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# New tissue priors for improved automated classification of subcortical brain structures on MRI<sup>\*</sup>

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#### ABSTRACT

Despite the constant improvement of algorithms for automated brain tissue classification, the accurate 16 delineation of subcortical structures using magnetic resonance images (MRI) data remains challenging. The 17 main difficulties arise from the low gray-white matter contrast of iron rich areas in T1-weighted (T1w) MRI 18 data and from the lack of adequate priors for basal ganglia and thalamus. The most recent attempts to obtain 19 such priors were based on cohorts with limited size that included subjects in a narrow age range, failing to 20 account for age-related gray-white matter contrast changes. Aiming to improve the anatomical plausibility of 21 automated brain tissue classification from T1w data, we have created new tissue probability maps for subcortical 22 gray matter regions. Supported by atlas-derived spatial information, raters manually labeled subcortical 23 structures in a cohort of healthy subjects using magnetization transfer saturation and R2\* MRI maps, which 24 feature optimal gray-white matter contrast in these areas. After assessment of inter-rater variability, the new 25 tissue priors were tested on T1w data within the framework of voxel-based morphometry. The automated 26 detection of gray matter in subcortical areas with our new probability maps was more anatomically plausible 27 compared to the one derived with currently available priors. We provide evidence that the improved delineation 28 compensates age-related bias in the segmentation of iron rich subcortical regions. The new tissue priors, allowing 29 robust detection of basal ganglia and thalamus, have the potential to enhance the sensitivity of voxel-based 30 morphometry in both healthy and diseased brains. 31

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#### 45 Introduction

**41** 43

Computer-based assessment of brain anatomy with magnetic reso-46 nance imaging (MRI) has become a powerful method to investigate 47 in vivo the healthy and diseased brain. Aiming to provide reliable 4849 estimates of local gray matter (GM) volume across the whole brain, a substantial amount of work has been devoted to the improvement of 50the accuracy of algorithms for automated tissue classification and 5152spatial registration (Ashburner and Friston, 2000, 2005; Klein et al., 2010). Despite major methodological advances, the robust and accurate 53 delineation of the deep brain nuclei - thalamus, caudate, putamen, 5455pallidum, subthalamic nucleus, substantia nigra, and red nucleus -56remains challenging (Lim et al., 2013; Streitbürger et al., 2014;

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http://dx.doi.org/10.1016/j.neuroimage.2016.01.062 1053-8119/© 2016 Published by Elsevier Inc. Callaert et al., 2014). The basal ganglia play a crucial role in goal- 57 directed behavior and movement control, which explains their involve- 58 ment in many neurological and neuropsychiatric disorders such as 59 Parkinson's and Huntington's disease, dystonia, tremor, Tourette's 60 syndrome, and schizophrenia (Utter and Basso, 2008). The reliable ana- 61 tomical assessment of these regions is important not only to accurately 62 monitor disease-related changes but also to facilitate accurate target 63 identification for functional neurosurgery in basal ganglia disorders. 64 There is therefore a clear need to improve the automated detection of 65 basal ganglia structures (Ahsan et al., 2007). 66

Automated tissue classification relies on the distributions of image 67 intensities and gray-white matter contrast in MRI images (Ashburner 68 et al., 2003), which are determined by the local values of the MRI 69 parameters and the microstructural composition of brain tissue 70 (Fukunaga et al., 2010; Streitbürger et al., 2014; Lutti et al., 2014). In 71 particular, the inaccurate classification of subcortical structures from 72 T1-weighted (T1w) images—the most widely used data in computa-73 tional anatomy, arises from the high concentration of iron in these 74 regions (Hallgren and Sourander, 1958; Haacke et al., 2005; Lorio 75

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et al., 2014). Importantly, this effect is further modulated by age-related
tissue property changes (Lorio et al., 2014).

In addition to its dependence on image intensity and gray-white 78 79 matter contrast, the automated tissue classification relies on prior spatial information based either on stereotaxic atlases (Fischl et al., 80 2002; Pohl et al., 2006; Khan et al., 2008) or on probabilistic maps of 81 tissue class distributions derived from MRI data (Ashburner and 82 83 Friston, 2005). The currently used tissue probability maps are based on T1w data (Mazziotta et al., 2001) with the major drawback of a 84 85 regional contrast differences driven by microstructural tissue properties (Lorio et al., 2014). More recent attempts to improve the priors for 86 robust classification of subcortical structures have benefited from new 87 MRI protocols that highlight the impact of tissue properties on gray-88 white matter contrast. These recent achievements are limited by the 89 relatively low number of used data samples, which hampers the 90 91 accurate detection of inter-individual variations in brain anatomy and their modulation by age (Ahsan et al., 2007; Prodoehl et al., 2008; Lim 92 93 et al., 2013; Keuken et al., 2014). Common to the previous studies on the topic is that there was no attempt to statistically assess the impact 94 of new anatomically plausible tissue probability maps on the automated 95 tissue classification within computational anatomy frameworks. 96

97 The purpose of this study is to build new tissue probability maps 98 (TPMs) for the automated tissue classification of thalamus, caudate, putamen, globus pallidus, substantia nigra, subthalamic nucleus, red nucleus, 99 and cerebellar dentate. The new TPMs were derived from the manual la-100 beling of subcortical structures on magnetization transfer saturation (MT) 101 and  $R2^*$  (=1/T2<sup>\*</sup>) maps, which provide optimal contrast in these areas 102 103 (Helms et al., 2009). The obtained TPMs were then included as a new tissue prior in the Bayesian framework for tissue classification of the 104 well-established SPM software (Ashburner and Friston, 2005). To test 105the anatomical accuracy of the tissue classification performed with the 106 new TPMs, we carried out a cross-validation between the manual labeling 107 108 results and the gray matter volume maps obtained from the automated tissue classification based on MT images. Finally, the new TPMs were 109 applied on an independent data set of T1w images. Our hypothesis was 110 that the new tissue probability maps would enable the accurate delinea-111 112 tion of subcortical structures and would prove particularly robust against the effects of age-related microstructural tissue changes on T1w data. 113

#### 114 Methods

#### 115 Data acquisition

We used quantitative MRI (qMRI) data for the manual labeling of subcortical structures. The qMRI images were originally acquired for previous studies (Chowdhury et al., 2013; Lorio et al., 2014). The data 118 set comprised 96 healthy adults (40 male, age range 27–74 years, 119 mean 55  $\pm$  15; 56 female, age range 21–88 years, mean 57  $\pm$  19) 120 scanned on a 3 T whole-body MRI system (Magnetom TIM Trio, Siemens 121 Medical Systems, Germany), using a standard 32-channel radio- 122 frequency receive head coil and body coil for transmission. On visual 123 inspection, study participants showed neither macroscopic brain 124 abnormalities, i.e., major atrophy, nor signs of overt vascular pathology, 125 i.e., micro-bleeds and white matter lesions. Elderly subjects with white 126 matter lesions of Grade 2 or more by the Scheltens' rating scale 127 (Scheltens et al., 1993; Wardlaw et al., 2013) were excluded from the 128 study. We obtained quantitative measures of brain atrophy by calculating 129 the brain volume fraction (Rudick et al., 1999) from MT images. 130

The quantitative MRI acquisitions consisted of three multi-echo 3D 131 fast low angle shot (FLASH) acquired with predominant proton density, 132 PD-, T1-, and MT-weighting (PD-weighted:  $TR/\alpha = 23.7 \text{ ms/6}^\circ$ ; T1- 133 weighted:  $TR/\alpha = 18.7 \text{ ms}/20^\circ$ ; MT-weighted:  $TR/\alpha = 23.7 \text{ ms}/6^\circ$ ) 134 with 1 mm<sup>3</sup> isotropic resolution (Helms et al., 2008a; Weiskopf et al., 135 2013). The MT-weighting was achieved by applying an off-resonance 136 Gaussian-shaped pulse (4 ms duration, 220 nominal flip angle, 2 kHz 137 frequency offset from water resonance) prior to the excitation. Multiple 138 gradient echoes were acquired for each FLASH acquisition with alternat- 139 ing readout polarity: 6 equidistant echo time (TE) were used for the T1- 140 and MT-weighted sets (TE between 2.34 ms and 14.7 ms) and 8 141 equidistant TE were used for PD-weighted sets (TE between 2.34 ms 142 and 19.7 ms). The image resolution was 1 mm isotropic. To shorten 143 the acquisition time, parallel imaging (acceleration factor 2, GRAPPA), 144 and partial Fourier acquisition were used. To correct the quantitative 145 maps for the effect of RF transmit inhomogeneities, we measured the 146 transmit field B1 + using 3D echo-planar imaging (EPI) spin-echo (SE) 147 and stimulated echo (STE) images. The EPI images were acquired with 148 the 4 mm isotropic resolution, parallel imaging using GRAPPA factor 149  $2 \times 2$  in PE and partition direction, TESE/TESTE/TM (mixing time)/ 150 TR = 37.06/37.06/31.2/500 ms. A B0 map was acquired to correct the 151 RF transmit field maps for geometric distortion and off-resonance 152 effects. The acquisition protocol used a 2D double-echo FLASH sequence 153 with the following parameters (Lutti et al., 2012, 2010): slice 04 thickness = 2 mm, TR = 1020 ms, TE1/TE2 = 10/12.46 ms,  $\alpha = 90^{\circ}$ , 155 BW = 260 Hz/pixel and flow compensation. The total acquisition time 156 was 24 min (for details on MRI acquisition parameters see Table 1, 157 Supplementary material). 158

Quantitative MRI maps were calculated from the acquired data using 159 an in-house code running under SPM12 (Wellcome Trust Centre 160 for Neuroimaging, London, UK; http://www.fil.ion.ucl.ac.uk/spm) and 161 Matlab 7.11 (Mathworks, Sherborn, MA, USA). The R2\* maps were 162

t1.1 Table 1

t1.2 Manual labeling results. Subcortical structures' mean volume, global percentage of voxels not included by all raters (disagreement voxels), and inter-rater agreement indices (Dice index,
 t1.3 Cohen's kappa, and intraclass coefficient (ICC)), RN = red nucleus; STN = subthalamic nucleus; SN = substantia nigra; GP = globus pallidus.

S	Structure		Volume (n	nm <sup>3</sup> )	% of disagreement voxels		Dice index		Cohen's kappa		ICC	
			Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
C	Caudate	Left	3421	900	17	3	0.83	0.06	0.85	0.06	0.83	0.06
		Right	3306	700	16	3	0.85	0.06	0.86	0.06	0.85	0.06
Б	Putamen	Left	3906	650	19	3	0.80	0.05	0.8	0.05	0.83	0.05
г	utamen	Right	3966	690	18	4	0.85	0.03	0.86	0.03	0.84	0.04
	<b>~D</b>	Left	1319	235	20	4	0.79	0.08	0.8	0.08	0.78	0.08
	GP	Right	1263	201	21	5	0.76	0.09	0.77	0.09	0.77	0.09
	ri 1	Left	5110	1100	16	4	0.86	0.04	0.86	0.04	0.86	0.04
Т	Thalamus	Right	5495	1301	15	3	0.87	0.05	0.87	0.05	0.87	0.04
	SN	Left	330	94	25	6	0.7	0.11	0.74	0.12	0.67	0.11
S	210	Right	330	90	23	5	0.76	0.14	0.77	0.14	0.68	0.12
г	RN	Left	220	49	29	7	0.68	0.13	0.71	0.13	0.64	0.1
R	KIN	Right	220	50	28	8	0.69	0.11	0.77	0.11	0.67	0.11
		Left	86	28	33	7	0.65	0.14	0.70	0.12	0.67	0.1
} S	STN	Right	85	20	31	7	0.7	0.1	0.73	0.19	0.69	0.1
	Developer	Left	1032	215	20	5	0.76	0.11	0.73	0.11	0.7	0.11
	Dentate	Right	1013	195	23	6	0.77	0.14	0.76	0.13	0.69	0.12

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