CABLD: Contrast-Agnostic Brain Landmark Detection with Consistency-Based Regularization

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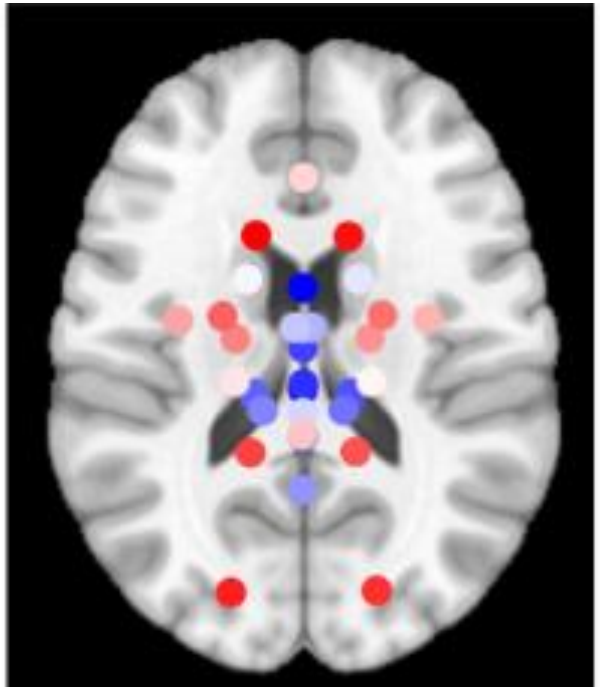
Code

Paper

Introduction

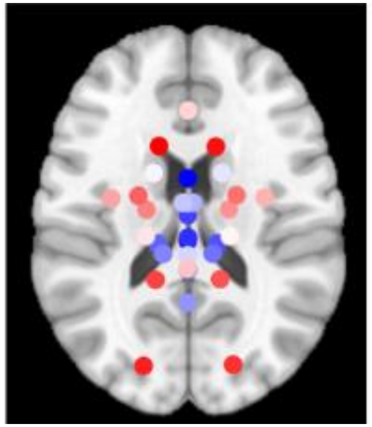
- **Brain MRI landmarks** are instrumental tools for neurological disease diagnosis, surgical planning, and image registration quality control.
- Existing deep learning (DL) landmark methods often depend on **large annotated data**, but expert labeling is slow, costly, and scarce.
- **Cross-scanner/contrast variability** (e.g., T1w vs T2w, different field strengths) degrades performance in many prior approaches.
  - ✓ Previous works rely on costly metrics (e.g., Mutual Information) or multi-contrast training data
  - ✓ Multi-contrast data are scarce & contrast synthesis needs dense segmentations



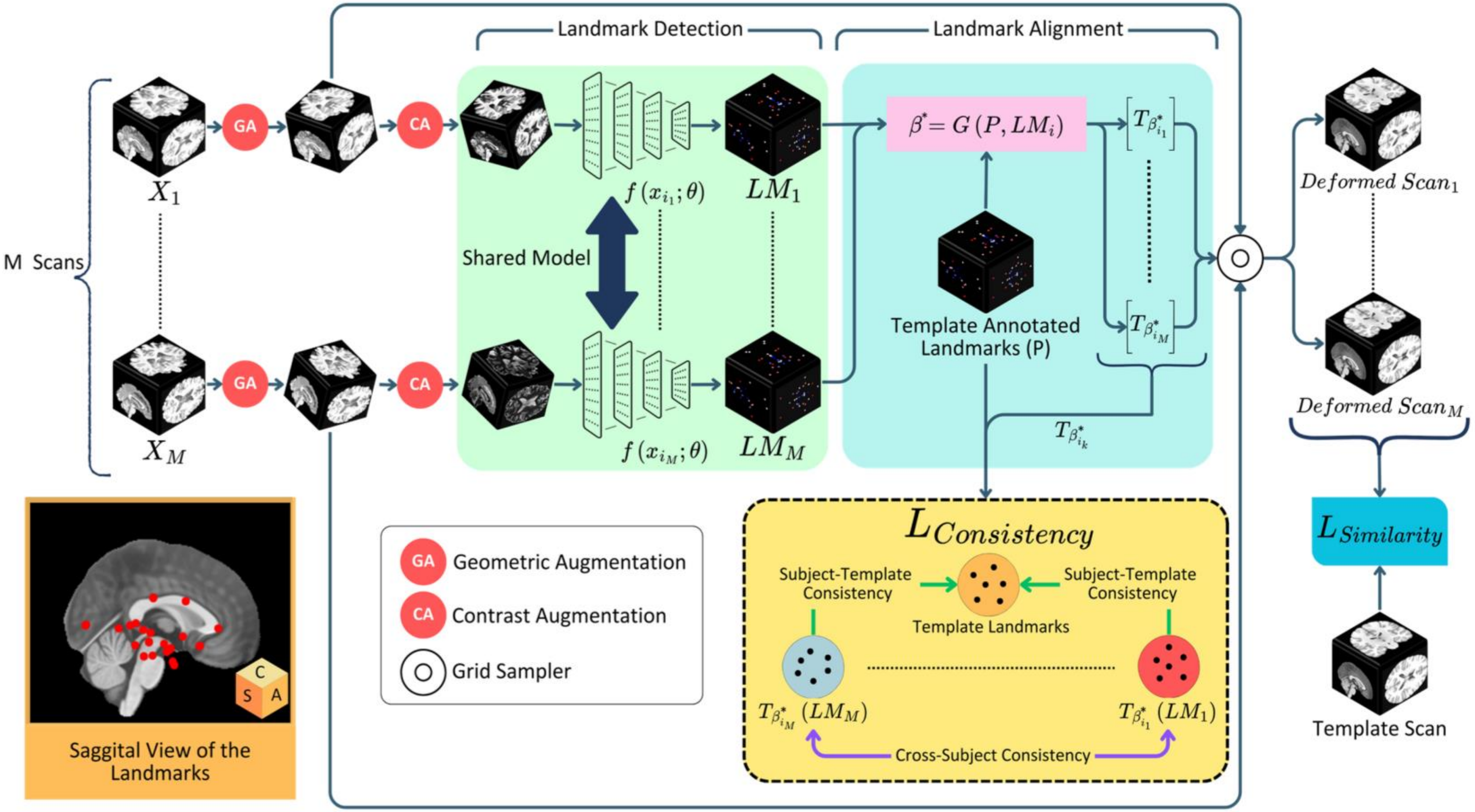
AFIDs landmarks on the MNI ICBM152-sym template

CABLD framework Overview

We proposed **CABLD,** a self-supervised framework that learns 3D brain landmarks from unlabeled scans using only **a single annotated template**.



Annotated template



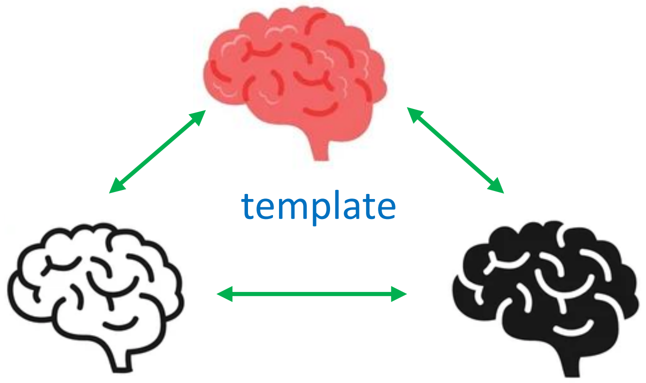
Overview of CABLD framework

CABLD Key Components

- **Consistency-Based Regularization $L_{consistency}$**
  - ✓ Inter-subject and subject-template consistency losses with a registration loss $L_{Registration}$ to enforce anatomical consistency for landmark detection with a single template annotation.

$$\mathcal{L}_{\text{consistency}_1} = \frac{1}{\binom{M}{2}} \sum_{1 \le r < j \le M} \left\| T_{\beta^*_{i_r}}(\boldsymbol{f}(x_{i_r};\theta)) - T_{\beta^*_{i_j}}(\boldsymbol{f}(x_{i_j};\theta)) \right\|_2$$

$$\mathcal{L}_{\text{consistency}_2} = \frac{1}{M} \sum_{k=1}^{M} \left\| T_{\beta^*_{i_k}}(\boldsymbol{f}(x_{i_k};\theta)) - \mathbf{P} \right\|_2$$



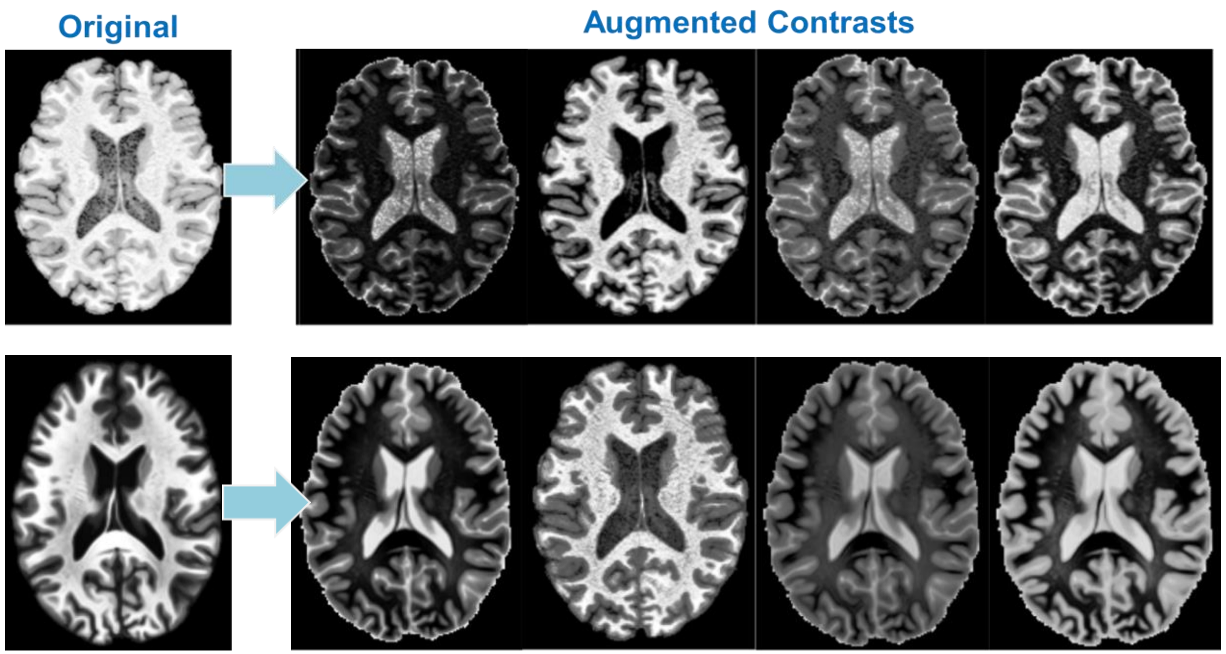
$$\boxed{\mathcal{L}_{\text{registration}} = \frac{1}{M} \sum_{k=1}^{M} \mathcal{L}_{\text{sim}}\left(x_{i_k} \circ T_{\beta^*_{i_k}}, I_{\text{template}}\right)}$$

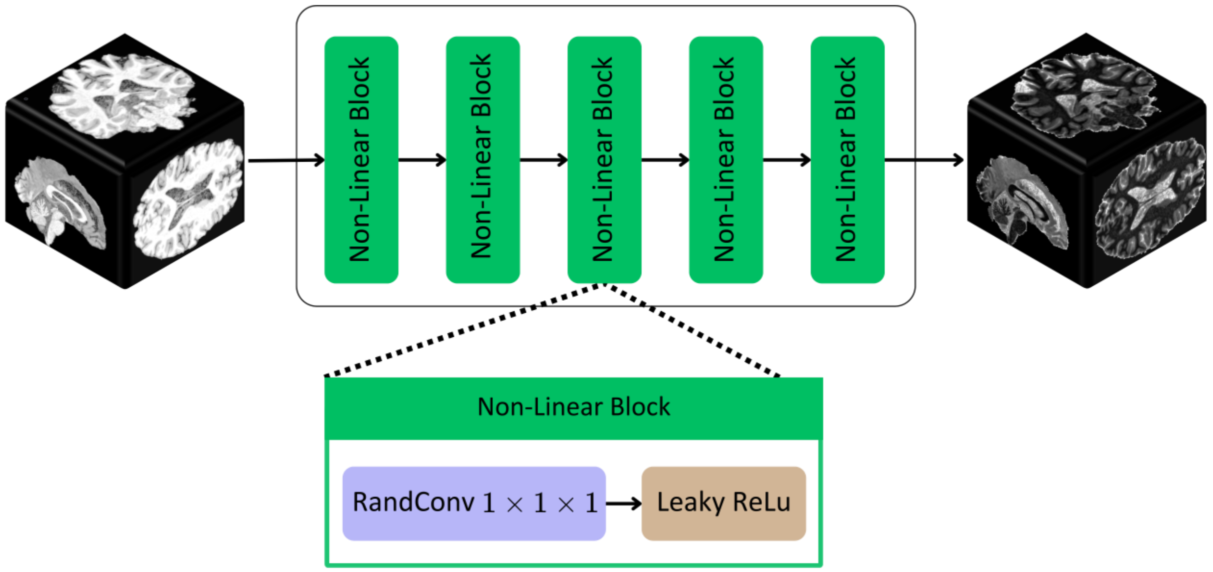
$$\boxed{\mathcal{L}_{\text{consistency}} = \mathcal{L}_{\text{consistency}_1} + \mathcal{L}_{\text{consistency}_2}}$$

$$\mathcal{L}_{\text{total}} = (1-\alpha)\mathcal{L}_{\text{registration}} + \alpha\mathcal{L}_{\text{consistency}} \qquad \alpha = \frac{2}{1+\exp(-5\eta)} - 1 \qquad \eta = \frac{\textit{current training iteration}}{\textit{total training iterations}}$$

3D Contrast Augmentation

To generalize the model across unseen MRI contrasts, **CABLD** uses novel **3D random convolution** to augment MRI contrasts, without needing multi-contrast training data.





Datasets & Evaluation Metrics

- **Training MRI data (no landmarks):** 1544 brain MRIs (3T & 7T) from IXI, AHEAD, HCP-Aging, OpenNeuro repository datasets.
- **AFIDs brain landmark dataset (testing set):** 122 brain MRIs, each with 32 landmarks, from the HCP (T1w & T2w), OASIS-1, and SNSX datasets.
- **Brain MRI template (with AFIDs landmarks):** T1w MNI ICBM152-sym MRI template.

Landmark Detection Accuracy Metrics

- **Mean Radial Error (MRE):** Average Euclidean distance between predicted and ground truth landmarks.
- **Success Detection Rate (SDR)**: Percentage of predictions within accuracy thresholds.

Results

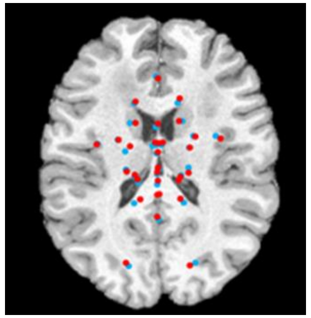
- Validated on 3 diverse datasets (3T & 7T, T1w MRIs), **CABLD** achieves **SOTA accuracy**

Method	HCP T1w			OASIS			SNSX		
	MRE (mm) ↓	SDR (3mm) ↑	SDR (6mm) ↑	MRE (mm) ↓	SDR (3mm) ↑	SDR (6mm) ↑	MRE (mm) ↓	SDR (3mm) ↑	SDR (6mm) ↑
3D SIFT (-)	39.44 ± 31.02	5.72%	20.62%	39.08 ± 29.70	3.70%	17.71%	41.67 ± 31.84	4.52%	17.13%
NiftyReg (NMI)	4.43 ± 2.42	25.00%	81.25%	8.23 ± 3.29	1.85%	22.69%	9.61 ± 4.03	0.43%	12.71%
ANTs (CC)	3.85 ± 2.26	36.97%	89.16%	4.38 ± 2.64	29.39%	81.25%	6.36 ± 3.28	10.88%	49.78%
ANTs (MI)	3.65 ± 2.29	45.52%	92.29%	4.15 ± 2.65	38.88%	85.38%	6.06 ± 3.22	18.75%	54.43%
KeyMorph (64 KPs, Dice)	8.05 ± 4.51	10.93%	38.43%	8.20 ± 4.64	10.30%	36.57%	9.73 ± 5.35	6.03%	31.35%
KeyMorph (128 KPs, Dice)	5.77 ± 2.91	13.95%	58.43%	6.41 ± 3.41	13.31%	51.62%	8.99 ± 4.16	3.66%	25.43%
KeyMorph (256 KPs, Dice)	5.37 ± 3.12	20.83%	66.04%	6.44 ± 3.81	12.61%	55.20%	8.80 ± 5.22	7.65%	35.56%
KeyMorph (512 KPs, Dice)	4.67 ± 2.47	23.30%	78.12%	7.15 ± 3.63	6.82%	40.97%	5.77 ± 3.27	18.10%	60.66%
BrainMorph (MSE+Dice)	4.11 ± 2.30	31.35%	86.15%	5.28 ± 3.07	17.36%	74.31%	13.66 ± 18.21	14.66%	41.38%
uniGradICON (LNCC)	4.12 ± 2.53	34.38%	84.06%	4.63 ± 3.00	30.09%	76.97%	5.27 ± 3.53	29.53%	70.63%
MultiGradICON (LNCC^2)	4.10 ± 2.56	34.90%	84.17%	4.62 ± 3.01	30.79%	77.89%	5.21 ± 3.40	28.68%	70.84%
Fully Supervised 3D CNN (-)	4.65 ± 2.40	24.27%	72.81%	4.53 ± 2.81	25.00%	79.28%	6.64 ± 3.86	12.61%	52.26%
CABLD (Ours, MSE)	**3.27 ± 2.24**	**54.48%**	**93.69%**	**3.89± 2.69**	**39.24%**	**87.15%**	**5.11 ± 3.19**	**29.63%**	**71.01%**

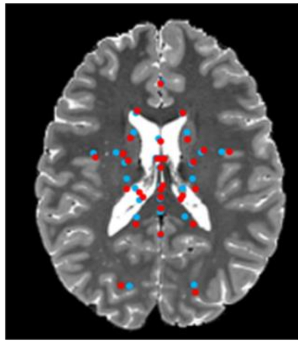
CABLD and baseline methods performance on three different T1w MRI datasets

Results

- **CABLD** is robust against unseen MRI contrasts (T2w HCP MRIs)



T1w [Trained]



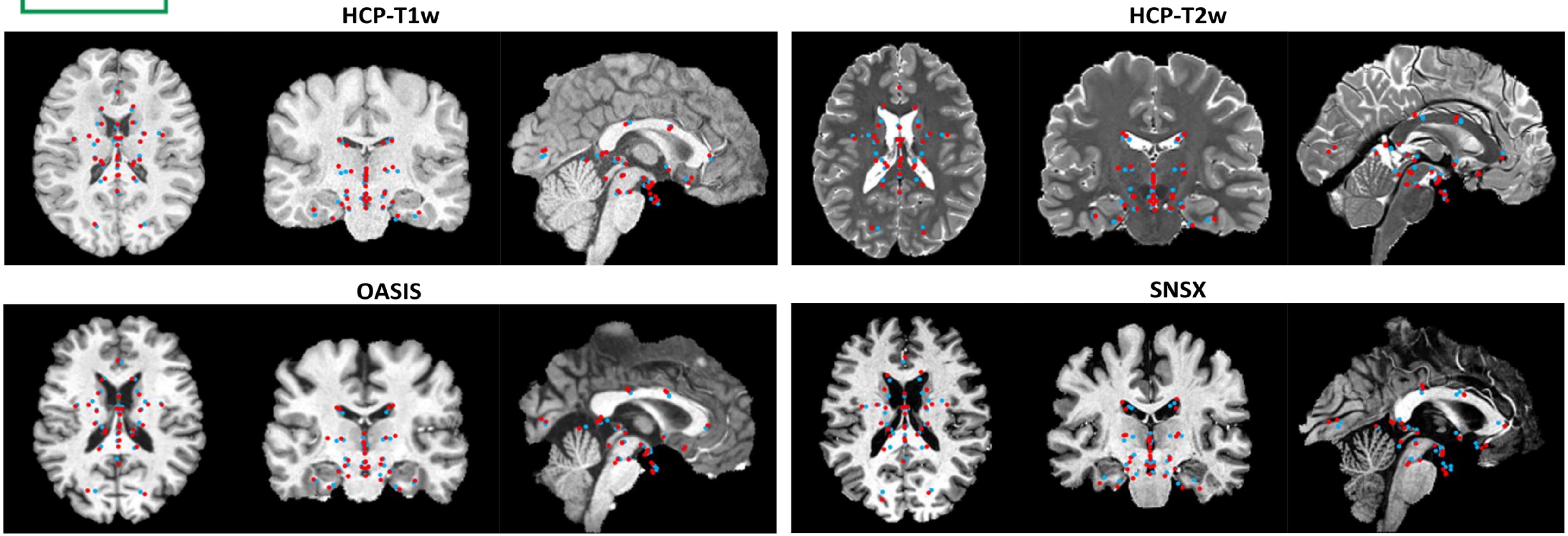
T2w [Tested]

Method	MRE (mm) ↓	SDR (3mm) ↑	SDR (6mm) ↑
3D SIFT (-)	54.90 ± 24.51	0.00%	0.73%
NiftyReg (NMI)	4.40 ± 2.41	25.50%	82.25%
ANTs (MI)	**3.91 ± 2.19**	**35.00%**	84.27%
KeyMorph (64 KPs, Dice)	6.00 ± 2.64	11.87%	52.08%
KeyMorph (128 KPs, Dice)	8.66 ± 4.29	5.93%	28.64%
KeyMorph (256 KPs, Dice)	6.41 ± 3.06	8.65%	51.56%
KeyMorph (512 KPs, Dice)	5.54 ± 3.31	22.18%	64.06%
BrainMorph (MSE+Dice)	4.24 ± 2.43	32.71%	82.19%
uniGradICON (LNCC)	13.44 ± 3.88	0.42%	3.33%
MultiGradICON ($LNCC^2$)	4.31 ± 2.70	33.33%	81.83%
CABLD (Ours, MSE)	**3.99 ± 2.25**	27.19%	**86.43%**

Performance on an unseen T2w MRI dataset

Results

Visual demonstration [3D landmarks are projected to 2D]



Ablation Studies: Different Components Impact

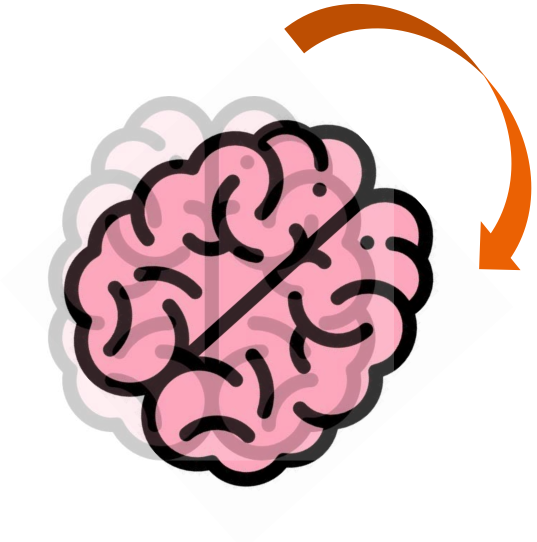
- Ablation Studies to reveal impacts of different components in CABLD
  - ✓ Adding consistency loss significantly improved MRE
  - ✓ Random convolution further enhanced generalization across unseen contrasts (T2w MRI)

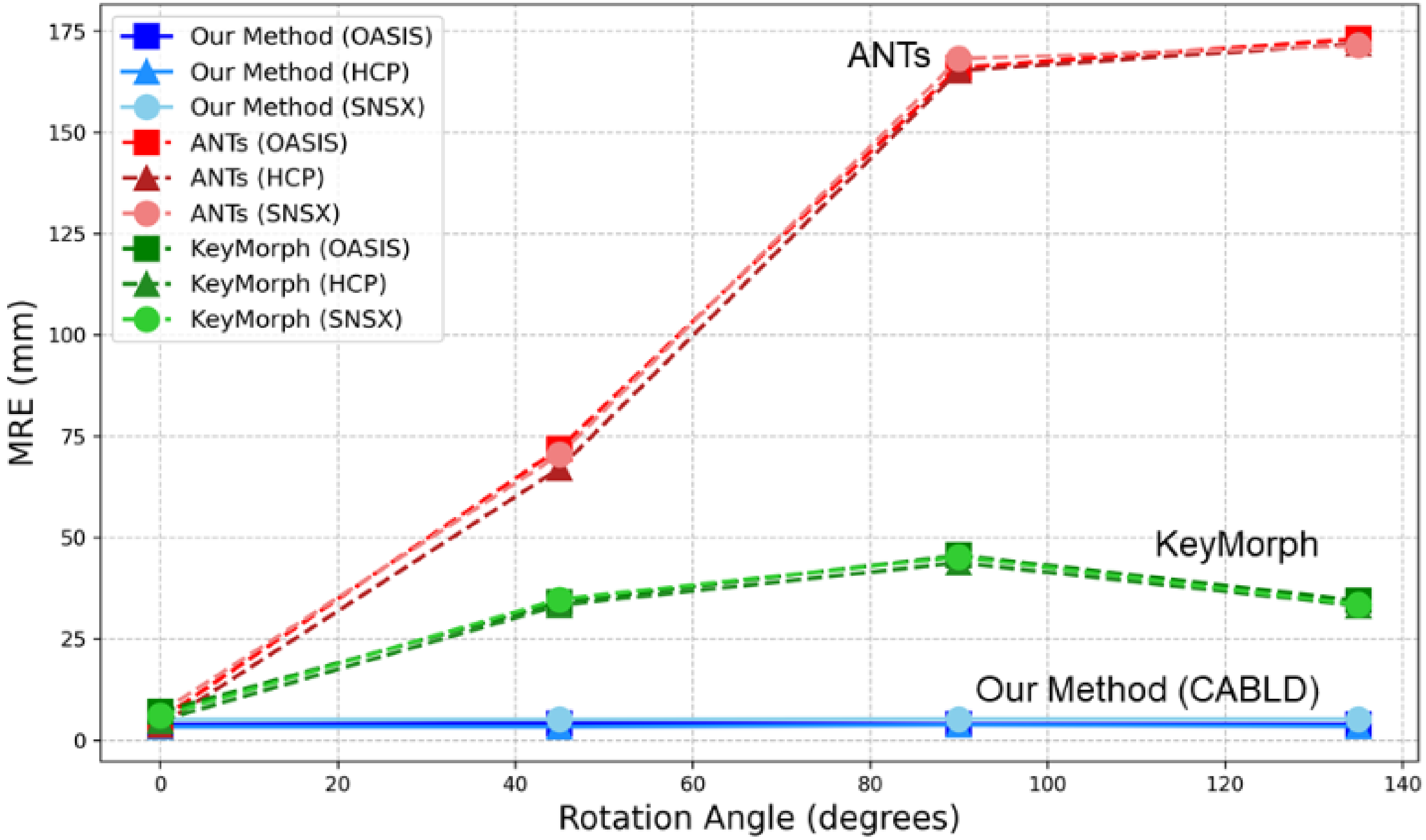
Methods	**HCP-T1w**	**OASIS**	**SNSX**	**HCP-T2w**
Base Model	53.69 ± 25.63	55.02 ± 25.68	53.11 ± 29.18	59.79 ± 26.39
$+\mathcal{L}_{consistency}$	3.70 ± 2.41 (-49.99)	4.03 ± 2.69 (-50.99)	6.43 ± 3.64 (-46.68)	45.90 ± 17.77 (-13.89)
+ Random Convolution	3.27 ± 2.24 (-0.43)	3.89 ± 2.69 (-0.14)	5.11 ± 3.59 (-1.32)	3.99 ± 2.25 (-41.91)

Impact of different components of CABLD on MRE

Ablation Studies: Robustness Test

- Robustness against random rotations (common in MRI acquisition)
  - ✓ Maintained high accuracy under augmented rotational misalignments





Age Robustness & Downstream Tasks

- **Robustness against age-related anatomical variations**
  - Performance across different age groups analyzed:
    - ✓ 20–40 years: MRE = 3.65 ± 1.56 mm
    - ✓ 40–60 years: MRE = 4.38 ± 2.00 mm
    - ✓ 60–90 years: MRE = 4.38 ± 0.81 mm
  - ANOVA test showed no significant group-wise difference ($p = 0.07$)

- **CABLD-generated inter-landmark distances for brain disease biomarkers**
  - Support vector machines on 10-fold cross-validation.
  - Detection of **Parkinson's disease** (PPMI dataset): F1 score = 81.2 ± 8.8%
  - Detection of **Alzheimer's disease** (ADNI dataset): F1 score = 93.5 ± 6.3%