Dement Neurocogn Disord. 2024 Jul;23(3):127-135
https://doi.org/10.12779/dnd.2024.23.3.127
pISSN 1738-1495·eISSN 2384-0757

DND Dementia and Neurocognitive Disorder

Original Article

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Assessing the Impact of Defacing Algorithms on Brain Volumetry Accuracy in MRI Analyses

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OPEN ACCESS

Received: Apr 15, 2024
Revised: Apr 26, 2024
Accepted: Apr 26, 2024
Published online: May 8, 2024

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ABSTRACT

Background and Purpose: To ensure data privacy, the development of defacing processes, which anonymize brain images by obscuring facial features, is crucial. However, the impact of these defacing methods on brain imaging analysis poses significant concern. This study aimed to evaluate the reliability of three different defacing methods in automated brain volumetry.
Methods: Magnetic resonance imaging with three-dimensional T1 sequences was performed on ten patients diagnosed with subjective cognitive decline. Defacing was executed using mri_deface, BioImage Suite Web-based defacing, and Defacer. Brain volumes were measured employing the QBraVo program and FreeSurfer, assessing intraclass correlation coefficient (ICC) and the mean differences in brain volume measurements between the original and defaced images.
Results: The mean age of the patients was 71.10±6.17 years, with 4 (40.0%) being male. The total intracranial volume, total brain volume, and ventricle volume exhibited high ICCs across the three defacing methods and 2 volumetry analyses. All regional brain volumes showed high ICCs with all three defacing methods. Despite variations among some brain regions, no significant mean differences in regional brain volume were observed between the original and defaced images across all regions.
Conclusions: The three defacing algorithms evaluated did not significantly affect the results of image analysis for the entire brain or specific cerebral regions. These findings suggest that these algorithms can serve as robust methods for defacing in neuroimaging analysis, thereby supporting data anonymization without compromising the integrity of brain volume measurements.

Keywords: Data Anonymization; Image Processing, Computer-Assisted; Magnetic Resonance Imaging; Information Dissemination

INTRODUCTION

Recent advancements in high-resolution brain imaging and 3-dimensional (3D) reconstruction techniques have significantly increased the utilization of brain imaging within neuroscience. Despite these advancements enhancing our understanding and diagnostic capabilities, they introduce privacy concerns due to the potential for facial reconstruction

Funding

This study was supported by a grant from the Ministry of Health and Welfare (HI18C0530).

Conflict of Interest

The authors have no financial conflicts of interest.

Author Contributions

Conceptualization: Ryu DW, Yang DW; Data curation: Ryu DW, Cho JH, Yang DW; Formal analysis: Ryu DW, Cho JH, Yang DW; Funding acquisition: Yang DW; Investigation: Ryu DW, Yang DW; Methodology: Ryu DW, Yang DW; Project administration: Lee C, Lee HJ; Resources: Ryu DW, Kim S, Lee JM, Yang DW; Software: Kim S, Lee JM; Supervision: Yang DW; Validation: Ryu DW, Yang DW; Visualization: Ryu DW, Cho JH; Writing - original draft: Ryu DW; Writing - review & editing: Ryu DW, Lee C, Lee HJ, Shim YS, Hong YJ, Yang DW.

from brain images. The burgeoning practice of data sharing in large-scale studies further exacerbates these privacy concerns. In response, defacing technologies, which remove facial features from brain images, have become pivotal in preserving data privacy. However, the implications of these technologies on subsequent analyses warrant further investigation.

Effective defacing should obscure personal identity, without compromising the quality or interpretability of the imaging data. While numerous defacing methodologies have been validated, showing minimal impact on overall analysis, instances of significant errors have raised concerns.[1-3] Such discrepancies can be influenced by factors that include the patient cohort, the defacing technique employed, and the specific imaging analysis utilized.[4-6] This issue becomes particularly pronounced in examining regional brain volumes, where the analysis of smaller brain regions near the face is susceptible to alterations through defacing processes.

This study sought to evaluate the reliability of three distinct defacing methods within the context of automated brain volumetric analyses. Specifically, it aims to assess the impact of these methods on the analysis of regional brain volumes, thereby contributing to our understanding of the balance between data privacy and analytical integrity in neuroscientific research.

METHODS

Patients and assessments

This observational study included ten patients with Subjective Cognitive Decline (SCD) who were evaluated at Seoul St. Mary's Hospital in 2020. All participants conformed to the established research criteria for SCD.[7] Comprehensive medical evaluations were performed, encompassing neurological examinations, cognitive assessments via the Mini-Mental Status Examination (MMSE) and Clinical Dementia Rating (CDR), and detailed magnetic resonance imaging (MRI) for brain analysis. Exclusion criteria encompassed cognitive test performance impairments (MMSE scores <1.5 standard deviation [SD] from age- and education-adjusted norms), CDR scores >0, MRI findings that might confound brain imaging analysis, previous dementia diagnosis or current treatment for dementia, any history of psychiatric or neurological disorders, facial anomalies, and significant head trauma history.

Defacing procedure

This study utilized T1-weighted 3D images (magnetization-prepared rapid gradient-echo; MPRAGE) acquired through MRI, as detailed in **Table 1**. Three defacing methods were applied: mri_deface, BioImage Suite Web (BSW)-based defacing, and Defacer, with **Fig. 1** illustrating 3D reconstructed head images pre- and post-defacement. For anonymization, a mosaic effect was applied to the periocular region in the 3D reconstructed images derived from the original brain MRI scans (**Fig. 1A**). The mri_deface program (version 1.22; Morphometry Biomedical Informatics Research Network)[8] automates the defacement process by generating a facial mask from the image, which is then used to obliterate identifiable features, such as the eyes, nose, and mouth (**Fig. 1B**). The BSW, developed at the Yale School of Medicine, provides an open-source solution for image processing, masking out the nose and mouth areas (**Fig. 1C**). Defacer, originating from the Asan Medical Center, South Korea, leverages deep learning to detect and remove facial features, focusing on the eyes, nose, mouth, and ears, to maintain privacy without biasing the brain images (**Fig. 1D**).[9]

https://doi.org/10.12779/dnd.2024.23.3.127

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Table 1. Clinical characteristics of the included patients and MR parameters in this study

Characteristics	Patients with SCD (n=10)
Clinical characteristics	
Age (yr)	71.10±6.17
Male	4 (40.0)
Educational history (yr)	13.40±3.44
MMSE score	27.50±1.58
MR sequence	
MR scanner	Philips Intera Achieva
Field strength	3 T
Head coil	8-channel sensitivity-encoding head coil
Scan image type	T1-weighted 3D images (MPRAGE)
Repetition time	1,780 ms
Echo time	2.2 ms
Field angle	9°
Field of view	256×256×256 mm
Voxel size	1×1×1 mm
Thickness	1.0 mm

Data are expressed in terms of frequency (%) or a combination of mean and standard deviation.
MR: magnetic resonance, SCD: Subjective Cognitive Decline, MMSE: Mini-Mental Status Examination, MPRAGE: magnetization-prepared rapid gradient-echo.

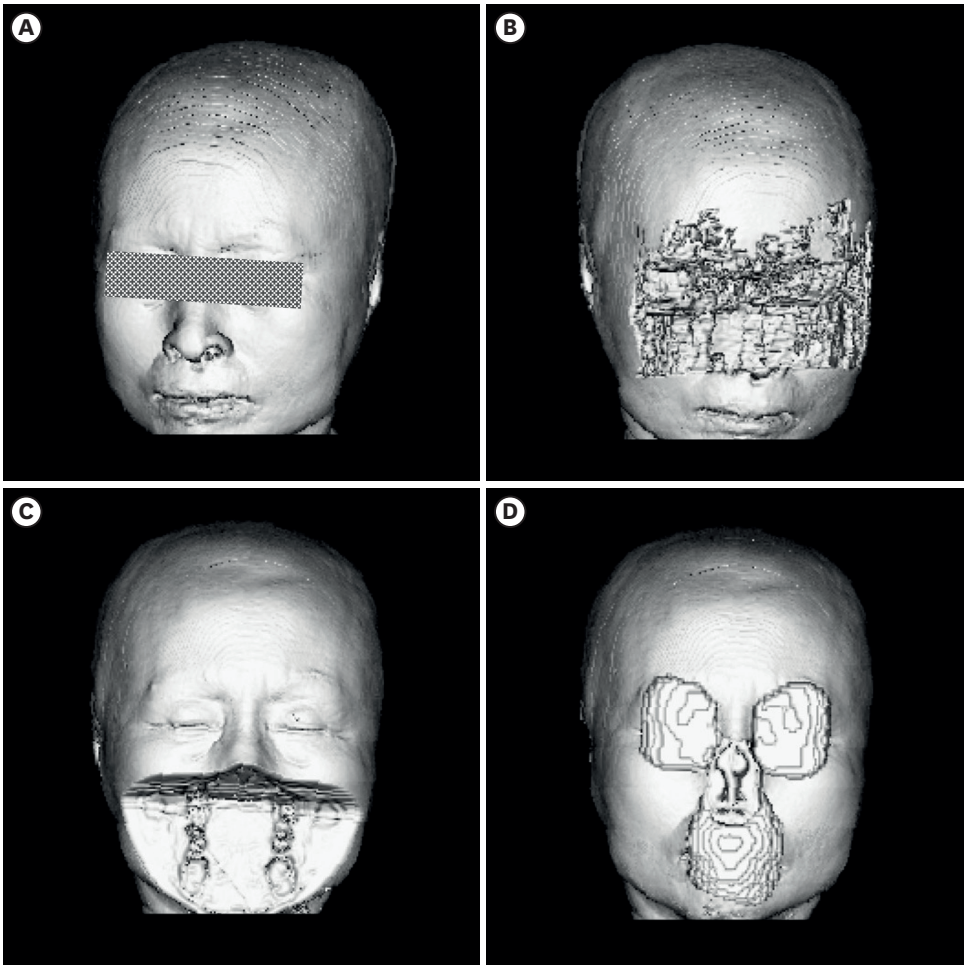

Fig. 1. Three-dimensional reconstructed images from the original and defaced magnetic resonance brain images.
(A) Original, (B) mri_deface, (C) BioImage Suite Web-based defacing, and (D) Defacer.
For anonymization, a mosaic effect was applied around the eyes in A.

https://doi.org/10.12779/dnd.2024.23.3.127

Volumetry analysis

This study utilized the QBraVo program and FreeSurfer to measure brain volumes from the original and defaced images accurately. The measured brain volume parameters included total intracranial volume (TIV), total brain volume (TBV), ventricle volume, and hippocampal volume. Beyond these global measures, the study also performed a detailed analysis of regional brain volumes in specific areas: anterior frontal, anterior medial frontal, dorsolateral frontal, posterior medial frontal, inferior frontal, orbital frontal, lateral temporal, anterior temporal, medial temporal, lateral parietal, medial parietal, occipital lobes, and the cerebellum.

QBraVo, software based on the Statistical Parametric Mapping framework (Wellcome Trust Centre for Human Neuroimaging, London, UK; SPM Website), was developed for regional brain volumetry. Our prior research on the development and validation of QBraVo extensively describes the volumetric process employed by this program. Importantly, QBraVo has proven to be highly accurate in measuring regional brain volumes, establishing its reliability for neuroimaging studies.[10] In addition, FreeSurfer was employed for brain segmentation and parcellation, facilitating atlas-based measurements of brain volume.

Statistical analysis

Data are expressed in terms of frequency (%) or a combination of mean and standard deviation. Statistical evaluations were performed using SPSS (version 24.0 for Windows; IBM Corp., Armonk, NY, USA), utilizing the intraclass correlation coefficient (ICC) to assess the reliability of brain volumetry from defaced images. Paired *t*-tests compared regional brain volumes across defacing methods, with the mean volume difference quantifying the defacing impact. Significance was determined at $p<0.05$.

Ethical approval

The Institutional Review Board of Seoul St. Mary's Hospital (2024-0084-0001) approved the study protocol.

RESULTS

Table 1 outlines the clinical characteristics of the study participants and the MRI acquisition parameters. The average age of the participants was 71.10±6.17 years. The study cohort consisted of ten patients, of whom 4 (40.0%) were male. These patients had an average educational background of 13.40±3.44 years, and their mean score on the MMSE was 27.50±1.58.

Table 2 displays the ICCs for brain volume measurements between the original and defaced images. High ICCs were observed for TIV, TBV, and ventricle volume across various defacing methods (mri_deface, BSW-based defacing, and Defacer) and analytical tools (QBraVo and FreeSurfer). However, ICCs for hippocampal volume were consistently higher with QBraVo analyses compared to FreeSurfer, with the lowest observed in conjunction with mri_deface (ICC, 0.742; 95% confidence interval [CI], 0.296–0.996; $p=0.008$). This was followed by BSW-based defacing (ICC, 0.880; 95% CI, 0.165–0.974; $p<0.001$), and Defacer (ICC, 0.911; 95% CI, 0.236–0.982; $p<0.001$).

Table 3 and **Fig. 2** present the ICCs for regional brain volume measurements using QBraVo and the comparison of mean differences in volume between the original and defaced images,

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respectively. High ICCs exceeding 0.995 (p<0.001) were noted across multiple regions, including the anterior frontal, anteromedial frontal, dorsolateral frontal, posteromedial frontal, inferior frontal, orbital frontal, anterior temporal, medial temporal, lateral temporal,

Table 2. The interclass reliability of brain volume measurements between the original and defaced images, using mri_deface, BSW-based defacing, and Defacer

Variables	Volumetric method	mri_deface			BSW-based defacing			Defacer		
		ICC (2,1)	95% CI	*p*-value	ICC (2,1)	95% CI	*p*-value	ICC (2,1)	95% CI	*p*-value
TIV	QBraVo	1.000	0.999–1.000	<0.001	1.000	0.999–1.000	<0.001	1.000	0.999–1.000	<0.001
	FreeSurfer	0.998	0.992–0.999	<0.001	0.999	0.997–1.000	<0.001	0.999	0.998–1.000	<0.001
TBV	QBraVo	0.999	0.997–1.000	<0.001	1.000	0.998–1.000	<0.001	0.999	0.997–1.000	<0.001
	FreeSurfer	0.981	0.368–0.997	<0.001	0.987	0.184–0.998	<0.001	0.983	0.263–0.997	<0.001
Ventricle volume	QBraVo	1.000	0.999–1.000	<0.001	1.000	0.999–1.000	<0.001	1.000	0.999–1.000	<0.001
	FreeSurfer	0.978	0.296–0.996	<0.001	0.984	0.147–0.998	<0.001	0.980	0.206–0.997	<0.001
Hippocampus volume	QBraVo	0.996	0.984–0.999	<0.001	0.996	0.985–0.999	<0.001	0.996	0.985–0.999	<0.001
	FreeSurfer	0.742	−0.024–0.936	0.008	0.880	0.165–0.974	<0.001	0.911	0.236–0.982	<0.001

The interclass reliability was represented as the ICC, accompanied by the 95% CI and p-value.
BSW: BioImage Suite Web, ICC: intraclass correlation coefficient, CI: confidence interval, TIV: total intracranial volume, TBV: total brain volume.

Table 3. The interclass reliability of regional brain volume measurements between the original and defaced images, using mri_deface, BSW-based defacing, and Defacer

Variables	mri_deface			BSW-based defacing			Defacer		
	ICC (2,1)	95% CI	*p*-value	ICC (2,1)	95% CI	*p*-value	ICC (2,1)	95% CI	*p*-value
Anterior frontal lobe	0.998	0.993–1.000	<0.001	0.999	0.997–1.000	<0.001	0.999	0.992–1.000	<0.001
Anterior medial frontal lobe	0.999	0.998–1.000	<0.001	1.000	0.996–1.000	<0.001	1.000	0.999–1.000	<0.001
Dorsolateral frontal lobe	0.998	0.991–0.999	<0.001	0.998	0.992–1.000	<0.001	0.998	0.993–1.000	<0.001
Posteromedial frontal lobe	0.998	0.994–1.000	<0.001	0.999	0.995–1.000	<0.001	0.999	0.994–1.000	<0.001
Inferior frontal lobe	0.998	0.994–1.000	<0.001	0.999	0.997–1.000	<0.001	0.999	0.996–1.000	<0.001
Orbital frontal lobe	0.998	0.991–0.999	<0.001	0.999	0.997–1.000	<0.001	0.999	0.996–1.000	<0.001
Anterior temporal lobe	0.995	0.926–0.999	<0.001	0.996	0.969–0.999	<0.001	0.997	0.989–0.999	<0.001
Medial temporal lobe	0.997	0.988–0.999	<0.001	0.996	0.986–0.999	<0.001	0.998	0.990–0.999	<0.001
Lateral temporal lobe	0.999	0.997–1.000	<0.001	1.000	0.999–1.000	<0.001	0.999	0.997–1.000	<0.001
Lateral parietal lobe	0.999	0.995–1.000	<0.001	0.999	0.998–1.000	<0.001	0.999	0.996–1.000	<0.001
Medial parietal lobe	0.998	0.993–1.000	<0.001	0.999	0.997–1.000	<0.001	0.998	0.993–1.000	<0.001
Occipital lobe	0.999	0.998–1.000	<0.001	0.999	0.998–1.000	<0.001	0.999	0.996–1.000	<0.001
Cerebellum	0.996	0.985–0.999	<0.001	0.997	0.981–0.999	<0.001	0.996	0.985–0.999	<0.001

The interclass reliability was represented as the ICC, accompanied by the 95% CI and p-value. The regional brain volume was measured using QBraVo program.
BSW: BioImage Suite Web, ICC: intraclass correlation coefficient, CI: confidence interval.

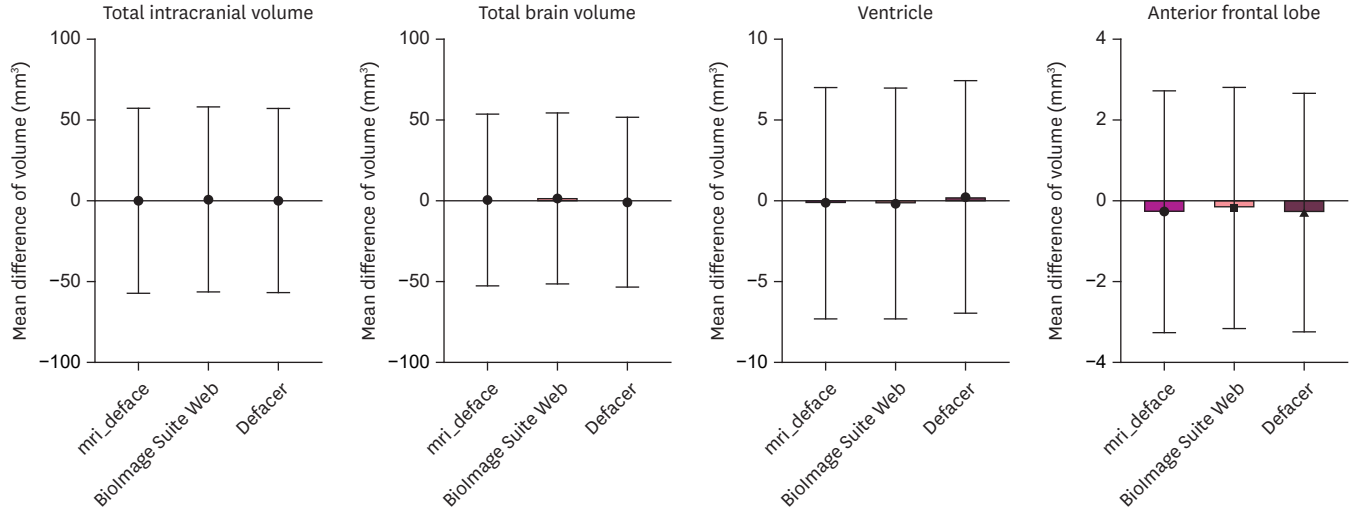

Fig. 2. Mean differences of regional brain volumes between the original and defaced images, using mri_deface, BioImage Suite Web-based defacing, and Defacer. Mean and standard errors are displayed.
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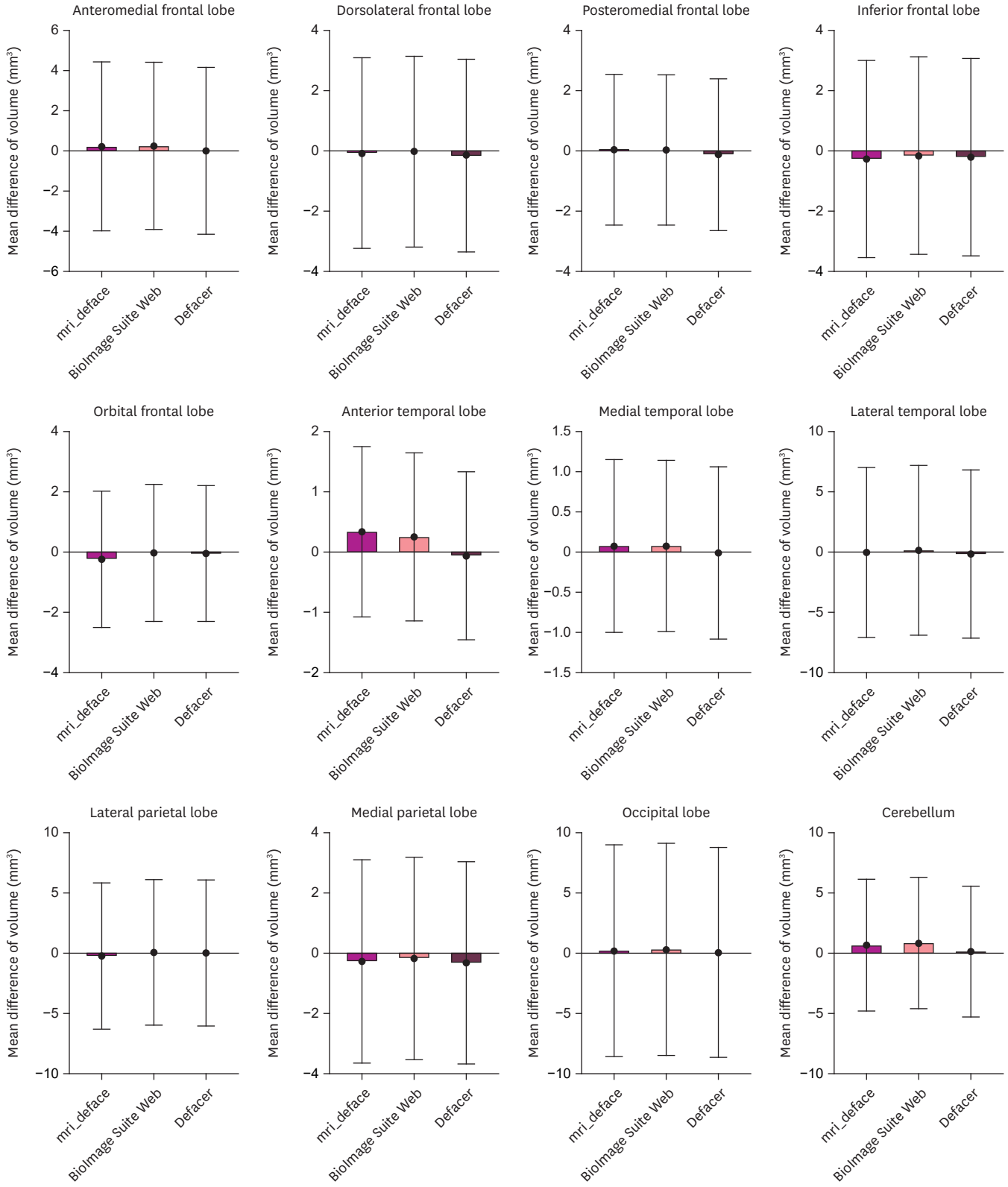

Fig. 2. (Continued) Mean differences of regional brain volumes between the original and defaced images, using mri_deface, BioImage Suite Web-based defacing, and Defacer. Mean and standard errors are displayed.

https://doi.org/10.12779/dnd.2024.23.3.127

lateral parietal, medial parietal, occipital lobe, and cerebellum. No significant differences in regional brain volumes between the original and defaced images were detected, although the anterior temporal lobe, medial parietal lobe, and cerebellum exhibited relatively larger discrepancies. The mean differences (standard error) in volume for these regions were as follows: 1) anterior temporal lobe, 0.337 (1.414) for mri_deface, 0.249 (1.392) for BSW-based defacing, and −0.063 (1.394) for Defacer; 2) medial parietal lobe, −0.267 (3.378) for mri_deface, −0.168 (3.368) for BSW-based defacing, and −0.313 (3.360) for Defacer; and 3) cerebellum, 0.662 (5.466) for mri_deface, 0.842 (5.454) for BSW-based defacing, and 0.133 (5.434) for Defacer.

DISCUSSION

This study established that the three distinct defacing algorithms do not markedly influence the outcomes of the 2 automated brain volumetry methods. Although specific brain regions were relatively more affected than others, the analysis of defaced images demonstrated high reproducibility across most brain areas. To the best of our knowledge, this is the first investigation into the effects of defacing on regional brain volume analysis. Amidst growing demand for effective and secure defacing methods to address concerns about potential image impacts, our findings affirm that the examined defacing methods maintain robustness in whole and regional brain analyses.

Various defacing algorithms have been developed to significantly reduce the risk of facial recognition, notwithstanding that some negatively impact the images.[1,8,11] Previous investigations have shown that defacing images with different methods and a skull stripping technique did not compromise the integrity of image analysis results.[11] Another study highlighted that defacing with 'mri_reface' effectively thwarted re-identification with minimal impact on T1 and non-T1 magnetic resonance (MR) sequences.[1] Nevertheless, the effects of defacing can vary depending on the algorithm used, differences in patient demographics, and analysis techniques.[5]

In contrast, some studies have noted discernible effects of defacing on brain imaging. Most defacing algorithms were reported to affect brain atrophy estimation, especially in accelerated MR images.[3] Defacing processes have generally resulted in reduced brain volume measurements, likely due to partial volume effects.[4] However, meticulous quality control can significantly reduce the biases introduced by defacing.[2]

The influence of defacing algorithms on the quantification of specific brain lesions has been minimal for white matter hyperintensities, but significant for tumor volumes.[1,6] Additionally, defacing has been proven to anonymize brain PET images effectively,[12] minimally affecting the quantification of Tau and amyloid PET tracers.[13] Innovations such as a nose-sparing defacing algorithm for EEG or MEG co-registration exemplify how defacing facilitates the sharing of diverse brain imaging data for secondary analyses.[14]

The influence of defacing algorithms on brain imaging is multifaceted. A primary concern is the unintentional removal of brain tissue, a risk exacerbated by the variability in brain size and morphology across individuals. Additionally, the process of removing non-brain structures can inadvertently modify the signal of brain tissues. This alteration occurs during bias correction and estimation steps in the segmentation pipeline, where to differentiate

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between tissue types, the algorithm probabilistically adjusts for heterogeneous signals. Consequently, the removal of external features, like the skin and skull, can inadvertently affect the signal interpretation of adjacent brain tissues. Moreover, the excision of anatomical landmarks, such as the nose or ears, may disrupt reference points critical for accurate template matching. Despite numerous contributing factors, it has been observed that brain regions proximal to the face are particularly susceptible to these effects.[1] This suggests that changes in the signal of brain tissue during segmentation significantly contribute to the observed bias in defaced brain images.

It is imperative to further refine defacing algorithms tailored to specific imaging types, patient groups, and analytical methods to mitigate bias. Detailed planning and careful execution of defacing procedures are crucial. Sharing defaced images requires caution regarding potential artifacts, and rigorous quality control post-defacing is essential to ensure accurate de-identification and undistorted images. Although quality control in large-scale data sharing poses challenges, emerging deep learning technologies promise innovative solutions.[15]

This study has several limitations to consider. Firstly, the study's cohort was limited in size, and solely comprised patients with SCD, restricting the generalizability of the findings. Expanding future analyses to include a broader range of patient groups is imperative to validate the applicability of the results across diverse clinical populations. Secondly, while the study assessed the impact of defacing on brain volume measurements, it did not systematically evaluate the success rate of defacing operations, or their efficacy in preventing the re-identification of individuals. Establishing these metrics is crucial to confirm the functional adequacy of defacing techniques. Notably, no instances of defacing failure were reported in this analysis, suggesting a preliminary level of reliability. Thirdly, although this study undertook a comparative approach between defaced and original images to determine the reliability of defacing, it lacked a test–retest analysis. Such an analysis could provide essential insights into the consistency and reproducibility of defacing outcomes over time. Finally, future investigations should explore a range of factors, including variations in MRI techniques, image sequences, and data formats. A comprehensive comparative analysis of these factors is essential to fully understand their impact on the efficacy and reliability of defacing algorithms.

In conclusion, our analysis revealed that the application of the three distinct defacing algorithms did not significantly alter the outcomes of brain image analysis. The integrity of volumetric measurements, both globally across the entire brain, and locally within specific brain regions, remained unaffected. This finding reinforces the viability of these defacing methods for conducting detailed analyses of brain areas that are particularly susceptible to various pathologies. Nevertheless, it is important to recognize that several factors can influence the outcomes of defacing procedures, necessitating careful consideration in future brain imaging analyses. Therefore, the development of more sophisticated and robust defacing methodologies represents a crucial area for ongoing research. Such advancements enhance the accuracy of brain analysis, while also ensuring the protection of patient privacy, thereby supporting the broader application of neuroimaging studies in the medical field.

https://doi.org/10.12779/dnd.2024.23.3.127

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