



HAL
open science

Robust Unsupervised Image to Template Registration Without Image Similarity Loss

Slim Hachicha, Célia Le, Valentine Wargnier-Dauchelle, Michaël Sdika

► **To cite this version:**

Slim Hachicha, Célia Le, Valentine Wargnier-Dauchelle, Michaël Sdika. Robust Unsupervised Image to Template Registration Without Image Similarity Loss. Colloque Français d'Intelligence Artificielle en Imagerie Biomédicale, IABM, Feb 2024, Grenoble, France. hal-04531824

HAL Id: hal-04531824

<https://hal.science/hal-04531824>

Submitted on 4 Apr 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

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:

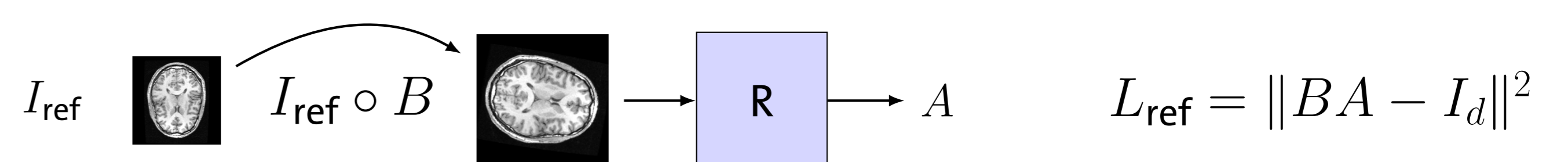
- ▷ any architecture
- ▷ a single image as input: do not create feature from unrelated voxel
- ▷ an affine matrix as output: the matrix that realigns the image in the reference space

Regularisation Loss: prevent null network

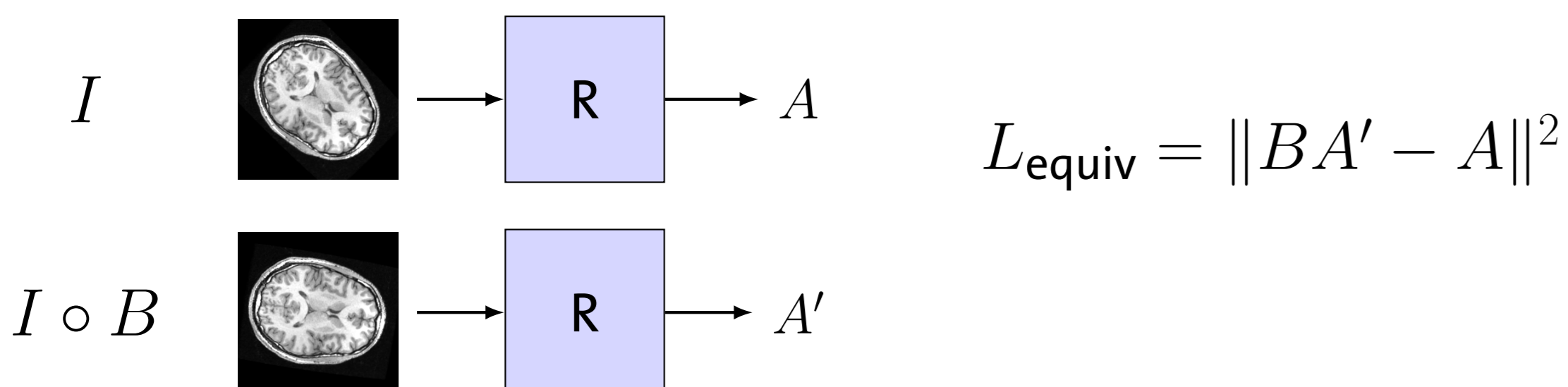
$$Ax = U\Sigma Vx + b \quad L_{\text{size}} = \text{penalize large / small } \sigma$$

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

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	$\pm 10\%$	$\pm 10\%$	$\pm 10\%$	$\pm 50\%$	$\pm 50\%$

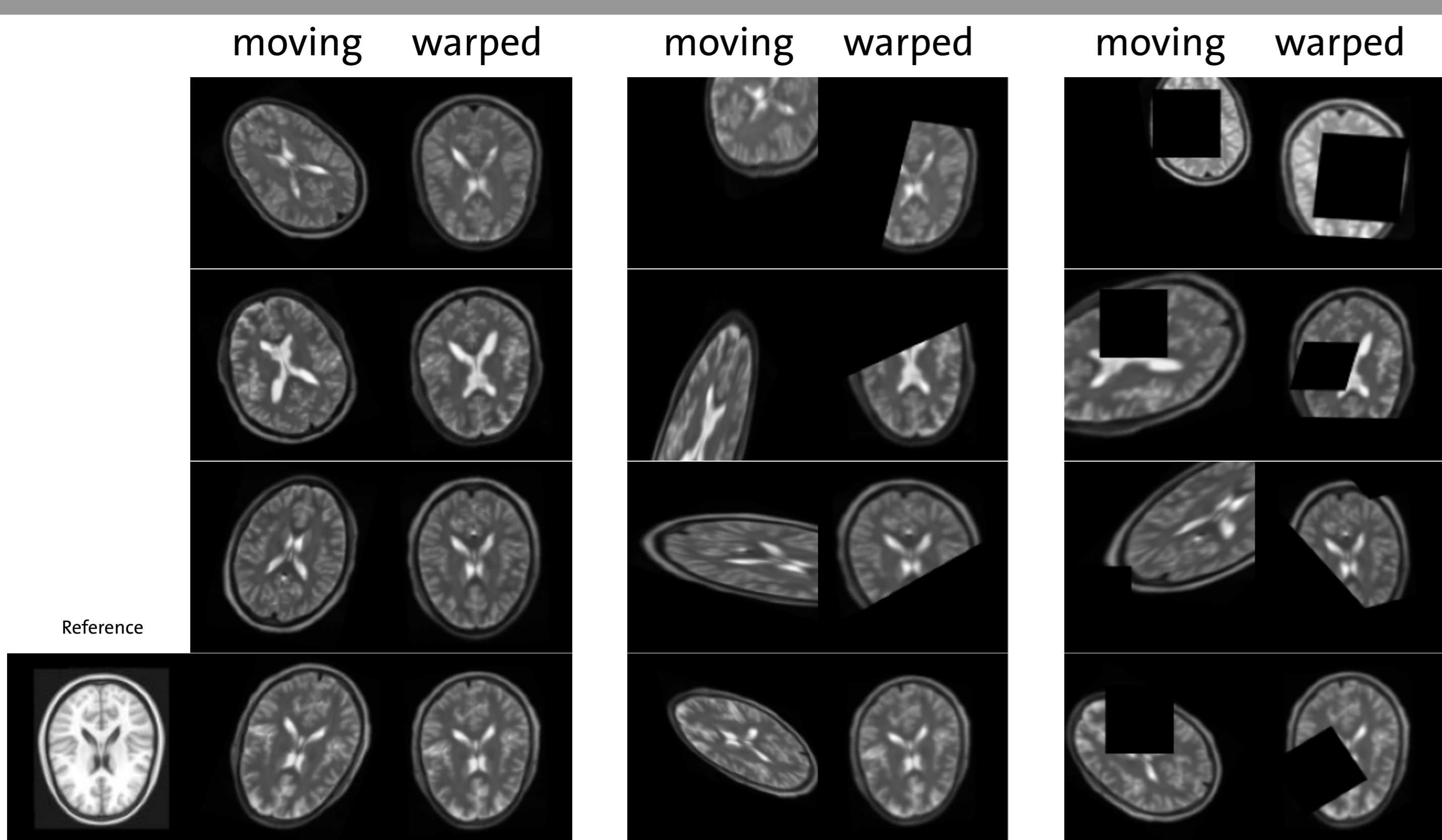
Metrics:

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

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

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.