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Robust Unsupervised Image to Template Registration Without Image Similarity Loss

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Introduction

Problem with unsupervised registration

- ▷ Often trained using dissimilarity loss such as, mutual information
- ▷ ⇒ same limit as classical registration routine (for ex: local minima)

Objectives:

- ▷ Unsupervised learning
- ▷ No dissimilarity metric or other matching during training
- ▷ Robust to large transforms and abnormalities

Method

The network:

- ▷ any architecture
- ▷ a single image as input: do not create feature from unrelated voxel
- ▷ an affine matrix as output: the matrix that realigns the image in the reference space

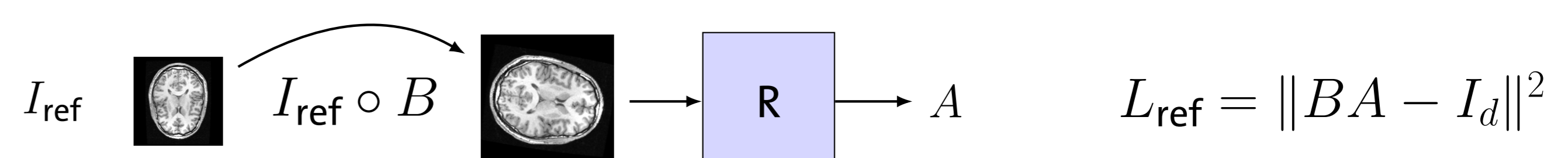
Regularisation Loss: prevent null network

$$Ax = U\Sigma Vx + b$$

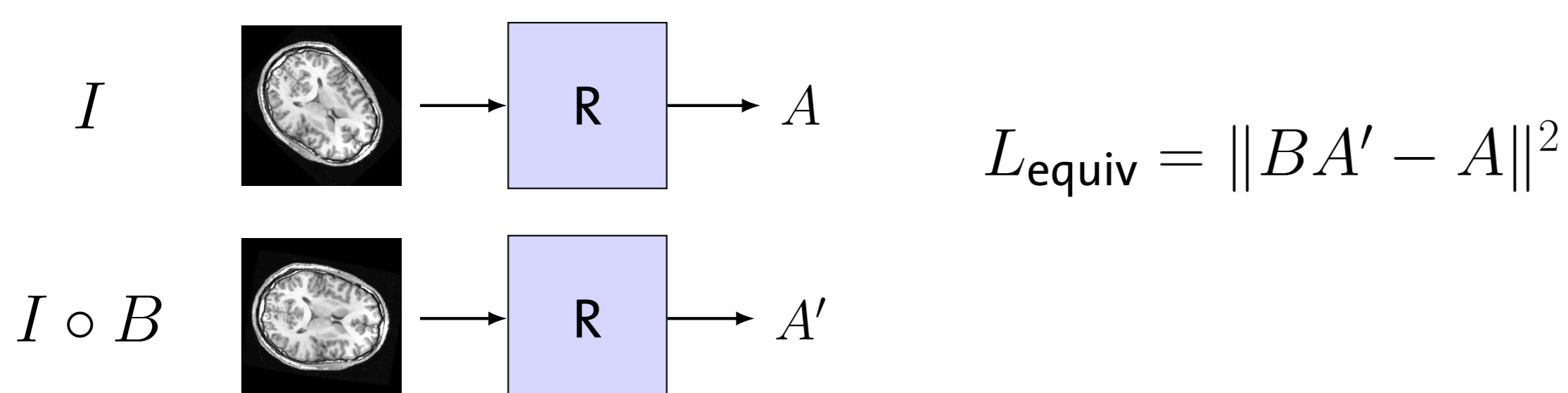
$$L_{\text{size}} = \text{penalize large / small } \sigma$$

$$L_{\text{anis}} = \|\log(\sigma_{\text{min}}) - \log(\sigma_{\text{max}})\|^2$$

Reference Loss: A unique image in the reference space, I_{ref} , is given



Equivariance Loss: if a known transform B is applied to the image I , then $BA' = A$



A two steps procedure to increase the registration range:

- ▷ First step : unsupervised training with **small transforms**
- ▷ Apply the network to the training dataset ⇒ registered training dataset
- ▷ Second step : supervised training with **large transforms**

Experiments

Data:

- ▷ HCP database : 2D middle slice of T2 brain images.
- ▷ train / validation / test : 500 / 100 / 500
- ▷ I_{ref} : 2mm T1 MNI atlas

Registration range

	D_0	D_{trans}	D_{shear}	D_{scale}	D_1
Translation	± 10 pixels	± 54 pixels	± 10 pixels	± 10 pixels	± 54 pixels
Rotation	$\pm \pi$	$\pm \pi$	$\pm \pi$	$\pm \pi$	$\pm \pi$
Shearing	$\pm 10\%$	$\pm 10\%$	$\pm 50\%$	$\pm 10\%$	$\pm 50\%$
Scaling	$\pm 10\%$	$\pm 10\%$	$\pm 10\%$	$\pm 50\%$	$\pm 50\%$

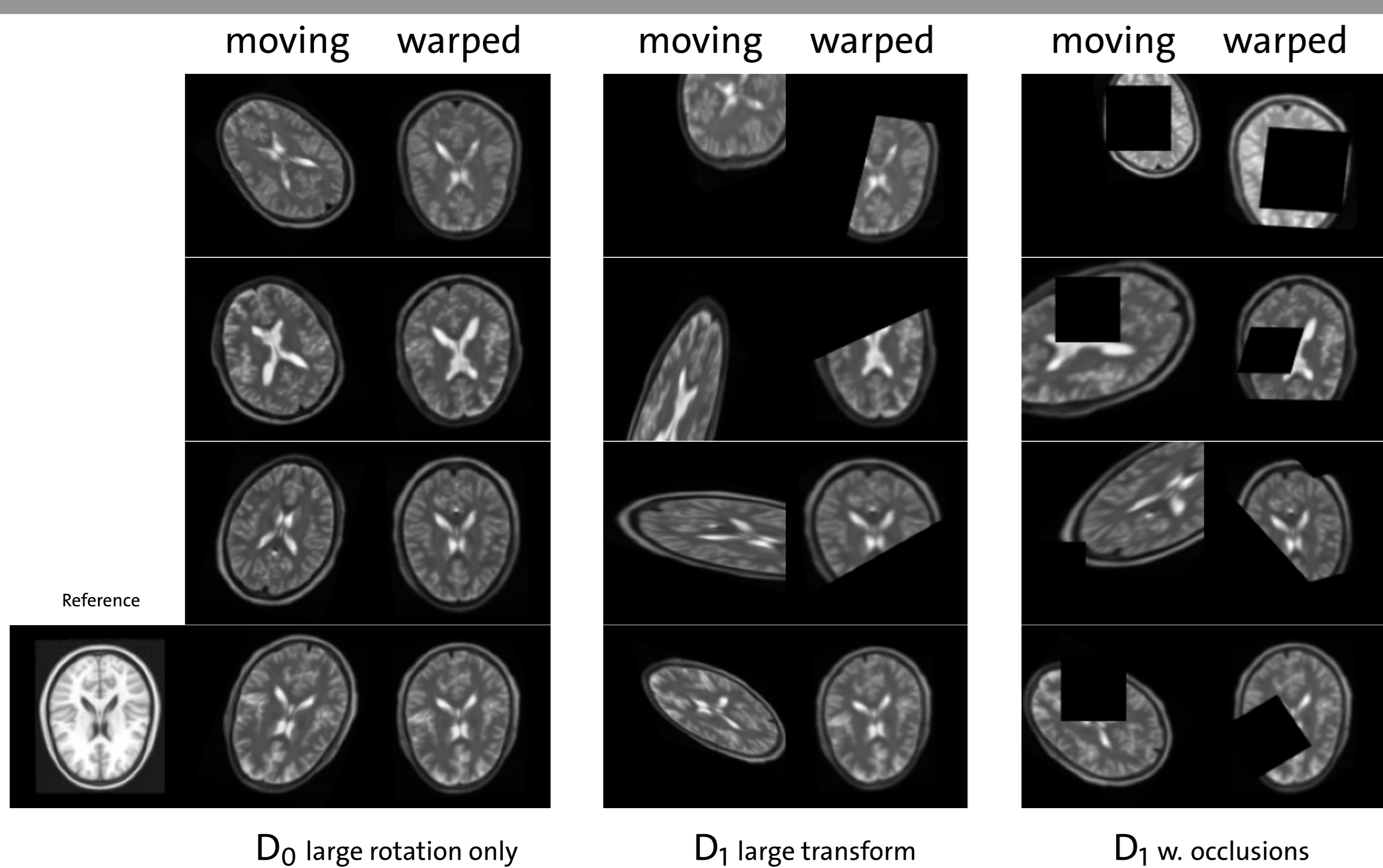
Metrics:

$$\text{Mat}_{\text{err}} = \|A_{\text{pred}} \circ A_{\text{GT}} - Id\|^2$$

$$\theta = \arccos \frac{\text{tr}(A_{\text{pred}} \circ A_{\text{GT}})}{2}$$

Robustness: θ_t = percentage of images with a rotation error $\theta \geq t$.

Results



Visual Results on D_0 with our one step or D_1 with our two steps method

Loss	Mat_{err}	θ_{90}	θ_{45}
L_{equiv}	1.68 ± 0.14	50.49	100.00
$L_{\text{equiv}} + L_{\text{size}} + L_{\text{anis}}$	2.18 ± 0.12	35.36	100.00
$L_{\text{equiv}} + L_{\text{size}} + L_{\text{anis}} + \text{MI}$	2.56 ± 0.12	99.84	100.00
$L_{\text{equiv}} + L_{\text{ref}}$	1.66 ± 0.13	33.39	100.00
$L_{\text{equiv}} + L_{\text{ref}} + L_{\text{size}}$	0.45 ± 0.29	0.00	0.00
$L_{\text{equiv}} + L_{\text{ref}} + L_{\text{size}} + L_{\text{anis}}$	0.45 ± 0.27	0.00	0.00
$L_{\text{equiv}} + L_{\text{ref}} + L_{\text{size}} + L_{\text{anis}} + \text{MI}$	0.39 ± 0.26	0.00	0.00
MI	3.63 ± 1.08	50.55	100.00
FSL flirt - MI	2.58 ± 1.21	49.22	98.08
supervised - L_{ref}	0.32 ± 0.22	0.00	0.00

Ablation study and comparison to SOTA on D_0 for our unsupervised **one step** method.

Range		Mat_{err}	θ_{90}	θ_{45}
L_{ref}	L_{equiv}			
D_0	D_0	0.41 ± 0.27	0.00	0.00
D_{shear}	D_{shear}	1.29 ± 0.68	0.00	0.00
D_{trans}	D_{trans}	2.96 ± 1.70	49.51	84.70
D_{scale}	D_{scale}	3.27 ± 0.58	83.39	83.39
D_1	D_0	20.33 ± 17.11	7.89	44.08
D_0	D_1	11.71 ± 6.06	46.71	86.68
D_1	D_1	12.08 ± 5.70	41.78	81.10

Influence of B matrix parameter range, **one step**

Method	Mat_{err}	θ_{90}	θ_{45}
1-step	12.08 ± 5.70	41.78	81.10
2-steps - MI	10.28 ± 5.59	38.98	56.09
2-steps - Frob.	1.88 ± 0.90	0.49	8.55
2-steps - Grid	3.69 ± 3.54	0.00	1.32
2-step - Frob - w. occ	4.55 ± 4.68	3.78	18.91
2-step - Grid - w. occ	3.79 ± 3.67	0.00	1.64

One Step vs Two Steps on D_1 , different losses in the second step, with/without occlusions.

Conclusion

- ▷ Equivariance is sufficient to train an affine registration network
- ▷ Future work: investigate deformable registration

References

[1] David Van Essen Kamil Ugurbil. The human connectome project, 1200 subjects data release, 2017.