Ultrasound-Based Deformable Image Registration for Tendon Fiber Tracking

Jayotsana Sharma

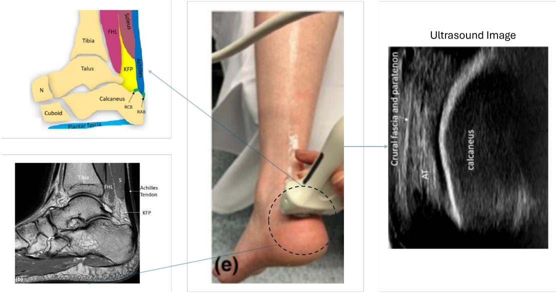
École Centrale de Nantes

Supervisors: Clément Huneau, Diana Mateus Lamus, LS2N

Outline

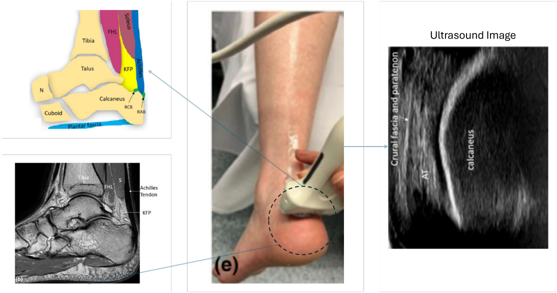
Motivation

- The **Achilles tendon**, composed of bundles of fibers called **fascicles**, plays a key role in transmitting muscular forces to the bone and undergoes significant **deformation**, including stretching, compression, and out-of-plane motion, during activities such as walking, running, and jumping.



[Fenech *et al.*, 2024]

- The **Achilles tendon**, composed of bundles of fibers called **fascicles**, plays a key role in transmitting muscular forces to the bone and undergoes significant **deformation**, including stretching, compression, and out-of-plane motion, during activities such as walking, running, and jumping.



[Fenech *et al.*, 2024]

- **Ultrasound images** allow us to observe the Achilles tendon motion in real time in a non-invasive and cost-effective manner.
- Consecutive ultrasound images contain speckle patterns generated by micro-scatterers in tendon tissue.

Motivation

- The speckle pattern **moves and deforms with the underlying tissue motion**.
- Tendon motion is **non-rigid**:
  - Different fascicles slide relative to each other.
  - Local stretching and compression occur.
- As a result, speckle undergoes **spatially varying deformation**.

Motivation

- The speckle pattern **moves and deforms with the underlying tissue motion**.
- Tendon motion is **non-rigid**:
  - Different fascicles slide relative to each other.
  - Local stretching and compression occur.
- As a result, speckle undergoes **spatially varying deformation**.

$\Rightarrow$ Need for deformable image registration to enable robust and consistent tracking of non-rigid tendon motion.

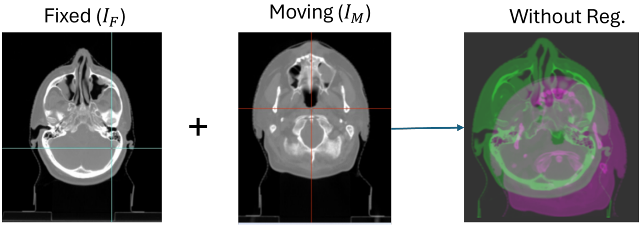
Objective & Problem Statement

Objective: Overview of classical and learning–based deformable image registration methods to estimate motion of Achilles tendon motion.

Objective & Problem Statement

Objective: Overview of classical and learning–based deformable image registration methods to estimate motion of Achilles tendon motion.

Image registration ?

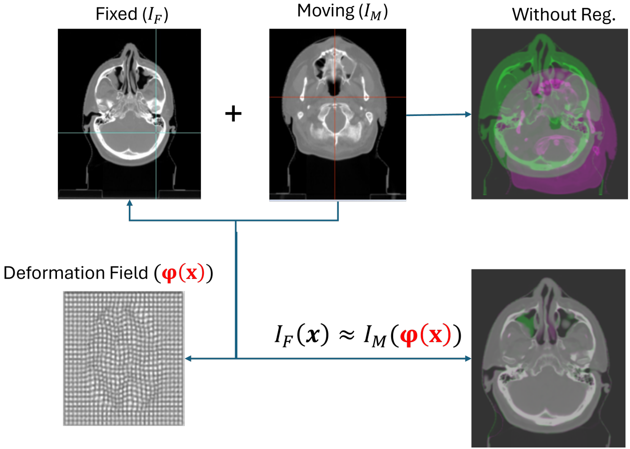


[Duchâteau, INSA Lyon (2022)]

Objective & Problem Statement

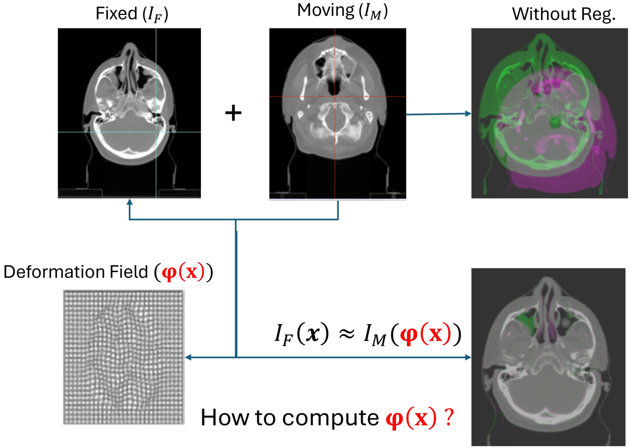
Objective: Overview of classical and learning–based deformable image registration methods to estimate motion of Achilles tendon motion.

Image registration ?



Objective: Overview of classical and learning–based deformable image registration methods to estimate motion of Achilles tendon motion.

Image registration ?



Outline

Standard Formulation of deformable Image Registration

A standard image registration formulation estimates the transformation φ by minimizing :

$$\varphi^* = \arg\min_{\varphi \in \mathcal{A}} \left[\underbrace{D(I_F,\ I_M \circ \varphi)}_{\text{data / dissimilarity}} \right]$$

where

- D: Sum of Squared Differences (SSD), (Local) Normalized Cross-Correlation (NCC / LNCC)
- $\mathcal{A}$: Set of admissible transformations (rigid, affine, deformable)
- $(I_M \circ \varphi)(x) = I_M(\varphi(x))$: Warping of the moving image

A standard image registration formulation estimates the transformation φ by minimizing :

$$\varphi^* = \arg\min_{\varphi \in \mathcal{A}} \left[\underbrace{D(I_F,\ I_M \circ \varphi)}_{\text{data / dissimilarity}} \right]$$

Ill-posed problem without regularization!
where

- D: Sum of Squared Differences (SSD), (Local) Normalized Cross-Correlation (NCC / LNCC)
- $\mathcal{A}$: Set of admissible transformations (rigid, affine, deformable)
- $(I_M \circ \varphi)(x) = I_M(\varphi(x))$: Warping of the moving image

Standard Formulation of deformable Image Registration

A standard image registration formulation estimates the transformation φ by minimizing :

$$\varphi^* = \arg\min_{\varphi \in \mathcal{A}} \Big[\underbrace{D(I_F,\ I_M \circ \varphi)}_{\text{data / dissimilarity}} + \lambda \underbrace{R(\varphi)}_{\text{regularization}} \Big]$$

Ill-posed problem without regularization!

where

- D: Sum of Squared Differences (SSD), (Local) Normalized Cross-Correlation (NCC / LNCC)
- $\mathcal{A}$: Set of admissible transformations (rigid, affine, deformable)
- $(I_M \circ \varphi)(x) = I_M(\varphi(x))$: Warping of the moving image
- $R(\varphi)$: Smoothness, diffeomorphic, physical regularization

Deformable Image Registration Methods

1. **Conventional:** Demons, SyN.....
2. **Speckle Tracking/Block Matching:** 2D and 3D.
3. **Learning Based:** Voxel Morph, CNN-Based, Implicit....

Outline

Demons: [Thirion, 1998]

- **Goal:** align fixed I_F and warped moving $I_M \circ \varphi$
- **Deformation model:** $\varphi(x) = x + u(x)$
- **Iterative scheme:** start with $\varphi^0(x) = x$

Demons: [Thirion, 1998]

- **Goal:** align fixed I_F and warped moving $I_M \circ \varphi$
- **Deformation model:** $\varphi(x) = x + u(x)$
- **Iterative scheme:** start with $\varphi^0(x) = x$
- **1) Compute intensity mismatch**

$$\Delta I(x) = I_F(x) - \left(I_M \circ \varphi^k\right)(x)$$

Demons: [Thirion, 1998]

- **Goal:** align fixed I_F and warped moving $I_M \circ \varphi$
- **Deformation model:** $\varphi(x) = x + u(x)$
- **Iterative scheme:** start with $\varphi^0(x) = x$
- **1) Compute intensity mismatch**

$$\Delta I(x) = I_F(x) - \left(I_M \circ \varphi^k\right)(x)$$

- **2) Compute incremental update (optical-flow style)**

$$u^k(x) = \frac{\Delta I(x)\, \nabla I_F(x)}{\|\nabla I_F(x)\|^2 + \Delta I(x)^2}$$

Demons: [Thirion, 1998]

- **Goal:** align fixed I_F and warped moving $I_M \circ \varphi$
- **Deformation model:** $\varphi(x) = x + u(x)$
- **Iterative scheme:** start with $\varphi^0(x) = x$
- **1) Compute intensity mismatch**

$$\Delta I(x) = I_F(x) - \left(I_M \circ \varphi^k\right)(x)$$

- **2) Compute incremental update (optical-flow style)**

$$u^k(x) = \frac{\Delta I(x)\, \nabla I_F(x)}{\|\nabla I_F(x)\|^2 + \Delta I(x)^2}$$

- **3) Regularize (smooth the update)**

$$u^k \leftarrow G_\sigma * u^k$$

Demons: [Thirion, 1998]

- **Goal:** align fixed I_F and warped moving $I_M \circ \varphi$
- **Deformation model:** $\varphi(x) = x + u(x)$
- **Iterative scheme:** start with $\varphi^0(x) = x$
- **1) Compute intensity mismatch**

$$\Delta I(x) = I_F(x) - \big(I_M \circ \varphi^k\big)(x)$$

- **2) Compute incremental update (optical-flow style)**

$$u^k(x) = \frac{\Delta I(x)\,\nabla I_F(x)}{\|\nabla I_F(x)\|^2 + \Delta I(x)^2}$$

- **3) Regularize (smooth the update)**

$$u^k \leftarrow G_\sigma * u^k$$

- **4) Update transformation**

$$\varphi^{k+1}(x) = \varphi^k(x) + u^k(x)$$

Outline

SyN: [Avants *et al.*, 2008]

- **Goal:** diffeomorphic (smooth + invertible) registration
- **Key idea:** optimize a **velocity field** and integrate it to obtain φ

SyN: [Avants *et al.*, 2008]

- **Goal:** diffeomorphic (smooth + invertible) registration
- **Key idea:** optimize a **velocity field** and integrate it to obtain φ
- **1) Diffeomorphic flow (ODE)**

$$\frac{d}{dt}\,\psi_t(x) = v\big(\psi_t(x), t\big), \qquad \psi_0(x) = x$$

$$\Rightarrow\ \varphi = \psi_1$$

SyN: [Avants *et al.*, 2008]

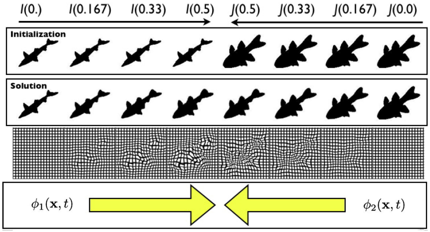
- **Goal:** diffeomorphic (smooth + invertible) registration
- **Key idea:** optimize a **velocity field** and integrate it to obtain φ
- **1) Diffeomorphic flow (ODE)**

$$\frac{d}{dt}\psi_t(x) = v\big(\psi_t(x), t\big), \qquad \psi_0(x) = x$$

$$\Rightarrow \ \varphi = \psi_1$$

- **2) Symmetric half-way mapping**

$$I_F \circ \varphi_{0\to 1/2} \ \approx \ I_M \circ \varphi_{1\to 1/2}$$



SyN: [Avants *et al.*, 2008]

- **Goal:** diffeomorphic (smooth + invertible) registration
- **Key idea:** optimize a **velocity field** and integrate it to obtain φ
- **1) Diffeomorphic flow (ODE)**

$$\frac{d}{dt}\,\psi_t(x) = v\big(\psi_t(x), t\big), \qquad \psi_0(x) = x$$

$$\Rightarrow\ \varphi = \psi_1$$

- **2) Symmetric half-way mapping**

$$I_F \circ \varphi_{0\to 1/2}\ \approx\ I_M \circ \varphi_{1\to 1/2}$$

- **3) Energy to optimize (velocity regularization + similarity)**

$$E(v) = \int_0^1 \|L\,v(\cdot,t)\|^2 dt\ +\ D\big(I_F \circ \varphi_{0\to 1/2},\ I_M \circ \varphi_{1\to 1/2}\big)$$

SyN: [Avants *et al.*, 2008]

- **Goal:** diffeomorphic (smooth + invertible) registration
- **Key idea:** optimize a **velocity field** and integrate it to obtain φ
- **1) Diffeomorphic flow (ODE)**

$$\frac{d}{dt}\psi_t(x) = v\big(\psi_t(x), t\big), \qquad \psi_0(x) = x$$

$$\Rightarrow \;\; \varphi = \psi_1$$

- **2) Symmetric half-way mapping**

$$I_F \circ \varphi_{0\to 1/2} \;\approx\; I_M \circ \varphi_{1\to 1/2}$$

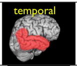
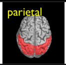
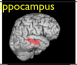
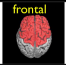
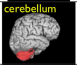
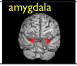
- **3) Energy to optimize (velocity regularization + similarity)**

$$E(v) = \int_0^1 \|L\, v(\cdot, t)\|^2 dt \;+\; D\big(I_F \circ \varphi_{0\to 1/2},\, I_M \circ \varphi_{1\to 1/2}\big)$$

- **4) Update via exponentiation and composition**

$$\text{Compute update } \exp(\delta v) \;\;\Rightarrow\;\; \varphi \leftarrow \varphi \circ \exp(\delta v)$$

SyN vs Demons: Quantitative Results

Structure	Demons	Elastic XCor > Demons	SyN XCor > Elastic
temporal 	Mean+-Sigma: 0.76 +- 0.021	0.81 +- 0.02	0.84 +- 0.019
	Min - Max : [0.69-0.79]	[0.76-0.84]	[0.79-0.87]
	Significance:	p< 0.0001	p< 0.0001
parietal 	0.69 +- 0.034	0.74 +- 0.03	0.78 +- 0.027
	[0.62-0.73]	[0.68-0.79]	[0.70-0.83]
	-	p< 0.0001	p< 0.0001
occipital 	0.78 +- 0.030	0.79 +- 0.024	0.83 +- 0.022
	[0.72-0.82]	[0.73-0.84]	[0.78-0.87]
	-	p < 0.011	p< 0.0001
hippocampus 	0.62 +- 0.070	0.72 +- 0.036	0.72 +- 0.038
	[0.48-0.73]	[0.65-0.77]	[0.63-0.79]
	-	p< 0.0001	p<0.7
frontal 	0.74 +- 0.026	0.81 +- 0.026	0.85 +- 0.024
	[0.65-0.77]	[0.73-0.84]	[0.79-0.88]
	-	p< 0.0001	p< 0.0001
cerebellum 	0.89 +- 0.012	0.89 +- 0.011	0.92 +- 0.011
	[0.87-0.92]	[0.88-0.92]	[0.91-0.93]
	-	p<0.2	p< 0.0001
amygdala 	0.59 +- 0.053	0.73 +- 0.065	0.74 +- 0.05
	[0.5-0.68]	[0.59-0.81]	[0.63-0.81]
	-	p<0.0001	p<0.24

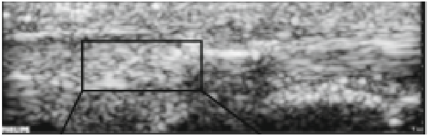
Dice score comparison: SyN consistently outperforms Demons in anatomical alignment [Avants et al., MedIA 2008].

Outline

2D Speckle Tracking for Tendon Motion [Korstanje *et al.*, 2010]

Deformation model: $\varphi(x) = x + u(x)$

- Speckle pattern acts as a natural texture for motion estimation in B-mode ultrasound.
- User-defined elongated ROI along the tendon.

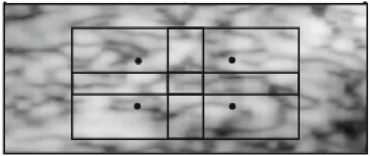


Porcine ultrasound of the tendon

2D Speckle Tracking for Tendon Motion [Korstanje *et al.*, 2010]

Deformation model: $\varphi(x) = x + u(x)$

- Speckle pattern acts as a natural texture for motion estimation in B-mode ultrasound.
- User-defined elongated ROI along the tendon.
- Multiple overlapping kernels are automatically placed inside the ROI.

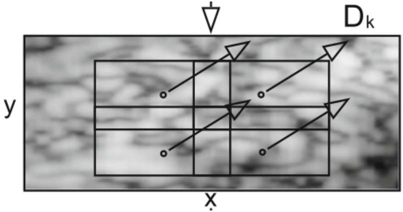


Frame at $t-1$

2D Speckle Tracking for Tendon Motion [Korstanje *et al.*, 2010]

Deformation model: $\varphi(x) = x + u(x)$

- Speckle pattern acts as a natural texture for motion estimation in B-mode ultrasound.
- User-defined elongated ROI along the tendon.
- Multiple overlapping kernels are automatically placed inside the ROI.



Frame at t

- For each kernel, displacement $u(x) = D_{t,k}$ is estimated by maximizing **NCC** in the next frame.

2D Speckle Tracking for Tendon Motion [Korstanje *et al.*, 2010]

Deformation model: $\varphi(x) = x + u(x)$

- Speckle pattern acts as a natural texture for motion estimation in B-mode ultrasound.
- User-defined elongated ROI along the tendon.
- Multiple overlapping kernels are automatically placed inside the ROI.
- For each kernel, displacement $u(x) = D_{t,k}$ is estimated by maximizing **NCC** in the next frame.
- Sub-pixel accuracy obtained by interpolation of the NCC peak.
- Final displacement as regularise $R(\varphi)$ = correlation-weighted average of kernel motions.

$$\boxed{\vec{D}_t = \sum_{k=1}^{K} \frac{f_k \cdot D_{t,k}}{\sum f_k},\ f_k = \begin{cases} NCC_k & > T \\ 0 & \leq T \end{cases}}$$

2D Speckle Tracking for Tendon Motion [Korstanje *et al.*, 2010]

Deformation model: $\varphi(x) = x + u(x)$

- Speckle pattern acts as a natural texture for motion estimation in B-mode ultrasound.
- User-defined elongated ROI along the tendon.
- Multiple overlapping kernels are automatically placed inside the ROI.
- For each kernel, displacement $u(x) = D_{t,k}$ is estimated by maximizing **NCC** in the next frame.
- Sub-pixel accuracy obtained by interpolation of the NCC peak.
- Final displacement as regularise $R(\varphi) =$ correlation-weighted average of kernel motions.

Experimented on:

- Porcine cadaver tendons
- Human cadaver tendons
- In-vivo human wrists

Works best when:

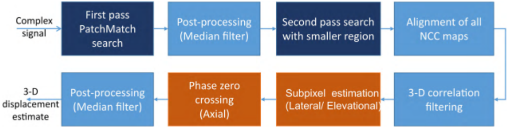
- Motion mainly <u>in-plane</u>
- Inter-frame deformation <u>small</u>
- High <u>frame rate</u> and Kernel preserves speckle correlation

Outline

3D Speckle Tracking – Two-Pass Method [Jeng *et al.*, 2018]

Deformation model: $\varphi(x) = x + u(x),\ u(x) \in \mathbb{R}^3$

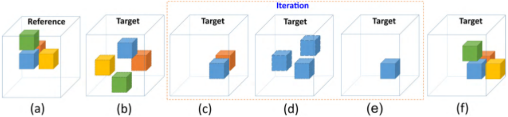
- Volumetric RF speckle acts as a natural texture for 3D motion estimation.
- 3D kernels are defined in the reference volume $I_F(x, y, z)$.



3D Speckle Tracking – Two-Pass Method [Jeng *et al.*, 2018]

Deformation model: $\varphi(x) = x + u(x),\ u(x) \in \mathbb{R}^3$

- Volumetric RF speckle acts as a natural texture for 3D motion estimation.
- 3D kernels are defined in the reference volume $I_F(x, y, z)$.
- **Pass 1 – Coarse Search (PatchMatch):**
  - Random initialization and propagation among neighboring voxels.
  - Efficient estimation of large 3D displacements.



3D Speckle Tracking – Two-Pass Method [Jeng *et al.*, 2018]

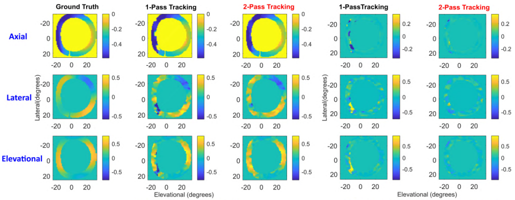
Deformation model: $\varphi(x) = x + u(x),\ u(x) \in \mathbb{R}^3$

- Volumetric RF speckle acts as a natural texture for 3D motion estimation.
- 3D kernels are defined in the reference volume $I_F(x, y, z)$.
- **Pass 1 – Coarse Search (PatchMatch):**
  - Random initialization and propagation among neighboring voxels.
  - Efficient estimation of large 3D displacements.
- **Pass 2 – Refined Correlation (Block Matching):**
  - Phase-sensitive 3D NCC computed around coarse estimates.
  - Lag-space alignment and correlation filtering for robustness.

3D Speckle Tracking – Two-Pass Method [Jeng *et al.*, 2018]

Deformation model: $\varphi(x) = x + u(x),\ u(x) \in \mathbb{R}^3$

- Volumetric RF speckle acts as a natural texture for 3D motion estimation.
- 3D kernels are defined in the reference volume $I_F(x, y, z)$.
- **Pass 1 – Coarse Search (PatchMatch):**
  - Random initialization and propagation among neighboring voxels.
  - Efficient estimation of large 3D displacements.
- **Pass 2 – Refined Correlation (Block Matching):**
  - Phase-sensitive 3D NCC computed around coarse estimates.
  - Lag-space alignment and correlation filtering for robustness.
- Computed $u(x)$



(a) Displacement estimate (b) Error with respect to ground truth

3D Speckle Tracking – Two-Pass Method [Jeng *et al.*, 2018]

Deformation model: $\varphi(x) = x + u(x),\ u(x) \in \mathbb{R}^3$

- Volumetric RF speckle acts as a natural texture for 3D motion estimation.
- 3D kernels are defined in the reference volume $I_F(x, y, z)$.
- **Pass 1 – Coarse Search (PatchMatch):**
  - Random initialization and propagation among neighboring voxels.
  - Efficient estimation of large 3D displacements.
- **Pass 2 – Refined Correlation (Block Matching):**
  - Phase-sensitive 3D NCC computed around coarse estimates.
  - Lag-space alignment and correlation filtering for robustness.
- Computed $u(x)$

Experimented on:

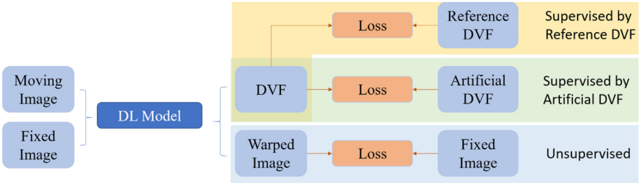
- Simulated 4D cardiac phantom
- In-vivo canine heart (ECG-gated 4D, Philips iE33)

Works best when:

- Significant 3D / out-of-plane motion
- Large inter-frame displacement
- Low volume rate (PatchMatch enables coarse search)

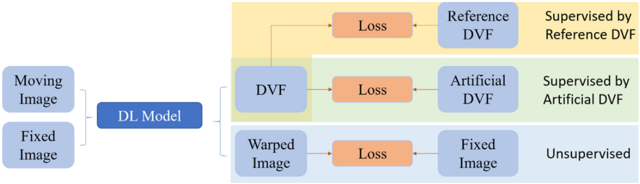
Outline

Learning-Based Deformable Registration



[Xiao *et al.*, 2020]

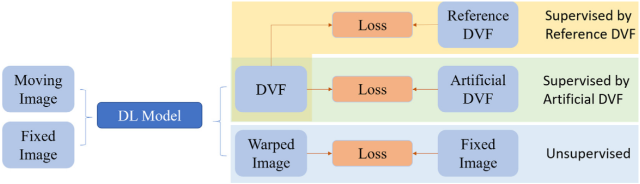
Learning-Based Deformable Registration



[Xiao *et al.*, 2020]

- Training is typically **unsupervised** (no ground-truth deformation).
- Loss = Image similarity + deformation regularization.

Learning-Based Deformable Registration

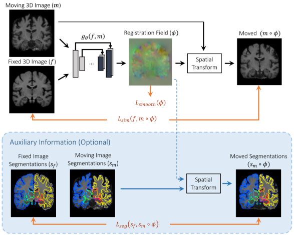


[Xiao *et al.*, 2020]

- Training is typically **unsupervised** (no ground-truth deformation).
- Loss = Image similarity + deformation regularization.
- Learn a global mapping from many image pairs (**VoxalMorph**: CNN-based methods). Or optimize a neural network separately for each image pair (**Implicit networks**).

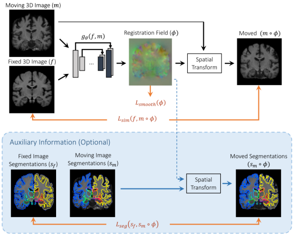
Outline

VoxelMorph: CNN-Based Registration [Balakrishnan *et al.*, TMI 2019]



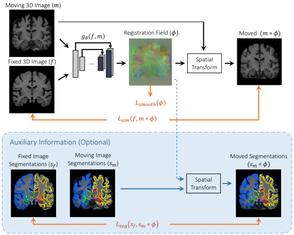
- **Deformation model:** $\varphi(x) = x + u(x)$ with $u(x) = f_\theta(I_F, I_M)$ predicted by a 3D U-Net.
- The network learns a global mapping f_θ instead of solving per-pair image.

VoxelMorph: CNN-Based Registration [Balakrishnan *et al.*, TMI 2019]



- **Deformation model:** $\varphi(x) = x + u(x)$ with $u(x) = f_\theta(I_F, I_M)$ predicted by a 3D U-Net.
- The network learns a global mapping f_θ instead of solving per-pair image.
- A Spatial Transformer Network enables backpropagation through $I_M \circ \varphi$.

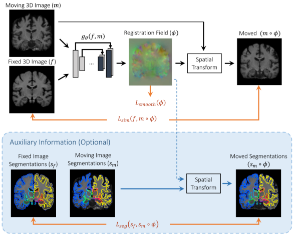
VoxelMorph: CNN-Based Registration [Balakrishnan *et al.*, TMI 2019]



- **Deformation model:** $\varphi(x) = x + u(x)$ with $u(x) = f_\theta(I_F, I_M)$ predicted by a 3D U-Net.
- The network learns a global mapping f_θ instead of solving per-pair image.
- A Spatial Transformer Network enables backpropagation through $I_M \circ \varphi$.
- **Training loss:**

$$\mathcal{L} = D(I_F, I_M \circ \varphi) \text{ (NCC / MSE)} + \lambda \|\nabla u\|^2$$

VoxelMorph: CNN-Based Registration [Balakrishnan *et al.*, TMI 2019]



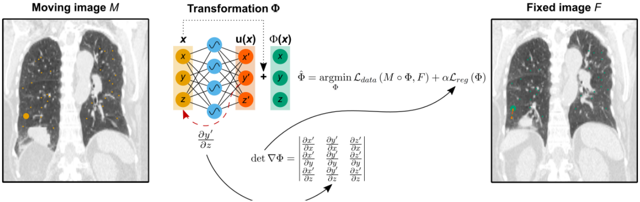
- **Deformation model:** $\varphi(x) = x + u(x)$ with $u(x) = f_\theta(I_F, I_M)$ predicted by a 3D U-Net.
- The network learns a global mapping f_θ instead of solving per-pair image.
- A Spatial Transformer Network enables backpropagation through $I_M \circ \varphi$.
- **Training loss:**

$$\mathcal{L} = D(I_F, I_M \circ \varphi)\ (\text{NCC / MSE}) + \lambda \|\nabla u\|^2$$

- **Pros / Cons:** very fast inference (< 1 s on GPU), but requires large training datasets and may generalize poorly to new ultrasound settings.

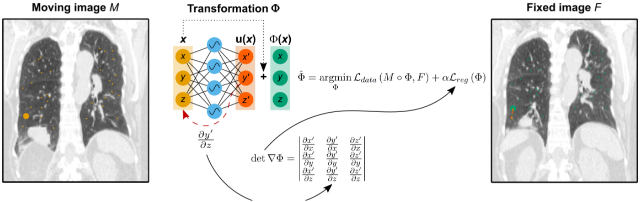
Outline

Implicit Neural Representation [Wolterink *et al.*, 2022]



- **Model:** $\varphi(x) = x + u_\theta(x)$, u_θ represented by MLP
- Network input: spatial coordinate $x = (x, y, z)$.
- Output: displacement $u(x)$ (continuous field).
- Optimized per image pair (no training dataset required).
- **Periodic activations (SIREN)**: The MLP uses sinusoidal functions (e.g., $\cos(x)$) instead of ReLU, enabling the representation of both smooth global motion and fine local deformations.

Implicit Neural Representation [Wolterink *et al.*, 2022]



- **Model:** $\varphi(x) = x + u_\theta(x)$, u_θ represented by MLP
- Network input: spatial coordinate $x = (x, y, z)$.
- Output: displacement $u(x)$ (continuous field).
- Optimized per image pair (no training dataset required).
- **Periodic activations (SIREN)**: The MLP uses sinusoidal functions (e.g., $\cos(x)$) instead of ReLU, enabling the representation of both smooth global motion and fine local deformations.
- Regularization:
  - **Jacobian penalty:** $\left|\det(\nabla\varphi) - 1\right|$ (prevents folding, ensures invertibility)
  - **Bending energy:** $\|\nabla^2\varphi\|^2$ (enforces spatial smoothness)
  - **Hyperelastic energy:** $W_{\text{hyper}}(\nabla\varphi)$ (physically plausible tissue deformation)

Outline

Conclusion & Discussion

- **Conclusions**
  - Classical methods (Demons, SyN): physically meaningful deformations, but can be computationally expensive.

Conclusion & Discussion

- **Conclusions**
  - Classical methods (Demons, SyN): physically meaningful deformations, but can be computationally expensive.
  - Speckle tracking: ultrasound-adapted, but sensitive to decorrelation and kernals.

Conclusion & Discussion

- **Conclusions**
  - Classical methods (Demons, SyN): physically meaningful deformations, but can be computationally expensive.
  - Speckle tracking: ultrasound-adapted, but sensitive to decorrelation and kernals.
  - CNN-based registration (VoxelMorph): real-time inference, but requires large training data and may generalize poorly.

Conclusion & Discussion

- **Conclusions**
  - Classical methods (Demons, SyN): physically meaningful deformations, but can be computationally expensive.
  - Speckle tracking: ultrasound-adapted, but sensitive to decorrelation and kernals.
  - CNN-based registration (VoxelMorph): real-time inference, but requires large training data and may generalize poorly.
  - Implicit neural Network: high accuracy and topology preservation, but slower due to per-pair optimization.

Conclusion & Discussion

- **Conclusions**
  - Classical methods (Demons, SyN): physically meaningful deformations, but can be computationally expensive.
  - Speckle tracking: ultrasound-adapted, but sensitive to decorrelation and kernals.
  - CNN-based registration (VoxelMorph): real-time inference, but requires large training data and may generalize poorly.
  - Implicit neural Network: high accuracy and topology preservation, but slower due to per-pair optimization.
- **Discussion**
  - Hybrid approaches: combine physics-based regularization with learning-based models.

Conclusion & Discussion

- **Conclusions**
  - Classical methods (Demons, SyN): physically meaningful deformations, but can be computationally expensive.
  - Speckle tracking: ultrasound-adapted, but sensitive to decorrelation and kernals.
  - CNN-based registration (VoxelMorph): real-time inference, but requires large training data and may generalize poorly.
  - Implicit neural Network: high accuracy and topology preservation, but slower due to per-pair optimization.
- **Discussion**
  - Hybrid approaches: combine physics-based regularization with learning-based models.
  - Tendon-specific priors: fascicle orientation constraints and sliding interfaces.

Conclusion & Discussion

- **Conclusions**
  - Classical methods (Demons, SyN): physically meaningful deformations, but can be computationally expensive.
  - Speckle tracking: ultrasound-adapted, but sensitive to decorrelation and kernals.
  - CNN-based registration (VoxelMorph): real-time inference, but requires large training data and may generalize poorly.
  - Implicit neural Network: high accuracy and topology preservation, but slower due to per-pair optimization.
- **Discussion**
  - Hybrid approaches: combine physics-based regularization with learning-based models.
  - Tendon-specific priors: fascicle orientation constraints and sliding interfaces.
  - Move toward 3D/4D ultrasound to explicitly handle out-of-plane motion.

Conclusion & Discussion

- **Conclusions**
  - Classical methods (Demons, SyN): physically meaningful deformations, but can be computationally expensive.
  - Speckle tracking: ultrasound-adapted, but sensitive to decorrelation and kernals.
  - CNN-based registration (VoxelMorph): real-time inference, but requires large training data and may generalize poorly.
  - Implicit neural Network: high accuracy and topology preservation, but slower due to per-pair optimization.
- **Discussion**
  - Hybrid approaches: combine physics-based regularization with learning-based models.
  - Tendon-specific priors: fascicle orientation constraints and sliding interfaces.
  - Move toward 3D/4D ultrasound to explicitly handle out-of-plane motion.
  - Robust validation on phantoms, ex-vivo and in-vivo datasets.

Outline

References

- J.-P. Thirion, *Image matching as a diffusion process: an analogy with Maxwell's demons*, MedIA, 1998.
- B. Avants *et al.*, *Symmetric diffeomorphic image registration with cross-correlation*, MedIA, 2008.
- J.-W. Korstanje *et al.*, *Ultrasound speckle tracking to quantify tendon displacement*, J. Biomech., 2010.
- G.-S. Jeng *et al.*, *Efficient two-pass 3D speckle tracking*, IEEE Access, 2018.
- G. Balakrishnan *et al.*, *VoxelMorph: A learning framework for deformable registration*, IEEE TMI, 2019.
- J. Wolterink *et al.*, *Implicit neural representations for deformable image registration*, MIDL, 2022.
- H. Xiao *et al.*, *A review on 3D deformable image registration*, Rad. Med. Prot., 2020.
- M. Fenech *et al.*, *Ultrasound assessment of Achilles tendon*, Australas. J. Ultrasound Med., 2024.