NEURAL INFORMATION PROCESSING SYSTEMS

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BrainODE: Neural Shape Dynamics for Age- and Disease-aware Brain Trajectories

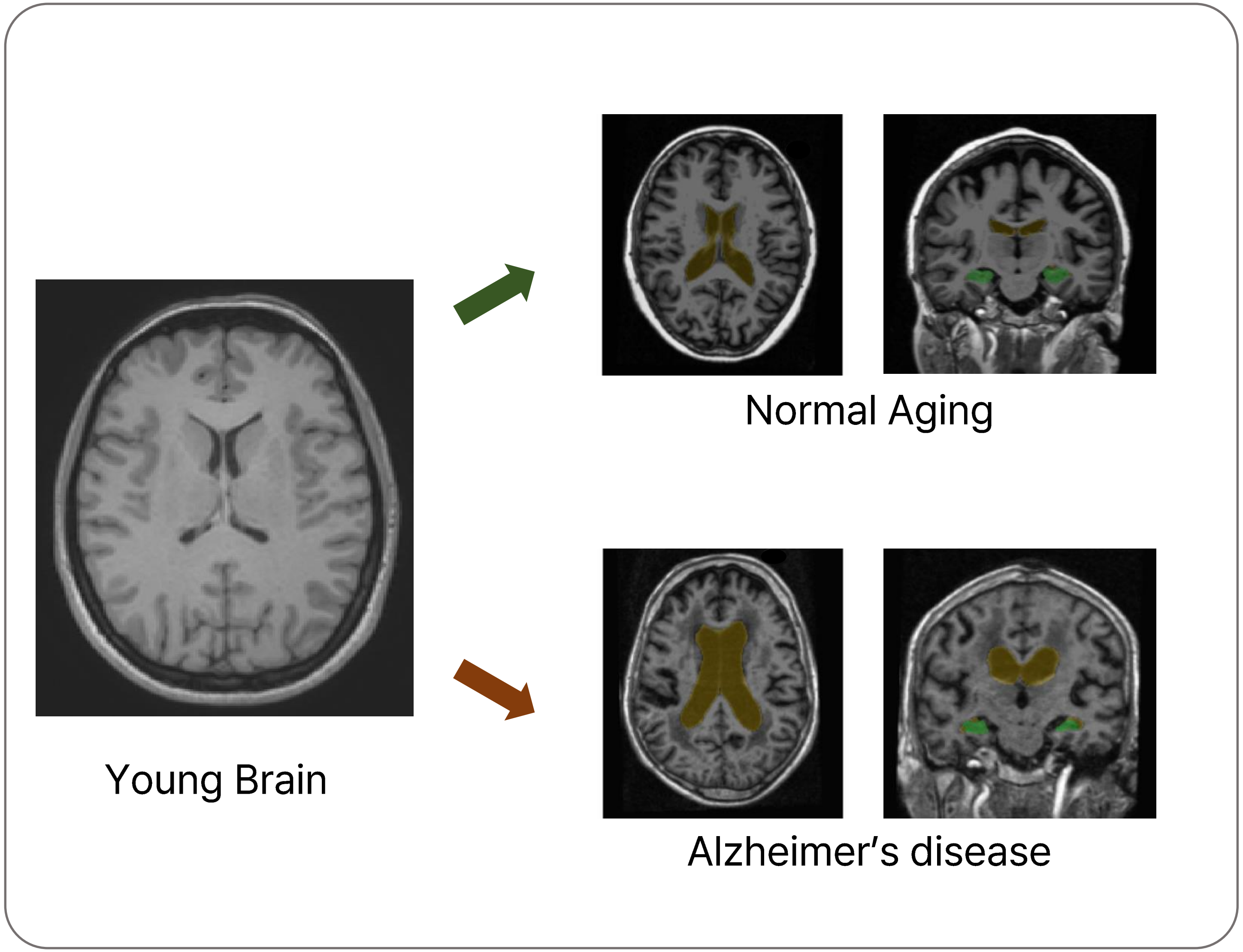
Wonjung Park[1]
Suhyun Ahn[1]
Maria C. Valdes Hernandez[2]
Susana Muñoz Maniega[2]
Jinah Park[1]

[1]Korea Advanced Institute of Science and Technology (KAIST)

[2]The University of Edinburgh

Computer Graphics & Visualization Lab

Brain shape alterations over aging



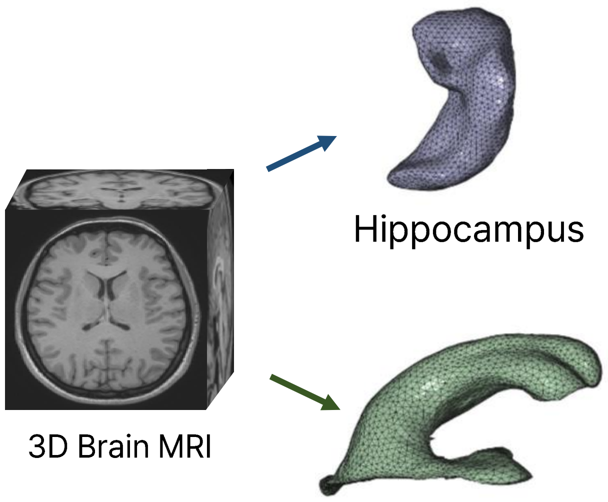
Brain atrophy during aging is more pronounced in subjects with neurodegenerative disease

e.g, **large LV & small hippocampus** of the subjects with Alzheimer's disease

Research Question

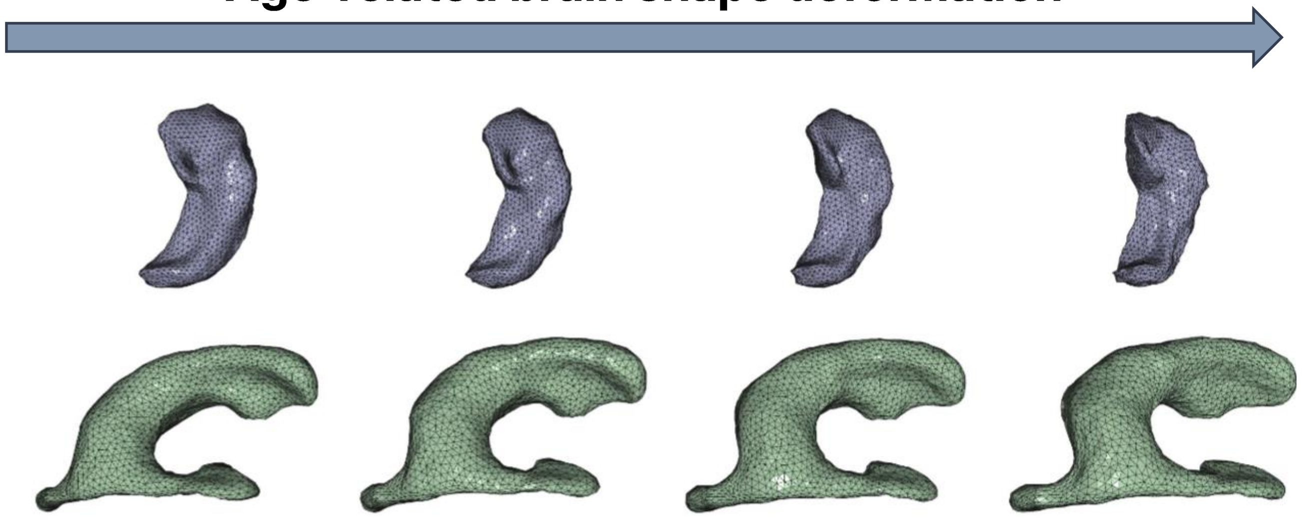
Brain subregions (lateral ventricle & hippocampus) are important biomarkers in Alzheimer's disease.

Q. Can we predict individual brain shape trajectory?



Individual present brain shapes

Age-related brain shape deformation



Predicted future brain shapes

Research Problem

Challenges in longitudinal prediction

1) Data deficiency which requires **effective data representation** to learn dynamics
2) Varied subject **ages and irregular time intervals** between observations
3) Influence of **medical priors**: Demographic & clinical conditions affecting shapes
4) Practical use case to predict future shapes **from a single observation** (where extrapolation methods are not applicable)

For time-series data

RNN-, NeuralODE-, Flow-based and generative approaches

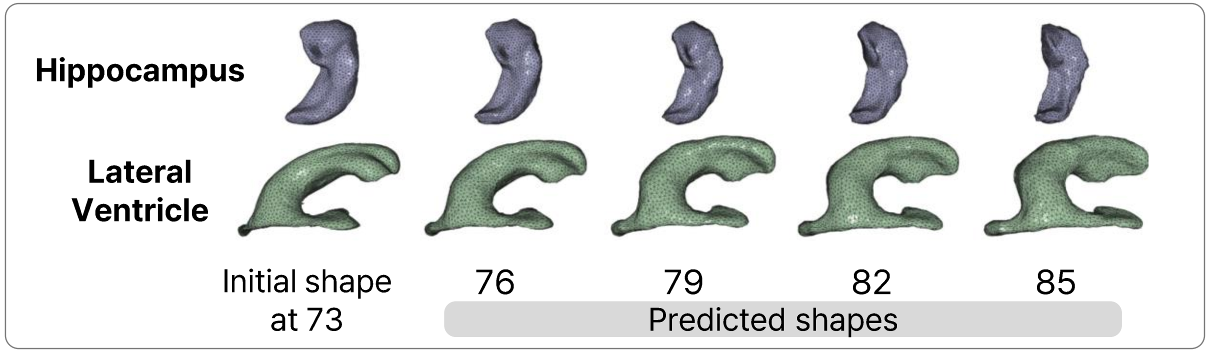
→ ✗ Did not deal with above challenges at scale

Method

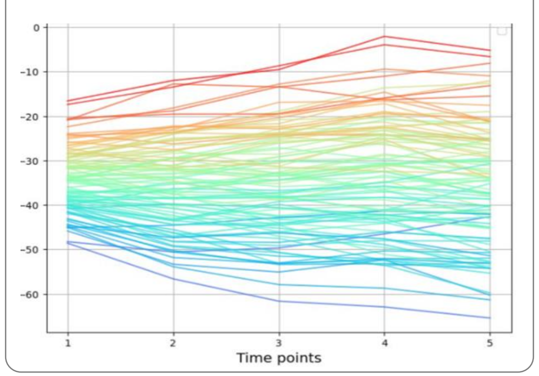
BrainODE: NeuralODE for brain shape dynamics

- Modeling brain 3D shape parameters dynamics with NeuralODE

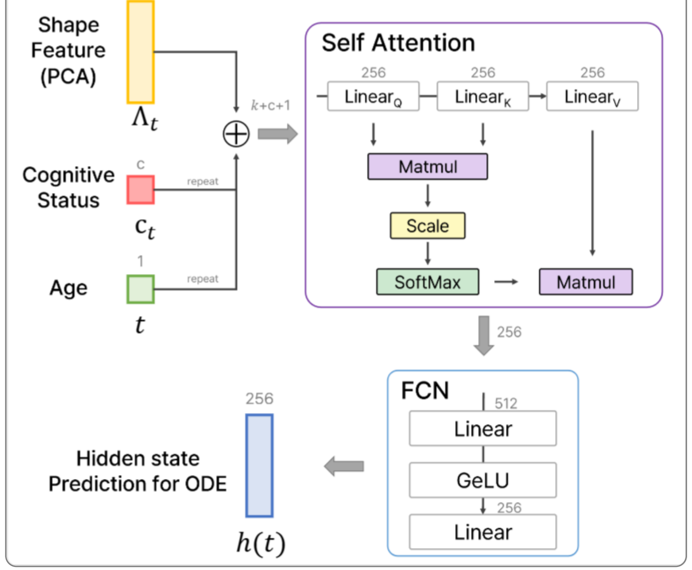
- BrainODE $f_\theta(\Lambda_t, c_t, t) = \frac{d\Lambda_t(c_t, t)}{dt}.$
  - **Deformation** at the age of **t** and cognitive status **c** from the shape $\boldsymbol{\Lambda_t}$
    - $t \in [0,1]$: normalized ages in range [65, 95]
    - $c_t \in [0,1]$: cognitive status, where NC=0, AD=1
    - Λ_t: shapes in PCA coefficients
  - Predicted shapes $\Lambda_{t+\Delta t} = \Lambda_t + \int_t^{t+\Delta t} f_\theta(\Lambda_t, c_t, t)dt.$



Longitudinal flows of the first shape PCA parameter



BrainODE f_θ

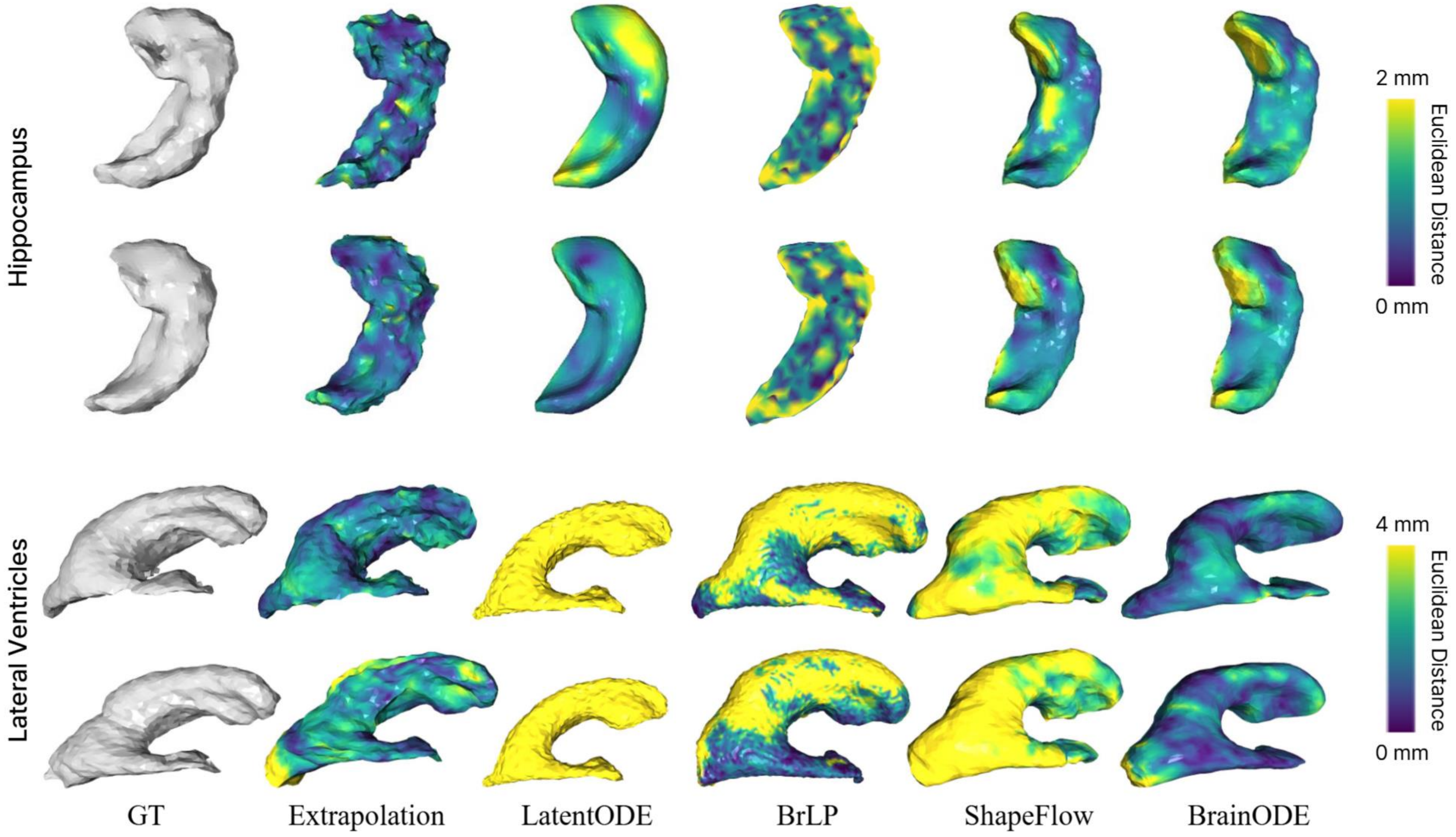


Results

Prediction results comparison

Quantitative results in shape alignment (mm)

Method	LBC ↓		AIBL ↓	
	hippo	LV	hippo	LV
Linear extrap.	0.737	2.075	0.666	2.013
RNN	1.060	5.528	0.964	5.561
LSTM	1.044	5.723	0.957	6.745
RNN-Decay	1.075	5.549	0.967	5.587
ShapeFlow	0.652	7.112	0.776	3.149
LatentODE	0.880	5.759	1.126	8.095
BrLP	1.078	2.230	1.019	1.893
Ours	**0.488**	**1.630**	**0.461**	**1.635**

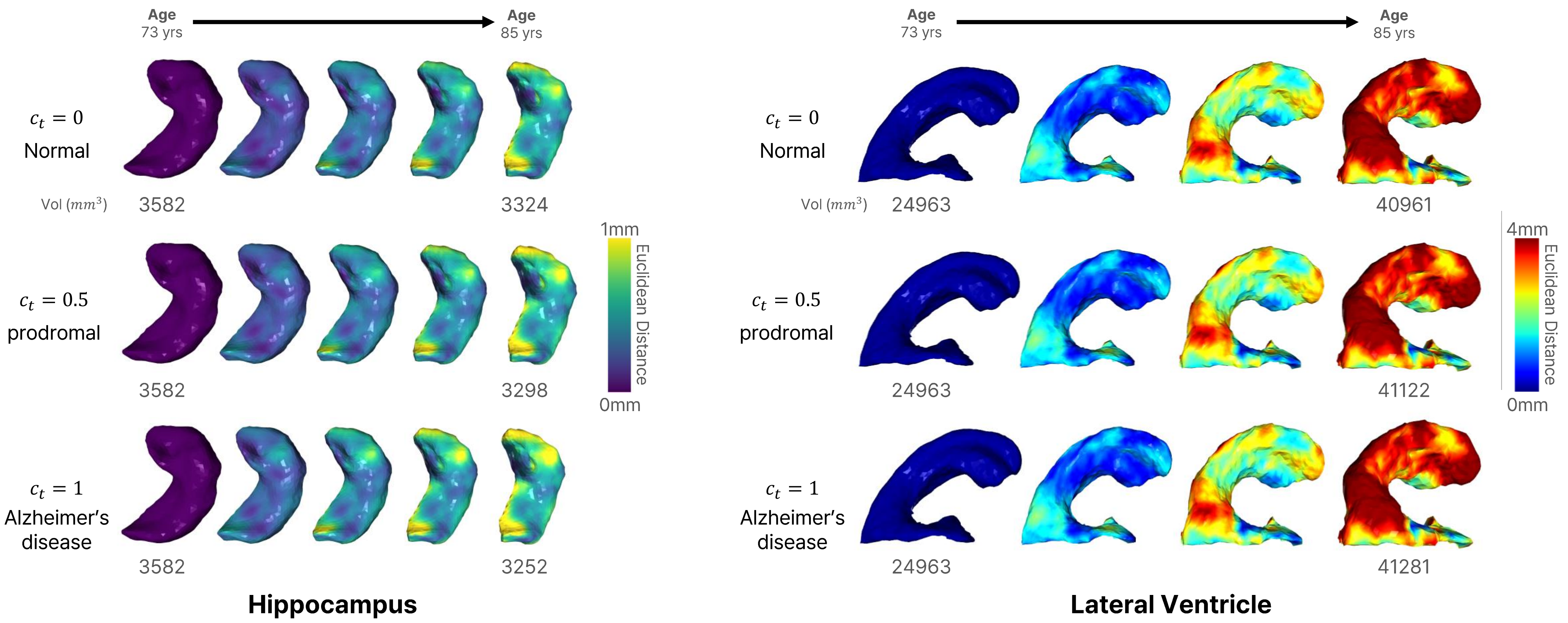


- **BrainODE** (ours)
  - Best alignment with GT
  - Preserves individual local details
- Linear Extrapolation
  - Bumpy and noisy
- RNN- methods
  - Trivial solutions
- Latent ODE
  - Trivial solutions
- BrLP
  - Image generation-based
  - Often loses local details
  - Accuracy↓ in small brain areas
- ShapeFlow
  - Handles only regular intervals
  - Accuracy↓ due to ignoring age factors

Additional results

Condition fidelity of BrainODE

Starting from the same shape sample, BrainODE infers greater brain atrophy with lower cognition, consistent with medical prior knowledge (i.e., smaller hippocampus & enlarged lateral ventricles).



Conclusion

Summary

1) Bridged **neural ODE–based** 3D shape modeling with **longitudinal neurodegenerative disease prediction**.
2) Conducted the first **large-scale study of longitudinal brain** shape dynamics across age and multi-site datasets.
3) **Identified and addressed core challenges in longitudinal shape modeling** within a unified framework.

Future works

1) Extend BrainODE to **broader cognitive categories**, including the NC–MCI–AD continuum.
2) Explore advanced **n-shot aggregation methods** for subjects with multiple prior observations.
3) Generalize BrainODE to **additional brain regions** and apply to early diagnosis task.

Acknowledgement

Contact Information

Wonjung Park

fabiola@kaist.ac.kr
fabiola32768@gmail.com

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