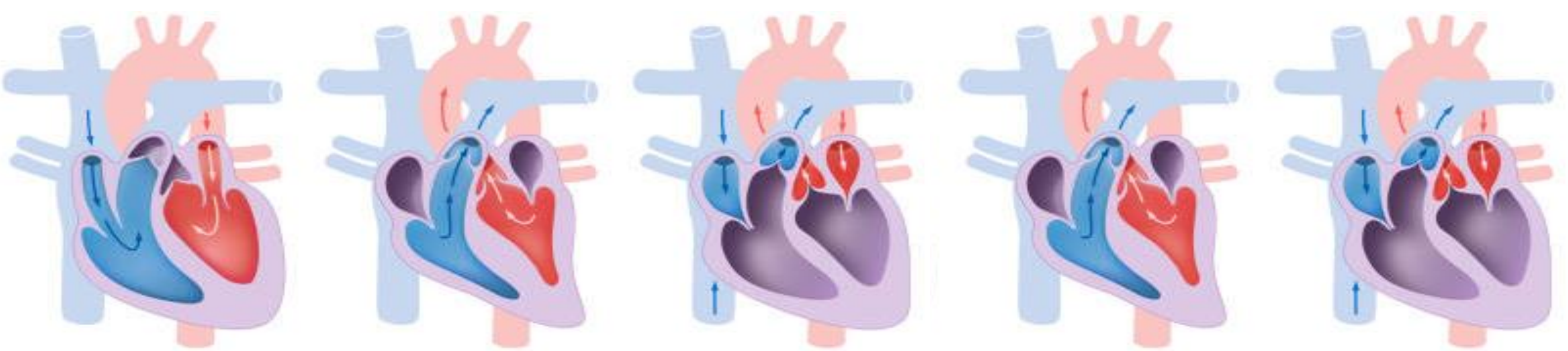
Cardiac Registration & Motion Tracking

Abdul Qayyum (Ph.D.)

National Heart & Lung Institute, Imperial College London



Why Study the Heart's Motion?

Following tissue/points/regions across frames

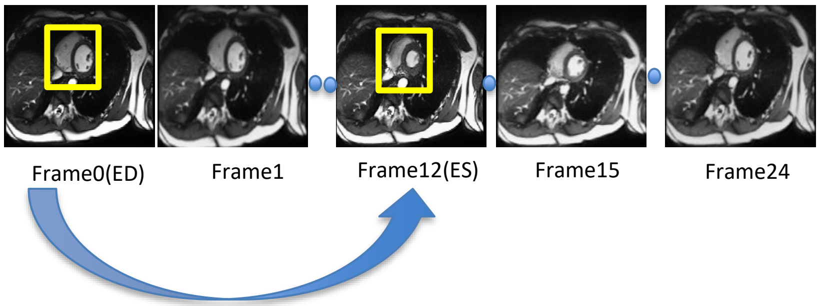
- Tracking specific areas of the heart over time reveals how they move during the cardiac cycle.

Applications: strain analysis, function measurement

- Motion tracking quantifies the deformation and performance of heart muscles.

Key in detecting abnormal motion

- Identifying irregular movement patterns helps detect cardiac dysfunction early.



Why Study the Heart's Motion?

Heart is a moving organ – beating and breathing motion:

- The heart constantly changes shape and position with each beat and during respiration, reflecting its dynamic nature.

Helps in diagnosis and treatment planning:

- Observing heart motion allows clinicians to detect abnormalities, plan interventions, and monitor therapy effectiveness.

Understanding motion = understanding function:

- The way the heart moves directly indicates how well it is pumping blood, linking mechanical motion to physiological performance.

Clinical Applications

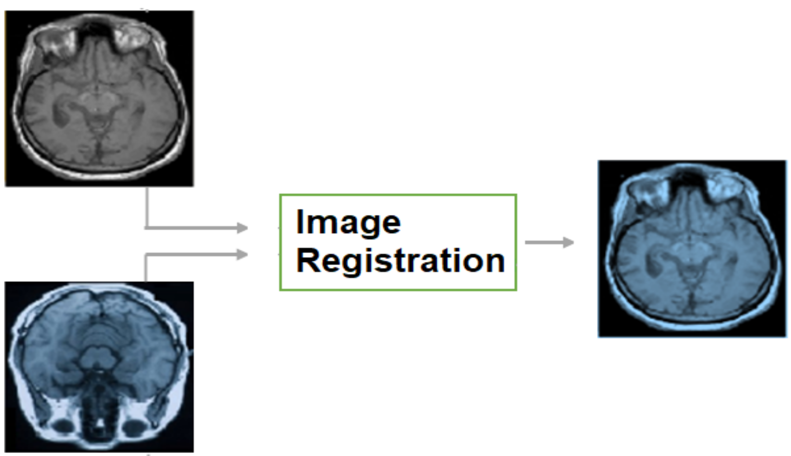
⚠️ Detect abnormal motion (e.g., infarct)

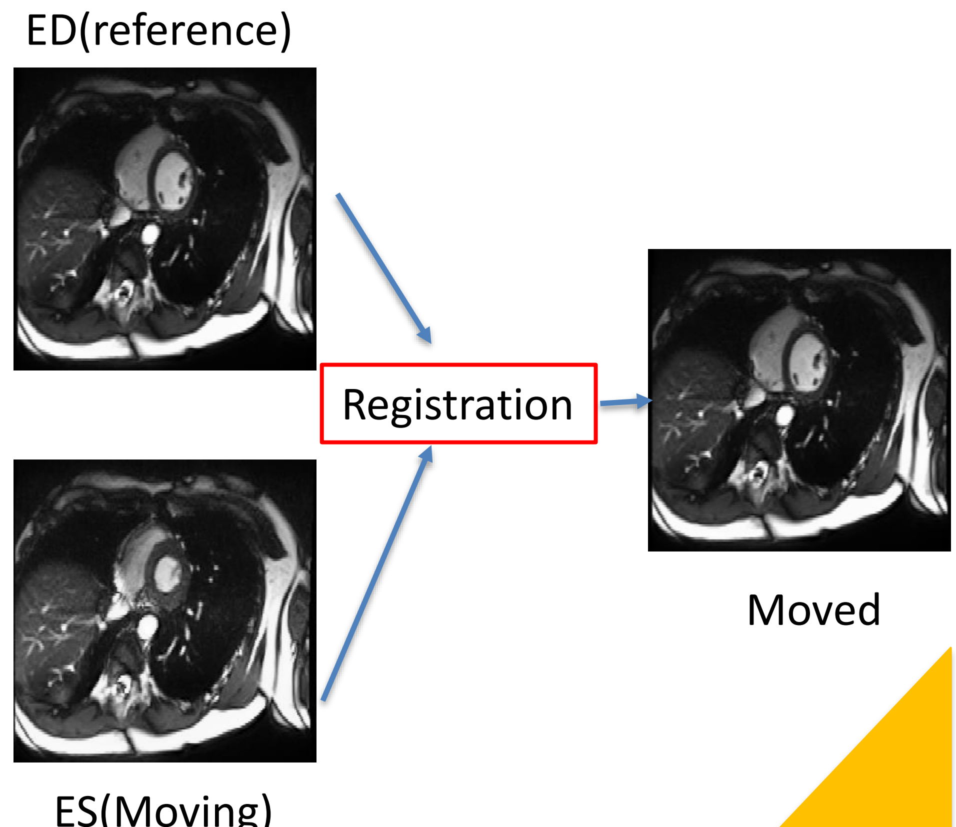
🗺️ Guide interventions (surgery, device placement)

🩺 📊 Functional assessment (strain, EF%)

What is Image Registration?

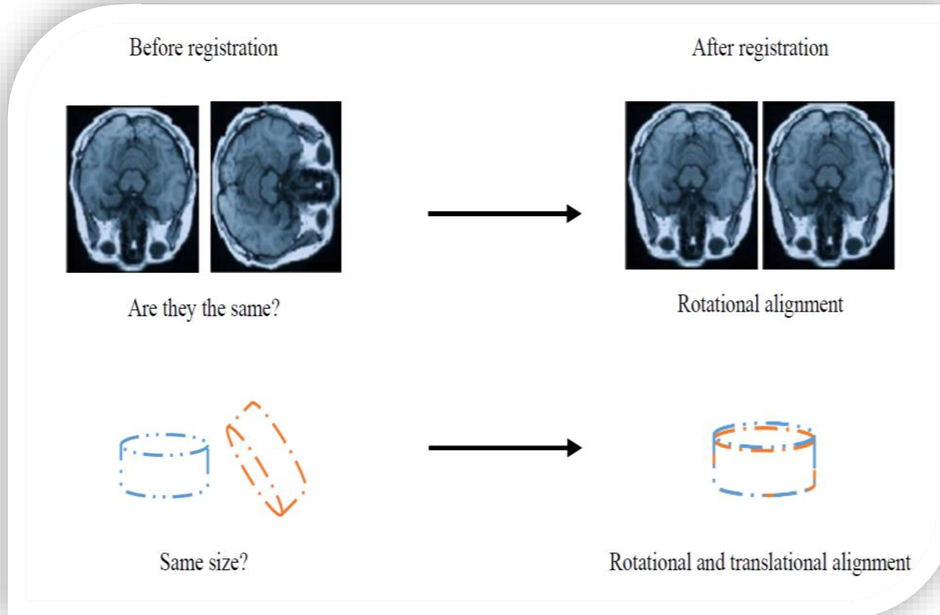
- Aligning two or more images into the same coordinate system
- Example: Aligning end-diastole with end-systole frames
- Important for comparison and motion analysis



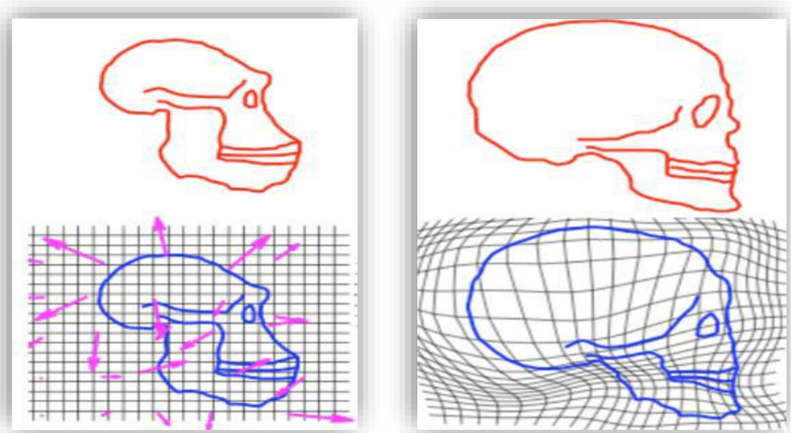


Types of Registration

- **Rigid:**
- translation
- rotation
- **Affine:**
- Translation
- Rotation
- Scaling(zoom in/out)
- Shearing (slanting/skewing)
- **Non-rigid/deformed:**
- complex local deformations



Rigid = translation + rotation only.
Affine = rigid + scaling + shear.
Non-rigid / deformable = affine + local, complex warping.

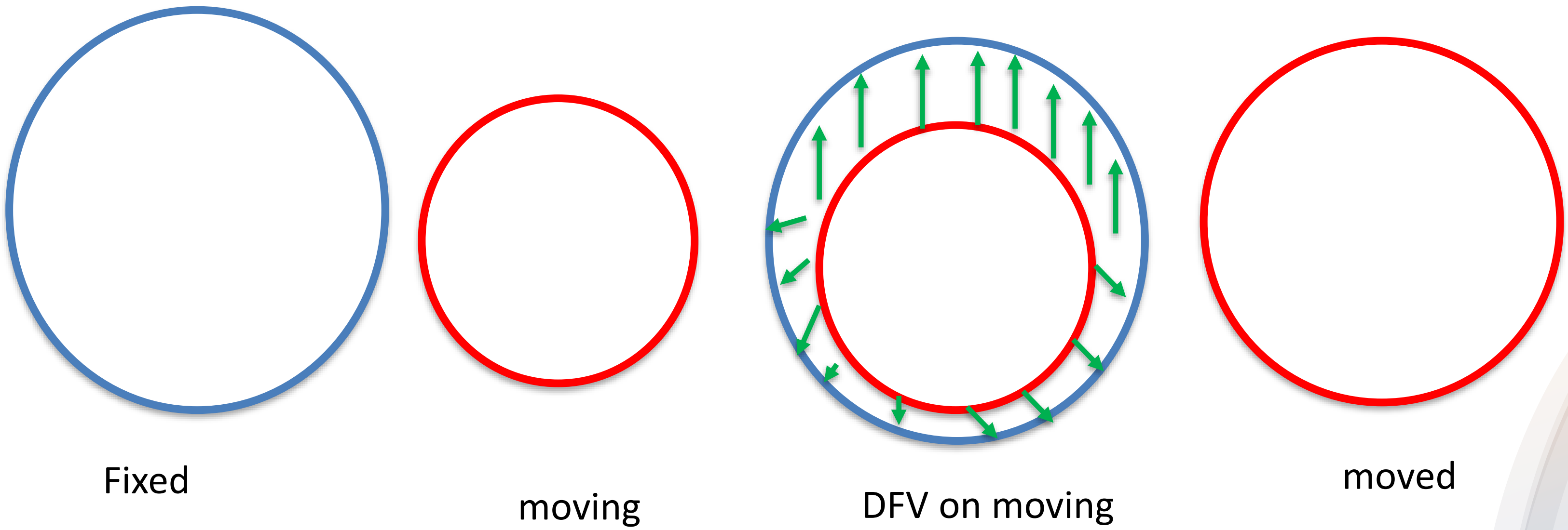


Deform underlying spatial domain

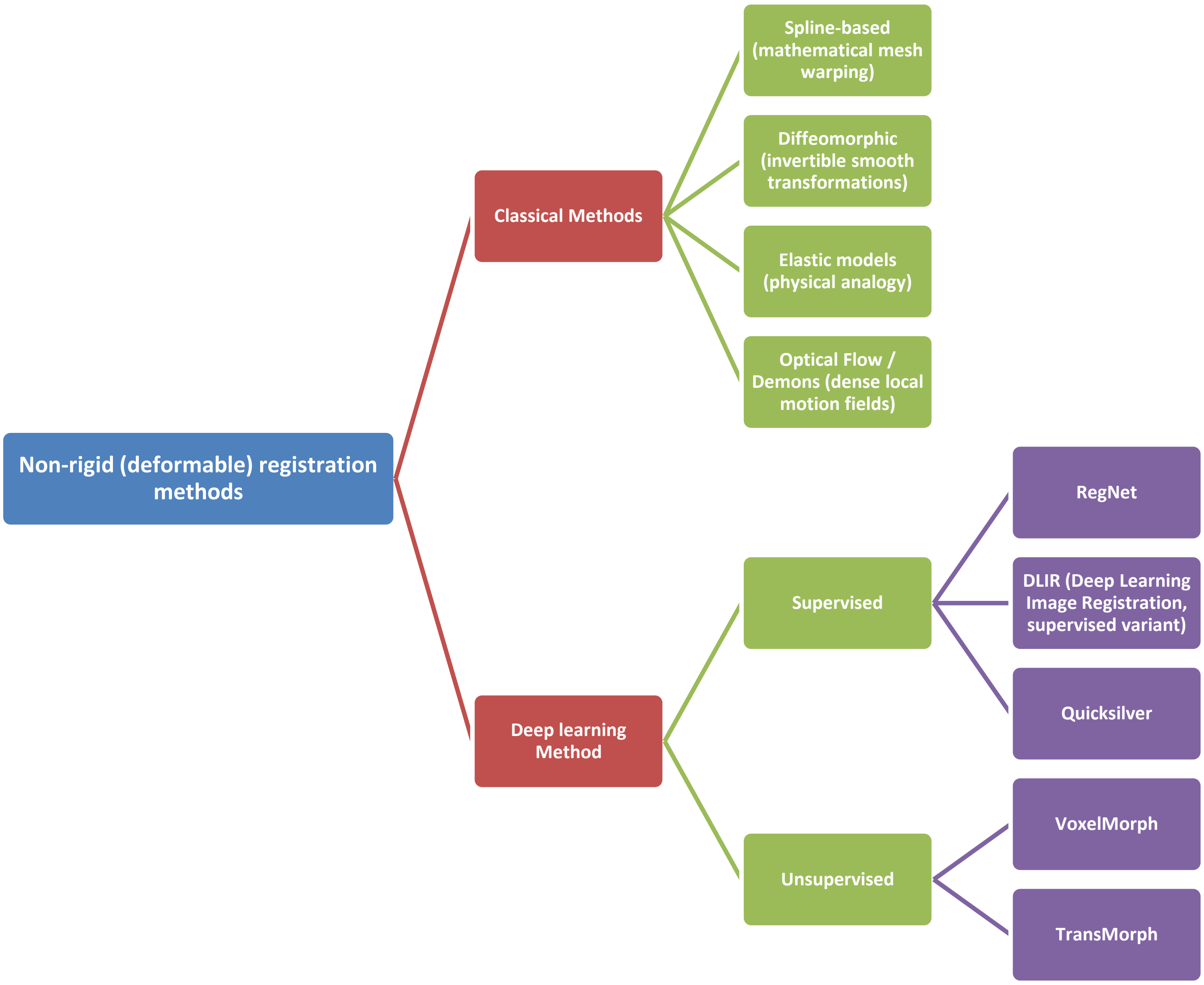
Durrleman et al., *Morphometry of anatomical shape complexes with dense deformations and sparse parameters*, NeuroImage 2014.

Types of Registration

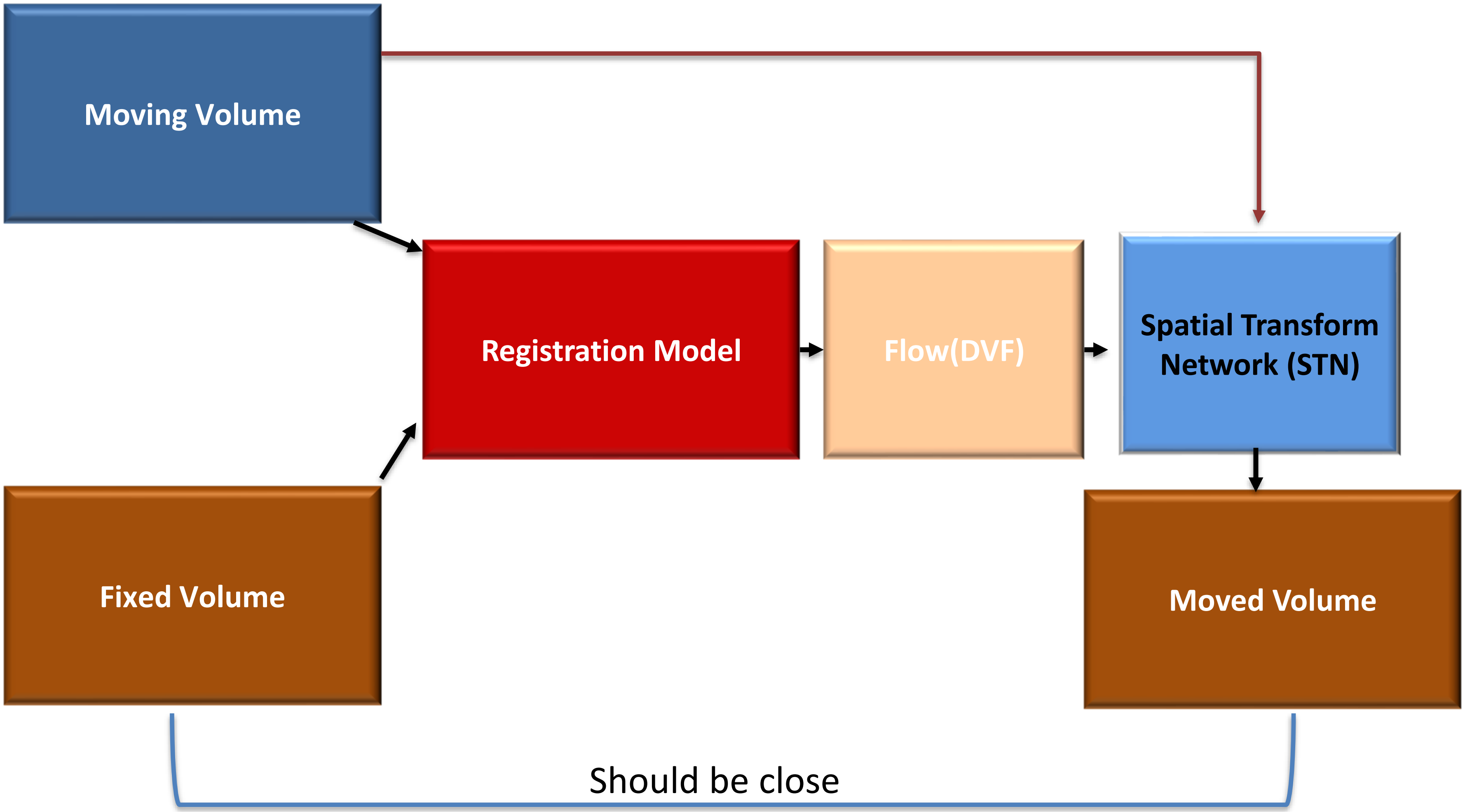
- Fixed vs moving images
- Deformation Vector Field (DVF) visualization



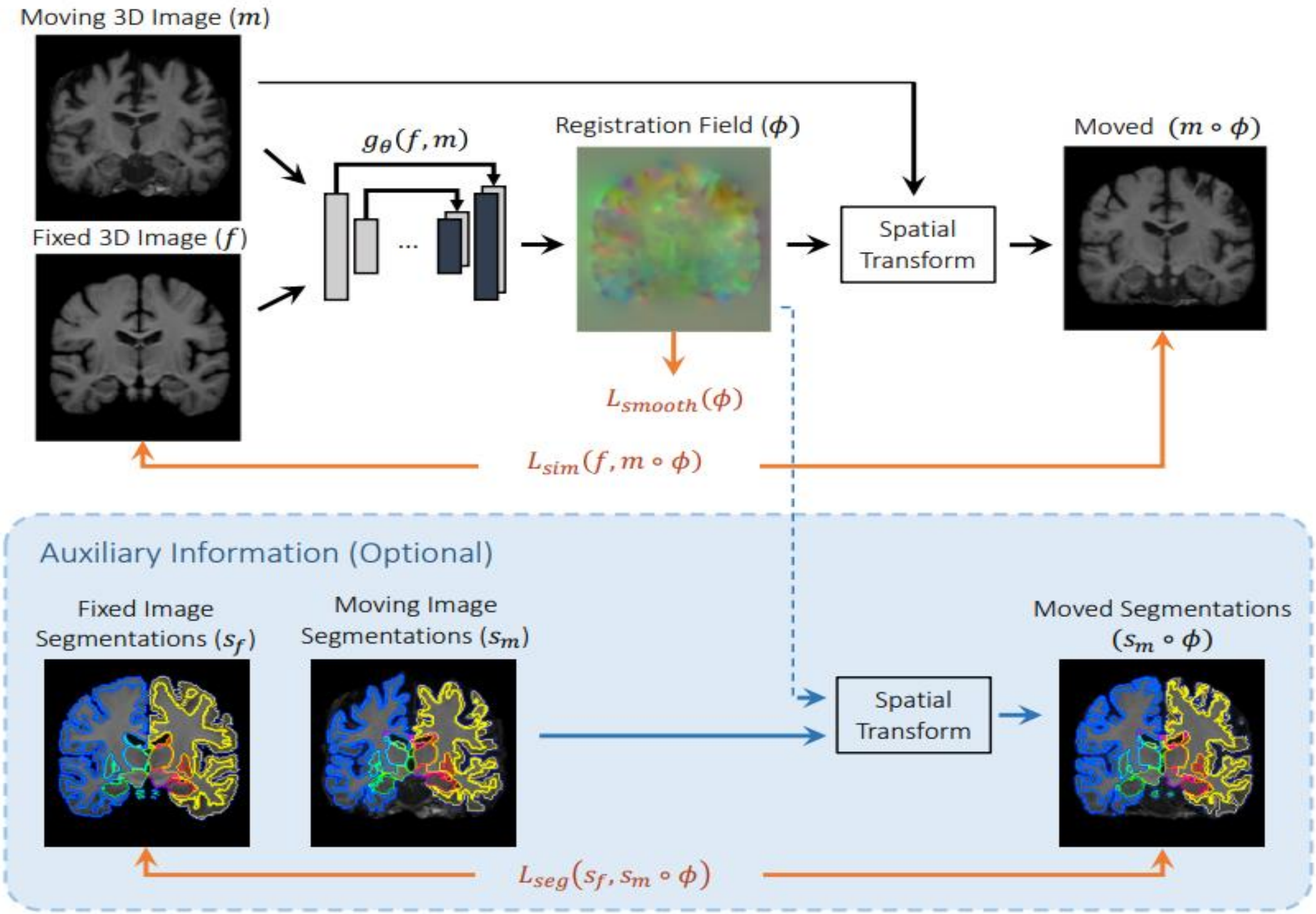
Types of Registration



Deep Learning Approaches

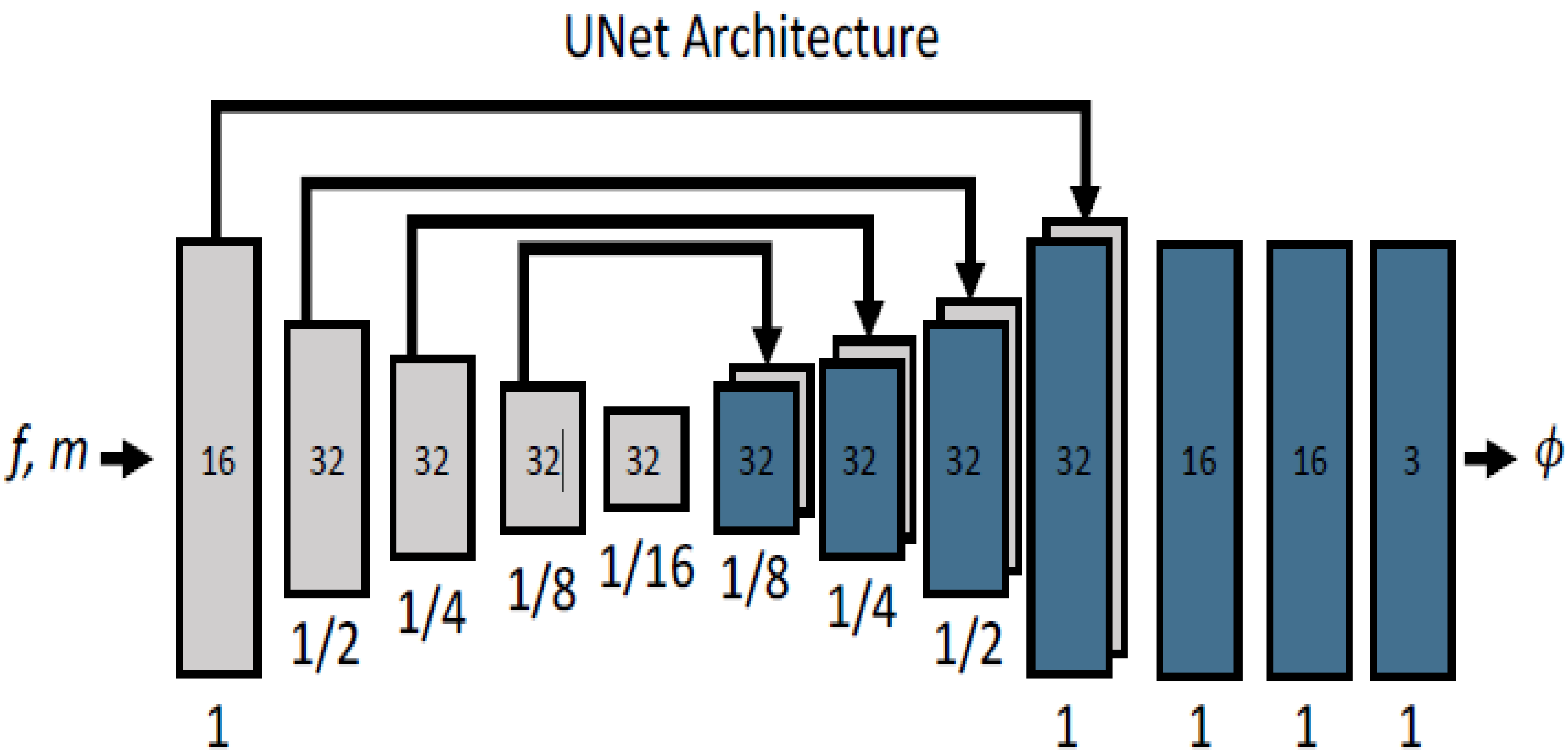


Deep Learning Approaches



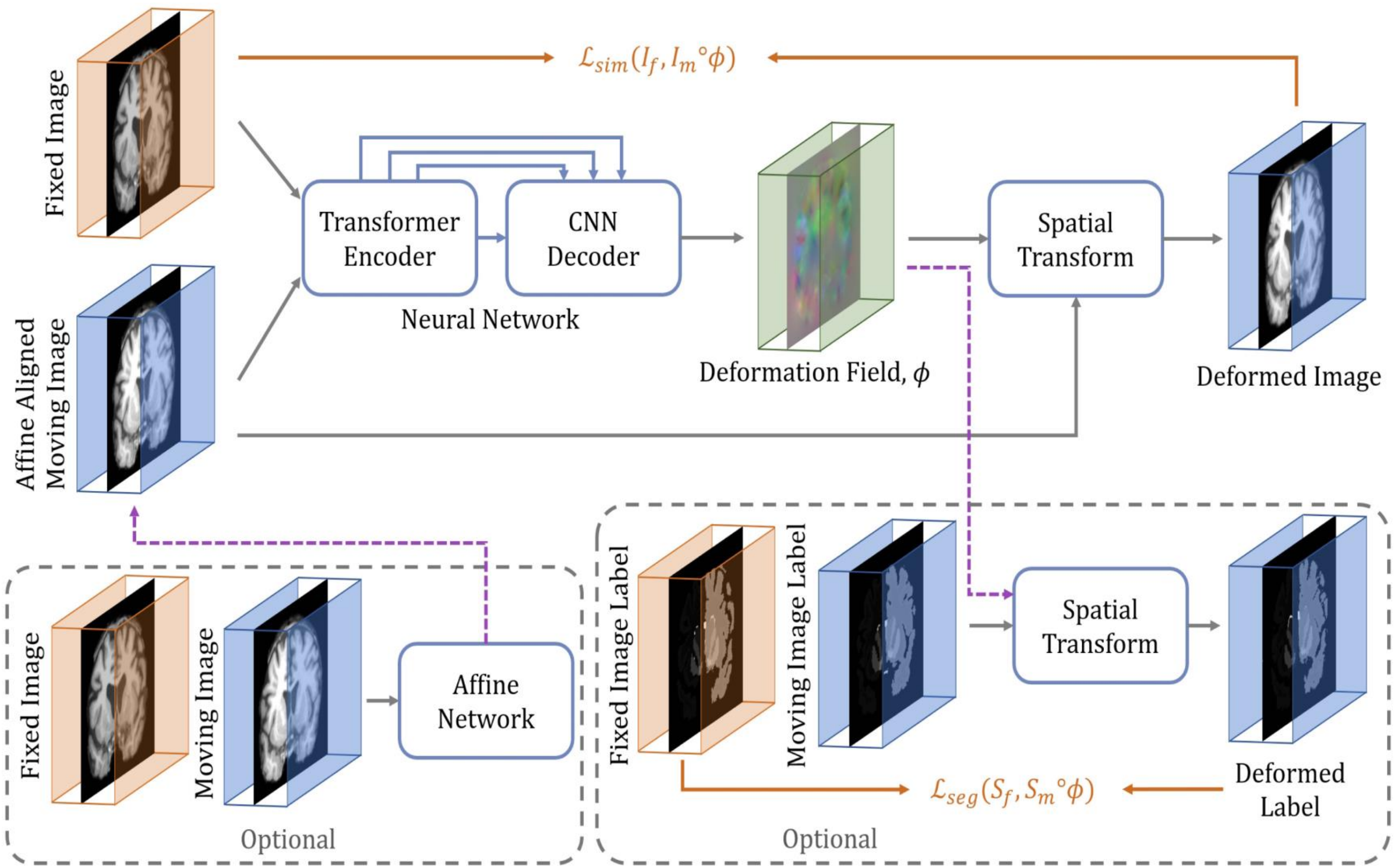
VoxelMorph: A Learning Framework for Deformable Medical Image Registration

Deep Learning Approaches



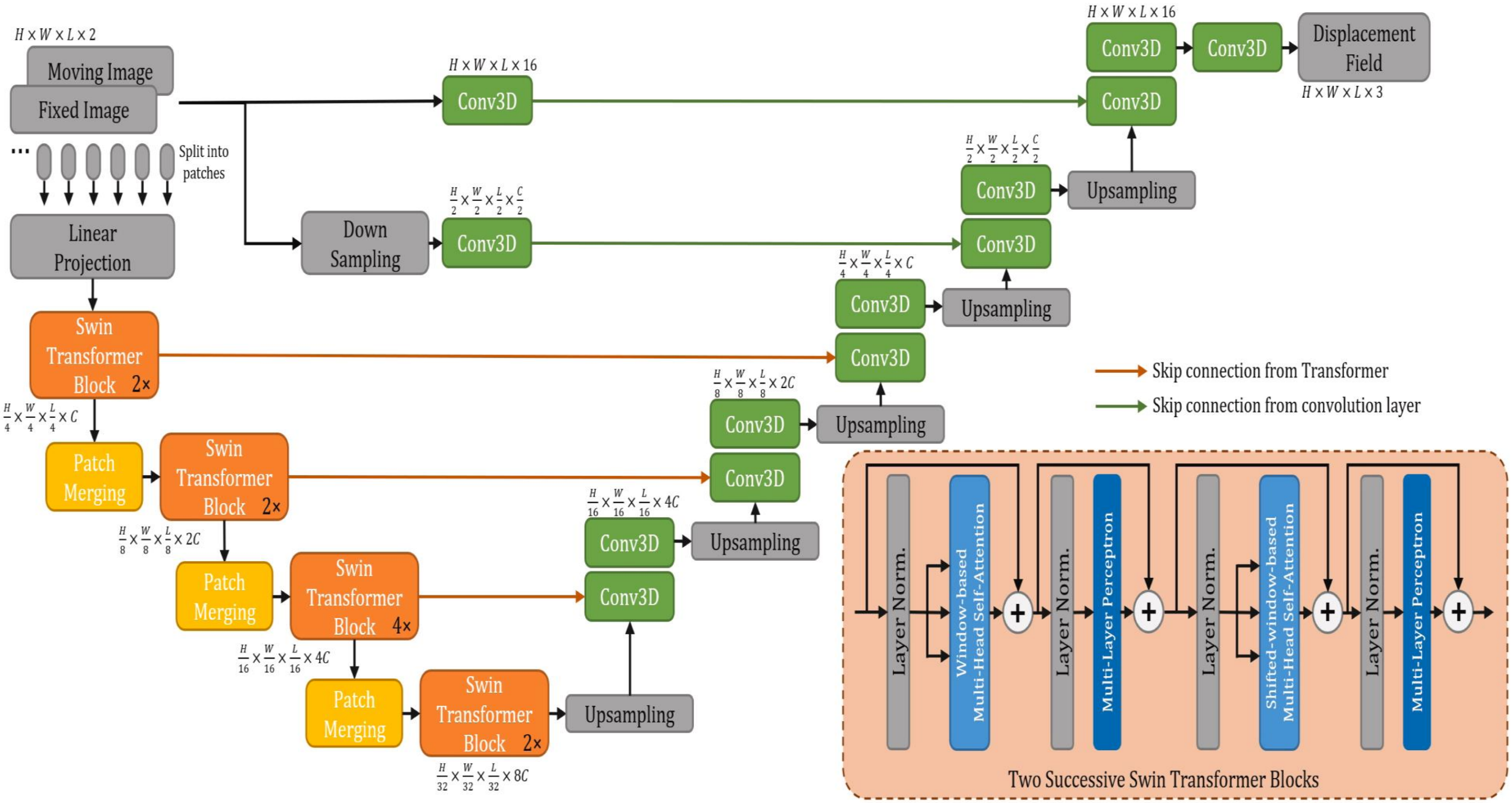
VoxelMorph: A Learning Framework for Deformable Medical Image Registration

Deep Learning Approaches



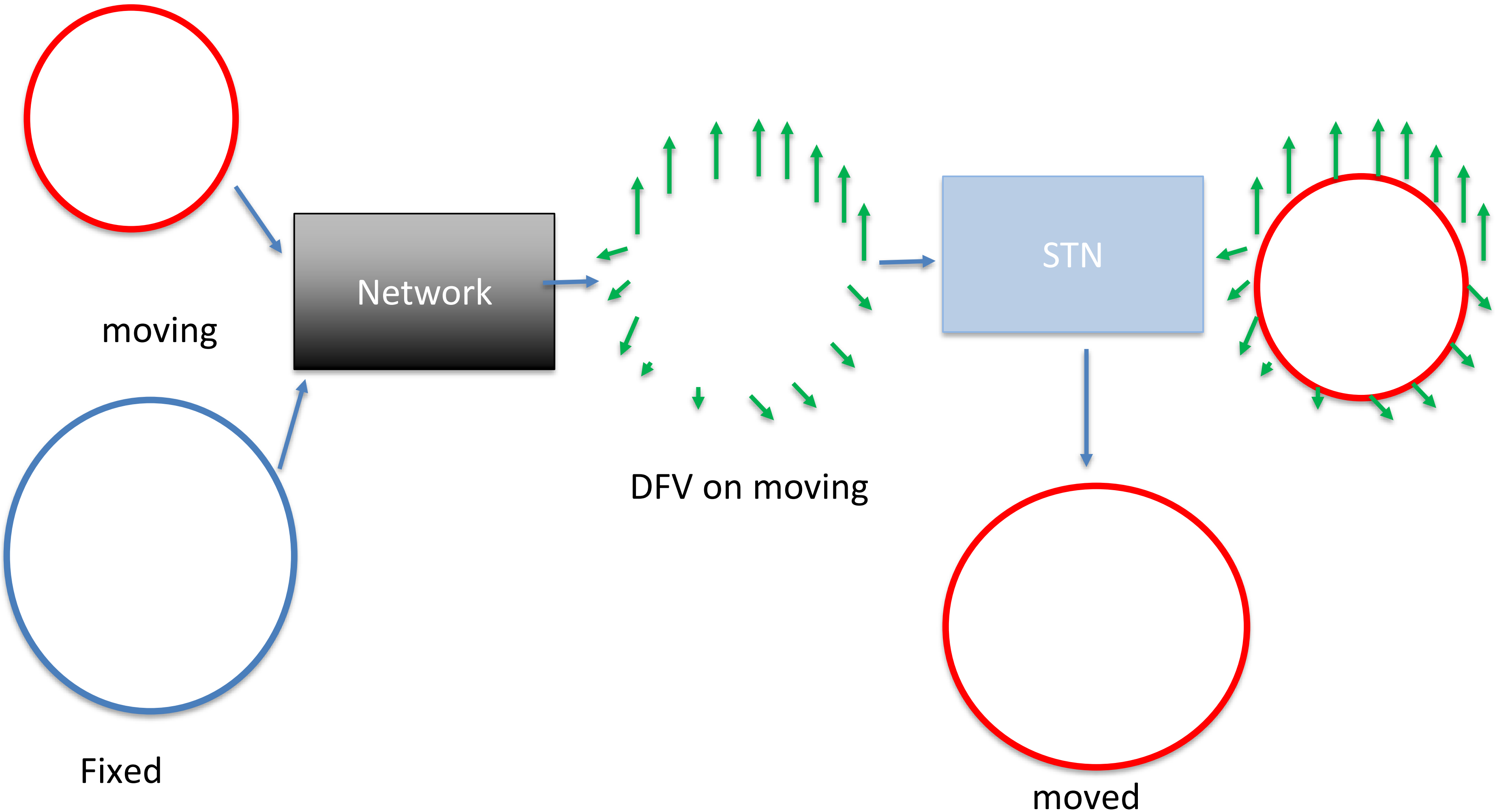
TransMorph: Transformer for unsupervised medical image registration

Deep Learning Approaches

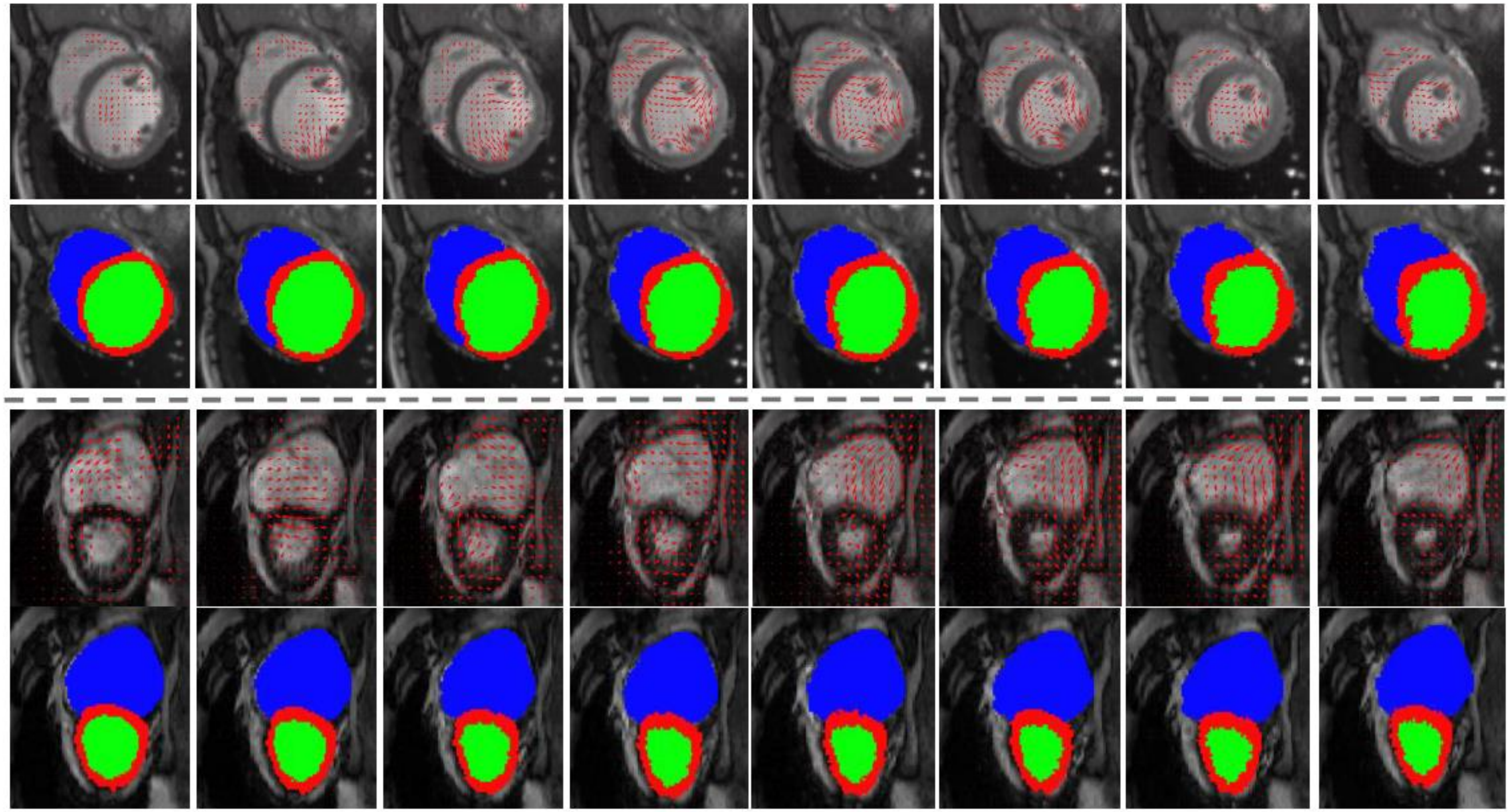


TransMorph: Transformer for unsupervised medical image registration

Deep Learning Approaches



Example Outputs



Frame 1 (ED)	Frame 2	Frame 3	Frame 4	Frame 5	Frame 6	Frame 7	Frame 8 (ES)

Figure B1: The visualization in 4D Cardiac MRI of estimated motion field and motion tracking results. We visualised the tracking result of the first frame (ED) to the last frame (ES) in ACDC [17]. Colours Red, Blue, and Green denote cardiac structures MYO, LA, and LV, respectively.

Example Outputs

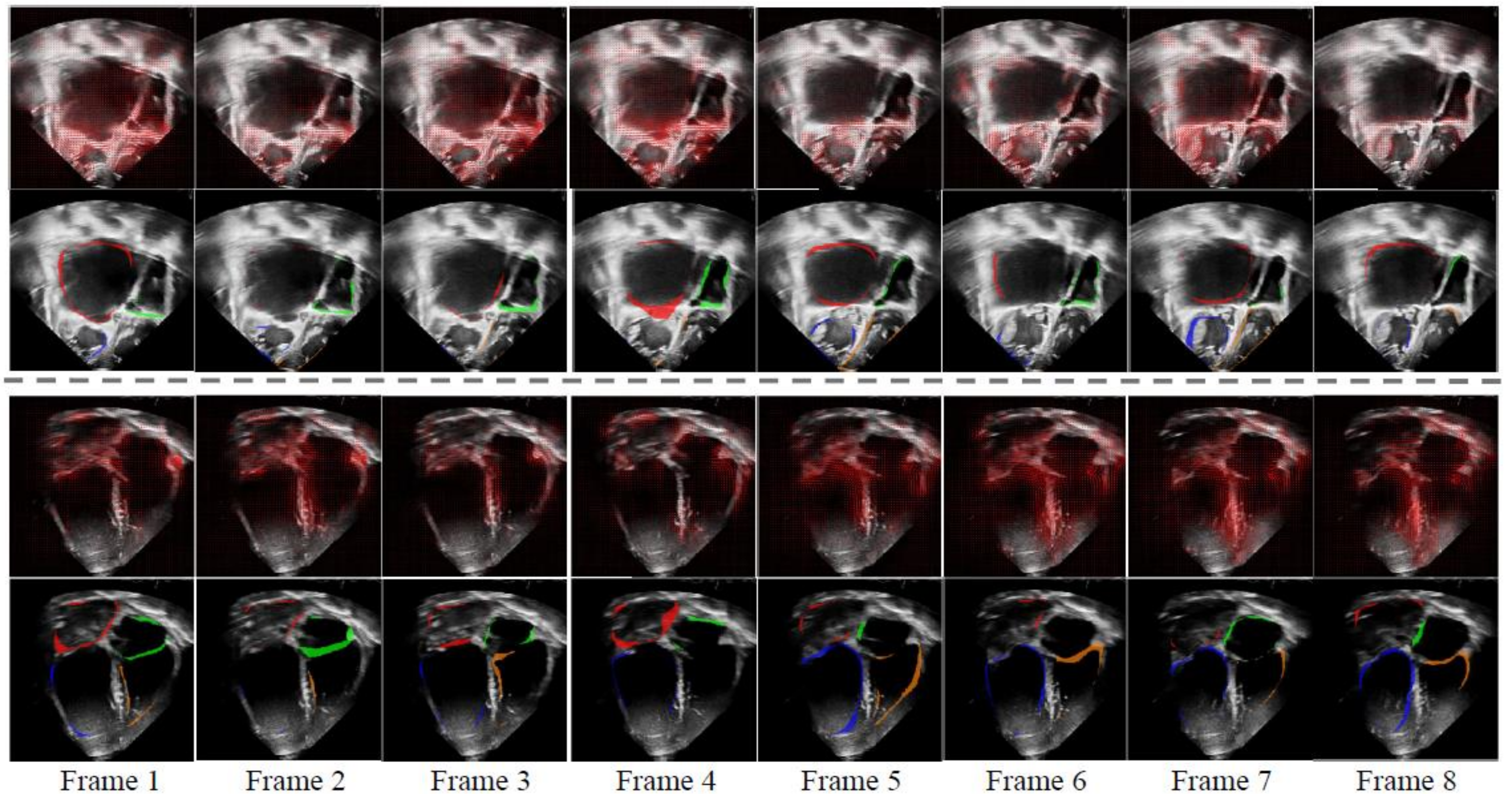
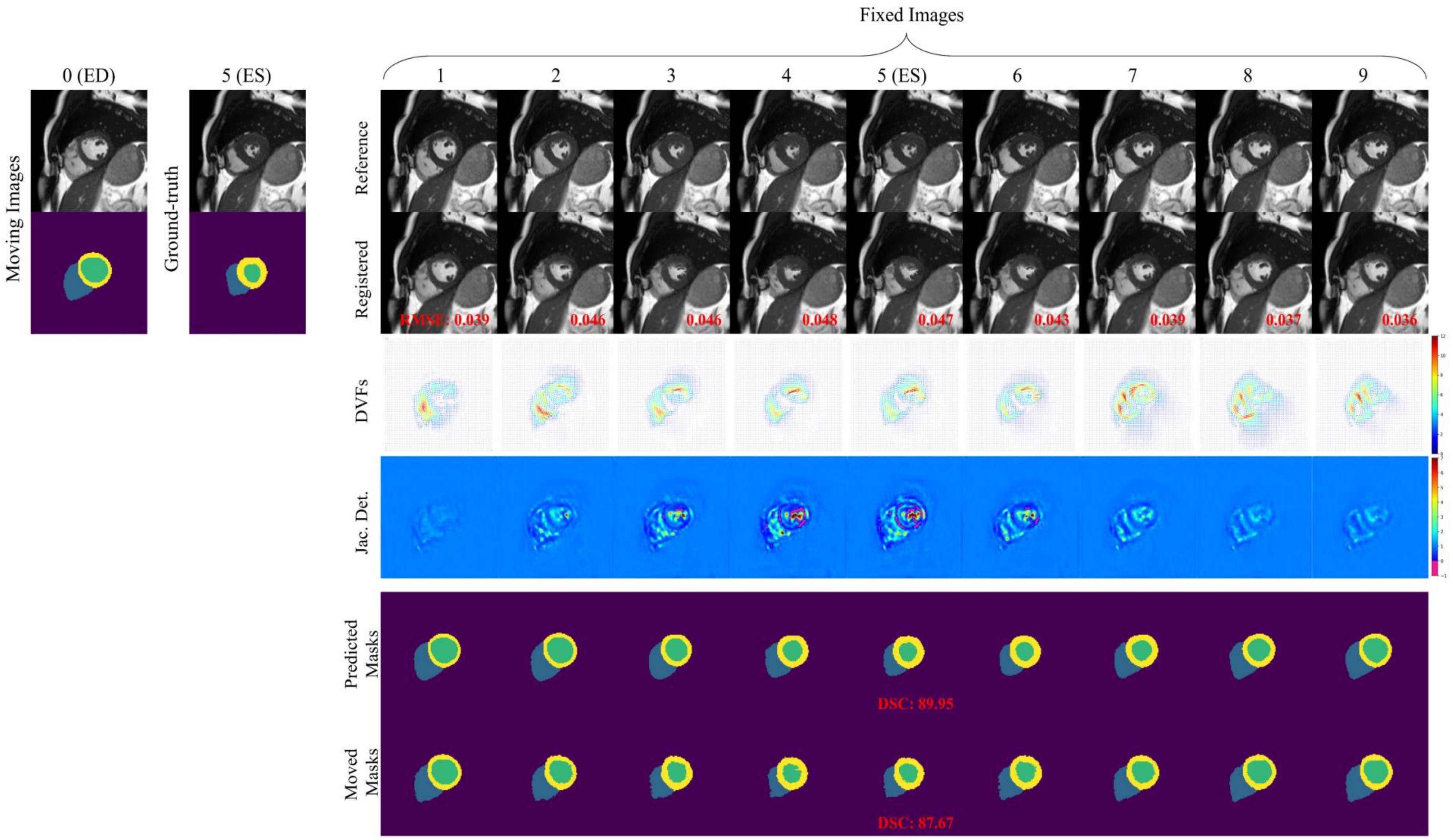


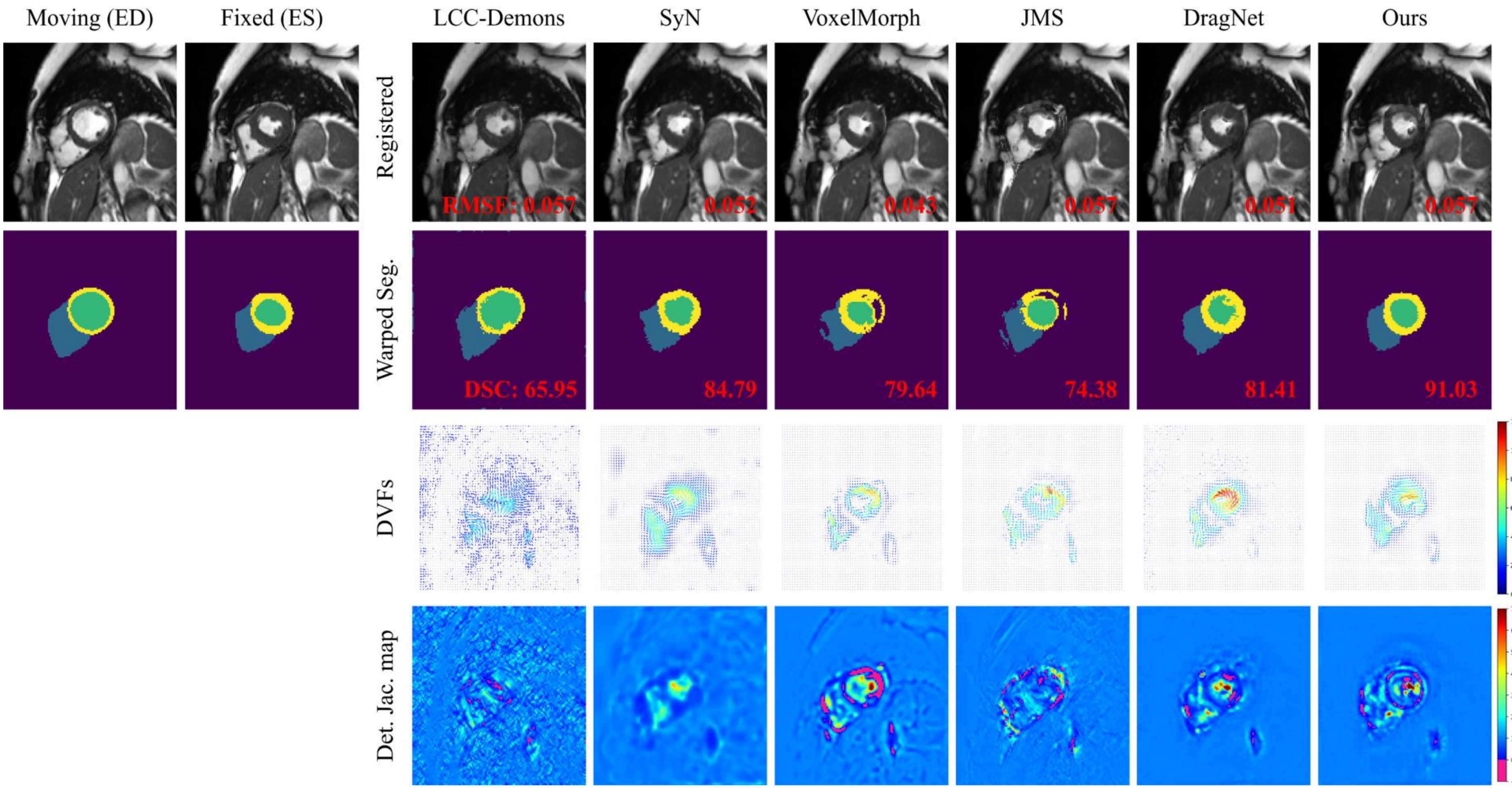
Figure B2: The visualization in 3D Echocardiogram video of estimated motion field and motion tracking error. We visualised tracking results from the first frame to the last frame, with ground truth from 8 consecutive frames in CardiacUDA [17]. Colours Red, Blue, Green and Orange denote cardiac structures RA, RV, LV and LA, respectively.

Example Outputs



SegMorph: Concurrent Motion Estimation and Segmentation for Cardiac MRI Sequences

Example Outputs



SegMorph: Concurrent Motion Estimation and Segmentation for Cardiac MRI Sequences

4D Composed Registration(Full Cycle)

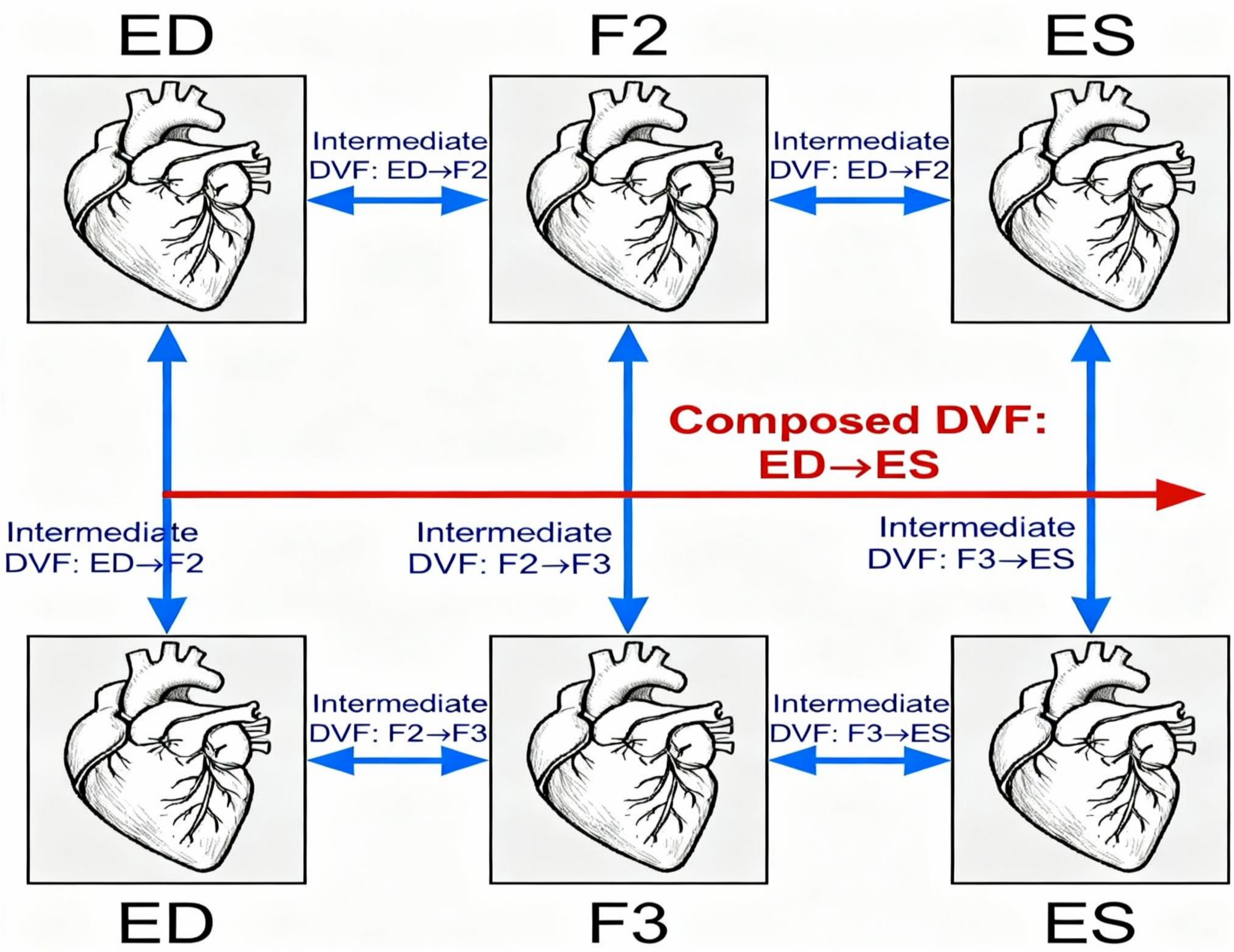
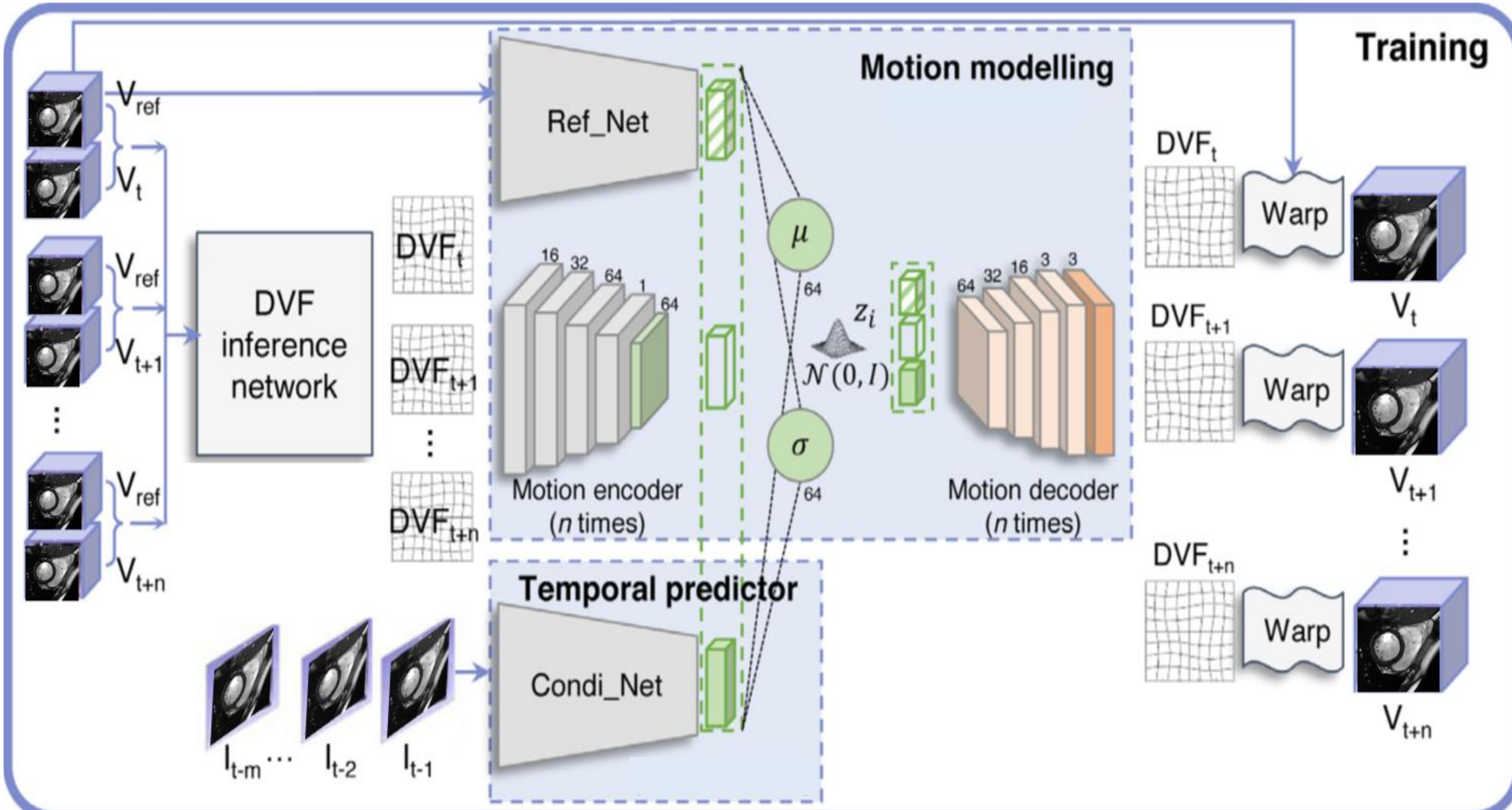


Image generated from https://www.perplexity.ai

4D PairWise Registration(Full Cycle)

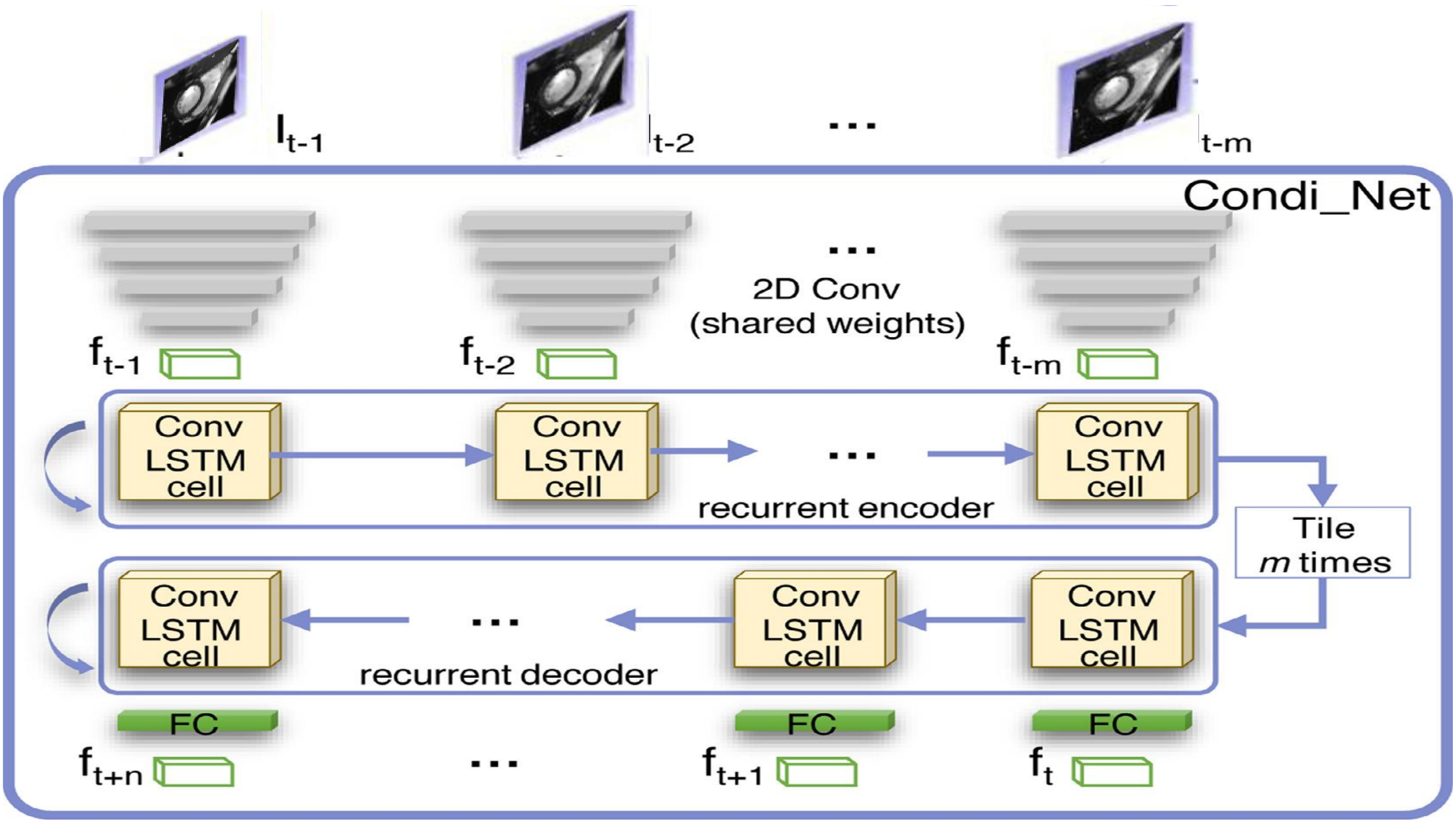
```
# Assume: cine_frames is a list of 3D cardiac MRI volumes for all timepoints, length N
# registration_method can be any function/model: classical or deep learning based (e.g.,
VoxelMorph)
# Output: list of DVFs (N-1 elements), one for each consecutive frame pair
# Step 1: Load cine frames
cine_frames = load_cardiac_cine_sequence(path_to_data)
N = len(cine_frames)
# Step 2: Initialize storage for DVFs
dvf_list = []
# Step 3: For each timepoint, perform pairwise registration to next frame
for t in range(N - 1):
    fixed = cine_frames[t]
    moving = cine_frames[t + 1]
    # Step 4: Compute DVF between consecutive frames
    dvf = registration_method(fixed, moving)  # returns 3D displacement field
    # Step 5: Store results
    dvf_list.append({
        'dvf': dvf,'fixed_frame_idx': t,
        'moving_frame_idx': t + 1
    })
return dvf_list, composed_dvf  # Use for downstream biomechanics and motion analysis
```

4D Registration(Full Cycle)



Schematic representation of the proposed probabilistic motion model. Top: During training, the inputs are: a reference volume (V ref) and a set of target volumes { V t , V t+1 , ···, V t+ n } at n time steps. The deformation between each pair of volumes, i.e. V ref and V i , are estimated through a pre-trained inference DVF network. These deformations and the inputs volumes are fed to a multi-branch convolutional neural network composed of three branches: (1) an auxiliary encoder that receives the reference volume, namely Ref-Net; (2) a motion encoder, which is repeated according to the amount of input deformations (n times), and (3) a temporal predictive network, which outputs the extrapolated-in-time feature vectors used as conditioning variables, namely Condi-Net. The outputs of each branch are combined together according to each time. Then it is constrained to form a Gaussian distribution, conditioned on the predictive variables. The decoder generates a DVF from each input feature vector, meaning a phase-specific dense 3D deformation.

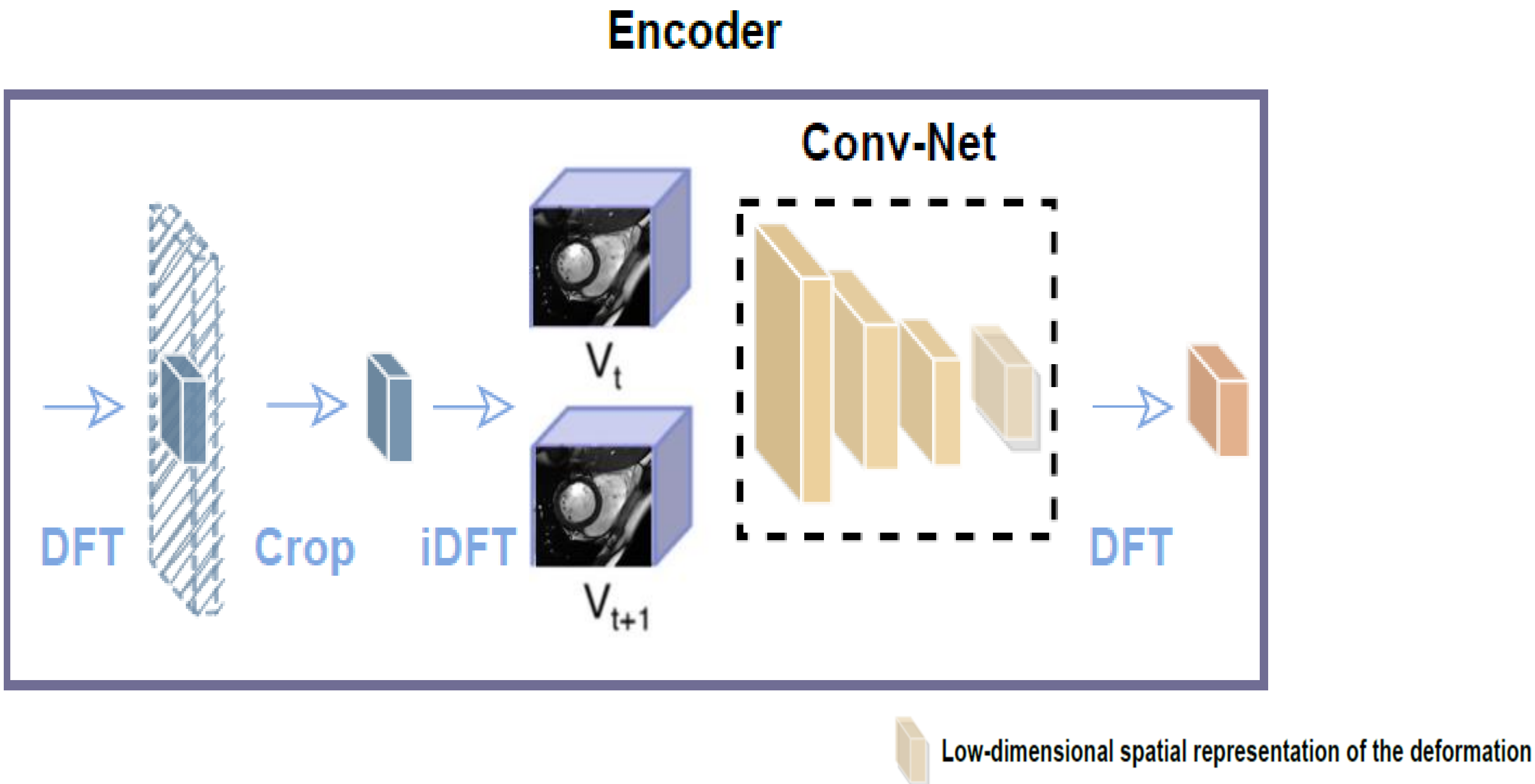
4D Registration(Full Cycle)



Schematic representation of the temporal predictive network, which receives an input image sequence and outputs the extrapolated-in-time feature vectors used as conditioning variables.

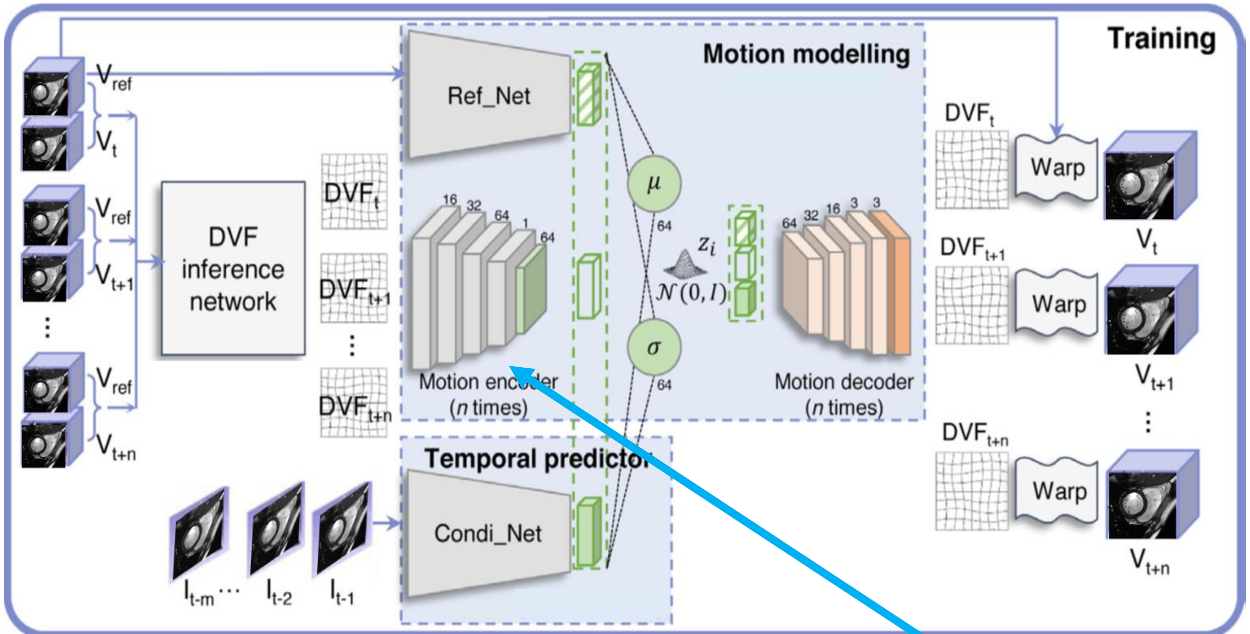
4D Registration(Full Cycle)

Original DFV into a low-dimensional band-limited representation of such images followed by 3D convolutions. This encoder enables 3D convolutions to operate on smaller resolutions, making DFT module a much lighter network

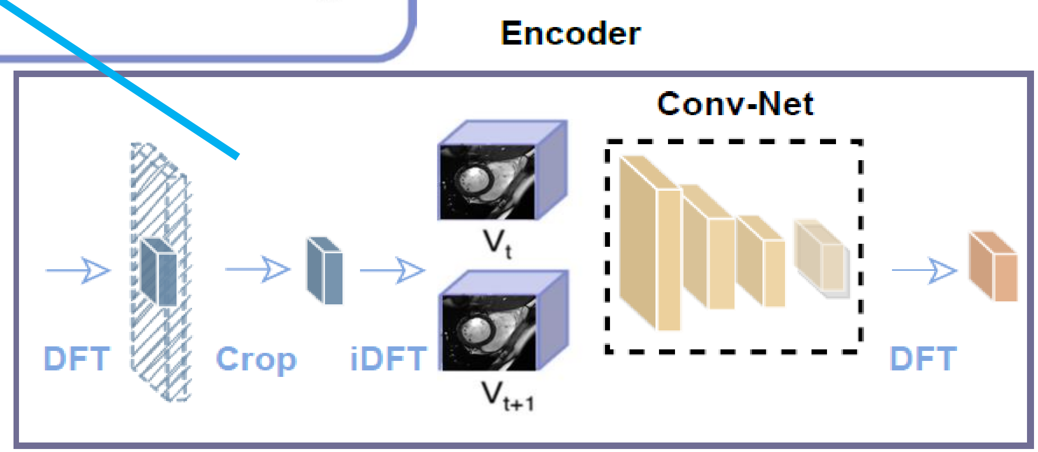


Small number of coefficients in the band-limited Fourier domain are sufficient to reconstruct a full resolution deformation accurately.

4D Registration(Full Cycle)



It may be feasible to learn the band-limited displacement field directly from a band-limited representation



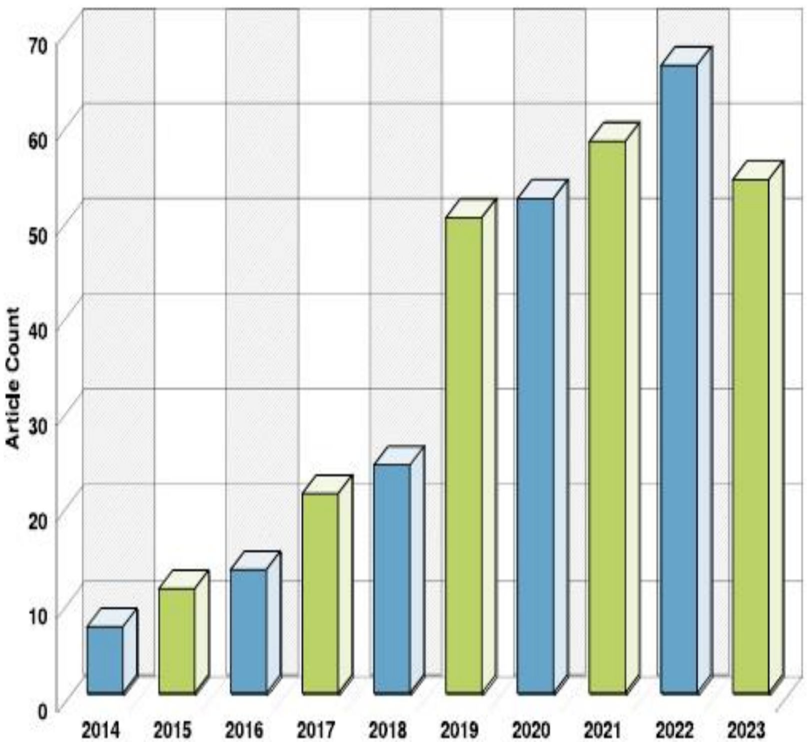
An end-to-end unsupervised registration model that can learn such a low-dimensional, band-limited representation of the displacement field.

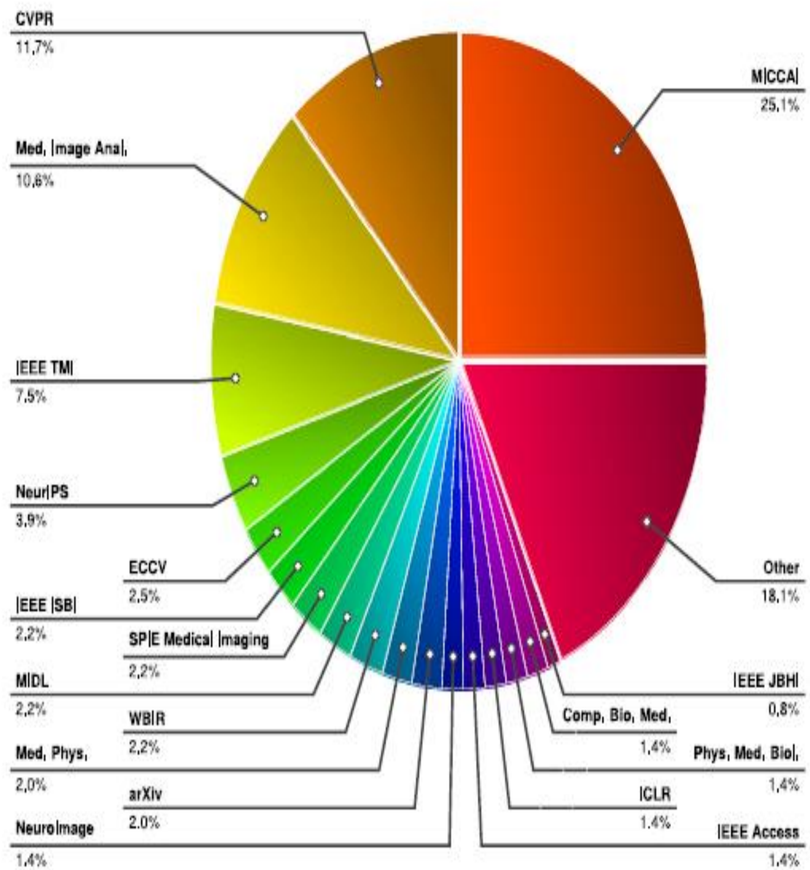
Training and inference efficiency is improved by learning a low-dimensional representation of the displacement field in the band-limited Fourier domain

Performance Analysis Tools

Dice Similarity Coefficient (DSC)	• $DSC = \frac{2\lvert A\cap B\rvert}{\lvert A\rvert+\lvert B\rvert}$)range 0–1) • Measures overlap between two segmentations; 1 = perfect overlap, 0 = no overlap
Hausdorff Distance (HD)	• Maximum distance between points on the boundary of two images/segmentations. • Quantifies the worst-case boundary mismatch; lower is better.
Jacobian Determinant (Jac)	• Determinant of the deformation field at each voxel. • Measures local volume changes; values <0 indicate folding (non-physical deformation).
Mean Squared Error (MSE)	• Measures intensity difference between images; lower values indicate better alignment.
Normalized Cross-Correlation (NCC)	• Measures similarity of intensity patterns between images; higher is better.
Mutual Information (MI)	• Quantifies statistical dependence between images; commonly used in multimodal registration.
Target Registration Error (TRE)	• Euclidean distance between corresponding landmarks • Measures geometric accuracy of registration at specific points.

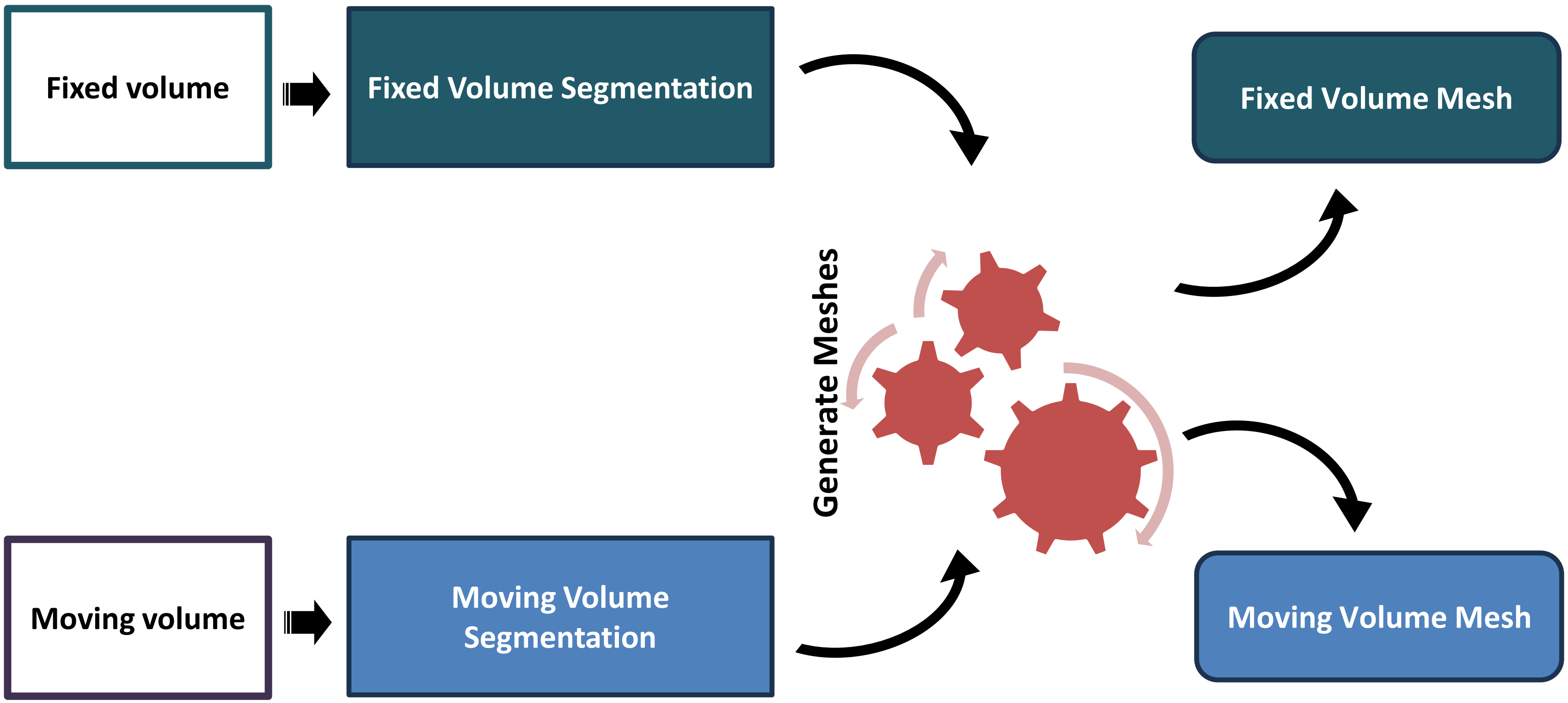
Medical Imaging Registration



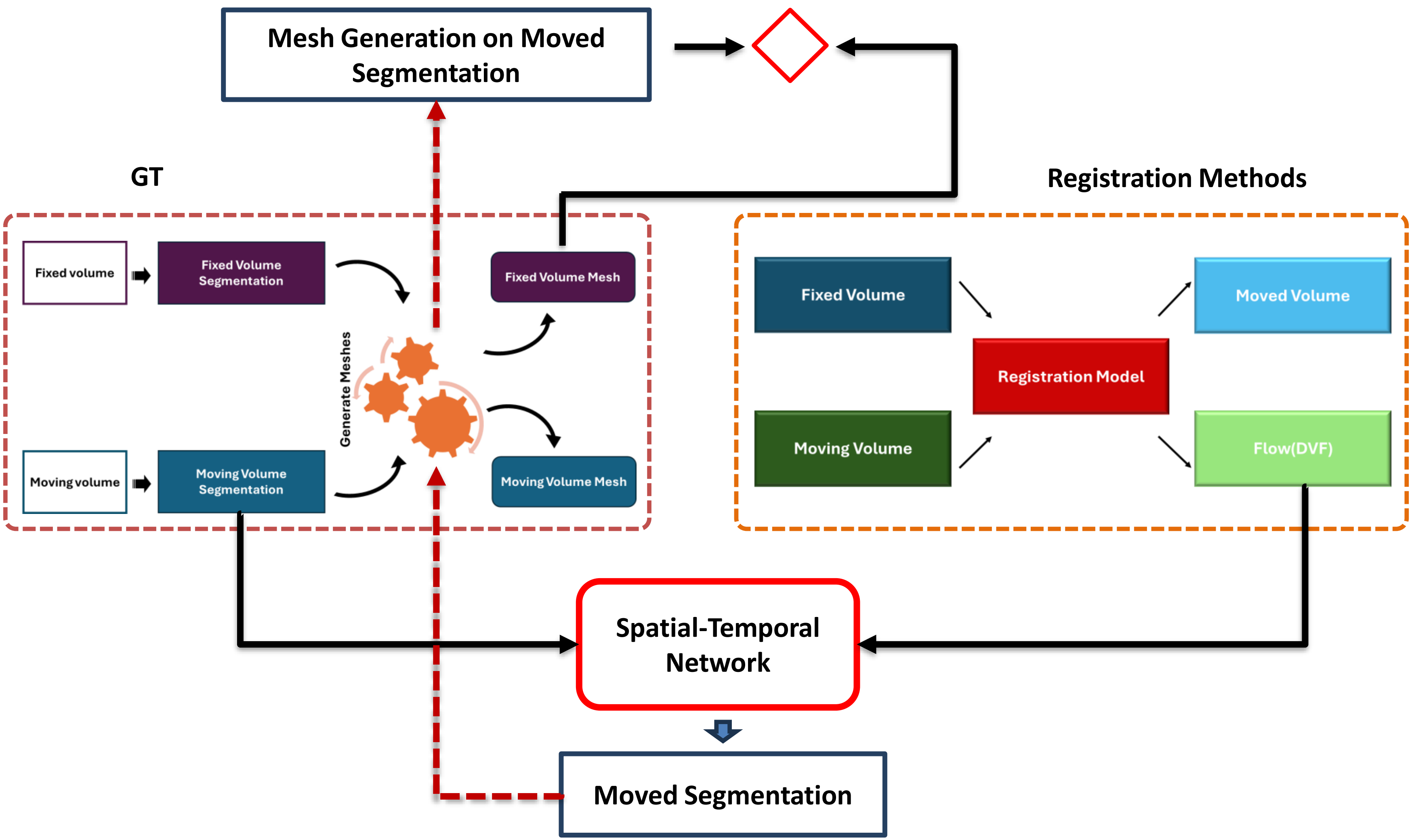


A survey on deep learning in medical image registration: New technologies, uncertainty, evaluation metrics, and beyond

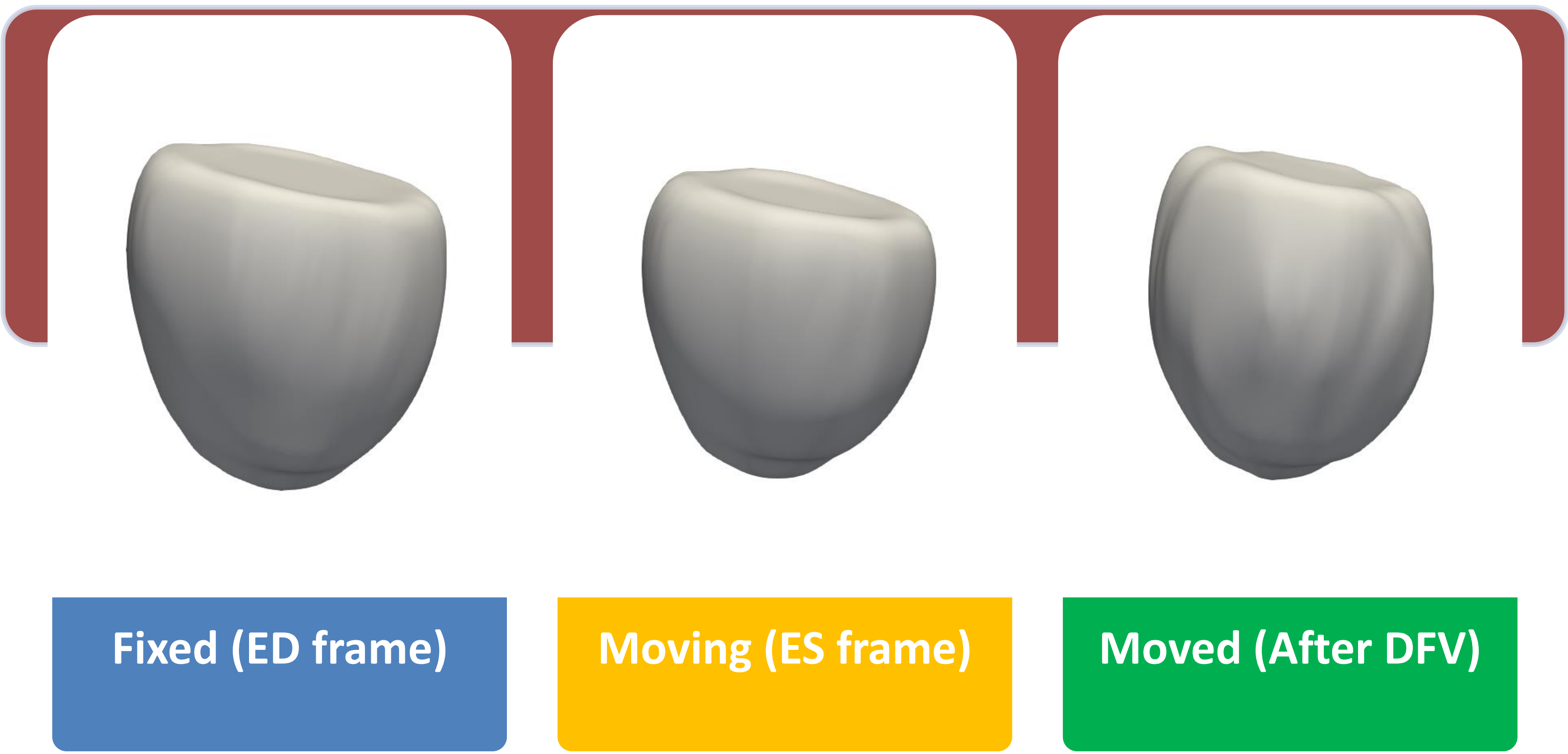
Mesh Generation for Motion Tracking



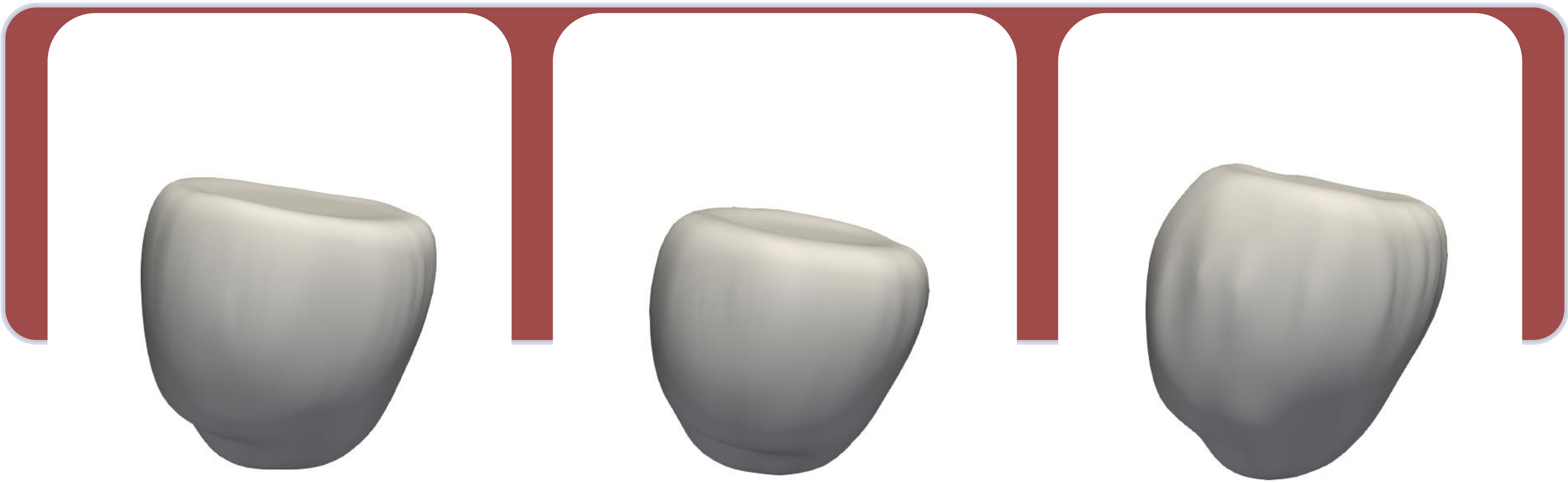
Mesh Generation for Motion Tracking using Deformation Vector Field



Motion Tracking and Mesh Generation based on Registration models



Motion Tracking and Mesh Generation based on Registration models

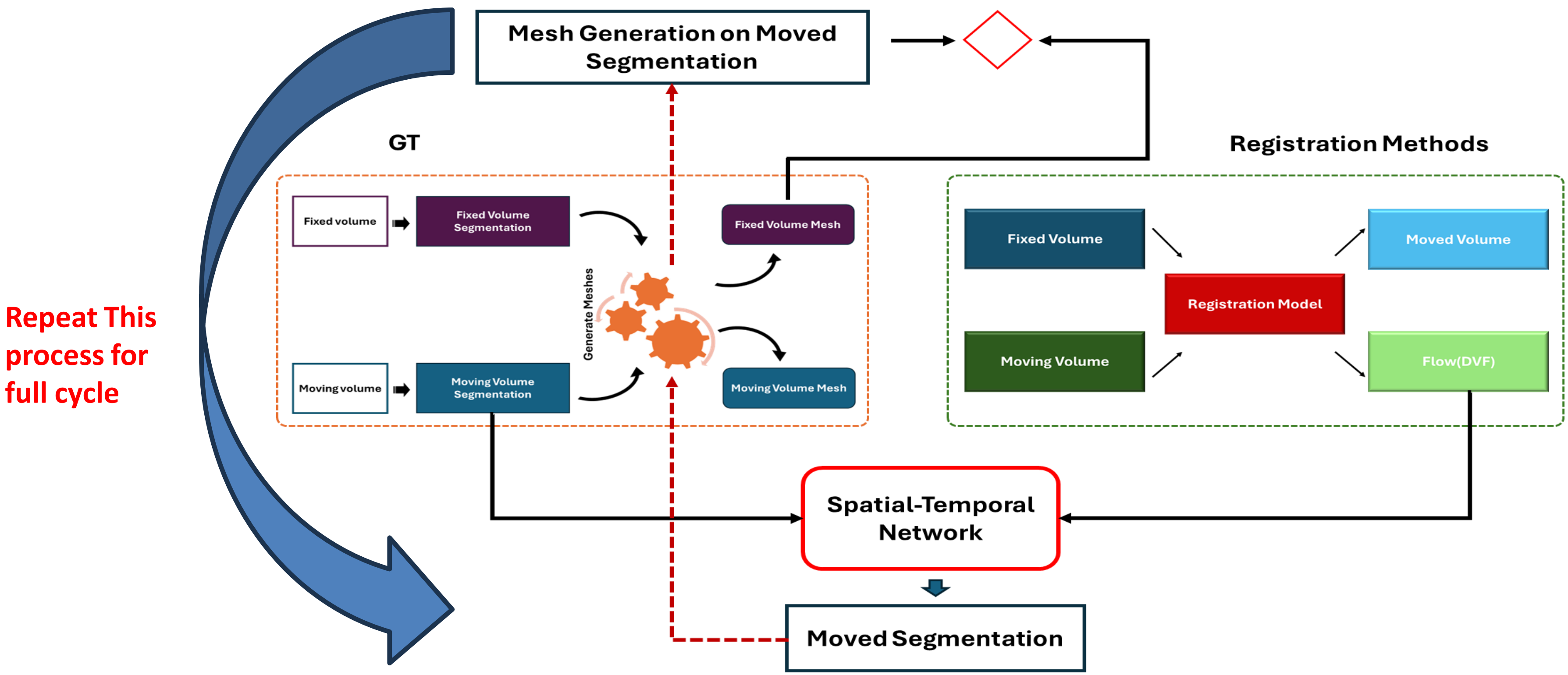


Fixed (ED frame)

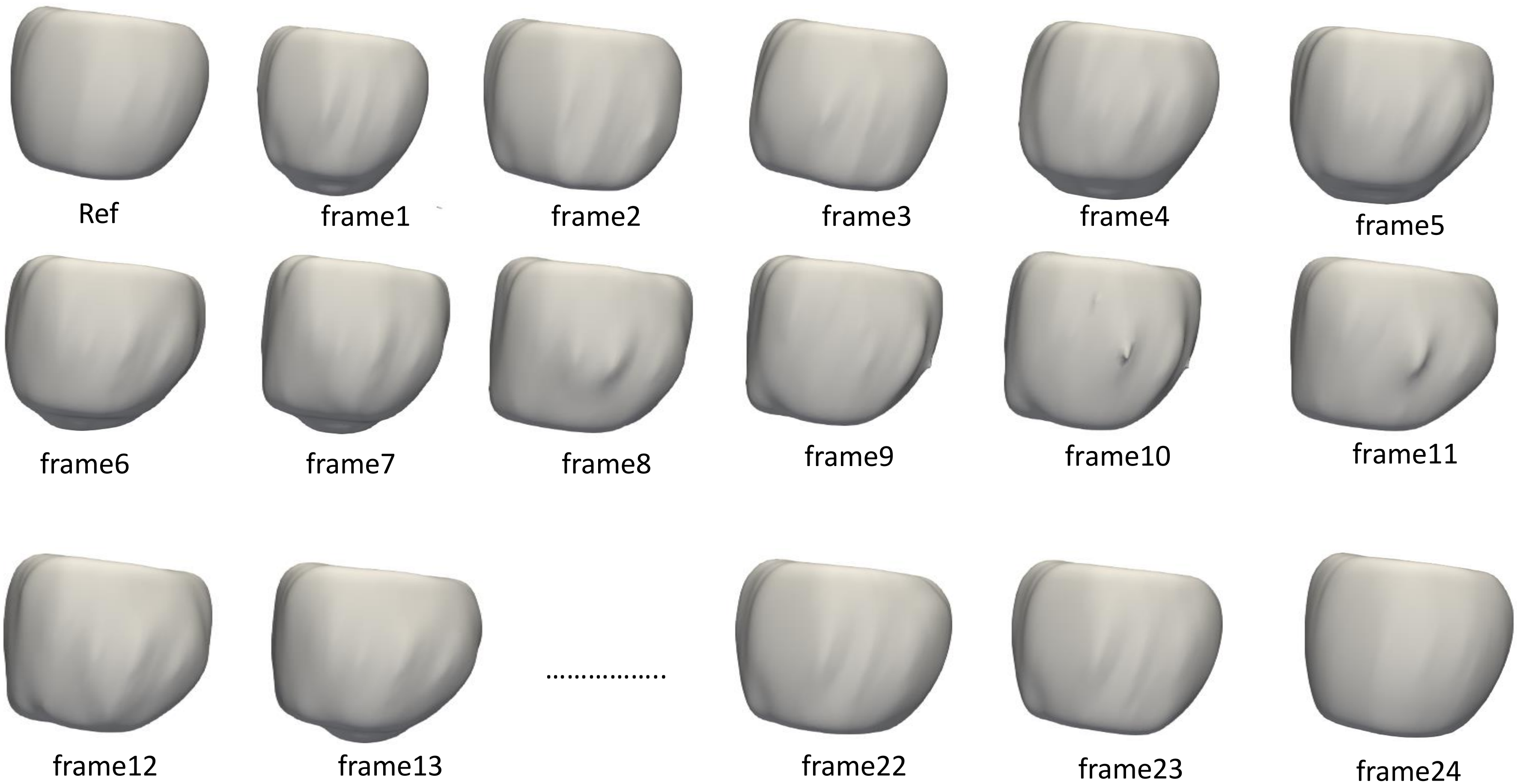
Moving (ES frame)

Moved (After DFV)

Mesh Generation for Motion Tracking using Deformation Vector Field for Full Cardiac Cycle



Motion Tracking and Mesh Generation based on Registration models

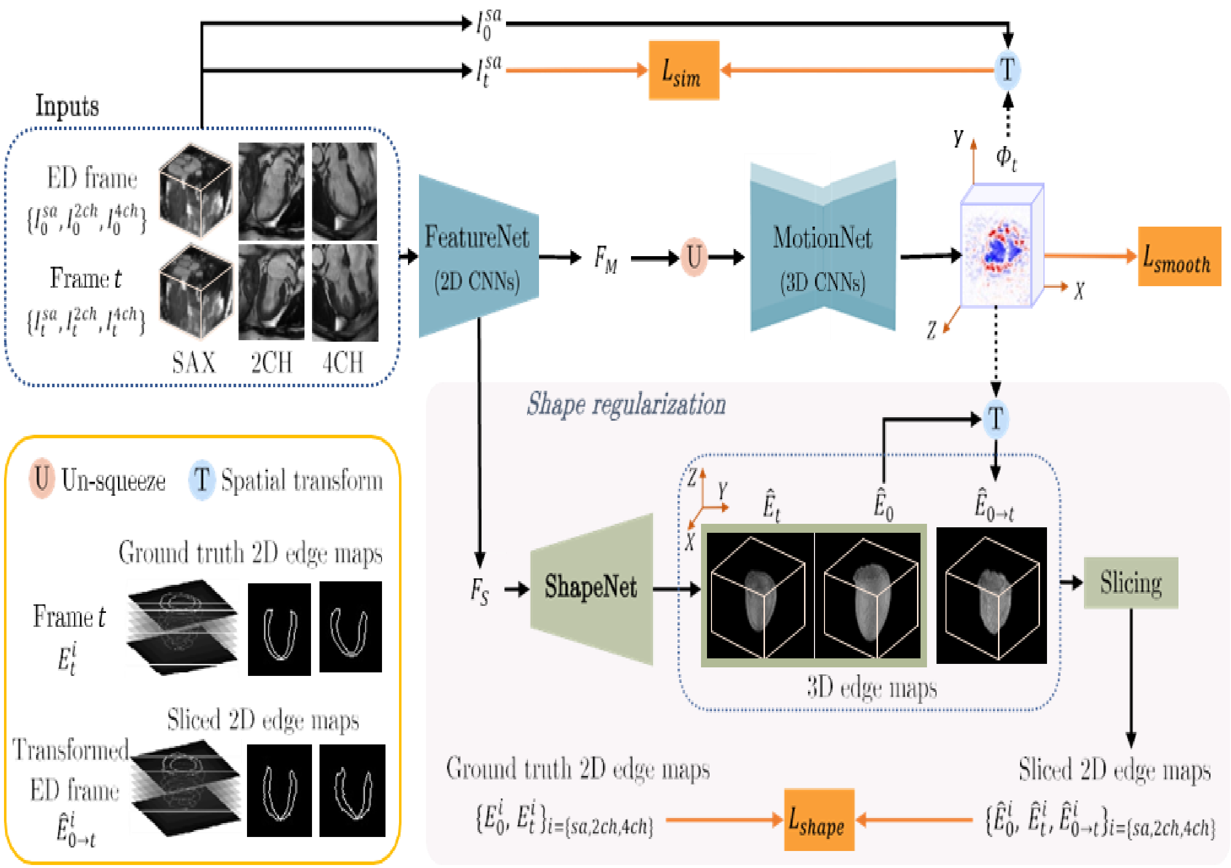


Motion Tracking on Voxel Space

MulViMotion: Shape-Aware 3D Myocardial Motion Tracking From Multi-View Cardiac MRI

1. They multi-view motion estimation network integrates 2D cine CMR images acquired in short-axis and long-axis planes to learn a consistent 3D motion field of the heart.

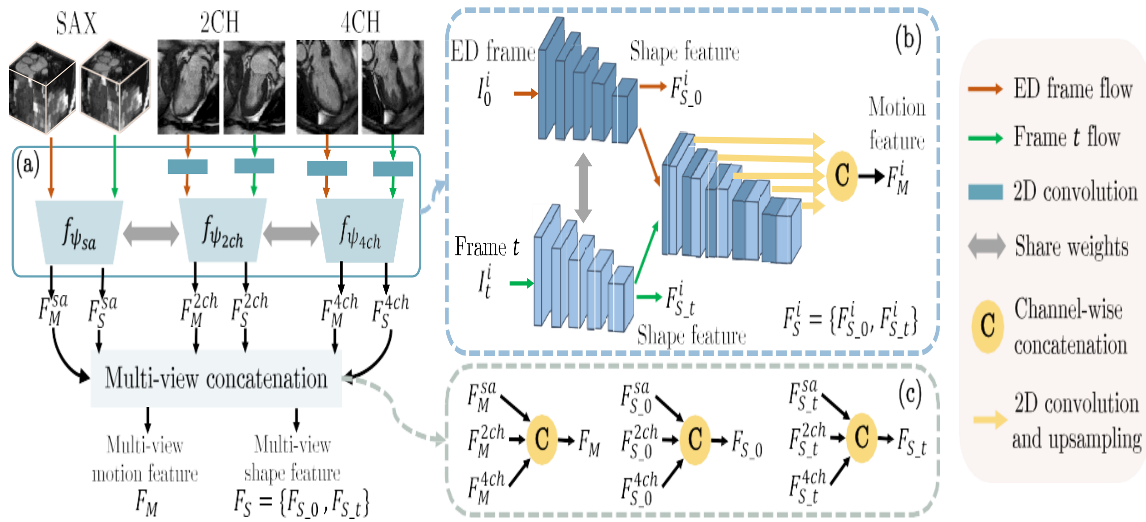
2. hybrid 2D/3D network is built to generate dense 3D motion fields by learning fused representations from multi-view images.



MulViMotion: Shape-Aware 3D Myocardial Motion Tracking From Multi-View Cardiac MRI

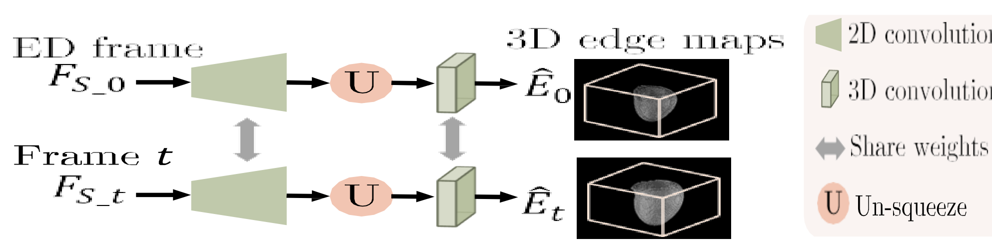
3. To ensure that the motion estimation is consistent in 3D, a shape regularization module is introduced during training, where shape information from multi-view images is exploited to provide weak supervision to 3D motion estimation.

4. Use 2D cine CMR images from 580 subjects of the UK Biobank study for 3D motion tracking of the left ventricular myocardium.



An overview of FeatureNet

Ref: Meng, Qingjie, Chen Qin, Wenjia Bai, Tianrui Liu, Antonio De Marvao, Declan P. O'Regan, and Daniel Rueckert. "MulViMotion: Shape-aware 3D Myocardial Motion Tracking from Multi-View Cardiac MRI." IEEE Transactions on Medical Imaging (2022).

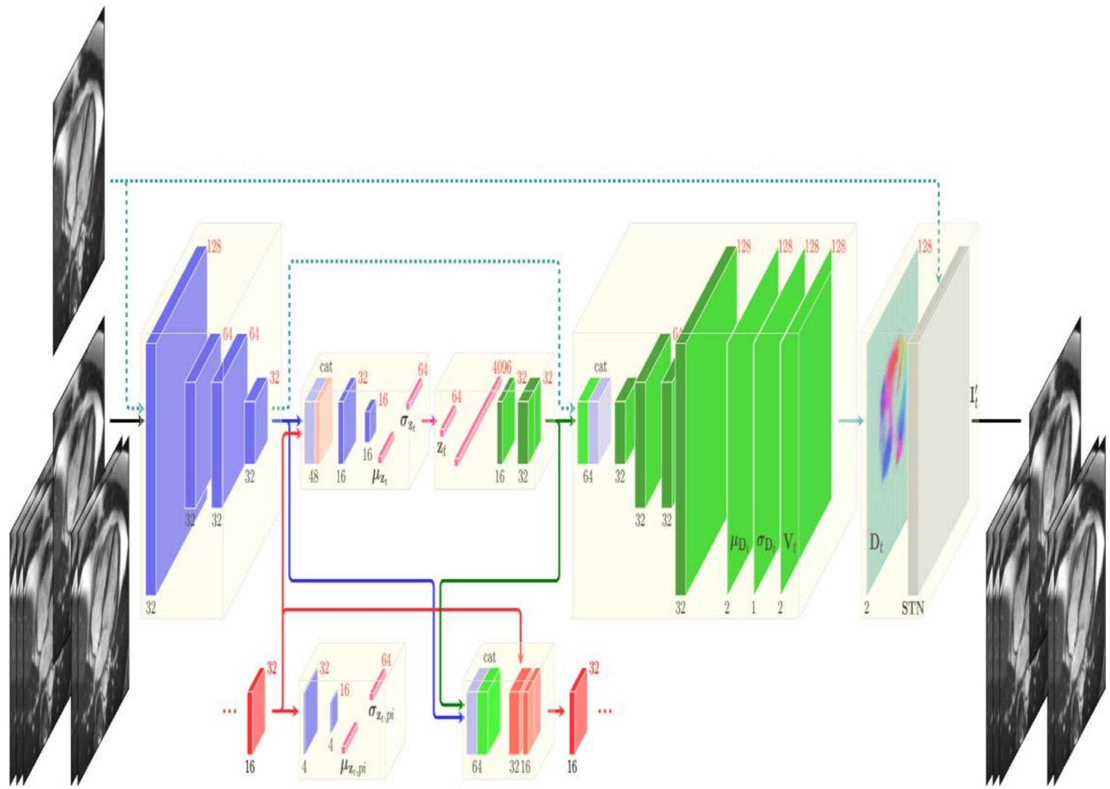


An overview of ShapeNet

DragNet: Learning-based deformable registration for realistic cardiac MR sequence generation from a single frame

1. Proposed hierarchical probabilistic model, termed DragNet, for fast and reliable spatio-temporal registration in cine cardiac magnetic resonance (CMR) images and for generating synthetic heart motion sequences.

2. DragNet is a variational inference framework, which takes an image from the sequence in combination with the hidden states of a recurrent neural network (RNN) as inputs to an inference network per time step.



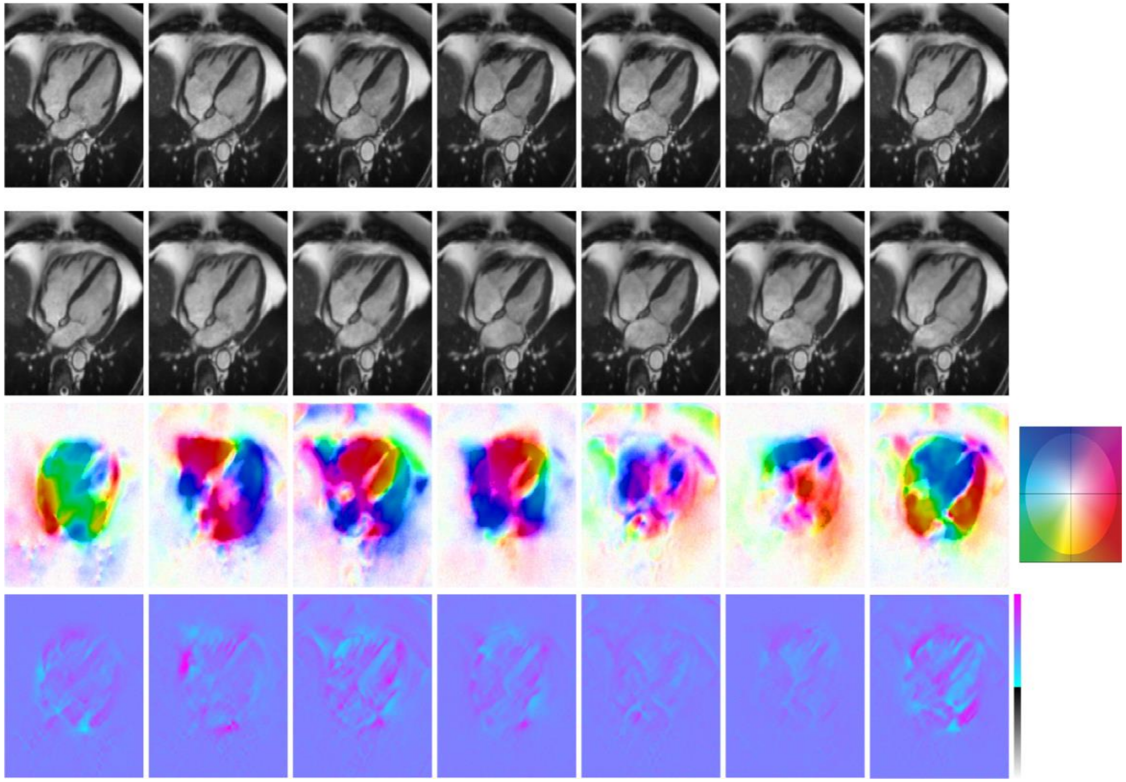
Ref: Zakeri, Arezoo, Alireza Hokmabadi, Ning Bi, Isuru Wijesinghe, Michael G. Nix, Steffen E. Petersen, Alejandro F. Frangi, Zeike A. Taylor, and Ali Gooya. "DragNet: learning-based deformable registration for realistic cardiac MR sequence generation from a single frame." Medical Image Analysis 83 (2023): 102678.

DragNet: Learning-based deformable registration for realistic cardiac MR sequence generation from a single frame

3. DragNet performs registration on unseen sequences in a forward pass, which significantly expedites the registration process.

4. DragNet enables generating a large number of realistic synthetic image sequences given only one frame, where the corresponding deformations are also retrieved.

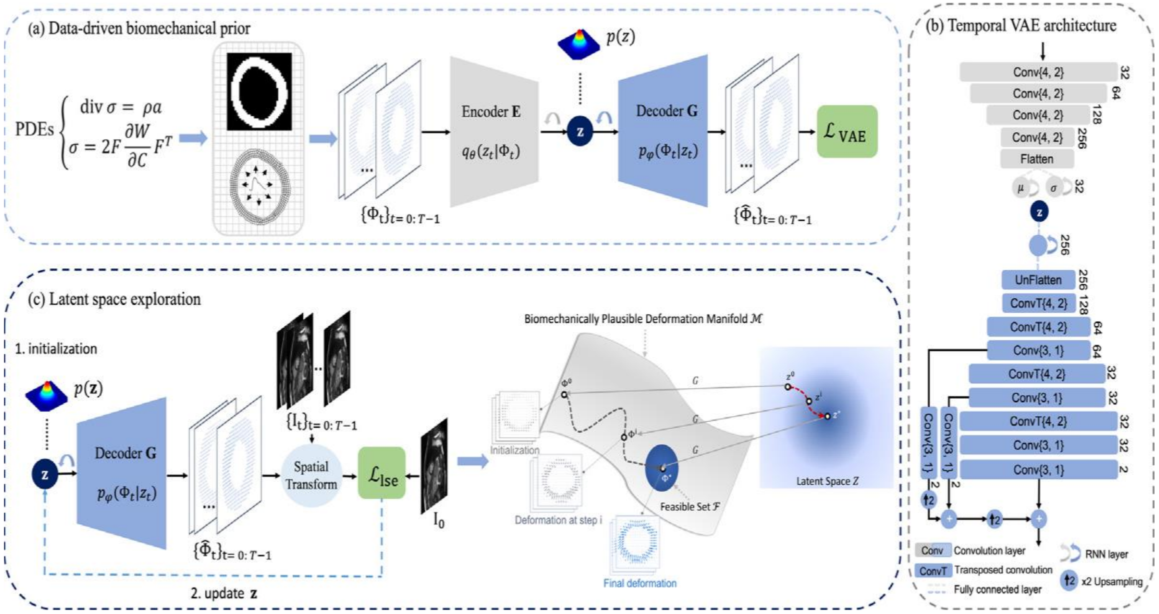
5. The probabilistic framework allows for computing spatial-temporal uncertainties in the estimated motion fields.



Generative myocardial motion tracking via latent space exploration with biomechanics-informed prior

1. They propose a novel method that can implicitly learn application-specific biomechanics-informed prior and embed it into a neural network-parameterized transformation model.
2. The proposed method leverages a variational autoencoder-based generative model to learn a manifold for biomechanically plausible deformations.
3. The motion tracking then can be performed via traversing the learnt manifold to search for the optimal transformations while considering the sequence information

1. **UK biobank dataset (3D+t)**
2. **ACDC dataset (3D+t)**
3. **M&Ms dataset (3D+t)**



Ref: Qin, Chen, Shuo Wang, Chen Chen, Wenjia Bai, and Daniel Rueckert. "Generative myocardial motion tracking via latent space exploration with biomechanics-informed prior." Medical Image Analysis 83 (2023): 102682.

DiffuseMorph: Unsupervised Deformable Image Registration Using Diffusion Model

1. Proposed a novel diffusion-model-based image registration method, called DiffuseMorph. DiffuseMorph not only generates synthetic deformed images through reverse diffusion but also allows image registration by deformation fields.

2. Specifically, the deformation fields are generated by the conditional score function of the deformation between the moving and fixed images, so that the registration can be performed from continuous deformation by simply scaling the latent feature of the score.

3. Experimental results on 2D facial and 3D medical image registration tasks demonstrate that our method provides flexible deformations with topology preservation capability.

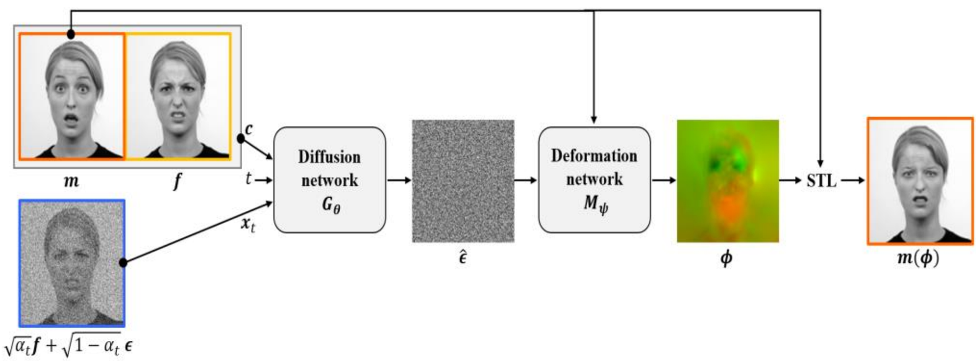
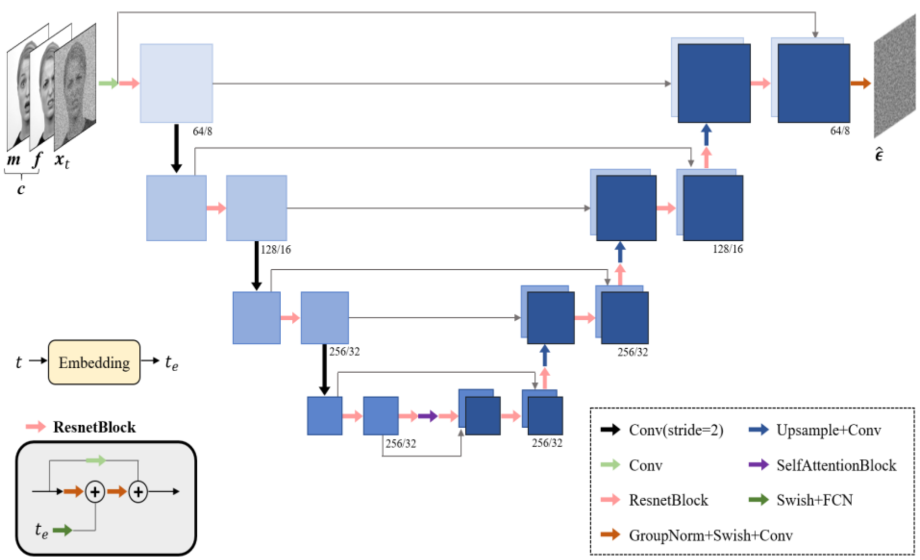
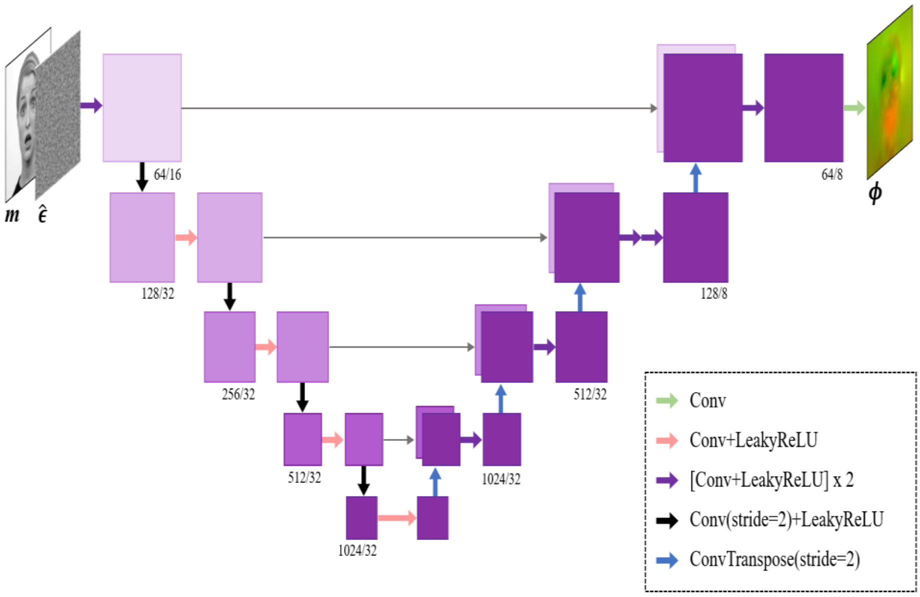


Fig. The training framework of DiffuseMorph. Given a condition with a pair of a moving image m and a fixed image f, the diffusion network G_θ estimates the conditional score function of the deformation, and the deformation network M_ψ outputs the registration field φ. Then, using the spatial transformation layer (STL), the moving image is warped into the fixed image.

DiffuseMorph: Unsupervised Deformable Image Registration Using Diffusion Model



Diffusion Network



Deformation Network

DiffuseMorph: Unsupervised Deformable Image Registration Using Diffusion Model

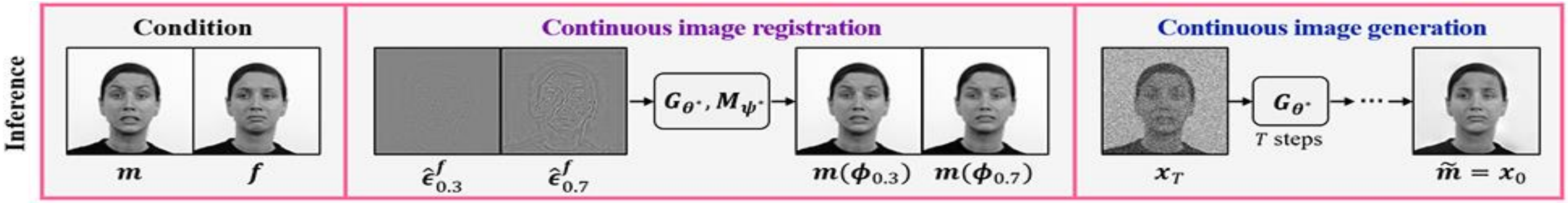
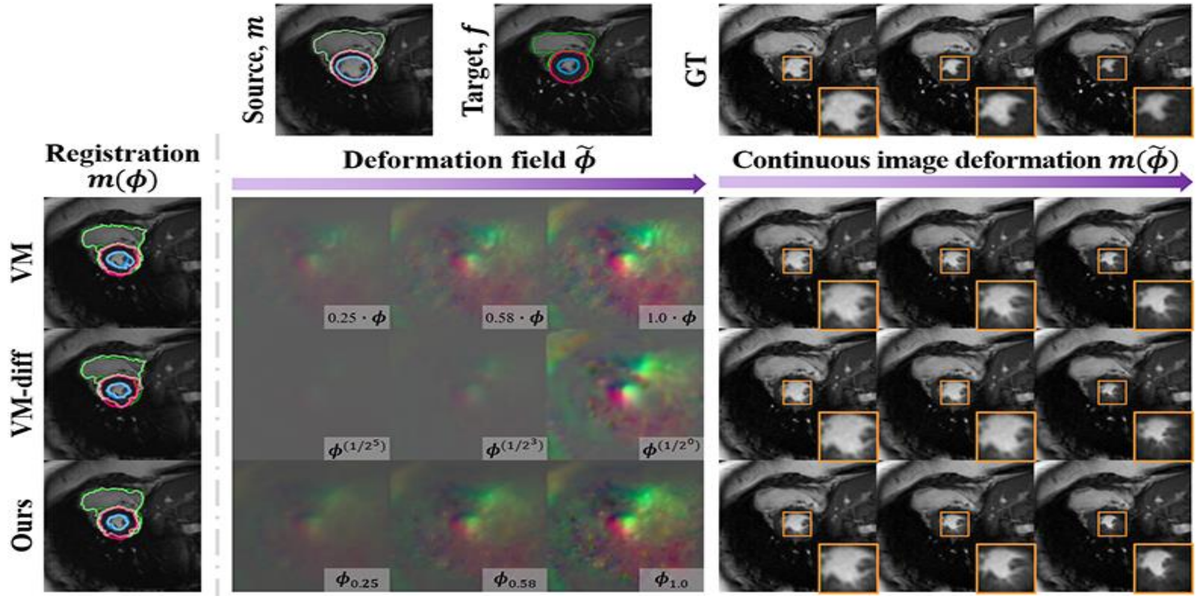


Fig. In the inference phase, our model provides not only the image registration m(φ) that warps the moving image, but also generates synthetic images ˜m.



Ref: Kim, Boah, Inhwa Han, and Jong Chul Ye. "DiffuseMorph: Unsupervised Deformable Image Registration Using Diffusion Model." In *Computer Vision–ECCV 2022: 17th European Conference, Tel Aviv, Israel, October 23–27, 2022, Proceedings, Part XXXI*, pp. 347-364. Cham: Springer Nature Switzerland, 2022.

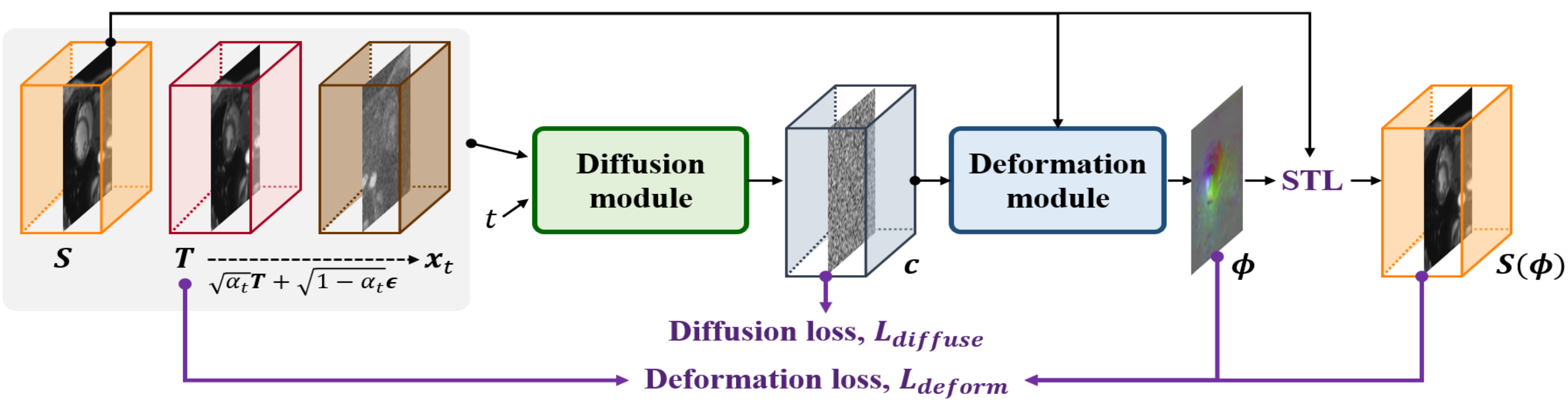
Diffusion Deformable Model for 4D Temporal Medical Image Generation

1. Temporal volume images with 3D+t (4D) information are often used in medical imaging to statistically analyze temporal dynamics or capture disease progression.

2. deep-learning-based generative models for natural images have been extensively studied, approaches for temporal medical image generation such as 4D cardiac volume data are limited.

3. They present a novel deep learning model that generates intermediate temporal volumes between source and target volumes.

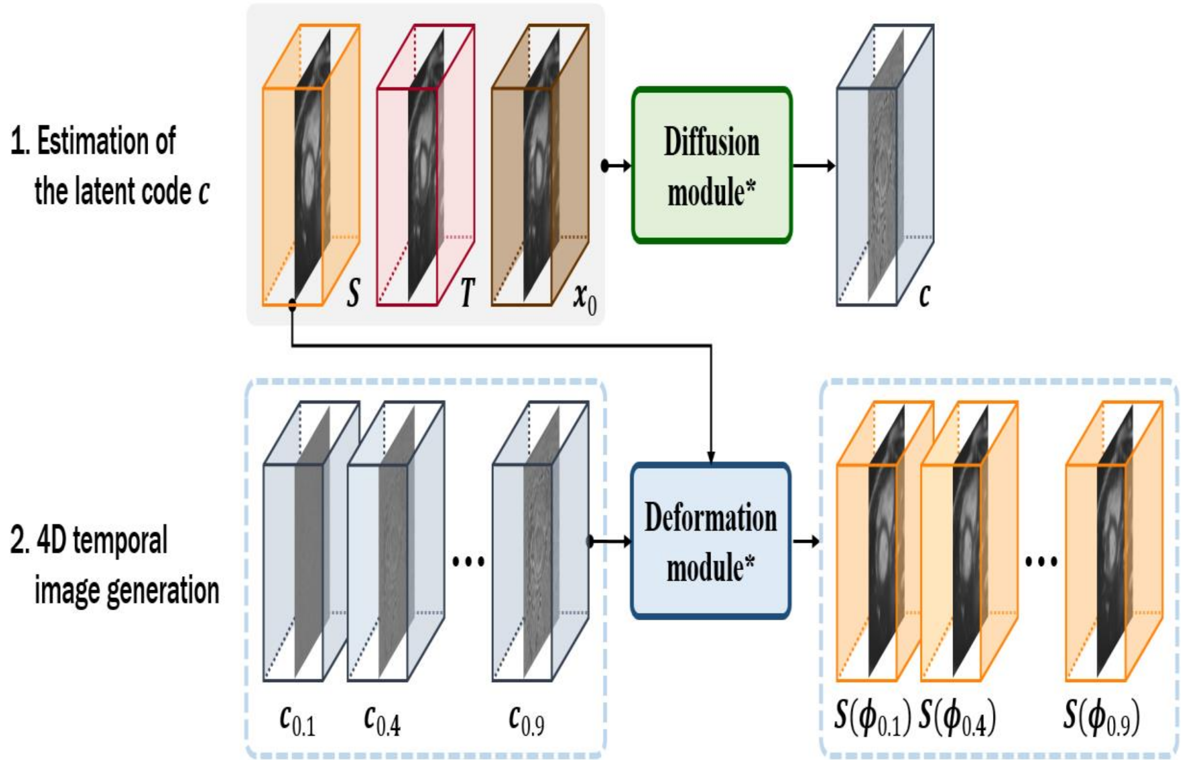
4. They propose a diffusion deformable model (DDM) by adapting the denoising diffusion probabilistic model that has recently been widely investigated for realistic image generation.



Diffusion Deformable Model for 4D Temporal Medical Image Generation

5. Our proposed DDM is composed of the diffusion and the deformation modules so that DDM can learn spatial deformation information between the source and target volumes and provide a latent code for generating intermediate frames along a geodesic path.

6. Once our model is trained, the latent code estimated from the diffusion module is simply interpolated and fed into the deformation module, which enables DDM to generate temporal frames along the continuous trajectory while preserving the topology of the source image



Ref: Kim, Boah, and Jong Chul Ye. "Diffusion deformable model for 4D temporal medical image generation." In Medical Image Computing and Computer Assisted Intervention–MICCAI 2022: 25th International Conference, Singapore, September 18–22, 2022, Proceedings, Part I, pp. 539-548. Cham: Springer Nature Switzerland, 2022.

Motion Tracking on Anatomical Space

DeepMesh: Mesh-based Cardiac Motion Tracking using Deep Learning

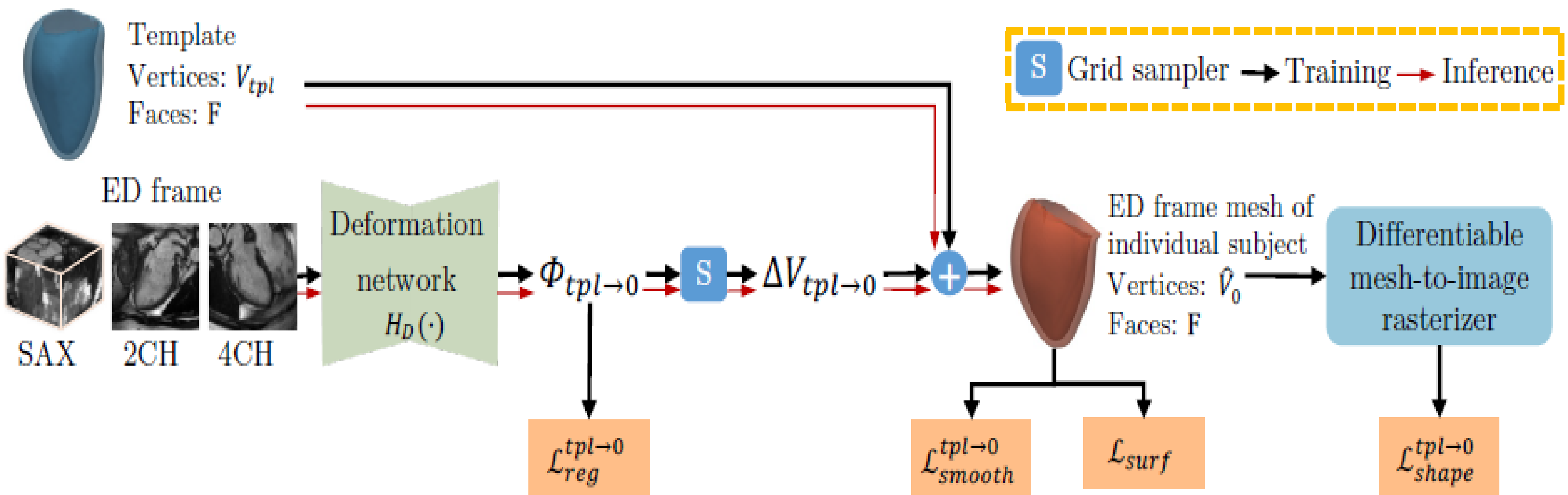


Fig. 2: An overview of the mesh reconstruction module. This module reconstructs the ED frame mesh of individual subjects from a template mesh and multi-view images. In this module, the deformation network ($H_D(\cdot)$) predicts an intermediate voxel-wise displacement $\Phi_{tpl\to 0}$, and then $\Delta V_{tpl\to 0}$ containing the per-vertex displacement is generated by sampling from $\Phi_{tpl\to 0}$.

DeepMesh: Mesh-based Cardiac Motion Tracking using Deep Learning

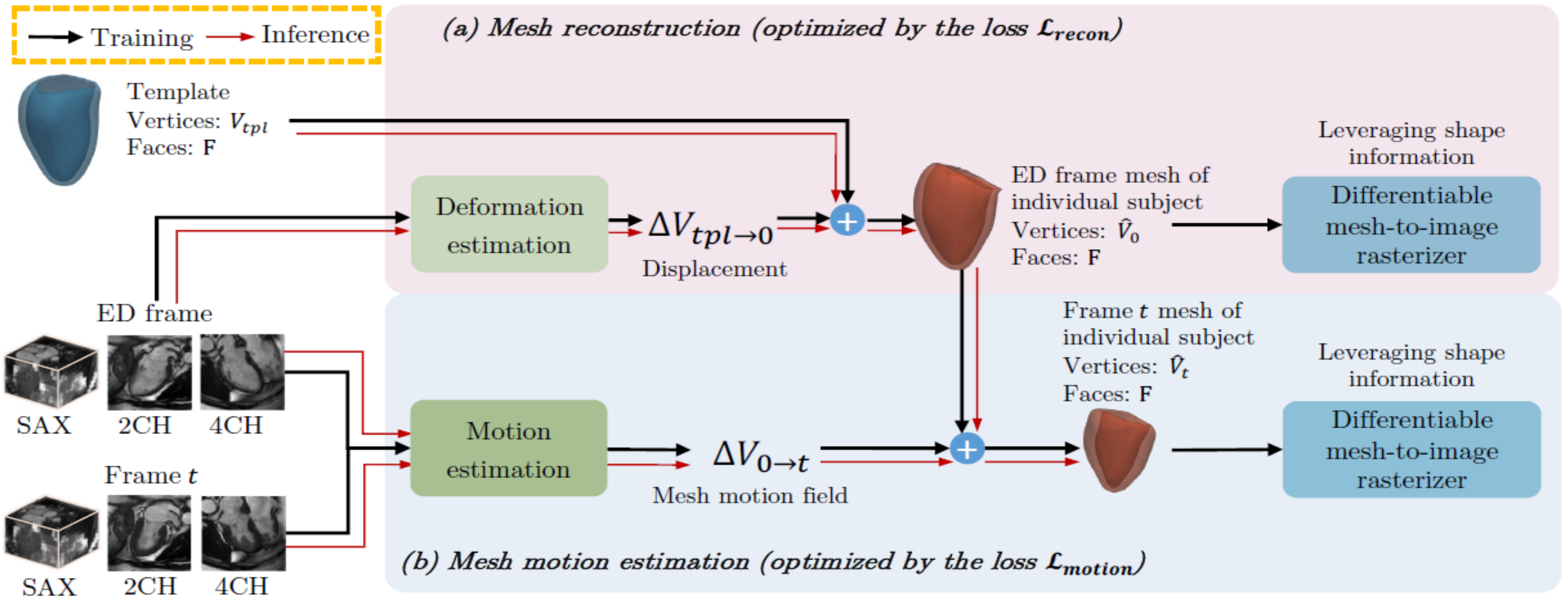


Fig. 1: An overview of the proposed method. Panel (a) describes the mesh reconstruction module which reconstructs the ED frame mesh from a template mesh and the ED frame multi-view images. Panel (b) is the mesh motion estimation module, which takes multi-view images as input and learns 3D mesh motion field $\Delta V_{0\to t}$. By updating the reconstructed ED frame mesh with $\Delta V_{0\to t}$, the mesh of the t-th frame is predicted. During training, a differential mesh-to-image rasterizer is introduced to extract different 2D anatomical view planes from the predicted 3D meshes, which generates 2D soft segmentations. By comparing the predicted soft segmentations with ground truth segmentations, the rasterizer enables leveraging 2D shape information for 3D mesh reconstruction and motion estimation. Losses of each module are shown in Fig. 2 and Fig. 4, accordingly.

4D Myocardium Reconstruction with Decoupled Motion and Shape Model

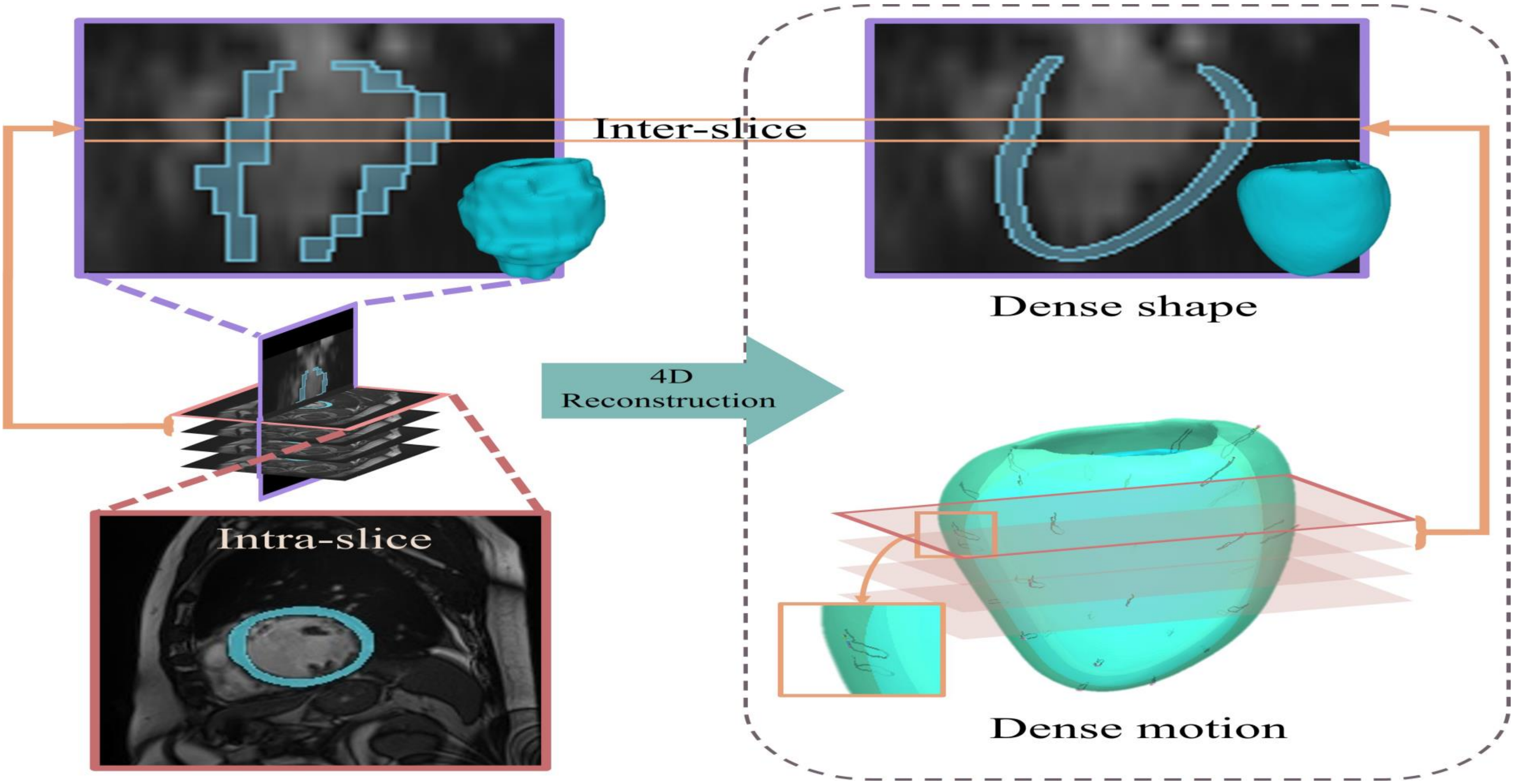


Figure 1.We propose a 4D cardiac reconstruction method predicting the inter-/intra- shape and motion of a cardiac cycle.

4D Myocardium Reconstruction with Decoupled Motion and Shape Model

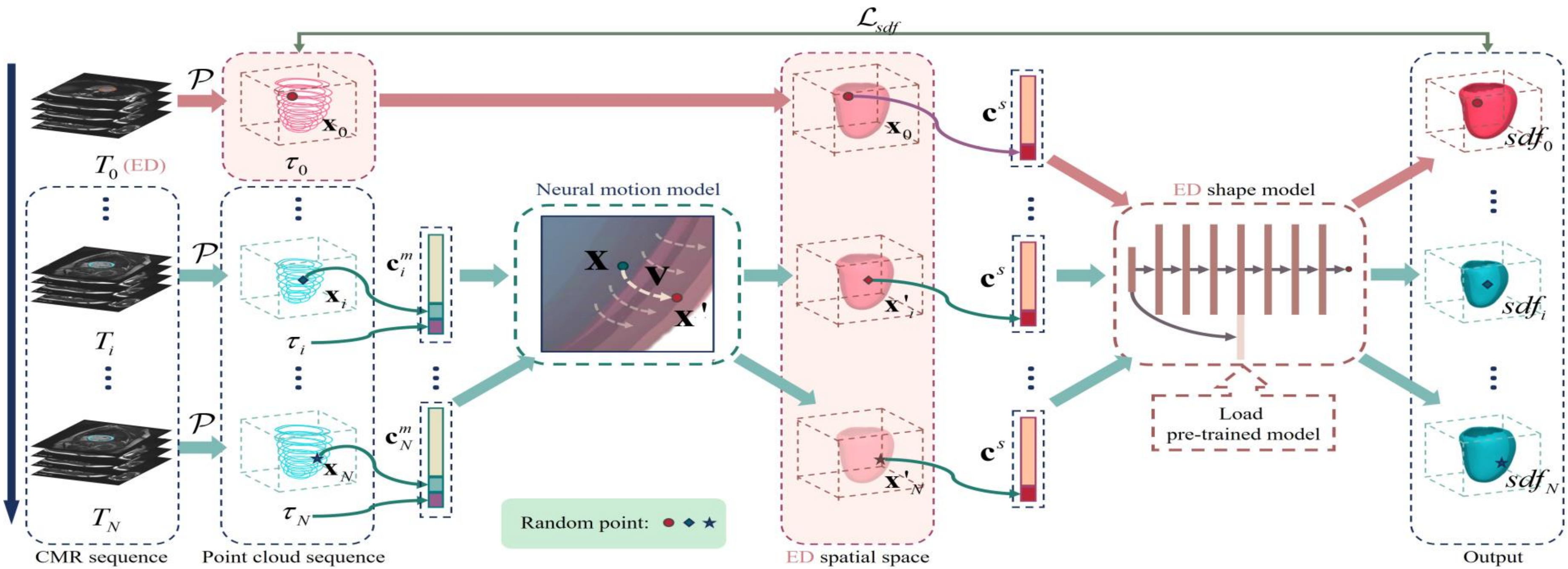


Figure 2. Method Overview. The point cloud sequence is first segmented from the input CMR sequence. We register the point cloud at the ED phase to the pre-defined statistical mean shape $\overline{s}$ in the ED spatial space and broadcast the obtained transformation to all phases. For any query point at T_i phase, the neural motion model takes its coordinate and phase indicator as input and predicts the point's deformation to the ED spatial space under the condition of motion code. The pre-trained implicit ED shape model estimates the SDF(signed distance function) value of the deformed point under the condition of shape code. Finally, the shape reconstruction is completed by extracting the boundary.

Motion Tracking and mesh generation based on Deep Learning Methods

Authors	Year	Motion Modeling	Network	Methods
Xiaohan Yuan et.al [1]	2023	**4D**	shape and motion Network using dense-sparse-dense	3D shape CNN Model
Qingjie Meng et.al [2]	2022	**4D**	shape and motion Network	3D shape CNN model
Qingjie Meng et.al [3]	2023	**4D**	shape and motion Network	3D shape CNN model
Guo et al.[4]	2021	3D	shape and motion Network using dense-sparse-dense	3D segmentation
Pingjun Chen et al.[5]	2020	3D	2D motion Network	2D Registration
Julian Krebs et al.[6]	2019	3D	2D motion Network	2D Registration (Non-DL)
Chen Qin et al.[7]	2018	3D	2D motion Network	2D Registration+2D segmentation
Chen Qin et al.[8]	2020	3D	2D motion Network	2D registration
Hanchao Yu et al. [9]	2020	3D	2D motion Network	2D registration
Hanchao Yu et al. [10]	2020	3D	2D motion Network	2D registration
Xiaoran Zhang et.al [11]	2022	3D	2D motion Network	2D Registration
Udaranga W et.al [12]	2020	3D	3D CNN network	Voxel2Mesh
Chen, Xiang et al.[13]	2021	3D	Coined Mesh Reconstruction Network (MR-Net),	2D segmentation models

Motion Tracking and Mesh Generation based on Registration models

Authors	Year	Motion Modeling	Network	Methods
Kong et al. [14]	2020	4D	2D Multiview-segmentations	Non-rigid image registration for mesh generation
Upendra et al. [15]	2022	4D	3D CNN	3D voxlmorph Registration
Bello et al. [16]	2019	4D	2D and 3D segmentation method	B-spline image registration method
Xia et al. [17]	2022	4D	Multi-Cue Shape Inference Network + statistical shape model	Coherent point drift (CPD) registration

References

[1] Yuan, Xiaohan, Cong Liu, and Yangang Wang. "4D Myocardium Reconstruction with Decoupled Motion and Shape Model." In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pp. 21252-21262. 2023.

[2] Qingjie Meng, Chen Qin, Wenjia Bai, Tianrui Liu, Antonio de Marvao, Declan P. O'Regan, and Daniel Rueckert.Mulvimotion: Shape-aware 3d myocardial motion tracking from multi-view cardiac mri. IEEE Transactions on Medical Imaging, 41:1961–1974, 2022.

[3] Qingjie Meng, Wenjia Bai, Tianrui Liu, Declan P O'Regan, and Daniel Rueckert. Mesh-based 3d motion tracking in cardiac mri using deep learning. In International Conference on Medical Image Computing and Computer-Assisted Intervention, pages 248–258. Springer, 2022.

[4] Yuyu Guo, Lei Bi, Dongming Wei, Liyun Chen, Zhengbin Zhu, Dagan Feng, Ruiyan Zhang, Qian Wang, and Jinman Kim. Unsupervised landmark detection based spatiotemporal motion estimation for 4d dynamic medical images. IEEE transactions on cybernetics, PP, 2021.

[5] Pingjun Chen, Xiao Chen, Eric Z Chen, Hanchao Yu, Terrence Chen, and Shanhui Sun. Anatomy-aware cardiac motion estimation. In International Workshop on Machine Learning in Medical Imaging, pages 150–159. Springer, 2020.

[6] Julian Krebs, Tommaso Mansi, Nicholas Ayache, and Herv´e Delingette. Probabilistic motion modeling from medical image sequences: application to cardiac cine-mri. In International Workshop on Statistical Atlases and Computational Models of the Heart, pages 176–185. Springer, 2019.

[7] Chen Qin, Wenjia Bai, Jo Schlemper, Steffen E Petersen, Stefan K Piechnik, Stefan Neubauer, and Daniel Rueckert. Joint learning of motion estimation and segmentation for cardiac mr image sequences. In International Conference on Medical Image Computing and Computer-Assisted Intervention, pages 472–480. Springer, 2018.

[8] Chen Qin, Shuo Wang, Chen Chen, Huaqi Qiu, Wenjia Bai, and Daniel Rueckert. Biomechanics-informed neural networks for myocardial motion tracking in mri. In MICCAI, 2020.

[9] Hanchao Yu, Xiao Chen, Humphrey Shi, Terrence Chen, Thomas S Huang, and Shanhui Sun. Motion pyramid networks for accurate and efficient cardiac motion estimation. In International Conference on Medical Image Computing and Computer-Assisted Intervention, pages 436–446. Springer, 2020.

[10] Hanchao Yu, Shanhui Sun, Haichao Yu, Xiao Chen, Honghui Shi, Thomas S Huang, and Terrence Chen. Foal: Fast online adaptive learning for cardiac motion estimation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 4313–4323, 2020.

[11] Xiaoran Zhang, Chenyu You, Shawn S. Ahn, Juntang Zhuang, Lawrence H. Staib, and James S. Duncan. Learning correspondences of cardiac motion from images using biomechanics-informed modeling. ArXiv, abs/2209.00726, 2022.

[12] Udaranga Wickramasinghe, Edoardo Remelli, Graham Knott, and Pascal Fua. Voxel2mesh: 3d mesh model generation from volumetric data. In International Conference on Medical Image Computing and Computer-Assisted Intervention, pages 299–308. Springer, 2020.

[13] Chen, Xiang, Nishant Ravikumar, Yan Xia, Rahman Attar, Andres Diaz-Pinto, Stefan K. Piechnik, Stefan Neubauer, Steffen E. Petersen, and Alejandro F. Frangi. "Shape registration with learned deformations for 3D shape reconstruction from sparse and incomplete point clouds." Medical Image Analysis 74 (2021): 102228.

[14] Kong, F., & Shadden, S. C. (2020). Automating model generation for image-based cardiac flow simulation. *Journal of Biomechanical Engineering*, *142*(11), 111011.

[15] Upendra, R. R., Wentz, B. J., Simon, R., Shontz, S. M., & Linte, C. A. (2021, June). CNN-based cardiac motion extraction to generate deformable geometric left ventricle myocardial models from cine MRI. In International Conference on Functional Imaging and Modeling of the Heart (pp. 253-263). Cham: Springer International Publishing.

[16] Bello, Ghalib A., Timothy JW Dawes, Jinming Duan, Carlo Biffi, Antonio De Marvao, Luke SGE Howard, J. Simon R. Gibbs et al. "Deep-learning cardiac motion analysis for human survival prediction." Nature machine intelligence 1, no. 2 (2019): 95-104.

[17] Xia, Yan, Xiang Chen, Nishant Ravikumar, Christopher Kelly, Rahman Attar, Nay Aung, Stefan Neubauer, Steffen E. Petersen, and Alejandro F. Frangi. "Automatic 3D+ t four-chamber CMR quantification of the UK biobank: integrating imaging and non-imaging data priors at scale." Medical Image Analysis 80 (2022): 102498.

https://github.com/RespectKnowledge/Motion_Alan_Turing