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Semi-automated generation of individual computational models of the human head and torso from MR images

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Abstract

Purpose

Simulating the interaction of the human body with electromagnetic fields (EMF) is an active field of research. Individualized models are increasingly being used since anatomical differences impact the simulation results. We introduce a processing pipeline for creating individual surface-based models of the human head and torso for application in simulation software based on unstructured grids. The pipeline is designed for easy applicability and is publicly released on *figshare*.

Methods

The pipeline covers image acquisition, segmentation, generation of segmentation masks, and surface mesh generation of the single, external boundary of each structure of interest. Two gradient-echo sequences are employed for image acquisition. Structures of the head and body are segmented using several atlas-based approaches. They comprise bone/skull, subarachnoid cerebrospinal fluid, gray matter, white matter, spinal cord, lungs, the sinuses of the skull, and a combined class of all other structures including skin. After minor manual preparation, segmentation images are processed to segmentation masks, which are binarized images per segmented structure free of misclassified voxels and without an internal boundary. The proposed workflow is applied to two healthy subjects.

Results

Individual differences of the subjects are well represented. The models are proven to be suitable for simulation of the radio-frequency EMF distribution.

Conclusion

Image segmentation, creation of segmentation masks and surface mesh generation are highly automated. Manual interventions remain for preparing the segmentation images prior to segmentation mask generation. The generated surfaces exhibit a single boundary per structure and are suitable inputs for simulation software.

Keywords

Computational modeling, human head models, RF simulations, atlas-based segmentation, MR safety, finite element method

1 Introduction

Computational modeling of the interaction between the human body and electromagnetic fields (EMF) has become important in many scientific fields as it can provide quantities, such as amplitudes and phases of electromagnetic fields, specific absorption rate (SAR), or temperature, that would be difficult to directly acquire in vivo. Subject-specific human models are increasingly needed for MRI radiofrequency (RF) safety assessment [1] as it has been shown that anatomical differences impact simulations [2], [3]. Techniques to generate models can be sufficiently accurate to closely reproduce the shape of human tissues [4] for studying inter-subject variability or exploring specific anatomical phenotypes. However, the commonly manual creation of such models is rather laborious.

Human models are discretized either voxel-based or surface-based. In a voxel-based model, structures thinner than the employed resolution (e.g. cerebrospinal fluid (CSF) in the sulci), are represented as separated, non-continuous segments in space. In this case the electrical contact between anatomically connected parts of the same tissue is not ensured. Moreover, the curved structure of human tissues can only be discretized in an approximate and rigid staircase manner. These problems are avoided with anatomically correct surface-based models. Such models preserve electrical contact within and between tissues and better reproduce the complex shape of curved structures. Currently, several open source and commercial surface- and voxel-based models of the human head or entire body exist with different levels of detail. For example, the MIDA model is an ultra-high resolution human head and neck model [5] whereas the “Virtual Population 2.0” is a set of full body models [6]. Further instances of full-body, surface-based models include the female model of the Visual Human Project® [7], and models included in commercial software, such as ANSS HFSS (ANSYS, Inc., Canonsburg, PA, USA).

For EMF simulations, software based on regular, hexahedral volume meshes, for example finite-difference time domain solvers, have mostly been employed because the integration of a voxel-based human model is straightforward. However, the size of the hexahedral mesh elements should be substantially smaller than the thickness of the considered tissues, which results in a significant increase in computation time. Subgridding approaches have been used to overcome this limitation but are inefficient for human body simulations due to the geometrical complexity of the tissues.

Tetrahedra, pyramids and extruded triangles are used as mesh elements in software based on unstructured meshes. For example, simulation software implementing the finite-element method (FEM) or the boundary element method (BEM) provide a flexible discretization of structures bounded by complex surfaces [8]. This preserves electrical contact between all parts of the numerical model and ensures continuous mesh representations of individual structures of the surface-based model. For

simulation software based on unstructured grids, it is beneficial to have only one boundary between adjacent structures [7]. When these boundaries are triangulated, the resulting surfaces are free of intersections or intermediate gaps, and the number of triangles of the entire model is reduced.

The generation of surfaces of realistic human tissue is a non-trivial task. Images obtained by different modalities (e.g. MRI, CT) commonly serve as a starting point. These images are segmented to a pre-defined set of structures to derive a voxel-based model. Subsequently, a surface-based model can be generated using the surface representations of the boundaries of the structures present in the voxel-based model. In this process, the image segmentation is critical. The number and type of structures that can be included in the model essentially depend on the ability to segment them (preferably automated). This may be difficult to accomplish, for instance, for bone or air spaces if only MRI data are available. Moreover, the generated surfaces must meet specific geometric quality criteria (e.g. surfaces should be manifold) to be suitable for EMF simulation software packages.

In this work we focus on accomplishing this task solely based on freely available tools. To date, only a few free and ready-to-use packages comprehensively handle the task of generating surface-based models from imaging data. Most pipelines are designed for a rather restricted purpose and generate application-specific volume meshes coupled to a particular simulation software. *SCIRun*, for example, is a generalized Problem Solving Environment, which includes modules for segmenting various tissue types, computing corresponding isosurfaces as well as improving the resulting triangular surface meshes [9] [10]. However, it requires user expertise, and the segmentation process lacks a high level of automation [11]. *BrainStimulator* [12] has previously been implemented using SCIRun but is limited to modeling of the head and is specifically aimed at simulating transcranial electric brain stimulation. *3D Slicer* is another general software package including numerous modules for segmentation and surface meshing [13]. Despite the availability of these tools, a complete head and torso segmentation pipeline has not yet been implemented in freely available software.

Based on previous work [14], [15], in the current paper we introduce a processing pipeline for creating surface-based models with a single continuous surface between adjacent structures of the human head and torso from MRI data. Being designed for easy applicability, the pipeline offers a high level of automation, uses only freely available tools and provides full disclosure of scripts, workflow definitions, and documentation.

2 Methods

The pipeline comprises four major steps: image acquisition, segmentation, creation of segmentation masks and surface mesh generation. Image acquisition includes a head and a combined head and torso MRI scan. The subsequent processing treats each MRI scan separately in a highly automated manner, utilizing the *Java Image Science Toolkit (JIST)* [16], a plugin of the *Medical Image Processing, Analysis and Visualization (MIPAV)* toolset [17]. The information from both acquisitions is consolidated at the end of the segmentation process.

2.1 Image Acquisition

All investigations involving human subjects had been approved by the local ethics committee. After obtaining informed written consent, images were recorded from two healthy male volunteers (age 29 and 22 years; body weight 75 and 90 kg; height 180 and 188 cm) at 3 T on a MAGNETOM Prisma^{fit} (Siemens Healthcare, Erlangen, Germany). A high-resolution (nominal 1mm isotropic) 3D head scan was acquired with a 32-channel (receive) head coil employing a T_1 -weighted MP-RAGE sequence with previously established parameters (TR 2.3 s; TI 0.9 s; TE 3 ms; flip angle, α , 9°; field of view, FOV, 256×240×176 mm³; sagittal orientation; acquisition time, TA, 9:12 min) [18]. Additional imaging of the head and upper body, at a lower resolution (nominal 1.6×1.6×5 mm³), was performed with a body coil and a 2D FLASH sequence (TR 100 ms; TE 2 ms; α 30°; FOV 500×328 mm²; 5 axial slices; thickness 5 mm; gap 5 mm; TA 16 s). In our case, the generated models were intended for assessments of head coils in high-field MRI, specifically regarding RF field homogeneity and SAR. For this purpose, a model truncated at the shoulders provided a sufficient approximation [19]. Depending on the subject's size, 15-17 acquisition steps were necessary to capture the entire region from the head to the iliac crest. Artifacts due to diaphragm motion were mitigated by acquiring the images during a breath-hold after exhalation.

2.2 Segmentation

Segmentation poses challenges primarily due to low contrast between certain structures (e.g. bone and air) or similar textures of structures with poorly pronounced boundaries, especially on torso scans. Atlas-based segmentation methods were, therefore, adapted to the various sub-structures to be segmented. Employing atlases, as prior knowledge, enables a highly automated segmentation procedure; a major goal of the proposed pipeline. However, unsupervised atlas-based segmentation may not yield sufficient accuracy, for example, for morphometric neuroanatomical studies. Importantly, the surface-based models generated by our pipeline are not intended for these applications. Section S1 of the supporting information and Ref. [20] provide an overview of multi-atlas-based segmentation techniques.

2.2.1 Head Segmentation

The head image is segmented into six brain and non-brain structures employing three atlas-based techniques.

Segmentation of skull and scalp

The skull exhibits a low contrast on T_1 -weighted scans, hardly distinguishable from CSF. Although common segmentation tools like FSL BET2 [21], [22] or FreeSurfer [23], [24] offer skull estimates, the results (Figure 1A, Figure 1B) are not sufficient for modeling purposes. BET2 underestimates the skull extent and fails to produce a continuous boundary whereas the watershed algorithm in FreeSurfer overestimates the skull and misses individual characteristics. To gain a better estimate, we employ a rater-based, majority-voting approach for skull and scalp segmentation. Multiple anatomically unique atlases (see below) are registered to the subject's head image data, both linearly with a customized implementation of FLIRT [25] and non-linearly with the SyN algorithm [26] from ANTS in MIPAV. The resulting segmentations are considered "decisions" of independent "raters" in the *Simultaneous Truth And Performance Level Estimation* (STAPLE) algorithm [27]. Based on the complete set of segmentation images, the algorithm performs an optimized, voxel-wise, majority vote. A performance evaluation is computed and a probabilistic estimate of the true segmentation image is provided (Figure 1C). The method was successfully applied using CT images as atlases before in [28].

We employ 20 segmented, individual images from the *BrainWeb* database [29] as atlases. This has two consequences. First, only structures that are present on those BrainWeb images can be segmented. Second, since the original BrainWeb images were only defined from the top of the head to the medial part of the nose, information about the mandibula and maxilla as well as the zygomatic bone are not included in the resulting head segmentation image.

The BrainWeb images feature a large number of segmented structures; each tagged with a name and an integer label, including scalp, skull and bone marrow. Including the bone marrow during the majority-voting process impaired the result by introducing considerable noise in the final skull estimate. Thus, the label of bone marrow in the original BrainWeb data was replaced with bone. To facilitate registration, we manually adapted the atlas structure labels to approximately match their average contrast values in the original MR images. Each average value was computed from manually-probed intensities, from five different, random locations within the respective structures in the original MR image. The labels in the atlases were then replaced with these values.

Segmentation of Air Cavities

The cranial bone features several air cavities referred to as sinuses which must be considered for accurate modeling. However, they are absent in the BrainWeb images and, therefore, not segmented

by our multi-atlas approach. While sinuses are hardly distinguishable from cranial bone with MRI, they are easily distinguished with CT. Thus, a single-atlas segmentation procedure was employed involving the generation of a subject-specific, pseudo-CT volume from a single, symmetrical CT template obtained from Ref. [30]. To facilitate the registration process, the template contrast range was linearly shifted by +1024 to yield only positive values. A compression of the contrast range, by a constant factor of 0.5, yielded a maximum intensity below 550 for intracranial tissues, which approximately matched the maximum intensity in the MR data.

The CT atlas is then registered linearly and non-linearly to the subject's MR volume. The air-filled cavities exhibit the lowest contrast values on the CT template, allowing easy identification and marking of such voxels. By deleting the largest connected component of those voxels, which extends to the image boundary, the background is removed yielding an image representing only internal air. A probability map of that volume can then be computed exhibiting a value of 1 at the center of air cavities and declining values towards their boundary. Additionally, the values of the MR volume are normalized into [0,1] and inverted to yield values close to 1 in areas of previously low intensity (i.e. air and bone) with lower values elsewhere. A multiplication of the probability map with the modified MR volume ensures that the shape of the segmented air cavities is primarily determined by the underlying subject's data and not the CT template. The final segmentation image is obtained after a binarization, followed by hole filling and opening operations (Figure 2).

Air cavities are surrounded by cranial bone. As this was not considered during the segmentation process, the segmented air structures may be overestimated and could overlap the skull boundary. This would result in holes that impact simulations [31]. To ensure a minimum width of the surrounding skull boundary, a binarized and eroded version of the skull was multiplied with the air segmentation image. This restricts air voxels to within the eroded skull mask and prevents possible overestimation.

Segmentation of Intracranial Tissues

Although CSF, gray matter (GM), and white matter (WM) are part of the BrainWeb images, the majority-voting approach is inadequate to segment the fine details of cortical folding and the complex branching of WM tracts. Their segmentation has been addressed in common toolboxes, such as FSL FAST [21], [32], SPM [33], BrainSuite [34] and FreeSurfer [23], [35]. Segmented intracranial structures ideally must be nested to ensure only one boundary between adjacent structures. BrainSuite [36] and FreeSurfer [37] offer a topological correction of the segmented GM cortex, but not for other tissue classes. Rather, the *Multi-object Geometric Deformable Model (MGDM)* algorithm [38] was used as it maintains the topology of all objects and their relationships. To prevent overlap of CSF and skull, from overestimation of CSF, the skull is provided as prior information to the MGDM algorithm. The algorithm

then computes a segmentation image comprising the subarachnoid CSF and ventricles as well as detailed cortical and subcortical structures and the cerebellum. The method was previously validated for 7T data in [39].

The MGDM algorithm relies on a combination of atlases from the BrainWeb database and a probability map of 30 different brain structures derived from the Internet Brain Segmentation Repository [40]. In addition to these atlases, a deformable model is employed to ensure compliance with the topological constraints. The labels of all structures segmented by MGDM are integrated into the four labels of subarachnoid CSF, ventricles, GM and WM. To further enhance the accuracy of the segmented GM, we subsequently applied the *Cortical Reconstruction Using Implicit Surface Evolution* (CRUISE) algorithm [41], which reconstructs the cortical geometry in more detail than conventional segmentation approaches.

2.2.2 Torso Segmentation

Automated methods do not exist for torso segmentation. Hence, we take a similar approach as above, registering a single full-body atlas linearly and non-linearly to the FLASH image. The result is a segmented upper torso that is merged with the head in a subsequent step (see below). The AustinMan full-body human model (version 2.4) from the visible human project [42] serves as the torso atlas. This model originally features a very high in-slice resolution of $0.3 \times 0.3 \text{ mm}^2$, with a slice thickness of 1 mm, and a total of 64 segmented structures. The model represents a single male of 90.27 kg body weight and 180.34 cm height [43].

For present purposes the atlas required a two-step manual preprocessing. Firstly, the atlas image was cropped to match the extent of the FLASH data, if they differed. Secondly, labels were assigned to the structures of interest. In our case, cropping was performed at the base of the lungs. Labels were combined to obtain: bone, air, CSF, GM, WM and an additional class for all other structures (see Supporting Information Table S1 for an overview).

2.2.3 Merging Head and Torso Segmentations

A complete head segmentation image was generated by merging the images of scalp and skull, air, as well as intracranial tissue. A prior registration was not required since the three segmentations were performed on the same MR volume. The image, including the segmented scalp and skull, was then prepared for merging by labeling all intracranial voxels as CSF. It was then merged with the segmentation images of the intracranial tissue and air cavities by transferring the non-zero voxel labels.

Merging the complete segmentation images of the head and body remains a manual operation. As they originate from different scans, they needed to be transformed into a common space. The body image was scaled to match the voxel-size of the head image. Subsequently, any information inferior to

a manually defined slice was deleted, sparing only the head volume. Then, a rigid-body registration of the head image to the manipulated body image was performed. Figure 3A shows the registered head image overlaid on the body image. It should be noted that the head image partly occludes several facial bones. Hence, a manual definition of the boundary along the bottom of the skull, close to the base of the brain stem of the segmented head as illustrated in Figure 3B, was necessary. This was followed by cropping of the inferior parts of the head volume and the superior parts of the body volume.

2.2.4 Generation of Binary Segmentation Masks

The segmentation images are insufficient to generate surface-based models for three reasons. First, due to their partially nested arrangement, most human body structures exhibit an external and internal boundary. In a surface-based model, the internal surface can resemble the external surface of an adjacent, internal structure. Keeping these surfaces would increase the triangle count without introducing additional information. Such adjacent surfaces are, furthermore, prone to numerical inaccuracies of the vertex locations, causing mutual intersections and intermediate gaps. Second, surface-based models require segmented structures that are continuous. However, our segmented scalp and skull may erroneously exhibit small clusters of non-classified voxels. Third, depending on the required detail of the end user, a coarser resolution of the segmentation image might be favored in exchange for faster subsequent processing in the EMF simulation software. Thus, segmentation images were converted to segmentation masks.

To standardize the subsequent procedures across structures, we created one image per structure, binarized the images by assigning values of 1 to voxels representing the segmented structure, and performed a zero-padding of ten voxels, at all image borders, to avoid undesired interactions of subsequent morphological operations. Temporarily, the segmentation image was manually split at the bottom of the brainstem to enforce the anatomically most reasonable topology for both the head and the body. For example, inside the head air is enclosed by bone but the air in the lungs is outside of bone.

Each resulting mask is morphologically closed which ensures a continuous external boundary. Finally, a morphological filling, followed by the addition of a morphological dilated version of the corresponding internal structure, ensures a minimum thickness of two voxels for every structure and eliminates the internal boundary. For bone and air in the torso, intersections were avoided by subtracting the dilated bone mask from the air mask, which ensured a spacing of at least two voxels between them. This yields strictly nested binary segmentation masks of the segmented structures, separately for the head and torso, with a single boundary between adjacent structures.

Masks of structures present in the head and torso (e.g. bone) are then joined by adding the associated binary images together. The mask of the spinal cord required additional processing to ensure that it did not overlap with the GM. More precisely, the spinal cord mask was split into aspects inside and outside of the GM by multiplying and subtracting the GM mask respectively. Adding the internal mask to the WM mask yielded two masks; the external spinal cord and the WM combined with the internal spinal cord. The two masks interface at the lower planar boundary of the GM.

2.2.5 Surface Mesh Generation

Surface meshes were generated from the segmentation mask of each structure utilizing the *Contour Filter* in *ParaView* [44], which implements the “*synchronized templates*” algorithm [45] based on the *Marching Cubes* algorithm [46]. The Contour Filter approximates, by triangulation, the polygonal representations of isosurfaces, that is, surfaces of identical values within a 3D volume. The resulting surface meshes are exported to STL files. Supporting Information Figures S1 and S2 show examples of the resulting triangular surface meshes of the skull and GM. The process of surface mesh generation is automated using a bash script invoking ParaView for each segmentation mask with a predefined execution plan.

2.3 Application to EMF simulations for MRI at 7T

We used the commercial, 3D, EMF simulation software ANSYS HFSS 2014, featuring a frequency domain solver, to conduct EMF simulations and compute the RF magnetic field distribution using the surface-based models of subjects 1 and 2 [14]. Because the models exhibited a high number of triangles, they were first remeshed with the geometry preprocessor ANSYS SpaceClaim 2017.2. For each surface, a respective triangulated wrapper surface was generated with increased smoothness and an adaptive number of triangles, depending on the individual curvature. The surface preprocessing workflow is also described in Ref. [14]. In ANSYS HFSS, a rectangular domain (*air box*) was defined with the model at the center. Initial conditions were set on the boundaries of the domain as follows. The top boundary was set to excite a traveling-wave at 297.2 MHz and 1 W transmit-power. A *HFSS radiation boundary* condition, modeling an electrically open surface [47], was defined for the other boundaries to absorb the EMF. Electrical properties (dielectric constant and conductivity) of the tissues were adopted from the IT'IS database [48].

3 Results

Segmentation of the MP-RAGE volume (Figure 4A and Supporting Information Figure S6A) based on our multi-atlas approach captured the individual shape of the scalp and skull but did not segment air cavities and failed to provide a sufficient level of detail of the intracranial structures. Furthermore, the segmentation was restricted to the extent of the atlases. The segmentation image after this step is

illustrated in Figure 4B and Supporting Information Figure S6B. The segmentation of air inside the skull, based on a pseudo-CT volume, captured individual characteristics of the cavities well (Figure 4C). A comparison of the results obtained in the two subjects revealed that for subject 2 the frontal sinus was not segmented (Supporting Information Figure S6C), due to sinusitis, which is also observed on the corresponding MP-RAGE images. The MGDM algorithm segmented the brain into a multitude of intracranial structures (Figure 4D and Supporting Information Figure S6D). The cortical gyrification was well represented and the topology of individual structures was preserved. The estimated cortical folding was further improved by the application of the CRUISE method in the subsequent process of generating the segmentation masks (Figure 5).

The FLASH volume, comprising the head and upper body, was segmented by registering it to the AustinMan template in a single-atlas-based approach. Note that the template deviates from subject 1 in terms of body weight and from subject 2 in terms of body height. The same template can be used for both subjects as the registration approach allows for the transfer of properties of the original MR images to the segmentation image (Figure 6B and Supporting Information Figure 7B), for example, variable body mass, chin shape, or curvature of the spinal column or cord.

Figure 7 shows the final segmentation images for both subjects after combining the segmented skull and skin, air, intracranial tissue, and upper torso. Visual inspection did not reveal large discrepancies between the produced anatomies and the underlying MRI, although the accuracy of the segmentation method could not be directly quantified. The results are geometrically accurate, yet still unsuitable for the surface generation. As can be observed in the axial views of Figure 7, the scalp exhibits several non-classified voxels, the sinus frontalis of subject 1 (axial view of Figure 7A) is incomplete. Further, the topological constraint that structures are nested within one another is not yet enforced for the torso (e.g. the spinal cord is not surrounded by CSF). These issues were addressed in the subsequent mask generation process.

The surfaces generated from the segmentation masks using ParaView (Figure 8 and Supporting Information Figure S8) are manifold, meaning, they do not contain holes. Further, they exhibit individual differences between subjects, which becomes particularly apparent for surface meshes of the skin and GM. The Contour Filter computes surfaces with a high number of regularly shaped triangles. The quality of these surfaces is adequate for further processing (e.g. remeshing, volumetric meshing) as demonstrated in Figure 9 and Supporting Information Figure S9.

Figure 10 shows the computed point-SAR (i.e., the local SAR without mass or volume averaging) and B_1^+ obtained with ANSYS HFSS using the model of subject 1. Importing of the surface-based model, remeshing and the computation of the tetrahedral volume mesh required approximately 10 hours on

an up-to-date Dell workstation. Radio-frequency EMF distribution was computed after approximately one hour.

4 Discussion

In this work, we established a processing pipeline to generate surface-based models from individual MRI data. The realization of individualized EMF and SAR simulations is facilitated by the semi-automated and, thus, faster generation of surface-based models.

The proposed pipeline is built solely upon the use of MR images as individual input. We tested the pipeline with standard gradient-echo sequences, however, we expect other sequences or protocol settings to work as well. Computed tomography is an imaging modality that provides a superior contrast of the skull and enclosed sinuses, facilitating the segmentation of these structures. However, CT leads to significant radiation exposure and was, therefore, excluded as a required source of input images.

We incorporated only a few relevant structures (e.g., bone, air, GM) in the proposed segmentation pipeline. In principle, integration of additional structures is straightforward since the applied atlases feature a multitude of structures, which may be included for specific applications. However, the segmentation accuracy would need to be investigated for such additional tissue classes. The majority voting approach used for the scalp and skull segmentation is unsuitable for segmenting highly variable structures, such as body fat or bone marrow. Likewise, the reliability of the single-atlas approach used for the body segmentation may be limited to structures that do not show major deviations in position or shape from the AustinMan atlas. The MGDM algorithm, however, segments the brain in greater detail than merely GM and WM, also allowing the incorporation of subcortical structures into the model.

Considering fat and muscle tissue, especially in the head part of the model, would be beneficial for simulations of transcranial direct-current stimulation (tDCS) [49], [50] or SAR of MRI head coils [3]. An investigation of methods to overcome the above-mentioned challenges in segmenting highly variable structures is left for future work. We also did not consider a more detailed representation of the body, for example, including the intestines and the vascular system, because the benefit of incorporating a detailed representation of the torso is negligible for the purpose of SAR simulations for head coils [19], which was our primary application.

Merging the head and body segmentation images was difficult to automate because the slice where they meet is identified by the base of the brainstem; a structure hard to identify automatically

on segmentation images. Our attempts at automatization were not deemed sufficiently robust, and so we opted for a quick to perform manual approach that ensured consistent results.

The “synchronized templates” algorithm utilized for surface meshing avoids the typical voxel-grid-like structure present in naïve surface reconstructions of voxel-based 3D volumes and generates high-resolution surfaces that preserve all details of the underlying segmentation masks. However, these surface triangulations exhibit a high number of equally sized triangles even in flat areas, which may be unfavorable for some simulation software. To decimate the number of triangles, either the resolution of the segmentation masks prior to surface meshing can be reduced, which simultaneously decreases the detail of the surfaces, or the surfaces can be remeshed. In supporting information section S2 and Supporting Information Figures S1 – S5, we provide a selection of remeshing techniques we tested. A mathematical description of the boundaries by non-uniform rational basis splines (NURBS) might constitute another alternative, as discussed in supporting information section S3.

Our approach is aimed at generating surface-based models with a single surface between adjacent structures. Consequences are ventricles enclosed by WM and a layer of two voxels of GM around the brainstem. For the spinal cord, which overlaps the GM, a common planar interface with the GM was introduced.

The pipeline has been tested with healthy male subjects as a proof of concept. The reliability of the results in female subjects, or those with largely divergent physiques, such as obese subjects or children remains to be evaluated. In such cases the body segmentation via registration to a single atlas may be more challenging and use of a corresponding template might be favored. Furthermore, segmentation of pathological or abnormal tissue, for example, brain lesions, was not tested. Such tissue may not be segmented or even impair the result. To account for such factors, implementation of other segmentation techniques is suggested as is the integration of alternative imaging sequences or modalities for the input.

The extent of the model may be varied according to the intended use. For example, SAR simulations of a whole-body coil require full-body models [3]. Extension to full body models, while possible with this approach, may be challenging due to the large number of separate structures to the model, as well as the variability in patient limb positioning and body shape. For other applications, such as simulations of tDCS [51], the model extent can be reduced by decreasing the extent of the body scan and atlas or using only the head model.

Conclusion

We introduce a semi-automatic pipeline for the generation of surface-based models of the human head and upper torso, with a single surface between adjacent structures and based solely on individual MR images. The segmentation process is implemented in JIST, a plugin of MIPAV, and surface mesh generation is realized in ParaView. All tools are freely available and open source, as is our pipeline, along with further documentation on the application of the proposed methods¹.

In a four-step process, CSF, GM, WM, air, the spinal cord, bones and a combined class of the remaining tissues of the head and upper torso are segmented using highly automated atlas-based approaches. Manual interventions are necessary to prepare the segmentation images for segmentation mask generation. The segmentation images are post-processed to generate continuous, voxel-based masks, which are free of classification errors. Finally, surface triangulations of the boundaries are obtained. The resulting surface-based models are applied for evaluation of MRI coils in FEM simulation software.

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¹ <https://figshare.com/s/f2e47b41e974ab67039b>, SH1: 6d3866719019778df09d549031466afdf76427b8

Bibliography

- 1 Kabil J, Belguerras L, Trattnig S, Pasquier C, Felblinger J, Missoffe A. A Review of Numerical Simulation and Analytical Modeling for Medical Devices Safety in MRI. *Yearb Med Inform.* 2016. 152-158.
- 2 Laakso I, Tanaka S, Koyama S, De Santis V, Hirata A. Inter-subject Variability in Electric Fields of Motor Cortical tDCS. *Brain Stimul.* 2015;8:906-913.
- 3 Homann H, Börnert P, Eggers H, Nehrke K, Dössel O, Graesslin I. Toward individualized SAR models and in vivo validation. *Magn Reson Med.* 2011;66:1767-1776.
- 4 Park JS, Jung YW, Choi HD, Lee AK. VK-phantom male with 583 structures and female with 459 structures, based on the sectioned images of a male and a female, for computational dosimetry. *J Radiat Res.* 2018;59:338-380.
- 5 Iacono MI, Neufeld E, Akinagbe E, et al. MIDA: A Multimodal Imaging-Based Detailed Anatomical Model of the Human Head and Neck. *PLoS One.* 2015;doi: 10.1371/journal.pone.0124126.
- 6 Gosselin MC, Neufeld E, Moser H, et al. Development of a new generation of high-resolution anatomical models for medical device evaluation: the Virtual Population 3.0. *Phys Med Biol.* 2014;59:5287.
- 7 Yanamadala J, Noetscher GM, Louie S, et al. Multi-purpose VHP-female version 3.0 cross-platform computational human model. In: 2016 10th European Conference on Antennas and Propagation (EuCAP); 10 - 15 April 2016; Davos, Switzerland.
- 8 Massey JW, Prokop A, Yilmaz AE. A comparison of two anatomical body models derived from the female visible human project data. In: 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); 11 - 15 July 2017; Jeju Island, Korea.
- 9 Parker SG, Johnson CR. SCIRun: A Scientific Programming Environment for Computational Steering. In: Proceedings of the 1995 ACM/IEEE Conference on Supercomputing; 1995. p. 52.
- 10 Callahan M, Cole MJ, Shepherd JF, Stinstra JG, Johnson CR. A meshing pipeline for biomedical computing. *Eng Compt.* 2009;25:115-130.
- 11 MacLeod RS, Stinstra JG, Lew S, et al. Subject-specific, multiscale simulation of electrophysiology: a software pipeline for image-based models and application examples. *Philos Trans A Math Phys Eng Sci.* 2009;367:2293-2310.
- 12 Dannhauer M, Khan A, White D, et al. Brainstimulator: A Flexible Extensible Software Tool for Modeling and Optimizing Transcranial Brain Stimulation. *Brain Stimul.* 2017;10:e12--e13.
- 13 Fedorov A, Beichel R, Kalpathy-Cramer J, et al. 3D Slicer as an image computing platform for the Quantitative Imaging Network. *Magn Reson Med.* 2012;30:1323-1341.
- 14 Kozlov M, Bode J, Bazin PL, Kalloch B, Weiskopf N, Moeller HE. Building a High Resolution Surface-Based Human Head and Torso Model for Evaluation of Specific Absorption Rates in MRI.

In IEEE International Conference on Microwaves, Antennas, Communications and Electronic Systems (COMCAS); Tel-Aviv, Israel; November 2017; p. 1-6.

- 15 Kozlov M, Kalloch B, Bazin PL, Hlawitschka M, Weiskopf N, Möller HE. Toward individualized specific absorption rates: building a surface based head model from MRI to study travel wave excitation. In 25th Annual Meeting of the International Society of Magnetic Resonance Imaging in Medicine (ISMRM); Honolulu, HI, USA, 2017; Abstract #0011.
- 16 Lucas BC, Bogovic JA, Carass A, Bazin PL, Prince JL, Pham DL, Landman BA. The Java Image Science Toolkit (JIST) for rapid prototyping and publishing of neuroimaging software. *Neuroinformatics*. 2010;8:5-17.
- 17 McAuliffe M, Lalonde F, McGarry DP, Gandler W, Csaky K, Trus B. Medical Image Processing, Analysis & Visualization in Clinical Research. In Proceedings of the 14th IEEE Symposium on Computer-Based Medical Systems; 2001 Feb. p. 381-386.
- 18 Streitbürger DP, Pampel A, Krueger G, et al. Impact of image acquisition on Voxel-Based-Morphometry Investigations of Age-Related Structural Brain Changes. *Neuroimage*. 2014;87:170-182.
- 19 Wolf S, Diehl D, Gebhardt M, Mallow J, Speck O. SAR simulations for high-field MRI: How much detail, effort, and accuracy is needed? *Magn Reson Med*. 2013;69:1157-1168.
- 20 Iglesias JE, Sabuncu MR. Multi-atlas segmentation of biomedical images: A survey. *Med Image Anal*. 2015;24:205-219.
- 21 Jenkinson M, Beckmann CF, Behrens TEJ, Woolrich MW, Smith SM. FSL. *Neuroimage*. 2012;62:782-790.
- 22 Jenkinson M, Pechaud M, Smith S, et al. BET2: MR-based estimation of brain, skull and scalp surfaces. In Eleventh Annual Meeting of the Organization for Human Brain Mapping; 2005. p. 167.
- 23 Fischl B. FreeSurfer. *Neuroimage*. 2012;62:774-781.
- 24 Ségonne F, Dale AM, Busa E, et al. A hybrid approach to the skull stripping problem in MRI. *Neuroimage*. 2004;22:1060-1075.
- 25 Jenkinson M, Smith S. A global optimisation method for robust affine registration of brain images. *Med Image Anal*. 2001;5:143-156.
- 26 Avants BB, Epstein CL, Grossman M, Gee JC. Symmetric diffeomorphic image registration with cross-correlation: evaluating automated labeling of elderly and neurodegenerative brain. *Med Image Anal*. 2008;12:26-41.
- 27 Warfield SK, Zou KH, Wells WM. Simultaneous truth and performance level estimation (STAPLE): an algorithm for the validation of image segmentation. *IEEE Trans Med Imaging*. 2004;23:903-921.

- 28 Angel TC, Herraiz Joaquin L, Hernandez-Tamames Juan A, Raul SJE, Yigitcan E, Yves R, Elfar A, Wald Lawrence L, Norberto M. Multi-atlas and label fusion approach for patient-specific MRI based skull estimation. *Magn Reson Med*. 75:1797-1807.
- 29 Aubert-Broche B, Griffin M, Pike GB, Evans AC, Collins DL. Twenty new digital brain phantoms for creation of validation image data bases. *IEEE Trans Med Imaging*. 2006;25:1410-1416.
- 30 Rorden C, Bonilha L, Fridriksson J, Bender B, Karnath HO. Age-specific CT and MRI templates for spatial normalization. *Neuroimage*. 2012;61:957-965.
- 31 Eichelbaum S, Dannhauer M, Hlawitschka M, Brooks D, Knösche TR, Scheuermann G. Visualizing simulated electrical fields from electroencephalography and transcranial electric brain stimulation: A comparative evaluation. *NeuroImage*. 2014;101:513-530.
- 32 Zhang Y, Brady M, Smith S. Segmentation of brain MR images through a hidden Markov random field model and the expectation-maximization algorithm. *IEEE Trans Med Imaging*. 2001;20:45-57.
- 33 Penny WD, Friston KJ, Ashburner JT, Kiebel SJ, Nichols TE. Statistical Parametric Mapping: The Analysis of Functional Brain Images. Academic press; 2011.
- 34 Shattuck D, Leahy R. BrainSuite: An automated cortical surface identification tool. In Medical Image Computing and Computer-Assisted Intervention - MICCAI 2000; 2000. p. 50-61.
- 35 Fischl B, Salat DH, Busa E, et al. Whole brain segmentation: automated labeling of neuroanatomical structures in the human brain. *Neuron*. 2002;33:341-355.
- 36 Shattuck DW, Leahy RM. Automated graph-based analysis and correction of cortical volume topology. *IEEE Trans Med Imaging*. 2001;20:1167-1177.
- 37 Ségonne F, Pacheco J, Fischl B. Geometrically accurate topology-correction of cortical surfaces using nonseparating loops. *IEEE Trans Med Imaging*. 2007;26:518-529.
- 38 Bogovic JA, Prince JL, Bazin PL. A multiple object geometric deformable model for image segmentation. *Comput Vis Image Underst*. 2013;117:145-157.
- 39 Bazin PL, Weiss M, Dinse J, Schäfer A, Trampel R, Turner R. A computational framework for ultra-high resolution cortical segmentation at 7Tesla. *NeuroImage*. 2014;93:201-209.
- 40 Worth AJ. The Internet brain segmentation repository (IBSR). Web site. <https://www.nitrc.org/projects/ibsr/>. 2007. Accessed 26 Feb 2018.
- 41 Han X, Pham DL, Tosun D, Rettmann ME, Xu C, Prince JL. CRUISE: Cortical Reconstruction Using Implicit Surface Evolution. *NeuroImage*. 2004;23:997-1012.
- 42 Massey JW, Yilmaz AE. AustinMan and AustinWoman: High-fidelity, anatomical voxel models developed from the VHP color images. In IEEE 38th Annual International Conference of the Engineering in Medicine and Biology Society (EMBC); 2016. p. 3346-3349.
- 43 Spitzer V, Ackerman MJ, Scherzinger AL, Whitlock D. The visible human male: a technical report. *J Am Med Inform Assoc*. 1996;3:118-130.

- 44 Kitware Inc. ParaView. Web site. <https://www.paraview.org/>. 2018. Accessed 23 Jan 2018.
- 45 Moreland K, Geveci B. A Pervasive Parallel Processing Framework for Data Visualization and Analysis at Extreme Scale. Tech. rep. Kitware, Inc., Clifton Park, NY (United States); Sandia National Lab.(SNL-NM), Albuquerque, NM (United States); 2014.
- 46 Lorensen WE, Cline HE. Marching cubes: A high resolution 3D surface construction algorithm. In: Proceedings of the 14th annual conference on Computer graphics and interactive techniques; 1987. p. 163-169.
- 47 Ansys Inc. ANSYS Resource Library. Web resource. <https://www.ansys.com/-/media/ansys/corporate/resourcelibrary/techbrief/ab-hfss-open-regions.pdf>. 2018. Accessed 02 February 2018.
- 48 Hasgall PA, Di Gennaro F, Baumgartner C, et al. IT'IS Database for thermal and electromagnetic parameters of biological tissues, Version 4.0, May 15, 2018, doi: 10.13099/VIP21000-04-0. www.itis.ethz.ch/database.
- 49 Shahid S, Wen P, Ahfock T. Effect of fat and muscle tissue conductivity on cortical currents - a tDCS study. In IEEE/ICME International Conference on Complex Medical Engineering (CME); 2011. p. 211-215.
- 50 Truong DQ, Magerowski G, Pascual-Leone A, Alonso-Alonso M, Bikson M. Finite Element study of skin and fat delineation in an obese subject for transcranial Direct Current Stimulation. In Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC); 2012. p. 6587-6590.
- 51 Indahlastari A, Chauhan M, Schwartz B, Sadleir RJ. Changing head model extent affects finite element predictions of transcranial direct current stimulation distributions. *J Neural Eng.* 2016;13:066006.
- 52 Pébay P, Baker T. Analysis of triangle quality measures. *Math Comput.* 2003;72:1817-1839.
- 53 Stimpson CJ, Ernst CD, Knupp P, Pébay PP, Thompson D. The Verdict Library Reference Manual. Sandia National Laboratories Technical Report. April 2007.

List of figure captions

CT template MRI subject

Figure 2. Air segmentation workflow. Using the acquired T_1 -weighted MP-RAGE data of the subject and a CT template, the air segmentation masks are created through a series of image manipulation steps. All images depict the same slice of the volume.

Figure 4.

Complete head segmentation of subject 1. **(A)** T_1 -weighted MPRAGE images. **(B)** Head segmentation computed by the STAPLE algorithm: A closed, continuous representation of the skull has been segmented, following the individual curvature of the skull of the subject. Note that internal air has not been segmented and is (falsely) represented as skull as well. Furthermore, the cortical folding is not well represented by the GM segmentation. **(C)** Segmentation of air cavities (sinus frontalis, sphenoidal sinus, external auditory meatus). **(D)** Segmentation of intracranial tissue by the MGDM algorithm into a multitude of subtypes. The dura mater is highly overestimated.

Figure 5. Sagittal, coronal and axial slice of the brain segmentation obtained by the MGDM algorithm. The MGDM algorithm segments the brain into various sub-structures, which have been integrated into GM (brown color) and WM (blue color) in this visualization. **(A)** Original T_1 -weighted MP-RAGE images. **(B)** Segmentation output of MGDM. **(C)** The detail of the cortical surface is enhanced by the CRUISE-algorithm. Note the cingulate sulcus or the interhemispheric fissure, which are only weakly or not present in the MGDM segmentation.