Quickshear Defacing for Neuroimages

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Abstract

Data sharing offers many benefits to the neuroscience research community. It encourages collaboration and interorganizational research efforts, enables reproducibility and peer review, and allows meta-analysis and data reuse. However, protecting subject privacy and implementing HIPAA compliance measures can be a burdensome task. For high resolution structural neuroimages, subject privacy is threatened by the neuroimage itself, which can contain enough facial features to re-identify an individual. To sufficiently de-identify an individual, the neuroimage pixel data must also be removed. Quickshear Defacing accomplishes this task by effectively shearing facial features while preserving desirable brain tissue.

1   Introduction

Data sharing offers many benefits to the neuroscience research community. It encourages collaboration and interorganizational research efforts, enables reproducibility and peer review, and allows meta-analysis and data reuse. However, protecting subject privacy and implementing HIPAA compliance measures can be a burdensome task. For high resolution structural neuroimages such as MRI, subject privacy is threatened by the neuroimage itself, which can contain enough facial features to re-identify an individual.

Some in the scientific community contend that automated facial recognition technologies are not mature enough to identify a subject with enough specificity to be a threat. Automated facial recognition, however, is improving, and the technology along with it. The challenges of automated facial recognition are not, however, limited to MRI-to-photograph comparisons, and they apply to photograph-to-photograph as well. Many of the volume rendering software packages allow the specification of light sources and viewing angles, two areas where facial recognition methods struggle.

Human perception is still the strongest facial recognition technique. Volumes rendered by MRI are clearly recognizable as human faces and thus require further consideration to fully protect subjects.

2   Neuroimage Redaction

The HIPAA Privacy Rule [6] designates eighteen identifiers as protected health information (PHI), including "full face photographic images and any comparable images." To satisfy these requirements, metadata, such as names and birth dates, must be removed prior to data sharing. There are a number of tools, both manual and automatic, that allow researchers to remove metadata from medical images.

To maintain the highest possible level of privacy for subjects, it is necessary to implement a technique that removes facial features from neuroimages. Existing approaches to removing facial features include skull stripping, the process of segmenting brain and non-brain elements to remove any extraneous tissue (such as the eyes, skin, etc) that may interfere with analysis [5, 13, 15], and thus facial features are removed. Skull stripping is used for improved registration, cortical segmentation, and cortical flattening. The primary challenge with any of the skull stripping methods is the difficulty of brain segmentation. It is often a subjective process even when performed manually and can be highly sensitive to parameter selection. Using a manual approach for correcting an automated segmentation may offer a balance between efficiency and accuracy, but is still costly in terms of time and resources.

Defacing, unlike skull stripping, does not fully distinguish between brain and non-brain tissue. The primary objective is de-identification rather than segmentation, and defacing algorithms can be conservative by including anything that may be brain tissue and only discarding areas that have zero probability of being brain. This avoids some of the more complex regions, such as the optical nerves that can often complicate the process [15]. However, skull stripping techniques developed for a whole brain volume may be sensitive to removal of non-brain tissue and defaced volumes may be more challenging to skull strip [2].

The MRI Defacer proposed in [2] defaces by removing identifying facial features only, leaving the brain

and surrounding tissue intact. The algorithm relies on a previously constructed atlas of manually labeled of facial features. An optimal linear transform is computed for the input volume. It then creates a mask of all voxels with a non-zero probability of being brain tissue, preserving voxels and surrounding areas with any possibility of being brain tissue. The remaining voxels are then removed if they have a non-zero probability of being a facial feature, thus removing only facial features with zero probability of being brain tissue.

While skull stripping seems like an ideal image de-identification technique since it is part of the natural analysis workflow, it is difficult to perform accurately and automatically. The process of skull stripping can discard potentially valuable brain tissue and preclude the application of other skull stripping techniques for future use. The MRI Defacer approach preserves more valuable tissue but requires a previously constructed atlas of facial features and in some cases, does not completely remove facial features.

3   Quickshear Algorithm

Quickshear Defacing offers an alternative to the existing image de-identification methods. It aims to improve upon existing methods by eliminating the need for a manually labeled face atlas and a computationally expensive transform to atlas space. Quickshear Defacing identifies a plane that divides the volume into two sections, one containing facial features and another containing the entire brain volume, as illustrated in Figure 1. All voxels of the "face" side are set to zero, effectively shearing off identifiable facial features.

To identify the plane, Quickshear uses a binary brain mask that designates the volume to protect. Since the goal of Quickshear is to prevent re-identification rather than remove all non-brain tissue, it collapses the original image and brain mask onto the sagittal plane (profile view) to reduce complexity. Using the two-dimensional representation, an edge-of-brain mask is constructed.

The convex hull of the edge mask will identify the "set Q of points is the smallest convex polygon P for which each point in Q is either on the boundary of P or in its interior" [4]. There are a number of convex hull algorithms, and Quickshear relies on Andrew's monotone chain [1]. It lexicographically sorts the points and finds the upper and lower hulls of the points. Because the points are already sorted, find-
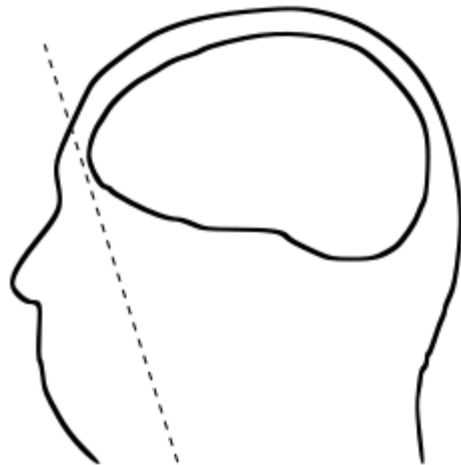

Figure 1: Quickshear defacing illustrated.

ing the hull is $O(n)$. It also provides a natural break point between finding the lower and upper hulls, since Quickshear is only interested in the lower hull.

The line formed by the first point on the lower hull (closest the forehead) and the next consecutive point is extended into three dimensions to form the shearing plane. All voxels that fall on the "face" side of the plane are set to zero. Voxels that fall on the plane are kept, and a buffer can be added to further preserve potential brain tissue.

Quickshear Defacing is implemented in Python. It uses NiBabel [8] to access neuroimages and NumPy [10] to interact with the data.

4   Results

Quickshear is evaluated using the Multi-modal MRI Reproducibility Study data set provided by Landman et al. [7], available through the Neuroimaging Informatics Tools and Resources Clearinghouse (NITRC). The data set consists of forty-two collected scans from twenty-one healthy subjects employing a wide range of MRI modalities, both structural and functional. The MPRAGE images tested were acquired with a 1.0x1.0x1.2 mm^3 resolution over an FOV of 240x204x256 mm acquired in the sagittal plane. All tests were completed in VirtualBox running Ubuntu 10.10 on an Intel Core i7-2600K with 4GB RAM.

Both Quickshear and MRI Defacer are applied to each image in the data set with default settings. The resulting volume after defacing with each technique
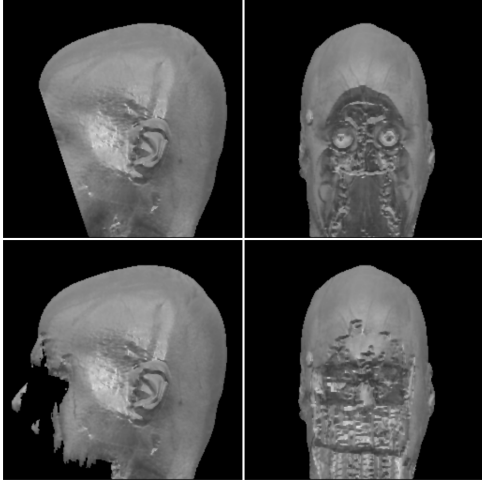
Figure 2: Volume after defacing using Quickshear (top) and MRI Defacer (bottom).

is shown in Figure 2. Quickshear defacing requires a skull stripped binary mask, and I tested three skull stripping techniques (`3dSkullStrip` in AFNI [9], Hybrid Watershed Algorithm (HWA) [13], and the Brain Extraction Toolkit (BET) [15]). Each technique uses the default settings. For each technique, the binary mask is created using the AFNI command-line `3dAutomask` program. Each skull stripping technique is applied with default parameters.

Performance is measured as wall clock time. Total running times are an average per image, averaged over five runs per image.

Defacing Method	Skull Stripping Time (s)		Defacing Time (s)
MRI Defacer	-		260.17
Quickshear	AFNI	205.71	4.30
	BET	13.72	4.33
	HWA	29.29	4.27

Table 1: Average running time for defacing on sample data set. Skull stripping time includes generating a binary mask.

Facial Feature Removal (FFR) is a validation metric to ensure that the image has been sufficiently de-identified. This is implemented as a binary score that indicates whether or not a face is present (1 indicates the presence of a face). Volume rendering is performed with MRIcron [12], a tool for viewing and analyzing MRI data. While other packages offer more

Defacing Method	Faces detected
MRI Defacer	9
Quickshear AFNI	10
BET	10
HWA	12

Table 2: Number of images determined to contain a face by OpenCV.

flexibility, MRIcron can be scripted and automated and requires fewer parameters to be selected, allowing for more uniform volumes. The OpenCV Face Detector [11, 3] is used to automate this process. The results are shown in Table 2.

Brain Volume Preservation (BVP) is a verification metric that determines how many potentially brain voxels are discarded by defacing. It relies on a designation of brain tissue, in this case, a mask generated by skull stripping. By design, Quickshear Defacing should not remove any voxels identified as brain by the binary mask it uses to deface. This serves as a basic sanity check when comparing the original mask to the defaced volume. The defaced volumes are compared voxelwise with the brain mask identified by each of the three skull stripping techniques. BVP performance is shown in Table 3.

5 Discussion

Quickshear defacing discarded fewer voxels on average than the MRI Defacer from the test images. As expected, Quickshear defacing did not discard any voxels when using the same masking approach as the verification approach. Quickshear defacing evaluated with a BET-generated brain mask discarded more voxels from more images than with the AFNI- or HWA-generated masks. This trend is also presented in the volumes defaced by MRI Defacer. In general, Quickshear defacing preserved more potentially brain voxels from more images. The overall number of voxels discarded is a small percentage of the total brain voxels (~1.3 million average in the BET-generated volume). An acceptable threshold of discarded voxels should be determined on a situational basis, and flagged volumes inspected by hand.

Using the frontal cascade, the OpenCV face detector found faces in 38 or 42 of the original anatomical images with 4 false negatives. The same detector found faces in 10 Quickshear defaced images using

Defacing Method		AFNI		Brain Mask BET		HWA	
MRI Defacer		408.74	(12)	75271.93	(42)	422.0	(7)
Quickshear	AFNI	0.0	(0)	5560.76	(13)	0.0	(0)
	BET	0.21	(1)	0.0	(0)	1.0	(2)
	HWA	0.0	(0)	7587.24	(12)	0.0	(0)

Table 3: Average number of brain voxels discarded for each defacing mechanism (Number of images with voxels discarded).

an AFNI-generated mask, 10 with a BET-generated mask, and 12 with HWA. By comparison, 9 were found in the images defaced with MRI Defacer. False positives are potentially due to the presence of eye sockets and nasal cavities that resemble a face. Some images may be recognizable from only one view. The process may benefit from introducing profile-view detection and combining the results to determine if a face is present.

In some instances, MRI Defacer left behind parts of the nose. There is potential that the remaining facial features could be reconstructed, but at present, feasibility is unproven. Several of the Quickshear defaced images left the shape of the face intact. Research on human facial recognition suggests that for unfamiliar faces, face shape plays a significant role [14], and it is yet to be determined if the features that remain after defacing can be re-identified.

The running time of Quickshear defacing, even with the slowest skull stripping mechanism, is less than that of MRI Defacer. Quickshear defacing excels when applied after a data set has already been skull stripped. It provides an efficient and effective defacing technique without encumbering the researcher.

References

[1] Andrew, A. M. Another efficient algorithm for conex hulls in two dimensions. *Information Processing Letters* (1979), 216–219.

[2] Bischoff-Grethe, A., et al. A technique for the deidentification of structural brain MR images. *Human Brain Mapping 28* (2007), 892–903.

[3] Bradski, G., and Kaehler, A. *Learning OpenCV: Computer Vision with the OpenCV Library.* O'Reilly Media, 2008.

[4] Cormen, T. H., Leiserson, C. E., Rivest, R. L., and Stein, C. *Introduction to Algorithms*, second ed. The MIT Press, 2007, pp. 947–957.

[5] Fennema-Notestine, C., et al. Quantitative evaluation of automated skull-stripping methods applied to contemporary and legacy images: Effects of diagnosis, bias correction, and slice location. *Human Brain Mapping 27* (2006), 99–113.

[6] HIPAA Administrative Simplification: Regulation Text, 2009.

[7] Landman, B. A., et al. Multi-parametric neuroimaging reproducibility: A 3T resource study. *NeuroImage* (2010).

[8] NiBabel. `http://nipy.sourceforge.net/nibabel/`, Accessed 2011.

[9] NIMH. 3dSkullStrip. `http://afni.nimh.nih.gov/pub/dist/doc/program_help/3dSkullStrip.html`, 1999.

[10] NumPy. `http://numpy.scipy.org/`, Accessed 2011.

[11] OpenCV. `http://opencv.willowgarage.com/`, Accessed 2011.

[12] Rorden, C. Mricron. `http://www.cabiatl.com/mricro/mricron/index.html`, 2010.

[13] Ségonne, F., et al. A hybrid approach to the skull stripping problem in MRI. *NeuroImage 22* (2004), 1060–1075.

[14] Sinha, P., Balas, B. J., Ostrovsky, Y., and Russell, R. *Face Recognition by Humans.* Elsevier Academic Press, 2006, ch. 8.

[15] Smith, S. M. Fast robust automated brain extraction. *Human Brain Mapping 17* (2002), 143–155.