Localized compression of grey matter maps for age prediction in healthy and clinical populations

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Authors:

Sarah Genon[1], Deepthi Varikuti[2], Aristeidis Sotiras[3], Holger Schwender[4], Felix Hoffstaedter[5], Kaustubh Patil[6], Christiane Jockwitz[7], Svenja Caspers*[8], Susanne Moebus[9], Katrin Amunts[10], Christos Davatzikos[11], Simon Eickhoff[12]

Institutions:

[1]Institute of Neuroscience and Medicine (INM-7), Research Center Jülich, Jülich, DEUTSCHLAND, [2]Institute of Neuroscience and Medicine (INM-7), Research Center Jülich, Jülich, Germany, [3]University of Pennsylvania, Philadephia, United States, [4]Mathematical Institute, Heinrich Heine University Düsseldorf, Düsseldorf, Germany, [5]Research Centre Jülich, INM-7, Jülich, Germany, [6]Heinrich-Heine University, Düsseldorf, Germany, [7]Institute of Neuroscience and Medicine - 1, Research Center Juelich, Juelich, Germany, [8]Institute of Neuroscience and Medicine (INM-1), Research Centre Juelich, Juelich, Germany, [9]6Institute of Medical Informatics, Biometry and Epidemiology, University of Duisburg-Essen, Essen, Germany, [10]Research Centre Jülich, Jülich, Germany, [11]University of Pennsylvania, Philadelphia, PA, [12]Institute of Systems Neuroscience, Heinrich-Heine University, Düsseldorf, Germany

First Author:

Sarah Genon - Lecture Information | Contact Me
Institute of Neuroscience and Medicine (INM-7), Research Center Jülich
Jülich, DEUTSCHLAND

Introduction:

With aging brain structure undergoes substantial changes, which are modulated by many factors and are aggravated in brain pathology. The relationship between grey matter volume (GMV) patterns and age can be captured by multivariate pattern analysis, allowing prediction of individuals' age based on structural imaging. In this aim, raw data, voxel-wise GMV and non-sparse factorization (with principal component analysis, PCA) show good performance, but do not promote spatially localized brain components for post-hoc examinations[1, 2]. Here we evaluated a non-negative matrix factorization (NMF) approach[3] to provide a reduced, but also interpretable representation of GMV in age prediction frameworks. We first investigated whether such data reduction can provide comparable performance with PCA. We then examined the convergence of the NMF spatial partition schemes with a parcellation based on functional MRI (fMRI) and the prediction performance of both representations for age prediction in population-based and clinical frameworks.

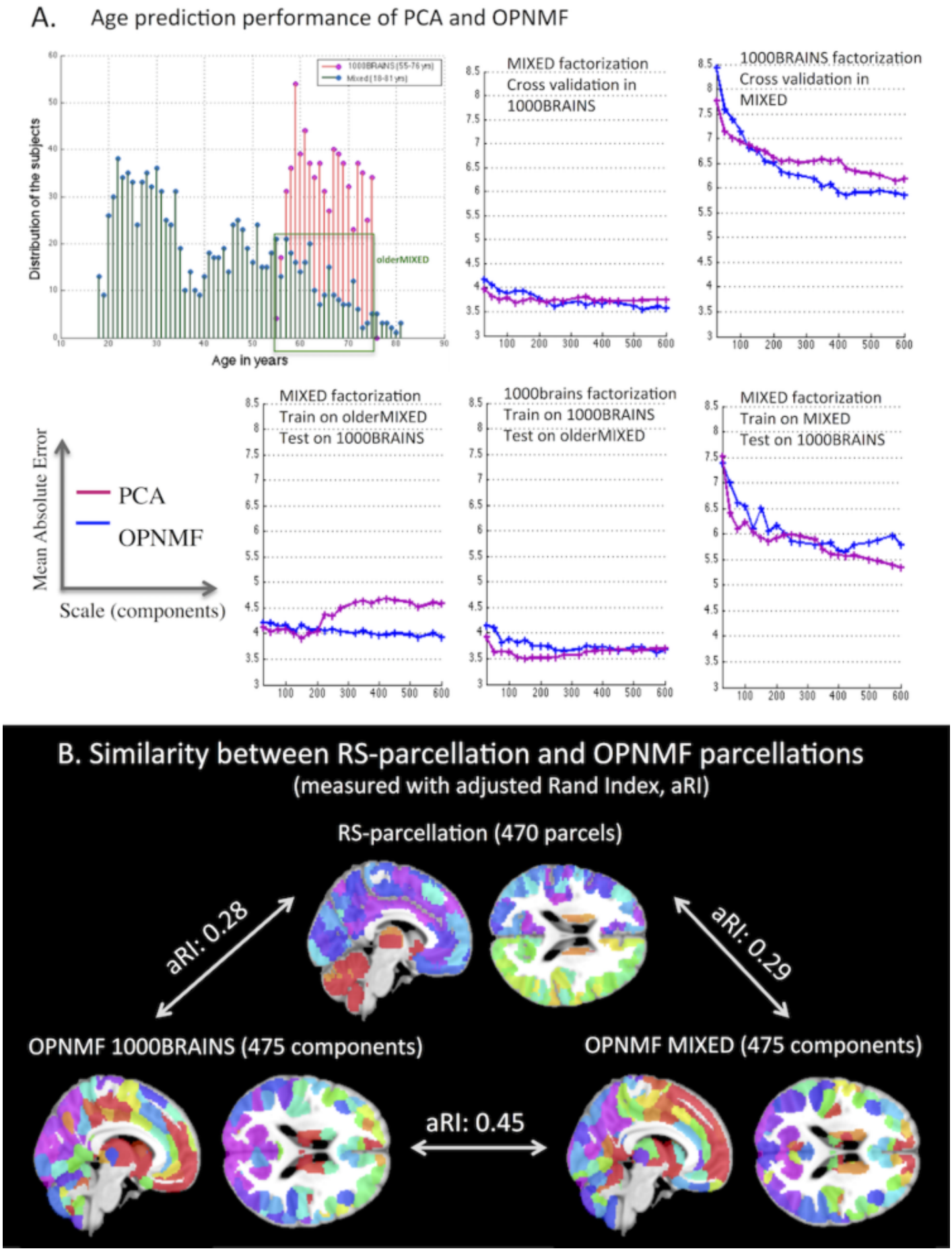
Methods:

We used T1 structural images of two healthy datasets (HD): 1000BRAINS Study (unisite: n= 693, age: 55-75)[4] and MIXED (multisite: n = 1084, age: 18-81), as well as in ADNI[5] samples including

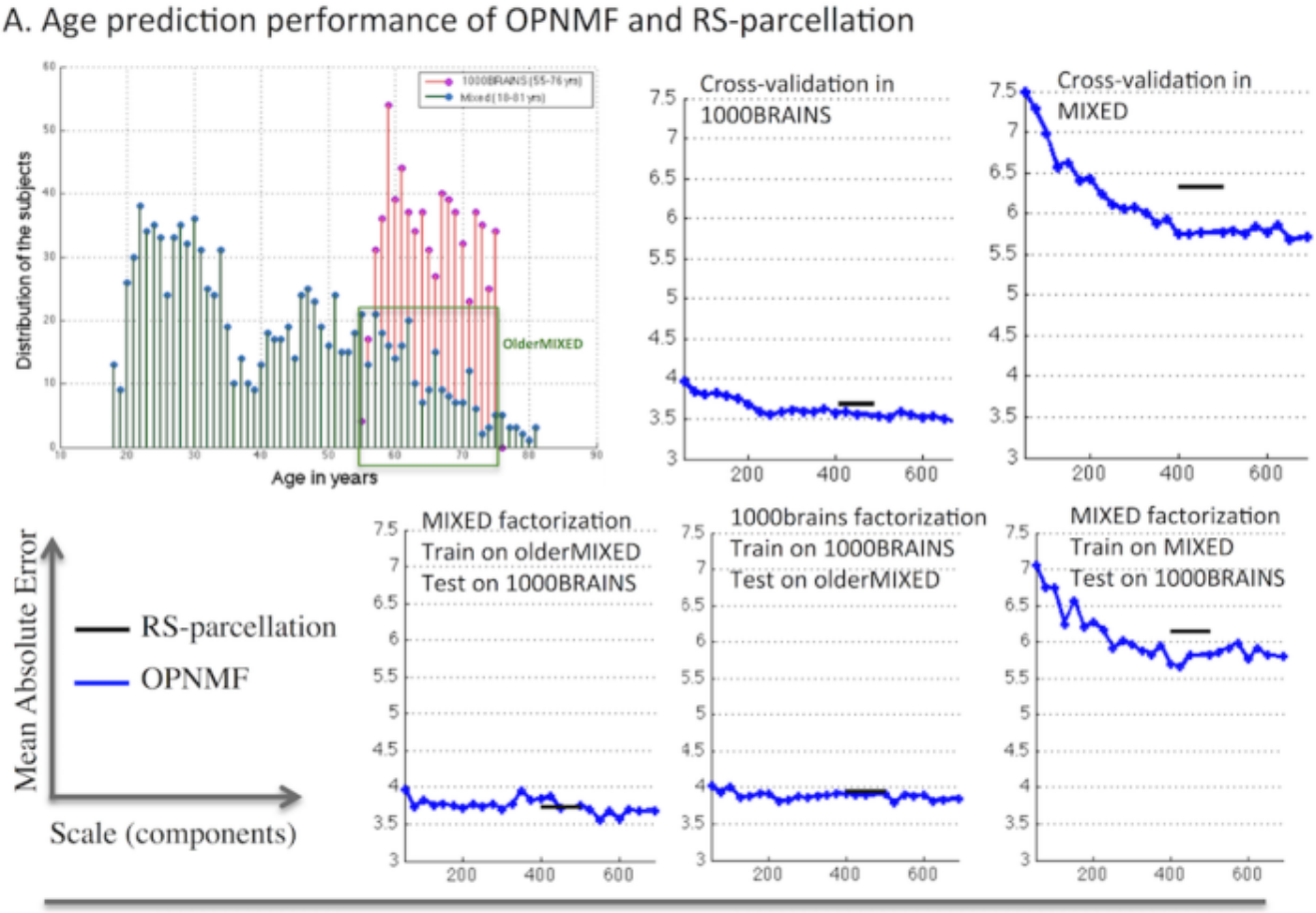
cognitively healthy (HC) participants (n = 244, age: 55-90), patients with Alzheimer's disease (AD, n = 163, age: 56-91) and Mild Cognitive Impairment classified according to their memory performance into MCI (n = 64; age: 55-87) and lMCI (late/amnestic MCI, n = 184, age: 56-92)[5]. Voxel-wise GMV modulated for non-linear normalization transformations were computed with VBM8. Orthonormal projective NMF (OPNMF)[6] and PCA were computed in the HD (scales: 50 to 690). Age prediction was performed with LASSO. We first evaluated OPNMF's as dimensionality reduction for LASSO prediction relative to PCA, and to a parcellation derived from resting-state fMRI in previous studies (RS-parcellation[7, 8]). Then, we examined the performance of both sparse representations (OPNMF and RS-parcellation) for BrainAGE (predicted minus chronological age, reflecting deviation from normal range) in ADNI.

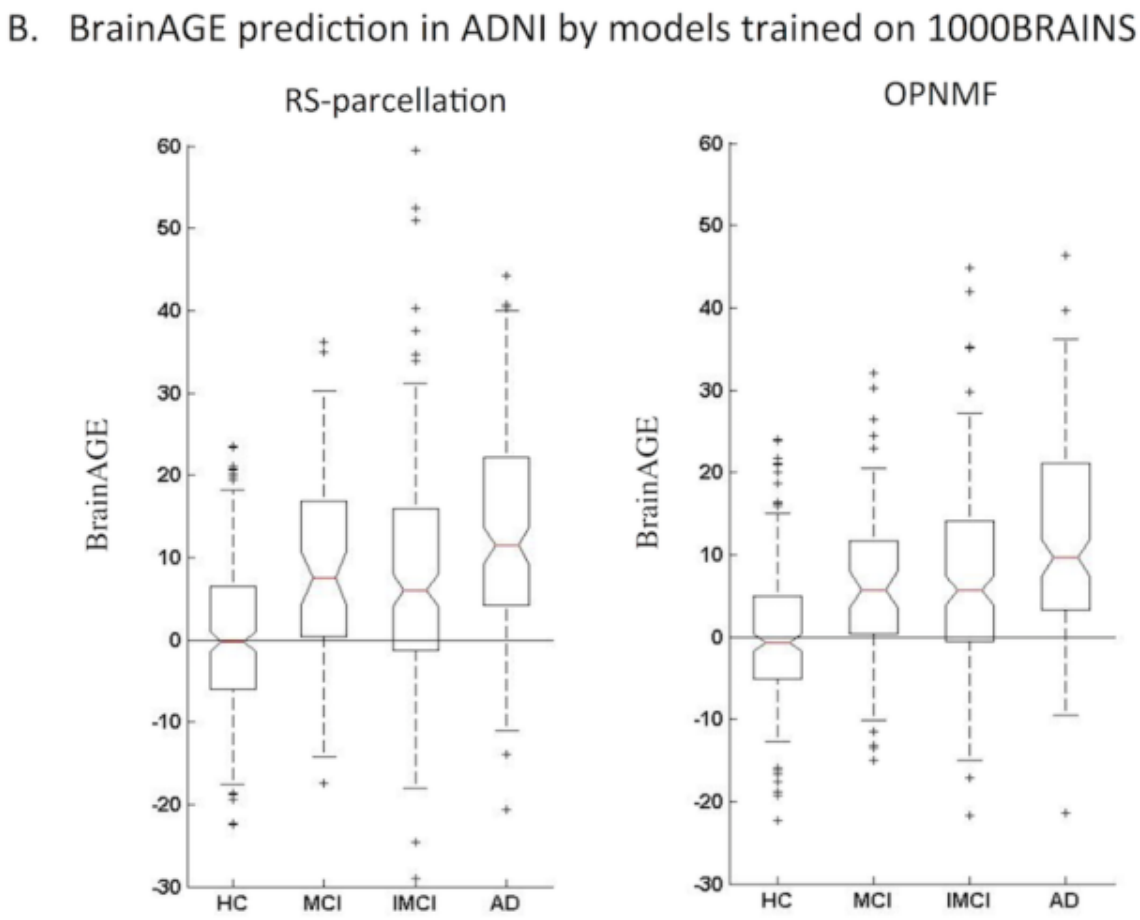
Results:

Mean Absolute Error (MAE) for age prediction in HD revealed that OPNMF reached similar performance as the more conventional but less interpretable PCA, even outperforming it at high scales (Fig. 1A). The spatial brain partitions from OPNMF in 1000BRAINS and in MIXED showed similar convergence with the RS-parcellation, but higher similarity among them (Fig. 1B). Comparisons between OPNMF and RS-parcellation for age prediction in HD revealed comparable performance, again slightly in favor of OPNMF (Fig. 2A). Examining BrainAGE in ADNI, both types of sparse representation models were sensitive to brain alterations in clinical populations with increased BrainAGE in all patients, but more in AD than in MCI groups. However, OPNMF showed less variable predictions in MCI than RS-parcellation (Fig. 2B).


A. Age prediction performance of PCA and OPNMF
Distribution of the subjects
Age in years
1000BRAINS (55-76 yrs)
Mixed (18-81 yrs)
olderMIXED
MIXED factorization
Cross validation in
1000BRAINS
1000BRAINS factorization
Cross validation in
MIXED
Mean Absolute Error
PCA
OPNMF
Scale (components)
MIXED factorization
Train on olderMIXED
Test on 1000BRAINS
1000brains factorization
Train on 1000BRAINS
Test on olderMIXED
MIXED factorization
Train on MIXED
Test on 1000BRAINS
B. Similarity between RS-parcellation and OPNMF parcellations
(measured with adjusted Rand Index, aRI)
RS-parcellation (470 parcels)
aRI: 0.28
aRI: 0.29
OPNMF 1000BRAINS (475 components)
OPNMF MIXED (475 components)
aRI: 0.45

·Figure 1





·Figure 2

Conclusions:

The use of a brain age prediction framework for better understanding how changes in brain structures are modulated by various factors raised the need for a sparse, biologically valid representation of GMV with good prediction performance. We showed here that OPNMF can fulfill this need by achieving comparable performance to PCA in age prediction frameworks and by providing sparse brain representations. This spatial partition converges with an independent parcellation based on a different modality (RS fMRI) confirming its biological validity[9]. Importantly, OPNMF showed slightly better performance in healthy and clinical frameworks than RS-parcellation, despite both approaches showing overall good performance. Thus, OPNMF provides an interpretable representation of GMV through well-localized spatial features that allows for good performance in age prediction in both healthy and clinical populations. However, parcellations from different modalities could also provide good performance in some conditions, which should be investigated in the future.

Disorders of the Nervous System:

Alzheimer's Disease and Other Dementias

Imaging Methods:

Anatomical MRI

Lifespan Development:

Aging

Modeling and Analysis Methods:

Classification and Predictive Modeling [1]
Segmentation and Parcellation [2]

Keywords:

Aging
Data analysis
Machine Learning
Multivariate
STRUCTURAL MRI

[1|2]Indicates the priority used for review

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Please indicate which methods were used in your research:

Structural MRI

For human MRI, what field strength scanner do you use?

3.0T

Which processing packages did you use for your study?

SPM

Provide references using author date format

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