Unifying Brain Age Prediction and Age-Conditioned Template Generation with a Deterministic Autoencoder

Pauline Mouches[1, 2], Matthias Wilms[1, 3], Deepthi Rajashekar[1, 2], Sönke Langner[4], Nils D. Forkert[1, 3]

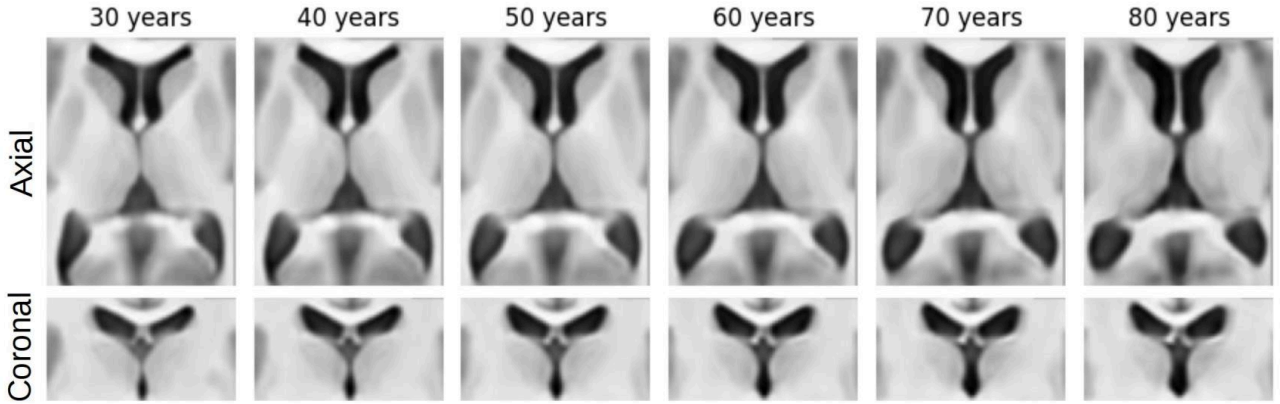
[1]Department of Radiology and Hotchkiss Brain Institute, University of Calgary, Canada. [2]Biomedical Engineering Program, University of Calgary, Canada. [3]Alberta Children's Hospital Research Institute, University of Calgary, Canada. [4]Institute for Diagnostic Radiology and Neuroradiology, Rostock University Medical Center, Germany.

Contact: pauline.mouches@ucalgary.ca

Code: https://github.com/pmouches/Brain-Age-Prediction-and-Age-Conditioned-Template-Generation

Introduction

Age-related morphological brain changes are different in healthy and disease affected aging. Biological brain age estimation from magnetic resonance imaging (MRI) scans is a common way to quantify this effect whereas an estimated biological brain age significantly older than the chronological age is an indicator for neurodegenerative diseases [1]. Several machine learning brain age estimation models have been recently developed; however, they don't allow to visualize age-specific morphological changes on the MRI scans directly. **The aim of this work was to develop a novel deep-learning based approach to unify biological brain age estimation and age-conditioned template creation in a single model.**



Generated age-conditioned templates (30-80 years)

[1] Cole, James H., et al. Trends in neurosciences 40.12 (2017): 681-690.

Material and Methods

Training data:

1918 T1-weighted brain MRI scans of predominantly healthy adults (1029 males, 1089 females) aged between 21 and 82 years (mean: 51±14) collected in the Study of Health in Pomerania [2].

Preprocessing:

- Affine registration to a common space.
- Patch cropping around the ventricles.

→ Reduces the computational time, resources, and number of datasets needed to train the model; the aging effects are highly visible in the ventricles.

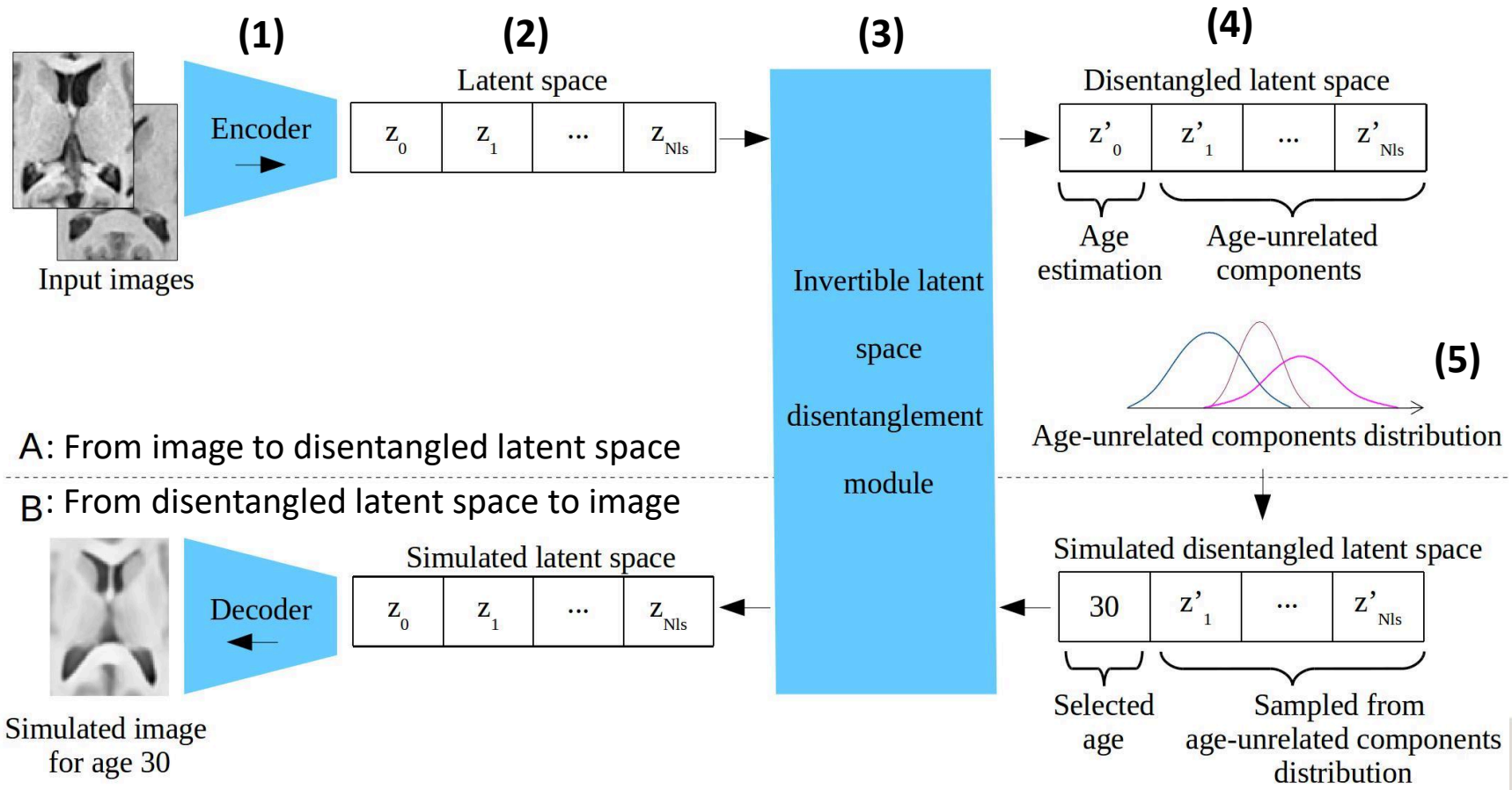
Model:

The model use a deterministic autoencoder that successfully disentangles the age-related morphological brain changes from the age-unrelated changes.

The unified model:

- Non-linearly maps the MRI scans to a low dimensional latent space **(2)** using an autoencoder **(1)**.
- Isolate the age-related component, representing the biological brain age **(4)** from the low dimensional latent space representations, using an invertible module **(3)**.

A Gaussian mixture model **(5)** estimates the distribution of the age-unrelated components. Synthetic age-unrelated components can be sampled from it.

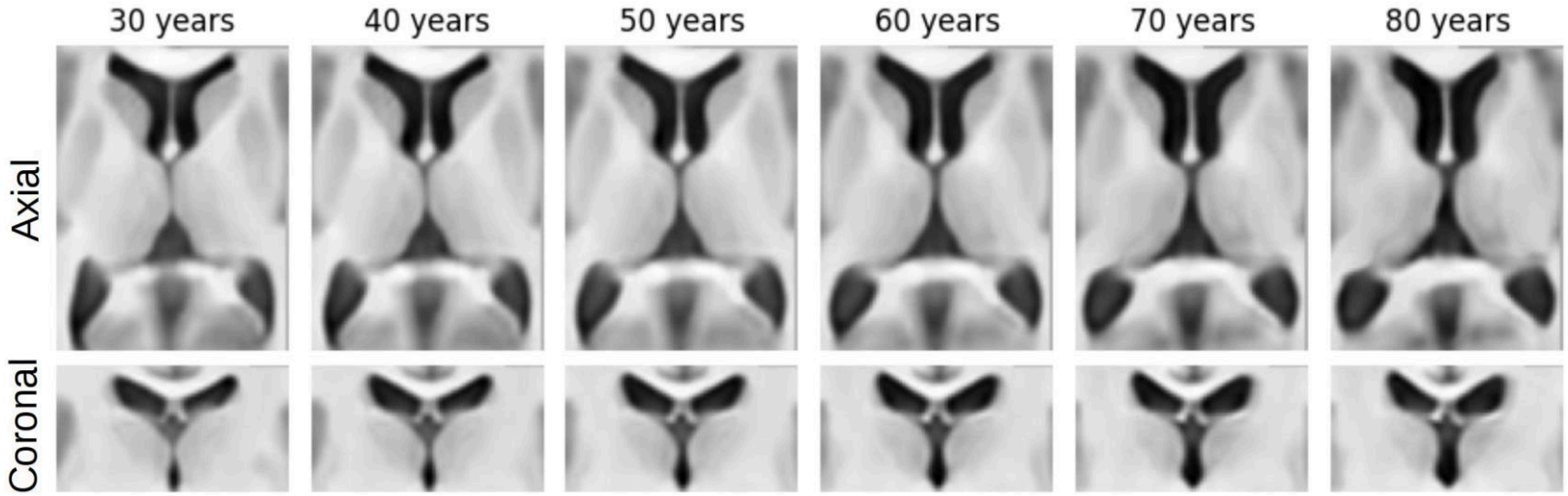


[2] Völzke Henry, et al. International journal of epidemiology, 40.2, (2011): 294-307

Results

Age-conditioned templates:

Age-unrelated components from the disentangled latent space representations of the training datasets were averaged, the age component was set to different values and the MRI scans were reconstructed. The resulting age-specific templates show natural age-related shape variations with a non-linear increased ventricular volume with aging.



Brain age prediction:

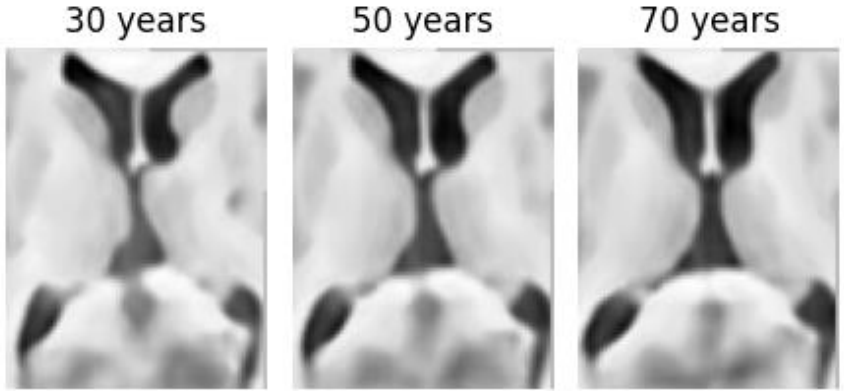
SHIP: 200 hold out datasets.

IXI [3]: Database of 563 healthy adults (20 to 86 years) used as an independent test set.

Model	MAE		R^2	
	SHIP	IXI	SHIP	IXI
Invertible NN [4]	5.05	6.95	NA	NA
Baseline CNN [5]	5.25	8.52	0.756	0.698
Ours	**4.95**	**6.97**	**0.780**	**0.758**

Simulated images and subject-specific aging:

Age-unrelated components were sampled from the Gaussian mixture model and the age component was set to different values. The simulated images show natural age-related changes and subject-specific features remain unchanged.



Conclusion

- The proposed approach achieves results comparable to state-of-the-art methods for brain age prediction.
- The model allows to visualize age-related changes on MRI scans.
- These results contribute to improve the understanding of healthy brain aging.

[3] https://brain-development.org/ixi-dataset/; [4] Wilms, Matthias, et al. Machine Learning in Clinical Neuroimaging and Radiogenomics in Neuro oncology Springer, Cham, (2020): 23-33; [5] Cole, James H et al. NeuroImage, 163, (2017): 115-124