Age differences in head motion and estimates of cortical morphology

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Abstract

Head motion during MRI scanning influence estimates of cortical morphology. Previous studies have found that older adults demonstrate greater head motion than younger adults, while other studies have found task-related differences in head motion. Cortical morphology also differ with age, as measured by cortical thickness, fractal dimensionality, and gyrification. Here I replicated all three of these prior findings within a larger dataset than these results have been demonstrated previously, with a sample size of more than 600 adults across the adult lifespan (Centre for Ageing and Neuroscience, CamCAN). Furthermore, I additionally test for the influence of head motion on cortical fractal dimensionality and gyrification; effects were statistically significant in some cases, but small in magnitude.

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1 Introduction

Head motion during the acquisition of magnetic resonance imaging (MRI) can lead to artifacts when estimating brain activity and structure. With functional MRI (fMRI), volumes are acquired relatively quickly–often every 1-3 seconds–allowing for the estimation and correction of head motion artifacts. Using innovative techniques such as prospective motion correction (Dosenbach et al., 2017; Federau & Gallichan, 2016; Maclaren et al., 2013; Stucht et al., 2015; Tisdall et al., 2016) and custom-designed, individualized head-cases (`https://caseforge.co`), head motion can be further restricted. However, prior studies have demonstrated that more head motion often occurs with older adults (Andrews-Hanna et al., 2007; Chan et al., 2014; Savalia et al., 2017) and that head motion can lead to decreased estimates of cortical thickness (Alexander-Bloch et al., 2016; Pardoe et al., 2016; Reuter et al., 2015; Savalia et al., 2017). Taken together, studies of brain morphology involving large sample sizes and across the lifespan may benefit from novel methods that do not necessitate changes to the MRI scan sequence or custom-built equipment for each participant.

There is evidence that fMRI tasks can differ in the degree of associated head movement (Huijbers et al., 2017; Greene et al., 2018; Vanderwal et al., 2015; Wylie et al., 2014; Yuan et al., 2009). With this in mind, it may be beneficial to present participants with a task to attend to *during structural scans*, with the objective of decreasing head motion; typically structural scans are accompanied by the presentation of a blank screen or otherwise lack of instruction of attending to a visual stimulus. Here I first examined head motion in relation to age during rest and movie watching fMRI scans to test for differences between the two tasks and in relation to age.

Madan and Kensinger (2016) showed that a structural metric, fractal dimensionality (FD), may be more sensitive to age-related differences in cortical structure than cortical thickness (also see Madan & Kensinger, 2018). In a preliminary analysis to examine the influence of head motion on age-related differences in cortical

fractal dimensionality, Madan and Kensinger (2016) showed qualitative evidence of age-related differences in fractal dimensionality in a small sample ($N = 7$) of post-mortem MRIs. However, as this sample was small and also less indicative of potential head motion effects in *in vivo* MR imaging, further work was needed. To more directly test for the additive influence of head motion on estimates of cortical morphology, beyond aging, here I also tested for a relationship of fMRI-estimated head motion on cortical fractal dimensionality, as well as on mean cortical thickness. Additionally, as recent studies have found that gyrification also decreases with age (Cao et al., 2017; Hogstrom et al., 2013; Madan & Kensinger, 2016, 2018), it was also included in the analysis presented here. Test-retest reliability of estimates for these structural measures has recently been compared (Madan & Kensinger, 2017b), but reliability to head motion has yet to be directly assessed.

2 Methods

2.1 Dataset

Data used in the preparation of this work were obtained from the Centre for Ageing and Neuroscience (CamCAN) repository, available at `http://www.mrc-cbu.cam.ac.uk/datasets/camcan/` (Shafto et al., 2014; Taylor et al., 2017). The CamCAN dataset includes structural and functional MRI data for a sample of 648 adults across the adult lifespan (ages 18-88). 8 participants were excluded from further analyses due to problems with cortical reconstruction or gyrification estimation, yielding a final sample size of 640 adults.

Head motion was estimated from two fMRI scans, during rest and a movie-watching task. Both scans lasted for 8 min and 40 s (i.e., 520 s total). For the rest scan, participants were instructed to rest with their eyes closed. For the movie scan, participants watched and listened to an excerpt of Alfred Hitchcock's "Bang! You're Dead" film. Note that different scan sequences were used for both of these scans, with volumes collected every 1.970 s or 2.470 s for the rest and movie scans, respectively (see

Taylor et al., 2017, for more details); both scans had the same voxel size, 3×3×4.44 mm. Structural MRI analyses are based on a T1-weighted volume collected using an MPRAGE sequence with 1 mm^3 isotropic voxels.

2.2 Preprocessing of the structural MRI data

The T1-weighted structural MRIs were processed using FreeSurfer v6.0 (`https://surfer.nmr.mgh.harvard.edu/`) (Dale et al., 1999; Fischl, 2012; Fischl & Dale, 2000). Surface meshes and cortical thickness was estimated using the standard processing pipeline, i.e., `recon-all`, and no manual edits were made to the surfaces. Gyrification was calculated using FreeSurfer, as described in Schaer et al. (2012).

Fractal dimensionality is a measure of the complexity of a structure and has previously been shown to decrease in relation to aging for cortical (Madan & Kensinger, 2016, 2018) and subcortical (Madan & Kensinger, 2017a; Madan, 2018) structures. It has also been shown to have high test-retest reliability (Madan & Kensinger, 2017b). FD was calculated using the calcFD toolbox (`http://cmadan.github.io/calcFD/`) (Madan & Kensinger, 2016) using the dilation method and filled structures (denoted as FD_f in prior studies). See Madan and Kensinger (2016, 2018) for additional background on fractal dimensionality and it's application to brain imaging data.

2.3 Estimates of head motion

Head motion was measured as the frame-wise displacement using the three translational realignment parameters, from the already preprocessed fMRI data (Taylor et al., 2017). Frame-wise displacement was substantially higher between volumes at the beginning of each scan run, so the first five volumes were excluded.

2.4 Model comparison approach

Effects of head motion on estimates of cortical morphology (thickness, fractal dimensionality, and gyrification) were assessed using a hierarchical regression

procedure. Age was first input, followed by estimates of head motion from each fMRI scan, as well as interaction terms with age. Model fitness was assessed using both R^2 and ΔBIC. Briefly, ΔBIC measures the fitness of the model to the data while also incorporating a penalty based on the number of model parameters. Models with differences in ΔBIC> 2 were considered to significantly differ in fit to the data.

3 Results

3.1 Head motion

As shown in Figure 1, head motion was greater in the rest scan than during the movie watching [$t(639) = 23.35$, $p < .001$, Cohen's $d = 0.99$, $M_{diff} = 1.528$ mm/min]. Nonetheless, head motion was correlated between the fMRI scans [$r(638) = .484$, $p < .001$] (also see Savalia et al., 2017). While this correlation between scans is expected, particularly since both were collected in the same MRI session, prior studies have suggested that head motion during scanning can be viewed as a trait (Engelhardt et al., 2017; Hodgson et al., 2017; Zeng et al., 2014). Moreover, this correlation provides additional evidence that motion during the fMRI scans is consistently larger in some individuals than others, suggesting it similarly affected the structural scans more for some individuals than others and appropriate to include as a predictor for the cortical morphology estimates.

While head motion was substantially lower in the movie condition than during rest, there is instead some evidence of systematic stimuli-evoked increases in head motion (e.g., around 290 s and 360 s), likely corresponding to events within the movie.

3.2 Cortical morphology

As shown in Figure 2, mean cortical thickness significantly decreased with age [$r(638) = -.652$, $p < .001$, -0.0432 mm/decade], as did fractal dimensionality [$r(638) = -.705$, $p < .001$, -0.0097 FD_f/decade] and gyrification [$r(638) = -.426$, $p < .001$, -0.0359 GI/decade]. All three slopes (change in metric per decade) are

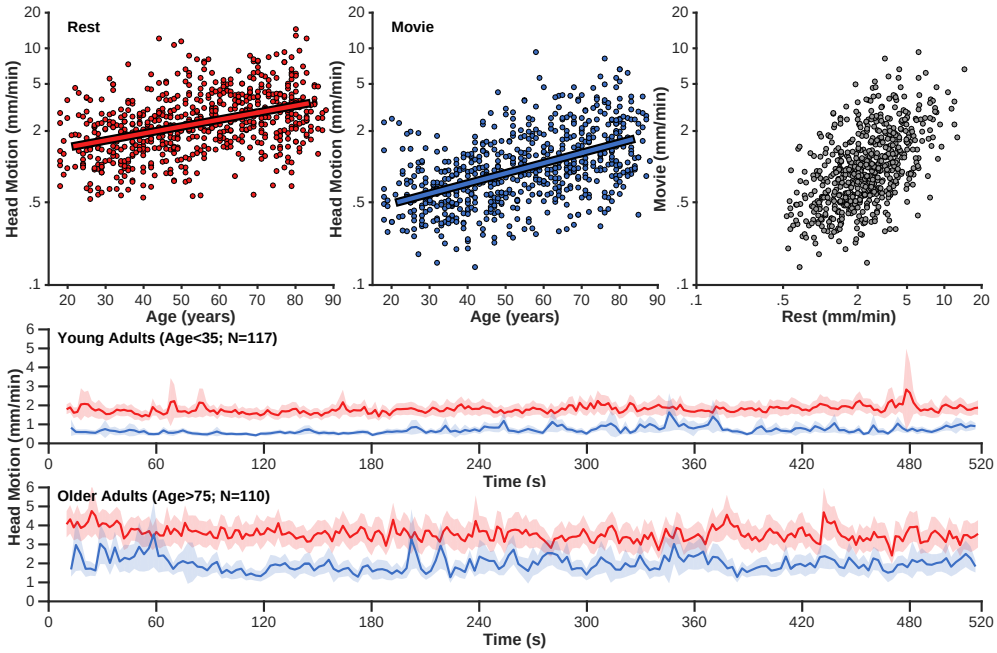

Figure 1. Age-related differences in head motion. *Upper row:* Correlations between average head motion (mm/min) with age for the rest and movie fMRI scans, and between fMRI scans. Head motion axes are log-10 scaled to better show inter-individual variability. *Lower row:* Averaged time-course of head motion for rest (red) and movie (blue) fMRI scans for young and older adults. Bands represent 95% confidence intervals.

nearly identical to those first calculated by Madan and Kensinger (2016), as is the general finding of higher age-related differences in fractal dimensionality and weaker differences in gyrification (also see Madan & Kensinger, 2018).

Of particular interest, I also examined the influence of head motion on the cortical morphology estimates. For all three measures, head motion explained only a small amount of additional variance beyond age, as shown in Table 1. Nonetheless, head motion from the movie scan did explain significant additional variance, as measured by ΔBIC, however, this only accounted for an additional 1% variance. In the model of cortical thickness including head motion from the movie scan (but not the interaction), age related changes corresponded to -0.0398 mm/decade, while head motion contributed -0.0135 mm/(mm/min).

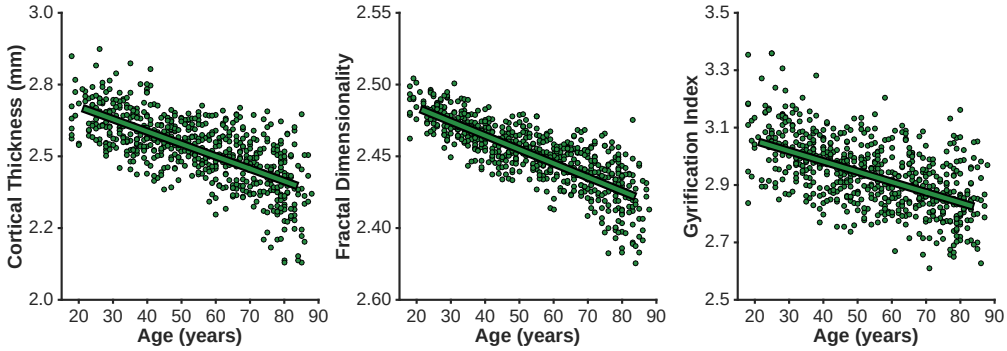

Figure 2. Age-related differences in cortical morphology estimates: cortical thickness and cortical fractal dimensionality.

Table 1

Variance explained and model fits of cortical measures by age and head motion estimates.

	Thickness		FD		Gyrification	
Predictors	R^2	ΔBIC	R^2	ΔBIC	R^2	ΔBIC
Age	.425	6.98	.497	3.15	.181	0
Age + Motion(Rest)	.429	10.01	.500	5.65	.183	4.91
Age + Motion(Movie)	.437	0	.504	0	.181	6.45
Age + Motion(Movie) + Age×Motion(Movie)	.443	0.23	.507	3.18	.181	12.82

4 Discussion

In the current study, I replicated several prior findings as well as tested for several novel effects of head motion. Likely most important, I found significantly more movement during resting state than watching a movie, but are quite correlated still (replicating the findings of Huijbers et al., 2017; Greene et al., 2018). Based on this evidence, I would recommend that participants be given movie-viewing task *during structural scans* to reduce movement during these longer volume acquisitions and improve scan quality. Suggestions of potential systematic increases in head motion, however, suggest that less eventful movie content may be preferable for both maintaining participants' attention and minimizing movement-based reactions (e.g.,

see Vanderwal et al., 2015).

Estimates of cortical thickness were significantly influenced by head motion (replicating Savalia et al., 2017), though the influence of this appeared to be small. Effects of head motion on fractal dimensionality were also significant, but even smaller in magnitude, while head motion did not significantly influence estimates of gyrification. The results here also served as a replication age-related differences in fractal dimensionality and gyrification (Madan & Kensinger, 2016).

While the results here are predominately replications of prior work, they nonetheless integrate the key findings of several papers through a single, open-access dataset, that also has a larger sample size than these previous studies. Moreover, these results serve as an example to highlight the benefits of open data sharing on improving our understanding of brain morphology (see Madan, 2017, for a detailed discussion).

5 Conclusion

Head motion influences estimates of cortical morphology, but can be attenuated by using an active task, such as movie watching, rather than merely instructing participants to rest. This is particularly important when studying aging populations, where head motion is greater than for young adults.

Acknowledgments

Data collection and sharing for this project was provided by the Cambridge Centre for Ageing and Neuroscience (CamCAN). CamCAN funding was provided by the UK Biotechnology and Biological Sciences Research Council (BB/H008217/1), together with support from the UK Medical Research Council and the University of Cambridge.

I would like to thank Darren Price and Rogier Kievit for assistance with accessing the CamCAN data.

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