Quantifying Knee Cartilage Shape and Lesion: From Image to Metrics

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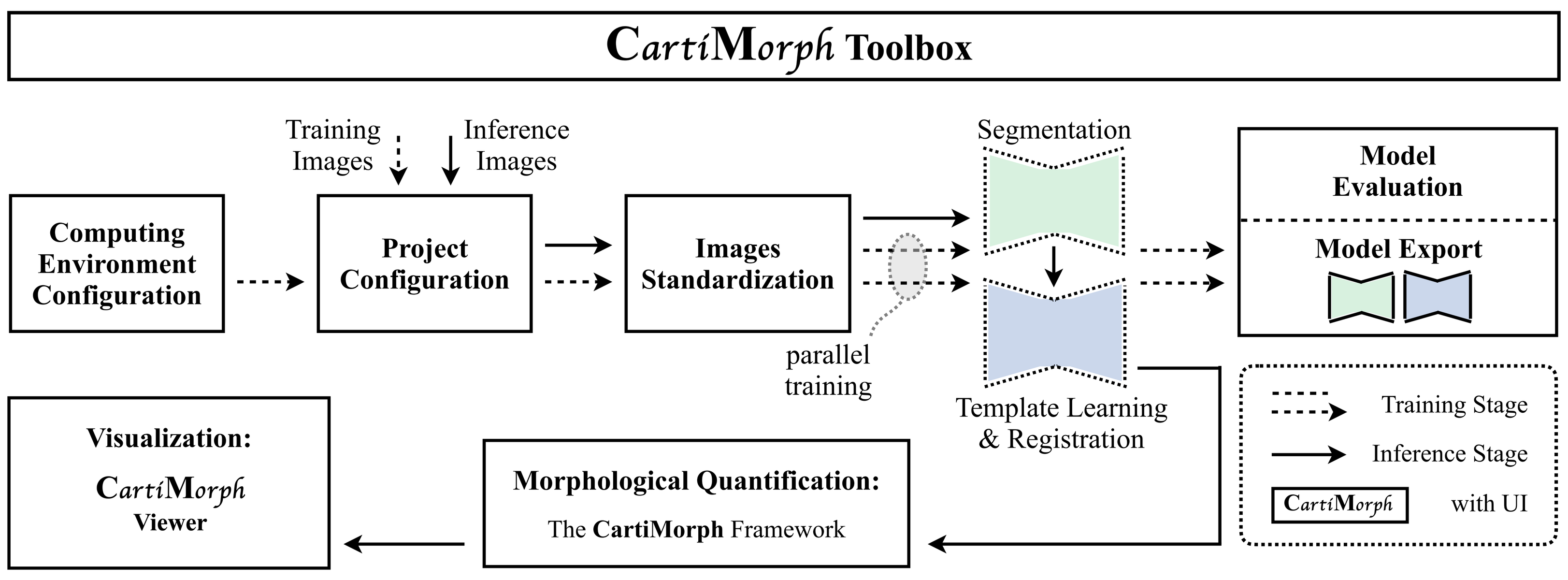
1. Objective

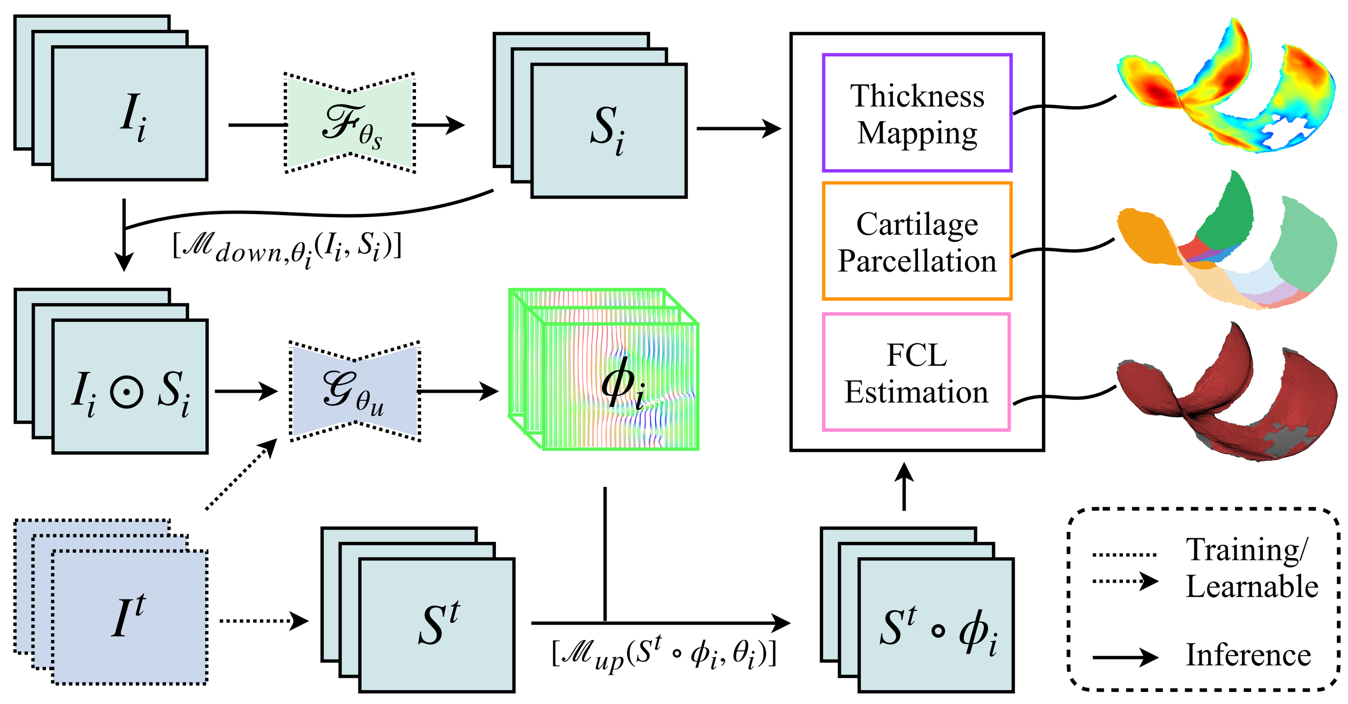
- ✓ AI tool for extracting imaging biomarkers (quantifying cartilage shape and lesion): MR image → quantitative metrics (surface area, volume, cartilage thickness, and full-thickness cartilage loss in 20 subregions)
- ✓ A joint template learning and registration model
- ✓ Q: *Are SoTA registration models always preferable for all tasks?*

2.1 Method: CartiMorph Toolbox (CMT) [1]

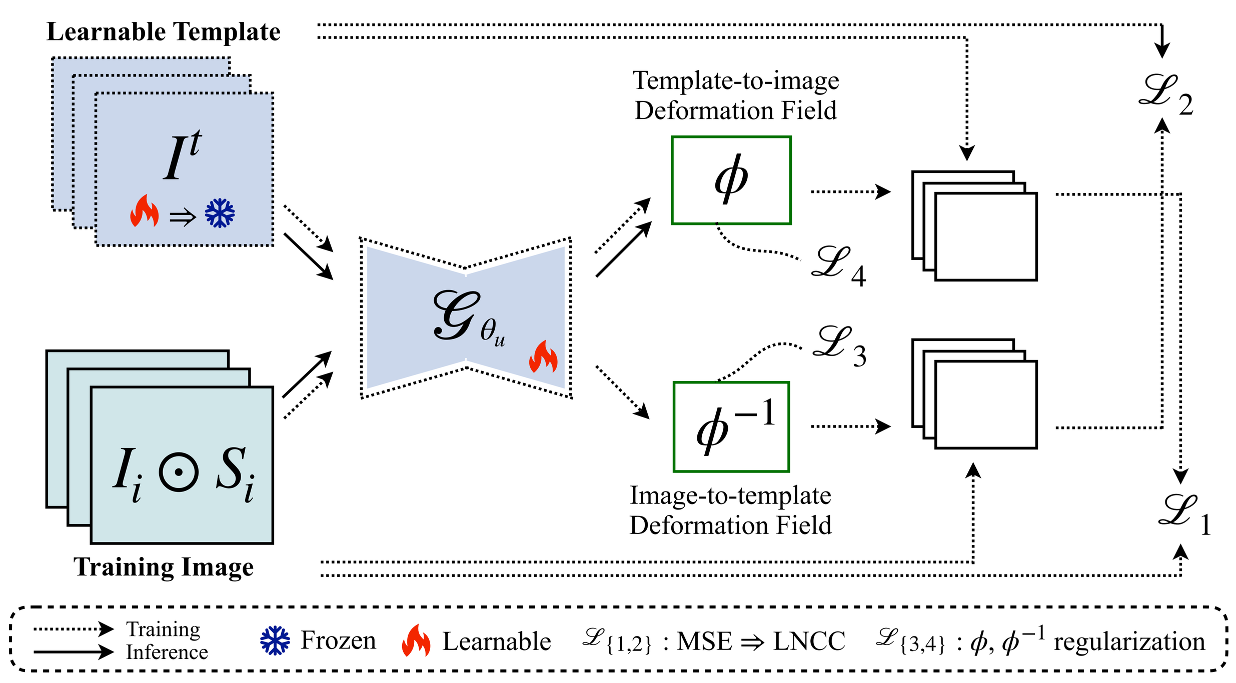


- Automatic medical image analysis with user interface (**CMT**)
- Models life-cycle management: training, fine-tuning, evaluation, inference, and sharing
- Framework: CartiMorph [2]
- Visualization: CartiMorph Viewer (CMV)

2.2 Method: Models



The segmentation model $\mathcal{F}_{\theta_s}$ (nnUNet) , the proposed joint template-learning-and-registration model $\mathcal{G}_{\{\theta_u, I^t\}}$ (**CMT-reg**), and the quantification algorithms adopted from CartiMorph [2].



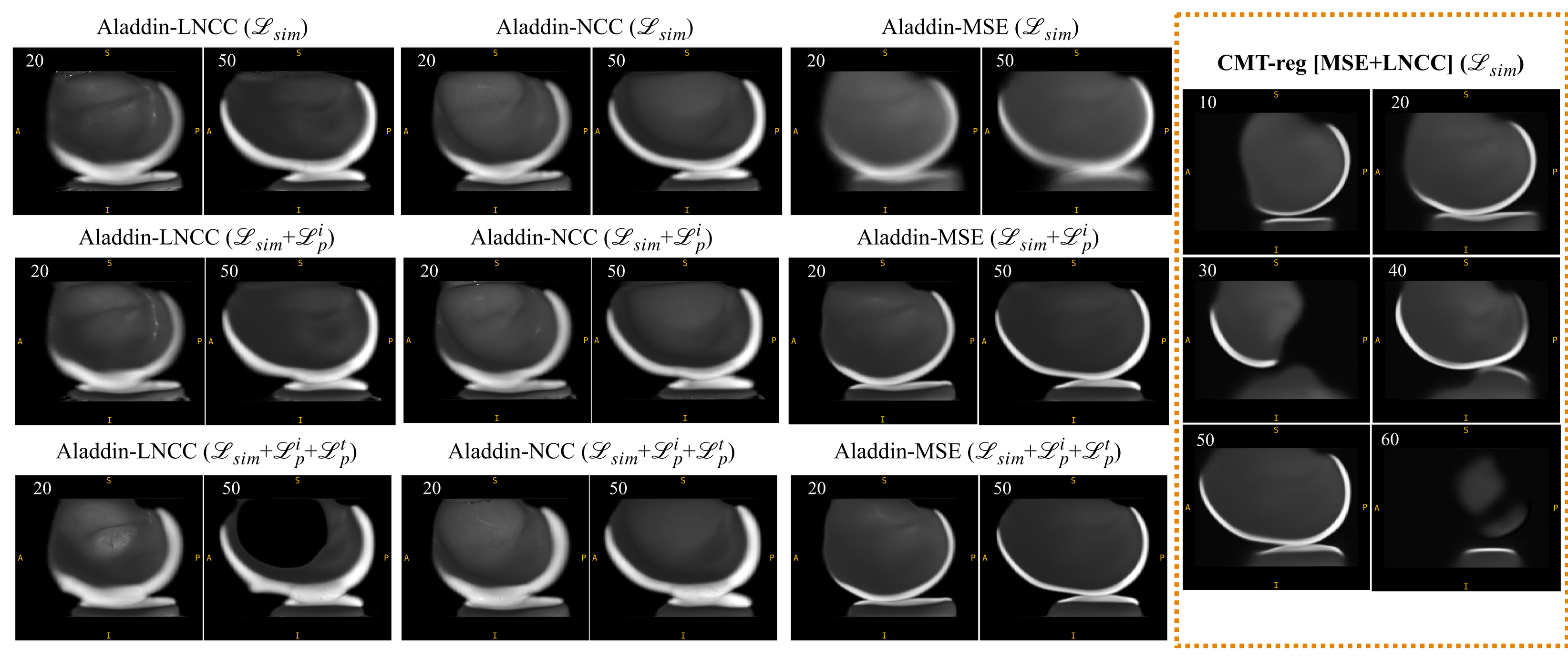
Training strategy of CMT-reg:

Stage 1: update θ_u and I^t with $\mathscr{L}_{\{1,2\}}$ being mean square error (MSE) loss

Stage 2: update θ_u with $\mathscr{L}_{\{1,2\}}$ being local normalized cross-correlation (LNCC) loss

3. Experiments & Results

❖ **Learn a representative template image from masked healthy and pathological MRIs**



◉ **Evaluate template-to-image registration accuracy (Table 2)**

❖ **Evaluate registration model behavior (Table 3)**

- ***Expected behavior:*** the registered template mask covers as much pseudo-healthy bone-cartilage interface (BCI) as possible
- ***Metric:*** $(A_i - A_i^{\text{pseudo}})/A_i^{\text{pseudo}}$, where A_i is the area of BCI extracted from the registered template mask, and A_i^{pseudo} is the area of human-calibrated pseudo-healthy BCI

Table 2. Template-to-image registration accuracy.

Model (Loss)	DSC ↑			HD95 ↓ (mm)		
	FC	mTC	lTC	FC	mTC	lTC
Aladdin-LNCC ($\mathcal{L}_{sim}$)	**0.905**	0.816	0.839	**0.58**	**0.92**	0.94
Aladdin-LNCC ($\mathcal{L}_{sim}+\mathcal{L}_p^i$)	**0.905**	0.817	0.839	0.59	**0.92**	0.92
Aladdin-LNCC ($\mathcal{L}_{sim}+\mathcal{L}_p^i+\mathcal{L}_p^t$)	0.904	0.809	0.831	0.64	1.09	1.16
Aladdin-NCC ($\mathcal{L}_{sim}$)	0.904	0.818	0.842	0.59	**0.92**	0.89
Aladdin-NCC ($\mathcal{L}_{sim}+\mathcal{L}_p^i$)	**0.908**	**0.829**	**0.858**	**0.55**	**0.85**	**0.72**
Aladdin-NCC ($\mathcal{L}_{sim}+\mathcal{L}_p^i+\mathcal{L}_p^t$)	0.904	0.819	0.840	0.62	0.99	1.03
Aladdin-MSE ($\mathcal{L}_{sim}$)	0.505	0.368	0.305	3.49	5.69	6.51
Aladdin-MSE ($\mathcal{L}_{sim}+\mathcal{L}_p^i$)	0.889	0.808	0.849	0.65	0.97	**0.76**
Aladdin-MSE ($\mathcal{L}_{sim}+\mathcal{L}_p^i+\mathcal{L}_p^t$)	0.885	0.803	0.841	0.65	0.98	0.82
LapIRN-diff ($\mathcal{L}_{sim}$)	0.855	0.740	0.731	1.09	1.69	2.01
LapIRN-disp ($\mathcal{L}_{sim}$)	0.898	0.806	**0.850**	0.81	1.38	1.28
CMT-reg ($\mathcal{L}_{sim}$)	0.895	**0.821**	**0.850**	0.70	1.10	0.89

Table 3. Registration models behavior analysis.

Model (Loss)	$(A_i - A_i^{\text{pseudo}})/A_i^{\text{pseudo}}$ |↓|		
	FC	mTC	lTC
Aladdin-LNCC ($\mathcal{L}_{sim}$)	-0.035	-0.115	-0.140
Aladdin-LNCC ($\mathcal{L}_{sim}+\mathcal{L}_p^i$)	-0.029	-0.106	-0.143
Aladdin-LNCC ($\mathcal{L}_{sim}+\mathcal{L}_p^i+\mathcal{L}_p^t$)	-0.026	-0.080	-0.133
Aladdin-NCC ($\mathcal{L}_{sim}$)	-0.031	-0.112	-0.150
Aladdin-NCC ($\mathcal{L}_{sim}+\mathcal{L}_p^i$)	-0.029	-0.098	-0.145
Aladdin-NCC ($\mathcal{L}_{sim}+\mathcal{L}_p^i+\mathcal{L}_p^t$)	-0.032	-0.088	-0.134
Aladdin-MSE ($\mathcal{L}_{sim}$)	-0.203	-0.393	-0.468
Aladdin-MSE ($\mathcal{L}_{sim}+\mathcal{L}_p^i$)	-0.021	-0.079	-0.142
Aladdin-MSE ($\mathcal{L}_{sim}+\mathcal{L}_p^i+\mathcal{L}_p^t$)	**-0.002**	-0.070	-0.129
LapIRN-diff ($\mathcal{L}_{sim}$)	**0.007**	-0.087	-0.134
LapIRN-disp ($\mathcal{L}_{sim}$)	0.040	**-0.047**	**-0.103**
CMT-reg ($\mathcal{L}_{sim}$)	0.036	**-0.048**	**-0.124**

4. Conclusion

✦ **CMT** can benefit human knee cartilage morphometrics (watch the video)

✦ **CMT-reg** is suboptimal in terms of volume overlap (DSC) and surface alignment (HD95), yet prevails in pseudo-healthy BCI coverage which is crucial for accurate estimation of full-thickness cartilage loss (FCL). Therefore, CMT-reg is best suited for the CartiMorph framework.

video

Acknowledgement

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References & Resources

1. Yongcheng Yao and Weitian Chen. "Quantifying Knee Cartilage Shape and Lesion: From Image to Metrics." In: *International Workshop on Applications of Medical AI*, 2024
2. Yongcheng Yao, et al. "CartiMorph: A framework for automated knee articular cartilage morphometrics." *Medical Image Analysis* 91 (2024): 103035.

CMT: https://github.com/YongchengYAO/CartiMorph-Toolbox

CartiMorph: https://github.com/YongchengYAO/CartiMorph

Code: https://github.com/YongchengYAO/CMT-AMAI24paper