Predicting age from brain MR imaging data using algorithms for machine learning

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Introduction

On a group level, significant correlations between MRI-derived brain regional volumes, cortical thicknesses, and structural and functional connectivity with age [1] or disease have been well documented. Extending this framework from group correlations to assessment and prediction of individual brain trajectories ("brain age") is of clinical importance, and could be used for risk assessment of disease and to initiate early therapy. In this pilot study, we have extracted brain volumetric measures and trained a neural network for age prediction.

Methods and materials

Three repeated MRI acquisitions in 2005, 2008 and 2011 (waves) from 81 healthy individuals were recorded on a GE Sigma 1.5T MR scanner and segmented with FreeSurfer [2]. From this analysis, regional brain volume estimates were extracted for left and right lateral ventricles, hippocampus, thalamus, caudate, as well as the putamen. Using data from wave three and a sub-sample of 40 individuals, a two-layer feedforward neural network with 10 neurons in the hidden layer was trained in MATLAB with age as response variable and the ten regional volume measurements as input features. The trained network was then used to predict age of the 41 remaining subjects in the dataset. For development of the current methodology, chronological age was used for prediction, where ground truth is easily available.

Results

We found strong correlations between the volume of several investigated regions & CSF filled compartments and age (Table 1).

Region	rho	p
Left lateral ventricle	0.36	$<10^{-3}$
Right lateral ventricle	0.45	$<10^{-3}$
Left hippocampus	-0.45	$<10^{-3}$
Right hippocampus	-0.39	$<10^{-3}$
Left thalamus	-0.15	0.18
Right thalamus	-0.22	0.04
Left caudate	-0.02	0.81
Right caudate	-0.03	0.78
Left putamen	-0.29	0.009
Right putamen	-0.31	0.004

Table 1: Correlations (rho) between regional volume and age and corresponding p-values.

Figure 1 shows scatter plots for the volume of left lateral ventricle versus age for all waves.

Results – *continued*

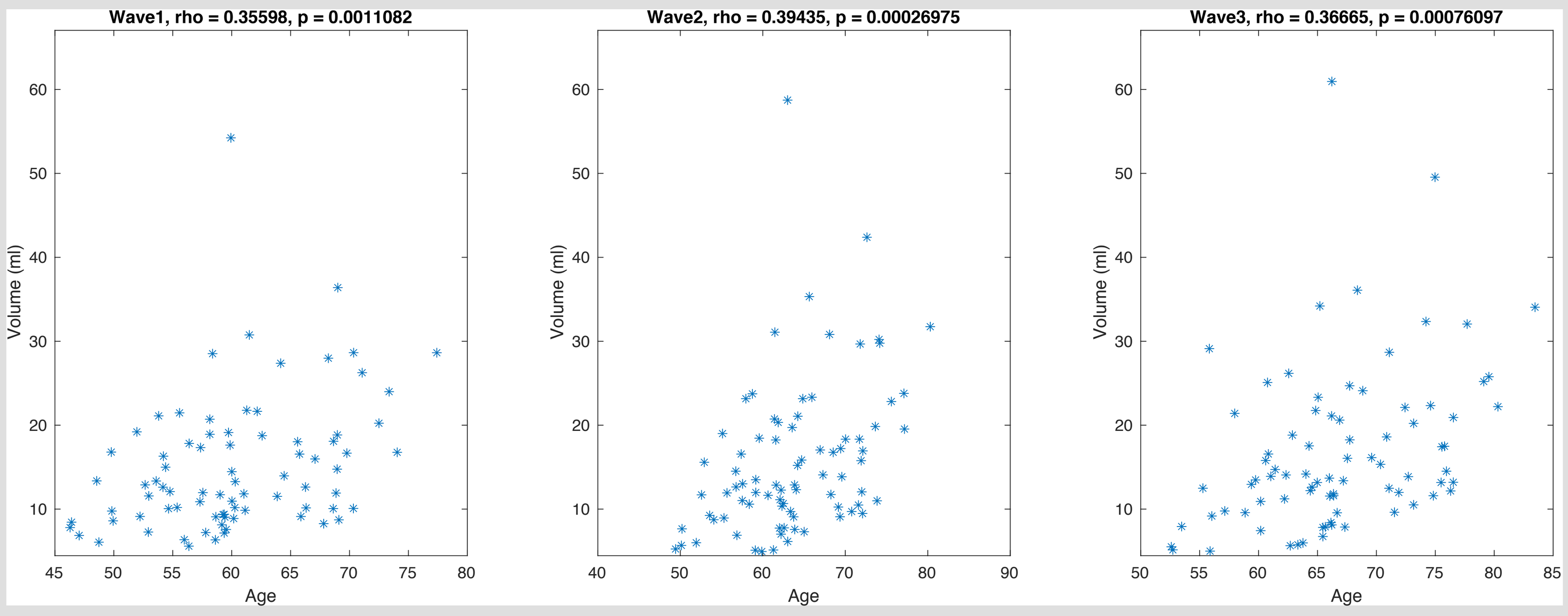

Figure 1: Scatterplots of left lateral ventricle volume versus age for each of the three waves. In all three waves there is a significant increase of the ventricular volume.

A longitudinal trajectory approach for viewing the same subjects across repeated measurements is shown in Figure 2. The plots reveal a trend of increasing ventricular volume with age.

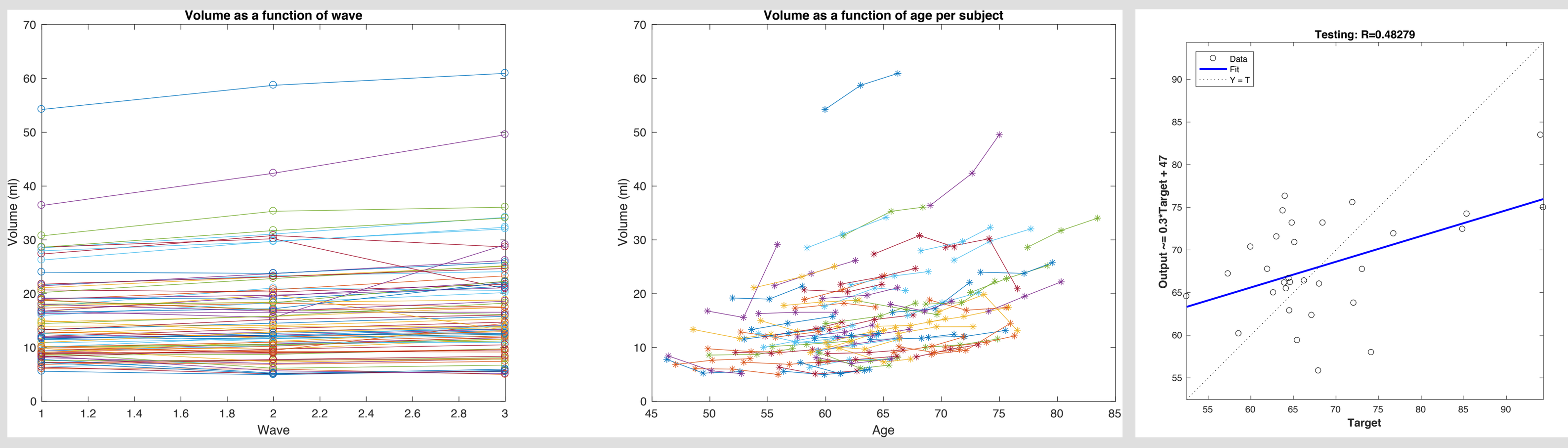

Figure 2: Left and middle panel: Longitudinal plots of data in Figure 1. Each subject corresponds to one line, plotted versus the three waves (left) and as a function of age (middle). Right: Regression plot of neural network prediction versus true age, resulting in an average prediction error of *E = 10.3%*.

Average prediction error was measured as $E = 100mean(\Sigma_i|age_i(predicted)-age_i(true)|/age_i(true))$ for $i = 1,\dots,41$ subjects used for simulation. The trained neural network based on the ten regional volumes, used to predict age, performed with an average prediction error of $E = 10.3\%$, corresponding to mean *7.78* years in our dataset. Regression plot of the prediction is shown in the right panel of Figure 2.

Discussion/conclusions

In our data we found, on a group level, strong correlations with age for several gray matter regions and fluid filled compartments. However, using a simple feed-forward neural network approach individual prediction of age revealed a moderately high error rate. Recent initiatives on deep learning [3] achieved lower errors of *4.66* years, and seem very promising. As a follow up, we will train a deep learning network for age prediction. A next step will also include performance on cognitive tests as outcome variables.

References

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